Article Type: Research Paper

Exploring illiquidity risk pre and during the COVID-19 pandemic era: Evidence from international financial markets

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DOI: 10.18196/jai.v24i3.18139

CITATION:
Enow, S. T. (2023). Exploring illiquidity risk pre and during the COVID-19 pandemic era: Evidence from international financial markets. *Journal of Accounting and Investment, 24*(3), 676-686.

ARTICLE HISTORY
Received:
11 Mar 2023
Revised:
21 Mar 2023
Accepted:
02 May 2023

JAI Website:

Abstract

Research aims: Illiquidity risk is one of the complex issues that institutional investors and market participants continually face over time. It is because the constructs of illiquidity risk are sometimes complicated, robust, and not so evident in secondary markets. Hence, this study aims to empirically explore illiquidity risk before and during the COVID-19 pandemic to understand how much investors were expected to lose if they invested in stock markets during these periods.

Design/Methodology/Approach: This study used a GARCH model and the Amihud illiquidity ratio to achieve its objective. Trading volumes and price returns for the JSE, CAC 40, DAX, Nasdaq, BIST 100, and SSE were from June 30, 2017, to June 30, 2019, and January 1, 2020, to December 31, 2021.

Research findings: As expected, the findings revealed higher illiquidity risk during periods of financial distress, such as the COVID-19 pandemic. During the financial crisis, investors could lose up to $22268.44 a day in less developed markets, such as the JSE, while the average loss in developed markets ranged between $0.22 to $11.53 in the Nasdaq and DAX, respectively. On average, a much lower figure was observed before the financial crisis. The BIST100, CAC 40, DAX, and Nasdaq are excellent options for those seeking lower-risk premiums.

Theoretical and Practitioner/Policy implication: Policies such as adequate market microstructure and greater transparency in trading are strongly recommended for less developed markets, especially during periods of financial distress. Also, the findings of this study provide valuable insight into short-term traders and market participants attracted to liquid markets, where they can easily enter and exit their positions with minimal transaction costs. To the author's knowledge, this paper is the first to model illiquidity risk in stock markets.

Research limitation/Implication: It is possible that the current study did not accurately capture the cost of illiquidity in the sampled financial markets and cannot be applied to other financial markets.

Keywords: Illiquidity risk; Financial markets; GARCH; Trading volume; Risk premium

Introduction

Illiquidity in financial markets has made headlines in recent years by springing out many surprises to unsurprising market participants. Apart from making headlines, illiquidity risk and the lack of liquidity are among the most important aspects of portfolio formation and financial market analysis (Pedersen, 2018).

During the past decade, several liquidity crunches in financial markets have been observed, ranging from the credit crunch in 2007 to the Argentinian crisis in 2002, where investors faced serious liquidity problems. In addition, illiquidity risk can be best understood when considering listed and unlisted securities. Listed securities are perceived to be liquid compared to their counterparts due to the ease with which buyers and sellers can easily exit or enter a position (Enow, 2023). Hence, illiquidity risk normally arises when there are insufficient market participants to trade. It can be on a daily, intra-day, or even monthly basis, where the ability to exit or enter a market quickly is severely impaired.

Also, the search time to execute or settle a trade lengthens, which bears little reality regarding financial market trading. It is well documented (Brunnermeier & Pedersen, 2008; Jiao & Sarkissian, 2021) that illiquidity risk in security indexes is sometimes a global issue in which traders face greater security discounts or fire sales. These illiquidity discounts may be as high as 20% (Albuquerque & Schroth, 2015). Several authors also contend that illiquidity risk results from liquidity mismatch between buyers and sellers in financial markets (Sarr & Lybek, 2002; Keating et al., 2016; Marozva, 2017). However, the lack of a price discovery mechanism is unanimously agreed as the main factor (Virgilio, 2022). In essence, market participants cannot rely on quoted prices because they are not fair and efficient, which results in asymmetric information and disequilibrium. Other reasons, such as increased uncertainty in the financial system, insufficient market infrastructure, and inadequate settling mechanisms, have also been attributed to illiquidity risk. Whatever the cause, this type of exposure presents a great danger for market participants, especially when trading large volumes of securities.

Since illiquidity risk is not static but varies with time, this study explores the following research questions:

1) What is the state of illiquidity risk before and during financial distress periods?
2) What are the expected exposures regarding illiquidity risk before and during financial distress?
3) What is the expected dollar loss associated with trading 1,000,000 shares of the security index?

In providing answers to the above questions, as per the author's knowledge, this study is the first to empirically explore illiquidity risk and the associated exposures in international financial markets. The findings of this study may be relevant not only for financial market participants but also for institutional traders who engage in trading large positions daily; hence, it is a notable contribution.

Literature Review and Hypotheses Development

The theoretical underpinning of illiquidity risk stems from Black's (1971) liquidity preference theory. Black (1971) proposes that illiquidity risk in financial markets arises from slow price recovery mechanisms, mainly from uninformative shocks. Consequently, the volatility of illiquid markets is exacerbated, resulting in price disequilibrium and may further enhance disparities between an asset's fundamental value and market value. In essence, price volatility is significantly affected by the order flow of trading volumes due to distortions in equilibrium prices (Black, 1971). Moreover, the main source of illiquidity risk is the inability to trade quickly or settle out of a position without significantly moving the market price (Enow, 2023). Essentially, an optional sale or a purchase strategy will involve a considerable amount of time, increasing both the transaction and participation costs required to execute a trade.

The above mentioned limitations also characterize asymmetric information due to information disparity between market participants (Crawford, Pavanini & Schivardi, 2018). Market imperfections are another illiquidity risk source, where some market participants have greater influence to move the market by trading out large positions (Acharya & Pedersen, 2019). These large buy or sell positions can move the market price considerably, resulting in a liquidity freeze.

In portfolio and fund management, many anomalies increase illiquidity risk: survivorship bias, selection bias, and infrequent trading (Eling & Faust, 2010). Survivorship bias occurs when portfolios with low returns are not included in estimating the total fund's performance (MacGregor, Schulz & Zhao, 2021). Consequently, the portfolio's performance is overestimated, which results in misguided investment decisions. Meanwhile, selection bias occurs when the returns of a portfolio are only presented when the fund's value is high (Eling & Faust, 2010). On the other hand, infrequent trading, as the name suggests, occurs when the beta of the security or portfolio is biased due to infrequent trading (Hollstein, Prokopczuk & Simen, 2019). Illiquidity risk can therefore be understood vividly by considering the market depth and breadth level. Therefore, the first set of hypothesis to be examined are;

***H_0**: There is no difference in illiquidity risk before or during the financial distress period.*

***H_1**: Illiquidity risk during the financial distress period is higher than normal.*

As mentioned, market depth involves trading large positions without any price change (Enow, 2023), while market breadth describes the width of interest, considering the number of participants actively trading. Where there are wider spreads due to large bids and ask prices, financial markets occasionally cease and shut down, as seen in Hong Kong in 1987. The Figure 1 depicts a liquidity framework in financial markets.

Prior literature mainly focused on liquidity risk management in asset pricing and financial markets (Jelena & Evica, 2018; Gaurav & Misra, 2019; Guijarro, Moya-Clemente & Saleemi, 2019; King & Lewis, 2020; Enow, 2023). Nevertheless, research on illiquidity risk exposures in financial markets is almost inexistent. Thus, this study also examines the following hypotheses:

***H_2**: There is no difference in expected exposures during or before financial distress.*

***H₃**: The expected exposures during the financial distress period are higher than normal due to higher illiquidity risk.*

As per the author's knowledge, no prior literature study estimated the illiquidity cost. Considering that illiquidity risk is synonymous with heightened volatility, the market value of a security trading in an illiquid market may be grossly mispriced. The findings of this study provide valuable insight into short-term traders and market participants attracted to liquid markets, where they can easily enter and exit their positions with minimal transaction costs. Therefore, in providing answers to the above hypotheses, this study significantly contributes to the literature on illiquidity and liquidity management. The section below highlights the research method applied.

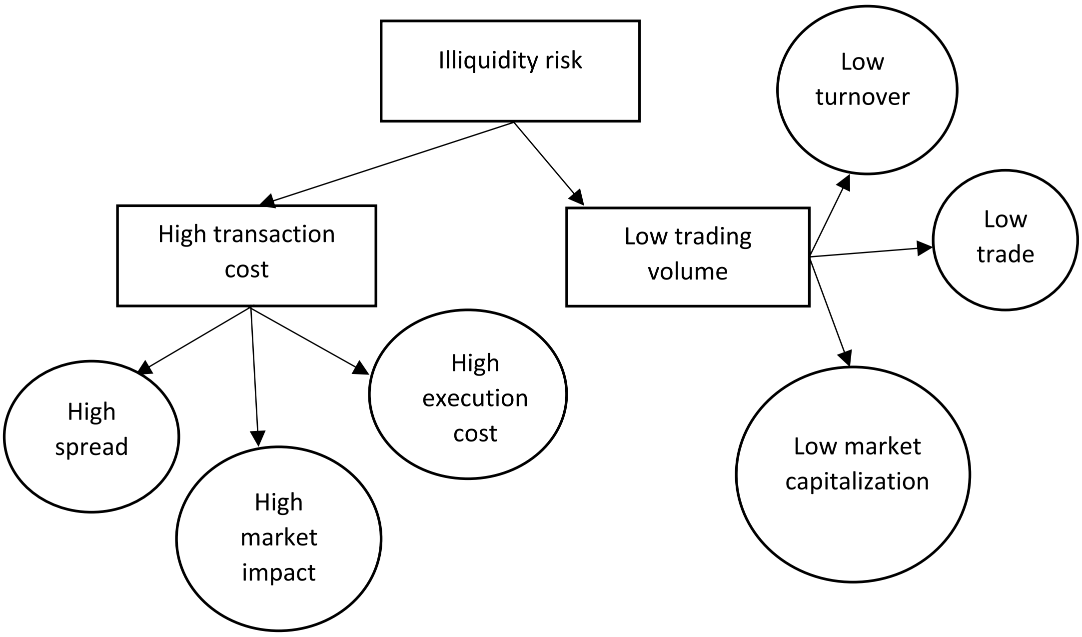

Figure 1 Illiquidity Risk Framework

Research Method

To achieve its objectives, this study used a Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model and the Amihud (2002) illiquidity ratio. The GARCH model was employed to estimate the illiquidity level before and during the pandemic. As stated in the literature, illiquidity risk is present when a significant relationship exists between price returns and trading volumes. Accordingly, the GARCH blueprints provide meaningful time dependency and clustering effects between price returns and trading volumes (Bollerslev, 1986). In essence, the autoregressive properties of these models can be used to predict the unquoted illiquidity in financial markets using the actual values of market price and trading volumes (Paul, Walther & Küster-Simic, 2022). Although these models have been widely utilized for volatility estimates (Enow, 2023; Zahid, Iqbal &

Koutmos, 2022), they are also suitable for exploring the time-varying properties of illiquidity risk. As Bollerslev (1986) states, a GARCH model can be expressed mathematically.

$$p_t = \alpha + \phi P_{t-1} + \beta V_{t-1}^2 \quad (1)$$

Where P_t = price returns, α = intercept ϕ = ARCH term, β = GARCH coefficient, and V= trading volume. Amihud's ratio was used to relate the absolute return of the stock index valuation to its daily volume. Basically, Amihud's (2002) ratio reveals the amount of illiquidity risk that stock markets cannot absorb. It is explained through the dynamic relationship between price returns and trading volumes, where the number of stocks that needs to be traded to initiate a price move is presented. Considering that illiquidity risk is simply the possibility of losing on price change, the more responsive the absolute return to changes in volume, the more illiquid the market is. Amihud's (2002) ratio is given by the following.

$$Illiquidity\ (\%) = \sum_{i=1}^{n} \frac{|R_t|}{TV_t} \quad (2)$$

Where R_t is the daily price returns, and TV is the daily trading volume. The daily prices and trading volumes were retrieved from Yahoo Finance for a sample period from June 30, 2017, to June 30, 2019, for the pre-pandemic period and January 1, 2020, to December 31, 2021, for the COVID-19 pandemic. Six financial markets were randomly considered, including the Johannesburg Stock Exchange (JSE), the French Stock Market Index (CAC 40), the German blue-chip companies (DAX) and the Nasdaq Index, the Borsa Istanbul 100 (BIST 100), and Shanghai Stock Exchange (SSE). These markets represent the largest stock indexes in each continent. Then, the section below highlights the findings and discussion of the data analyzed.

Results and Discussion

This section outlines the findings of the data analyzed. The Table 1 presents the findings regarding illiquidity in financial markets before the COVID-19 pandemic. As expected, no major liquidity concerns were observed in the sampled financial markets. Specifically, all the financial markets under consideration portrayed strong signs of liquidity except for Nasdaq, where a significant relationship between price and trading volume was observed.

In essence, trading volumes in the Nasdaq played a major role in determining the market price, giving rise to illiquidity risk. In all the financial markets, the ARCH and GARCH terms were statistically significant at 5%, and their sums were less than one, satisfying the stability conditions (Enow, 2021). The sum of the ARCH and GARCH coefficients also indicates the absence of illiquidity risk during bullish periods.

Table 1 ARCH and GARCH Output Before the COVID-19 Pandemic

		JSE		
Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.000435	0.001148	-0.37938	0.7044
VOLUME	6.46E-09	3.54E-09	1.825683	0.0679
		Variance Equation		
C	5.44E-06	1.44E-06	3.786749	0.0002
ARCH term	-0.010177	0.003776	-2.69489	0.007*
GARCH term	0.990804	0.00406	244.0619	0.000*
		CAC 40		
C	0.002556	0.001172	2.180934	0.0292
VOLUME	-2.34E-11	1.23E-11	-1.90228	0.0571
		Variance Equation		
C	3.99E-06	1.50E-06	2.666836	0.0077
ARCH term	0.120141	0.03094	3.883098	0.0001*
GARCH term	0.819849	0.04197	19.534	0.000*
		DAX		
C	0.001763	0.001058	1.667041	0.0955
VOLUME	-1.71E-11	9.39E-12	-1.81917	0.0689
		Variance Equation		
C	1.71E-06	1.08E-06	1.58162	0.1137
ARCH term	0.057506	0.020447	2.812371	0.0049*
GARCH term	0.922256	0.028709	32.12425	0.000*
		Nasdaq		
C	0.009289	0.002148	4.324946	0.000*
VOLUME	-3.81E-12	9.15E-13	-4.16885	0.000*
		Variance Equation		
C	6.28E-06	1.58E-06	3.987278	0.0001
ARCH term	0.193338	0.039743	4.864738	0.000*
GARCH term	0.763215	0.041493	18.3936	0.000*
		BIST100		
C	0.002461	0.002424	1.015481	0.3099
VOLUME	-1.94E-12	1.91E-12	-1.01712	0.3091
		Variance Equation		
C	1.68E-05	8.15E-06	2.058374	0.0396
ARCH term	0.100665	0.030376	3.313935	0.0009*
GARCH term	0.805422	0.063685	12.64696	0.000*
		SSE		
C	-0.000949	0.001107	-0.8576	0.3911
VOLUME	5.76E-09	4.99E-09	1.155699	0.2478
		Variance Equation		
C	1.46E-06	4.81E-07	3.040109	0.0024
ARCH term	0.088921	0.013806	6.440907	0.000*
GARCH term	0.910311	0.012703	71.65924	0.000*

Table 2 The Results of Multiple Linear Regression Analysis

		JSE		
Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.001072	0.001179	-0.909146	0.3633
VOLUME	3.63E-09	3.91E-09	0.930214	0.3523
		Variance Equation		
C	6.82E-06	3.10E-06	2.204693	0.0275*
Arch term	0.051075	0.012829	3.981267	0.0001*
GARCH term	0.927408	0.019135	48.46611	0.0000*
		CAC 40		
C	0.005725	0.001038	5.515057	0.0000*
VOLUME	-6.95E-11	1.08E-11	-6.407809	0.0000*
		Variance Equation		
C	7.84E-06	1.54E-06	5.097527	0.0000*
Arch term	0.142399	0.024093	5.910482	0.0000*
GARCH term	0.819423	0.027645	29.64086	0.0000*
		DAX		
C	0.006617	0.001359	4.867457	0.0000*
VOLUME	-8.81E-11	1.38E-11	-6.363572	0.0000*
		Variance Equation		
C	7.26E-06	1.55E-06	4.685315	0.0000*
Arch term	0.139982	0.023673	5.913246	0.0000*
GARCH term	0.829761	0.025847	32.10240	0.0000*
		Nasdaq		
C	0.004749	0.001614	2.941873	0.0033*
VOLUME	-8.06E-13	3.16E-13	-2.547730	0.0108*
		Variance Equation		
C	1.38E-05	4.27E-06	3.220988	0.0013*
Arch term	0.223328	0.051878	4.304883	0.0000*
GARCH term	0.729801	0.050935	14.32821	0.0000*
		BIST100		
C	-0.004814	0.013404	-0.359113	0.7195
VOLUME	1.25E-12	3.30E-12	0.379708	0.7042
		Variance Equation		
C	0.000993	0.002003	0.495889	0.6200
Arch term	-0.001486	0.002921	-0.508771	0.6109
GARCH term	0.568798	0.870502	0.653414	0.5135
		SSE		
C	0.001211	0.001751	0.691518	0.4892
VOLUME	-2.44E-09	5.31E-09	-0.459770	0.6457
		Variance Equation		
C	1.21E-05	3.58E-06	3.388871	0.0007*
Arch term	0.190789	0.019362	9.853939	0.0000*
GARCH term	0.723687	0.035193	20.56309	0.0000*

The findings of Table 2 are unsurprising as illiquidity in financial markets is expected to increase during periods of distress, such as the COVID-19 pandemic. The CAC 40, DAX and Nasdaq showed illiquidity because of the significant relationship between market price returns and trading volumes. Hence, it was more difficult to trade during the COVID-19 pandemic than before due to wider bid and ask spreads and the difficulty of locating other market participants. A potential reason for the increase in illiquidity was the prevalence of asymmetric information, where information was filtered through the market in sequential order. Consequently, the information disparity between buyers and sellers increased. Combining the above findings in Tables 1 and 2 confirm that illiquidity risk in financial markets increased during periods of financial distress. Table 3 outlines the expected cost of illiquidity before and during the COVID-19 market crisis.

Table 3 Cost of Illiquidity in Financial Markets

	Before the COVID-19 pandemic		
	Illiquidity risk (%)	Trading Volume	Illiquidity Cost (In US dollars)
JSE	1.15%	1000000	11540
CAC 40	0.001428%	1000000	14.28
DAX	0.000619%	1000000	6.19
Nasdaq	0.000034%	1000000	0.34
BIST100	0.000005%	1000000	0.05
SSE	1.26%	1000000	12620
	During the COVID-19 pandemic		
JSE	2.2268%	1000000	22268
CAC 40	0.00107%	1000000	10.7
DAX	0.00115%	1000000	11.53
Nasdaq	0.000022%	1000000	0.22
BIST100	0.000003%	1000000	0.03
SSE	0.69%	1000000	6860

On average, the cost of illiquidity risk was higher during a financial crisis than in the pre-crisis era. From Table 3, investors lost around $11,540 for one million JSE traded securities, with a significantly high amount of $12620 in the SSE before the pandemic. However, the illiquidity costs in the BIST100, DAX, and Nasdaq were exceptionally low for each one million batches traded before the pandemic. This finding suggests that market participants trading in the BIST100, DAX, and Nasdaq were very optimistic about their positions, resulting in the low cost of illiquidity. Hence, market participants could easily enter and exit the market. During the pandemic, the cost of illiquidity in the JSE and DAX almost doubled the amount before the pandemic. However, the amount in the SSE reduced significantly during the pandemic. These lower margins were also seen in the CAC 40, Nasdaq, and BIST 100. Therefore, the null and third hypotheses were rejected, and hypotheses one and two were accepted. Therefore, short-term traders and market participants attracted to liquid markets could not easily enter and exit their positions without incurring significant transaction costs. Also, this significant illiquidity risk may result in heightened volatility, enhancing mispricing in financial markets. In essence, market participants in the JSE and SSE will experience increasing price volatility where a small number of transactions will have a significant impact on asset prices. This will create an environment of uncertainty and make it difficult for investors to accurately value assets, leading to larger price swings and potential market distortions. Investors in the JSE and SSE will be more susceptible to market manipulation and information asymmetry as well as a cascade of selling pressures and a domino effect due to the heightened illiquidity risk.

Conclusion

An important concept in portfolio management is holding a well-diversified portfolio that can be easily traded with minimal losses or "very low illiquidity risk." Analyzing illiquidity risk cannot be overlooked as investors tend to withdraw from illiquid markets with low trading prospects. Therefore, this study aimed to empirically explore illiquidity risk in financial markets before and during the COVID-19 pandemic. The findings of this study revealed that illiquidity risk tended to increase in stock indexes during distress periods, increasing illiquidity cost. More specifically, less developed markets, such as the JSE, experienced high illiquidity costs than developed markets, such as the Nasdaq. Policies, such as adequate market microstructure and greater transparency in trading, are strongly recommended for less developed markets, particularly during financial distress periods. Also, with lower risk premiums, investors should strongly consider the BIST100, CAC 40, DAX, and Nasdaq.

Different financial markets exhibit varying levels of liquidity and liquidity dynamics. This study assumes a homogenous market structure, which may not capture the nuances of illiquidity risk across different asset classes, sectors, or regions. Future research could explore how to incorporate market heterogeneity into the estimation models, considering factors such as asset-specific characteristics, market microstructure features, and regulatory environments. Also, Illiquidity risk is not necessarily linear and may exhibit time-varying characteristics. Also, the model used in this study to estimate illiquidity risk assumes linearity and constant liquidity measures, which may oversimplify the complexities of illiquidity risk dynamics in the selected financial markets. Future research could investigate nonlinear models that capture changing liquidity regimes, regime shifts, or nonlinear relationships between liquidity measures and asset prices.

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