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Flight-to-Liquidity and Excess Stock Return: Empirical Evidence from a Dynamic Panel Model

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Abstract: This study examines the impact of the flight-to-liquidity (FTL) phenomenon on the excess stock return by applying the previously developed generalised method of moments (GMM) framework. For this purpose, we use the data covering the period from 2004 to 2018 for 122 public companies listed on the Pakistan Stock Exchange (PSX). This study uses six proxies to measure the expected and unexpected illiquidity. The empirical investigation reveals that expected and unexpected illiquidities greatly influence smaller firms more notably than larger ones, which induces FTL phenomena into the market. Moreover, a FTL phenomenon triggered the Pakistani equity market during the financial crisis, when a significant decline appeared and the less liquid stocks were strongly affected. The results reveal that FTL risk is priced in the Pakistan equity market, making large stocks relatively more attractive in times of dire liquidity. These findings further suggest that the market participants in the Pakistan equity market, including policymakers, regulators and investors, should not ignore FTL phenomena while designing their portfolios.

Keywords: flight-to-liquidity; stock return; financial crisis; Pakistani equity market; investors

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1. Introduction

Flight-to-liquidity (FTL)[1] represents an ongoing debate in the academic literature (see Li et al. 2019). This debate among academicians and investors has emphasised the importance of different aspects of the FTL (also see Robatto 2019). This emphasis is consistent with the argument that there are different empirical dimensions of this financial market phenomenon (Acharya and Pedersen 2005). Despite all this, one of the possible reasons for the inclusive evidence is that liquidity is a multi-dimensional phenomenon, and it is hard to empirically incarcerate all dimensions of liquidity (Saeed and Hassan 2018). Therefore, it seems timely and appropriate that its multi-faceted aspect should be further investigated by incorporating six identified empirical dimensions of liquidity, including volume, turnover rate, the Amihud ratio, a modified form of the Amihud ratio, the percentage of zero returns, and a roll estimator.[2]

Liquidity was considered a key concern during the recent COVID-19 pandemic. In this regard, Chebbi et al. (2021) reported that the current, lingering pandemic is expected to deteriorate stock liquidity. The existing literature reveals that households and investors reallocate their investment portfolios during crises (Cardak et al. 2019). Along these lines, Beber et al. (2009) revealed that investors form a new portfolio during economic distress and prefer a less risky asset with more liquidity.[3] Over the last couple of decades, studies have provided important information on this financial market phenomenon. In particular, the history of this topic goes back to the mid-1980s.

Liquidity risk is used interchangeably for FTL by researchers (e.g., Li et al. 2019 and Amihud 2002) and has been reported as varying across time in terms of both individual stocks and equity market levels. Studies using the liquidity risk for FTL in market–maker-driven equity markets are extensive (Hasbrouck and Saar 2009; Hasbrouck and Seppi 2001; Chordia et al. 2001; Chang and Hsueh 2013). However, studies on liquidity risk and its impact on emerging equity markets are scarce and the impact is potentially different from that on developed equity markets. This difference is due to the dominant role of particular investors, different trading rules, or order-driven market structures such as the non-equity market that exists in Pakistan, and its study should add to the body of knowledge for other market structures by examining FTL in Pakistan (Li et al. 2019). The information asymmetry and transaction costs are more significant in such equity markets. Therefore, it is essential to analyse the impact of liquidity on stock return by using different dimensions of liquidity risk.

Furthermore, based on the above discussion, we examine how liquidity risk or FTL could affect stock returns. The core purpose of this study is to help answer this question by studying the effect of illiquidity on stock returns via panel data analysis of the period between 2004 and 2018. These 15 years were selected because the financial crisis of 2008 permeated the Pakistani equity market and was notably different from the Asian financial crisis of 1997. In addition, it is considered the largest financial crisis after the Great Depression of the 1930s. The findings of this study will help elucidate whether these elements are related to fundamental factors or are included for pricing purposes regarding individual stocks. Due to the postulated multi-dimension nature of FTL, a single measure of illiquidity is needed to provide a conclusive answer to the questions of this study. Therefore, this study considers several proxies for the illiquidity measures to examine the association of these proxies with excess stock return in the Pakistanis' equity market. Like most other markets, during the market crash between 2007 and 2008, the Pakistani equity market suffered a loss of billions of rupees. No one could escape the damage that led to the regulator's market freeze intervention. Liquidity is significant in an emerging economy such as Pakistan, due to the impacts on financial resource allocations and individual stock prices (also see Rahman et al. 2021).

This study applies the generalised method of moments (GMM) framework, proposed by Arellano and Bond (1991), to estimate the dynamic model of panel data. Within this framework, this study examines the impacts of expected and unexpected liquidity on the excess stock returns in the Pakistan Stock Exchange (PSX). The existing empirical literature has applied only a single measure of liquidity that would only capture some aspects of the equity market because it has been argued that liquidity is multi-dimensional. First, this study contributes to the current empirical literature by using several proxies for liquidity measures to address this critical concern of treating liquidity as unidimensional in scope. Second, this study provides evidence that expected and unexpected illiquidity influences smaller firms more strongly than larger firms, which induces the FTL phenomenon in the market. The study also investigates whether FTL risk is priced in the Pakistan equity market, making large stocks relatively more attractive in times of dire liquidity. These findings have some crucial policy implications. For instance, the market participants in the Pakistan equity market, including policymakers, regulators and investors, should not ignore FTL phenomena while designing their portfolios.

The rest of the paper is organised as follows. Section 2 presents the literature review, followed by Section 3, which explains the data, variables, framework of analysis and empirical strategy. Section 4 presents the results and a discussion, followed by a robustness analysis (Section 5). The study conclusions are provided in Section 6.

2. Literature Review

Comparatively recently, Li et al. (2019) revealed a positive association between almost all dimensions of stock illiquidity and excess stock returns. The empirical specifications of Li et al. (2019) refer back to Amihud (2002) and Liu (2006).[4] Li et al. (2019) further reveal that firms of different sizes respond differently to expected and unexpected illiquidity changes. In particular, the smaller size and the less-liquid stock react significantly to the changes in illiquidity. This finding of Li et al. (2019) supports the FTL phenomenon, as elaborated by Amihud (2002). On this nexus, some studies reveal that high-frequency bid–ask spreads also play a significant role when analysing the relationship between stock illiquidity and excess return (see Clark et al. 1992). Li et al. (2019) also provided evidence for the theoretical asset pricing model with liquidity risk, as employed by Acharya and Pedersen (2005). In addition, Tauseef and Dupuy (2022) stated that investors worldwide will invest in stocks with higher returns and low liquidity risk, owing to a direct association between liquidity and yield (also see Gholami et al. 2023; Arian and Sands 2022).

Interestingly, the findings of Li et al. (2019) also provide some evidence on most private investors and price impacts, revealing that these factors are the source of liquidity risk (FTL) in an order-driven market like China's stock market. However, the current study examines whether FTL phenomena exist in the Pakistani equity market, which has a different trading mechanism to the Chinese market. The Pakistani stock market is a weak, efficient market where outside news greatly affects investors. In turn, investors in the pre-crisis, within-crisis, and post-crisis periods exhibit excessive risk-taking aversion (Said et al. 2021). Furthermore, in 2016, the Pakistani equity market generated a higher return for investors than the Chinese market (Yousaf et al. 2018). Consequently, by using the exact liquidity dimensions used by Li et al. (2019) but working under a different trading mechanism to the Pakistani market, we should be able to identify whether the model is consistent in both countries.

This paper is the first to jointly test the cross-sectional and time-series effects of stock illiquidity, based on data from Pakistan's stock market, and examine their underlying mechanism. A critical review of the existing literature reveals that the related studies can be categorised into three strands. The first strand of the literature consists of cross-sectional studies (see Amihud and Mendelson 1986; Eleswarapu 1997; Brennan and Subrahmanyam 1996; Chalmers and Kadlec 1998; Easley et al. 2002; Amihud 2002; Bekaert et al. 2007). In particular, Amihud and Mendelson (1986) and Eleswarapu (1997) investigated the association between the quoted bid–ask spread and the stock return. Their findings reveal that the quoted bid–ask spread positively and statistically significantly impacted the stock returns. Some researchers have applied price impacts (Brennan and Subrahmanyam 1996) and the amortised effective spread (Chalmers and Kadlec 1998) to measure stock illiquidity. Both studies report that illiquidity has a positive effect on stock returns. In the early 2000s, Easley et al. (2002) contributed to the existing literature by investigating the role of information-based trading in asset prices. Their findings reveal that information affects asset prices. Emerging markets are expected to provide an ideal setting in which to analyse the impact of liquidity on stock returns. Along these lines, Bekaert et al. (2007) reported that local market liquidity is one of the critical drivers of expected returns.

The second strand of the literature is based on time-series studies (Amihud 2002; Jones 2002). Amihud (2002) reveals that the expected increase in illiquidity enhances the expected stock returns. Conversely, an unexpected rise in illiquidity decreases the stock returns. Working on similar lines, Jones (2002) applied the transaction cost as a proxy for illiquidity. The study published by Jones (2002) also reveals that illiquidity can be used as a predictor of stock returns. Another strand of literature (Zhang et al. 2009; Narayan and Zheng 2010; Yang 2015) relates to the liquidity-adjusted asset-pricing model. Furthermore, several prior studies claim that various dimensions in different stock markets can measure liquidity because it is a multi-dimensional concept (see Bhattacharya et al. 2019). Bervas (2006) identified five liquidity dimensions: immediacy, tightness, depth, breadth, and resilience. Along these lines, Díaz and Escribano (2020) argued that these dimensions are distinct. However, some have a close relationship (see Goyenko et al. 2009). Similarly, Díaz and Escribano (2022) demonstrated that it is vital to analyse the different dimensions of liquidity when deciding the extent of liquidity in a market.

The current empirical investigation investigates the relationship between illiquidity and stock returns. This study is different from previous studies in two distinct ways. First, a literature search did not find another published study that used the empirical designs employed in this framework. Second, the study applies various dimensional measures of illiquidity, compared to focusing on a single measure, as has occurred in prior studies. This discussion presents the relevant empirical conjecture below to test the impact of expected and unexpected liquidity on excess stock returns.

Hypothesis 1. *The* FTL *phenomenon affects the excess stock return.*

The FTL phenomenon is captured through expected and unexpected illiquidity. We can re-write the above hypothesis in this setting as "expected and unexpected illiquidity affects the excess stock return". Following Ali and Fraz (2020), we used six proxies for the expected and unexpected illiquidity. These six proxies and other control variables are elaborated on in the following section (Section 3).

3. Data, Variables, Framework of Analysis and Empirical Strategy

This section provides a concise and precise description of the experimental results, their interpretation, and the experimental conclusions that can be drawn.

3.1. Data

The study examines the impact of illiquidity on excess stock return by employing the firm-level data of 122 non-financial listed companies at PSX over 15 years from 2004 to 2018. Most variables have legitimate zero values or are less than zero. We added a constant with all those variables to resolve this issue. Kelly et al. (2019) argued that the interpretation is slightly changed by adding a constant; however, the sign of the coefficient remains the same. Following these suggestions, we add a constant in all those variables of zero or less than zero before taking the natural log. The variables used in the study are elaborated upon in the following sub-sections. We have compiled the proxies and formulas of the variables used in the study in Table A1 (Appendix A).

3.2. Dependent Variables

Following Ali and Fraz (2020), we used the excess stock return (ESR) as the dependent variable. This variable is measured as the the difference between annualised individual and annualised market returns from the monthly share prices and market index. The excess stock return can be represented as $Excess\ Stock\ Return = (R_{it} - R_{mt})$, where R_{it} is calculated as $Ln(P_{it}/P_{it-1})$. In this setting, P_{it} denotes the current stock price, $P_{it\text{-}1}$ denotes the previous stock price, and R_{ft} is the 6-month risk-free rate.

3.3. Independent Variables

3.3.1. Illiquidity

Illiquidity refers to trading smoothness in the financial market. In this study, we use six proxies to measure illiquidity. These proxies include (1) volume (VOL), (2) turnover rate (TOR), (3) Amihud ratio (AHR), (4) modified form of the Amihud ratio (MAH), (5) percentage of zero returns (POZ), and (6) roll estimator (ROL).[5] These proxies are measured using the daily trading data. The first liquidity proxy is daily trading volume, representing the average number of shares traded yearly. The second measure is the turnover rate, representing the ratio of a stock, and it reveals how many shares of a stock are sold at a specific time. Numerous studies measured it by dividing the daily average volume by the number of shares outstanding. The turnover rate was first introduced by Datar et al. (1998). Later, Brennan et al. (2011) insisted that turnover rate is a more suitable liquidity proxy than trading volume. The turnover rate is calculated by dividing the average number of stocks traded on day *t* by the shares outstanding.

The third measure is AHR, which captures the price impact. The existing literature has used it as an alternative measurement of illiquidity (see Amihud 2002). Here, we calculate it as $\mathrm{AHR\_}it = |〖Return〗\ \_(i,t)|/〖Volume〗\ \_(i,t)$. The denominator denotes the absolute daily return on stock i at time t. The numerator represents the daily averaged dollar volume of stock i at time t.

Brennan et al. (2011) used the modified form of Amihud's model (2002). In particular, Brennan et al. (2011) used the turnover rate instead of dollar volume. In this setting, the MAH is calculated as $〖\mathrm{MAH}〗\ \_(it) = ln(|〖Return〗\ \_(i,t)|/〖Turnover〗\ \_(i,t))$. Then, we use the percentage of zero-volume days as a fourth measure of illiquidity (Bekaert et al. 2007). This measure is calculated as the number of zero-return days of security i during time t, divided by the total trading days of security i for time t. The stock illiquidity directly relates to the percentage of zero-volume days. The high value of zero-return days shows that the market is illiquid.

The transaction cost feature of liquidity also matters in this nexus. Along these lines, Goyenko and Sarkissian (2010) proposed an improved version for measuring the transaction cost feature of liquidity. Following this version, we apply the roll estimator as the last measure of liquidity. However, this measure is only meaningful when the sample serial covariance is negative. The roll estimator is measured as follows:

$$ROL = {}^{2}_{0}\sqrt{-cov(\Delta P_t, \Delta P_{t-1})}\ \begin{array}{l} when\ Cov(\Delta \mathrm{P_t}, \Delta \mathrm{P_{t-1}}) < 0 \\ when\ Cov(\Delta \mathrm{P_t}, \Delta \mathrm{P_{t-1}}) \geq 0 \end{array} \tag{1}$$

where $-$Cov denotes the negative covariance between stock prices, ΔPt denotes the change in the current stock price, and $\Delta \mathrm{P_{t-1}}$ indicates the change in the previous stock price. A negative autocorrelation has been observed between the prices of securities when a bounce exists between the prices. More bounce in the price causes the high value of the roll estimator that shows a high transaction cost, indicating that the market is less liquid and less resilient.

3.3.2. Excess Market Return (EMR)

The EMR measures how much a fund has under- or outperformed the benchmark against which it is compared. This study uses excess market return to confirm the size robustness and is measured as $\mathrm{EMR}_t = \ln\left(R_{it} - R_{ft}\right)$, where $R_{it} = (P_{it}/P_{it-1})$, P_{it} denotes the current market price, $P_{it\text{-}1}$ denotes the previous market price, and R_{ft} is the 6-month risk-free rate.

3.3.3. Size (SIZ)

Size, sometimes known as market capitalisation, indicates the number of outstanding shares of a firm, and it is believed that $\ln(stock\ price * shares\ outstanding)$ is an appropriate measure of firm size since it has been employed in prior studies (see Lee et al. 2018). We use size as a moderating variable, along with liquidity risk, to check for strong liquidity and excess stock return. It can also be used to divert the attention of investor coverage. We calculate the size by taking the natural log of market capitalisation.

3.3.4. Momentum (MOM)

Momentum is a tool used to measure the price change, and it is measured as the cumulative return of the past twelve months. We calculate it as $MOM = \sum R_{t12} - R_{t-1}$, where R_{t12} denotes the returns of the past twelve months and R_{t-1} denotes the return of the previous month.

3.3.5. Dummy for Global Financial Crises

This study introduces a time t and time $t+1$ dummy of the crisis period of 2008 to test the liquidity difference during the crisis period. The Pakistani equity markets were badly affected during this crisis and the trading floor remained closed for 108 days.

3.3.6. Framework of the Analysis and Empirical Strategy

To test the basic CAPM, we estimate that this study will calculate the following equation:

$$E\left(R_{it} - R_{ft}\right)|Rmrf_t) = \alpha_0 + \alpha_1 EMR_t + \varepsilon_{it} \tag{2}$$

In Equation (2), R_{it} is the natural log of returns for stock i at time t, R_{ft} is the risk-free rate in the current period and ε_{it} represents the error term. *EMR* denotes the excess market return. Fama and French (1992) introduced the variable of size to check the asset performance and argued that the character associated with assets performed better than the beta. Carhart (1997) extended the Fama and French (1992) factor-based model by introducing the momentum factor. Following the existing literature, we present the size, value and momentum factor in Equation (2) with a risk factor.

$$E\left(R_{it} - R_{ft}\right)|Rmrf_t) = \alpha_0 + \alpha_1 EMR_t + \alpha_2 SIZ_{it} + \alpha_3 MOM_{it} + \varepsilon_{it} \tag{3}$$

In Equation (3), $Size_{it}$ denotes the market capitalisation of stock i at time t and MOM_{it} represents the momentum of stock i by time t. This study's main objective is to analyse the impact of illiquidity on the excess stock return. Therefore, we extend Equation (3) as follows.

$$E\left(R_{it} - R_{ft}\right)|lnILLIQ^E_{it}\right) = \alpha_0 + \alpha_1 EMR_t + \alpha_2 SIZ_{it} + \alpha_3 MOM_{it} + \alpha_4 lnILLIQ^E_{it} \tag{4}$$

In Equation (4), $ILLIQ_{it}$ denotes the stock illiquidity for each time and $〖lnILLIQ〗\_itE$ is the natural log of expected stock illiquidity for stock i at time t. In this setting, the natural log of the illiquidity for stock i at time t is represented as follows:

$$lnILLIQ〗\_it = \alpha\_0 + \alpha\_4〖lnILLIQ〗\_(it-1) + \varepsilon\_it \tag{5}$$

where $〖lnILLIQ〗\_(it-1)$ is the illiquidity of the previous year for stock i. Primarily, the investor predicts the current time illiquidity based on available information in the last time (t − *1*) and further uses forecasting to set the prices and generate the desired return for time t. The predicted illiquidity can be expressed as $〖lnILLIQ〗\_itE = \alpha\_0 + \alpha\_4〖lnILLIQ〗\_(it-1)$. By incorporating the unexpected illiquidity, we can express Equation (4) as follows:

$$E\left(R_{it} - R_{ft}\right)|lnILLIQ^E_{it}\right) = \alpha_0 + \alpha_1 EMR_t + \alpha_2 SIZ_{it} + \alpha_3 MOM_{it} + \alpha_5 lnILLIQ^U_{it} \tag{6}$$

where $lnILLIQ^U_{it}$ denotes the unexpected illiquidity at time t, and $lnILLIQ^U_{it}$ is equal to $\varepsilon_{\mathrm{it}}$. From here onwards, we use *EXP* and *UEX* to denote the expected and unexpected illiquidity, respectively. In this setting, we present our regression model as follows:

$$ESR_t = \alpha_0 + \alpha_1 EXP_{it-1} + \alpha_2 UEX_{it} + \alpha_3 EMR_t + \alpha_4 SIZ_{it} + \alpha_5 MOM_{it} + \mu_{it}. \tag{7}$$

The investor sets the prices at the start of the current period (time t) to generate the expected returns for the current period. In this framework, the error term denotes the unexpected excess return. Finally, to explore the effect of the crisis period on excess stock return, we introduce the crisis dummy at time t and time $t + 1$ in Equation (7), where D_t denotes the effect of crisis at time t and D_{t+1} represents the effect of crisis at time $t + 1$. By introducing a crisis dummy, we develop Equation (8).

$$\begin{aligned} ESR_t = \alpha_0 + \alpha_1 EXP_{it-1} + \alpha_2 UEX_{it} + \alpha_3 EMR_t + \alpha_4 SIZ_{it} + \alpha_5 MOM_{it} + \alpha_6 D_t \\ + \alpha_7 D_{t+1} + \mu_{it} \end{aligned} \tag{8}$$

We start our empirical strategy by selecting an appropriate technique for the panel data. It is, perhaps, essential to note that the panel data has advantages over the time series data. For instance, the panel setting helps mitigate the multicollinearity between the explanatory variables. Furthermore, the panel setting enhances the efficiency level of estimation by overcoming the omitted variable biases. The panel data address other estimation issues, including heterogeneity and serial correlation. However, the existing empirical literature reveals that panel data are prone to problems. Therefore, an appropriate estimation technique section is critical for arriving at unbiased and efficient estimates (Neagu and Teodoru 2019; Baltagi 2005; Sarafidis and Wansbeek 2012). We estimated Equation (7) by applying the generalised method of moments (GMM) framework proposed by Arellano and Bond (1991). Busu (2019) revealed that panel datasets have several advantages over other datasets. Our panel dataset used a wide range of data from 122 firms from 2004 to 2018. This setting helps in decreasing the multicollinearity between the independent variables.

Furthermore, panel data estimation overcomes the issue of omitted variables and enhances the estimation efficiency (Rahman et al. 2020). Following Equation (7), the excess stock return is a lagged dependent variable. The empirical literature reveals that the estimates via ordinary least squares are subject to biases in the presence of lagged dependency (also see Alí et al. 2017; Beaver and Ryan 2000). Nickell (1981) indicated that the alternative estimation techniques of standard fixed effects are also subject to the Nickell bias, especially when the number of cross-sections is larger than the time, as in our dataset. We have a panel dataset with a cross-section ($N = 122$) that is significantly greater than the time ($T = 15$). Furthermore, there might be autocorrelation in the residuals of Equation (7). Rahman et al. (2020) suggested that one should carefully model the dynamic data-generating process and autocorrelation to arrive at consistent and unbiased estimates (also see Rahman and Ali 2022; Rahman et al. 2023; Gholami et al. 2022).

In this setting, the lags of the dependent variables are suggested for use as instruments (Anderson and Hsiao 1981).[6] Furthermore, regarding these lags of dependent variables, Cameron and Trivedi (2010) indicated that the residuals of the Blundell/Bond or Arellano/Bover usually are not serially correlated. However, the Blundell/Bond or Arellano/Bover residuals can sometimes be serially correlated. In these cases, Cameron and Trivedi (2010) suggested that the additional lags of the dependent variables should be added as the regressors to overcome this problem. Following these suggestions, we applied the generalised method of moments (GMM) framework proposed by Arellano and Bond (1991) since the excess stock returns are the lagged dependent. Furthermore, the dynamic panel data estimation allows the predetermined variables to incorporate complex structures. The following section presents the results, along with a discussion.

4. Results and Discussion

This study uses the firm-level data of 122 non-financial listed companies at PSX for 15 years from 2004 to 2018, employing them in a regression equation to observe the impact of illiquidity on excess stock return. Based on the empirical strategy outlined in Section 3.3.6, we applied the generalised method of moments (GMM) framework proposed by Arellano and Bond (1991) to arrive at unbiased and consistent estimates. Here, the excess stock return was the dependent variable, while illiquidity was the explanatory variable used in this study. As elaborated in Section 3.3.1, illiquidity was further divided into expected and unexpected illiquidity. Following the existing empirical literature, we used the market risk factor, size, momentum, and crisis dummy for 2008 and 2009 as the additional explanatory variables. The following section presents the descriptive statistics, panel unit root, and dynamic panel estimation results.

4.1. Descriptive Statistics

Table 1 presents an overview of the statistical trend of the study's dependent and independent variables. In particular, Table 1 provides the descriptive statistics, including the mean, standard deviation, minimum and maximum variables included in the study. In Table 1, the overall value (N) shows the overall observations, between (n) indicates the total number of companies and within (T) shows the number of years. The results from the descriptive analysis of the average excess stock return, market risk factor, size and momentum are summarised in Table 1. Furthermore, (1) the average expected volume, (2) unexpected volume, (3) expected turnover, (4) unexpected turnover, (5) expected Amihud, (6) unexpected Amihud, (7) expected Amihud2, (8) unexpected Amihud2, (9) expected percentage of zero-volume days, (10) unexpected percentage of zero-volume days expected roll estimator and (11) unexpected roll estimator are also summarised in Table 1.

Table 1. Summary statistics.

Variable		Mean	Std. Dev.	Min	Max	Observations
ESR	Overall	0.7214	0.2647	0.0723	2.0357	$N = 1830$
	Between		0.0475	0.6125	0.8979	$n = 122$
	Within		0.2604	0.0739	1.9556	T = 15
EMR	Overall	0.7414	0.1250	0.4076	0.9226	$N = 1830$
	Between		0.0000	0.7414	0.7414	$n = 122$
	Within		0.1250	0.4076	0.9226	T = 15
SIZ	Overall	3.0601	0.0998	2.7477	3.2984	$N = 1830$
	Between		0.0913	2.8418	3.2429	$n = 122$
	Within		0.0410	2.9158	3.1706	T = 15
MOM	Overall	1.3997	0.1299	0.6781	1.9873	$N = 1830$
	Between		0.0245	1.3351	1.4593	$n = 122$
	Within		0.1276	0.7427	1.9899	T = 15
eVOL	Overall	10.1058	1.5095	6.0345	16.6249	$N = 1830$
	Between		1.3562	7.6426	13.4022	$n = 122$
	Within		0.6734	7.7857	13.3284	T = 15
uVOL	Overall	−0.0164	1.0584	−6.0788	8.8312	$N = 1830$
	Between		0.2974	−0.7429	0.5933	$n = 122$
	Within		1.0161	−5.8474	8.4526	T = 15
eTOR	Overall	0.0021	0.0033	−0.0009	0.0443	$N = 1830$
	Between		0.0031	0.0000	0.0162	$n = 122$
	Within		0.0012	−0.0020	0.0386	T = 15
uTOR	Overall	0.0000	0.0043	−0.0398	0.0508	$N = 1830$
	Between		0.0004	−0.0007	0.0022	$n = 122$
	Within		0.0043	−0.0391	0.0486	T = 15
uAHR	Overall	0.0000	0.0000	0.0000	0.0001	$N = 1830$
	Between		0.0000	0.0000	0.0000	$n = 122$
	Within		0.0000	−0.0001	0.0001	T = 15
eMAH	Overall	3.9215	0.8602	0.8156	8.1736	$N = 1830$
	Between		0.6636	2.8836	5.8909	$n = 122$
	Within		0.5504	1.8535	6.2042	T = 15
uMAH	Overall	0.0096	1.0372	−4.5649	6.9235	$N = 1830$
	Between		0.3050	−0.5845	0.8587	$n = 122$
	Within		0.9917	−4.5764	6.0744	T = 15
ePOZ	Overall	0.2803	0.2252	0.0057	0.8508	$N = 1830$
	Between		0.2236	0.0104	0.8471	$n = 122$
	Within		0.0333	0.0556	0.5701	T = 15
uPOZ	Overall	0.0025	0.1585	−0.5613	0.8950	$N = 1830$
	Between		0.0064	−0.0168	0.0201	$n = 122$
	Within		0.1584	−0.5701	0.9020	T = 15
eROL	Overall	0.0073	0.0139	−0.0054	0.1418	$N = 1830$
	Between		0.0135	0.0000	0.0865	$n = 122$
	Within		0.0035	−0.0053	0.0915	T = 15

Table 1. *Cont.*

Variable		Mean	Std. Dev.	Min	Max	Observations
uROL	Overall	0.0000	0.0158	−0.1623	0.1880	N = 1830
	Between		0.0005	−0.0020	0.0029	n = 122
	Within		0.0158	−0.1607	0.1869	T = 15

Note. Descriptive statistics are calculated for each variable from 2004 to 2018. ESR, EMR, SIZ, MOM, eVOL, uVOL, eTOR, uTOR, uAHR, eMAH, uMAH, ePOZ, uPOZ, eROL and uROL represent (1) excess stock return, (2) the excess market return, (3) the total capitalisation of a firm, (4) the momentum of each stock, (5) expected illiquidity, measured through volume, (6) unexpected illiquidity, measured through volume, (7) expected illiquidity, measured through turnover rate, (8) unexpected illiquidity, measured through turnover rate, (9) unexpected illiquidity, measured through the Amihud ratio, (10) expected illiquidity, measured through a modified form of the Amihud ratio, (11) unexpected illiquidity, measured through a modified form of the Amihud ratio, (12) expected illiquidity, measured through the percentage of zero returns, (13) unexpected illiquidity, measured through the percentage of zero returns, (14) expected illiquidity, measured through a roll estimator and (15) unexpected illiquidity, measured through a roll estimator, respectively. See Section 3.3.1 and Table A1 (Appendix A) for further details. We removed eAHR (expected illiquidity, measured through the Amihud ratio) due to the significantly lower values. The total number of observations (N) is 1830, the entire companies (n) are 122, and the total number of years (T) is 15.

4.2. Panel Unit Root Test

Chang et al. (2011) suggested that a unit root test is also required for panel data estimation. Furthermore, Lee et al. (2021) stated that the panel unit root test has higher power than individual time-series data. However, it is better to analyse the data stationarity before analysing the panel data. Following these guidelines, we conducted a panel unit-root test to check the data stationarity. This study employed the Levin–Lin–Chu and Breitung unit-root tests to provide reliable and unbiased findings. Prior studies by Chen et al. (2013) and Olaniyi (2017) also employed both tests to check data stationarity. The results of the panel unit root test are reported in Table 2. The p-values for all variables are less than 0.05, which shows that the null hypothesis of the unit root is rejected, revealing that all variables are stationary at a five per cent significance level. Before regression analysis, the assumption is fulfilled, indicating that there is no problem when examining the effect of FTL on excess stock return.

Table 2. Panel unit root tests.

	Levin–Lin–Chu Unit-Root Test		Breitung Unit-Root Test	
	t-Statistics	p-Value	z-Statistics	p-Value
ESR	−10.4868	0.0000	−9.1768	0.0000
EMR	−16.1771	0.0000	−13.2449	0.0000
SIZ	−6.9266	0.0000	−3.9662	0.0000
MOM	−10.4304	0.0000	−9.5532	0.0000
VOL	−13.9921	0.0000	−9.5207	0.0000
TOR	−39.5634	0.0000	0.4967	0.6903
AHR	−19.2556	0.0000	−10.3210	0.0000
MAH	−11.2729	0.0000	−7.6693	0.0000
POZ	−10.5674	0.0000	−9.0050	0.0000
ROL	−79.0874	0.0000	−7.4975	0.0000

Note. We report adjusted t-statistics for the Levin–Lin–Chu unit root test. Levin–Lin–Chu hypotheses: Ho: panels contain unit roots. Ha: panels are stationary. L.R. variance: Bartlett kernel, 7.00 lags average (chosen by LLC). ESR, EMR, SIZ, MOM, VOL, TOR, AHR, MAH, POZ and ROL represent excess stock return, the market risk factor, the total capitalisation of a firm, the momentum of each stock, volume, turnover rate, the Amihud ratio, the modified form of the Amihud ratio, the percentage of zero returns, and the roll estimator, respectively. The panel unit root is applied to the unexpected VOL, TOR, AHR, MAH, POZ and ROL series. See Section 3.3.1, along with Table A1 (Appendix A) for further details.

4.3. Dynamic Panel Estimation Results

Columns 1 to 6 of Table 3 present the results of six separate models, estimated using six proxies for illiquidity, including (1) volume (VOL), (2) turnover rate (ToR), (3) the Amihud ratio (AHR), (4) a modified form of the Amihud ratio (MAH), (5) the percentage of zero returns (POZ), and (6) roll estimator (ROL), respectively.[7] We ran six models separately by using six different dummies of illiquidity. One model was estimated for each proxy. For instance, the results of the first model are presented in column 1. In this model, ESR is the dependent variable, and Vol is the proxy for illiquidity. The rest of the models use TOR, AHR, MAH, POZ and ROL as the proxies for illiquidity. These six proxies represent volume, turnover rate, the Amihud ratio, a modified form of the Amihud ratio, the percentage of zero returns, and the roll estimator, respectively.

Table 3. Impact of illiquidity risk on excess stock return for the period from 2004 to 2018.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	**ESR**	**ESR**	**ESR**	**ESR**	**ESR**	**ESR**
Independent Variable:	**VOL**	**TOR**	**AHR**	**MAH**	**POZ**	**ROL**
EXP	0.0195 ***	9.8595 ***	−104035.6 ***	−0.0235 ***	0.7785 ***	4.0610 ***
	6.1393	1.2304	−7.5304	−6.7391	6.9951	12.7250
UEX	0.0067 ***	4.7376 ***	−1249.5560 ***	−0.0038 ***	−0.0291 ***	−0.2154 ***
	5.7974	0.4983	−4.5594	−3.0811	−4.7610	−3.8115
ESR_1	−0.0028 *	−0.0079 ***	−0.0089 ***	−0.0075 ***	−0.00778 ***	−0.0092 ***
	−1.6611	0.0020	−5.1577	−4.3856	−4.4780	−5.6724
EMR	0.1079 ***	0.1184 ***	0.1340 ***	0.1103 ***	0.1184 ***	0.1314 ***
	13.7506	0.0096	17.3542	11.5220	13.6315	15.3556
SIZ	0.4596 ***	0.3998 ***	0.4280 ***	0.5212 ***	0.5168 ***	0.4216 ***
	13.1500	0.0278	19.1242	14.7988	21.3765	16.8849
MOM	1.9663 ***	1.9614 ***	1.9717 ***	1.9729 ***	1.9701 ***	1.9697 ***
	185.6430	0.0090	231.1130	175.1271	207.1737	222.7955
Dt	−0.1211 ***	−0.1193 ***	−0.1172 ***	−0.1223 ***	−0.1218 ***	−0.1206 ***
	−24.6004	0.0049	−23.6118	−23.1721	−25.4775	−26.4882
Dt+1	0.1361 ***	0.1369 ***	0.1415 ***	0.1401 ***	0.1458 ***	0.1439 ***
	23.2053	0.0059	23.8861	21.5424	27.2340	25.6830
AR1	−6.3552	−6.2733	−6.3372	−6.2964	−6.2579	−6.3075
(m, *p*-value)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
AR2	−0.3302	−0.4281	−0.2212	−0.4332	−0.3940	−0.4561
(m, *p*-value)	0.7413	0.6686	0.8250	0.6649	0.6935	0.6483

Note. ESR is the dependent variable in all the models. EXP, UEX, EMR, SIZ and MOM represent (1) expected illiquidity, (2) unexpected illiquidity, (3) excess market return, (4) the total capitalisation of a firm, and (5) the momentum of each stock, respectively. D_t is the effect of crisis at time t. D_{t+1} is the dummy of the crisis (2008) period of stock i at time t. EXP indicates the expected illiquidity of stock i at time t and UEX is the unexpected illiquidity, which is shown as $ILIQ_{it-1}$, $ILLIQ^U_{it}$ in Equation (8). We ran six models separately by using six different dummies of illiquidity. One model was estimated for each proxy. For instance, the results of the first model are presented in column 1. In this model, ESR is the dependent variable, and Vol is the proxy for illiquidity. The rest of the models use TOR, AHR, MAH, POZ and ROL as the proxies for illiquidity. These six proxies represent volume, turnover rate, the Amihud ratio, a modified form of the Amihud ratio, the percentage of zero returns, and the roll estimator, respectively. See Section 3.3.1 and Table A1 (Appendix A) for further details. Standard errors are presented in parentheses. * $p < 0.1$, *** $p < 0.01$.

Table 3 is quite revealing in several ways. Table 3 provides estimation results of the generalised method of moments (GMM) framework proposed by Arellano and Bond (1991). The results of Table 3 show that the market risk factor has a significant positive coefficient. These results are consistent with those in the study by Liu (2006); these findings suggest that excess stock returns also catalyse market risk. The variable coefficient for the size is significant and positive at a five per cent significance level. These results are supported by the study of Saeed and Hassan (2018) and show that no firm size anomaly exists in the Pakistan equity market. Furthermore, the results of this study indicate that momentum is positively significant, which finding is inconsistent with the study by Saeed and Hassan (2018).

Moreover, this study uses six proxies to measure the expected and unexpected illiquidity. Four of the six expected and unexpected illiquidity measures reveal a positive and negative association with excess stock returns, respectively (see the EXP and UEX coefficient estimates in Table 3).[8] The existing empirical literature (Li et al. 2021; Amihud 2002; Liu 2006; Bekaert et al. 2007; Fama and French 1989) provided the same findings and documented the fact that expected and unexpected illiquidity responded differently as concerning measures. Furthermore, the results of this study suggest that both effects should be weaker for more liquid firms or stocks because these stocks are more attractive than less liquid firms or stocks during a period of dire illiquidity. This finding reveals that expected and unexpected illiquidity affects smaller firms more strongly than larger ones, which induces the FTL phenomenon. Moreover, Pástor and Stambaugh (2003) stated that no investor included those stocks in their portfolio.

Turning now to the results for the dummies, the excess stock return was affected during crisis time. Furthermore, it is apparent from Table 3 that the effect of the crisis exists after the crisis period. However, the impact is positive after the crisis. The results for the crisis dummies are consistent with the existing literature (Amihud et al. 1990; Shiller et al. 1991). These results further reveal that illiquidity increases during the crisis period, which induces FTL phenomena in the market and influences less liquid stock. The prices of stocks decline during the crisis period if they have higher return exposure to market illiquidity shocks (Dang and Nguyen 2020). Hence, investors should be concerned about the high liquidity risk of stocks. Table 3 demonstrates that most of the findings are consistent with prior studies, which reveal that FTL risk is priced in the Pakistan equity market. In light of the global financial crisis (GFC) in 2008, it should be emphasised that market liquidity is a significant systematic risk. Therefore, investors should consider this risk more specifically when designing portfolios because it has been observed that investors demand liquidity from their investments. Moreover, FTL makes large stocks relatively more attractive in times of dire liquidity.

5. Robustness Analysis

In this section, we extend our analysis to robustness to ensure the reliability of the results. Furthermore, this section is also used for model selection purposes. We start our analysis by estimating nine separate models for each proxy of illiquidity. Following our framework of analysis, we use six proxies for illiquidity, including volume, turnover rate, the Amihud ratio, a modified form of the Amihud ratio, the percentage of zero returns, and the roll estimator. In the first step, we estimate 54 (9×6) models to select the best model for each proxy in this setting. In simple terms, we estimate nine sets of models for each proxy. For instance, we estimate the first set of nine models using VOL as the proxy for illiquidity. We estimate the first model of the first set by including EMR as an explanatory variable (adjusted R2 = 0.199; F-statistics = 454.880, $p < 0.00$). In addition to EMR, SIZ and MOM are the explanatory variables in the second model of the first set (adjusted R2 = 0.875; F-statistics = 4275.148, $p < 0.00$). We include expected and unexpected illiquidity as the explanatory variables, in addition to EMR, SIZ and MOM in the third (adjusted R2 = 0.889; F-statistics = 3425.234, $p < 0.00$), fourth (adjusted R2 = 0.891; F-statistics = 3495.264, $p < 0.00$) and fifth (adjusted R2 = 0.891; F-statistics = 2797.146, $p < 0.00$) models of the first set. The statistical analysis reveals that the independent variables explain 88.90, 89.10 and 89.10 per cent variations in the dependent variable by the third to fifth models of the first set.

We include the interaction of size and unexpected illiquidity in model five, which improves the model's explanatory power (adjusted R2 = 0.892; F-statistics = 2331.972, $p < 0.00$). In the seventh model of the first set, we include D_t and D_{t+1} as the additional explanatory variables, which further improves the explanatory power (Adjusted R2 = 0.895; F-statistics = 2083.273, $p < 0.00$) and, interestingly, all the variables are statistically significant at a one per cent level of significance. In addition to all the variables of model seven, we include the interactions of D_t and D_{t+1} with the unexpected illiquidity in model eight of the first set (Adjusted R2 = 0.895; F-statistics = 1619.756, $p < 0.00$). However, both interactions are statistically insignificant at any significance level, including 1%, 5%, and 10%. Ultimately, we include the interaction of size and unexpected illiquidity in model number eight (Adjusted R2 = 0.898; F-statistics = 1459.391, $p < 0.00$). Nonetheless, the interaction of size and unexpected illiquidity is not statistically significant at any significance level, including 1%, 5%, and 10%.

We repeat these nine sets of models for the rest of the illiquidity proxies, including turnover rate, the Amihud ratio, a modified form of the Amihud ratio, the percentage of zero returns, and the roll estimator. The estimates of all 54 models reveal that our results are consistent in terms of the explanatory power, the explanatory variables' individual significance, and the model's overall significance. Furthermore, the results of these 54 models reveal that illiquidity explains a significant portion of the excess stock returns. Therefore, the results of these nine sets of models are robust and confirm the results presented in Table 3, above.

6. Conclusions

The study examines the FTL phenomenon in the context of the Pakistan equity market. This study uses six proxies to measure the expected and unexpected illiquidity and analyse whether the FTL phenomena exist during and after a crisis. The findings of this study reveal that expected and unexpected illiquidity influences smaller firms more strongly than larger firms, which induces the FTL phenomena in the market. These findings are consistent with prior studies (Li et al. 2021; Amihud 2002; Liu 2006; Bekaert et al. 2007; Fama and French 1989). Moreover, the FTL phenomenon triggered the Pakistani equity market during the financial crisis when a significant decline appeared and less liquid stocks were highly affected. These results also align with previous studies (Amihud et al. 1990; Shiller et al. 1991). Our investigation also reveals that FTL risk is priced in the Pakistan equity market. This phenomenon makes large stocks relatively more attractive in times of dire liquidity. These findings suggest that market participants in the Pakistani equity market, including policymakers, regulators and investors, should not ignore FTL phenomena when designing their portfolios.

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Appendix A

Table A1. Variable names, symbols, proxies and their definition/construction.

Variable Name.	**Symbol/Proxy.**	**Definition/Construction.**
Excess stock return.	ESR.	Annualized individual returns (R_it)–Annualized market returns (R_mt). For further details, see Section 3.2.
Excess market return.	EMR.	$\ln\left(R_{it} - R_{ft}\right)$. For further details, see Section 3.3.2.
Size.	SIZ.	ln [(Stock price) X* (shares outstanding)].
Momentum.	MOM.	The return of the past twelve months—The return of the previous month.
Illiquidity Proxies		
Volume.	VOL.	The average number of shares traded in a year.
	eVOL	The expected illiquidity, measured through VOL
	uVOL	The unexpected illiquidity, measured through VOL
Turnover rate	TOR	The average number of stocks traded on day t by the shares outstanding.
	eTOR	The expected illiquidity, measured through TOR
	uTOR	The unexpected illiquidity, measured through TOR
Amihud ratio	AHR	The absolute daily return/the daily averaged dollar volume
	eAHR	The expected illiquidity, measured through AHR
	uAHR	The unexpected illiquidity, measured through AHR
Modified form of Amihud ratio	MAH	The absolute daily return/turnover rate
	eMAH	The expected illiquidity, measured through MAH
	uMAH	The unexpected illiquidity, measured through MAH
Percentage of zero returns	POZ	The number of zero-return days/the total trading days
	ePOZ	The expected illiquidity, measured through POZ
	uPOZ	The unexpected illiquidity, measured through POZ
Roll estimator	ROL	$Roll =_0^2 \sqrt{-cov(\Delta P_t, \Delta P_{t-1})}$
	eROL	The expected illiquidity, measured through ROL
	uROL	The unexpected illiquidity, measured through ROL

Note. Please see Section 3 for the details of these variables. For further details, see Ali and Fraz (2020).

Notes

1 FTL is a financial market phenomenon in which investors sell less liquid or higher-risk investments and replace them with more liquid ones. The market participants trade based on their perception. In particular, they perceive that less liquid stock is a highly risky asset. Conversely, they perceive that highly liquid stock has less associated risk. Typically, FTL leads to fear, which then leads to a crisis.

2 See Section 3.3.1 for the complete details on these dimensions.

3 This phenomenon is commonly referred to as FTL.

4 However, these time-series studies focused on the individual stock and ignored the market average illiquidity. We attempt to capture the common behaviour of the group by incorporating more information, variability, and efficiency. For this purpose, we use panel data, which allows us to control for stock common-effects in our estimations.

5 We use "VOL", "ToR", "AHR", "MAH", "POZ" and "ROL" to represent the volume, turnover rate, Amihud ratio, modified form of the Amihud ratio, percentage of zero returns, and roll estimator, respectively.

6 However, it must be ensured that these lags are not correlated with the residuals.

7 In terms of model specification, we used model number seven. For further details, see Section 5, Robustness Analysis.

8 Comparatively recently, Li et al. (2019) revealed a positive association between almost all dimensions of stock illiquidity and excess stock returns. The empirical specifications of Li et al. (2019) refer back to Amihud (2002) and Liu (2006). However, these time-series studies focused on the individual stock and ignored the market average illiquidity. We attempt to capture

the common behaviour of the group by incorporating more information, variability and efficiency. For this purpose, we use panel data, which allows us to control for stock common-effects in our estimations. Li et al. (2019) further revealed that firms of different sizes respond differently to changes in expected and unexpected illiquidity. In particular, smaller-sized and less liquid stocks respond significantly to changes in illiquidity. This finding, reported by Li et al. (2019), supports the FTL phenomenon, as elaborated by Amihud (2002).

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