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Market volatility and illiquidity during the COVID-19 outbreak: Evidence from the Saudi stock exchange through the wavelet coherence approaches

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ABSTRACT

The aim of this paper is to examine the explanatory power of realized volatility on the illiquidity in Saudi stock market during the COVID-19 outbreak. To achieve this objective, we consider the Wavelet Coherence approaches as empirical tools to investigate the combined effect of realized volatility and COVID-19 counts on the market illiquidity across frequencies and over time space by taking in account the number of infected cases in Saudi Arabia and over the World, and the number of death cases in Saudi Arabia as well as over the World. Our study reaches two main findings. First, the preliminary results reported by the ARDL bound test as a benchmark model showed significant long-run and short-run effects of the market volatility on illiquidity in contemporaneous and lagged manner. Second, the wavelet coherence analysis tools exhibited important results: (i) the wavelet coherency between illiquidity ratio and realized volatility in Saudi Arabia appear highly pronounced over all time horizons. (ii) PWC plots showed a significant mutual effect between liquidity risk and realized volatility when eliminating the effect of local COVID-19 cases. (iii) MWC plots highlighted that the response of the market illiquidity index to both the amplification in confirmed local cases (resp. international confirmed cases) and the stock market volatility appear significant in the short and middle horizons.

1. Introduction

Since the domestic financial crisis of 2006, the prime aim of the Saudi financial authorities is to improve the transparency, liquidity, and stability of the financial market. All financial reports have affirmed that the principal reason behind this crisis is the growing number of transactions that rely on random trading by non-experienced investors (four million investors). After this crisis, the Saudi financial authorities have undertaken many reforms and measures to improve market performance remarkably. This improvement is distinctly reflected in the increase of the number of foreign investors attracted to the Saudi market in 2015, the inclusion of the global giant, the Saudi oil industry ‘Aramco’ in the Saudi stock market in 2019, the successful inclusion of 30 Saudi companies in the Morgan...
Stanley Capital International (MSCI) Index during 2019 and the Saudi stock market’s inclusion in the Financial Times Stock Exchange (FTSE) Russell Index for Secondary Emerging Markets from June 2020. Following a popular saying in the field of finance that ‘markets take the stairs up and the elevator down’, the Saudi financial market was struck by an unexpected crisis with the spread of the coronavirus disease (COVID-19) since the beginning of 2020; the Tadawul All Share Index (TASI) saw a rapid point loss that took years to attain. On Wednesday, 1 January 2020, the TASI was closed at 8,358.85. Three months later, the index closed at 5990.23 on Monday, 23 March 2020, a level that had not been reached since October 2016. Furthermore, the entire world has been living under difficult economic conditions in the last six months due to the COVID-19 pandemic, spreading rapidly, severely affecting the global economy, financial markets, oil markets, banks, and insurance companies (Goodell, 2020; Goodell & Goutte, 2020; Okorie & Lin, 2020). The World Health Organization reports declared COVID-19 as a pandemic that has touched 235 nations and regions worldwide with 32,110,656 confirmed cases and 980,031 deaths as of 25 September 2020.

Notably, the current crisis differs from all previous crises; for the first time, investors are concerned about the value of their portfolios and investments and their health, security, personal safety, well-being, and that of their families. This has created uncertainty for even the most experienced investors. Moreover, it is an unprecedented time in history that an influenza pandemic has triggered stock and oil markets’ dynamic volatility spillover and crises. This new circumstance prompts us to use recent Saudi stock market data to investigate the impact of COVID-19 confirmed cases and deaths combined with the realised volatility on the liquidity of the Saudi stock market. Several reasons have led to this issue, which we limit to the following: (i) The Saudi stock market is considered the largest financial market in the Middle East and North Africa in terms of the market value of listed companies and market capitalisation. Additionally, because of the COVID-19 pandemic, many Saudi companies had temporarily interrupted production, delayed important projects, making adjustments to financial forecasts and dividend distribution in the uncertainty about investment in the financial market. (ii) The considerable uncertainty in the economic consequences of the COVID-19 outbreak has led the Saudi equity market volatility reflected in the realised volatility to spike to substantial levels, particularly in March 2020. This significant volatility deteriorated liquidity and increased investors’ uncertainty. (iii) The impacts of the dramatic collapse of oil prices during the COVID-19 outbreak following the struggle between Saudi Arabia and Russia, from 8 March 2020, about oil supply and prices, are seriously transmitted to the stock market. The dynamic spillover effect between the oil and stock markets during the COVID-19 outbreak is significant, providing notable implications for investors and portfolio decision-makers. This standoff remains and generates additional uncertainty (Ashraf, 2020). Therefore, investigating the combined link between the realised volatility and confirmed cases of and deaths due to the COVID-19 outbreak in the Saudi stock market is simulating. Regarding the organic link of Saudi Arabia’s economy with crude oil, we cannot rule out the impact of this economic war, which resulted in an oil price collapse, on the financial market, the global oil exports and the oil production.

Additionally, we stress that our research is consistent with the strategic and farsighted vision of the Kingdom of Saudi Arabia, aiming to build a financial market, attracting both domestic and foreign investment and which can develop the Saudi economy and diversify investors’ sources of income despite numerous challenges, such as financial and epidemiological crises, mentioned in the Saudi Vision 2030 (page 43): ‘All of this will require the formation of an advanced financial and capital market open to the world, allowing greater funding opportunities and stimulating economic growth. To this end, it is important to continue facilitating access to investing and trading in the stock markets’. Our study contributes to the literature in several veins: First, we contribute to the wave of research exploring the response of stock markets to disasters and crises. We refer to studies by Gangopadhyay et al. (2010) about financial markets’ responses and stock price patterns to Hurricane Katrina in 2005. Subsequently, many authors (e.g. Dimitriou et al., 2013; Luchtenberg & Vu, 2015; Yarovaya et al., 2016) considered the response of stock markets to the global financial crisis of 2007–2009. The authors showed that the sub-prime financial turmoil had a significant impact on stock markets. Many other authors have examined the link between air crash disasters and stock markets. Bosch et al. (1998) revealed a positive response of the stock prices of non-crashing airlines to crashing airlines. Several authors investigated the ‘spillover effects’ of terrorist attacks, such as the September 11 terrorist attacks, on the financial markets (e.g. Brounen & Derwall, 2010; Choudhry, 2005). These authors proved that financial markets are significantly affected by terrorist events. More recently, Kowalewski and Śpiewanowski (2020) discussed the stock exchange response to mine catastrophes. The authors showed a great stock market reaction to natural disasters over 1986–2019. From these studies, we understand that the stock market’s response to different types of distress materialises with worrying changes in prices and volatility. Following the global financial turmoil, the transmission of economic shocks to stock markets is well documented. However, market liquidity, considered a risk factor for volatility, has attracted less attention in the financial market behaviour literature during crisis periods. We aim to extend the findings of these studies and address the gap in the literature by discussing the combined influence of the COVID-19 pandemic and realised volatility on the illiquidity of the Saudi stock exchange.

Specifically, we attempt to provide new insights and a comprehensive understanding of the relationship between liquidity in the Saudi stock market and the COVID-19 pandemic. At least two main aspects motivate our choice. First, during the last decade, the Saudi stock market has witnessed significant growth. For instance, the number of listed firms increased from 70 in 2004 to 179 in 2018, whereas the number of brokerages, asset management, and investment banking companies increased to 86. Second, TADAWUL and the Capital Market Authority (hereafter, CMA) announced the new regulations regarding market settlement and Qualified Foreign Investors (hereafter, QFI). This is another example of the Saudi stock market development that will increase the market depth and level of liquidity. These developments, among other factors, influence the stock market behaviour and liquidity inflows.

1 https://www.who.int/emergencies/diseases/novel-coronavirus-2019.
2 The Saudi Vision 2030 (page 43)
To the best of our knowledge, the recent literature on the effect of COVID-19 on equity markets is limited. We aim to contribute to the emerging body of work on the substantial effect of the COVID-19 pandemic on financial markets. A considerable number of studies (e.g. Al-Awadhi et al., 2020; Alfaro et al., 2020; Baker et al., 2020; Ozili & Arun, 2020; Sharif et al., 2020; Zhang et al., 2020) found that the COVID-19 pandemic has a significant impact on financial markets. Our research is the first to investigate the influence of changes in COVID-19 infected cases and deaths at the national and international levels on the illiquidity of the Saudi financial market. Additionally, we propose the wavelet approach that can efficiently test the co-movements and lead-lag connectedness among different variables on any date (Bouri et al., 2018; Huang & Vo, 2021). Other authors have indicated that wavelet methods are used in all cases, even when the sample size is small (Sharif et al., 2020). Therefore, we exploit these tools to understand the interaction between illiquidity and volatility during the pandemic. This allows us to determine the stability level of the Saudi market and the reasons for this situation, especially with new traders joining the market with the Aramco IPO at the end of 2019. Finally, our contribution is examining the semi-strong efficiency hypothesis of the Saudi financial market during the COVID-19 pandemic, which has not yet been studied.

Therefore, our study has many important implications: (i) It provides a clear insight into the impact of the COVID-19 outbreak on the stability of the Saudi financial market. (ii) It assists the Saudi financial authorities and quoted companies to understand the impact of COVID-19, both confirmed cases and deaths, with realised volatility on illiquidity of the Saudi stock market so that they may respond with appropriate measures and mechanisms. (iii) To assist both national and international investors in better understanding the situation of the Saudi stock exchange during the pandemic and in defining the appropriate investment strategy to adopt: short (sell) or long (buy) positions.

The remainder of this paper proceeds as follows. Section 2 presents the relevant literature, Section 3 highlights the data analysis and methodological framework, Section 4 discusses the main results, Section 5 represents a robustness check, and Section 6 presents the summary and implications.

2. Literature review

Since Demsetz’s (1968) seminal paper on liquidity in the financial market, many authors working on microstructure theory have explained this concept theoretically and empirically (Chordia et al., 2000; Chung and Chuwonganant, 2018; Fernando et al., 2008; Kyle, 1985; Ma et al., 2018). Some authors such as Chordia et al. (2003), Tissaoui and Ftiti (2016), and Tissaoui et al. (2018) asserted that a good understanding of the dynamics of stock market liquidity is important for investors and regulators. First, it allows traders to optimise their trading policies by managing liquidity risks, leading to an optimal allocation of funds, and increases their confidence in the future. Second, regulators can advance legislation to protect the stock market against liquidity drop and insider trading. Given these significant implications, extensive studies have focused on liquidity pricing concerning another feature in the stock market: return volatility. Several empirical studies have analysed the nexus between liquidity and volatility from multiple perspectives. Many have affirmed that these two concepts are closely connected and share common characteristics, influencing each other in several ways.

Although evidence of a negative link between liquidity and volatility was provided by inventory models (Stoll, 1978; Foster & Viswanathan, 1990) and information models (Foster & Viswanathan, 1990), a positive association was also found by Barclay and Warner (1993). The authors justified this by the trading positions adopted by informed traders ahead of a larger group of uninformed liquidity traders.

Chordia et al. (2000) were the first to apply a modified market model to prove the effect of market liquidity on stock liquidity in the New York Stock Exchange (NYSE). They showed that the commonality in liquidity exists, meaning that the variation in market liquidity, both in spread and depth, has significant explanatory powers for stock liquidity. This commonality is important despite firm-specific factors, such as price, trading volume, and risk. Brunnermeier and Pedersen (2009) illustrated that market liquidity diminishes and that stock prices move further away from their fundamental values. Finally, Haugom and Ray (2017) showed that the connectivity between volatility and liquidity follows a U-pattern or inverted U-pattern, according to different types of operators in the crude oil futures market.

Xu et al. (2019a) investigated the heterogeneous effect of liquidity on volatility in the futures market of Chinese stock market indexes using the quantile regression method. The finding indicates that illiquidity leads to a significant increase in volatility, suggesting a significant J-pattern behaviour between illiquidity and volatility.

Bedowska-Sójka and Kliber (2019) examined the causal link between liquidity and volatility of listed securities on the Warsaw Stock Exchange. Using the causality tests of Toda-Yamamoto and Granger, they found two-way causality between two variables. However, the liquidity-volatility causal relationship is more frequently observed than the volatility-liquidity causal relationship, and both relationships are often asymmetric.

Xu et al. (2019b) considered the dynamic effect of market liquidity on volatility using a Markov switching regime approach. The findings suggest that liquidity has a non-linear and significantly stronger influence on realised volatility when the market is unstable. Ramos and Righi (2020) investigated the link between liquidity and implied volatility. They illustrated that implied volatility engenders an increase in liquidity. The authors decompose the implied volatility into two components: conditional variance and variance premium. The findings indicate that both components affect liquidity.

Likewise, Chuliá et al. (2020) investigated the link between liquidity and volatility. They indicated that the commonality in liquidity is high immediately after significant market drops, occurring at times of crisis. They additionally illustrated that while volatility causes aggregate liquidity over the entire period under study, aggregate liquidity increases only market volatility in sub-periods.

Since December 2019, financial markets have entered a state of communal panic generated by the COVID-19 pandemic first
detected in Wuhan, China. This panic suggests that the COVID-19 is a financial market ‘black swan’ event with more severe consequences than the 2008 financial crisis. Therefore, many researchers have attempted to study the effect of the pandemic on the global economy and capital markets. For instance, Goodell (2020) pioneered the discussion on the economic and social consequences of COVID-19 on stock markets. Corbet et al. (2020) discussed the implications of the pandemic on stock returns and volatility. The results show that firms’ securities display negative returns and significant volatility and trading volumes after the publication of COVID-19 pandemic news. Baker et al. (2020) reported that the COVID-19 crisis represents the world’s first infectious disease pandemic referred to in the media and is accompanied by substantial daily market fluctuations. Corbet et al. (2020) demonstrated that Bitcoin was not used as a hedge or security during the COVID-19 pandemic. Al-Awadhi et al. (2020) used data from Chinese firms and examined the preliminary effects of the COVID-19 outbreak on share prices in China. The findings demonstrate that financial markets responded negatively to increase in COVID-19 cases. Returns decreased as the number of cases increased. The authors concluded that stock markets reacted more effectively to an increasing number of confirmed cases than an increasing number of deaths. Zhang et al. (2020) also highlighted that the pandemic’s influence on financial markets was negative, indicating that more cases lead to a higher negative effect.

Additionally, Ashraf (2020) studied the stock exchange response to the COVID-19 outbreak. He used daily data on confirmed cases and deaths related to COVID-19 and market returns from 64 markets between 22 January 2020 and 17 April 2020. His findings revealed that stock markets reacted negatively to the increased number of confirmed cases and deaths.

Sansa (2020) explored the effect of COVID-19 on financial markets from 1 March 2020 to 25 March 2020 for China and the United States. The research findings indicated a positive and significant relationship between the COVID-19 confirmed cases and all financial markets (Shanghai Stock Exchange in China and Dow Jones in New York) from 1 March 2020 to 25 March 2020 in China and the United States. Simultaneously, Okorie and Lin (2020) investigated how the COVID-19 outbreak had contagion effects on equity markets fractionally. The results indicated that the equity markets are affected by the COVID-19 outbreak. Additionally, equity market returns and volatility decrease over time with a decrease in the COVID-19 transmission risk.

Albulescu (2020) investigated the practical effect of announcements of infections and deaths produced by the COVID-19 pandemic on the volatility of financial markets in the United States (US). He reported that the COVID-19 pandemic led to an increase in volatility in the S&P 500. The author also highlighted that the continuation of the COVID-19 outbreak is a major contributor to financial volatility, posing a challenge to risk management activities. Akhtaruzzaman et al. (2020) studied the financial contagion that occurred through financial and non-financial companies between China and the G7 countries during the COVID-19 outbreak. They show that financial firms contributed more to financial contagion than non-financial firms. Baig et al. (2020) examined the effect of the pandemic on liquidity and volatility dynamics using indices designed to capture the many dimensions of the outbreak. They concluded that the growth in the number of COVID-19 infected cases and deaths is accompanied by a marked increase in illiquidity and volatility. More recently, Zaremba et al. (2021) focused on bond markets. They investigated the reaction of international sovereign bond markets with government policies during the COVID-19 pandemic. Using a sample of 31 countries, the authors proved that government measures significantly decreased the risk related to local sovereign bonds. Additionally, Albulescu et al. (2021) applied a panel-quantile approach to a sample of 31 countries. Their main goal was to examine the effect of government interventions regarding containment and closure on the risk related to sovereign bonds. The authors showed that these governmental measures increase the volatility of sovereign bonds.

3. Methodology design

3.1. Data

Our study uses sample data on the daily values of the Saudi Tadawul and COVID-19 cases. We collect data on the Tadawul index from the Saudi stock exchange website. Simultaneously, we obtain data related to the COVID-19 pandemic from the European Union Open Data Portal (EU ODP) from 1 January 2020 to 30 August 2020. Based on the Tadawul index data, we compute two main variables: realised volatility and illiquidity indexes.

Refer to Luo and Qin (2017) and Tissaoui and Azibi (2019) to determine the realised volatility variable as follows:

\[ RV_t = r_t^2 \]  \hspace{1cm} (1)

where \( RV_t \) represents the realised volatility on day \( t \) in the Saudi stock market. \( r_t \) is the daily return of the Saudi stock market, calculated using the following formula: \( 100 \times \log(p_t/p_{t-1}) \), where \( p_t \) and \( p_{t-1} \) represent the closing values of days \( t \) and \( t-1 \), respectively.

The illiquidity index: We use the Amihud illiquidity measure as a proxy for liquidity. It is computed as follows:

\[ LQ_t = \frac{|r_t|}{p_t \times V_t} \] \hspace{1cm} (2)

where \( r_t, p_t, \) and \( V_t \) represent the daily return, the closing price of day \( t \), and the trading volume at day \( t \), respectively. \( LQ_t \) represents the Amihud illiquidity ratio at day \( t \). From the COVID-19 pandemic data, we calculate the following variables: the number of infected cases

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3 https://www.ecdc.europa.eu/en/publications-data/download-todays-data-geographic-distribution-covid-19-cases-worldwide
methodology was met. The next step consists of testing the no-cointegration between variables using the ARDL bounds test. Arabia and worldwide are stationary at I(1). This means that the requirement for applying the autoregressive distributed lag (ARDL) stationary at I(0). However, the unit root tests proved that the number of infected cases in Saudi Arabia, globally, and deaths in Saudi

3.2. Benchmark model: the autoregressive distributed lag bound test

Table 1
Descriptive statistics.

| Variables | Mean     | Median   | Maximum | Minimum | Std. Dev. | Skewness | Kurtosis | Jarque-Bera(p-value) | Observations |
|-----------|----------|----------|---------|---------|-----------|----------|----------|---------------------|--------------|
| LQ        | 5.05E-06 | 1.51E-06 | 6.55E-05 | 0.0000  | 9.66E-06  | 3.860130 | 21.043   | 3915.85***          | 244          |
| RVT       | 0.37707  | 0.0107   | 14.22547 | 0.0000  | 1.5680    | 6.809144 | 52.1667  | 26462.1***          | 244          |
| LSC       | 2.14743  | 3.0663   | 3.69187  | 0.0000  | 1.47355   | -0.61017 | 1.57495  | 35.7862***          | 244          |
| LWC       | 3.19906  | 3.3822   | 5.24858  | 0.0000  | 1.66217   | -0.31655 | 1.71998  | 20.7323***          | 244          |
| LDC       | 1.88733  | 0.8740   | 5.47437  | 0.0000  | 2.26156   | 0.801242 | 1.81497  | 40.38457***         | 244          |
| LDW       | 2.94951  | 3.6102   | 4.02073  | 0.0000  | 1.19879   | 3.62858  | 79.7781*** |                     |              |

***Statistical significance at 1% level.

Table 2
Correlation matrix.

|       | LQ      | RVT     | LSC     | LWC     | LDS     | LDW     |
|-------|---------|---------|---------|---------|---------|---------|
| LQ    | 1.00    | 0.91*** | -0.14   | 0.19    | -0.24*  | -0.04   |
| RVT   | 1.00    |         | -0.12   | 0.10    | -0.16   | -0.05   |
| LSC   | 1.00    |         | 0.20**  | 0.65*** | 0.87*** | 0.41*** |
| LWC   | 1.00    |         |         |         | -0.52** | 0.54**  |
| LDS   | 1.00    |         |         |         |         |         |
| LDW   | 1.00    |         |         |         |         |         |

Note: ***, ** and * show significance at 1, 5 and 10% level respectively.

in Saudi Arabia (LSC), infected cases worldwide (LWC), deaths in Saudi Arabia (LDS), and deaths worldwide (LDW).

The summary statistics for all variables are presented in Table 1. The distribution of all variables is asymmetric because the skewness statistic values are different from 0. Furthermore, the results show that the kurtosis values are superior to 3 for the number of infected cases in Saudi Arabia, infected cases worldwide, and deaths in Saudi Arabia. This indicates that the distribution of these variables is leptokurtic. For the remaining variables, the distribution is platykurtic.

Table 2 shows the weak correlation between explanatory variables, except in the association between the number of infected cases in Saudi Arabia and deaths worldwide (0.87), where the level of the correlation is higher than 0.70. This indicates that LSC and LDW

3.2. Benchmark model: the autoregressive distributed lag bound test

This study analyses the short- and long-run connectedness between illiquidity and volatility in Saudi stock exchanges over the COVID-19 period. To perform this, we refer to the ARDL model developed primarily by Pesaran et al. (2001) as our benchmark model. This tool has many advantages compared to traditional approaches, such as the Johansen cointegration tool (Johansen, 1988; Johansen & Juselius, 1990). Malik et al. (2020) affirmed that the ARDL approach was more flexible than the Johansen cointegration tool because all variables need not be integrated in the same order. However, the variable can be stationary at I(0), I(1), or both. Additionally, the ARDL model can be applied to a small sample of data to estimate the long- and short-run relationships between variables. The ARDL model enables the examination of the long-term association between market illiquidity and volatility during the COVID-19 pandemic period. Thus, the ARDL bound model is represented by Equation (3):

$$\Delta Y_t = \beta_0 + \gamma_1 Y_{t-1} + \gamma_2 X_{t-1} + \gamma_3 COVID - 19_{t-1} + \gamma_4 Break + \sum_{i=1}^{p} a_i \Delta Y_{t-i} + \sum_{i=1}^{q} \beta_i \Delta X_{t-i} + \sum_{i=1}^{r} \delta_i \Delta COVID - 19_{t-i} + \epsilon_t \tag{3}$$

where $Y$ is the market illiquidity, $X$ represents the market volatility, and COVID – 19 is the variable representing the number of infected cases in Saudi Arabia, infected cases worldwide, deaths in Saudi Arabia, and deaths worldwide. $\Delta Y$, $\Delta X$ and $\Delta COVID$ – 19 are the difference values of $Y$, $X$ and COVID-19 variables, respectively. $\gamma_1$, $\gamma_2$, and $\gamma_3$ are coefficients that measure the short-run link. $\gamma_4$ is the coefficient of the dummy variable representing the break dates. The breakpoint effect was measured using the coefficient $\gamma_4$.

Pesaran et al. (2001) recommended the Wald or Fisher tests to judge the significance of the cointegration interaction between variables. The refusal of the null hypothesis $H_0 : \gamma_1 = \gamma_2 = \gamma_3 = 0$ specifies the existence of a long-term association between the response and the set of explanatory variables. When the computed F-statistic is below the lower limit of the boundary value, the null hypothesis is supported, meaning that cointegration is not present between the variables. However, if the computed F-statistic is above
the upper limit of the bound value, the null hypothesis is rejected, implying a cointegrating relationship between the variables. Nevertheless, the results are unclear if the calculated value is between the lower and upper limits of the boundary values.

We opt for a standard time-series model, the ARDL, to jointly check the short- and long-run connectedness. The ARDL model is considered a traditional approach to time-series econometric modelling and has the advantage of generating consistent assessments of the long- and short-run coefficients. Using this model, we can detect a cointegration relationship between the considered variables. Additionally, the ARDL can provide various types of information on the causality links between these variables. However, this model cannot concurrently detect the causality and co-movement between time-series for different timescales (short, medium, and long-run) and over time. We believe that this limitation can be overcome by applying the wavelet approach. The wavelet methodology presents several advantages over traditional methods for assessing the contagion phenomenon. In our study, wavelet tools can systematically examine the correlation and movement between time-series in the time and frequency space and provide richer information than time-series models.

3.3. Wavelet coherence analysis

We initially analyse the connectedness between liquidity and volatility in the Saudi market over the COVID-19 outbreak period

| Table 3 |
| --- |
| Unit roots tests. |
| Panel A: Unit root test (PP) |
| At level |
| | LQ | RVT | LSC | LWC | LDS | LDW |
| With Constant t-Statistic | -10.2438 | -9.2975 | -1.7234 | -1.9451 | -0.4170 | -2.6621 |
| Prob. | 0.0000 | 0.0000 | 0.4182 | 0.3113 | 0.9028 | 0.0822 |
| With Constant & Trend t-Statistic | -10.4517 | -9.3867 | -2.6233 | -2.1252 | -2.1077 | -1.6982 |
| Prob. | 0.0000 | 0.0000 | 0.2704 | 0.5287 | 0.5385 | 0.7494 |
| Without Constant & Trend t-Statistic | -8.9190 | -8.9055 | -0.1554 | -0.5986 | 0.5280 | 0.6662 |
| Prob. | 0.0000 | 0.0000 | 0.6291 | 0.4573 | 0.8293 | 0.8592 |
| At first difference |
| | d(LQ) | d(RVT) | d(LSC) | d(LWC) | d(LDS) | d(LDW) |
| With Constant t-Statistic | -86.8904 | -121.2148 | -33.7492 | -19.0902 | -17.1615 | -24.4961 |
| Prob. | 0.0001 | 0.0001 | 0.0001 | 0.0000 | 0.0000 | 0.0000 |
| With Constant & Trend t-Statistic | -86.9895 | -125.1344 | -35.3980 | -19.3300 | -17.1600 | -25.9532 |
| Prob. | 0.0001 | 0.0001 | 0.0001 | 0.0000 | 0.0000 | 0.0000 |
| Without Constant & Trend t-Statistic | -87.2316 | -121.6804 | -31.8413 | -19.1232 | -17.0739 | -25.3689 |
| Prob. | 0.0001 | 0.0001 | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
| Panel B: Unit root test (ADF) |
| At level |
| | LQ | RVT | LSC | LWC | LDS | LDW |
| With Constant t-Statistic | -3.0366 | -4.1345 | -1.4520 | -2.0639 | -0.2810 | -3.6948 |
| Prob. | 0.0330 | 0.0010 | 0.5563 | 0.2597 | 0.9243 | 0.0048 |
| With Constant & Trend t-Statistic | -3.2475 | -4.2796 | -0.0372 | -2.2467 | -2.2117 | -2.5611 |
| Prob. | 0.0779 | 0.0040 | 0.9956 | 0.4611 | 0.4805 | 0.2987 |
| Without Constant & Trend t-Statistic | -2.3102 | -3.4893 | 0.8502 | -0.7038 | 0.7151 | 0.5342 |
| Prob. | 0.0205 | 0.0005 | 0.8933 | 0.4111 | 0.8689 | 0.8307 |
| At first difference |
| | d(LQ) | d(RVT) | d(LSC) | d(LWC) | d(LDS) | d(LDW) |
| With Constant t-Statistic | -7.0013 | -12.2691 | -11.3127 | -19.0913 | -17.1580 | -3.8484 |
| Prob. | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0029 |
| With Constant & Trend t-Statistic | -6.9936 | -12.2440 | -11.4687 | -19.3010 | -17.1600 | -4.6961 |
| Prob. | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0009 |
| Without Constant & Trend t-Statistic | -7.0166 | -12.2957 | -11.0596 | -19.1239 | -17.0548 | -3.4434 |
| Prob. | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0006 |

Notes: (*) Significant at the 10%; (**)Significant at the 5%; (***) Significant at the 1%. and (no) Not Significant. *MacKinnon (1996) one-sided p-values.
using the ARDL bound test. This class of models has shown effectiveness in considering the relationship between variables in the short and long run. However, this approach is unable to consider (i) a complex structure with nonlinearity and time-series spectral features and (ii) the relationship in the very short run, short run, medium run, and long run. Furthermore, we re-examine this study’s main interest by using different wavelet methods to inspect the association between COVID-19 cases and the realised volatility and illiquidity ratio in Saudi Arabia. The reason for selecting different wavelet tools is their ability to spot and follow varying timescale outlines and consider the nonlinearity in time-series data.

3.3.1. Bivariate wavelet coherence

The wavelet tool evaluates the spectral features of time-series as a time function and exposes how their periodic constituents differ with time. Additionally, it can visualise the relationship between time-series variables across frequencies and over time. Notably, investors are heterogeneous, and their heterogeneous investment horizons support several scale bands (high and low scales). Thus, investors make portfolio management decisions differently at different frequency ranges. Wavelet analysis is proving to be a powerful tool for analysing market operators’ behaviour, especially self-similar behaviour, over different time scales. For example, some participants have an investment horizon of several minutes or hours to several days (e.g. when considering short-term movements of stock markets), while others may have an investment horizon of several weeks or months (e.g. with medium-term movements of stock markets) or several years (e.g. with long-term movements). Therefore, we chose different wavelet tools, such as bivariate, partial, and multiple wavelet coherence.

The wavelet is defined as a ‘small wave’, given as $\psi_{\omega}(t) = \frac{1}{\sqrt{2\pi}} e^{|\omega|/2}$. First, a wavelet is a real-valued or complex-valued function $\psi(.)$ defined over the real axis. Moreover, it is assumed that the wavelet is a square-integrable function $\psi(.) \in L^2(\mathbb{R})$. In the above equation, $\frac{1}{\sqrt{2\pi}}$ is the normalisation factor, ensuring that the unit variance of the wavelet satisfies $\|\psi_{\omega}\|^2 = 1$, and udones the location parameter, providing the exact position of the wavelet. $s$ is the scale dilatation parameter of the wavelet, defining the dilation of the wavelet. Particularly, a larger scale implies a more stretched wavelet, appropriate for detecting lower frequencies. Formally, Morlet’s wavelet is given by $\psi_{\omega}(t) = \frac{1}{\sqrt{\pi}} \omega_0 e^{j\omega_0^2 t^2/2}$ where $\psi_{\omega}(t)$ is the wavelet value at non-dimensional time $t$ and $\omega_0$ is the central frequency of the wavelet, which is equal to six.

Mathematically, the cross wavelet method can decompose initially and then restructure the $x(t)$ function (Rua and Nunes, 2009) as follows:

$$x(t) = \sqrt{C} \int_0^\infty \int_{-\infty}^{\infty} W_x(u,s) \psi_{\omega,s}(t) du ds \quad s > 0 \quad (4)$$

where $W_x(u,s)$ is obtained by projecting a specific wavelet. Wavelet coherence is a suitable tool for computing the local correlation coefficients across a series in a time–frequency domain. The absolute smoothed cross-wavelet value is utilised to quantify wavelet coherence, standardised by the product of each series-smoothed individual wavelet power spectrum.

$$R^2(u,s) = \frac{|S_x^{-1} W_x(u,s)|^2}{S_x^{-1} W_x(u,s)^2} \quad (5)$$

The wavelet coherence gives the localised correlation coefficient between these two signals over time and across frequencies. Wavelet coherence can detect co-movements between signals over different investment horizons. From Equation (5), $S$ provides the smoothing parameter. The $R^2(u,s)$ is similar to the correlation coefficient, which meets the ensuing dissimilarity $0 \leq R^2(u,s) \leq 1$. When the squared wavelet coherence value is close to zero, it indicates that the correlation between the two time signals is weak. A correlation coefficient value close to the unit indicates a strong correlation. The phase difference provides an idea about the lateness of the oscillations between the two variables as a function of frequency. The interpretation of the phase difference refers to the direction of the arrows. Precisely, from the wavelet coherence graphs, the lead-lag relationship between two time-series can be detected through the direction of the arrows. The two signals can be in-phase when the arrows are pointing in the right direction, whereas they are in anti-phase when the arrows are pointing in the left direction.

3.3.2. Multiple wavelet coherence

In addition to wavelet coherence analysis, we opt for partial and multiple wavelet techniques (PWC and MWC, respectively). Both these techniques allow the inclusion of control variables in a multivariate framework, which does not allow for other wavelet approaches such as cross-wavelet coherence and wavelet coherence. Even in the framework of a bivariate wavelet, the application of multiple wavelet coherence techniques circumvents the comparison of various series. The bias of low-frequency oscillations is eliminated by employing multiple wavelets, appearing in the estimates of the wavelet power spectrum (see Y. Liu et al., 2007; Veleda et al., 2012). Lastly, multivariate wavelet approaches permit the enclosure of the third variable, the conditioning factor, which is ignored in bivariate wavelet methods. Likewise, the combined effect of the two variables on a third variable is not recognised by the bivariate wavelet coherence technique. The principle of the partial wavelet coherence approach is detecting the wavelet coherence between two time-series after eliminating the power of the third. According to Mihailović et al. (2009), partial wavelet coherence is analogous to a simple correlation and is expressed as given in Equation (3).
Multiple wavelet coherence and multiple correlations are similar, meaningful for exploring the impacts of multiple explanatory variables on an explained variable. The multiple wavelet coherence detailed in the equation below is used following the wavelet coherence application, similar to multiple correlations. However, multiple wavelet coherence can assess many variables’ combined effects on a particular dependent variable.

\[ RM^2(y, x_1, x_2) = \frac{R^2(y, x_1) + R^2(y, x_2) - 2R_yR_x^*R_yR_x^* \cdot R_x}{(1 - R_y^*)} \]

(7)

4. Results and discussion

4.1. Benchmark model results

Table 4 reports the results of the Fisher-Bounds test estimated in Equation (3) and compared to tabulated values fixed by Pesaran et al. (2001). For the nexus between the market illiquidity and market volatility when considering both the Saudi infected cases and structural breakpoint, Table 4 reports that the calculated F-fisher (equal to 8.53) is greater than the upper bound of the tabulated values for all significance levels (1%; 2.5%; 5%; and 10%) indicating that the null hypothesis of no cointegration is rejected for the Equation (3). Then, we confirm a long-run link between the market illiquidity and volatility and Saudi infected cases. The same findings hold for the relationship between the market illiquidity and volatility when considering Saudi deaths and global infected cases and deaths.

Table 4 reports that the calculated F-fisher is greater than the upper bound of tabulated values for all significance levels in the cases of Saudi deaths (equal to 8.81), the global infected cases (equal to 7.94), and deaths (equal to 7.55). Thus, our results support Hoque and Yusop’s (2010) and Fuinhas and Marques’s (2012) proposition stipulating that the variables move together, and therefore, cannot move separately from each other.

Next, we estimate the nature of the relationship between market illiquidity and its independent variables using the ARDL methodology. First, we use the Akaike information criterion (AIC) to select our data’s best model. At the domestic level, we show that ARDL (8.7.10.0) and ARDL (7.8.2.3) are the best models representing the relationship between [market illiquidity-market volatility-Saudi infected cases] and [market illiquidity-market volatility-Saudi deaths]. The results of the conditional error correction regression (Equation (3)) are reported in Table 5 (Appendix A) and Table 7 (Appendix A). We highlight the Saudi infected cases (LQ (−1) = −0.6885) and the Saudi deaths (LQ (−1) = −0.6875). This confirmed our results of the bounds test, indicating a long-run relationship between variables. This reveals a very high speed of change from short-run disequilibrium to long-run equilibrium.

The ARDL results, for both Saudi infected cases and deaths, also show that the recent change in market volatility (D(RVT)) has a
positive and significant effect on market illiquidity, meaning that there is a short-run relationship between variables. We also observe that the lagged change in market volatility (D(RVT (-1) and D(RVT(-2)) has no significant impact on market illiquidity in the short run. However, our results show that the lagged change in market volatility (D(RVT (-3) and D(RVT(-6)) positively and significantly influences market illiquidity in the short run when we include the Saudi infected cases. However, when we include the Saudi deaths, the results prove that lagged changes in market volatility (D(RVT(-3), D(RVT(-4), and D(RVT(-7)) positively and significantly influence market illiquidity in the short-run.

The Wald test $\chi^2$ indicates that the aggregate influence of the lagged change in market volatility in both cases is positive and significant, meaning that the past information relating to market volatility predicts market illiquidity across time in the short run. The ARDL also exhibited that the contemporaneous change in Saudi infected cases (D(LSC)) is positive and significant, implying a relationship between market illiquidity and Saudi infected cases in the short run. However, the relationship with Saudi deaths was non-significant.

The lagged change in Saudi COVID-19 infected cases (D[LSC(-1)], D[LSC(-2), D(LSC(-4), D(LSC(-5), D(LSC(-6), D(LSC(-7)) and Saudi deaths (D(LSC(-1))) positively and significantly influence the current market illiquidity in the short run. However, D(LSC(-3)) and D(LSC(-8)) have no impact on Saudi cases. The Wald test with $\chi^2 = 31.66$ and p-value of 0.000 indicates that the aggregate impact of the lagged change in Saudi infected cases (D[LSC(-1)] = ... = D(LSC(-9)) = 0) is positive and significant. This signifies that the number of COVID-19 cases in Saudi Arabia helps predict market illiquidity over time in the short run.

At the international level, the Akaike information criterion (AIC) reveals that ARDL (8.7.0.0) is the best model to represent the relationship between market illiquidity and its independent variables, infected cases, and deaths worldwide. The findings from the conditional error correction regression (Equation (3)) are reported in Table 6 (Appendix A) and Table 8 (Appendix A). Negative and significant values of ECT$_{1}(LQ(-1)) = -0.64$ and (LQ(-1) = -0.56) are detected in both cases, indicating the existence of a long-run relationship between market illiquidity and volatility—the global infected cases and between market illiquidity and market volatility—and deaths worldwide. This indicates a very high speed of adjustment from short-run disequilibrium to long-run equilibrium.

The ARDL results for the infected cases and deaths worldwide show that the recent change in market volatility (D(RVT)) has a positive and significant effect on the market illiquidity, meaning that there is a short-run relationship between variables. However, this is not the case for lagged changes in market volatility in lag (1) and lag (2). The results show that D(RVT (-1) and D(RVT(-2)) are positive and non-significant in the short run. Furthermore, we observe that lagged changes in market volatility (D(RVT(-3) to D(RVT (-6)) have a positive and significant impact on market illiquidity in the short run. Wald test $\chi^2$ highlights that the aggregate influence of lagged change in market volatility (D(RVT(-1)) to D(RVT(-6)) is positive and significant. This indicates that past information relating to market volatility persists in forecasting market illiquidity across time in the short run. However, the non-significance of the contemporaneous and lagged change in COVID-19 infected cases and deaths globally, confirming that there is no short-run relationship between market illiquidity and global infected cases and between market illiquidity and global deaths. This signifies that the number of COVID-19 infected cases and deaths worldwide does not help forecast and explain Saudi market liquidity over time in the short run.

We now discuss the long-run correlation between market illiquidity and volatility in the Saudi stock market. The results reported in Tables 5–8 (Appendix A) highlight the positive and significant contemporaneous (RVT) and lagged (RVT (-1)) effects of market volatility on illiquidity in the long run. Moreover, Table 8 (Appendix A) shows a long-run correlation between Saudi deaths and market illiquidity at a contemporaneous and lagged level. However, Saudi infected cases, global infected cases, and deaths do not impact Saudi market illiquidity in the long run.

This certifies that the Saudi stock market is only affected by the information about COVID-19 related to Saudi Arabia in the short run. However, this influence does not exist in the long run, except in Saudi deaths. Additionally, our results revealed that global information about COVID-19 disease does not influence market illiquidity in the Saudi stock market, both in the short run and in the long run.

Next, we apply the Breusch-Godfrey correlation LM test and the heteroskedasticity test. The findings show that the residuals generated by ARDL estimates are not affected by serial correlation and heteroskedasticity. This demonstrates the validity and reliability of ARDL (8.7.10.0), ARDL (7.8.2.3), ARDL (8.7.0.0), and ARDL (8.7.0.0). Cumulative sum (CUSUM) and CUSUM of squares tests are also used to check the stability of all the best models. Figs. 1–4 (Appendix B) showing the CUSUM test results indicate that all models are stable. However, the CUSUM of squares shows that the models’ estimated coefficients are higher than the 5% bounds, implying they are unstable. The non-normality and nonlinearity of time-series data provide the main explanation for this finding. Given this main result, the wavelet tools appear appropriate to study the link between the illiquidity ratio and the stock market realised volatility in Saudi Arabia during the COVID-19 pandemic period.

4.2. Wavelet tools results

4.2.1. Bivariate wavelet coherency findings

The wavelet analysis allows us to detect the coherence between the illiquidity ratio and the stock market realised volatility for Saudi Arabia during the COVID-19 outbreak period. We recognise a strong coherence between the two variables over time and across the scale bands from the following plot. In addition to colour map coding, the wavelet coherence graph permits us to perceive the lead-lag relationship between these two time-series through arrows. The two signals can be in-phase or in a positive relationship when the arrows are pointing in the right direction. In contrast, they are in an anti-phase relationship when the arrows are pointing in the left direction, indicating a negative relationship in the frequency-time space. In this graph, based on the scalogram decoding, the
degradation of the blue colour stipulates that the causality relationship is non-linear; in other words, the correlation $R_{xy}(s, \tau) = 0$ indicates a lack or low dependency between the two variables, whereas red indicates a linear relationship and high dependency between time-series where $R_{(x, y)}(s, \tau) = 1$.

The wavelet coherence between the illiquidity ratio and realised volatility in Saudi Arabia is highly pronounced over all scales, signifying that the coherence is scattered; thus, it varies over the short, medium, and long-term horizons COVID-19 outbreak period. The main conclusions emerged from this plot. First, we categorised coherence localisation into four horizon types. The very short run corresponds to the (2–4) band of scale, whereas the short run remains in the (4–8) band of scale. While the medium-run coherence between the variables will be included over the (8–16 and 32–64) frequency band, the long-run will be comprised especially over the (16–32) frequency band. Therefore, in the very short band of scale, Fig. 5 reveals a positive relationship and a strong coherence between the illiquidity ratio and realised volatility. In addition, for this horizon, the arrows change direction over time. During the sub-period sample starting from 1/1/2020 to 29/2/2020, these arrows indicate that the two variables are in phase, and the lead-lag connectedness is not easily understandable. A remarkable change in the direction of arrows was perceived from mid-March to the end of the same month. They are right and up, revealing that the illiquidity ratio leads the stock market realised volatility movement in the short term. Interestingly, this period corresponds to the post-period after the first COVID-19 infected cases were officially declared in Saudi Arabia (3/3/2020). This finding is not surprising, as this period corresponds to the crash of oil prices following the tussle between Saudi Arabia and Russia. After this sub-period, no interesting change in the leader–follower relationship is observed. However, the relationship is still positive; the shockwave to oil flustered the Saudi stock market, which was already exposed to COVID-19 pandemic.

A general view of the rest of the sample period, for the very short run, reveals that this pattern continues, again indicating a unidirectional linear causality relationship between the illiquidity ratio and Saudi stock market realised volatility. In the short and middle runs, the highest coherence was dispersed over two sub-periods. Precisely, from 1/1/2020 to 29/4/2020, the arrows are pointing right and down, indicating that the stock market realised volatility is leading; in other words, this variable causes an illiquidity problem. The same pattern is shown for the period from 18/5/2020 to the end of the sample period, as this period is characterised by an increasing number of COVID-19 infected cases. The long-term horizon shares the same pattern as the horizons mentioned above. Besides the strong linear causality relationship between the variables, the realised volatility leads to illiquidity in the Saudi stock market.

4.2.2. Multivariate wavelet findings

4.2.2.1. Co-movement between illiquidity risk and realised volatility on local COVID-19 cases. As observed globally, the COVID-19 virus continued to generate anxiety, uncertainty, and distress in Saudi Arabia, surpassing the international economy, intensifying the financial markets’ volatility, and creating market liquidity problems. The Saudi Arabian stock market was not immune to the severe impact of the COVID-19 outbreak, where the market index plunged by more than 7% with the increasing number of confirmed cases. Notably, the shock of oil prices during the same period spilt over financial markets. Together, the COVID-19 outbreak and the oil crisis
created serious problems in stock market volatility and liquidity.

This section focuses on the effect of COVID-19 cases worldwide and in Saudi Arabia on the co-movement between illiquidity risk and realised volatility in the Saudi Arabian context. In Fig. 6, the PWC exhibits this co-movement between illiquidity risk and realised volatility when cancelling out the effect of COVID-19 infected cases in Saudi Arabia. When eliminating this impact, over the sample period, except for a few days, the strong positive co-movement between the two variables is scattered in the short term. In contrast, in the medium-scale bands, the co-variation is only localised in the middle of the sample period. The long-term co-movement between the two variables is localised over three months, corresponding to the sub-period from 17/2/2020 to 14/4/2020. This result confirms our findings from the ARDL bound test, showing a strong correlation between volatility and liquidity in long-term horizons.

Fig. 7 demonstrates the combined effect of the realised volatility and local COVID-19 infected cases on the Saudi market illiquidity risk fluctuation over time and across scale bands. The existence of small islands of yellow in the short- and medium-term horizons cannot overlook the remarkable joined impact of the realised volatility and COVID-19 infected cases on Saudi stock market illiquidity.

From this plot, the synchronised contribution of these two independent variables in explaining the market illiquidity risk movement is localised over the sample period and viewed both at high and low frequencies, while it is mostly displayed at high frequencies. This indicates that this combined effect is revealed in the short term, especially the period from 20/1/2020 to 29/4/2020, where the squared correlation ranges from 0.8 to 1. Thus, the growing number of Saudi COVID-19 cases, which added to the uncertainty.
characterising the Saudi market during the pandemic, can explain the strong movement of market illiquidity risk. Our results corroborate those of Baiga et al. (2020). Interestingly, the response of the market illiquidity index to the rise in confirmed cases and stock market volatility is significant in the short and middle runs.

The effect of Saudi deaths on the relationship between illiquidity risk and realised volatility is revealed in the PWC and MWC plots (Figs. 8 and 9). The PWC plot (Fig. 8) shows small islands of blue and green distributed over the sample period across high frequencies. Eliminating the effect of deaths shows a reasonable coherence between illiquidity risk and realised volatility in the short run during April 2020–June 2020. The first Saudi deaths were disclosed on 25/3/2020. The sub-periods including this date, when eliminating the COVID-19 death effect, did not show co-movement between illiquidity and volatility in the low scale (2–4 band). However, the co-movement is more pronounced during the same sub-period over the medium horizon, with a correlation ranging from 0.7 to 0.9. These findings are consistent with Ashraf (2020); the stock market reaction to the increase in COVID-19 deaths is weak.

Moreover, in the short run, it is clearly shown that the combined effect of realised volatility and deaths (Fig. 9) on illiquidity risk is relatively strong, including the first death announcement. In contrast, over the pre- and post-sub-periods, a strong correlation ranging
from 0.9 to 1 is perceived, indicating a strong joint impact of realised volatility and deaths on illiquidity risk. Although this correlation decreases slightly in the medium term, it remains strong, especially from 9/2/2020 to 9/4/2020, where the correlation ranges from 0.8 to 0.9. This result confirms the findings of Baiga et al. (2020). The authors revealed a quick and significant increase in market illiquidity and volatility when death announcements were revealed. These results are consistent with those reported in the ARDL approach, showing a short-term positive relationship between volatility and illiquidity in the Saudi stock market.

Additionally, in the long term, with increasing uncertainty and deaths, the combined impact of the realised volatility and deaths announcement is pronounced during the period 9/2/2020 to 9/4/2020. Thus, our findings from the ARDL bound test indicate a strong relationship between market liquidity and market volatility.

4.2.3. Nexus between illiquidity risk and realised volatility on World COVID-19 counts

The COVID-19 outbreak has affected human life as global infection cases and deaths continue to rise. Six months after the outbreak of the COVID-19 pandemic was declared, this pandemic continued to increase, and the number of deaths approached one million cases.
This pandemic’s dramatic economic repercussions were recorded in financial markets, where they chronicled shockwaves from February 2020. As was the case worldwide, Saudi Arabia suffered an economic dip. Additionally, the crude oil warfare in March 2020 between Saudi Arabia and Russia injected volatility into the financial market. Therefore, the Saudi stock market had moved into a bear market during this crash, with more than a 7% cut in the TASI index. The plot of the relationship between realised volatility and COVID-19 numbers worldwide (Fig. 10) reveals that the realised volatility in Saudi Arabia increased during the sample period, especially from the beginning of March 2020, explaining the significant influence of the oil price shock on the stock market volatility and investors’ lack of confidence before making investment decisions.

The combined effect of global COVID-19 infected cases and realised volatility (Fig. 12) positively and significantly influences the variation in the illiquidity ratio in Saudi Arabia. From January 2020 to April 2020, a strong impact is perceived in the short horizon. In
contrast, this pattern is becoming increasingly remarkable and has spread to the medium run from June 2020 to the end of the sample period. This finding confirms the market microstructure theory (Stoll, 1978), stipulating that higher return volatility increases the detention costs or the inventory costs of stocks and leads to an increase in the bid-ask spread, significantly affecting the illiquidity of the market.

Figs. 13 and 14 correspond to the PWC and MWC of Saudi market illiquidity and market volatility, respectively, controlled by the global COVID-19 deaths. When the global COVID-19 death variable is controlling, the relationship between Saudi market illiquidity...
and market volatility remains strong but dispersed over the whole sample period, especially over the short horizon. Big islands of blue are shown in the middle run, whereas a relatively strong co-movement is perceived in the long horizon. The combined effect of market volatility and COVID-19 deaths (Fig. 14) shows a strong effect on the movement of the illiquidity market, especially across high frequencies (short term). During the COVID-19 pandemic, market confidence retreated rapidly. This makes investors (especially short-term investors) more uncertain about transactions and the pattern of financial markets over the coming period. Therefore, investors rapidly pursued to avoid risk and stockpile cash, thus creating a problem of illiquidity in the market. Furthermore, our findings confirm a causal effect of volatility on illiquidity (in the same country), even if we control for this effect using another variable (global risk factor). Meanwhile, the combined effect of the COVID-19 outbreak and realised volatility is strongly revealed in the short horizon, thus confirming the anxiety and restlessness of short-term investors during the COVID-19 outbreak.

Fig. 16. PWC: Illiquidity Amihud, conditional volatility and Saudi COVID-19 infected cases. Notes: The Partial wavelet coherencies between Illiquidity Amihud, conditional volatility controlling by the Saudi COVID-19 infected cases. The black contour recognizes the regions in which the spectrum is significant at the 5% level against red noise. The cone of influence (COI) designated by the lighter shade which delimits the high-power regions. The horizontal and vertical axes denoted time and scale bands, respectively. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Fig. 17. MWC: Illiquidity Amihud, realised volatility and Saudi COVID-19 infected cases. Notes: The Multiple wavelet coherencies of the combined effect of the realised volatility and the Saudi COVID-19 infected cases on the Illiquidity Amihud. The black contour recognizes the regions in which the spectrum is significant at the 5% level against red noise. The cone of influence (COI) designated by the lighter shade which delimits the high-power regions. The horizontal and vertical axes denoted time and scale bands, respectively. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)
5. Robustness check

In this section, we try to check the robustness of our main findings. It is worth to note that various approaches are employed to estimate the volatility of time series. We understand, among them the historical volatility consisting on calculating the variance of returns over a period and this measure will be useful to estimate the volatility over the forthcoming period. As well, the implied volatility also serves to for forecasting volatility. In addition, the autoregressive volatility models can also be employed to model volatility of time series. These models suppose that future values are based on passed terms. Among the autoregressive models, we recognize EGARCH model. To validate the choose of the volatility measure, we use a EGARCH (1,1) model to extract the conditional volatility of the Saudi Stock market during the same sample period.

For the conditional volatility, we estimate the following EGARCH (1,1) suggested by Nelson (1991), and then we extract the variances series as proxy of volatility:

![Figure 18: PWC: Illiquidity Amihud, conditional volatility and Saudi COVID-19 death cases. Notes: The Partial wavelet coherencies between Illiquidity Amihud, conditional volatility controlling by the Saudi COVID-19 death cases. The black contour recognizes the regions in which the spectrum is significant at the 5% level against red noise. The cone of influence (COI) designated by the lighter shade which delimits the high-power regions. The horizontal and vertical axes denoted time and scale bands, respectively. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)](image1)

![Figure 19: MWC: Illiquidity Amihud, conditional volatility and Saudi COVID-19 death cases. Notes: The Multiple wavelet coherencies of the combined effect of the conditional volatility and the Saudi COVID-19 death cases on the Illiquidity Amihud. The black contour recognizes the regions in which the spectrum is significant at the 5% level against red noise. The cone of influence (COI) designated by the lighter shade which delimits the high-power regions. The horizontal and vertical axes denoted time and scale bands, respectively. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)](image2)
\[ \ln(h_t^2) = \omega + \alpha_1 \frac{\varepsilon_{t-1}}{h_{t-1}} + \alpha_2 \ln(h_{t-1}^2) + \alpha_3 \frac{\varepsilon_{t-1}}{h_{t-1}} \]

where \( \ln(h_t^2) \) is the conditional variances of Tadawul index at time t. \( \alpha_1 \) and \( \alpha_2 \) represent respectively the previous error term and the previous conditional variances at time t. \( \alpha_3 \) is the leverage effect parameter.

The following plot (Fig. 15) reveals the wavelet coherency between illiquidity ratio and the conditional volatility of the Saudi stock market. We interestingly note the high coherency between the two variables over time and across different scales. Merely, big red islands are scattered over high as well as short scales indicating strong co-movements between liquidity and volatility during the selected period of COVID-19 epidemic. While for some sub-periods we obviously remark that the lead-lag relationship between the variables display arbitrarily as the arrows’ direction was not clear, in the short and medium horizons, the graph clearly stipulates that the liquidity ratio is out-of-phase with the conditional volatility as a lagging variable. It means that, in the high scales, illiquidity problem precedes an increase in the conditional volatility in the Saudi stock market. In the long run, a positive relationship between the two variables is clearly pronounced indicating that an increase in the conditional volatility is followed by an illiquidity problem in the Saudi stock. It is interesting to note that for this horizon these finding corroborate our previous results. The change of the volatility measure did not affect the relationship between liquidity ratio and volatility in the Saudi Stock market.

Looking now to the plots (Fig. 16 and Fig. 17) respectively corresponding to the partial and multiple wavelet coherencies when considering the Saudi infected cases as a control variable. When eliminating the effect of this variable, we perceive a strong co-movement between the illiquidity ratio and conditional volatility over time and across scales. In addition, the combined effect of the conditional volatility and infected cases is well observed in the time–frequency domain. Again, the relationship between the illiquidity ratio and the conditional volatility remains strong even with the use of the conditional volatility extracted from an EGRACH (1,1) model.

Fig. 18 and Fig. 19 exhibit the partial and multiple wavelet coherency between illiquidity ratio, conditional volatility and death cases counts in Saudi Arabia. Controlling out the effect of the death cases allows us to show a strong coherency between the two variables in the short and long terms. The join positive and significant effect of death cases and conditional volatility is remarkably perceived on the illiquidity ratio.

Overall, from these findings, we can confirm that the use of another measure of volatility did not change the relationship between the illiquidity ratio and volatility in the Saudi stock market.

6. Conclusion and implications

Since the World Health Organization’s declaration on 11 March 2020 that COVID-19 was a global influenza pandemic, there has been a worldwide increase in fear about all aspects of the pandemic. Financial markets have captured a large part of these uncertainties, where trading volumes have fallen sharply in most economies worldwide. More particularly, this fear quickly spread to investors, who were worried about the market’s stability in the short and long term. In Saudi Arabia, the TASI index was also affected by this pandemic, and there was a rapid loss of points until the end of March 2020. Many authors, as discussed previously, have tried to consider the link between the COVID-19 pandemic and financial markets. They found that this pandemic had a significant impact on financial markets.

This study investigates the explanatory power of realised volatility on illiquidity in the Saudi stock market during the global COVID-19 pandemic. Therefore, the ARDL bound test and a wavelet coherence approach have been considered to identify the nature of the impact of the number of infected cases in Saudi Arabia, the number of infected cases worldwide, the number of deaths in Saudi Arabia, and the number of deaths worldwide on the relationship between realised volatility and market illiquidity across frequencies and over time.

Our main results are as follows: the bound test and the conditional error correction regression prove evidence of a significant long-run association between market illiquidity and volatility in a contemporaneous and lagged manner when considering the Saudi infected cases, Saudi deaths, and both infected cases and death worldwide. A significant relationship was also detected between variables at the contemporaneous and lagged levels in the short-run horizon. The empirical results also revealed that Saudi infected cases, global infected cases, and deaths do not impact the long-run market illiquidity in contemporaneous and lagged levels. On the contrary, significant explanatory power is confirmed in the short run. Additionally, the findings show that Saudi deaths significantly affect the long-run market illiquidity in contemporaneous and lagged levels. However, recent changes in the number of COVID-19 cases in Saudi Arabia have a non-significant impact on market illiquidity.

Additionally, interesting results emerged from the wavelet coherence approaches. First, the bivariate wavelet analysis provides evidence that the wavelet coherence between the illiquidity ratio and realised volatility in Saudi Arabia is highly pronounced over all scales, signifying that the coherence is scattered; thus, in the short, medium, and long-term horizons, and that it varies over time during the COVID-19 outbreak period. Second, the PWC shows a significant mutual effect between liquidity risk and realised volatility when we eliminate the effect of local COVID-19 cases during the pandemic period. This significant co-movement is evident for all time horizons. Similarly, the MWC plot highlighted that the response of the market illiquidity index to the amplification in confirmed local cases and the stock volatility market is significant in the short and middle horizons. MWC found similar results globally, showing that the combined effect of the amplification influences Saudi Arabia in the illiquidity ratio in global confirmed cases and stock volatility market in the short and middle horizons. Additionally, the MWC plots confirmed a significant combined impact of the realised volatility and Saudi death announcements on the illiquidity market, especially in the short-and long-run horizons. However, our results...
show a strong effect of the explanatory power of both market volatility and COVID-19 deaths on the movement of the liquidity market, especially across high frequencies (short term). Financially, investors’ panic and fear can represent the main reason for this state of the Saudi market, especially in the case of new investors entering the market with the Aramco IPO at the end of 2019. Amid this crisis, these investors sensed that the market would not recover in the short- and middle-run. This lead to investors’ confusion and inability to make optimal buying and selling decisions, which increased market return volatility and thus affected market liquidity stability.

Furthermore, the contribution of our work is the relevance of the results found in the Saudi context. These findings provide new, institutional, and foreign investors with a clear vision of the nature of the relationship between risk and liquidity during a pandemic. This will allow them to judge the solidity and stability of the Saudi financial market after the inclusion of Saudi shares in the MSCI index, FTSE Russell index, and the IPO of ARAMCO; particularly, market participants consider MSCI’s and FTSE Russell decisions and the IPO of ARAMCO as a certification of the conformity of the standards of the Saudi financial market to the requirements of the global investment community.

Our results have many practical implications. First, useful information about COVID-19 infected cases and deaths at the local and global levels can serve investors in the Saudi stock market as a forecaster of illiquidity. Thus, the predictive power of these variables for illiquidity can help individual investors formulate their investment strategies better and efficiently use hedging instruments in the short and long horizons. Second, the significant impact of COVID-19 infected cases and deaths on market illiquidity does not support the semi-strong efficiency hypothesis of the Saudi stock market in the short run. This indicates that the available information about COVID-19 infected cases and death is not fully reflected in the current Saudi market illiquidity. In other words, investors can use previous information about COVID-19 data to forecast the current Saudi market illiquidity.

CRediT authorship contribution statement

Kais Tissaoui: Data curation, Methodology, Formal analysis, Investigation, Writing - original draft. Besma Hkiri: Investigation, Methodology, Writing - review & editing, Supervision, Validation, Visualization, Project administration. Mariem Talbi: Conceptualization, Investigation, Writing - review & editing. Waleed Alghassab: Supervision, Investigation, Visualization. Khaled Issa Alfereahat: Data curation, Software, Writing - original draft, Visualization, Investigation.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendices

Appendix A

Fig. 1. CUSUM Test and CUSUM of Squares test: Market liquidity, Market volatility and Saudi infected COVID-19 cases.
Fig. 2. CUSUM Test and CUSUM of Squares test: Market liquidity, Market volatility and infected COVID-19 cases in the world.

Fig. 3. CUSUM Test and CUSUM of Squares test: Market liquidity, Market volatility and Saudi death COVID-19 cases.

Fig. 4. CUSUM Test and CUSUM of Squares test: Market liquidity, Market volatility and death COVID-19 cases in World.
### Appendix B

Table 5
Estimated ARDL (8.7.10.0) of Relationship between market liquidity, Market volatility and Saudi infected cases.

| ARDL(8.7.10.0) | Variable | Coefficient | Std. Error | t-Statistic | Prob. | Wald test $\chi^2$ |
|----------------|----------|-------------|------------|-------------|-------|-------------------|
| Short run level |          |             |            |             |       |                   |
|                 | C        | 1.77E-06    | 5.96E-07   | 2.972748    | 0.0033*** |                   |
|                 | LQ(-1)*  | -0.688565   | 0.135808   | -5.070117   | 0.0000*** |                   |
|                 | BRK**    | -3.33E-06   | 1.79E-06   | -1.863702   | 0.0638*  |                   |
|                 | D(LQ(-1))| -0.296124   | 0.124541   | -2.377729   | 0.0183**  | 1091.07 (0.000)   |
|                 | D(LQ(-2))| -0.256539   | 0.117229   | -2.188368   | 0.0298**  |                   |
|                 | D(LQ(-3))| -0.410841   | 0.106497   | -3.857792   | 0.0002*** |                   |
|                 | D(LQ(-4))| -0.410375   | 0.093873   | -4.371616   | 0.0000*** |                   |
|                 | D(LQ(-5))| -0.378161   | 0.078919   | -4.791734   | 0.0000*** |                   |
|                 | D(LQ(-6))| -0.323285   | 0.069908   | -4.624443   | 0.0000*** |                   |
|                 | D(LQ(-7))| -0.077656   | 0.030033   | -2.585659   | 0.0104**  |                   |
|                 | D(RVT)   | 5.15E-06    | 1.79E-07   | 28.69757    | 0.0000*** |                   |
|                 | D(RVT(-1))| 6.37E-08   | 7.04E-07   | 0.9280      | 23.48 (0.000) |                   |
|                 | D(RVT(-2))| 2.65E-07   | 6.46E-07   | 0.499359    | 0.6827    |                   |
|                 | D(RVT(-3))| 1.47E-06   | 5.96E-07   | 2.457925    | 0.0148**  |                   |
|                 | D(RVT(-4))| 1.31E-06   | 5.38E-07   | 2.441768    | 0.0155**  |                   |
|                 | D(RVT(-5))| 8.31E-07   | 4.64E-07   | 1.791173    | 0.0747*   |                   |
|                 | D(RVT(-6))| 7.77E-07   | 4.04E-07   | 1.920392    | 0.0562*   |                   |
|                 | D(LSC)   | 2.78E-06    | 1.05E-06   | 2.663483    | 0.0083***|                   |
|                 | D(LSC(-1))| 3.88E-06   | 1.33E-06   | 2.918007    | 0.0035***| 31.66 (0.000)     |
|                 | D(LSC(-2))| 2.62E-06   | 1.51E-06   | 1.732078    | 0.0847*   |                   |
|                 | D(LSC(-3))| 2.32E-06   | 1.46E-06   | 1.586017    | 0.1143    |                   |
|                 | D(LSC(-4))| 2.49E-06   | 1.48E-06   | 1.681239    | 0.0942*   |                   |
|                 | D(LSC(-5))| 2.81E-06   | 1.48E-06   | 1.891114    | 0.0604*   |                   |
|                 | D(LSC(-6))| 3.17E-06   | 1.45E-06   | 2.181751    | 0.0303**  |                   |
|                 | D(LSC(-7))| 2.62E-06   | 1.44E-06   | 1.823034    | 0.0698*   |                   |
|                 | D(LSC(-8))| -1.17E-06  | 1.29E-06   | -0.908223   | 0.3648    |                   |
|                 | D(LSC(-9))| -2.08E-06  | 9.75E-07   | -2.135933   | 0.0339**  |                   |
| Long run level  |          |             |            |             |       |                   |
|                 | RVT      | 6.67E-06    | 5.41E-07   | 12.32973    | 0.0000***|                   |
|                 | RVT(-1)  | 4.59E-06    | 7.64E-07   | 6.010321    | 0.0000***|                   |
|                 | LSC      | -1.71E-07   | 2.22E-07   | -0.770480   | 0.4419   |                   |
|                 | LSC(-1)  | -1.18E-07   | 1.54E-07   | -0.761820   | 0.4470   |                   |
|                 | BRK      | -4.83E-06   | 2.85E-06   | -1.694880   | 0.0916*  |                   |
|                 | C        | 2.57E-06    | 6.35E-07   | 4.052176    | 0.0001***|                   |

Residual diagnostics
- Breusch-Godfrey Correlation LM Test: 0.788 (0.405)
- Heteroskedasticity Test: 0.187 (0.0664)*

Notes: (*)Significant at the 10%; (**)Significant at the 5%; (***) Significant at the 1%.
| Variable       | Coefficient | Std. Error | t-Statistic | Prob.  |
|---------------|-------------|------------|-------------|--------|
| ARDL(8.7.0.0) |             |            |             |        |
| Short run level |             |            |             |        |
| C             | 7.78E-07    | 5.30E-07   | 1.467685    | 0.1436 |
| LQ(-1)*       | -0.642690   | 0.131323   | -4.893953   | 0.0000*** |
| D(LQ(-1))     | -0.309664   | 0.127442   | -2.429841   | 0.0159**  |
| D(LQ(-2))     | -0.329964   | 0.122472   | -2.694192   | 0.0076*** |
| D(LQ(-3))     | -0.463720   | 0.109927   | -4.218434   | 0.0000*** |
| D(LQ(-4))     | -0.448866   | 0.094966   | -4.726593   | 0.0000*** |
| D(LQ(-5))     | -0.404327   | 0.082488   | -4.901669   | 0.0000*** |
| D(LQ(-6))     | -0.314144   | 0.070412   | -4.461491   | 0.0000*** |
| D(LQ(-7))     | -0.081231   | 0.029986   | -2.708970   | 0.0073*** |
| D(RVT)        | 5.21E-06    | 1.86E-07   | 28.01559    | 0.0000*** |
| D(RVT(-1))    | -1.66E-07   | 7.56E-07   | -2.220125   | 0.8260  |
| D(RVT(-2))    | 3.76E-07    | 7.00E-07   | 0.536934    | 0.5919  |
| D(RVT(-3))    | 1.55E-06    | 6.33E-07   | 2.455057    | 0.0149** |
| D(RVT(-4))    | 1.49E-06    | 5.45E-07   | 2.742351    | 0.0066*** |
| D(RVT(-5))    | 9.65E-07    | 4.78E-07   | 2.017537    | 0.0449** |
| D(RVT(-6))    | 7.01E-07    | 3.99E-07   | 1.758955    | 0.0800* |
| Long run level |             |            |             |        |
| Variable      | Coefficient | Std. Error | t-Statistic | Prob.  |
| RVT           | 7.37E-06    | 5.46E-07   | 13.50627    | 0.0000*** |
| RVT(-1)       | 4.74E-06    | 8.01E-07   | 5.915247    | 0.0000*** |
| LWC           | 3.24E-07    | 2.30E-07   | 1.411984    | 0.1594  |
| BRC           | -2.09E-06   | 2.69E-06   | -0.776596   | 0.4382  |
| C             | 1.21E-06    | 8.00E-07   | 1.512441    | 0.1319  |

Residual diagnostics

| Test                        | Value | Prob.  |
|-----------------------------|-------|--------|
| Breusch-Godfrey Correlation | 0.535 (0.5863) |
| Heteroskedasticity Test     | 0.002 (0.9630) |

Notes: (*) Significant at the 10%; (**) Significant at the 5%; (***) Significant at the 1%.
Table 7
Estimated ARDL (7.8.2.3) of Relationship between market liquidity, Market volatility and Saudi death cases.

| ARDL(7.8.2.3) | Variable | Coefficient | Std. Error | t-Statistic | Prob.       | Wald test $\chi^2$ |
|----------------|----------|-------------|------------|-------------|-------------|-------------------|
| Short run level | C        | 2.01E-06    | 6.02E-07   | 3.331721    | 0.0010***   |                   |
|                | LQ(-1)*  | -0.687563   | 0.132603   | -5.185133   | 0.0000***   |                   |
|                | D(LQ(-1))| -0.254296   | 0.126060   | -2.017257   | 0.0449**    | 1046.04 (0.000)   |
|                | D(LQ(-2))| -0.292832   | 0.119011   | -2.460542   | 0.0147**    |                   |
|                | D(LQ(-3))| -0.390157   | 0.107029   | -3.645350   | 0.0003***   |                   |
|                | D(LQ(-4))| -0.363903   | 0.091803   | -3.963946   | 0.0001***   |                   |
|                | D(LQ(-5))| -0.347770   | 0.078438   | -4.433672   | 0.0000***   |                   |
|                | D(LQ(-6))| -0.259596   | 0.064033   | -4.054080   | 0.0001***   |                   |
|                | D(RVT)   | 5.20E-06    | 1.89E-07   | 2.749849    | 0.0000***   |                   |
|                | D(RVT(-1))| -5.27E-07  | 7.59E-07   | -0.694447   | 0.4882      | 25.05 (0.000)    |
|                | D(RVT(-2))| 2.24E-07   | 7.01E-07   | 0.318956    | 0.7501      |                   |
|                | D(RVT(-3))| 1.29E-06   | 6.40E-07   | 2.013565    | 0.0457**    |                   |
|                | D(RVT(-4))| 1.08E-06   | 5.59E-07   | 1.942466    | 0.0534      |                   |
|                | D(RVT(-5))| 7.07E-07   | 4.82E-07   | 1.466280    | 0.1441      |                   |
|                | D(RVT(-6))| 4.27E-07   | 3.99E-07   | 1.069935    | 0.2859      |                   |
|                | D(RVT(-7))| -4.54E-07  | 1.80E-07   | -2.516491   | 0.0126**    |                   |
|                | D(LDS)   | -6.18E-07   | 9.40E-07   | -0.657547   | 0.5116      |                   |
|                | D(LDS(-1))| 2.24E-06   | 9.43E-07   | 2.370626    | 0.0187**    |                   |
|                | D(BRK)   | -3.60E-07   | 1.78E-06   | -0.202059   | 0.8401      |                   |
|                | D(BRK(-1))| 7.27E-06   | 2.68E-06   | 2.712521    | 0.0072***   | 15.47 (0.000)    |
|                | D(BRK(-2))| 3.86E-06   | 1.82E-06   | 2.124259    | 0.0348**    |                   |
| Long run level | RVT      | 7.41E-06    | 5.34E-07   | 13.85890    | 0.0000***   |                   |
|                | RVT(-1)  | 5.09E-06    | 8.10E-07   | 6.289904    | 0.0000***   |                   |
|                | LDS      | -2.84E-07   | 1.53E-07   | -1.856743   | 0.0647      |                   |
|                | LDS(-1)  | -1.96E-07   | 1.17E-07   | -1.664059   | 0.0976*     |                   |
|                | BRK      | -9.32E-06   | 5.42E-06   | -1.720506   | 0.0868*     |                   |
|                | BRK(-1)  | -6.41E-06   | 3.52E-06   | -1.819418   | 0.0703*     |                   |
|                | C        | 2.92E-06    | 5.24E-07   | 5.568518    | 0.0000***   |                   |

Residual diagnostics
Breusch-Godfrey Correlation LM Test 1.803 (0.1672)
Heteroskedasticity Test 0.24 (0.6241)

Notes: (*)Significant at the 10%; (**)Significant at the 5%; (***) Significant at the 1%.
Table 8
Estimated ARDL (8.7.0.0) of Relationship between market liquidity, Market volatility and death cases in world.

| ARDL(8.7.0.0) | Coefficient | Std. Error | t-Statistic | Prob. | Wald test χ² |
|---------------|-------------|------------|-------------|-------|--------------|
| Short run level |             |            |             |       |              |
| C             | 1.18E-06    | 7.49E-07   | 1.574041    | 0.1169|              |
| LQ(1)^*       | -0.564816   | 0.117046   | -4.825605   | 0.0009***| 1068.52 (0.000) |
| DLQ(1)        | -0.379753   | 0.115720   | -3.281752   | 0.0012*** |              |
| DLQ(2)        | -0.390509   | 0.113565   | -3.438647   | 0.0007***|              |
| DLQ(3)        | -0.512270   | 0.103707   | -4.939604   | 0.0000***|              |
| DLQ(4)        | -0.483716   | 0.091369   | -5.294071   | 0.0000***|              |
| DLQ(5)        | -0.427896   | 0.080752   | -5.298882   | 0.0000***|              |
| DLQ(6)        | -0.326643   | 0.070047   | -4.663224   | 0.0000***|              |
| DLQ(7)        | -0.082145   | 0.030091   | -2.729932   | 0.0069***|              |
| DRVT(11)      | 5.218E-06   | 1.86E-07   | 2.794873    | 0.0000***|              |
| DRVT(22)      | 1.76E-07    | 7.11E-07   | 0.246717    | 0.8054 |              |
| DRVT(33)      | 6.75E-07    | 6.63E-07   | 1.017944    | 0.3098 |              |
| DRVT(44)      | 1.80E-06    | 6.07E-07   | 2.964194    | 0.0034***|              |
| DRVT(55)      | 1.67E-06    | 5.30E-07   | 3.157241    | 0.0018***|              |
| DRVT(66)      | 1.09E-06    | 4.71E-07   | 2.313467    | 0.0216** |              |
| Long run level |             |            |             |       |              |
| Variable      | Coefficient | Std. Error | t-Statistic | Prob. |              |
| RVT           | 7.73E-06    | 5.98E-07   | 12.9306     | 0.0000***|              |
| RVT(-1)       | 4.37E-06    | 7.52E-07   | 5.808015    | 0.0000***|              |
| LDW           | 1.81E-08    | 3.72E-07   | 0.048762    | 0.9612 |              |
| BRK           | -2.57E-06   | 3.12E-06   | -0.823702   | 0.4110 |              |
| C             | 2.09E-06    | 1.23E-06   | 1.692480    | 0.0920* |              |
| Residual diagnostics |         |            |             |       |              |
| Breusch-Godfrey Correlation LM Test | 0.414 (0.6614) | | | | |
| Heteroskedasticity Test | 0.0004 (0.9822) | | | | |

Notes: (*)Significant at the 10%; (**)Significant at the 5%; (***) Significant at the 1%.

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