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The Relationship Between Financial Patterns and Exogenous Variables: Empirical Evidence from Symmetric and Asymmetric ARDL

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ABSTRACT

Purpose: This study investigated the impact of unexpected earnings, interest rates, and liquidity risk on cumulative abnormal returns to explain the underreaction phenomenon. Our sample consists of firms that belong to the information transmission and technology industry stocks from 2010 through 2020.
Design/Method/Approach: We first used unit root and cointegration tests to demonstrate the tests' levels and differences. We then used the ARDL and error correction models to develop underreaction measures.
Findings: Our empirical results showed a positive but insignificant influence of unexpected earnings and interest rates on cumulative abnormal returns. However, the result showed a negative and significant relationship between liquidity risk and cumulative abnormal returns. Our research result also showed that the ARDL and error correction model explained 43.20% and 44.12% of the variation in the percentage of cumulative abnormal returns, respectively. The models were robust.
Research Limitations: Our underreaction study was restricted to the relationships between cumulative abnormal returns and three explanatory variables. Thus, using more than three explanatory variables to explain the underreaction might result in more robustness of the ARDL model.
Practical Implication: our study presents several significant findings and their implications for scholars as well as policymakers which helps the latter make the appropriate decision.

1. Introduction

Over the last several decades, there have been debates about the analytical aspect of firms' performance announcements on their market value and financial returns. Investment patterns differ from person to person and are influenced by factors such as the community's economic conditions and investment constraints, as well as personal factors such as the amount of savings held by individuals who make decisions about purchasing shares or real estate in a specific area (Kovács et al. 2021). Indeed, varied factors exist for the investment patterns observed in various financial assets. First, financial markets provide opportunities to invest and obtain returns on invested capital. Second, the flexibility of financial market instruments allows individuals to liquidate funds quickly; third, diversification will enable investors to find assets that meet their investment objectives (Akhtar & Das 2019). The 2008 financial crisis and its ongoing consequences, as well as the emergence of a new situation beyond the economic-financial field in the 2019s, have fundamentally altered the global economy and finance paradigm (Traverso 2022, p.3). Thus, persistent market volatility is detrimental to the smooth functioning of the stock market. Indeed, stock market volatility could raise investors' consciousness of the explosive causes and consequences, deterring their participation and risk-sharing and distorting investment decisions (Hussain, Akbar et al. 2021, p.3). Due to such determents, individuals form beliefs about an uncertain environment with the primary goal of making the best decisions possible. Lausegger (2021, p.177) referred to uncertainty as a situation where economic agents have limited information about current and future events. The notion that financial information should influence the expectation of financial information users as reflected in a change in share prices (Kormendi & Lipe, 1987) has been argued concerning the relationship between information certainty and investors.

Nevertheless, behavioural economics, psychology, and introspection research suggest that the desire for certainty is not the only factor driving belief formation because people may value what they believe (Hagenbach & Koessler, 2022). Further, a normative theory explicitly assumes a goal that an agent wishes to fulfil, the knowledge that the agent has access to, and the restrictions under which it is encoded (Summerfield & Parpart, 2022, p.3). Additionally, it has been argued that the environment, rather than internal tendencies, determines behaviour (Daniel et al. 2002, p. 140). Consistent with information uncertainty, there has been much research into investors' investment decisions. However, evidence on the association between firms' performance practices and earning announcements is unclear and ambiguous (Al-dhamari & Ku Ismail, 2013). Indeed, attempts to quantify the impact of performance announcements on firm market value revealed that the market reacts selectively to performance announcements, with some types of reports even being valued negatively (Jacobs et al. 2010). To remedy the problem of information uncertainty, researchers identified various market elements, such as overreactions, underreaction, historical trends, and investor preferences, that influence decision-making regarding

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financial performance announcements. Although there is extensive literature on market responses to performance announcements in the developed market, evidence of information in an international context is in its infancy (Jones et al. 2021). Martins & de Campos Barros (2021) documented a significant positive association between firm-level information and the quality of financial information in emerging countries with weaker information environments.

This paper explored the theoretical and empirical implications of the autoregressive distributed lag (ARDL) model. The study focused on the underreaction phenomenon using stocks that belong to the information transmission and technology industry to study the model. The study examined the relationship between commutative abnormal returns, unexpected earnings, interest rates and liquidity risk as a subject of inquiry. The study is motivated by the literature recognising firms' heterogeneous nature, for it is also empirically identified that the firms and the sectors are heterogeneous (Narayan & Sharma, 2014). Abnormalities that emphasise the equity market's volatility and unpredictability in the stock markets, such as a mean reversal, have been thoroughly documented in the developed market literature (Reddy et al. 2020). Although some studies on heuristic biases have succeeded in explaining the abnormalities in financial markets (Barberis et al. 2018), behavioural and rational explanations for asset pricing abnormalities can be difficult to distinguish (Fink 2021). According to Olsen (1998), a large body of literature examined the anomalies from the 1980s to the 1990s, but traditional finance theories could not explain them, and none successfully reduced the inaccuracies. These abnormalities occur from time to time, and all existing finance models could not account for them, manifested in several ways, one of which is abnormal asset price movement.

Indeed, when gathering sentiments and providing investment recommendations, modelling and forecasting the features of investor sentiments has been a significant problem (Chang et al. 2021). Interest rates play a central role in financing decisions. Following the Great Recession, several Central Banks worldwide used negative interest rates as an additional policy tool, whereas others maintained favourable interest rates despite the need for further monetary regulation (De Groot & Haas, 2022). Much research is in the literature regarding interest rates and their central role in global banks. According to Liu et al. (2022), a decrease in the long-term interest rate can cause market leaders to invest more aggressively than market followers, resulting in more concentrated markets, higher profits, and poorer aggregate productivity growth. Liu et al. (2022) further argued that lower interest rates have a strategic effect on market concentration, which means that when the interest rate approaches zero, aggregate productivity growth slows. Huber (2022) examines the role of regulation in shaping financial firms' hedging intentions and records the recent buildup of interest rate risk exposure in the US life insurance market. He calculated how much life insurers bear interest rate risk and found a one-percentage-point reduction in interest rates would have lowered their capital by 26%. López-Penabad et al. (2022) investigate the impact of a negative interest rate policy (NIRP) on the European banking sector's risk-taking; the effect varies depending on the bank's business strategy. Using a dataset of 2596 banks from 29 European nations from 2011 through 2019 and a static modelling technique, they conclude that installing NIRPs reduces a sample bank's net interest margin by 14.5. They also concluded that when short-term interest rates are already negative, lowering them lowers the net interest margin. Burke & Warfield (2021) investigated banks' interest rates and their implications for earnings persistence and valuation by developing a novel measure of interest rate risk management that incorporates asymmetric changes in interest rates on assets and liabilities in response to market rate changes. They showed that US bank holding firms with better interest rate risk management used this metric to have more consistent net interest income and a higher net interest income valuation. According to Bauer & Rudebusch (2020), researchers have attempted to link macroeconomic variables to interest rates using a variety of approaches ranging from reduced-form no-arbitrage models to fully edged dynamic macro models. Despite theoretical and empirical progress, results are inconclusive regarding the relationship between interest rates and macroeconomic information. Liquidity, on the other hand, significantly impacts profitability (see, for example, Adelopo et al. 2022; Gregoire & Martineau 2020; Saleh et al. 2020). The statistical results of several studies showed liquidity exhibited significant impacts on profitability (e.g., Kesraoui et al. 2022; Abbas et al.2019; Al-Homaidi, et al. 2018).

However, the relationship between interest rate, liquidity risk, unexpected earnings, and cumulative abnormal returns is still inconclusive. Furthermore, the ARDL model, which Pesaran et al. (2001) introduced to incorporate 1(0) and 1(1) variables in the exact estimation, has been used to model the relationship between variables in a single-equation time-series setup. Indeed, whether the dependent variable is estimated at levels or first differences, the model can test a host of theoretically essential theories, such as the effect of tax rates or analyzing dynamic changes over time (Jordan & Philips 2018). We used the standard ARDL model in our research, but before applying the model, we ran a stationarity test. Indeed, it is necessary to run a stationarity test to determine the order of integration among variables before adopting the ARDL models' approach (Agboola et al., 2022). Because the current study considers cross-section panel data to generate more powerful unit root tests, the study uses Levin, Lin, and Chu (LLC). Augmented Dickey-Fuller (ADF), Phillips-Perron (PP), and Im, Pesaran unit root tests. We discussed each of these tests in their respective sections. After determining the stationarity properties of all variables, we proceeded to the estimation of co-integration tests.

Such approaches help us examine if there is a structural cointegration among the sample variables. We proposed seven tests (Pedroni 1999); (Kao, 1999). Then we applied the standard ARDL model followed by the error correction model. The error correction representation helps test the existence of a long-run relationship, and the bound testing procedure is

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available to draw conclusive inference without knowing whether the variables are integrated of order zero or one, I (0) or I (1), respectively (Kripfganz & Schneider, 2016). Finally, the last distinguishing feature of our approach is we focused on long-run and short-run (Granger causal) relationships because the relationship between cumulative abnormal returns and the explanatory factors is best examined with such a technique. Therefore, our analysis considered whether cumulative abnormal return and explanatory factors are significantly associated. The remainder of the paper is organized as follows: section 2 below underpins the theoretical background of the underreaction. The section reviewed the relevant studies of the underreaction phenomenon. Section 3 focuses on the study's hypotheses, followed by the study's methodological process in section 4. Section 5 discusses the study's result, Section 6 focuses on the discussion and implication of the study, and finally, section 7 concludes the study.

2. Theoretical Background of Underreaction

Traditionally, investment decisions assumed that all financial stakeholders, including individuals and institutions, make rational investment decisions to maximise profits (Uddin et al. 2021). Typically, investment decisions are based on market efficiency, a market in which prices fully represent available information and provide reliable signals for resource allocation (Fama 1991). Therefore, the forecast of stock returns should not be possible since market prices will represent all available information (Audrino et al. 2020). Furthermore, the efficient market hypothesis (EMH) holds that stock prices reflect all market information, making a significant abnormal return impossible (Basu 1977). As evidenced by the preceding statements, and as several neoclassical scholars have pointed out, in an efficient market, prices are expected to represent fundamentals that cannot adjust rapidly and significantly in the short term but only when new and unexpected information becomes available. However, with the return reversal effect, an investor could earn a significant abnormal return, which causes scholars to doubt the effectiveness of the hypothesis (Reddy et al. 2020).

Nevertheless, the concept of market efficiency holds that investors form expectations and infer the probability distribution of uncertain outcomes of future events (Lausegger 2021). Information uncertainty can be a behavioural factor since investors underreact to information releases and earnings news (Fink, 2021). According to De Bondt & Thaler (1995), investors' behaviour affects financial markets due to over and underreaction, a key point discussed in behavioural finance. Several studies documented analysts' tendency to systematically underreact to information inconsistent with rationality (Easterwood & Nutt 1999). Because investors could not react sensibly to new information, they often appeared overconfident and adjusted their overall model. Much earlier behavioural finance investigations provide theoretical underpinnings outlining the relevance of investor sentiments in asset pricing, for example (De Long et al. 1990).

Further, growing empirical evidence has shown that the futures price may deviate significantly from the current price (Jacobs 2016). Indeed, investors respond to information in diverse ways, which is one of the reasons for the deviation from the efficient market hypothesis, resulting in information uncertainty. Research has shown that trading practices and investor structure significantly impact the relationship between futures and current prices (Park and Shi 2017). Due to these inconsistencies having become increasingly essential phenomena, a new change in basic assumptions in psychology known as behavioural finance emerged (Bouteska & Regaieg, 2018). Due to the irrational way market participants make financial decisions; researchers initiated Behavioural finance. Behavioural finance biases emanate from research suggesting that individual financial choices under uncertainty contradict rational financial decisions (Ferreira & Dickason-Koekemoer 2019,p..6). Because investors act irrationally, prices diverge and create predictable patterns from time to time, which can even continue for a long time (Malkiel 2003). One of the many instruments to measure market value is underreaction which affects investment return. Underreaction events are one of the most puzzling anomalies in finance (Fink 2021). Extensive research has been conducted in the literature since its discovery as a stock market anomaly by Ball & Brown (1968), who documented the return predictability for up to two months after the annual earnings announcements. Several earlier studies empirically showed price movements significantly impact investors' investing decisions. For example, Foster et al. (1984) found that systematic post-announcement drifts in security returns are only observed for a subset of earnings expectations models when testing drifts in the trading day period. Cited in the work of Zhang et al. (2021), the study results of Bernard & Thomas (1989), showed a positive (negative) drift of around 2% over 60 trading days for the good (bad) news stocks, which can generate annualised abnormal returns of 18%.

Furthermore, seasonal sales affect financial markets; when sales are at their height, stock prices are at their top, but after that, they slow down; however, such processes vary depending on the market segment (Zhang et al. 2021). Barber & Odean (2001) argued that stock market events significantly impact investors' decisions because these events draw the attention of investors and individuals who may not know if a step is a good or bad investment. According to De Bondt et al. (1995), any information in the stock market leads stocks to over/underreact in price. Odean (1999) found that overconfident investors invest more than those less confident because of the poor quality of information and their approach to making sound financial selections. Easterwood and Nutt (1999) examined three hypotheses on the line between the nature of new information and the type of reaction by analysts and indicated that analysts underreact to negative information but overreact to positive news, which is consistent with systematic optimism in response to new information. Hence, investors under/overreact to new information or any price changes in the market, and such price changes could lead to abnormal returns. In the following, we developed our hypothesis.

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3. Hypothesis Development

There is a large body of research regarding the underreaction of investor sentiments. In terms of prior patterns, most previous studies focused on investors' general past performance to determine investor sentiments (Chang et al. 2021). In recent years, however, the literature has focused on the direct predictions of stock price movement using stocks' fundamental and technical information with varying success rates (Ye & Schuller, 2021). Tsai et al. (2020) divided their study into groups based on the proportion of individual and institutional shareholdings and examined the relationship between information asymmetry and abnormal returns in each group. They also investigate the link between information asymmetry and abnormal returns, among other factors. Their empirical findings were: (1) no substantial difference in abnormal return between a large proportion of individual shares and a high proportion of institutional shares. (2) Long-term abnormal returns were much more significant than short-term abnormal returns when the proportion of individual or institutional shareholdings varies dramatically. (3) Among the shocks that affected information asymmetry, the abnormal returns had a positive and insignificant effect on the information asymmetry. (Hendra et al. 2021) investigated stock return behaviour on days before and after reverse stock split events announcements on an Indonesian stock exchange between 2002 and 2018. Their study result revealed positive abnormal returns before the announcement, followed by negative abnormal returns after the announcement. Utilising the Dow Jones Index from 1890 to 2018, Plastun et al. (2021) thoroughly examined price repercussions following one-day abnormal returns and their evolution in the US stock market. They employed a variety of statistical tests and econometric methodologies. Their findings showed a significant momentum effect existed after a day of positive abnormal returns in the US stock market between 1940 and 1980; however, that had subsequently vanished since the 1980s. Overall, price effects following one-day abnormal returns throughout the studied period were inconsistent in terms of strength and direction (momentum or contrarian effect). Rai & Pandey (2021) investigated the significance of news material about the privatisation of two public sector banks in India using a sample of 22 banks. The researchers used a typical event research methodology and the market model to estimate the expected returns. Their research showed how the privatisation of public sector banks affected the returns of the Indian banking system. While private sector banks enjoyed positive average abnormal returns on the event day, the cumulative effect of the announcement was negative for both private and public sector banks. The statistical results also showed information leakage, with significant results occurring before the release date. The examination of shorter event windows yields large positive returns in the 5-days (negative 2, positive 2) window for the private sector banks and the entire sample, signifying a positive short-term impact on the private sector banks. Song et al. (2022) examined whether market strength and information asymmetry experienced during the 2019s crisis and industrial characteristics influence abnormal returns for shareholders. They employed market strength measured by trading volume and information asymmetry measured by bid-ask spread to recommend potential investment opportunities in various industry categories to investors. They used data from 620 companies listed on the Bursa Malaysia from March 16 to June 9, 2020. They then divided the data into three event windows based on Movement Control Order (MCO) announcements. Using the event study method, they calculated cumulative abnormal returns as the dependent variable and evaluated the impact using multiple regression analysis with hierarchical model specifications. Their research findings showed that larger and older enterprises were at a disadvantage in times of uncertainty compared to smaller and younger firms. In terms of market characteristics, they found that increased trading volume resulted in higher returns for investors. However, the wider bid-ask spread linked with higher abnormal returns showed the stock market's inefficiencies. Their analysis also discovered that in the month following the introduction of the first MCO, the cumulative abnormal returns of firms categorized under unstable industries fell by an additional 5% compared to firms not categorized under unstable industries. As the MCO lasted, the cumulative abnormal return of firms under unstable industries declined by a further 9.5 per cent compared to other firms listed on the Bursa Malaysia. Up to this, we discussed the effects of cumulative abnormal returns on firms' profits during the 2019s crisis. In the following sections, we reviewed the influence of unexpected earnings, interest rate, and liquidity risk on the underreaction proxied by cumulative abnormal returns and formulated three research hypotheses. We began our development of the hypothesis based on relevant empirical studies. Therefore, In the following section, we reviewed the relationship between unexpected earnings and cumulative abnormal returns, followed by the relationship between interest rates and cumulative abnormal returns. In the subsequent section, we reviewed the relationship between liquidity risk and cumulative abnormal returns.

3.1 The Relationship Between Unexpected Earnings and Cumulative Abnormal Returns

According to Zhang et al. (2021), researchers use quarterly earnings figures to divide stocks into quantiles based on unexpected, standardized earnings and form a zero-investment portfolio long (short) in stocks from the highest (lowest) surprise decile and record abnormal returns after earnings announcements. Kuang (2022) investigated the relationship between real earnings smoothing and one-year-ahead firm-specific crash risk in Japan's institutional financial ownership and J-SOX implementation and discovered a significant and negative relationship between real earnings smoothing and asymmetric timeliness regarding bad news. Using data from the Dow Jones 30 and NASDAQ 100 from 2011 to 2020 and 1991 to 2020. Day et al. (2022) investigated whether stock trading profitability matters in the fourth quarter. They used technical trading rules and found that investors had higher cumulative abnormal returns in quarter four than in quarters one to three. Mukhtarov et al. (2022) examined European insurance companies' earnings under the regulatory regimes of Solvency I and Solvency II. Using an event study research design, they investigated a sample of 571 announcements from

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46 insurance firms from 2012 to 2018. Under the regulatory regime of the solvency I directive, they discovered that investors found unexpected earnings informativeness. Under the regulatory control of the solvency II directive, on the other hand, unexpected earnings were relevant to investors. Antônio et al. (2022) sought to assess the influence of debenture issue announcements on the stock market of firms listed on the Brazilian stock exchange. They constructed the data timeliness as a natural contribution due to the temporal opportunity, the extent of the sample and the technique that distinguish the study. They used the analysis of events based on Bootstrap to determine abnormal returns and accumulated abnormal returns from a large selection of 723 debenture announcements between October 1989 and May 2020. Their result showed that the market reacts negatively to debenture issuing announcements in two ways. The abnormal returns indicated the first, offering a heightened risk perception among issuing companies, and the second was the accumulative abnormal returns, which were negative following the announcement.

3.2 The Relationship Between Interest Rates Risk and Cumulative Abnormal Returns

The impact of abnormal returns, such as low or even negative interest rates, among others, could contribute to market volatility affecting the ability of entities to generate returns. Olbrys (2021) assessed whether the interest rate cuts during the 2019 pandemic period in Poland affected asset returns on the Warsaw Stock Exchange. He used an event-study methodology that accommodates event-induced variance to investigate the event-induced abnormal returns performance. According to the researcher, during the pandemic period and immediately after the first lock-down announcement on March 12, 2020, interest rates were substantially reduced by the National Bank of Poland to support the economy against the pandemic crisis. Consequently, within three months, the interest rate fell from 1.84% on 27 February 2020 to 0.30% on 4 June 2020. Given the interest rate cuts in 2020, the researcher considered three-event windows with the corresponding estimation periods. His empirical findings indicated that the interest rate declines significantly drove the stock price's reaction, but the results differ among event windows. YILMAZ (nd.) investigated the existence of abnormal returns with the effect of interest rate changes in Borsa Istanbul using the event study method. The researcher aimed to determine whether the interest rate decisions taken by the Monetary Policy Committee cause abnormal returns on stock prices. Using 131-month data between May 2010 and March 2021, he tested the presence of abnormal returns around the date of meetings when deciding to change the interest rate on the BIST100 index. The researcher indicated that although the effect on the index was observed within five days after the date of the interest rate increase/decrease decision, it was observed that that effect remained very weak. So, his result showed that interest rate change decisions had a shallow impact on the BIST100 index. Guo, Zhang, & Chao (2021) used the event study method to measure and test the impact of the open market reverse repo operation on the Chinese stock market. Their results showed that the open market reverse repo operation generated a positive daily abnormal return and cumulative abnormal return on average for all stocks. The impact was more significant for non-state-owned enterprise firms than state-owned firms, for supplies of non-Hubei provinces than those of the Hubei province, and for stocks of the information transmission and technology industry than those of other industries. Al-Qudah & Houcine (2021) investigated the effects of the 2019 pandemic outbreak on daily stock returns for Africa, the Americas, the Eastern Mediterranean, Europe, South-East Asia, and the Western Pacific. The researchers used an event study method and panel-data regression models to examine the effect of the daily increase in the number of 2019 confirmed cases on daily stock returns from 1 March to 1 August 2020 for the leading stock market in major affected countries in those countries. Their results revealed an adverse impact of the increasing daily number of 2019 cases on stock returns and the falling of stock markets quickly in response to the pandemic. The findings also indicated a strong negative market reaction during the early stage of the outbreak between the 26th and 35th days after the initial confirmed cases. The study further found that stock markets in the Western Pacific region experienced more negative abnormal returns than other regions. The results also demonstrated that feelings of fear among investors turned out to be a mediator and a transmission channel for the effect of the 2019 outbreak on the stock markets. Dang Ngoc et al. (2021) investigated the impact of the 2019 pandemic on listed firms' abnormal stock returns in Vietnam. To study the effect of 2019 on abnormal stock returns, they employed the event research method with three events related to the 2019 pandemic in Vietnam. They used a sample of 364 listed firms on the Ho Chi Minh Stock Exchange. Their result revealed that the 2019 event affected the abnormal returns of stocks, and the level of influence varied from each stage of the 2019 prevention measure in Vietnam. Beckmann and Czudaj (2022) conducted an event study analysis to find abnormal returns on foreign exchange markets since the beginning of the 2019 pandemic. Their findings point to cumulative excess returns for major currencies, which macroeconomic fundamentals partly influenced. However, they found that policy responses to the 2019 pandemic significantly impacted cumulative excess returns. In contrast, expectations for minor currencies react more strongly to response policies. Coën & Desfleurs (2022) examined and contrasted the accuracy and bias of financial experts' projections and the abnormal earnings announcement returns of green and non-green US real estate investment trusts from 2010 to 2018. They found that the levels of accuracy and optimism differed for both categories and argued that there was a possible link between abnormal stock returns to implementing green and sustainable policies. Nguyen et al. (2022) used a unique dataset from the Wharton Research Data Services database and a completed combination of classic and current statistical approaches to explore the topic of return predictability in the USA, the UK, and Japan. They used several standard linear and nonlinear tests to evaluate the efficient market hypothesis, the most recent multiple-break unit root tests and spectrum analysis. Their findings indicated that those stock markets were often inefficient. They then investigated whether the deviations from market efficiency may be leveraged to make profitable trades and discovered that abnormal returns occurred in all three markets. They found evidence of abnormal returns linked

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to the break dates identified in the models, which were linked to key historical events worldwide. Pynnonen (2022) substituted financial assets' multiple-day cumulative abnormal returns with cumulated ranks in rank tests. His research suggested changes to existing methodologies to improve the robustness of the cross-sectional correlation of recoveries resulting from calendar time overlapping event windows. Simulations revealed that the proposed rank test was adequately described in testing cumulative abnormal returns and was resistant to the whole and partial overlapping event windows. Günay & Bayraktaroğlu (2022) investigated the impact of the central bank of Turkey's interest rate announcements on Borsa Istanbul tourist index returns. The researchers used the event research approach to evaluate the effects of the Bank's 20 drop announcements and eight boost announcements on tourism index daily returns from 2010 to 2020. According to the study results, out of 20 announcements of interest rate decreases, only three demonstrated statistically significant Abnormal Returns on the event date using the mean adjusted return model. Based on the above argument, we hypothesize as follows:

3.3 The Relationship Between Liquidity Risk and Cumulative Abnormal Returns

Anolick et al. (2021) investigated the role of market uncertainty as a market-based determinant of positive average abnormal announcement returns to explain share repurchase announcements in nine European countries from 2000 to 2017. They considered liquidity risk among other firm-related control variables and discovered that both individually and jointly, economic policy uncertainty and financial uncertainty positively affect abnormal returns. Nguyen (2021) investigated whether good liquidity management can help mitigate adverse stock price reactions to the 2019s pandemic crisis. the result showed that firms with a high liquidity risk have a lower average cumulative abnormal return than firms with low liquidity risk. Using samples of Taiwan's listed stock market from 2006 to 2019, Gumus & Gumus (2021) studied the effect of stock splits on stock returns, riskiness, and liquidity. They examined the daily abnormal returns, volatility fluctuations, and volume variations surrounding company split announcements and execution dates using a sample of 94 stock splits at Borsa Istanbul between 2010 and 2019. Their results showed considerable positive abnormal returns near the announcement date but no significant abnormal returns near the execution date. Their study results also showed stock volatility and dramatic liquidity increase around announcement and execution dates. In an event-study framework, Cao & Petrasek (2014) investigated whether abnormal returns influence stock performance during liquidity crises. They discovered that abnormal stock returns were a reliable predictor of projected abnormal stock returns during liquidity crises. They also found a substantial correlation between abnormal stock returns and liquidity risk, as measured by stock return co-movement with market liquidity. They argued that the degree of information asymmetry explained abnormal stock returns on crisis days. Haykir & Çetenak (2022) analysed the impact of Turkey's pandemic announcement and policy rate reduction on the liquidity of Borsa Istanbul. They use an event study methodology with 243 listed firms. The pandemic announcement and three interest rate hikes were the event dates. They found a negative reaction to the pandemic news and the announcement of the first interest rate cut but a favourable reaction to the 2 and 3 interest rate cuts in terms of liquidity. Furthermore, they argued that the pandemic influenced less the liquidity of enterprises listed on the index and linked derivatives. Based on the above arguments, we hypothesised the following three hypotheses:

H1: Unexpected earnings significantly and positively affect cumulative abnormal returns
H2: Interest rate risk significantly and negatively affects cumulative abnormal returns
H3: Liquidity risk significantly and positively affects cumulative abnormal returns

4. Methodology

4.1 Data Source Variables and Measurement

In this study, we use annual panel data of 66 observations that belong to stocks of the information transmission and technology industry. Using panel data helps confine the significant relationships among variables over time, improving econometric estimates' efficiency. And it offers more variability more degree of freedom, reduces the correlation among explanatory variables, enhances the reliability of the regression results, and controls for unobservable individual heterogeneity (Baltagi, 2021). When we pooled all 66 observations together and ran the pooled OLS regression model, neglecting the cross-section and time series of data, that is, if individual effects were correlated with the explanatory variables, OLS estimates omitting individual results were biased. Thus, we employed panel data estimation for the empirical model of underreaction. The dependent variable used in the analysis is the commutive abnormal return. The data spanned from 2010 to 2020. This study does include specified lag effects since the lag effect is recognized in the literature. Table 4.1 shows the variable selection, measurements, and the specified lag period.

Table 4.1: Variables and measurement

Variables	Symbols	Specified lags period
cumulative abnormal return	CAR	2
Unexpected earnings	UE	2
Interest rate	IR	2
Liquidity rate	LR	2

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4.2 Model Specification

In many areas of econometrics research, regression equations are used to investigate whether changes in one explanatory variable X are related to changes in another response variable Y which can mathematically be expressed as:

$$CAR_{it} = \beta_{it} + UE_{it} + \varepsilon_{it} \tag{4.1}$$

$$CAR_{ijt} = \beta_0 + \beta_1 UE_{ijt} + \beta_2 IR_{ijt} + \beta_3 LR_{ijt} + +\alpha_i + \varepsilon_{ijt} \tag{4.2}$$

Where:

$CAR_{it}$is the cumulative abnormal returns at time t,

UE_{it} is the unexpected return of firms at time t,
LR_{it}L is the liquidity risk of the firms at time t,
IR_{it} is the interest rate risk of firms at time t, and

ε_{it} is the error terms assumed to be normally distributed across firms, see for example, (Cai & Omay, 2022)

Up to this, we have discussed the empirical model to demonstrate the relation between the dependent and independent variables; in the following section, we focus on the unit root stochastic process.

4.3 Unit Root Stochastic Process

$$Y_{it} = X_{it} + \varepsilon_i \tag{4.3}$$

Where:

Y_{it} is equal to y_i observation at time t,

$X_{it}$is equal to x_i observation at time t

ε_{it} is equal to the stationary error terms with a variance of σ_e^2, d_t and is a deterministic trend.

Similarly, following Levin et al. (2002), a unit root stochastic process with a simple regression model can be formulated as follows:

$$\Delta y_{it} = \delta y_{it-1} = \zeta_{it} \tag{4.4}$$

The above model is without constant and trend. A model of this type with a constant can be written as:

$$\Delta y_t = \alpha + \delta y_{t-1} = \zeta_t \tag{4.5}$$

A model with constant and trend can be written as:

$$\Delta y_t = \alpha + \beta T + \delta y_{t-1} = \zeta_t \tag{4.6}$$

$$-1 \leq \delta \leq 1$$

In the above simple regression model without drift, if δ =1, there exists a unit root problem in the model, that is, a situation of non-stationarity. By extension, the variable y_{it} is not stationary. By contrast, if $|\delta| \leq 1$, that is, if the absolute value of δ is less than one, then the variable y_t is said to be stationary (Nkoro & Uko 2016, p.69).
The error process ζ_i is distributed independently across individuals and follows a stationary invertible ARMA process for each individual (Levin et al., 2002) and can be written as:

$$\zeta_{it} = \sum_{j=1}^{\infty} \theta_{it}\zeta_{it-1} + \varepsilon_{it}$$

for all i=1,…., N and t=1,…., T

There are various methods of testing unit roots alongside the unit root test of Levin et al. (2002) (LLC), and in this paper, we performed three widely used unit root tests besides the LLC unit root test. Those are augmented (Dickey & Fuller, 1979), (Phillips & Perron, 1988) with the null hypothesis that data is not stationary and (Pesaran & Shin, 1995) with the null hypothesis that data is stationary. They are explained below.

4.3.1 Augmented Dicky-Fuller (ADF) Test

Following Enders & Lee (2012), the Augmented Dicky-fuller (ADF) test can be written as:

$$y_t = \alpha(t) + \rho y_{t-1} + \gamma.t + \varepsilon_t \tag{4.7}$$

Where ε_t is a stationary error term with a variance of σ^2, and α(t) denotes the deterministic intercept and trend. According to Omay & Baleanu (2021), estimating equation Eq (4.4) directly is problematic and studying the unit root hypothesis ρ=1 without knowing the functional structure of α(t).

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4.3.2 Philip-Perron (PP) Test

Unlike the Augmented Dickey-fullers test, the Phillip-Perron test is nonparametric, ignores serial correlation, and concentrates on heteroskedasticity. Because it is applied to a large sample, Phillip Perron's non-parametric assumes there is no functional error process form and no lag period. However, by changing the Dickey-Fuller test statistics, the Phillip-Perron test for unit root nonparametrically corrects for any autocorrelation and heteroskedasticity in the errors (Chiwira, & Muyambiri 2012).

4.3.3 Im, Pesaran and Shin Test

In their theoretical framework, Im et al. (2003) supposed that the stochastic process, y_{it}, is generated by the first-order autoregressive process, which can be written as:

$$\Delta y_{it} = (1-\phi_i)\mu_i + \phi_i y_{i,t-1} + \varepsilon_{it} \quad \text{i=1,…, N, t=1,…., T} \tag{4.8}$$

where initial value, y_{i0} , are provided. Im et al. (2003) tested the null hypothesis of unit roots ϕ_i=1 for all i. (4.8) can be expressed as follows:

$$y_{it} = \alpha_i + \beta_i y_{i,t-1} + \varepsilon_{it}, \tag{4.9}$$

Where $\alpha_i = (1-\phi_i)\mu_i$,$\beta_i = -(1-\phi_i)$ and $\Delta y_{it} = y_{it} - y_{i,t-1}$. The null hypothesis of unit roots then becomes

$$H_0: \beta_i = 0 \text{ for all i.} \tag{4.10}$$

Against the alternative hypothesis,

$$H_1: \beta_i < 0, \quad \text{i = 1,2,…,}N_1, \beta_i = 0, \text{i=}N_1+1, N_1+2, \dots, N. \tag{4.11}$$

This alternative hypothesis permits β_i to differ among groups and is more general than the homogeneous alternative hypothesis, $\beta_i = \beta < 0$ for all I, which is implied in Levin and Lin's (LL) testing approach, which will be explored later. Under the alternative hypothesis, some (but not all) of the series can have unit roots.

Up to these points, we have discussed the different methodological applications of unit root processes, including the basic frameworks of (Im et al. 2003). In the following section, we explain the co-integration test.

4.4 Cointegration Test

The existence of a long-run equilibrium relationship between X and Y is referred to in the literature as cointegration (Francis 2022). The concept of cointegration was first defined in the 1980s see, for example, (Granger, 1981); (Engle & Granger, 1987), offering tests and estimate procedures for determining the existence of a long-run link between a collection of variables within a dynamic specification framework. Cointegration involves a linear regression on given time series data; however, which variable is used as the dependent variable is irrelevant (Leung & Nguyen, 2019). Cointegration can be used to model time series to preserve their long-run information because the test of the model looks at how time series that are individually non-stationary and drift far from equilibrium can be coupled so that the workings of equilibrium forces keep them from drifting too far apart (Nkoro & Uko 2016, p.75). Nevertheless, most time series are wide-sense non-stationary, resulting from stochastic trends and distributional shifts (Castle et al. 2021). There is bi-directional causality if the investigation reveals that X Granger causes Y and Y; likewise, Granger causes X for both variables under consideration must be stationary to avoid a false basis of causality (Francis and Iyare 2006). Cointegration testing is required to determine whether a model experimentally demonstrates meaningful long-run relationships. If cointegration among underlying variables cannot be established, it is necessary to work with variables in differences instead; nevertheless, long-term information will be lacking (Nkoro & Uko 2016, p.75). There are several cointegration tests other than the Engle & Granger, (1987) procedure. Among them is the Autoregressive Distributed Lag cointegration technique or bound cointegration testing described below. This model is explained in the section below.

4.5 Autoregressive Distributed Lag (ARDL) Model

The autoregressive distributed lag (ARDL) model by (Pesaran, Shin, & Smith, 1999) was used to test the symmetric effect of the exogenous variables (UE, IR, and MR) on the endogenous (cumulative abnormal return. ARDL models have a more adaptive capacity for establishing relationships between variables, i.e., regardless of sample size, can be either small or finite, consisting of 30 to 80 observations. Second, the issue pertinent to mixed order of integration is fully accommodated in ARDL. Third, Pesaran et al., (2001) advocated that serial correlation and the problem of indignity can be resolved by selecting appropriate lags. And finally, empirical model estimation with ARDL can simultaneously produce long-run and short-run coefficients (Pesaran et al., 2001). When one co-integrating vector exists, the cointegration procedure cannot be applied. Therefore, it becomes imperative to explore the Autoregressive Distributed Lag (ARDL) approach to cointegration or bound procedure for a long-run relationship, irrespective of whether the underlying variables are I (0), I (1) or a combination of both (Nkoro & Uko 2016). The Autoregressive Distributed Lag (ARDL) model is a least squares regression model that includes the lag of endogenous and exogenous variables (Memdani and Shenoy 2019). Indeed, one frequently argued favour of the autoregressive distributed lag (ARDL) model is a dynamic single-equation error-correction specification (Goh et al. 2017). The ARDL model has shown whether there is a short- or long-term

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relationship between the endogenous variable and exogenous variables consideration. Following the model specification provided in the work of Nkoro & Uko (2016), we express the long-run, and short-run relationships between the endogenous variable and the exogenous variables in the following ARDL model can be written as follows:

$$\Delta y_i = \beta_i + \sum_{i=1}^{n} \beta_i \Delta y_{t-1} + \sum_{i=1}^{n} \delta_i \Delta x_{i=1} + \sum_{i=1}^{n} \theta_i \Delta z_{i=1} + \varphi_1 y_{t-1} + \varphi_2 x_{t-1} + \varphi_3 z_{t=1} + \mu_t \tag{4.12}$$

Where:
$\beta_1 \beta_2, and\ \delta_3$, θ_1, are long-run coefficients whose sum is equivalent to the error correlation terms at the VECM model φ_2, φ_2 and φ_3 are short-run coefficients and ε_t is white noise and identically and independently distributed across firms. The multiple regression model based on the ADRL model for examining the relationship between the dependent variable and the independent variables CAR, UE, IR, and LR in selected computer companies based on lag two-period criteria can be written as follows:

$$\begin{aligned}\Delta CAR_{it} = \alpha_0 + \beta_1 CAR_{it} + \beta_2 CAR_{it} + \beta_3 UE_{it} + \beta_4 UE_{it} + \beta_5 IR_{it} + \beta_6 IR_{it} + \beta_6 LR_{it} + \beta_7 LR_{it} \\ + \sum_{j=0}^{m1} \lambda \Delta CAR_{t-j} + \sum_{j=0}^{m2} \lambda_1 \Delta CAR_{t-j} + \sum_{j=0}^{m3} \lambda_2 \Delta UE_{t-j} + \sum_{j=0}^{m2} \lambda_3 \Delta UE_{t-j} + \sum_{j=0}^{m4} \lambda_4 \Delta IR_{t-j} \\ + \sum_{j=0}^{m5} \lambda_5 \Delta IR_{t-j} + \sum_{j=0}^{m6} \lambda_6 \Delta LR_{t-j} + \sum_{j=0}^{m7} \lambda_7 \Delta LR_{t-j} + \varepsilon_{ijt}\end{aligned} \tag{4.13}$$

Where α is an intercept, the long-run coefficients of the empirical model are represented by $\beta_1, \ldots\ldots.. \beta_7$, the short-run coefficients exhibited by $\lambda_0, \ldots\ldots\ldots. \lambda_7, \varepsilon_t$ are the error correction term and m1, m2, m3, m4, m5, m6, and m7 are the optimal lag for the first difference variables selected by the Akaike Information Criterion (AIC). To implement the ARDL model, the statistic, cross-sections method is used to estimate the equation in (4.5), and then cointegration between the variables can be established in three different ways, first using the F-test of Pesaran et al., (2001) with the null hypothesis of no cointegration ($H_0 = \beta_1 = \beta_2 = \beta_3 = \beta_4 = \beta_5 = \beta_6 = \beta_7 = 0$) against the alternative of cointegration ($H_0 = \beta_1 \neq \beta_2\ etc.,$). Second, the Im, Pesaran, and Shin W-stat test the above joint null. Third, the ADF - Fisher Chi-square, PP - Fisher Chi-square with the null hypothesis of no-cointegration ($H_0 = \beta_1 = \beta_2$) against the alternative of cointegration ($H_0 = \beta_1 \neq \beta_2$) . The testing procedure uses two critical bounds: upper and lower. If the ADF - Fisher Chi-square and PP-Fisher Chi-square values exceed the upper bound, the null hypothesis is rejected. If they lie below the lower critical bound, the null hypothesis cannot be rejected, and if they lie between the critical bounds, the test is inconclusive. The ARDL bounds test short-run causality model can be written as follows:

$$\Delta y_i = \beta_0 + \sum_{i=1}^{p} \lambda_1 \Delta y_{t-1} + \theta_2 \sum_{i=1}^{q1} \delta_{1i} \Delta X_{1i-1} + \sum_{i=1}^{q2} \delta_{2i} \Delta X_{2,t-1} + \varepsilon_{1t} \tag{4.14}$$

5. Results

This section summarizes the main findings of the study, followed by the contributions of the study in the following section. Finally, it provides the limitations of the study.

5.1 Statistical Results

5.1.1 Descriptive Statistics

The underreaction (CAR) is positive, with a mean of 0.002379. Compared with unexpected earnings, the cumulative abnormal return has a less positive mean and lower volatility, but it displays much higher negative skewness and lowers positive kurtosis.

Table 5.1: Descriptive Statistics

	CAR	UE	IR	LR
Mean	0.002379	-0.018659	1.407155	0.385995
Median	0.010597	-0.014799	1.407233	0.357195
Maximum	0.524437	2.454876	1.910452	1.535242
Minimum	-0.824679	-2.785799	-1.470902	-0.426725
Std. Dev.	0.187788	0.813714	0.286112	0.248923
Skewness	-0.573032	-0.338706	-6.922316	2.701916
Kurtosis	4.248682	4.660930	68.29346	14.59414

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Jarque-Bera	29.68428	33.24827	46034.07	1690.797
Probability	0.000000	0.000000	0.000000	0.000000
Sum	0.590109	-4.627451	348.9745	95.72681
Sum Sq. Dev.	8.710296	163.5464	20.21941	15.30474

Almost all the variables in the sample follow a normal distribution, as seen in the table above. The skewness value for the variable cumulative abnormal return is -0.573032, showing that the distribution is approximately asymmetric because the value is not near 0. In contrast, the kurtosis value is positive and greater than 3, implying that the distribution is none platykurtic. The skewness of the unexpected earnings variable is negative -0.338706 and is less than 1, and the kurtosis is positive and more than 3, indicating a right-skewed and non-leptokurtic distribution. The interest rate skewness of -6.922316 and kurtosis of 68.29346 suggest that the distribution is neither symmetric nor platykurtic. The skewness value for the variable liquidity risk is positive and more than 1, 2.701916. In contrast, the kurtosis value is positive and greater than 3, 14.59414, indicating that the distribution is none skewed and non-leptokurtic.

Table 5.2: Correlational Analysis

	CAR	UE	IR	LR
CAR	1	0.14128	0.044487	0.023599
UE	0.14128	1	0.036557	0.118278
IR	0.044487	0.036557	1	-0.02079
LR	0.023599	0.118278	-0.02079	1

The correlation between cumulative abnormal return and unexpected earnings of 0.14128 is significantly positive, and the correlation between cumulative abnormal return and interest rate of 0.044487 is also insignificantly positive. The correlation between cumulative abnormal return and liquidity risk is 0.023599 and insignificantly positive. In the following section, we analyze the panel unit root test.

5.2 Panel Unit Root Test to Test for Stationarity

It is well documented in the existing time series economic literature that the results of regression methodology may be spurious if the estimated variables are none stationary and not co-integrated (Yang & Rehm 2021). We hypothesize that H0: Series has unit-roots. In other words, the series is nonstationary. The alternative is that series has no unit root or is not nonstationary. We say we have a unit root in the series if the null hypothesis is accepted. We are interested in understanding this point. Therefore, first, we must check whether cumulative abnormal returns, and the unexpected earnings, interest rates, and liquidity risk (collectively called series) have unit root or not to proceed with them. Therefore, before evaluating the multivariate case of the ARDL model, it is essential to estimate the univariate case of the simple regression model to demonstrate whether the model captures the data and shows the co-integrating relationship between variables, which needs unit root tests. Thus, the unit root tests would be the first step in analysing and determining potentially co-integrating relationships between the variables under investigation. We employed the Levin, Lin and Chu test, Im, Pesaran, and Shin W-stat., and Augmented Dicky and fuller (ADF) test (Dickey & Fuller 1981). Indeed, the ADF unit root tests are the first step in applying the co-integrating procedure to study such relationships and show relationships that need unit root tests (Ullah et al. 2021). And then Perron and Philips (PP) test (Phillips & Perron 1988). First, our series assume intercept, which is our decision to choose between without constant and trend, with constant, and with constant and trend. But these assumptions will be included in Fisher and Johansen's co-integration tests because they are part of the analysis of the co-integration test discussed in section 5.3. Therefore, the unit root test on panel data of cumulative abnormal returns, unexpected returns, interest rate risk, and liquidity risk data at levels would be performed. Our model with intercept (i.e., constant) can be written as:

$$\Delta y_{it} = \alpha + \delta y_{it-1} = \zeta_{it} \tag{5.1}$$

If H_0 is accepted, that is, if the series has a unit root, it must be differenced to see if stationarity is achieved after the first differencing. Accordingly, taking the log, first differences and including intercept but excluding both without constant and trend and with constant and trend have been performed separately on the test mentioned above methods. The lags selection process for the panel unit root tests was based on the automatic selection of maximum lags. The tables below show the outcomes of the unit root tests of all the variables, including the cumulative abnormal return and its explanatory factors. The partial sum of positive and negative changes in levels of cumulative abnormal return and its determinant factors at first differences is presented in table 5.2. These partial sums of positive and negative changes at levels and intercepts, and first differences and intercepts, are presented in table 5.3 and table 5.4 after that, respectively.

Table 5.3: level and first difference of LLC, Im,Pesaran and Shin W-stat., ADF and PP Unit Root Tests

Variables	Levin, Lin & Chu t*	Im, Pesaran and Shin W-stat	ADF-Fisher Chi-square	PP-Fisher Chi-square

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	Level	1st Difference	level	Difference	Level	Difference	Level	Difference
CAR	-6.29691	-16.8892	-2.20799	-9.09172	79.347	190.916	85.8027	239.447
UE	-8.16327	-16.3930	-3.99927	-7.84206	110.938	173.178	138.960	231.571
IR	-4.97464	-10.6031	-0.68171	-4.57249	71.4636	121.977	53.5071	155.243
LR	-8.16741	-21.9820	-3.77403	-6.98161	104.711	134.698	60.0034	115.282

Note: ** Probabilities for Fisher tests are computed using an asymptotic Chi-square distribution. All other tests assume asymptotic normality.

5.2.1 Assumption of Common Unit Root Process

The null hypothesis for the at levels versus the at-first differences of Levin, Lin, and Chu t* (hereafter referred to as LLC) for the CAR, UE, IR, and LR assumes a common unit process. The statistical result shows that for at the level of CAR is -6.29691 and the first difference of D(CAR) is -16.8892 (see table 5.3), and their probability value is 0.0000 at a significant level of 10%. Thus, the null hypothesis was rejected at the level because the series has no unit root. The statistical result for the level of UE is -8.16327 and for the first differences of D (UE) is -16.3930, respectively, at a significant level of Prob.** 0.0000 for both. These are significantly less than the significant level of 10% or the 0.10 acceptance and rejection criterion. Thus, the hypothesis is rejected because the series has no unit roots at the level. The statistical results for the levels versus for first differences of LLC for IR show that at levels of IR is equal to -4.97464 and at the first difference of D(IR) is equal to -10.6031 at a significant level of Prob.** 0.0000 for both. The hypothesis is rejected, for the series has no unit roots at levels. The statistical result for LR also shows that the at levels are equal to -8.16741, and the at-first difference is equal to -21.9820 at a significant level of Prob.** 0.0000 for both is significantly less than the statistically accepted critical value of 10%. Therefore, the null hypotheses are rejected at the level of LCC statistical results because the common unit process has no unit roots at levels.

5.2.2 Assumption of Individual Unit Root Process

The null hypothesis for levels versus at first differences of the Im, Pesaran, and Shin W-stat, and both ADF and PP-Fisher Chi-square assume individual unit root process instead of the common unit process as explained above. Table 5.3 presents such a process and is discussed subsection by subsection.

Table 5.4: Level and Intercept of LLC, Im, Pesaran and Shin W-sta, ADF, and PP-Unit Root Test

Variables	Levin, Lin & Chu t*		Im, Pesaran and Shin W-stat		ADF-Fisher Chi-square		PP-Fisher Chi-square	
	Level	Intercept	Level	Intercept	Level	Intercept	Level	Intercept
	T-Stat.	Prob.**	T. Stat.	Prob.**	T-Stat.	Prob.**	T-Stat.	Prob.**
CAR	-6.29691	0.0000	-2.20799	0.0136	79.347	0.0086	85.8027	0.0022
UE	-8.16327	0.0000	-3.99927	0.0000	110.938	0.0000	138.960	0.0000
IR	-4.97464	0.0000	-0.68171	0.2477	71.4636	0.0379	53.5071	0.4162
LR	-8.16741	0.0000	-3.77403	0.0001	104.711	0.0000	60.0034	0.2083

Notes: * and ** are significant at significant levels of 1% and 5%, respectively

5.2.2.1 Im, Pesaran and Shin W-stat

The null hypothesis of CAR, UE, IR, and LR assumes individual unit processes for Im, Pesaran, and Shin W-stat. The statistical results showed that CAR's level is -2.20799, and the first difference of CAR is -9.09172 at significant levels of 0.0136 and 0.0000. the hypothesis was rejected because the series no longer has unit roots at first difference. The result for the at levels of UE is -3.9927 and for the at first differences of UE is -7.84206 at a significant level of Prob.** 0.0000 respectively (see table 5.3). These are significantly greater than the significance level of 10% or the 0.10 acceptance and rejection criterion. We rejected the null hypothesis because the series had no unit roots at the level. Im, Pesaran, and Shin W-stat's statistical results for the at levels versus at first differences for IR show that IR is equal to -0.68171 at a significant level of Prob.** 0.2477, which is significantly greater than the statistically accepted critical value of 10%. Thus, the null hypothesis cannot be rejected at the level. However, after testing the first difference, D(IR) equals -4.57249 at a significant probability of 0.0000, which is less than 10%. Thus, the null hypothesis is rejected because the series no longer has unit roots at first difference. The statistical result for the at levels versus for the at first differences of Im, Pesaran, and Shin W-stat., for LR shows that for the at levels is equal to -3.77403 and for at the first differences is equal to -6.98161 at a significant level of probability ** 0.0001 and 0.0000 respectively which is significantly less than the statistically accepted critical value of 10%. We rejected the null hypothesis and accepted the alternative hypothesis because the series has no unit roots at the level.

5.2.2.2 ADF-Fisher Chi-square

The null hypothesis for the level versus the first difference of ADF-Fisher Chi-square for the CAR, UE, IR, and LR assumes individual unit processes as indicated above. The statistical result shows that the level of CAR is 79.347 and at first difference of CAR is 190.816 at a significant probability level of 0.0086 and 0.0000, respectively. The at the level of UE is 110.938 and at the first difference of UE is 173.178 at a significant level of probability 0.0000 for both

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respectively. These are significantly less than the significant level of 10% or the 0.10 acceptance and rejection criterion. So, we can reject the null hypothesis at levels because the series has no unit roots. The statistical results for the level versus for first difference of IR show that at the level, IR is equal to 71.4636. At the first difference, it is equal to 121.977 at a significant level of probability 0.0378 greater than 10%, but for at first difference 0.000, which is less than 10%. We can reject the null hypothesis at first difference because the individual unit process no longer has unit roots at-first difference. The statistical result for LR also shows that the level is equal to 104.711 at a significant level of probability 0.0000, and the at-first difference is equal to 134.698 at a significant level of probability 0.0000, which is significantly less than the statistically accepted value of 10%. So, the null hypotheses are rejected at the level because the series has no unit roots.

5.2.2.3 PP-Fisher Chi-square

The null hypothesis for the level versus for first difference of PP-Fisher Chi-square for the CAR, UE, IR, and LR similarly assumes individual unit processes. The statistical result shows that the level of CAR is 85.8027 with an intercept of 0,0022 and the first difference of D(CAR) is 239.447 with an intercept of 0.0000. thus, the null hypothesis is rejected at the level because the series has no unit root. The result for the level of UE is 138.960 with an intercept of 0.0000 and for at first difference of D(UE) is 231.571 with an intercept of 0.0000 respectively (see table 5.3), which is significantly less than the significant level of 10% or the 0.10 acceptance and rejection criterion. Therefore, the hypothesis is rejected at the level because the series has no unit-roots.

Table 5.5: First difference and Intercept of LLC, Im,Pesaran and Shin W-stat., ADF and PP Unit Root Tests

Variables	Levin, Lin & Chu t*		Im, Pesaran and Shin W-stat		ADF-Fisher Chi-square		PP-Fisher Chi-square	
	1st Difference	Intercept	Difference	Intercept	Difference	Intercept	Difference	Intercept
	T. stat.	Prob.**	T. Stat.	Prob.**	T-Stat.	Prob.**	T-Stat.	Prob.**
D(CAR)	-16.8892	0.0000	-9.09172	0.0000	190.916	0.0000	239.447	0.0000
D(UE)	-16.3930	0.0000	-7.84206	0.0000	173.178	0.0000	231.571	0.0000
D(IR)	-10.6031	0.0000	-4.57249	0.0000	121.977	0.0000	155.243	0.0000
D(LR)	-21.9820	0.0000	-6.98161	0.0000	134.698	0.0000	115.282	0.0000

Notes: * and ** are significant at significant levels of 1% and 5%, respectively.

The statistical results for the level versus for first difference of PP-Fisher Chi-square for IR show that the level of IR is equal to 53.5071 at a significant level of probability 0.4162, for which we can accept the null hypothesis. But after differencing, the first difference of D(IR) is equal to 155.243, and the probability value is 0.0000 at a significant level of 10%. We reject the null hypothesis assumption at this junction and accept the alternative hypothesis because the series no longer has a unit root. Similarly, the statistical result for LR also shows that at level is equal to 60.0034 at a significant level of 0.2085, which is significantly greater than the statistically accepted value of 10%. But at first, D(LR) is equal to 115.282 at a significant probability level of 0.0000. Therefore, we reject the null hypothesis and accept the alternative hypothesis because the series is no longer unit root at first difference. As seen from the above statements, there are mixed results in the individual unit root process at levels, but after differencing the results, it disappears. As a result, we proceed to the cointegration test model explained below.

5.3 Cointegration Tests

The next step is to run cointegration tests to see if the sample variables have a structural (cointegrated) relationship and analyses the resulting outcome. Cointegration analysis is suitable for exploring the long-term connection between exogenous and endogenous variables (Matzana et al. 2022). This means among response and explanatory variables, at levels or the first differences. Cointegration analysis effectively examines the long-term relationship between cumulative abnormal returns, unexpected returns, interest rate, and liquidity risk. As a result, multiple cointegration tests are carried out (Pedroni tests, Kao tests, and Fisher and Johansen). The null hypothesis in panel co-integration tests assumes that H_0: There is no cointegration, whereas the alternative hypothesis is that H_0: there is cointegration. To run the panel cointegration test model. These variables are assumed to be none stationary at levels. But when all variables are converted into at first differences, they become stationary. Therefore, our variables are assumed to be none stationary at levels. In the Jonson cointegration model, the null hypothesis assumes no cointegration exists. The alternative hypothesis is that there is cointegration. The model assumes common AR coefficients., (within dimension) and individual AR coefficients., (between dimensions). The trend assumption of the model is also not deterministic. We analyze each of them in this section. First, we will check the individual intercept, go for individual intercept and trend, and then finally, for no trend and intercept. Table 5.6 shows the resulting statistical output of the Pedroni Residual Cointegration Test for Individual intercept.

table 5.6: Individual No Cointegration and Deterministic Trend

Alternative hypothesis: common AR coefficients, (within-dimension)

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	Statistic	Prob.	Weighted Statistic	Prob.
Panel v-Statistic	0.077109	0.4693	-0.295506	0.6162
Panel rho-Statistic	2.088926	0.9816	1.986368	0.9765
Panel PP-Statistic	-6.846952	0.0000	-6.961627	0.0000
Panel ADF-Statistic	-1.605242	0.0542	-2.068874	0.0193
Alternative hypothesis: individual AR coefficients (between-dimension)				
	Statistic	Prob.		
Group rho-Statistic	3.857290	0.9999		
Group PP-Statistic	-12.95025	0.0000		
Group ADF-Statistic	-2.438097	0.0074		

The analysis results show eleven outcomes based on the seven tests, four common AR coefficients (within dimension), and three individual AR coefficients (between dimensions). We cannot reject the null hypothesis for common AR coefficients (within-dimension) for panel v-statistic and panel rho-statistic because their probabilities are significantly more significant than the critical level of 5% for both statistics and the weighted statistic. But for panel ADF-statistic we can reject the null hypothesis for weighted statistics only, but not the null hypothesis for statistics. For between dimensions, we can reject the null hypothesis for group rho-statistic because its probability is greater than 5%. Generally, out of the 11 statistical results, five are significant, and six are not significant. We cannot reject the null hypothesis but accept the null hypothesis because, based on the result, variables CAR, UE, IR, and LR are not cointegrated. This implies that they have no long-run association. This also means that variables are not cointegrated when there is no deterministic trend. Table 5.7 provides the individual trend and individual intercept of the Pedroni residual cointegration test.

table 5.7: Individual Trend and Individual Intercept of Pedroni Residual Cointegration Test

Alternative hypothesis: common AR coefficients (within-dimension)				
	Statistic	Prob.	Weighted Statistic	Prob.
Panel v-Statistic	-1.544418	0.9388	-1.975393	0.9759
Panel rho-Statistic	4.285895	1.0000	4.134312	1.0000
Panel PP-Statistic	-9.571245	0.0000	-10.04225	0.0000
Panel ADF-Statistic	-0.671519	0.2509	-1.489798	0.0681
Alternative hypothesis: individual AR coefficients (between-dimension)				
	Statistic	Prob.		
Group rho-Statistic	6.131529	1.0000		
Group PP-Statistic	-13.31334	0.0000		
Group ADF-Statistic	-0.780416	0.2176		

Out of the 11 statistical results of individual intercept and individual trend, only panel PP-Statistic is significant in the within dimension in the case of both statistics and weighted statistics. For between dimensions, again, the group PP-statistic is significant. Therefore, out of 11 statistical results, only one is significant, and therefore we cannot reject the null hypothesis; instead, we accept the null hypothesis. That implies that our variables are not cointegrated. The next task is to see the no intercept and no trend assumption explained below. Table 5.8 presented the no intercept or trend of the Pedroni residual cointegration test.

Table 5.8: No Intercept or Trend of Pedroni Residual Cointegration Test

Alternative hypothesis: common AR coefficients (within-dimension)				
	Statistic	Prob.	Weighted Statistic	Prob.
Panel v-Statistic	1.312664	0.0946	0.454719	0.3247
Panel rho-Statistic	0.547460	0.7080	0.457769	0.6764
Panel PP-Statistic	-4.870622	0.0000	-4.675421	0.0000
Panel ADF-Statistic	-1.279744	0.1003	-0.756811	0.2246
Alternative hypothesis: individual AR coefficients (between-dimension)				
	Statistic	Prob.		
Group rho-Statistic	2.475644	0.9934		
Group PP-Statistic	-9.367145	0.0000		
Group ADF-Statistic	-1.205556	0.1140		

Out of the 11 statistical results of no intercept and no trend of Pedroni, residual cointegration test, only Panel PP-Statistic and Group PP-Statistic are significant. So, we cannot reject the null hypothesis. That implies that our variables are not cointegrated. So far, we have performed three cointegration tests, but these three tests showed that variables are not cointegrated. Since the decision of acceptance and rejection of the null Hypothesis in the co-integration test is determined based on majorities, we cannot reject the test based on statistics of the co-integration as a whole; instead, we accept the null hypothesis. The next test is Kao residual cointegration test. Table 5.9 shows the statistical result of such a test.

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Table 5.9: Kao Residual Cointegration Test

			t-Statistic	Prob.
ADF			0.387050	0.3494
Residual variance			0.062174	
HAC variance			0.024167	
Variable	Coefficient	Std. Error	t-Statistic	Prob.
RESID (-1)	-1.056500	0.109747	-9.626688	0.0000
D (RESID (-1))	0.057356	0.077380	0.741221	0.4595
R-squared	0.432420	Mean dependent var		-0.032084
Adjusted R-squared	0.429494	S.D. dependent var		0.249636
S.E. of regression	0.188555	Akaike info criterion		-0.488706
Sum squared resid	6.897257	Schwarz criterion		-0.455256
Log-likelihood	49.89316	Hannan-Quinn criter.		-0.475163
Durbin-Watson stat	1.868280			

The result showed that the variables are not cointegrated; they have no long-run association. Thus, our hypothesis was not rejected; instead, it was accepted. As seen from the above results, we estimated the determinants of CAR by including UE, IR, and LR, in the test. We take the first difference and evaluate the models. But such estimation may ignore the long-run relationship. As a result; we used the ARDL model because it can capture both the long-run and short-run relationship of the co-integrated variables. Thus, the ARDL model has been employed in many studies to determine the long-run co-integration of variables. In our case, the long-run association between unexpected earnings and the underreaction phenomenon. So, we developed the ARDL model, also widely known as the bound test for CAR, UE, IR, and LR. Some are I (0), and some maybe I (1) but none of them is 1(2). The following section developed the regression equation based on the ARDL model.

5.4 The Autoregressive Distributed lag (ARDL) Model

To develop our regression equation, the development of the standard ARDL model is necessary. The standard ARDL model can, as demonstrated in section three, be rewritten as follows:

$$\Delta y_i = \beta_i + \sum_{i=1}^{n} \beta_i \Delta y_{t-1} + \sum_{i=1}^{n} \delta_i \Delta x_{i=1} + \sum_{i=1}^{n} \theta_i \Delta z_{i=1} + \varphi_1 y_{t-1} + \varphi_2 x_{t-1} + \varphi_3 z_{t=1} + \mu_t \quad (5.2)$$

But before the development of the standard ARDL model, the selection of an optimum number of lags is required, and thus we selected lag based on VAR selection criteria. To perform the ARDL bounds testing for integration valuation, we must choose a suitable lag time by measuring the F-statistic based on the Akaike Information Criterion (AIC) lowest value (Rehman et al. 2022). The type of lag time selected is based on the VAR selection criteria. The first selected VAR selection criteria of the model were having two lag time orders. Then we checked the model's AIC and SIC criteria, and the result showed -0.768001 and -0.514669* for both AIC and SIC, respectively. The model's second VAR selection criteria were three lag times. Then we checked the AIC and SIC criteria of the 3-lag time, which also the result showed -0.782205* and -0.486651 for both AIC and SIC, respectively. Unfortunately, we cannot use three lag times because its AIC and SC values are lower. So, the best selected VAR selection criteria of the standard ARDL model was with two lag times. Checking the AIC and SIC criteria of this 2 lags model showed higher values than the values of 3 lag times for both AIC and SIC, respectively which is theoretically acceptable. Table 5.10 below shows the summary result of the VAR lag order selection criteria.

Table 5.10 VAR Lag Order Selection Criteria

Lag	LogL	LR	FPE	AIC	SC	HQ
0	14.25220	NA	0.035091	-0.512610	-0.343722	-0.451546
1	17.57594	5.816545	0.031262	-0.628797	-0.417687	-0.552466
2	21.36002	6.432939*	0.027226	-0.768001	-0.514669*	-0.676404*
3	22.64409	2.118715	0.026878*	-0.782205*	-0.486651	-0.675342
4	23.50702	1.380683	0.027112	-0.775351	-0.437575	-0.653222
5	23.73432	0.352309	0.028247	-0.736716	-0.356718	-0.599321
6	24.48168	1.121038	0.028692	-0.724084	-0.301864	-0.571422
7	25.53706	1.530306	0.028719	-0.726853	-0.262411	-0.558925
8	26.34337	1.128828	0.029129	-0.717168	-0.210504	-0.533975

Note: * indicates lag order selected by the criterion LR: sequential modified LR test statistic (each test at 5% level) FPE: Final prediction error AIC: Akaike information criterion SC: Schwarz information criterion HQ: Hannan-Quinn information criterion

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E-views software was used to select the lag order selection for the models. As shown in Table 5.2, the Akaike Information Criteria (AIC), and Schwarz Information Criteria (SC) for selected lag 2 are -0.0768001 and -0.514669*, respectively. The model selection criteria indicated that two lag time is the best of the available models. In theory, both the AIC and SC values should be negative. Therefore, we proceed with the model having two lag times to complete the standard ARDL model development, and thus throughout the rest of the analysis, we focus on such lag time. Therefore, the first thing to proceed with the lag 2-period ARDL model is to check whether it has serial correlation or not, then check its stability. Table 5.11 shows the statistical result of standard ARDL:

Table 5.11: statistical result of Panel Least Square Method of Lag 2 period ARDL Model

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.111760	0.118430	-0.943684	0.3468
D (CAR (-1))	0.159128	0.144852	1.098559	0.2736
D (CAR (-2))	0.085724	0.110551	0.775423	0.4393
D (UE (-1))	0.023161	0.030425	0.761240	0.4477
D (UE (-2))	0.004221	0.020733	0.203570	0.8390
D (IR (-1))	-0.034411	0.074884	-0.459519	0.6465
D (IR (-2))	-0.056174	0.059127	-0.950047	0.3435
D (LR (-1))	0.172311	0.217207	0.793304	0.4288
D (LR (-2))	0.356554	0.220456	1.617353	0.1078
CAR (-1)	-1.179087	0.183210	-6.435719	0.0000
UE (-1)	0.052320	0.036617	1.428868	0.1550
IR (-1)	0.052150	0.076594	0.680866	0.4970
LR (-1)	0.027791	0.065868	0.421919	0.6737
R-squared	0.472359	Mean dependent var		-0.034365
Adjusted R-squared	0.432030	S.D. dependent var		0.258460
S.E. of regression	0.194786	Akaike info criterion		-0.360446
Sum squared resid	5.956805	Schwarz criterion		-0.120650
Log-likelihood	43.63790	Hannan-Quinn criter.		-0.263139
F-statistic	11.71258	Durbin-Watson stat		1.997686
Prob(F-statistic)	0.000000			

ARDL Estimated Theoretical Equation

$$\Delta y_i = \beta_i + \sum_{i=1}^{n} \beta_i \Delta y_{t-1} + \sum_{i=1}^{n} \delta_i \Delta x_{i=1} + \sum_{i=1}^{n} \theta_i \Delta z_{i=1} + \varphi_1 y_{t-1} + \varphi_2 x_{t-1} + \varphi_3 z_{t=1} + \mu_t \quad (5.3)$$

Standard ARDL Model Estimated Equation

$$\log(\mathrm{CAR_t}) = \alpha_1 + \beta_1 \log(\mathrm{CAR_{t-1}}) + \beta_2(\mathrm{CAR_{t-2}}) + \beta_3(\mathrm{UE_{t-1}}) + \beta_4(\mathrm{UE_{t-2}}) + \beta_5(\mathrm{IR_{t-1}}) + \beta_6(\mathrm{IR_{t-2}}) + \beta_7(\mathrm{LR_{t-1}}) + \beta_8(\mathrm{LR_{t-2}}) + \varepsilon_t \quad (5.4)$$

Regression Equation:

$\log(\mathrm{CAR_t})$ = -0.111760 +0.159128*(CARt-1) (0.2736) +0.085724*(CARt-2) (0.4393) (5.5)

+0.023161*(UEt-1) (0.4477) +0.004221*(UEt-2) (0.8390) +(-0.034411) *(IRt-1) (0.6465)

+(-0.056174) *(IRt-2) (0.3435) +0.172311*(LRt-1) (0.4288) +0.356554 *(LRt-2) (0.1078)

+-1.179087*CAR(t-1) (0.0000) 0.052320*UE(t-1) (0.1550) 0.052150*IR(t-1) (0.4970)

0.027791*(LR(t-1) (0.6737)

The model fits the data well (F= 11.71258, p<0.000000 and R squared = 0.4723559).

In the following section, we check whether the model has serial correlation first, then check its stability.

5.4.1 Serial Correlation of the Standard ARDL Model

To understand whether the model has serial correlation or not, we check the Residual Cross Section Dependency Test. One of the most crucial diagnostics a researcher should look at before undertaking a panel data analysis is cross-sectional dependence (Menegaki 2020). The null hypothesis of the model assumes that there is no cross-section dependence (correlation) in residuals. The result is presented in table 5.12 below.

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Table 5.12: Residual Cross-Section Dependence Test

Null hypothesis: No cross-section dependence (correlation) in residuals Test employs centered correlations computed from pairwise samples			
Test	Statistic	d.f.	Prob.
Breusch-Pagan LM	576.8882	325	0.0000
Pesaran scaled LM	9.879866		0.0000
Pesaran CD	16.10192		0.0000

Table 5.12 shows the hypothesis and information on the number of cross-section and period observations in the panel displayed at the top of the table. The test results are listed at the bottom of the table. The first line contains the Breusch-Pagan LM test findings. The test statistic value, test degree of freedom, and corresponding p-value are displayed in tabular forms. The test statistic value of 576,8882 is well into the top tail of the coefficient at a significant level of 5%. The findings of the Pesaran scaled LM, and Pesaran CD tests are 9.879866 and 16.10192, respectively, at 5%. Then we check whether these variables of the model are normally distributed or not. Figure 5.1 shows the series of standardized residuals.

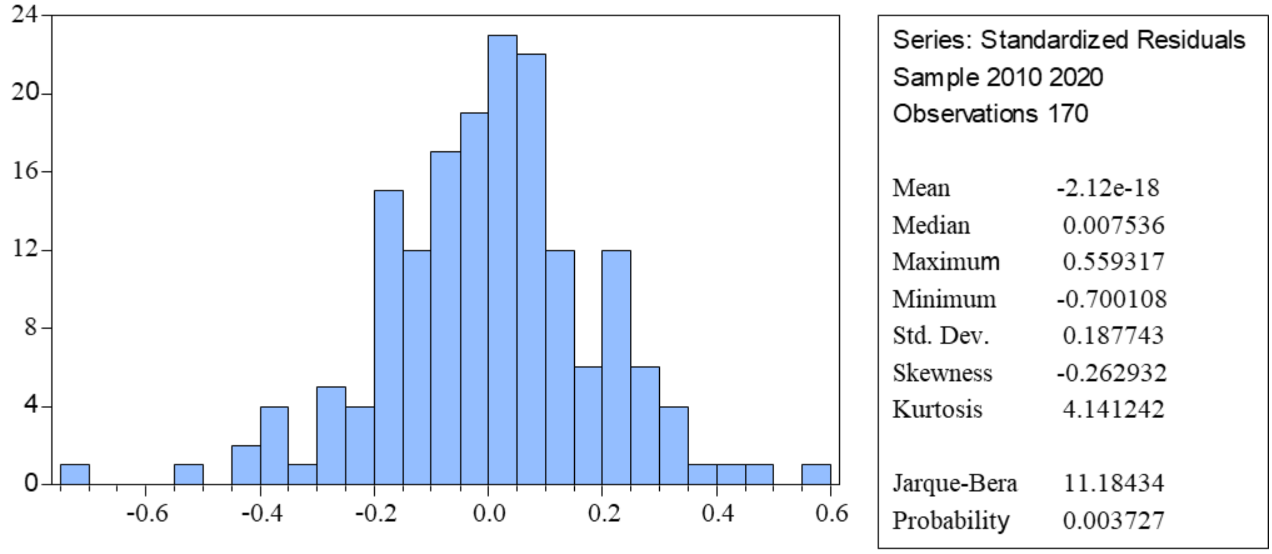

Figure 5.1 Standardized Residuals

As seen in the figure above, the sample follows a normal distribution. The skewness value for the variables is -0.262932, showing that the distribution is approximately asymmetric because the value is not near 0. In contrast, the kurtosis value is positive 4.141242 and is greater than 3, implying that the distribution is none platykurtic.

5.4.2 Bound Testing

The subsequent analysis using the model is whether our variables have a long-run association or not, which this model is our hypothesis. Where CAR lag 1, UE lag 1, IR lag 1, and LR lag one period are jointly zero or not.

Table 5.13: Wald Test:

Test Statistic	Value	df	Probability
F-statistic	10.52338	(4, 157)	0.0000
Chi-square	42.. 09352	4	0.0000
Null Hypothesis: C (10) = C (11) = C (12) = C (13) = 0			
Null Hypothesis Summary:			
Normalized Restriction (= 0)		Value	Std. Err.
C (10)		-1.179087	0.183210
C (11)		0.052320	0.036617
C (12)		0.052150	0.076594
C (13)		0.027791	0.065868
Restrictions are linear in coefficients.			

F. statistic = 10.52338, which should be compared to the Pesaran Critical value at the 5 per cent level. Our model is the unrestrictedly available intercept and has no trend. From the Pesaran table, the lower bound: is 3.79 and the upper bound value: is 4.85. the guideline is that we can reject the null hypothesis when the F. statistic is more than the upper bound value. That is the guideline. Our F. statistics is 10.52338 (10.52338 > 4.85) is more than the upper bound value. So, we can reject the null hypothesis and accept the alternative hypothesis (simple) because the null Hypothesis is that C (10) =

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C= (11) = (12) = C (13) = 0. But they are not jointly 0. This implies that the three variables, CAR, UE, IR, and LR, have long-run associations. This also means that these four variables move together in the long run.

5.4.3 Long Run and Short Run

We can develop the model further using short-run and long-run concerns and set the model correctly. First, we write up the original model and analysis our data using our original model, which ARDL bounds test regression equation can be rewritten as follows:

$$\Delta Y_t = \beta_0 + \sum_{i=1}^{p} \lambda_i \Delta Y_{t-i} + \sum_{i=0}^{q} \delta_i \Delta X_{t--i} + \varphi_2 Y_{t-1} + \varphi_2 X_{t-1} + \upsilon_t \quad 5.6$$

The left side of the above equation with λ_i and δ_i are short-run model equations, whereas the right side of the equation with φ_1 and φ_2 are the long run of the model equation. To understand and take measures, we need to know whether we have co-integration (long-run relationship) among the variables under consideration or not. To find out, we hypothesize as:

$$H_0 = \varphi_1 = \varphi_2 = \varphi_3 = 0$$

The table below shows the statistical result of the long-run model equation.

5.14: Long Run Result

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.035902	0.063014	-0.569749	0.5694
UE	0.032052	0.014729	2.176209	0.0305
IR	0.025976	0.041604	0.624360	0.5330
LR	0.006031	0.048125	0.125322	0.9004
R-squared	0.021571	Mean dependent var		0.002379
Adjusted R-squared	0.009542	S.D. dependent var		0.187788
S.E. of regression	0.186890	Akaike info criterion		-0.500595
Sum squared resid	8.522402	Schwarz criterion		-0.443927
Log-likelihood	66.07383	Hannan-Quinn criter.		-0.477783
F-statistic	1.793161	Durbin-Watson stat		1.765410
Prob(F-statistic)	0.149045			

The table above shows the long-run model result.

Long Run Estimated Theoretical Equation:

$$CAR_{it} = \alpha_{it} + \beta_1 UE_{it} + \beta_2 IR_{it} + \beta_3 LR_{it} + \varepsilon_{it} \quad (5.7)$$

Long Run Regression Equation:

$$CAR_{it} = -0.035902 \underset{(0.0305)}{+0.032052{*}UE_{it}} \underset{(0.5330)}{+0.25976{*}IR_{it}} \underset{(0.9004)}{+0.006031{*}LR_{it}} \quad (4.8)$$

We can derive the residual from this exact model and check the long-run model by taking the residual, which gives the error correction terms explained below.

5.4.4 Error Correction Terms

If the nonstationary but I (1) time series are cointegrated, we can run the VECM to examine both the series' short-run and long-run dynamics. The error correction model co-integrated series can be written as follows:

$$\Delta Y_t = \beta_0 + \sum_{i=1}^{n} \beta_i \Delta Y_{t-i} + \sum_{i=0}^{n} \delta_i \Delta X_{t--i} + \varphi z_{t-1} + \mu_t \quad (5.9)$$

where: z is the ECT and is panel least square (OLS) residuals from the following long-run co-integrating regression equation

$$y_t = \beta_0 + \beta_1 x_t + \varepsilon_t \quad (5.10)$$

and is defined as follows:

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$$z_{t-1} = ECT_{t-1} = y_{t-1} = \beta_0 + \beta_1 x_t + \varepsilon_t$$

The result of the vector error correction model constructed above can be presented in the following tabular form.

Table 5.15: Vector Error Correction Terms

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.029505	0.016775	-1.758889	0.0805
D (CAR (-1))	0.159939	0.143192	1.116954	0.2657
D (CAR (-2))	0.092924	0.108731	0.854621	0.3940
D (UE (-1))	0.032361	0.018669	1.733454	0.0849
D (UE (-2))	0.008226	0.017272	0.476277	0.6345
D (IR (-1))	-0.015385	0.044372	-0.346738	0.7292
D (IR (-2))	-0.046824	0.050801	-0.921715	0.3581
D (LR (-1))	0.175493	0.215385	0.814786	0.4164
D (LR (-2))	0.367533	0.217351	1.690967	0.0928
ECT (-1)	-1.174662	0.180496	-6.507954	0.0000
R-squared	0.470940	Mean dependent var		-0.034365
Adjusted R-squared	0.441180	S.D. dependent var		0.258460
S.E. of regression	0.193210	Akaike info criterion		-0.393053
Sum squared resid	5.972831	Schwarz criterion		-0.208595
Log-likelihood	43.40953	Hannan-Quinn criter.		-0.318202
F-statistic	15.82478	Durbin-Watson stat		2.001443
Prob(F-statistic)	0.000000			

The error-correction term relates to the fact that the last period deviation from the long-run equilibrium (error) influences the short-run dynamics of the dependent variable. Therefore, the coefficient of ECT (-1) (see table 5.15, column 10), φ, is the speed of adjustment. Because it measures the rate at which the dependent variable (Y) returns to the equilibrium after a change in the independent variable (X). Therefore, the speed of adjustment toward CAR is -1.174662 or -1.1747 per cent (see table 5.15). Theoretically, ECT should be negative and significant. The term ECT denotes the lagged error correction terms. The presence of long-run causality (relationship) requires a significant negative effect of ECT on CAR (Shrestha & Bhatta 2018).

Error Correction Estimated Theoretical Equation: (5.11)

$$\mathrm{CAR}_{it} = \alpha_{it} + \beta_1 \mathrm{UE}_{it} + \beta_2 \mathrm{IR}_{it} + \beta_3 \mathrm{LR}_{it} + \varepsilon_{it}$$

Error Correction Model Estimated Equation:

$$\log(\mathrm{CAR}_t) = \alpha_1 + \beta_1 \log(\mathrm{CAR}_{t-1}) + \beta_2(\mathrm{CAR}_{t-2}) + \beta_3(\mathrm{UE}_{t-1}) + \beta_4(\mathrm{UE}_{t-2}) + \beta_5(\mathrm{IR}_{t-1}) + \beta_6(\mathrm{IR}_{t-2}) + \beta_7(\mathrm{LR}_{t-1}) + \beta_8(\mathrm{LR}_{t-2}) + ECT_{t-1} \quad (5.12)$$

Error Correction Regression Equation: (5.13)

$\log(\mathrm{CAR}_t)$ = -0.029505 +0.159939*(CARt-1) +0.092924*(CARt-2)
(0.2657) (0.3940)

+0-032361*(UE_{t-1}) +0-008226*(UE_{t-2}) +(-0.015385) *(IR_{t-1})
(0.0849) (0.6345) (0.7292)

+(-0.046824) *(IRt-2) +0.175493*(LRt-1) +0.367533 *(LRt-2)
(0.3581) (0.4164) (0.0928)

+(-1.174662*ECT (-1)
(0.0000)

This model fits the data well (F= 15.82478, p< 0.000000 and R-squared = 0.470940).

5.4.5 Serial Correlation Test of ECT Model

To understand whether the ECT model has serial correlation or not, we check the Residual Cross Section Dependency Test. The null hypothesis of the model assumes that there is no cross-section dependence (correlation) in residuals. The result is presented in table 5.16 below.

table 5.16: Residual Cross-Section Dependence Test

Null hypothesis: No cross-section dependence (correlation) in residuals

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The test employs centred correlations computed from pairwise samples

Test	Statistic	d.f.	Prob.
Breusch-Pagan LM	419.0903	325	0.0003
Pesaran scaled LM	3.690527		0.0002
Pesaran CD	6.173113		0.0000

The top table shows the hypothesis, and information on the number of cross-section and period observations in the panel is displayed at the top of the table. The test results are listed at the bottom of the table. The first line contains the Breusch-Pagan LM test findings. The test statistic value, test degree of freedom, and the corresponding p-value are displayed in tabular forms. The test statistic value of 419.0903 is well into the top tail of the coefficient at a significant level of 5%. The findings of the Pesaran scaled LM, and Pesaran CD tests are 3.690527 and 6.173113, respectively, at 5%. Then we check whether these variables of the ECT model are normally distributed or not. Figure 2 shows the residual-actual-fitted value. The fitted value lies between the two green lines. This implies the data are normally distributed

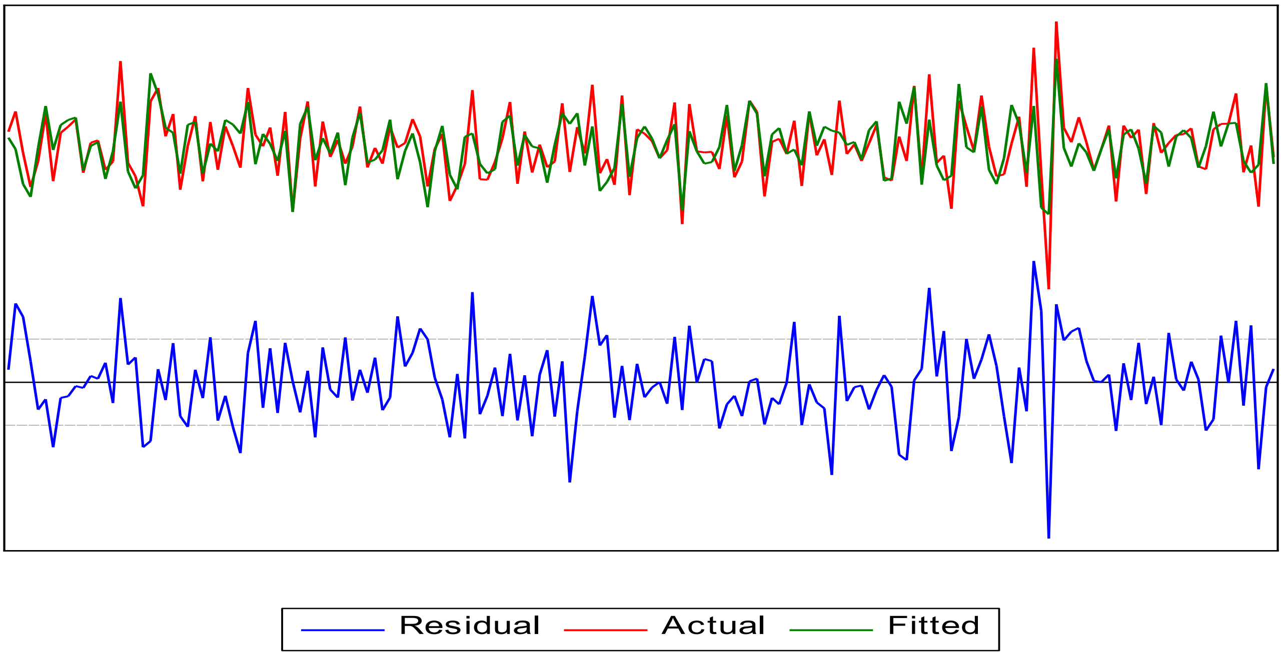

Figure 5.2: Residual-Actual-Fitted Values

Note: the orange colour bar on the upper bound corresponds to actual and fitted values, and the lower corresponds to the residual value.

5.5 Result of Causality Test

The granger causality test is implied to determine whether one or more exogenous variables explain an endogenous variable or whether an endogenous variable and one exogenous variable move together in the same direction. The word granger causality test, first suggested by Granger (1969), has been used in many fields of studies in econometrics to determine the short-run causality tests of the endogenous and exogenous variables under consideration. Given that the critical value of the test is less than 5% levels of significance, the null hypothesis is rejected. The Wald test determines the relationships because it examines linear hypotheses that a single matrix can represent in its standard form. Table 5.17 provides the statistical outcomes of the Wald tests for the exogenous variables under consideration concerning the endogenous variable (CAR).

Table 5.17: Wald Test:

Test Statistic	Value	df	Probability
F-statistic	1.551953	(2, 160)	0.2150
Chi-square	3.103905	2	0.2118
Null Hypothesis: C (4) = C (5) = 0			
Null Hypothesis Summary:			
Normalized Restriction (= 0)		Value	Std. Err.
C (4)		0.032361	0.018669
C (5)		0.008226	0.017272
Test Statistic	Value	df	Probability

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F-statistic	0.426552	(2, 160)	0.6535
Chi-square	0.853104	2	0.6528
Null Hypothesis: C (6) = C (7) = 0			
Null Hypothesis Summary:			
Normalized Restriction (= 0)		Value	Std. Err.
C (6)		-0.015385	0.044372
C (7)		-0.046824	0.050801
Test Statistic	Value	df	Probability
F-statistic	1.782111	(2, 160)	0.1716
Chi-square	3.564222	2	0.1683
Null Hypothesis: C (8) = C (9) = 0			
Null Hypothesis Summary:			
Normalized Restriction (= 0)		Value	Std. Err.
C (8)		0.175493	0.215385
C (9)		0.367533	0.217351
Restrictions are linear in coefficients.			

Based on the statistical summaries of the Wald tests (see table 5.17), we demonstrate the results of each of the short-run causality tests of exogenous variables towards endogenous variables. In other words, more broadly, tests of unexpected earnings, interest rates, and liquidity risk towards cumulative abnormal returns. The null hypothesis is that $\Delta\big(UE(-1)\big) = \Delta\big(UE(-2)\big) = 0$. The alternative hypothesis is that the differences between one unexpected earnings and the difference between two unexpected returns are not zero. We cannot reject the null hypothesis because they are zero implying that ΔUE does not granger cause ΔCAR. This hypothesis is rejected at a 5% level of significance. The probability value for $\Delta(UE\ (-1))$ and $\Delta\ (UE\ (-2))$ is 0.2150, which is higher than the critical value of 5%, implying that there is no short-run causality between ΔUE and ΔCAR. The second hypothesis is that $\Delta\big(IR(-1)\big) = \Delta\big(IR(-2)\big) = 0$. The results show that the probability value of $\Delta\big(IR(-1)\big)$ and $\Delta\big(IR(-2)\big)$ is 0.6528. We cannot reject the null hypothesis at a 5% significance level, but we accept the null hypothesis. This implies that ΔIR does not granger cause ΔCAR. The third and final hypothesis is that $\Delta(LR - 1) = (\Delta LR(-2) = 0$. The result shows that the probability value for $\Delta(IR(-1)$ and $\Delta(LR(-2)$ is 0.1683, and we cannot reject the null hypothesis because their probability value is more than 5%. In almost all cases, short-run causalities run from exogenous variables to the endogenous variable under consideration.

6. Discussion and Implication

In the unit root test, there were the assumptions of the common unit root process and the assumptions of the individual unit root process. The Assumption of the common unit process for our analysis was restricted to LLC unit root tests. Because the null hypothesis of LLC for the cumulative abnormal returns, unexpected earnings, interest rates and liquidity risk assumed a common unit process. As the statistical results indicated, the null hypothesis for all was rejected at the levels because the series has no unit root at levels. Unlike the LLC unit root tests, the null hypothesis for the Im, Pesaran, and Shin W-stat, ADF-Fisher Chi-square, and PP-Fisher Chi-square assumed individual unit root processes. In Im, Pesaran, and Shin W-stat, the null hypothesis for the cumulative abnormal return, unexpected earnings, interest rates, and liquidity rates assumed individual unit processes. After considering the statistical result of cumulative abnormal returns, the null hypothesis was rejected at the first difference because the series no longer has the unit root at the first difference. By contrast, the null hypothesis for the unexpected earnings was rejected at levels because the series has no unit roots at the level. Similarly, based on the statistical results for interest rates, the null hypothesis was not rejected at levels; however, after testing it at the first difference, the null hypothesis was rejected at the first difference because the series no longer has unit roots. Statistical results for liquidity risk showed a significant probability of 0.0001. Therefore, the null hypothesis was rejected, and the alternative was accepted because the series has no unit roots at the levels.

The null hypothesis for the levels versus the first difference of ADF-Fisher Chi-square for the cumulative abnormal return, unexpected earnings, interest rates, and liquidity risk assumed individual unit processes. The null hypothesis for cumulative abnormal return, unexpected earnings, and liquidity risk was rejected at the levels because the series has no unit roots. However, the null hypothesis was rejected for interest rates at the first difference because the series no longer has unit roots at the first difference. The null hypothesis for the cumulative abnormal returns, unexpected earnings, interest rates, and liquidity rates of the PP-Fisher Chi-square assumed individual unit processes as indicated above. The null hypothesis of cumulative abnormal return and unexpected earnings were rejected at the levels because their series had no unit root. However, the null hypothesis of interest rates and liquidity risk were rejected at the first differences because their series no longer has a unit root at the first differences. Generally, there is a mixed result in the individual unit root process at levels, but after differencing the results, that mixed result disappeared. In terms of the statistical analysis of co-integration tests, individual intercept, individual trend, and intercept, as well as no intercept and no trend, were considered. So far, we have performed three cointegration tests of Pedroni tests.

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Further Kao residual cointegration test was also considered. But all these tests demonstrated that the variables were not cointegrated. Since the decision of acceptance and rejection of the null Hypothesis in the co-integration test is determined based on majorities, the test statistic of the null hypothesis for the co-integration was anonymous. There are exciting results regarding applying the ARDL model in investigating the relationship between the variables. As the statistical results of the relationships between the dependent and independent variables showed, positive and negative relationships existed. There was a positive relationship between cumulative abnormal returns and unexpected earnings, but that relationship was insignificant. In contrast, there was a negative and insignificant relationship between cumulative abnormal returns and interest rates. However, the result showed that liquidity risk significantly and positively affected cumulative abnormal returns. The model fits the data well because its F-statistics is 11.71258 with a probability < 0.000000, and its R square is equal to 0.4723559. That test result showed that the model had explained about 43.20% of the variation in the percentage of cumulative abnormal returns with the three explanatory variables, percentage of unexpected earnings and percentage of interest rates, and percentage of liquidity risk (see: section 5.4). Thus, the adjusted R square value demonstrates that the model accounts for 43.20% of the variance in cumulative abnormal returns, and the model is robust.

Further, in the serial correlation test of the ECT model, we checked the residual cross-section dependency test. The null hypothesis of the model assumes that there was no cross-section dependence (correlation) in residuals. The test results rejected the null hypothesis at a significant level of 5%. Furthermore, in the bound testing, the four variables, cumulative abnormal returns, unexpected earnings, interest rates, and liquidity risk, had long-run associations. Indeed, all those four variables move together in the long run. The error correction term relates to the fact that the last period deviation from the long-run equilibrium (error) influences the short-run dynamics of the dependent variable. Therefore, the coefficient of ECT (-1), φ, is the speed of adjustment. Because it measures the rate at which the dependent variable (Y) returns to the equilibrium after a change in the independent variable (X). Therefore, the speed of adjustment towards the dependent variable was negative and significant. Theoretically, ECT should be negative and significant. The error correction model fits the data well because its F-statistics is equal to 15.82478, its probability is < 0.000000, and its R-squared is equal to 0.470940. the test result showed that the model had explained about 44.12% of the variation in the percentage of cumulative abnormal returns with the three explanatory variables, percentage of unexpected earnings and percentage of interest rates, and percentage of liquidity risk (see: subsection 5.4.3). Thus, the adjusted R square value demonstrates that the model accounts for 44.12% of the variance in cumulative abnormal returns, and again, the model was robust. The short-run causality test is based on the statistical summaries of the Wald tests of the endogenous and exogenous variables under consideration, as seen from the hypothetical results. In almost all cases, there are no short-run causalities from exogenous variables to endogenous variables under consideration. This paper demonstrates the relationship between cumulative abnormal returns, unexpected earnings, interest rate, and liquidity risk to explain underreaction consistent with the existing theoretical heterogeneity models.

7. Conclusion

This study attempted to add to the literature by investigating the empirical relationship between underreaction proxied by cumulative abnormal return and unexpected earnings, interest rates, and liquidity risk as a subject of inquiry. The data spanned over ten years for 66 firms that belong to the information transmission and technology industry stocks. Although the empirical research on the relationship between cumulative abnormal returns and those explanatory variables under consideration is inconclusive, cumulative abnormal returns played a central role in studying financial asset evaluations. Underreaction, proxied by cumulative abnormal returns, here, in our case, resulted in financial crises worldwide because underreaction causes financial losses for businesses and even global economic problems, such as the global financial crisis between 2008 and 2009. Using unit root tests, cointegration tests, the ARDL model, and the Granger Causality technique, the study examined the relationship, the direction of the relationship, and the effects among exogenous variables using panel data of 66 cross-sectional dependence tests. Cumulative abnormal return was an endogenous variable, whereas unexpected earnings, interest rate, and liquidity risk were used as exogenous variables. According to the empirical findings, liquidity risk appeared to be a primary driver of underreaction. The Cointegration test reveals a long-term link between those variables and underreaction. According to the empirical results, all the explanatory variables are positively and insignificantly related to cumulative abnormal returns except liquidity risk indicating a negative association. The impacts of those variables were discovered after further study using the standard ARDL models. Finally, the Granger causality test supports the hypothesis that no short-run causalities run from exogenous variables to the endogenous variable under consideration. The summary results of the Granger causality test are presented in table 10. The Granger causality test confirms that all the variables, unexpected earnings, interest rate, and liquidity risk included in the model do not Granger cause cumulative abnormal returns. These relationships are also theoretically valid, and no other problems, such as endogeneity, are observed.

Furthermore, a proposed alternate strategy for future research is to adopt the same model but with different variables. Depending on the increased accessibility of relevant data in the future, it may be able to use other forms of data as a proxy for unexpected earnings, such as market risk, solvency risk, and currency risk. We conclude the validity of the hypothesis,

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which implies that explanatory variables understudy positively/negatively affect cumulative abnormal returns, after further evaluating the outcomes of this study and attempting to correlate them with the primary research hypotheses.

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