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Impact of oil price and market volatility on the relationship between Saudi stock prices and illiquidity

Hela Ben Soltane [1, 2, *]

[1]*Department of Economics and Finance, College of Business Administration, University of Ha'il, Ha'il, Saudi Arabia*
[2]*ESCT, LARIMRAF LR21ES29, University of Manouba, Manouba, 2010, Tunisia*

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ABSTRACT

This study examines whether stock price sensitivity to illiquidity shocks changes over time in the Saudi stock market. Using structural break analysis, the research identifies shifts in the sensitivity of stock prices to illiquidity. A Markov switching model is then applied to understand these changes. The results indicate that small firms experience two distinct regimes, with illiquidity shocks reducing stock prices in the first regime ten times more than in the second. For large firms, stock price responses to illiquidity shocks vary across three regimes: in the first, prices decrease; in the second, prices remain stable; and in the third, prices drop sharply. Further analysis shows that higher market volatility significantly increases the impact of illiquidity shocks on small firms, while large firms are more sensitive to illiquidity shocks following periods of negative market performance. The study finds no evidence that changes in oil prices influence the relationship between illiquidity shocks and stock prices. These findings provide valuable insights for investors to predict periods of high illiquidity risk and implement effective investment strategies.

1. Introduction

Illiquidity risk is defined by the systematic risk which measures the sensitivities of asset returns to market illiquidity shocks, through the beta of illiquidity (Pástor and Stambaugh, 2003; Acharya and Pedersen, 2005). Stocks whose returns are more sensitive to illiquidity shocks, i.e., with higher illiquidity beta, are considered as riskier. Theoretical and empirical literature that analyzed the illiquidity beta on different markets showed that shocks of market illiquidity have a pervasive negative effect on asset returns and that the magnitude of this effect depends on the firm size, i.e., stocks of small firms are more sensitive to market illiquidity shocks than those of large firms, and then have higher illiquidity risk (Pástor and Stambaugh, 2003; Acharya and Pedersen, 2005; Watanabe and Watanabe, 2008; Acharya et al., 2013; Amihud and Noh, 2021; Ben Soltane and Naoui, 2021; Soltane, 2023). Literature reveals also that the systematic illiquidity risk of assets varies over time. Watanabe and Watanabe (2008) proved that illiquidity betas of large and small stocks vary across two different regimes: one regime with high illiquidity beta and another regime with low illiquidity beta. They find that regimes with high illiquidity beta are characterized by a short duration, heavy trade, and high volatility. Brunnermeier and Pedersen (2009), Jensen and Moorman (2010), and Acharya et al. (2015) also found that illiquidity beta varies across two regimes. They found that the rise of illiquidity beta during one regime is related to the funding illiquidity of traders on markets. Indeed, traders have to provide liquidity on the market, and their ability to do that depends on their funding liquidity. Furthermore, Acharya et al. (2013) focused on US corporate bonds to describe the dynamics of illiquidity beta. They found that illiquidity shocks do not significantly affect bond returns in one regime, while they considerably reduce bond returns in another regime during which the illiquidity beta significantly increases. They prove that the increase in illiquidity risk is due to financial and economic distress. Amihud and Noh (2021) proved that the beta of IML (Illiquid Minus Liquid) rises during one regime which is characterized by market financial distress. Ben Soltane and Naoui (2021) also found in an emerging market that illiquidity risk rises during one regime

* Corresponding Author.
Email Address: he.ghazali@uoh.edu.sa
https://doi.org/10.21833/ijaas.2025.01.018
Corresponding author's ORCID profile:
https://orcid.org/0000-0002-0615-4807

which is characterized by the increase of funding illiquidity of traders and by economic distress.

The objective of this research is to explore the dynamics of the market illiquidity risk on the largest stock market in the Middle East, the Saudi Stock Exchange, and to examine the causes of these dynamics. The paper proceeds as follows. Section 2 describes the data. In section 3, I test the presence of structural breaks in market illiquidity risk and then the adequacy of Markov switching models that describe structural breaks for each portfolio, to quantify breaks over time. Section 4 aims to manage extreme illiquidity risk by examining the relationship between high illiquidity risk and oil prices as well as other market factors. Section 5 summarizes and concludes the research.

2. Description of data and methodology

I employ a large database that includes all stocks that are continuously listed on the Saudi Stock Exchange from December 31st, 2001, to June 30th, 2021. Studying covers a period of twenty and a half years. Data are daily and consist of prices and trading volumes of all stocks (214 stocks). Daily prices of the Saudi market index TASI (Tadawul All Share Index) and the daily Saudi Arabian Interbank Offered Rate (SAIBOR) are also included in the dataset. The latter is used as a proxy of the risk-free rate return. The empirical analysis relies also on the daily spot prices of WTI crude oil.

I characterize each stock by a return and by an illiquidity level. Return of stock i at day d, $r_{i,d}$, is computed by the following equation where $P_{i,d,t}$ and $P_{i,d-1,t}$ are respectively stock prices at days d and $d-1$ of the week t.

$$r_{i,d} = 100 \times \frac{P_{i,d,t} - P_{i,d-1,t}}{P_{i,d-1,t}}. \tag{1}$$

Stocks having zero daily returns and /or zero trading volumes during three consecutive weeks are removed from the sample, to avoid erratic values of illiquidity measures. I use the Amihud (2002) illiquidity ratio at a weekly frequency to measure the illiquidity of each stock. It is one of the most widely used liquidity measures in the finance literature (Lou and Shu, 2017). The first advantage of the Amihud (2002) measure is its simple construction that uses the absolute daily return to volume ratio. The second advantage of this measure is its strong relation with the expected asset return as shown in many studies (Amihud, 2002; Acharya and Pedersen, 2005; Acharya et al., 2013). Eq. 2 provides the expression of the illiquidity measure through the average over the week of the daily ratio of absolute stock return to trading volume as follows:

$$illiq_{i,t} = \frac{1}{D_{i,t}} \times \sum_{d=1}^{D_{i,t}} \frac{|r_{i,d,t}|}{Vol_{i,d,t}}. \tag{2}$$

where, $illiq_{i,t}$ provides the illiquidity level of stock i at week t, where $D_{i,t}$ is the number of daily observations of stock i during week t, $Vol_{i,d,t}$ is the stock's daily trading volume at week t (measured in million Saudi Riyal), and $|r_{i,d,t}|$ is the absolute value of daily stock return at week t computed by Eq. 1. $illiq_{i,t}$ is interpreted by the weekly price response to the trading volume. The higher value of $illiq_{i,t}$, the more illiquid the stock is. Stocks in the final sample are sorted into two-sized portfolios, the stock portfolio of small firms and the stock portfolio of large firms, based on the classification of the Saudi General Authority of Small and Medium Enterprises. Portfolio stock returns are computed each week t by:

$$r_{Sm,t} = \frac{1}{N_{Sm,t}} \sum_{i=1}^{N_{Sm,t}} r_{i,t} \tag{3}$$

$$r_{L,t} = \frac{1}{N_{L,t}} \sum_{i=1}^{N_{L,t}} r_{i,t} \tag{4}$$

where, $r_{Sm,t}$ ($r_{L,t}$) denotes the weekly portfolio returns of small (large) firms' stocks, $N_{Sm,t}$ ($N_{L,t}$) are the number of stocks included in small (large) firms' portfolios at week t, and $r_{i,t}$ is the weekly stock return which is computed by the following equation where $P_{i,d-4,t}$ is the stock price at day $d-4$ of week t.

$$r_{i,t} = 100 \times \frac{P_{i,d,t} - P_{i,d-4,t}}{P_{i,d-4,t}}. \tag{5}$$

Fig. 1 plots the behavior of each portfolio returns distribution. It shows that weekly returns of the largest portfolio vary less than those of the smallest portfolio. Returns of the smallest portfolio reach higher values than those of the largest portfolio. This is also confirmed in Table 1 which summarizes descriptive statistics of both distributions.

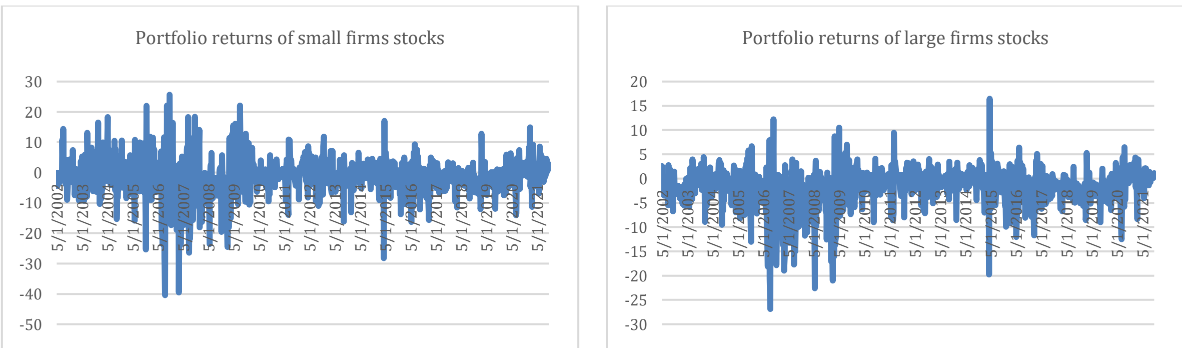

Fig. 1: Times series of portfolio returns of large firms' stocks and large firms' stocks

In Table 1, values of means and standard deviations prove that returns of the smallest portfolio are on average higher and more volatile than those of the largest portfolio. The skewness and kurtosis coefficients indicate that both distributions have heavier tails than a normal distribution and extend towards more negative values.

Table 1: Descriptive statistics of returns' distributions of both sized portfolios

	Mean	Median	Maximum	Minimum	Standard deviation	Skewness	Kurtosis
Large	0.284	0.582	17.309	-21.830	3.658	-0.887	8.267
Small	0.524	0.426	30.609	-35.386	6.138	-0.165	8.022

At the market level, the weekly market illiquidity degree, $\text{illiq}_{M,t}$, is measured by the equally average of illiquidity levels of all stocks listed on the market at week t (Amihud, 2002; Acharya and Pederson, 2005), as expressed in Eq. 6 where N_t is the number of all stocks listed on the Saudi market at week t, after eliminating stocks with frequent zero market data.

$$\text{illiq}_{M,t} = \frac{1}{N_t} \times \sum_{i=1}^{N_t} \text{illiq}_{i,t}. \quad (6)$$

Regarding shocks of market illiquidity, also called innovations in market illiquidity, they are obtained by extracting residuals from the autoregressive model which predicts market illiquidity, according to the methodology developed by Amihud (2002). The autoregressive model which predicts market illiquidity $\text{illiq}_{M,t}$ is specified in such a way that residuals are uncorrelated. I use the Durbin-Watson test of residuals as well as the Ljung-Box test to detect the correlation between residuals.

Following the methodology thus defined, the next section aims to investigate the dynamics of returns sensitivities to illiquidity shocks. In section 3, shocks of market illiquidity are estimated. Instability over time of returns sensitivities to illiquidity shocks is then tested, to establish a useful foundation for exploring dynamics of returns sensitivities.

3. Dynamics of illiquidity risk

3.1. Estimation of shocks of market illiquidity

Weekly market illiquidity, $\text{illiq}_{M,t}$, is persistent on the Saudi stock exchange during the study period (coefficient of autocorrelation is equal to 0,7). This means that past levels of market illiquidity are a good predictor of future market illiquidity levels. The autoregressive model that predicts market illiquidity level is specified in such a way that its residuals are not correlated (Amihud 2002). I detect the autocorrelation of residuals using the Durbin-Watson test and the Ljung-Box test. Both tests lead to choosing the autoregressive model of lag 3 (AR(3)) which uses the last three levels of weekly market illiquidity to predict the current level.

$$\text{illiq}_{M,t} = \alpha_0 + \alpha_1 \times \text{illiq}_{M,t-1} + \alpha_2 \times \text{illiq}_{M,t-2} + \alpha_3 \times \text{illiq}_{M,t-3} + \mu_t. \quad (7)$$

Therefore, the estimated shocks of market illiquidity at week t, $\text{illiq}_{S,t}$, are obtained by extracting the estimated residuals, $\hat{\mu}_t$, from the autoregressive model AR(3) in Eq. 7 where α_i (i= 0, 1, 2, 3) are the coefficients of the model and μ_t is its residual.

$$\text{illiq}_{S,t} = \hat{\mu}_t. \quad (8)$$

Weekly market illiquidity shocks, $\text{illiq}_{S,t}$, are plotted in Fig. 2 where they seem frequent in 2002. During this year, the stock market was impacted by the bursting of the internet bubble. Significant shocks also occurred at the start of 2006, a period known as "Black February," when the Saudi stock market collapsed, resulting in a loss of one trillion Saudi riyals. In 2009, illiquidity shocks were notably high, driven by the global financial crisis. Such shocks became frequent again from 2015, coinciding with the decline in petroleum prices and turbulence in the Chinese stock market. The occurrence of illiquidity shocks persisted during the COVID-19 pandemic and the oil price crash of 2020, both of which significantly affected the Saudi stock market, particularly trading volumes (AL-Najjar, 2022).

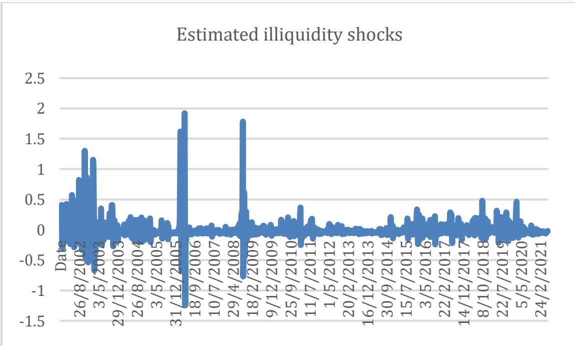

Fig. 2: Shocks of market illiquidity on the Saudi stock exchange

3.2. Instability test of illiquidity betas

To test whether sensitivities of Saudi stock returns to market illiquidity shocks change over time, I test the instability of the parameter "illiquidity beta" which measures returns sensitivities to $\text{illiq}_{S,t}$. Specifically, I test the presence of structural breaks in the time series of the illiquidity beta of each portfolio. To do that, I apply Bai and Perron's (2003) technique to the model of Watanabe and Watanabe (2008). Watanabe and Watanabe also sort stocks into large and small portfolios to examine the time-varying of illiquidity betas. I use their linear models that describe the relationships between excess portfolio returns and market illiquidity shocks are follows:

$$r_{Sm,t} - r_{f,t} = a_{Sm,t} + \beta_{illiq,Sm} \times illiq_{S,t} + \varepsilon_{Sm,t} \quad (9)$$
$$r_{L,t} - r_{f,t} = a_{L,t} + \beta_{illiq,L} \times illiq_{S,t} + \varepsilon_{L,t} \quad (10)$$

where, Sm refers to the smallest portfolio and L refers to the largest portfolio, $(r_{Sm,t} - r_{f,t})$ and $(r_{L,t} - r_{f,t})$ are the portfolio excess returns over the risk-free return $r_{f,t}$, β_{illiq} is the illiquidity beta that measures for each portfolio the sensitivity of returns to market illiquidity shocks $illiq_{S,t}$, a and ε are respectively the intercept and the residual of each regression.

Bai and Perron's (2003) technique allowed the detection of dynamics in the parameters $\beta_{illiq,Sm}$ and $\beta_{illiq,L}$ in Eqs. 9 and 10, by testing the null hypothesis of stability of illiquidity beta parameters, against the alternative hypothesis of the presence of structural breaks in these parameters. Specifically, the global optimization method that is used in this technique has the advantage to endogenously identify multiple breakpoints in the time series of the parameters without prior knowledge of their dates or their number (with a maximum number of 5 breaks). Testing the null hypothesis of no structural changes (stability) against the alternative of the presence of an unknown number of brakes employs the F-statistics based on critical values. Bai and Perron's (2003) technique is applied to each portfolio. Results are reported in Tables 2 and 3.

Table 2: Results of Bai and Perron's (2003) test for the smallest portfolio

Sequential F-statistic determined breaks		5
Breaks	F-statistic	Critical value
1 ***	79.32	8.58
2 ***	45.46	7.22
3 ***	33.84	5.96
4 ***	26.03	4.99
5 ***	21.35	3.91

***: significance at a level of 5%

Results of Bai and Perron's (2003) test for the smallest portfolio firstly indicate that there are at least five structural changes in the time series of $\beta_{illiq,Sm}$. This means that the sensitivity of small portfolio returns to the shocks of illiquidity changed at least five times during the study period. Individual statistics associated with each break far exceed the critical value. This leads to rejecting the null hypotheses of no structural breaks for the parameter $\beta_{illiq,Sm}$ in favor of the alternative of the presence of 5 structural breaks at a minimum. This implies that the relationship between excess returns of the smallest portfolio and market illiquidity shocks is not linear. In other words, responses from stock returns of the smallest firms to shocks of illiquidity vary over time.

For the largest portfolio, the test of Bai and Perron (2003) provided similar results which indicate that the relationship between excess returns of the largest firms and market illiquidity shocks contains at minimum 5 structural breaks, and then it is not linear. This is confirmed by all statistics of Fisher which are considerably higher than the critical values, rejecting the null hypotheses of stability of $\beta_{illiq,L}$ at the level of 5%. Based on these results, the aim of the next paragraph is to highlight the discontinuous variations of illiquidity betas and to describe how illiquidity risks (illiquidity betas) of portfolios fluctuate across sub-periods. To do that, I use a regime-switching analysis as in Watanabe and Watanabe (2008), Acharya et al. (2013), and Ben Soltane and Naoui (2021). In fact, two main types of transition mechanisms from one regime to another exist in the empirical literature, which are the endogenous transition mechanisms and the stochastic transition mechanisms governed by "Markov chain" type processes. In the endogenous transition mechanisms, the transition function depends on a random variable observed over time, and on a threshold, i.e., threshold models (Threshold Auto-Regressive model TAR, Smooth Threshold Auto-Regressive STAR, etc.) where linearity is verified piecewise. This is likely to be limiting, affecting the quality of the model in the event of a specification error of this observed variable. However, the Markov regime change model which are popularized by Hamilton (2010) assumed that the event responsible for the regime change is unobservable on the time scale, and the regime change is signaled by an exogenous transition variable. Therefore, by choosing a "Markov regime switching" type model in this study, it will be possible in the next section to assume that the change of the illiquidity beta from one regime to another is caused by a set of variables, which would lead to the consideration of several transition variables and the estimation of a system of equations if threshold models are employed.

Table 3: Results of Bai and Perron's (2003) test for the largest portfolio

Sequential F-statistic determined breaks		5
Breaks	F-statistic	Critical value
1 ***	153.59	8.58
2 ***	90.81	7.22
3 ***	64.34	5.96
4 ***	50.17	4.99
5 ***	40.09	3.91

***: significance at a level of 5%

3.3. Modeling the dynamics of illiquidity risks

To choose the appropriate switching regime model that explores the dynamics of illiquidity beta in each of the above Eqs. 9 and 10, I conduct four specification tests of Markov switching models developed by Hamilton (2010), i.e., tests for omitted autocorrelation, omitted ARCH, misspecification of the Markovian dynamics, and omitted variables. For each portfolio, the four tests are conducted on different switching regime models in order to select the most relevant one, starting from the basic model of switching regime, i.e., the model with two states MS(2) without heteroscedasticity of errors and without shifts in intercept.

In the first specification test, I determine whether the residuals of each model are correlated, using the Ljung-Box statistic and the Durbin-Watson statistic.

In this test, the null hypothesis of non-autocorrelation of residuals should be accepted to choose the suitable Markov switching model according to the standard procedure of Hamilton (2010). In the second test, autoregressive conditional heteroskedasticity (ARCH) errors are diagnosed by examining the autocorrelation of squared residuals, using the Ljung-Box statistics. The null hypothesis of non-autocorrelation in squared residuals should be accepted. The third test of misspecification of the Markov chain is about parameter restrictions. Precisely, the null hypothesis is $H_0: L\beta = c$ where L is a matrix of model parameters and c is a vector of constants. This hypothesis should be rejected to select the appropriate Markov model. To perform this test, I use the Wald statistics in Acharya et al. (2013) and in Ben Soltane and Naoui (2021). The fourth test verifies whether the added variables in the specification make a significant contribution in the description of illiquidity-returns relationships. I use the likelihood ratio (LR) statistic to test the null hypothesis H_0 which states that added variables are not jointly significant. H_0 should be rejected. Tables 4 and 5 summarize the conducted specification tests on the Markov switching models and show their results for both portfolios.

Table 4: Specification tests of the Markov switching model for the smallest portfolio

Specification tests/models	MS(2)	MSH(2)	MSIH(2)
H0: Non- autocorrelation of ε_S	Q-stat=0.38 (p-value=0.534) DW=1.96 H0 Accepted	Q=7.88 (p-value=0.005) DW=1.77 H0 Rejected	Q=7.82 (p-value=0.005) DW=1.77 H0 rejected
H0: Non-autocorrelation of ε_S^2	Q-stat=0.59 (p-value=0.44) H0 Accepted	Q=3.58 (p-value=0.05) H0 Rejected	Q=3.72 (p-value=0.05) H0 rejected
H0 : $L\beta = c$ (Unchanged parameters)	W=29.9 >χ (2) (p-value=0.000) H0 rejected	W=459.5 > χ(4) (p=0.000) H0 rejected	W=465.5 >χ(6) (p=0.000) H0 rejected
H0: Added regressors are not jointly significant	LR*=87.8 > χ (2) H0 (linear model better than MS2) is rejected	LR*=-158.1< χ (1) H0 (MS2 better than MSH2) is accepted	LR* = -1.02 < χ (1) H0 (MSH2 better than MSIH2) is accepted

LR*: Log-likelihood ratio tests; MSH: Markov switching model

Note: Four specification tests are conducted to select the Markov switching model that best describes the dynamics of the illiquidity beta, starting from the basic model MS (2) which is without heteroscedasticity of errors and without shifts in intercept. Based on test results on the basic model, variables are added to build the next Markov switching model and to test its relevance, and so on until obtaining the best Markov specification. MSH(2) refers to the Markov switching Heteroskedasticity which allows for residuals to be heteroscedastic across two regimes, and the MSIH(2) is the Markov Switching model with shifts in the intercept as well as the heteroscedasticity of residuals. In the first specification test, the null hypothesis of non-autocorrelation in residuals should be rejected at the significant level of 5% if the Ljung-Box statistic (Q-stat) is different from zero and statistically significant (p-value < 0,05). In the second test, the presence of ARCH errors should be confirmed when Ljung-Box statistics are different from zero and statistically significant (p-value < 0,05). In the third test of misspecification of Markov dynamics, the null hypothesis states that parameters are unchanged between regimes. Testing this hypothesis is based on the Wald statistic which has an asymptotic Chi-squared distribution with degrees of freedom equal to the number of restrictions. H_0 should be rejected when the Wald statistic (W) is greater than the Chi-squared critical value. In the fourth test of omitted variables, H_0 states that added parameters to the previous model are not jointly significant. The likelihood ratio (LR) statistic for testing H_0 is computed by $LR^* = (-2(l_1 - l_2))$, where l_1 and l_2 are respectively the maximized values of the log-likelihood function of the testable model and the previous model (the previous model in column 2 is the linear model expressed in Eq. 9). LR statistics have an asymptotic Chi-squared distribution with a degree of freedom equal to the number of added variables. H_0 should be rejected if the statistic LR^* Exceeds the Chi-squared critical value.

For the smallest portfolio (see Table 4), results of the four specification tests indicate that in the basic model MS(2), residuals are independent, ARCH errors are absent, model parameters effectively change between two regimes, and the added regressors significantly contribute to the description of illiquidity- returns relationship. In other words, the model MS(2) meets all the criteria to properly model the dynamics of the illiquidity beta of the smallest portfolio, unlike the following models, i.e., the Markov switching Heteroskedasticity model MSH(2) and the Markov switching Intercept Heteroskedasticity model MSIH(2), where residuals have proven to be correlated and the ARCH effects are present. These results lead to the use of the Markov Switching model with two regimes MS(2) for modeling the illiquidity beta dynamics of the smallest portfolio, as expressed in the following equations.

$$r_{Sm,t} - r_{f,t} = a_{Sm,t} + \beta^{st}_{illiq,Sm} \times illiq_{S,t} + \varepsilon_{Sm,t} \quad (11)$$
$$P[s_t = 1/s_{t-1} = 1] = P_1$$
$$P[s_t = 2/s_{t-1} = 2] = P_2$$

where, $r_{Sm,t} - r_{f,t}$ is the excess returns of the smallest portfolio in regime st, the state variable st $(st = 1,2)$ indicates if it is Regime 1 or Regime 2, the residual $\varepsilon_{Sm,t}$ is assumed to be independent and identically distributed following a normal distribution with zero mean and constant variance $\sigma^2_{\varepsilon,sm}$, and the probabilities of transition for regimes are P_1 and P_2. For the largest portfolio, selecting the relevant model of Markov switching regimes relies on the results of the four specification tests summarized in Table 5.

Table 5: Specification tests of Markov switching models for the largest portfolio

Specification tests/models	MS(2)	MSH(2)	MSIH(2)	MS(3)
H0: Non-autocorrelation of ε_L	Q-stat=1.55 (p-value=0.213) DW=1.92 H0 accepted	Q=11.5 (p-value=0.001) DW=1.64 H0 rejected	Q=5.7 (p-value=0.01) DW=1.83 H0 Rejected	Q=0.65 (p-value=0.42) DW=2.04 H0 accepted
H0: Non-autocorrelation of ε^2_L	Q-stat=10.87 p-value=0.001 H0 rejected	Q=1.48 p-value=0.223 H0 accepted	Q=3.32 p-value=0.07 H0 Accepted	Q=1.66 p-value=0.197 H0 accepted
H0: $L\beta = c$ (Unchanged parameters)	W=193.06 >χ (2) (p-value=0.000) H0 rejected	W=409 > χ(4) (p=0.000) H0 rejected	W=380 > χ(6) (p=0.000) H0 rejected	W=295.2 >χ(3) (p=0.000) H0 rejected
H0: Added regressors are not jointly significant	LR*= -189< χ (2) H0 (linear model better than MS2) accepted	LR*= -271.4< χ (1) H0 (MS2 better than MSH2) accepted	LR*= -38.73< χ (1) H0 (MSH2 better than MSIH2) accepted	LR* = 224.2> χ (1) H0 (MSIH2 better than MS3) rejected

DW: Durbin-Watson statistic

Note: Four specification tests are conducted to select the Markov switching model that best describes the dynamics of the illiquidity beta, starting from the basic model MS (2) which is without heteroscedasticity of errors and without shifts in intercept. Based on test results on the basic model, variables are added to build the next Markov switching model and to test its relevance, and so on until obtaining the best Markov specification. MSH(2) refers to the Markov switching Heteroskedasticity which allows residuals to be heteroscedastic across two regimes, the MSIH(2) is the Markov Switching model with shifts in the intercept as well as the heteroscedasticity of residuals, and MS(3) is the Markov Switching model with three regimes without residuals heteroscedasticity and intercept shifts. In the first specification test, the null hypothesis of non-autocorrelation in residuals should be rejected at the significant level of 5% if the Ljung-Box statistic (Q-stat) is different from zero and statistically significant (p-value < 0,05). In the second test, the presence of ARCH errors should be confirmed when Ljung-Box statistics are different from zero and statistically significant (p-value < 0,05). In the third test of misspecification of Markov dynamics, the null hypothesis states that parameters are unchanged between regimes. Testing this hypothesis is based on the Wald statistic which has an asymptotic Chi-squared distribution with degrees of freedom equal to the number of restrictions. H_0 should be rejected when the Wald statistic (W) is greater than the Chi-squared critical value. In the fourth test of omitted variables, H_0 states that added parameters to the previous model are not jointly significant. The likelihood ratio (LR) statistic for testing H_0 is computed by $LR^* = (-2(l_1 - l_2))$, where l_1 and l_2 are respectively the maximized values of the log-likelihood function of the testable model and the previous model (the previous model in column 2 is the linear model expressed in Eq. 10). LR statistics have an asymptotic Chi-squared distribution with a degree of freedom equal to the number of added variables. H_0 should be rejected if the statistic LR^* exceeds the Chi-squared critical value.

Table 5 shows that the basic model of Switching regime MS(2) cannot be chosen for modeling the dynamics of illiquidity beta of the largest portfolio, since the second specification test indicates the presence of ARCH effect. The models MSH(2) and MSIH(2) are also rejected from the analysis because of the autocorrelation of residuals which is found in the first specification test. By adding a third regime, the Markov switching model with three states MS(3) appears as the most relevant model for the largest portfolio. Indeed, neither its residuals nor its squared residuals are autocorrelated according to the results of the first two specification tests. Moreover, the parameter of illiquidity beta is proven to be significantly changed across the three states and the added regressors are jointly significant, based on the results of the third and the fourth specification tests. Therefore, changes over time in the illiquidity beta of the largest portfolio will be analyzed through the Markov switching model with three regimes MS(3) which is expressed as follows.

$$r_{L,t} - r_{f,t} = \alpha_{L,t} + \beta^{st}_{illiq,L} \times illiq_{S,t} + \varepsilon_{L,t} \quad (12)$$
$$P[s_t = 1/s_{t-1} = 1] = P_1$$
$$P[s_t = 2/s_{t-1} = 2] = P_2$$
$$P[s_t = 3/s_{t-1} = 3] = P_3$$

where, $r_{L,t} - r_{f,t}$ is the excess returns of the largest portfolio in regime st (st = 1,2,3), the residual $\varepsilon_{L,t}$ is assumed to be independent and identically distributed following a normal distribution with zero mean and constant variance $\sigma^2_{\varepsilon,L}$, and the probabilities of transition are P_1, P_2 and P_3.

The next paragraph presents and analyses the results of the estimation of the Markov switching model for each portfolio.

3.4. Regime switching analysis

Parameters of the Markov switching models selected for both portfolios in the previous paragraph are estimated by the maximum likelihood method. Estimation results of Eq. 11 for the smallest portfolio are reported in Table 6.

Table 6: Estimated parameters of the Markov switching MS(2) for the smallest portfolio

	Parameters	Estimates	P-value
Regime 1	a	-1.9	0.00
	$\sigma_{\varepsilon,s}$	1.68	0.00
	β^1_{illiq}	-9.74	0.00
	P_1	0.96	
	d (duration)	32.51	
Regime 2	β^2_{illiq}	-96.86	0.00
	P_2	0.86	
	d (duration)	7.65	

As shown in the empirical literature (Acharya et al., 2013; Watanabe and Watanabe, 2008; Acharya and Pedersen, 2005), market illiquidity shocks affect negatively contemporaneous stock returns. In other words, shocks of illiquidity reduce stock prices on the Saudi stock market too. This is indicated by the negative value of the estimated illiquidity beta, which measures the sensitivity of stock prices to illiquidity shocks, as well as its high statistical significance. Results in Table 6 also show a major difference between the two regimes: the first regime (Regime 1) has low illiquidity beta, and the second regime (Regime 2) has high illiquidity beta. During Regime 2, the estimated value of the illiquidity beta of the smallest portfolio multiplies almost by 10. This means that during this regime, market illiquidity shocks severely reduce stock prices of small firms, i.e., ten times more than in Regime 1. Moreover, the second regime is short-lived, with a duration of 7 weeks, while Regime 1 lasts 32 weeks. Furthermore, the probability of a short-lived regime is lower than that of Regime 1. These characteristics reflect the abnormal nature of Regime 2.

Table 7 reports the estimation results of Eq. 12 which focuses on the largest portfolio. Estimated parameters clearly show a discontinuous variation of the portfolio illiquidity beta across three distinct regimes. During the first regime (Regime 1), the illiquidity beta is equal to (-12.9) while in the second regime (Regime 2), the effect of market illiquidity shocks on the largest portfolio returns almost disappears. Regime 2 is the most lasting. If it occurs, it persists for over 75 weeks. Characteristics of Regime 2 prove that market illiquidity shocks usually do not significantly reduce the stock prices of the largest firms. In other words, stocks of the Saudi largest firms are often not affected by market illiquidity shocks. However, during the third regime (Regime 3), market illiquidity shocks strongly reduce the stock prices of the largest firms. Indeed, stock returns of the largest portfolio fall four times more than in Regime 1 (illiquidity beta equals -53.4). The third regime, which is characterized by the extreme illiquidity risk (the highest illiquidity beta) takes only 36 weeks, and its probability of occurrence equals 0.97.

Moving to the extreme scenario during which the illiquidity beta reaches its highest level, i.e., the extreme fall of stock prices in times of shocks of illiquidity, should be controlled and managed by investors on the stock market. Indeed, increasing the predictability of illiquidity risk leads to more effective trading strategies. The next section attempts to reveal the conditions that generate extreme illiquidity beta for stocks on the Saudi stock exchange.

Table 7: Estimated parameters of the Markov switching MS(3) for the largest portfolio

	Parameters	Estimates	P-value
Regime 1	α	-2.21	0.00
	$\sigma_{\varepsilon,L}$	1.15	0.00
	β^1_{illiq}	-12.93	0.00
	P_1	0.97	
	d (duration)	34.6	
Regime 2	β^2_{illiq}	-0.99	0.00
	P_2	0.98	
	d (duration)	75.45	
Regime 3	β^3_{illiq}	-53.39	0.00
	P_3	0.97	
	d (duration)	36.18	

4. Management of the extreme illiquidity risk

This section focuses on regimes that have been found in the previous section to be characterized by extreme illiquidity risk, i.e., Regime 2 for the smallest portfolio and Regime 3 for the largest portfolio. During these two regimes, prices of Saudi stocks extremely fall due to market illiquidity shocks. I investigate the factors that could predict in advance the occurrence of these extreme situations for each portfolio. This relies on the estimated weekly probabilities of being in these regimes, i.e., $P_{2,Sm,t}$ which is the probability for the smallest portfolio to be in Regime 2 at week t, and $P_{3,L,t}$ which is the probability for the largest portfolio to be in Regime 3 at week t. These probabilities are obtained by estimating the Markov switching specifications in Eqs. 11 and 12 by the Maximum Likelihood method.

To detect the factors that could generate regimes with extreme illiquidity risk, I estimate for each sized portfolio a regression where the dependent variable is the probability of being in a regime with high β_{illiq} at week t ($P_{2,Sm,t}$; $P_{3,L,t}$), whereas the independent variables describe financial market situations of the previous week, as in Acharya et al. (2013), Amihud and Noh (2021), and Ben Soltane and Naoui (2021). Independent variables are specified as follows:

- Market performance, measured by the market return at week t, $r_{M,t}$. Negative performance of the Saudi stock market at week t is expected to increase the probability of being in a regime associated with extreme illiquidity risk in the next week, as revealed by Watanabe and Watanabe (2008), Acharya et al. (2013), Amihud and Noh (2021), and Ben Soltane and Naoui (2021).

$$r_{M,t} = 100 \times \frac{P_{M,d,t} - P_{M,d-4,t}}{P_{M,d-4,t}} \quad (13)$$

where, $P_{M,d,t}$ and $P_{M,d-4,t}$ are values of the index of the Saudi stock exchange at day d and $d-4$ respectively, of the week t.

- Market volatility during the week t, is measured by the standard deviation of daily market returns.

$$\sigma_{M,t} = \sqrt{\frac{\sum_{d=1}^{5}(r_{M,d}-\overline{r_{M,t}})}{5}} \quad (14)$$

where, $r_{M,d}$ is the daily market return computed by $r_{M,d} = 100 \times \frac{P_{M,d,t}-P_{M,d-1,t}}{P_{M,d-1,t}}$, $P_{M,d-1,t}$is the value of the Saudi Stock Market index at day $d-1$, $\overline{r_M}$ is the mean of daily market return during the week t which includes 5 days. Market volatility was found to be a predictive factor of the regime with high illiquidity beta in Brunnermeier and Pedersen (2009), Acharya et al. (2013), and Ben Soltane and Naoui (2021).

- Crude oil return $r_{oil,t}$ at week t, which is computed as follows:

$$r_{oil,t} = 100 \times \frac{P_{oil,d,t}-P_{oil,d-4,t}}{P_{oil,d-4,t}} \quad (15)$$

where, $P_{oil,d,t}$ and $P_{oil,d-4,t}$ are the spot prices of the WTI crude oil at day d and $d-4$ respectively, of week t. This factor is introduced for the first time in the identification of regimes with high illiquidity risk. This is due to the particularity of the Saudi stock exchange which is strongly affected by oil prices (Azar and Basmajian, 2013; Samontaray et al., 2014; Khamis et al., 2018; Alshammari et al., 2020; Alturki and Aldughaiyem, 2020).

The abilities of these variables to predict regimes with extreme illiquidity risk are assessed for each portfolio via the estimation of the logit regressions in Eqs. 16 and 17.

$$P^*_{2,sm,t} = a_{s,t} + (a_{1,sm} \times r_{M,t-1}) + (a_{2,sm} \times \sigma_{M,t-1}) + (a_{3,sm} \times r_{oil,t-1}) + u_{sm,t} \quad (16)$$

$$P^*_{3,L,t} = a_{L,t} + (a_{1,L} \times r_{M,t-1}) + (a_{2,L} \times \sigma_{M,t-1}) + (a_{3,L} \times r_{oil,t-1}) + u_{L,t} \quad (17)$$

where, $P^*_{2,sm,t}$ is a dummy variable that equals 1 if the probability for the smallest portfolio to be in Regime 2 at week t $(P_{2,Sm,t})$ exceeds 0.6, and equals 0 otherwise; $P^*_{3,L,t}$ is a dummy variable that equals 1 if the probability for the largest portfolio to be in Regime 3 at week t $(P_{3,L,t})$ exceeds 0.6, and equals 0 otherwise. $a_{p,t}$ and $u_{p,t}$ are respectively the intercept and the residual term for each portfolio p ($p = Sm, L$); and $a_{i,p}$ are the coefficients that measure the predictive power of the lagged factor ($i = 1,2,3$) of the regime of extreme illiquidity beta for each portfolio p ($p = Sm, L$).

5. Results and discussions

Table 8 summarizes the estimation results of the logit regressions in Eqs. 16 and 17. For the smallest portfolio, coefficients related to stock market performance and oil prices are not statistically significant. This means that market performance and oil prices do not explain the occurrence of the extreme illiquidity regime. In other words, these two factors do not amplify the negative effect of market illiquidity shocks on the stock prices of the smallest firms on the Saudi stock exchange. This result is consistent with the findings of Tissaoui et al. (2018) where the Amihud (2002) measure is used to estimate the effects of boom/bust cycles in the Saudi stock market and in the oil market on the liquidity commonalities. Tissaoui et al. (2018) revealed that the liquidity commonality in the Saudi stock exchange is stronger in boom/bust stock exchange conditions than in boom/bust oil market conditions. Furthermore, the coefficient a_2 related to the volatility of the stock market is positive and statistically significant. This proves that the occurrence of the regime with extreme illiquidity beta is caused by the high volatility of the Saudi stock market observed in the previous week. This result is also found in Watanabe and Watanabe (2008) and Acharya et al. (2013). For the largest portfolio, results show a statistical significance of the coefficient a_1 which is associated with the market performance, but not for the coefficients of the two other variables. This means that neither oil prices nor volatility of the Saudi stock market generates the regime of extreme illiquidity beta for the largest portfolio. The resulting coefficient a_1 is negative. This proves that the higher the market returns, the lower the probability of occurrence of Regime 3. In other words, the negative performance of the Saudi stock market during week t increases the probability of being in an extreme illiquidity regime in the next week. This result is also revealed in Watanabe and Watanabe (2008) and Acharya et al. (2013). However, oil prices and stock market volatility do not lead the largest portfolio to the regime of extreme illiquidity risk.

Table 8: Estimation results of logit regressions for both portfolios

	Smallest portfolio		Largest portfolio	
Coefficients	Estimates	P-value	Estimates	P-value
a	-2.09	0.00	-0.47	0.00
a_1	0.01	0.79	-0.05	0.04
a_2	0.03	0.02	-0.01	0.46
a_3	0.01	0.42	0.01	0.32

6. Conclusion

This study presents a comprehensive overview of the systematic illiquidity risk over time on the Saudi stock exchange, i.e., how and why does the sensitivity of stock prices to illiquidity change over time? Answering these questions relies on a large daily database covering all stocks that are listed on the Saudi market from 2001, December 31st to 2021, June 30th, as well as the daily prices of crude oil.

First, I test whether sensitivities of stock prices to market illiquidity shocks (illiquidity betas of stocks) vary over time. This is accomplished by differentiating between stocks of large firms and stocks of small firms since empirical literature showed the firm size effect on the illiquidity risk. I employ Bai and Perron's (2003) technique to test, for each portfolio, the presence of structural breaks in the parameter "illiquidity beta". Results show that illiquidity betas of the largest portfolio, as well as the smallest portfolio, considerably change over time. Therefore, the relationship between market illiquidity shocks and stock returns is not linear and could be modeled after a Markov switching model.

Second, choosing for each portfolio the most relevant model of the Markov switching regime is based on the four specification tests that were developed by Hamilton (2010), i.e., tests for omitted autocorrelation, omitted ARCH, misspecification of the Markovian dynamics, and omitted variables. The results of the specification tests led to the selection of the Markov switching model with three regimes for modeling dynamics of the illiquidity beta of the largest portfolio, while for the smallest portfolio, the Markov switching model with two regimes is chosen.

Third, discontinuous variations of illiquidity betas are quantified for each portfolio to describe how sensitivities of stock prices to illiquidity change across subperiods. This is reached using the Markov switching analysis. The selected models in the previous step are estimated by the Maximum likelihood method. Estimation results corroborate previous empirical studies showing a significant negative relationship between market illiquidity shocks and all stock returns (of large and small firms). Obviously, the negative relationship is not constant over time. The estimated illiquidity beta of the smallest portfolio considerably fluctuates between the two regimes. It increases tenfold during the second regime. This means that during the second regime, market illiquidity shocks reduced returns of the Saudi smallest stocks ten times more than during the first regime. Estimation results show also that the second regime is short-lived reflecting its abnormal nature. For the largest portfolio, illiquidity risk significantly increases during the third regime compared to the first regime, while it almost disappears during the second regime. Regime 2 is the most lasting, proving that usually stock returns of the largest firms are not considerably affected by illiquidity shocks. However, in Regime 3 the largest portfolio returns fall four times more than in Regime 1.

Fourth, causes of discontinuous variations of stock price sensitivities are investigated to improve forecasting risk on the market and thus investment strategies. Specifically, I examine the factors that could lead to the occurrence of regimes associated with the extreme illiquidity beta for each portfolio. For this purpose, I use the weekly estimated probabilities of being in regimes with extreme illiquidity risks. For each portfolio, I regress this probability on lagged market factors that have been shown in most studies to be predictive of regimes with high illiquidity beta, i.e. market performance and market volatility. I add to these factors the oil market performance since the Saudi stock market is revealed strongly related to oil prices in literature. Estimation results show that high market volatility increases the probability of occurrence of the regime with extreme illiquidity risk of the smallest portfolio, and the regime with extreme illiquidity risk of the largest firms can be predicted by the negative performance of the Saudi stock market. However, results prove that oil prices are not related to the regimes with high illiquidity risks on the Saudi stock market.

Compliance with ethical standards

Conflict of interest

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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