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INFORMATION EFFICIENCY IN THE U.S. AND SHARIAH-COMPLIANT STOCKS IN MALAYSIA DURING COVID-19

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ABSTRACT

This study examines the impact of analysts' forecast on market liquidity and information efficiency in the U.S (developed) and Malaysia (emerging – Shariah-compliant stocks) before and during COVID-19. The results show that the analysts' forecast is significant to the market liquidity in the pre-COVID period but its influence diminishes during the COVID-19. Moreover, the impact of the analysts' forecast is significant in the upper quantiles (0.7 and 0.9 quantiles) of the U.S market and in the lower quantiles (0.1 and 0.3 quantiles) of Malaysia's Islamic market. Similarly, the buy-sell recommendations in the U.S market and all variables forecasted are significant before COVID-19. Both markets become inefficient during COVID-19, and analysts' forecast is no longer correlated to information efficiency. These results inform practitioners and investors to inspect the market conditions and investor's behaviour under market stress such as COVID-19, which has disrupted the international financial markets.

Keywords: Analysts' forecast, Market liquidity, Information efficiency, Investor behaviour, COVID-19.
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I. INTRODUCTION

The expert forecasts are a piece of information accessible by market participants. The analysts' forecasts of a stock performance are normally based on thorough financial analysis, and investors often respond to them. In scholarly research, analyst forecasting is linked to market liquidity and information efficiency.

According to the literature on market liquidity, investors' sentiments and expert forecasts might impact liquidity (Abudy, 2020). The dissemination of new information to the market is facilitated by analyst projections, enabling investors to react accordingly (Blankespoor, Miller & White, 2014). During a crisis, market liquidity is also more apparent (Galariotis, Krokida & Spyrou, 2016). In selected markets, such as South Africa, the United Kingdom, Germany, Chile, the United States, and Malaysia, there are studies on the association between analyst forecasts and market liquidity in the normal period (Dang, Doan, Nguyen, Tran & Vo, 2019). Nevertheless, few studies evaluate the effect of expert forecasts on market liquidity during a crisis, particularly during COVID-19 pandemic. Comparative research between established countries like the United States and developing markets like Malaysia is even scarce. Many Shariah-compliant equities are traded on the Malaysian stock exchange. Although other markets, such as Singapore and Egypt, also trade Shariah-compliant equities, the Malaysian market has a greater number of Islamic firms. Moreover, the Malaysian market is dominated by Muslim investors, who may have diverse investment objectives (Barom, 2019).

Ortmann, Pelster & Wengerek (2020) demonstrate that amid market stress, investors respond to information differently. Investors may increase their trading activity and sell shares to prevent investment loss due to panic trading. Pandey & Kumari (2021) demonstrate that investors may exhibit irrational behaviour during crisis episodes. Consequently, the behaviour of investors, particularly in reaction to the new information disclosed by analysts during the times of stress such as the COVID-19 outbreak, should be analysed. Based on a few studies, investors' behaviour in established and developing markets does vary during market stress due to events such as COVID-19 pandemic.

Analyst forecasting serves as an information. Analyst forecasting is related to information efficiency. The Efficient Market Hypothesis (EMH) asserts that efficient markets should rapidly reflect all available market data on stock prices. During COVID-19, the efficiency of several markets, including Saudi Arabia (Syed & Bajwa, 2018), Europe, Malaysia, and the United States (Dias, Teixeira, Machova, Pardal, Horak, & Vochozka, 2020), are thoroughly analysed. However, no research addresses the association between analyst forecasting as a source of new information and the stock market's information efficiency. This is because past research has often focused on the form of market efficiency rather than its drivers. Additionally, though it is important, studies on variations in efficiency between established and developing markets pre- and during-COVID-19 are still lacking.

Most research evaluates the link between analyst forecasting, market liquidity, and information efficiency using the basic ordinary least squares (OLS) regression technique. However, the OLS method does not control for unobserved variables in the regression, which might result in a biased conclusion. In this situation, panel data and quantile regressions might be used as alternatives to the OLS. Moreover, the quantile regression enables examination of the influence of analyst forecasts in various quantiles of market liquidity since investors may react differently across quantiles.

Therefore, this study examines the impact of analyst forecasting on market liquidity and information efficiency before and during COVID-19 using panel data and quantile regressions. It takes the U.S market and the Malaysian Islamic markets as case studies. The U.S is the World's largest stock market while Malaysia is one of the largest Islamic markets that trade Shariah-compliant stocks. The comparison between the two thus will shed some light on the differences in the market efficiency between the developed and emerging (Malaysia) markets, especially during the pandemic.

The rest of the paper is structured as follows. The next section reviews related literature and develop hypotheses to be tested. Then, section 3 presents the models and data. This is followed the results in section 4. Finally, section 5 provides conclusion of the paper.

II. LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

2.1. Analyst Forecasting, Market Liquidity and Information Efficiency

Analyst forecasting is the investment suggestion revealed by analysts through rigorous financial analyses (Firth, Lin, Liu & Xuan, 2013). Analyst forecasting is the predictions made by analysts who analyse the fundamentals and prospects of individual companies to assist investors in making wise investment decisions.

Analyst forecasting can affect market liquidity. The study by Zúñiga, Pincheira, Walker & Turner (2020) shows that analyst forecasting with lower forecast errors can lead to higher market liquidity. This is because the investors respond to the information released by analysts, and their trading behaviour is subsequently incorporated into stock prices. Similarly, Aouadi, Arouri & Roubaud (2018) argue that information can affect market liquidity as investors make use of the information to make investment decisions. They show that investors can be affected by new information from analysts in the market (see, for example, Dang et al., 2019; DeBoskey & Gillett, 2019). None of the studies looks at the impact of analyst forecasting on market liquidity in COVID-19, as investors can behave differently under stress and the market is disrupted during a pandemic (Loang & Ahmad, 2022).

Numerous papers have been devoted to studying information efficiency (Lalwani & Meshram, 2020; Dias et al., 2020), but limited studies are treating analyst forecasting as the determinant of information efficiency. Lalwani & Meshram (2020) argue that markets have become inefficient with the emergence of the pandemic because the information is delayed in being transmitted to the markets. Besides, Vasileiou (2021) shows that the U.S market has become less efficient when investors are panicking and consequently selling off securities. Nonetheless, no study examines the determinants of information efficiency, especially during the turbulent periods such as COVID-19.

The EMH states that markets shall reflect all private and public information, and efficient markets shall incorporate information into stock prices faster than less efficient markets. From this perspective, the New York Stock Exchange (NYSE) is the World's largest exchange and is expected to be more efficient than

Bursa Malaysia. Furthermore, the Malaysian Islamic market lacks the same level of openness and accountability as the U.S. market. Therefore, the Malaysia Islamic market shall be less efficient than the U.S market. Nevertheless, no study has compared the information efficiency of these two markets, especially during the COVID-19 pandemic.

Furthermore, most studies explore the impact of analyst forecasting using the ordinary least square (OLS) technique. The OLS technique is not appropriate for pooled time series and cross-sectional data (Loang & Ahmad, 2020). Therefore, panel data regression is an alternative technique that accounts for unobserved variables in the regression and gives an in-depth look at the influence of analyst forecasting on market liquidity and information efficiency. Furthermore, quantile regression, which measures the conditional median, can better address the impact of analyst forecasting on different quantiles of market liquidity. Quantile regression can provide a more comprehensive result than the OLS method.

Hence, this study examines the impact of analyst forecasting on market liquidity and information efficiency before and during COVID-19 by using panel data and quantile regressions. The following hypotheses are proposed:

H1. Analyst forecasting is correlated to market liquidity before and after COVID-19.

H2. Analyst forecasting is correlated to information efficiency before and after COVID-19.

H2(a). Malaysia's Islamic market is less efficient than the U.S market

III. ESTIMATED MODELS AND DATA

3.1. Market Liquidity

In finance, liquidity is a complex concept with many measures. A classical and conventional approach to measuring market liquidity is Amihud's illiquidity measure (ILLIQ), as proposed by Amihud et al. (2015). ILLIQ measures the magnitude of stock return at a given trading volume. It captures the transaction cost per volume and considers the bid-ask spread as part of the return measurement. The ILLIQ is estimated as:

$$\mathrm{ILLIQ}_{i,t} = \frac{1}{\mathrm{N}_i}\sum_{d=1}^{N_i}\left|\mathrm{R}_{i,d,t}\right| \;/\; \mathrm{VOL}_{i,d,t} \tag{1}$$

Where, $|R_{i,t}|$ is the absolute value of return on stock *i* on day *d* at period *t*, $VOL_{i,d,t}$ is the daily volume in of stock *i* on day *d* and N_i is the number of trading days of stock *i* in period *t*. A higher value of ILLIQ indicates that the stock is less liquid. Nonetheless, Lou & Shu (2017) argue that Amihud's measure heavily relies on the trading volumes and hence fails to capture the price impact and lead to a biased result.

In this context, Bernales, Cañón & Verousis (2018) argue that the bid-ask spread is an alternative approach that can better examine market liquidity. The bid-ask spread is simply the difference between the best bid and best ask prices that buyers and sellers are willing to accept in the market. The relative bid-ask spread by using daily bids and asks is given as:

$$\text{Bid} - \text{ask spread}_{i,t} = \frac{1}{N_i}\sum_{t=1}^{N_i}\frac{\text{ask}_{i,t} - \text{bid}_{i,t}}{(\text{ask}_{i,t} - \text{bid}_{i,t})/2} \tag{2}$$

Where, $\text{ask}_{i,t}$ is the best ask price of stock *i* on day *t* and $\text{bid}_{i,t}$ is the best bid price of stock *i* on day *t*. The lower bid-ask spread indicates higher liquidity of the stocks.

Another measurement of market liquidity is the turnover ratio. As proposed in the study of Fan (2018), the author argues that the turnover ratio captures the total shares traded in the market while not considering the costs such as price impact in the bid-ask spread. The turnover ratio is estimated as :

$$\text{TURN}_{i,t} = \sum_{t=1}^{N_i}\frac{\text{VOL}_{i,d,t}}{S_i} \tag{3}$$

Where, S_i is the total number of outstanding shares. A higher value of turnover ratio shows that the stocks have higher liquidity.

3.2. Information Efficiency

Information efficiency measures the accuracy of the information revealed by analysts in predicting the companies' future performance. The information efficiency can be determined by the proportion of the information revealed by analysts compared to the actual stock performance (Hou, Zhao & Yang, 2020). That is,

$$\text{Information Efficiency} = \frac{\text{Company Performance} - \text{Information revealed by analysts}}{\text{Company Performance} - \text{Information revealed in stock performance}} \tag{4}$$

One of the critical ratios forecasted by analysts is earning-per-share (EPS). Analysts forecast EPS to predict the expected profit divided by the total number of outstanding shares. It indicates a company's profitability, which directly impacts stock price and affects market response. Therefore, the information revealed by analysts can be proxied by relative EPS, expressed as:

$$\text{AFE}_{i,t} = \frac{|FEPS_{i,t} - AEPS_{i,t}|}{P_{i,t}} \tag{5}$$

$$\text{RFA}_{i,t} = \frac{AFEmax_{i,t} - AFE_{i,t}}{AFEmax_{i,t} - AFEmin_{i,t}} \tag{6}$$

Where, $\text{AFE}_{i,t}$ is the absolute value of forecast error of stock *i* at time *t*, $FEPS_{i,t}$ is the forecast EPS of stock *i* at time *t*, $AEPS_{i,t}$ is the actual EPS of stock *i* at time *t*, $P_{i,t}$ is the stock price of stock *i* at time *t*, $\text{RFA}_{i,t}$ is the relative forecast accuracy of stock *i* at time *t*, $AFEmax_{i,t}$ is the maximum value of relative forecast accuracy of stock *i* at time *t* and $AFEmin_{i,t}$ is the minimum value of relative forecast accuracy of stock *i* at time *t*.

The second part of measuring information efficiency is determining the information revealed in stock performance. The relative forecast accuracy can be transformed into relative information efficiency by capturing the impact of stock return synchronicity. The relative information efficiency is calculated as follows:

$$\mathrm{I.E.}_{\mathrm{i,t}} = \frac{\mathrm{RFA}_{\mathrm{i,t}}}{1-R^2{}_{i,t}} \tag{7}$$

$$\mathrm{RIE}_{\mathrm{i,t}} = \frac{\mathrm{I.E.}_{\mathrm{i,t}} - \mathrm{IEmin}_{\mathrm{i,t}}}{IEmax_{i,t} - IEmin_{i,t}} \tag{8}$$

Where, $\mathrm{I.E.}_{\mathrm{i,t}}$ is the information efficiency of stock *i* at time *t*, $\mathrm{RIE}_{\mathrm{i,t}}$ is the relative information efficiency of stock *i* at time *t*, $R^2{}_{i,t}$ is the stock return synchronicity of stock *i* at time *t* and $IEmax_{i,t}$ and $IEmin_{i,t}$ are the maximum and minimum values of information efficiency of stock *i* at time *t*.

3.3. Analysts' Forecasting

Other than the EPS forecasted by analysts (Eq.6), analysts also predict other financial ratios such as return on assets (ROA), return on equity (ROE), book value per share (BVPS) and earnings before interest, taxes, depreciation and amortisation (EBITDA). ROA and ROE allow the analysts to evaluate the performance of the management in utilising total assets and equities as the company's resources to generate profit. The relative ROA can be expressed as:

$$RROA_{i,t} = \frac{AROAmax_{i,t} - AROA_{i,t}}{AROAmax_{i,t} - AROAmin_{i,t}} \tag{9}$$

Where, $RROA_{i,t}$ is the relative forecast ROA of stock *i* at time *t*, $AROAmax_{i,t}$ and $AROAmin_{i,t}$ are the maximum and minimum of forecast ROA of stock *i* at time *t* and $AROA_{i,t}$ is the actual ROA of stock *i* at time *t*. The relative ROE is given as:

$$RROE_{i,t} = \frac{AROEmax_{i,t} - AROE_{i,t}}{AROEmax_{i,t} - AROEmin_{i,t}} \tag{10}$$

Where, $RROE_{i,t}$ is the relative forecast ROE of stock *i* at time *t*, $AROAmax_{i,t}$ and $AROAmin_{i,t}$ are the maximum and minimum of absolute forecast ROE of stock *i* at time *t* and $AROA_{i,t}$ is the actual ROE of stock *i* at time *t*. Furthermore, BVPS reveals the company's net asset value on a per-share basis to evaluate whether a stock is undervalued. The relative BVPS guides investors in stock selection as follow:

$$RBVPS_{i,t} = \frac{ABVPSmax_{i,t} - ABVPS_{i,t}}{ABVPSmax_{i,t} - ABVPSmin_{i,t}} \tag{11}$$

Where, $RBVPS_{i,t}$ is the relative forecast BVPS of stock *i* at time *t*, $ABVPSmax_{i,t}$ and $ABVPSmin_{i,t}$ are the maximum and minimum of forecast BVPS of stock *i* at time *t* and $ABVPS_{i,t}$ is the actual BVPS of stock *i* at time *t*. Moreover, EBITDA is an alternative measurement to net profit without considering the cost of capital investments. It is a simple measurement that analysts used as a metric of companies' profitability. The relative EBITDA is expressed as:

$$REBTIDA_{i,t} = \frac{AEBITDAmax_{i,t} - AEBITDA_{i,t}}{AEBITDAmax_{i,t} - AEBITDAmin_{i,t}} \quad (12)$$

Besides the financial ratios, analysts also provide buy-sell recommendations to investors to inform investors of suggested trading action. In this study, buy-sell recommendations are categorised into 5 different groups with 1 denoting a "Strong Buy", 2 is "Buy", 3 is "Hold", 4 is "Sell" and 5 is "Strong Sell", as in Loang & Ahmad (2021).

3.4. Control Variables

Company-specific factors such as leverage, company size, volatility, quick ratio and price/earnings to growth (PEG) ratio are included as control variables given that they have been found to be correlated to market liquidity and stock return.

Leverage is measured by total liabilities on total assets. Company size is proxied by market capitalisation. Volatility is calculated by realised volatility. The quick ratio measures the company's ability to meet short-term liquidity using current assets minus inventory divided by current liabilities. PEG ratio is a stock valuation measurement using the P/E ratio divided by the growth rate of a company.

3.5. Panel Data and Quantile Regressions

Panel data regression combines cross-sectional and time-series data and allows for unobserved variables by specifying the individual-specific effect as either fixed or random. It provides greater explanatory power compared to the OLS method. The panel data regressions for market liquidity and information efficiency are written respectively written as:

$$\begin{aligned} Market\ Liquidity_{i,t} = \alpha_i + {} & \beta_1 Recom_{i,t} + \beta_2 RFA_{i,t} + \beta_3 RROE_{i,t} + \\ & \beta_4 RROA_{i,t} + \beta_5 . RBVPS_{i,t} + \beta_6 REBITDA_{i,t} + \\ & \beta_7 . Lev_{i,t} + \beta_8 FS_{i,t} + \beta_9 Vola_{i,t} + \beta_{10} Q_{i,t} + \\ & \beta_{11} PEG_{i,t} + \varepsilon_{i,t} \end{aligned} \quad (13)$$

$$\begin{aligned} Information\ Efficiency_{i,t} = \alpha_i + {} & \beta_1 Recom_{i,t} + \beta_2 RROE_{i,t} + \beta_3 RROA_{i,t} + \\ & \beta_4 . RBVPS_{i,t} + \beta_5 REBITDA_{i,t} + \\ & \beta_6 . Lev_{i,t} + \beta_7 FS_{i,t} + \beta_8 Vola_{i,t} + \\ & \beta_9 Q_{i,t} + \beta_{10} PEG_{i,t} + \varepsilon_{i,t} \end{aligned} \quad (14)$$

Where, $Recom_{i,t}$ is the average buy-sell recommendations of stock i at time t, $Lev_{i,t}$ is the leverage ratio of stock i at time t, $FS_{i,t}$ is the company size of stock i at time t, $Vola_{i,t}$ is the realised volatility of stock i at time t, $Q_{i,t}$ is the quick ratio of stock i

at time t, $PEG_{i,t}$ is the PEG ratio of stock i at time t, and all other variables are as defined earlier.

Furthermore, quantile regression allows this study to examine the impact of analysts' forecasting in different quantiles of market liquidity. Unlike the OLS, the quantile regression measures conditional median rather than condition mean. The quantile regression is given as:

$$QY_i(\tau|X = x) = x_i'\gamma \tag{15}$$

Where, Y_i is the dependent variable, x_i is the vector of the independent variable and γ is the vector of coefficient. By minimising weighted deviations from the conditional quantile, the parameter vector of the τ-th quantile of the conditional distribution is expressed as (Jiang, Zhang & Sun, 2020):

$$\hat{\gamma} quantile, \tau = \arg min \sum_{i=1}^{n} \rho_\tau (y_i - x_i'\gamma) \tag{16}$$

The quantile loss function is written as:

$$\rho_\tau(u_i) = \begin{cases} \tau\, u_i & if\ u_i \geq 0 \\ (\tau - 1)u_i & if\ u_i \leq 0 \end{cases} \tag{17}$$

When, $u_i = y_i - x_i'\gamma$, the Equation (16) and (17) can be defined as:

$$\hat{\gamma} quantile, \tau = \arg min\ (\sum_{i:y>x_i'\gamma} \tau|y_i - x_i'\gamma| + \sum_{i:y>x_i'\gamma} (1-\tau)|y_i - x_i'\gamma| \tag{18}$$

Equation (18) shows that the quantile regression estimates can be measured when the weighted sum of the absolute errors are minimised. The weights are dependent on the quantile values. Therefore, the quantile regression can be expressed as below:

$$\begin{aligned} Q_\tau(\tau|V_\tau) = {} & \beta_{0,\tau} + \beta_{1,\tau}.Recom_{i,t} + \beta_{2,\tau}.RFA_{i,t} + \beta_{3,\tau}.RROE_{i,t} + \\ & \beta_{4,\tau}.RROA_{i,t} + \beta_{5,\tau}.RBVPS_{i,t} + \beta_{6,\tau}.REBITDA_{i,t} + \\ & \beta_{7,\tau}.Lev_{i,t} + \beta_{8,\tau}.FS_{i,t} + \beta_{9,\tau}.Vola_{i,t} + \beta_{10,\tau}.Q_{i,t} + \\ & \beta_{11,\tau}.PEG_{i,t} \end{aligned} \tag{19}$$

In the analysis, the quantile regression is employed for market liquidity model.

3.6. Data

The data span from 1-Jan-2014 to 31-Oct-2021 and only the stocks listed in NYSE and Bursa Malaysia were selected. The last seven years of data analysis allow this study to comprehensively evaluate stock market performance (Chatzis, Siakoulis, Petropoulos, Stavroulakis & Vlachogiannakis, 2018). The U.S has the World's largest and most developed stock market, and Malaysia is an emerging market. For comparison analysis, the data for pre-COVID-19 from 1-Jan-2014 to 1-Dec-2019 while the data for COVID-19 ranges from 1-Jan-2020 to 31-Oct-2021 are used. Quarterly bank-specific data are also gathered.

Other securities, such as funds and warrants, are excluded. All stocks shall be listed before Jan-2014 and maintain the listed status until Oct-2021. The sample size is 1287 from NYSE and 527 from Bursa Malaysia. As regards to shariah-compliant stocks in Bursa Malaysia, only those stocks that remain listed as of 31 December 2021 are chosen. Shariah-compliant stocks safeguard stakeholders' interests, prohibiting riba, gharar, suspicious transactions and gambling. All data are collected from the Standard and Poor's (S&P) Capital I.Q. Database.

IV. EMPIRICAL RESULTS AND ANALYSIS

4.1. Descriptive statistics

Table 1 provides descriptive statistics of the variables for both NYSE and Bursa Malaysia sample stocks. The NYSE has all positive mean values of analysts' forecasting, while Malaysia has all negative mean values of analysts' forecasting. It shows that analysts in NYSE tend to provide higher forecast values than actual stock performance. On the other hand, analysts in the Malaysian Islamic market predict decline in stock values in the near future. This difference can be caused by the information efficiency between emerging and developed markets.

Table 1.
Variables of NYSE and Malaysia

	Mean	Median	Maximum	Minimum	Std. Dev	Skewness	Kurtosis
NYSE							
Recommendation	0.258	0.307	1.380	-0.698	0.196	1.453	9.095
EPS	0.318	0.304	3.065	-0.667	0.288	2.013	1.211
ROE	0.001	0.000	0.614	-3.166	0.285	3.025	1.959
ROA	0.029	0.000	0.615	-2.488	0.213	3.205	2.487
BVPS	0.135	0.139	0.692	-2.229	0.188	1.704	1.731
EBITDA	0.098	0.000	0.593	-4.358	0.323	3.303	2.243
Malaysia							
Recommendation	0.108	0.101	0.698	-1.380	0.250	-1.628	9.748
EPS	-0.427	-0.238	2.258	-3.522	0.606	-0.866	4.574
ROE	-0.788	0.000	1.754	-5.379	0.956	-0.803	2.615
ROA	-0.099	0.000	0.928	-2.716	0.334	-2.220	1.022
BVPS	-0.972	0.000	2.045	-5.555	1.062	-0.470	1.891
EBITDA	-0.326	0.000	2.231	-3.630	0.551	-1.348	6.379

4.2. Estimate of Analysts' Forecasting and Market Liquidity in The US

Market liquidity is represented by three different measures - Amihud's ILLIQ, bid-ask spread and turnover ratio. The analysts' forecasting is proxied by buy-sell recommendation, EPS, ROE, ROA, BVPS and EBITDA as revealed in analyst reports.

Panel data regression is used to determine the impact of analysts' forecasting on market liquidity. The Hausman test evaluates whether a random or fixed model is suitable. According to Loang & Ahmad (2020), unobserved variables can have correlations with observable variables in a fixed-effects model, where the estimates would be consistent. On the other hand, random effect models presume that individual characteristics are unrelated to the dependent variable.

Table 2.
Impact of Analyst Forecasting and Company Information on Market Liquidity of NYSE before and during COVID-19

	Before COVID-19			During COVID-19		
	ILLIQ	**TURN**	**Bid-ask Spread**	**ILLIQ**	**TURN**	**Bid-ask Spread**
Panel Data	**Fixed-Effect**	**Fixed-Effect**	**Random-Effect**	**Fixed-Effect**	**Fixed-Effect**	**Random-Effect**
Constant	0.053 (0.628)	0.001*** (6.243)	0.079*** (4.890)	2.085*** (8.133)	-0.002*** (-4.599)	0.163*** (2.620)
Analyst Forecasting						
Recommendation	-1.599*** (-7.292)	0.004*** (12.508)	-0.073* (-1.754)	-0.773 (-1.420)	-0.001 (-0.938)	0.128 (0.989)
EPS	0.776*** (5.329)	-0.001** (-2.032)	0.116*** (4.163)	0.102 (0.263)	0.003 (0.866)	0.041 (0.431)
ROE	0.010* (0.076)	-0.008*** (-0.387)	0.092*** (3.419)	-0.001 (-0.045)	0.003 (0.310)	0.009 (0.796)
ROA	-0.128* (-0.674)	0.000* (0.620)	-0.078** (-2.141)	0.001 (0.024)	-0.009 (-0.132)	-0.004 (-0.578)
BVPS	-0.432** (-2.055)	0.002*** (6.818)	-0.178*** (-4.407)	-0.002 (-0.026)	0.008 (0.459)	0.023 (1.142)
EBITDA	0.373*** (3.057)	-0.005* (-1.886)	0.071*** (3.077)	-0.002 (-0.195)	0.002 (0.761)	-0.004 (-1.222)
Company Information						
Leverage	-0.209*** (-16.052)	0.000*** (16.028)	-0.038*** (-15.461)	-0.142*** (-2.678)	0.002*** (22.022)	0.026** (2.055)
Company Size	0.002*** (22.509)	-0.003*** (-17.933)	0.002*** (9.254)	-0.008*** (-9.626)	0.001*** (6.571)	0.003 (1.483)
Volatility	0.047*** (17.546)	0.000*** (34.485)	-0.006*** (-11.647)	0.004 (1.019)	0.000*** (15.068)	-0.010*** (-10.611)
Quick	-0.001 (-0.136)	-0.005 (-0.398)	-0.001 (-1.066)	0.004 (0.334)	0.001 (0.467)	-0.001 (-0.457)
PEG	-0.010 (-1.492)	-0.004 (-0.410)	-0.001 (-1.428)	-0.008 (-0.543)	-0.002 (-0.615)	0.003 (0.813)

Table 2.
Impact of Analyst Forecasting and Company Information on Market Liquidity of NYSE before and during COVID-19 (Continued)

	Before COVID-19			During COVID-19		
	ILLIQ	TURN	Bid-ask Spread	ILLIQ	TURN	Bid-ask Spread
Panel Data	**Fixed-Effect**	**Fixed-Effect**	**Random-Effect**	**Fixed-Effect**	**Fixed-Effect**	**Random-Effect**
Specification Tests						
Adjusted R^2	0.713	0.773	0.631	0.756	0.770	0.687
Hausman Test	0.000	0.034	0.731	0.000	0.000	0.892
Time Effect	Yes	Yes	Yes	Yes	Yes	Yes
Modified Wald	0.723	0.627	0.143	0.136	0.425	0.452
Breush-Pagan	0.126	0.426	0.352	0.142	0.535	0.632
Pesaran Scaled	0.583	0.235	0.532	0.134	0.123	0.134
Pesaran CD	0.534	0.532	0.435	0.135	0.324	0.452
Durbin-Watson	2.030	2.066	2.027	2.094	2.079	2.030

Note: ***, ** and * shows that significant level of 1%, 5% and 10%.

Table 3.
Quantile Regression of NYSE ILLIQ, TURN and Bid-Ask Spread before and during COVID-19

	NYSE ILLIQ				
	0.1	**0.3**	**0.5**	**0.7**	**0.9**
Analyst Forecasting					
Recom.	-0.035***	-0.133***	-0.274***	-0.486***	-1.523***
EPS	0.006**	0.024***	0.053***	0.103***	0.259***
ROE	0.000	0.003	0.011**	0.040***	0.172***
ROA	0.000	-0.013	-0.046***	-0.140***	-0.471***
BVPS	-0.010***	-0.046***	-0.128***	-0.294***	-1.022***
EBITDA	0.002	0.013***	0.034***	0.084***	0.220***
Recom_COVID	-0.063	-0.260	-0.548	-1.068**	-2.576***
EPS_COVID	0.011	0.050	0.120	0.222*	0.924***
ROE_COVID	0.000	0.000	0.000	0.000*	0.001***
ROA_COVID	0.002	0.003	0.004	0.003*	0.015***
BVPS_COVID	0.000	-0.001	-0.002	-0.006*	-0.023***
EBITDA_COVID	0.000	0.000	0.000	0.002	-0.008***
Company Information					
Leverage	-0.019***	-0.022***	-0.024***	-0.030***	-0.025***
Company Size	0.000	0.000	0.000	0.000***	0.000*
Volatility	0.001***	0.002***	0.004***	0.010***	0.039***
Quick	0.000***	0.000	0.000	0.000	0.000***
PEG	0.000***	-0.001***	-0.001***	-0.002***	-0.003***
Leverage_COVID	-0.017***	-0.018***	-0.018***	-0.016***	-0.011***
Company Size_COVID	0.000	0.000**	0.000***	0.000***	0.000**
Volatility_COVID	0.001***	0.001***	0.002***	0.004***	0.015***
Quick_COVID	0.000	0.000	0.000	0.002	0.018
PEG_COVID	0.000	-0.001***	-0.003***	-0.005***	-0.012***

Table 3.
Quantile Regression of NYSE ILLIQ, TURN and Bid-Ask Spread before and during COVID-19 (Continued)

			NYSE TURN		
	0.1	**0.3**	**0.5**	**0.7**	**0.9**
Analyst Forecasting					
Recom.	0.001***	0.002***	0.002***	0.002***	0.001***
EPS	-0.001***	-0.001***	-0.001***	-0.001***	0.000**
ROE	0.000	0.000	0.000**	0.000	0.000
ROA	0.000	0.001***	0.001***	0.001***	0.001*
BVPS	0.003***	0.003***	0.002***	0.001***	0.001***
EBITDA	0.000	-0.001***	0.000	0.000	-0.001
Recom_COVID	0.002	0.003	0.003***	0.003***	0.003***
EPS_COVID	-0.001	-0.001	-0.001*	0.000***	0.004***
ROE_COVID	0.000*	0.000	0.000	0.000***	0.000***
ROA_COVID	0.000	0.000	0.000	0.000***	0.000***
BVPS_COVID	0.000	0.000	0.000	0.000***	0.000***
EBITDA_COVID	0.000*	0.000	0.000	0.000***	0.000*
Company Information					
Leverage	0.000***	0.000***	0.001***	0.001***	0.002***
Company Size	0.000***	0.000***	0.000***	0.000***	0.000***
Volatility	0.000	0.000***	0.000***	0.000***	0.000***
Quick	0.000	0.000	0.000**	0.000**	0.000***
PEG	0.000***	0.000***	0.000**	0.000	0.000***
Leverage_COVID	0.000***	0.000***	0.001***	0.001***	0.002
Company Size_COVID	0.000***	0.000***	0.000***	0.000***	0.000*
Volatility_COVID	0.000***	0.000***	0.000***	0.000***	0.000***
Quick_COVID	0.000**	0.000	0.000**	0.000	0.000***
PEG_COVID	0.000***	0.000***	0.000***	0.000	0.000
			NYSE Bid-ask Spread		
	0.1	**0.3**	**0.5**	**0.7**	**0.9**
Analyst Forecasting					
Recom.	-0.187**	-0.042	0.006	0.024	-0.085
EPS	0.119	0.181***	0.100***	0.026	0.055
ROE	-0.001	0.112***	0.103***	0.041***	0.187***
ROA	-0.106	-0.151***	-0.048	0.007	-0.167**
BVPS	-0.176**	-0.253***	-0.137***	-0.067**	-0.203***
EBITDA	0.098***	0.052	0.074**	0.017*	0.064**
Recom_COVID	-0.007	-0.088	-0.081	-0.128**	-0.418***
EPS_COVID	0.144	0.200*	0.078	-0.010*	-0.104***
ROE_COVID	0.000	0.001	0.001	0.002*	0.002*
ROA_COVID	0.011*	0.002	-0.007	-0.002***	-0.008***
BVPS_COVID	0.037	0.023	0.015**	0.008***	-0.004**
EBITDA_COVID	-0.003	-0.002	0.002	0.000*	-0.003***

Table 3.
Quantile Regression of NYSE ILLIQ, TURN and Bid-Ask Spread before and during COVID-19 (Continued)

NYSE Bid-ask Spread					
	0.1	**0.3**	**0.5**	**0.7**	**0.9**
Company Information					
Leverage	-0.054***	-0.057***	-0.049***	-0.033***	-0.034***
Company Size	0.000	0.000*	0.000***	0.000***	0.000***
Volatility	-0.012***	-0.011***	-0.003***	-0.001***	-0.004***
Quick	0.000	0.000***	0.000	0.000***	0.000***
PEG	-0.004***	-0.004	-0.002	0.000	-0.002**
Leverage_COVID	-0.032***	-0.025***	-0.032***	-0.036***	-0.035***
Company Size_COVID	0.000	0.000***	0.000***	0.000***	0.000
Volatility_COVID	-0.014***	-0.011***	-0.007***	-0.006***	-0.007***
Quick_COVID	0.001***	-0.001	0.000	-0.001	0.003
PEG_COVID	-0.006	-0.002	-0.003	-0.004**	-0.005***

Note: ***, ** and * shows that significant level of 1%, 5% and 10%.

Table 2 outlines the impact of company information and analyst forecasting on NYSE market liquidity before and during COVID-19. A fixed effect model of panel data regression is adopted as the Hausman test is found to be significant except for the bid-ask spread, which uses the random effect model. The result shows that all the variables of analyst forecasting are significantly related to market liquidity (ILLIQ, TURN and bid-ask spread). Surprisingly, these variables of analyst forecasting, i.e. buy-sell recommendation, EPS, ROE, ROA, BVPS and EBITDA, turn insignificant during COVID-19.

As for the control variables, leverage, company size and volatility are discovered to be significant to market liquidity before and during COVID-19. There is no empirical evidence to indicate the impact of the quick and PEG ratios on market liquidity. According to Table 2, the impact of company information is not affected by the emergence of COVID-19 in the NYSE.

Furthermore, the modified Wald test detects the existence of group-wise heteroscedasticity in a regression model. The modified Wald test is insignificant, as shown in Table 2, and fails to reject the null hypothesis in claiming that the pane data regression is homoscedastic.

The alternative approaches to detecting heteroscedasticity are the Breush-Pagan test, Pesaran Scaled test and the Pesaran CD test. The Breusch-Pagan test determines whether the variance of regression errors is affected by the values of the independent variable in the regression. Nonetheless, the Breusch-Pagan Test is ineffective for determining sample size with a large N. Therefore, Pesaran, Schuermann, & Weiner (2004) present Pesaran Scaled and Pesaran CD as the standardised versions to address the Breusch-Pagan Test's limitations. Table 2 reveals that the Breush-Pagan, Pesaran Scaled, and Pesaran CD tests are insignificant, indicating that the panel data regression is homoscedastic.

For robustness, quantile regression is adopted to examine the impact of analyst forecasting on different quantiles of market liquidity. Table 3 shows the quantile regression of NYSE ILLIQ, TURN and bid-ask spread at the quantile of 0.1, 0.3, 0.5, 0.7 and 0.9. The impact of analyst forecasting tends to appear in the upper quantile of market liquidity at 0.7 and 0.9. Figure 1(a), 1(b), and 1(c) summarise the results of quantile regression for the NYSE ILLIQ, TURN and bid-ask spread before and during COVID-19.

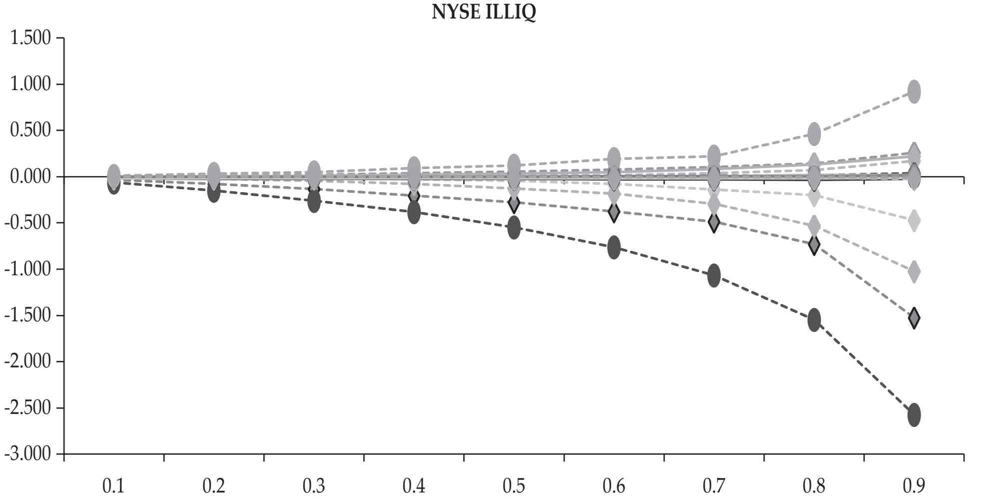

Figure 1(a).
Quantile Regression of NYSE ILLIQ

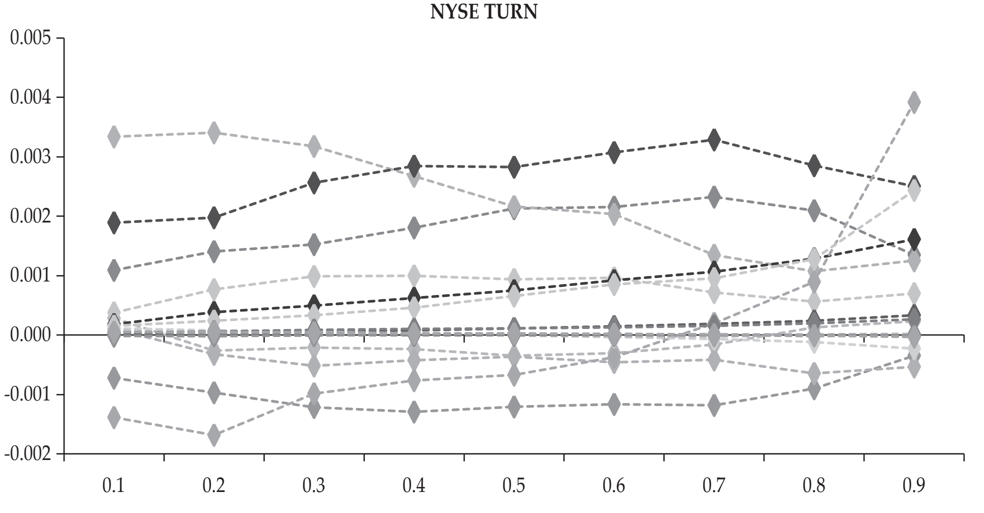

Figure 1(b).
Quantile regression of NYSE TURN

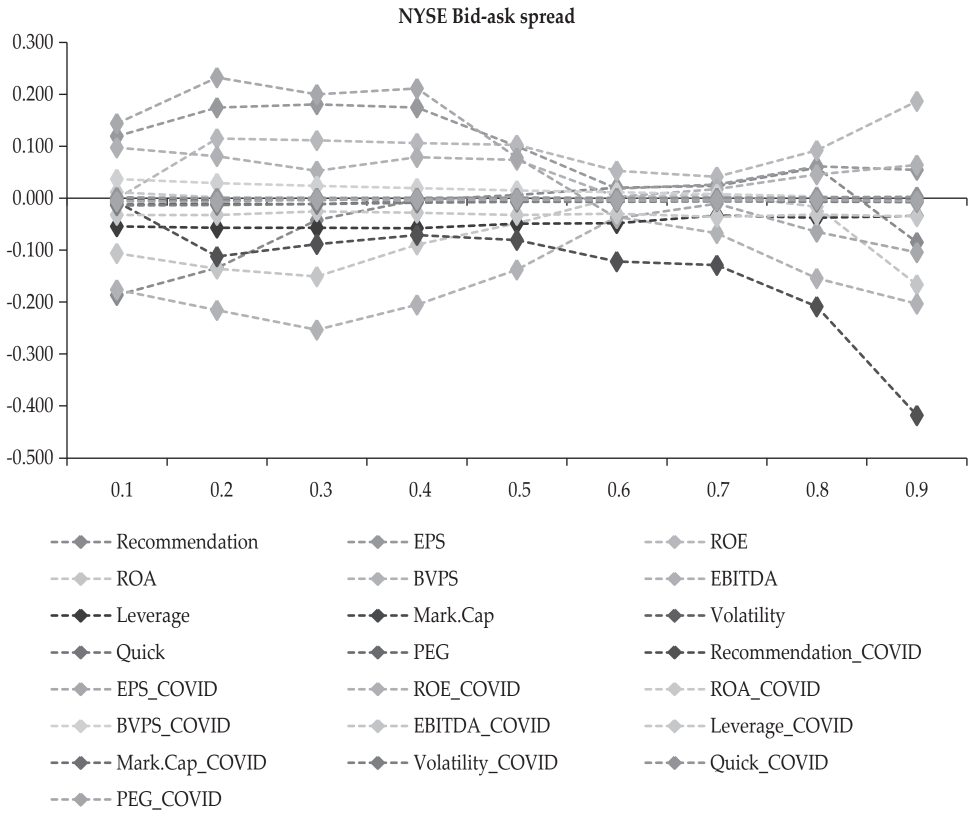

Figure 1(c).
Quantile Regression of NYSE Bid-Ask Spread

4.3. Estimate of Analysts Forecasting and Market Liquidity in Malaysia

Table 4 outlines the impact of company information and analyst forecasting on market liquidity in the Malaysian Islamic market before and during COVID-19. The fixed effect model is selected for the panel data regression as the results of the Hausman test show that the null hypothesis is rejected with p-values less than 0.05.

Surprisingly, the overall result is similar to the NYSE. Buy-sell recommendation, EPS, ROE, ROA and EBITDA are significant to market liquidity at the significant level of 10%, 5% and 1% before COVID-19. Nonetheless, BVPS is found to be insignificant. With the arrival of COVID-19, the impact of analyst forecasting has diminished, and all the variables of analyst forecasting are insignificant.

For company information, leverage, company size, volatility and quick ratio are found to be significant in different market liquidity measurements. The explanatory power of these variables is not affected during COVID-19. Besides, the PEG ratio is the only variable of the company information that is not significant.

Table 4.
Impact of Analyst Forecasting and Company Information on Market Liquidity of Malaysia Before and during COVID-19

	Before COVID-19			During COVID-19		
	ILLIQ	**TURN**	**Bid-ask Spread**	**ILLIQ**	**TURN**	**Bid-ask Spread**
Panel Data	**Fixed-Effect**	**Fixed-Effect**	**Random-Effect**	**Fixed-Effect**	**Fixed-Effect**	**Random-Effect**
Constant	-1.956*** (-20.895)	-0.006*** (-13.976)	0.079*** (4.890)	-0.008 (-0.289)	-0.012*** (-11.335)	-2.498*** (-3.659)
Analyst Forecasting						
Recommendation	-0.162*** (-3.866)	-0.001** (-1.996)	-0.073* (-1.754)	-0.005 (-0.203)	0.000 (0.897)	-0.027 (-0.447)
EPS	0.050*** (2.879)	0.000*** (2.776)	0.116*** (4.163)	0.009 (0.718)	-0.001 (-0.104)	0.000 (0.013)
ROE	-0.021* (-1.393)	0.000* (1.584)	0.092*** (3.419)	-0.001 (-0.124)	-0.006 (-0.173)	-0.017 (-0.599)
ROA	0.072** (2.069)	0.001*** (2.583)	-0.078** (-2.141)	-0.003 (-0.536)	-0.005 (-0.320)	0.004 (0.323)
BVPS	0.013 (0.989)	-0.002 (-1.133)	-0.178 (-4.407)	-0.031 (-0.204)	-0.004 (-1.007)	0.221 (0.639)
EBITDA	0.036* (1.864)	0.000*** (3.174)	0.071*** (3.077)	-0.008 (-0.025)	0.001 (0.179)	-0.001 (-0.206)
Company Information						
Leverage	-0.003*** (-12.225)	0.004*** (11.057)	-0.038*** (-15.461)	-0.001 (-1.006)	0.002*** (3.971)	0.008 (0.200)
Company Size	-0.007*** (-6.877)	-0.008*** (-5.448)	0.002*** (9.254)	0.001 (0.198)	-0.002*** (-3.237)	0.009 (0.748)
Volatility	0.003*** (5.980)	0.000*** (6.756)	-0.006*** (-11.647)	0.000 (1.073)	0.000*** (26.624)	0.023*** (14.440)
Quick	0.025*** (3.364)	-0.000 (-1.526)	-0.000 (-1.066)	0.010** (2.222)	-0.000 (-0.533)	-0.009 (-0.879)
PEG	-0.006 (-0.914)	-0.007 (-0.682)	-0.001 (-1.428)	-0.001 (-0.220)	-0.000 (-0.423)	-0.003 (-0.187)
Specification Tests						
Adjusted R^2	0.741	0.571	0.844	0.687	0.819	0.519
Hausman Test	0.000	0.031	0.742	0.000	0.042	0.836
Time Effect	Yes	Yes	Yes	Yes	Yes	Yes
Modified Wald	0.151	0.425	0.132	0.524	0.736	0.153
Breush-Pagan	0.672	0.735	0.134	0.535	0.622	0.523
Pesaran Scaled	0.241	0.424	0.325	0.143	0.524	0.435
Pesaran CD	0.241	0.425	0.562	0.524	0.734	0.243
Durbin-Watson	2.124	2.064	2.027	1.990	2.073	1.901

Note: ***, ** and * shows that significant level of 1%, 5% and 10%.

Table 5.
Quantile Regression of Malaysia ILLIQ, TURN and Bid-Ask Spread before and during COVID-19

			Malaysia ILLIQ		
	0.1	**0.3**	**0.5**	**0.7**	**0.9**
Analyst Forecasting					
Recom.	-0.001	-0.056	-0.134**	-0.244***	-0.241**
EPS	0.028*	0.033**	0.040	0.032	0.045
ROE	-0.015	-0.027**	-0.031	-0.065**	-0.060
ROA	0.015	0.018	0.066*	0.226***	0.218**
BVPS	0.022**	0.032***	0.051***	0.052**	0.074*
EBITDA	0.000	0.030**	0.054**	0.022	-0.012
Recom_COVID	0.000***	-0.001***	-0.001	-0.003	-0.002
EPS_COVID	0.000***	0.000***	0.001	0.002	0.005
ROE_COVID	0.000***	0.000**	0.000	0.000	0.003
ROA_COVID	0.000**	0.000**	0.000*	0.000	-0.001
BVPS_COVID	0.001**	0.002	0.003*	0.000	0.028
EBITDA_COVID	0.000*	0.000	0.000	0.000	0.000
Company Information					
Leverage	-0.015***	-0.014***	-0.012***	-0.008***	-0.006***
Company Size	0.000	0.000	0.000**	0.000	0.000***
Volatility	0.009***	0.012***	0.013***	0.010***	-0.003**
Quick	0.002	0.028***	0.034***	0.044***	0.041***
PEG	-0.003	-0.006	-0.003	-0.001	0.001
Leverage_COVID	0.000***	0.000***	0.000***	0.000***	0.000***
Company Size_COVID	0.000	0.000	0.000*	0.000	0.000
Volatility_COVID	0.000***	0.000***	0.000	0.000***	0.000***
Quick_COVID	0.000	0.000***	0.001***	0.001***	0.003*
PEG_COVID	0.000	0.000	0.000	0.000**	-0.001***

			Malaysia TURN		
	0.1	**0.3**	**0.5**	**0.7**	**0.9**
Analyst Forecasting					
Recom.	-0.001***	-0.002***	-0.002***	-0.002**	-0.004**
EPS	0.000	0.000	0.000	0.001**	0.001*
ROE	0.001***	0.001***	0.001**	0.000	0.000
ROA	0.002***	0.002***	0.002***	0.002***	0.003***s
BVPS	0.000	0.000*	0.000	0.000	0.000
EBITDA	0.000*	0.001***	0.001***	0.001***	0.001**
Recom_COVID	-0.003***	-0.004***	-0.004	-0.004	-0.004
EPS_COVID	0.001***	0.001***	0.002	0.002	0.002
ROE_COVID	0.000*	0.000***	-0.001	-0.001	-0.001
ROA_COVID	0.001***	0.000**	0.000	0.000	0.000
BVPS_COVID	0.006***	0.002*	0.004	-0.002	-0.008
EBITDA_COVID	0.000***	0.000***	0.000	0.000*	0.000

Table 5.
Quantile Regression of Malaysia ILLIQ, TURN and Bid-Ask Spread before and during COVID-19 (Continued)

Malaysia TURN					
	0.1	**0.3**	**0.5**	**0.7**	**0.9**
Company Information					
Leverage	0.000***	0.000***	0.000***	0.000***	0.000***
Company Size	0.000**	0.000***	0.000***	0.000***	0.000***
Volatility	0.000***	0.000***	0.000***	0.001***	0.001***
Quick	0.000	0.000	0.000	0.000	0.000
PEG	0.000	0.000	0.000	0.000	0.000
Leverage_COVID	0.000*	0.000***	0.000***	0.000***	0.000**
Company Size_COVID	0.000	0.000***	0.000**	0.000***	0.000***
Volatility_COVID	0.000***	0.000***	0.001***	0.001***	0.001***
Quick_COVID	0.000**	0.000	0.000	0.000	0.000
PEG_COVID	0.000	0.000	-0.001***	-0.001***	0.000
Malaysia Bid-ask Spread					
	0.1	**0.3**	**0.5**	**0.7**	**0.9**
Analyst Forecasting					
Recom.	0.056	0.015	0.024*	0.052*	-0.010
EPS	-0.016	-0.004	-0.009	-0.014	-0.018
ROE	0.013	0.002	-0.008	-0.026*	-0.016
ROA	-0.035	-0.008	-0.005	0.057***	0.151**
BVPS	-0.009	-0.002	0.007	0.016	0.015
EBITDA	-0.013	-0.003	-0.006	-0.001	0.012
Recom_COVID	0.000***	0.019***	0.015	-0.086	-0.185
EPS_COVID	0.000***	-0.006**	-0.013	-0.003	0.089*
ROE_COVID	0.000*	-0.002***	0.002	-0.006	-0.084
ROA_COVID	0.000***	-0.004*	-0.007	-0.015	0.024
BVPS_COVID	0.000**	0.089	0.278	0.313**	-0.224**
EBITDA_COVID	0.000**	0.000***	0.000	0.000	-0.001*
Company Information					
Leverage	-0.001**	-0.001***	-0.001***	-0.001***	-0.001
Company Size	0.000***	0.000***	0.000***	0.000**	0.000**
Volatility	-0.004***	0.000	0.005***	0.014***	0.035***
Quick	0.005	0.003*	0.003	0.003	-0.003
PEG	0.002	0.001	0.004	0.006	0.026
Leverage_COVID	0.000	0.000	0.000	0.000	-0.001***
Company Size_COVID	0.000	0.000	0.000	0.000	0.000
Volatility_COVID	0.000	0.001**	0.005***	0.040***	0.043***
Quick_COVID	0.000	0.001	0.002	-0.019**	0.018
PEG_COVID	0.000	0.002	0.004	0.001	0.030

Note: ***, ** and * shows that significant level of 1%, 5% and 10%.

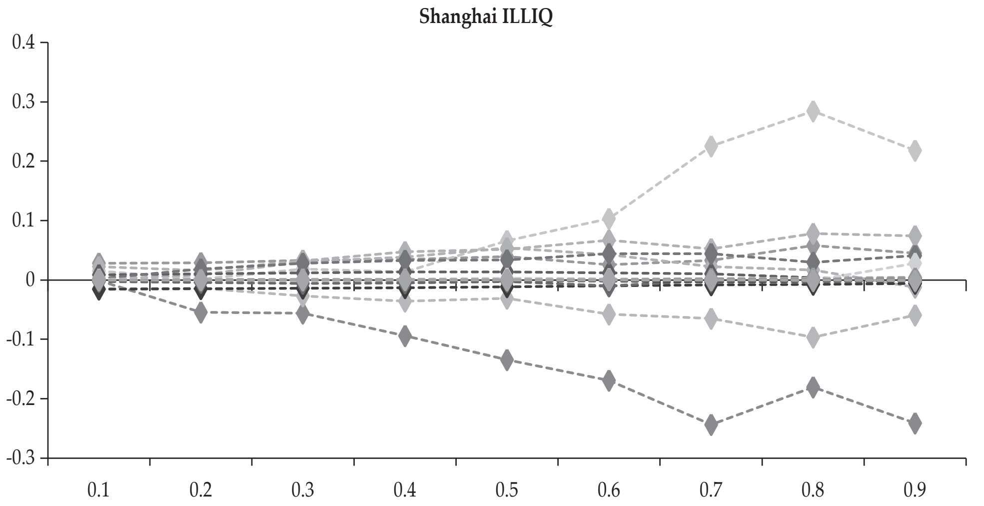

Figure 2(a).
Quantile Regression of Malaysia ILLIQ

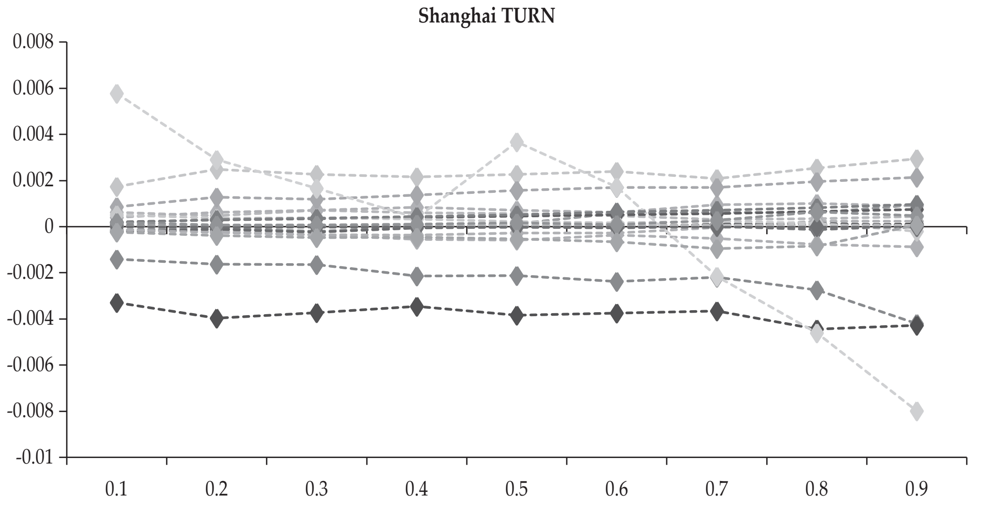

Figure 2(b).
Quantile regression of Malaysia TURN

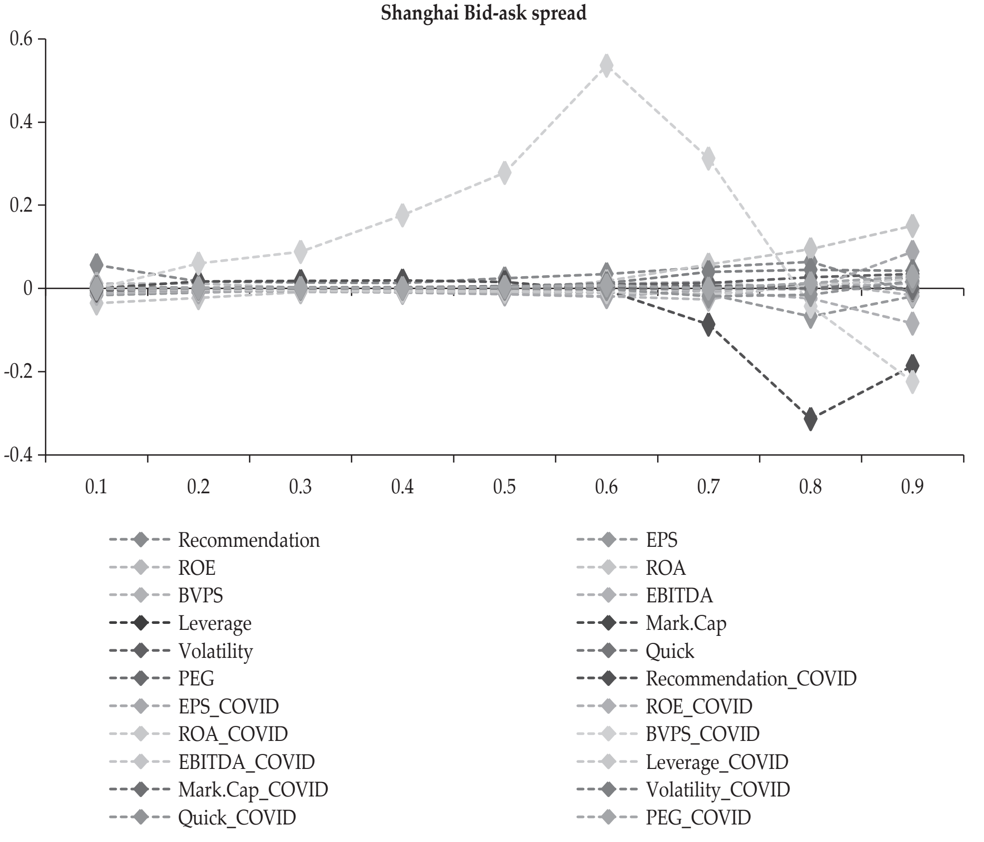

Figure 2(c).
Quantile Regression of Malaysia Bid-Ask Spread

The results for the NYSE and Malaysia show that the impact of analyst forecasting is no longer significant with the emergence of COVID-19. It is inconsistent with the study of Bilinski (2021) in which the author argues that investors react strongly to buying and selling shares based on the revision of analyst forecasts and recommendations during COVID-19. The author shows that investors value analyst information in investment decision-making. Nonetheless, the result of this study indicates differently by showing no relation between analyst forecasting and market liquidity during the COVID-19.

One reason is that analysts tend to generate prediction errors during uncertain times. The unanticipated introduction of COVID-19 is a chaos to the market. There are a lot of uncertainties in the information which affect the quality of the information used by analysts to come up with their forecast. It is impossible for experts to accurately predict market performance. There must be a delay in the release of fresh market information. Therefore, investors disregard expert predictions to trade. As a result of unforeseen occurrences, revisions of recommendations may also include several forecasting mistakes. In this situation, expert forecasts fail to accurately anticipate stock performance. Therefore, there is no relation between expert forecasts and market liquidity.

4.4. Estimate of Information Efficiency in NYSE and Malaysia

The second objective of this study is to examine the impact of company information and analyst forecasting on information efficiency. As shown in Equation 4, information efficiency is measured by the difference between the information revealed by analysts compared to the actual company's performance. The fixed effect model is chosen for the panel data regression as the Hausman tests have p-values less than 0.05.

The results of the modified Wald test, Breush-Pagan, Pesaran Scaled and Pesaran CD indicate that the panel data regression contains heteroscedasticity with p-values less than 0.05. Therefore, this study adopts panel-corrected standard error (PCSE) to rectify heteroscedasticity for pre-COVID-19.

Table 6 summarises the results of the relation between company-specific information, analyst forecasting and information efficiency in the NYSE and Malaysia before and during COVID-19. For the NYSE, the result shows that buy-sell recommendation is the only variable of analyst forecasting with a significant impact on information efficiency before COVID-19. The other variables, ROE, ROA, BVPS and EBITDA, are insignificant. Nonetheless, all variables of analyst forecasting are found to be significant to information efficiency in Malaysia before COVID-19 at the significant level of 1%.

With the emergence of COVID-19, none of the analyst predicting factors are important to the information efficiency of the NYSE and Malaysia. It demonstrates that the information disclosed by analysts is not reflected in the stock prices during COVID-19. Both markets are inefficient during the COVID-19. During COVID-19, company information is also insignificant on the Malaysian Islamic market.

One of the reasons is that the markets are not as efficient as in normal times during the pandemic. This is because COVID-19 has disrupted markets in response to analyst forecasts, and the amended information disclosed by analysts is not reflected in stock prices. Investors respond differently to market volatility (Economou, Hassapis & Philippas, 2018). The outcome is consistent with Vasileiou's (2021) examination of market efficiency during COVID-19. He contends that investors' anxiety has rendered the U.S. market inefficient, causing them to act irrationally when selling assets.

Table 6.
Correlation between Company-Specific Information, Analyst Forecasting and Information Efficiency in NYSE and Malaysia

	NYSE		Malaysia	
	Before COVID-19	**During COVID-19**	**Before COVID-19**	**During COVID-19**
	Fixed-Effect (PCSE)	**Fixed-Effect**	**Fixed-Effect (PCSE)**	**Fixed-Effect**
Constant	-0.009 (-0.277)	-0.113*** (-6.659)	0.155*** (16.123)	0.157 (7.257)
Analyst Forecasting				
Recommendation	-0.196*** (-3.007)	-0.036 (-1.034)	0.153*** (11.366)	0.124 (6.659)
ROE	-0.053 (-1.747)	0.005 (0.156)	-0.007*** (-1.646)	-0.007 (-1.129)
ROA	0.004 (0.112)	0.001 (0.689)	0.060*** (4.963)	0.010 (3.066)
BVPS	-0.103 (-1.788)	-0.002 (-0.413)	-0.049*** (-11.323)	-0.149 (-1.766)
EBITDA	-0.025 (-0.842)	-0.002 (-2.555)	-0.019*** (-3.207)	0.002 (0.166)
Company Information				
Leverage	0.025*** (3.013)	-0.025*** (-7.026)	-0.000 (-1.348)	0.000 (0.113)
Company Size	0.004*** (-4.854)	-0.003*** (-5.418)	-0.008 (-1.133)	0.005 (0.760)
Volatility	0.007*** (7.595)	0.012*** (28.762)	-0.004** (-2.532)	0.000 (0.554)
Quick	-0.004 (-0.238)	0.001 (0.130)	-0.006** (-2.129)	0.004 (0.951)
PEG	-0.001 (-0.794)	0.001 (0.018)	0.003* (1.846)	-0.013 (0.042)
Specification Tests				
Adjusted R^2	0.587	0.711	0.651	0.866
Hausman Test	0.034	0.013	0.047	0.032
Time Effect	Yes	Yes	Yes	Yes
Modified Wald	0.003*	0.425	0.295	0.436
Breush-Pagan	0.525	0.636	0.031**	0.183
Pesaran Scaled	0.047**	0.192	0.481	0.395
Pesaran CD	0.725	0.435	0.007*	0.561
Durbin-Watson	2.114	1.976	1.965	2.054

Note: ***, ** and * shows that significant level of 1%, 5% and 10%.

4.5. Robustness Checks

For robustness test, this study adopts the granger causality test to examine the potential causality between variables. The result presented in table 7 indicates that all independent variables are causally linked to the dependent variables, which are the market liquidity and information efficiency. Hence, the empirical evidence suggests that analysts' forecasting Granger causes market liquidity and efficiency in US and Malaysia.

Table 7.
Robustness Model

	US	**Malaysia**
Variable	P-Value	P-Value
REC does not Granger Cause LIQ	0.053	0.023
LIQ does not Granger Cause REC	0.481	0.372
ROE does not Granger Cause LIQ	0.085	0.001
LIQ does not Granger Cause ROE	0.829	0.633
ROA does not Granger Cause LIQ	0.041	0.013
LIQ does not Granger Cause ROA	0.571	0.552
BVPS does not Granger Cause LIQ	0.084	0.020
LIQ does not Granger Cause BVPS	0.568	0.672
EBITDA does not Granger Cause LIQ	0.034	0.028
LIQ does not Granger Cause EBITDA	0.853	0.683
LEV does not Granger Cause IE	0.044	0.074
IE does not Granger Cause LEV	0.582	0.274
SIZE does not Granger Cause IE	0.004	0.042
IE does not Granger Cause SIZE	0.181	0.341
VOL does not Granger Cause IE	0.018	0.052
IE does not Granger Cause VOL	0.583	0.483
QUI does not Granger Cause IE	0.049	0.023
IE does not Granger Cause QUI	0.646	0.731
PEG does not Granger Cause IE	0.072	0.051
IE does not Granger Cause PEG	0.149	0.631

V. CONCLUSION

This study examines the impact of analyst forecasting on market liquidity and information efficiency in the U.S (NYSE – developed market) and Malaysia (Bursa Malaysia - emerging market of Shariah-compliant stocks) before and during the COVID-19 pandemic. The data cover the period from 1-Jan-2014 for pre-COVID-19 and 1-Jan-2020 to 31-Oct-2021 for COVID-19. Panel data and quantile regressions are adopted in the analysis. Market liquidity is represented by Amihud's ILLIQ, TURN and bid-ask spread. The information revealed by analysts is proxied by buy-sell recommendation, EPS forecast, ROE forecast, ROA forecast, BVPS forecast and EBITDA forecast. Various company-specific characteristics are also included as control variables.

The results of this study show that all variables of analyst forecasting are significant to the U.S. All variables except BVPS are significant to Malaysia's Islamic market's liquidity. Nonetheless, the impact of analyst forecasting has diminished with the emergence of COVID-19. This is because COVID-19 is disastrous to the markets, and analysts faced a lot of uncertainties to provide accurate information to investors. Hence, investors may not rely on analyst information to trade and no significant relationship between analyst forecasting and market liquidity during the COVID-19 pandemic.

For the relationship between analyst forecasting and information efficiency, the buy-sell recommendation is the only variable of analyst forecasting that is found to be related to information efficiency in the U.S before COVID-19. All variables of analyst forecasting are significant to the information efficiency of Malaysia. Surprisingly, analyst forecasting is insignificant with the arrival of COVID-19. One of the reasons is that the markets are inefficient during the pandemic because analysts have yet to respond to unexpected events, and new information can be delayed to incorporate into stock prices.

The results of this study contribute to the academic research of behavioural finance, academic scholars and investors in understanding the impact of analyst forecasting on market liquidity and information efficiency, especially during the pandemic. This study shows that the influence of analyst information has diminished with COVID-19, as investors can react differently under market stress. The results suggest that analysts release new information promptly and deliberately. Otherwise, the investors may not rely on their recommendations to make investment decisions. Policymakers and regulators shall be aware of the determinants affecting market liquidity and information efficiency, which signals a financial crisis.

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