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Do Credit Rating Announcements Convey Valuable Information? Evidence from a Developing Country Perspective

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Abstract

This study delves into the critical role of information in capital markets, examining stock market response to credit rating announcements, with a focus on downgrades and affirmations. Using the Event Study Method (ESM), the analysis compares market responses across two distinct periods: pre and during the COVID-19 pandemic. The results indicate a negative market response to credit rating downgrades, which convey adverse credit signals, with the response being more pronounced during COVID-19 period, while no noticeable reaction to affirmations in either period. These results support the theory of loss aversion, indicating that investors respond more strongly to negative information because of potential losses, particularly under heightened uncertainty. Overall, the study demonstrates the informational relevance of credit rating downgrades in emerging markets and emphasizes the need for market participants to remain vigilant during periods of economic disruption such as the COVID-19 pandemic.

Keywords: Credit Ratings, Event Study Method, COVID-19, Stock Market

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1. Introduction

Information is crucial in capital markets, especially in the stock market, as it enables investors to make informed decisions, manage risks, and allocate resources efficiently. Investors continuously seek signals that convey the financial health, prospects, or risks associated with firms. Various corporate events act as information signals and elicit observable market reactions. For instance, mergers (Hackbarth & Morellec, 2008), stock splits (Fama et al.,1969; Grinblatt, Masulis, & Titman, 1984; Prabodini & Rathnasingha, 2022, dividend announcements (Chew & Liang, 1993; Dissabandara, 2000), earnings announcements (Trueman, Wong, & Zhang, 2003), extreme loss (Guo, Dong, & Patterson, 2024), IPO's (Grinblatt & Hwang, 1989; Allen & Faulhaber, 1989; Lowry & Schwert, 2010), economic uncertainty (Kamal, Hossain, Farooque & Wohar,2024), oil prices (Cakan, Demiralay & Ulusoy, 2021) liquidity announcements (Cardillo, Onali & Perdichizzi, 2023), debt announcements (Marshall, McCann, & McColgan, 2019), and many more provide information that market participants use to adjust their investment strategies. Empirical studies show that stock prices respond to these events, reflecting the incorporation of new information into market valuations.

In this context, credit rating announcements may represent another potentially valuable information signal to market participants. Acting as a common global language of credit quality (S&P Global, 2023; Freitas & Minardi, 2013), credit ratings provide investors with essential insights to assess risk, adjust investment strategies, and make informed decisions (Griffin & Sanvicente, 1982). Credit rating announcements serve as a vital signal to market participants by conveying information about a company's creditworthiness. Specifically, rating downgrades indicate a relatively weaker credit profile and a higher likelihood of failing to meet debt obligations on time and in full (Moody's, 2025). Moreover, affirmations indicate no change in the credit profile (Fitch Ratings, 2025). If credit rating announcements contain value-relevant information, rational investors are expected to react, leading to observable movements in stock prices. Accordingly, examining stock market reactions to credit rating announcements allows an assessment of whether such announcements convey meaningful information to investors. This study empirically tests the informational content of credit rating downgrades and affirmations by analyzing stock price responses surrounding announcement dates. While credit rating upgrades represent positive signals of improved creditworthiness, this study

focuses on downgrades and affirmations only due to the limited occurrence of upgrades in the Sri Lankan context, which constrains meaningful empirical analysis.

Despite the extensive literature on stock market reactions, limited attention has been given to credit rating announcements in developing economies. Most existing studies focus on developed markets, leaving the reactions in emerging markets, such as Sri Lanka, relatively underexplored. In addition to this, there is limited empirical evidence on whether stocks responds differently to credit rating announcements during the COVID-19 period compared to the pre-COVID period. The necessity to explore this distinction arises from the unique market dynamics introduced by the pandemic. During crises, credit rating agencies often face scrutiny for delayed or abrupt changes, and the same rating action may trigger different reactions depending on broader economic conditions. Therefore, understanding how investor responses to credit rating announcements differed during COVID-19 can refine the theoretical understanding of information processing in capital markets under stress, especially in emerging markets like Sri Lanka where the effects of global shocks tend to be more profound. The current study aims to fill both these gaps by exploring the market responses to credit rating announcements of companies listed in the Colombo Stock Exchange (CSE), while also examining whether the response varies between the pre-pandemic and pandemic periods.

This study adds to the body of literature in a number of ways. First, it extends the existing body of knowledge by focusing on the stock market of a developing country, Sri Lanka, which remains under represented in empirical finance literature, particularly in relation to credit rating announcements, while majority of the concurrent studies scrutinise on the developed capital markets. Second, it introduces a temporal comparison by analyzing the impact of such announcements across two distinct periods, pre-COVID and during COVID providing insights into how market behavior may shift in response to economic shocks and uncertainties. Third, by distinguishing between credit rating downgrades, and affirmations, the study offers a nuanced understanding of how each type influences investor sentiment and stock price behavior. Lastly, the findings of this research have practical implications for investors, policymakers, and financial analysts by enhancing their understanding of how credit-related information is absorbed and reflected in prices of stocks, particularly in the setting of emerging markets during periods of stability and crisis.

2. Literature Review

The study of credit rating announcements as informative events draws on multiple theoretical perspectives, primarily the Efficient Market Hypothesis (EMH), Signaling Theory, and Prospect Theory.

The **Efficient Market Hypothesis** posits that financial markets are informationally efficient when security prices fully reflect all available information (Malkiel, 1989). In an efficient market, stock prices should react immediately to new information, leaving no predictable patterns for investors to exploit. EMH provides a foundation for examining whether credit rating announcements convey new information or merely reflect previously known fundamentals. Event studies pioneered by Fama et al., 1969) demonstrated that stock prices adjust rapidly to information, showing little to no trend beyond the immediate reaction, underscoring the EMH assumption. Within this framework, downgrades and affirmations of a firm's credit rating considered in the current study should prompt immediate adjustments in stock prices if the market efficiently incorporates the information.

Signaling Theory complements EMH by addressing information asymmetry between firm insiders and external investors (Spence, 1973). Credit rating agencies serve as credible third-party intermediaries that evaluate a firm's financial health and ability to meet debt obligations. Ratings therefore act as signals to investors: a downgrade signals deterioration in creditworthiness, an upgrade signals improvement, and an affirmation conveys stability. By reducing information asymmetry, these announcements guide investors in their decision-making and help align market valuations with the firm's true risk profile. This theory also explains why markets may react differently to upgrades, downgrades, and affirmations depending on the perceived credibility of the rating agency and the pre-existing information available to investors.

Prospect Theory, a key concept in behavioral finance, provides an alternative lens by emphasizing how investor psychology affects decision-making under risk (Kahneman & Tversky, 1979). According to Prospect Theory, investors are loss-averse and evaluate gains and losses relative to a reference point, rather than in absolute terms. This implies that market reactions to negative events, such as downgrades, may be more pronounced than reactions to positive events, like upgrades, even when the underlying economic information is symmetric.

Prospect Theory also suggests that during periods of heightened uncertainty or market stress such as financial crises or pandemics investor behavior may deviate from the rational predictions of EMH, with emotions, fear, and risk perception significantly influencing stock price adjustments.

Collectively, these three theories provide a comprehensive foundation for studying the informational content of credit rating announcements.

Recognizing the importance of information in financial markets, a growing body of literature explores the informational content of credit rating announcements by examining how the stock returns responds to different types of credit rating announcements. Pinches and Singleton (1978), revealed that where the bond rating upgrade (downgrade) occurs, abnormally high (low) common stock returns are observable before the announcement of bond rating change is available to the market participants. Also, the study evidenced that only normal returns can be expected after the month of bond rating change. This suggest that the improved (deteriorated) financial and operating conditions of the firms were recognized by the investment community long before the bond rating agency change the rating. Similarly, Weinstein (1977) and Wakeman (1978) also found no evidence of a price response to rating changes after the bond rating change announcement, supporting the proposition that bond rating changes have a very low or no information content; in fact, the stock market appears to be highly efficient, thus, evidenced the Efficient Market Hypothesis (EMH).

Glascock, Davidson, and Henderson (1987) argued that daily data can better capture event-day reactions suggesting that earlier studies using monthly data (Weinstein, 1977; Pinches & Singleton, 1978; Wakeman, 1978) may have missed significant reactions because the surrounding returns covered the event day reaction. In contrast to Weinstein (1977), Pinches and Singleton (1978), and Wakeman (1978), it was evidenced by Glascock, Davidson, and Henderson (1987), negative abnormal returns are expected on the date on which the downgrade rating announcement is published, or the event date, and those negative abnormal returns are reversed on the same date, also there is no statistically significant reaction for rating upgrade announcements. Similarly, Griffin and Sanvicente (1982), Holthausen and Leftwich (1986), Dichev and Piotroski (2001), Choy, Gray and Ragunathan (2006), Li, Shin and Moore (2005), Goh and Ederington (1999), and Freitas and Minardi (2013) evidenced significant negative

abnormal returns for downgrades, while rating upgrades were statistically insignificant and not price-relevant. But in contrast, Elayan, Hsu and Meyer (2003), Hand, Holthausen and Leftwich (1992), Xie, Yang and Munir (2019) detected market response to rating upgrade announcements.

Angeline and Ariff (2019) found that affirmation announcements are strongly linked to statistically significant positive abnormal returns in the pre- and post-announcement periods. Additionally, it is acknowledged by investors that an affirmation rating is a certification signal of the issuer's credit worthiness. Investors don't need to freak out because the rating hasn't changed. As a result, the affirmation announcements raises market stock prices.

Despite extensive research on credit rating announcements in developed markets, there is relatively limited evidence from emerging markets. Recent studies conducted in developed economies generally show that downgrades trigger strong negative abnormal returns, while upgrades and affirmations often have muted or inconsistent effects. However, the applicability of these findings to developing countries like Sri Lanka remains unclear. The CSE, as a developing market, exhibits unique characteristics such as lower liquidity, a smaller investor base, and greater sensitivity to macroeconomic and political shocks. Furthermore, while downgrades have been widely studied, the impact of affirmation announcements has been rarely investigated even in developed countries, despite their potential role as signals of stability and investor confidence. Therefore, there is a clear need for empirical research that investigates whether different types of credit rating announcements carry informational value for stock returns in a developing market like Sri Lanka.

In addition, the COVID-19 pandemic introduced unprecedented shocks to the global and local financial markets (Anh & Gan, 2020); Liu, Manzoor, Wang, & Lei, 2020), altering investor behavior, and credit risk (Yin, Han, & Wong, 2022; Bystrom, 2021; Riani, 2021). Lockdowns, uncertainty, and economic disruptions may caused to increased anxiety and risk aversion among investors, potentially changing the way they respond to credit rating announcements. However, empirical evidence on how investors in developing markets, particularly in Sri Lanka, responded to credit rating announcements before and during the pandemic remains scarce. Therefore, this study aims to address these gaps by examining the impact of credit rating announcements, including downgrades, and affirmations on stock returns in the Sri Lankan

market, comparing periods of relative market stability with the extreme volatility and economic disruptions caused by the COVID-19 pandemic.

3. Research Methodology

3.1 Sample

The study's final sample consists of 214 credit rating announcements of Fitch Ratings Lanka Limited belonging to 30 listed companies. A comparison of sample sizes used in previous credit-rating event studies is presented in Annexure I, to demonstrate the adequacy of the sample used in this research.

A credit rating announcement was selected as eligible for the study only if all the below-mentioned criteria were satisfied.

I. Rating actions could only be downgrade and affirmation announcements.
II. The firm whose rating was changed required to be listed on the CSE for a minimum of one year.
III. Rating action should be non-contaminated news.

Criteria (I) is established as the current study investigates the impact of only the affirmations, and downgrade announcements of credit ratings on stock returns. Therefore, the new rating issues and withdrawal of ratings are beyond the scope of the study. Criteria (II) is established to ensure the availability of closing prices for the overall analysis period. Criteria (III) is established to remove the contaminated events and observations if there are concurrent disclosures in the period surrounding the publication date from the sample. This ensures that other similar events do not influence the sample to isolate the credit rating announcement's impact on stock prices. Linciano (2003) asserts that announcements preceded by contaminating information produce higher abnormal returns, which may indicate that the contaminating information, not the rating action, is primarily responsible for the stock price reaction. As a result, the sample does not include the contaminated observations.

3.2 Time Period

The time period that is covered for the study spans from 2016 to 2023. It is important to note that the COVID-19 pandemic existence was there during the sample period. The COVID-19 pandemic has resulted in unprecedented market volatility and economic shock, creating a

separate environment from more stable and predictable market settings. Understanding that the study's findings might be influenced by the unique factors associated with COVID-19, the overall time period is divided into two sub-periods: the period before the COVID-19 pandemic and the period during the COVID-19 pandemic. The time period prior to the COVID-19 pandemic is defined as January 1, 2016, to March 10, 2020, while the time period during the COVID-19 pandemic is defined as March 11, 2020, to May 5, 2023. This division is predicated on the World Health Organization's (WHO) declaration of COVID-19 as a worldwide pandemic on March 11, 2020. Figure 3.1 below provides a graphic representation of the overall and sub-time periods. Additionally, according to the Epidemiology Unit (2023), on May 5, 2023, WHO announced that COVID-19 is no longer a Public Health Emergency of International Concern (PHEIC), highlighting the fact that the illness is a recognized and persistent public health concern.

By forming two sub-periods, the study aims to eliminate potential biases in the study and account for the unexpected disruptions caused by the pandemic. The "before" period represents a comparatively stable and predictable market environment, while the "during" period reflects an era of exceptional market volatility and economic shocks directly linked to the pandemic. Further, this will contribute for investors, financial analysts, and policymakers to understand the complexities of financial markets during times of crisis and how the impact of rating changes on the stock returns differs in the face of unprecedented challenges from periods of stable market conditions. This makes the findings of the study more robust, relevant, and insightful.

3.3 Data

This study relies exclusively on secondary data and required stock market data; daily stock prices, and ASPI are collected from the CSE-Data Library. Credit rating announcement-related data, specifically the announcement dates, are obtained by monthly reports prepared by Fitch Rating, and also from their website.

3.4 Methodology

ESM is used to determine the impact of specific events, particularly those containing new information, on asset performance (Binder, 1998). ESM, was pioneered by Fama et.al.,(1969) and was further developed by Brown and Warner (1980), has become a widely used method

for studying the impact of varying events on stock price behavior (Yadav, 1992). The primary objective of an event study is to determine whether investors can generate excess or abnormal stock returns in reaction to an event that introduces new information into the market (Brown & Warner, 1980). Simply, event study aims to measure the magnitude of abnormal returns that are attributed to specific events (Yekini, Wisniewski, & Millo, 2016). Abnormal returns in this context are defined as the difference between the actual observed return and the return predicted by an appropriate model in the absence of the occurrence. This method enables researchers to separate the influence of the event from overall market fluctuations.

The methodology entails analyzing the direction and magnitude of abnormal returns observed around the release of unexpected information contained in credit rating announcements. Credit rating announcements can be considered as occurrences with the potential to raise or lower stock values, depending on the nature of the disclosed information. As a result, the ESM allows for a thorough investigation of how stock prices react to credit rating announcements, revealing light on the underlying informational dynamics.

3.4.1 Defining Event and Event Date

Occurrences that affect the value of a firm is known as “Events” (Dissabandara,2000). Accordingly, credit rating announcements, specifically downgrades, and affirmations are considered as events related to the current study. The first market date on which investors are able to respond to the event is known to be the "Event Date" (Dissabandara, 2000).

3.4.2 Defining Estimation Window and Event Window

The event window is the period of time during which the event's substantial impact is anticipated to be reflected in share prices and needs to be assessed. The 'estimation window' is used to estimate the expected/normal returns outside the event window to ensure that the event does not affect the normal model's parameter estimates.

Scholars have used varying lengths of time as the estimation and event window in their studies. The event window length employed in an event study is likely to be the most important research design consideration. As per Brown and Warner (1980, 1985), adopting a large event window significantly diminishes the power of the test statistic, hence resulting in inaccurate conclusions

about the relevance of an occurrence. Also, it was empirically evidenced that a short event window typically captures the significant effect of an event (Ryngaert & Netter, 1990). Long event windows make it difficult to account for confounding effects, therefore it's best to keep it as short as possible. The length of the event window should be sufficient to record its noteworthy influence while allowing for the exclusion of confounding events. The choice of the window is arbitrary and "should not be too long, because it would risk encompassing other events, generating biases, nor too small, because it would risk failing to fully capture the abnormality in prices" (Camargos & Barbosa, 2003),.

Early studies by Weinstein (1977) and Griffin and Sanvicente (1982) examined the reaction of bond prices to bond rating changes across more extended time periods, 7 months before and 6 months after bond rating changes, and 11 months before and during the month of the rating change, respectively. Recent studies indicate a tendency toward narrow event windows. Brown & Warner (1980,1985), in the study, 239 days, and 11 days are considered for the estimation window and event window, respectively, to emphasize a shorter timeframe for capturing the influence of the event being studied. Choy, Gray and Ragunathan (2006) investigated the effect of rating change announcements on stock prices in various windows surrounding the announcement day, pre-announcement and post-announcement, including (-10, +10), (-5, +5), and (-1, +1). Dawar, Bhati, and Bindal (2021) incorporated a 15-day event window (7 days before and after the event date) in their study to analyze the impact of credit ratings on stock returns. In the evolution of the ESM from the 1960s to recent years, the event window duration has significantly decreased. This change reflects the increased education of market participants, who now react quickly to new information, often within days rather than months.

The study utilized a 120-day estimation window and a 29-day event window, consisting of 14 trading days before and after the event date. Notably, these are share market trading days, not calendar days. Figure 3 shows the graphical illustration of the estimation and event window of the current study.

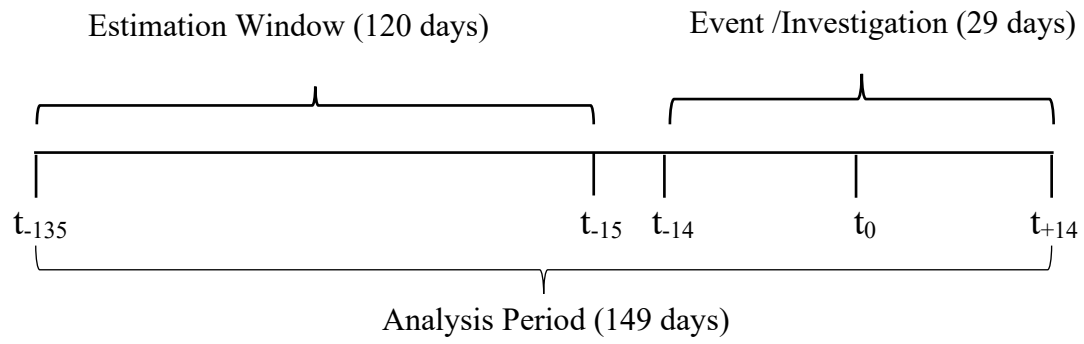

Figure 3 Analysis period

3.5 Calculating, Measuring, and Testing Abnormal Returns

The impact of the event is performed by calculating the Abnormal Returns (ARs). ARs is the difference between Actual Returns (R_{it}) in the defined event window and normal/expected returns (ER) during the period in which they are analyzed (MacKinlay, 1997). Thus, the ARs of an asset i at a date t is calculated by the following formula:

$$\boldsymbol{AR_{it} = R_{it} - E(R_{it})}$$

Where, AR_{it} is the abnormal return of the stock i on the day t, ER_{it} is the expected rate of return of the stock i on the day t and R_{it} is the actual return of the stock i on the day t.

The following formulae calculates the actual stock returns based on the closing price of the shares.

$$\mathbf{R_{it} = (Pt - P_{t-1})/ P_{t-1}}$$

Where, P_t is the closing share price on day t (current trading day) and P_{t-1} is the closing share price on the day t-1 (previous trading date)

The current study employed the market model in computing the ER due to the superiority of the market model compared to other models (MacKinlay, 1997). The market model states that the return on a particular security depends on the return of the market portfolio and the responsiveness measured by beta (β). Here, the market returns calculated using the estimation window are considered as an independent variable, while the dependent variable is the return of the stock 'i'. The market model can be estimated through Ordinary Least Square (OLS) regression to estimate the parameters of the two-variable regression models. Market returns

during the estimation window are treated as independent variables, while the dependent variable is the returns of the stock 'i' for the purpose of running the regression. Regression analysis produces estimates of regression intercept α and regression slope β.

Expected return using the market model can be computed as follows.

$$\mathbf{E(R_{it}) = \hat{\alpha}_i + \bar{\beta}iR_{mt}} \quad \text{.....(5)}$$

Where, $E(R_{it})$ is the expected return of stock i on the day t, $\hat{\alpha}_i$ is the estimated regression intercept (alpha) of stock i, $\bar{\beta}_i$ is the estimated systematic risk (beta) of stock i and R_{mt} is the rate of return on a market portfolio of stocks (ASPI) on day t.

Market return (R_{mt}) is calculated using the data in the estimation window, and Market return can be calculated as follows.

$$\mathbf{R_{mt} = (ASPI_t - ASPI_{t-1})/ASPI_{t-1}} \quad \text{.....(4)}$$

Where, $ASPI_t$ is the ASPI for t^{th} day (current day) and $ASPI_{t-1}$ is the ASPI for the day before t^{th} day (the previous day)

After calculating ARs for each day in the event window, a representative measure should be calculated for further analysis. The representative measure is the Average Abnormal Return (AAR_{it}) which normalizes the ARs of the selected sample. AAR can be calculated as follows,

$$\boldsymbol{AAR_{it} = \frac{1}{N}\sum_{i=1}^{N} AR_{it}}$$

Where, AAR_t is the average abnormal return for the day 't' and N is the number of events in the sample

The CAARs can be calculated as follows,

$$\boldsymbol{CAAR_{it} = \sum_{i=1}^{T} AAR_T}$$

Where, $CAAR_t$ is the Cumulative average abnormal return returns up to day 't'.

The significance of AARs for the event window is tested using t-statistics. The T-statistics are calculated as follows, Assume; $AR_{it} \sim (0, \sigma_i^2)$

$$\boldsymbol{T(AAR) = \frac{AAR_t}{\sigma_{AARt}}}$$

The significance of CAARs for the event window is tested using the t-statistics, and they are calculated as follows, Assume; $CAAR_{it} \sim (0, \sigma_T^2)$

$$T(CAAR) = \frac{CAAR_t}{\sigma_{CAARt}}$$

4. Results and Discussion

4.1 Analysis of the Sample

The study's final sample consists of 214 credit rating announcements of Fitch Ratings, comprised of credit rating downgrades and affirmation announcements. Panel A of Table 1 describes the sample breakdown by rating type for the overall time period. Out of the total sample, 85% of the announcements are credit rating affirmations, 15% are credit rating downgrades.

Table 1

Panel A: Distribution of the sample by rating type, period, and year

	Affirmations		Downgrades		Total
	Number	%	Number	%	
Final Sample	182	85%	32	15%	214

Panel B: Sub period analysis

Period	Affirmations		Downgrades		Total
	Number	%	Number	%	%
Period before COVID-19	104	57%	6	19%	52%
Period during COVID-19	78	43%	26	81%	48%
Final Sample	182		32		100%

Panel C: Number of credit rating announcements by year

	2016	2017	2018	2019	2020	2021	2022	2023	Total
Affirmations	18	24	23	34	38	30	13	2	182
Downgrades	1	2	2	1	4	2	8	12	32
Total	20	26	25	36	42	33	21	14	214

Source: Author's Construction

Panel B of Table 1 represents the breakdown of the total sample into two sub-periods, where 110 credit rating announcements (52%) belong to the period before the COVID-19 pandemic, and 104 credit rating announcements (48%) are during the COVID-19 pandemic. Out of the total affirmation announcements, 57% belong to the period before the COVID-19 pandemic,

whereas 43% belong to the period during the COVID-19 pandemic. Out of the total downgrade announcements, 19% belong to the period before the COVID-19 pandemic, whereas 81% belong to the period during the COVID-19 pandemic.

The final sample is further segregated based on the year, as depicted in Panel C of Table 1. It can be observed that the number of credit rating downgrades has increased in recent years, specifically when it moves to the period during the COVID-19 pandemic, reflecting the poor creditworthiness of the companies during the COVID-19 pandemic compared to the period before the COVID-19 pandemic. This evidence the worth of conducting the analysis by subdividing the overall period as before and during the COVID-19 pandemic.

4.2 Impact of credit rating downgrade announcements on stock returns

4.2.1 Overall period

The daily AARs and CAARs realized by the investors during the event window surrounding the credit rating downgrade announcement date considering the overall time period is presented in Table 2.

Negative AARs and CAARs on the event date are statistically significant at the levels of 10% and 5%, respectively. Also, the AAR on the event date, -1.09%, is the highest AAR recorded during the estimation window. That is also important to note the significant negative CAARs on the 13th day before the event date continuing until the 7th day before the event date, reflecting anticipation of information, and there are significant CAARs until the 6th day following the date on which the downgrade announcement is published, reflecting delayed (lagged) response. One could conclude that the credit rating downgrade announcements signal a negative flow of information to the market participants, as evidenced by the statistically significant negative AARs and CAARs on and around the event date.

The results of the study show the presence of negative abnormal returns in response to credit rating downgrade announcements in the overall analysis period, indicating rating downgrade announcements signal negative prospects to investors. Further, this suggests that when CRAs lower a company's creditworthiness, investors tend to respond by driving down the stock price due to the selling pressure. Griffin and Sanvicente (1982) also revealed that rating downgrades convey information to the common stockholders. Previous literature also supports the finding

of existence of negative abnormal returns in response to credit rating downgrade announcements (Holthausen & Leftwich, 1986; Glascock, Davidson & Henderson, 1987; Goh & Ederington, 1999; Dichev & Piotroski, 2001; Choy, Gray & Ragunathan, 2006; Halek & Eckles, 2010; Freitas & Minardi, 2013; Reddy, Bozman & Mirza, 2019).

Table 2 Daily AARs and CAARs for the downgrade announcements - Overall period

Analysis of the overall period				
Day	**Downgrade announcements**			
	AAR	**t-stat**	**CAAR**	**t-stat**
-14	-0.58%	-0.9393	-2.71%	-1.3613
-13	-0.67%	-1.0850	-3.38%	*-1.6983
-12	0.11%	0.1781	-3.27%	*-1.6430
-11	-0.22%	-0.3588	-3.49%	*-1.7544
-10	-0.55%	-0.8828	-4.03%	**-2.0286
-9	0.52%	0.8421	-3.51%	*-1.7671
-8	-0.74%	-1.2058	-4.26%	**-2.1415
-7	0.98%	1.5870	-3.28%	*-1.6487
-6	0.60%	0.9677	-2.68%	-1.3481
-5	-0.10%	-0.1570	-2.78%	-1.3969
-4	0.57%	0.9195	-2.21%	-1.1113
-3	-0.99%	-1.6052	-3.20%	-1.6098
-2	0.58%	0.9456	-2.62%	-1.3162
-1	-0.35%	-0.5730	-2.97%	-1.4941
0	**-1.09%**	***-1.7621**	**-4.06%**	****-2.0413**
1	0.74%	1.1984	-3.32%	*-1.6692
2	0.05%	0.0864	-3.27%	*-1.6423
3	-0.25%	-0.4056	-3.52%	*-1.7683
4	0.11%	0.1771	-3.41%	*-1.7133
5	0.75%	1.2077	-2.66%	-1.3382
6	-0.70%	-1.1332	-3.36%	*-1.6902
7	0.55%	0.8973	-2.81%	-1.4115
8	0.43%	0.6989	-2.38%	-1.1945
9	0.65%	1.0586	-1.72%	-0.8657
10	0.54%	0.8732	-1.18%	-0.5945
11	-0.97%	-1.5778	-2.16%	-1.0845
12	-0.10%	-0.1661	-2.26%	-1.1361
13	-0.49%	-0.7971	-2.75%	-1.3837
14	0.16%	0.2619	-2.59%	-1.3023

Note: *, ** and *: Statistically significant at 10%, 5% and 1% respectively**

Source: Author's Construction

4.2.2 Sub- periods

The daily AARs and CAARs realized by the investors in the period before and during the COVID-19 pandemic, during the event window surrounding the credit rating downgrade announcement date is presented in Table 3.

According to Table 3, credit rating downgrades generate significant negative AARs on and around the event date in both the pre-pandemic and COVID-19 periods. However, the magnitude and significance of the negative AARs and CAARs are notably stronger during the pandemic. This heightened reaction can be attributed to the elevated uncertainty and economic instability that characterized the COVID-19 period, which made investors more sensitive to adverse information. Overall, the results indicate that investor behaviour appeared more cautious and conservative during the pandemic period, as reflected in the stronger negative abnormal returns observed around downgrade announcements compared to the pre-pandemic period.

The study conducted by Dawar, Bhatia and Bindal (2021) to identify whether there is a differential impact of rating downgrades on the stock returns during the period before and after the global financial crisis also supports the findings of the current study. The study concludes that in the post-financial crisis period, investors are cautious and have conservative behavior. Their bias toward negative information generates a stronger reaction to downgrade announcements. Further, the study by Reddy, Bozman and Mirza (2019) also finds downward changes in credit ratings produce significant changes in security prices during the period after the global credit crisis. These findings emphasize that market participants exhibit very high vigilance and reactions to credit rating downgrades, particularly in times of economic uncertainty and crisis.

Table 3 Daily AARs and CAARs for the downgrade announcements - Sub-periods

Analysis of the sub-periods – Downgrade announcements								
Day	**Period before COVID-19 pandemic**				**Period during COVID-19 pandemic**			
	AAR	**t-stat**	**CAAR**	**t-stat**	**AAR**	**t-stat**	**CAAR**	**t-stat**
-14	-0.77%	-0.7069	0.53%	0.2133	-0.41%	-0.6147	-5.56%	***-2.3697
-13	-2.11%	*-1.9347	-1.58%	-0.6306	-0.03%	-0.0386	-5.59%	***-2.3806
-12	-1.78%	-1.6323	-3.36%	-1.3425	1.64%	1.4754	-3.94%	*-1.6802
-11	0.46%	0.4180	-2.90%	-1.1602	-0.38%	-0.5690	-4.32%	*-1.8412
-10	-0.06%	-0.0578	-2.96%	-1.1854	-0.66%	-0.9884	-4.98%	**-2.1208
-9	-0.01%	-0.0051	-2.97%	-1.1877	0.39%	0.5877	-4.59%	*-1.9546
-8	-0.11%	-0.1038	-3.08%	-1.2329	-0.89%	-1.3406	-5.48%	***-2.3338
-7	1.00%	0.9171	-2.08%	-0.8329	2.34%	1.5171	-3.14%	-1.3387
-6	-0.29%	-0.2641	-2.37%	-0.9482	0.80%	1.2075	-2.34%	-0.9971
-5	-2.10%	*-1.9259	-4.47%	-1.7882	-0.60%	-0.9081	-2.94%	-1.2540
-4	2.50%	***2.2927	-1.97%	-0.7882	-0.04%	-0.0566	-2.98%	-1.2700
-3	0.11%	0.1001	-1.86%	-0.7445	-1.25%	*-1.8749	-4.23%	*-1.8005
-2	-0.41%	-0.3777	-2.27%	-0.9092	0.81%	1.2253	-3.41%	-1.4538
-1	0.60%	0.5521	-1.67%	-0.6684	-0.57%	-0.8649	-3.99%	*-1.6986
0	**-1.78%**	***-1.6419**	**-3.45%**	***-1.6452**	**-1.25%**	***-1.8822**	**-5.24%**	***-2.2311**
1	0.45%	0.4092	-3.00%	-1.2017	0.93%	1.3977	-4.31%	*-1.8356
2	-0.73%	-0.6667	-3.73%	-1.4925	0.23%	0.3515	-4.08%	*-1.7362

3	-0.57%	-0.5203	-4.30%	*-1.7194	-0.18%	-0.2671	-4.25%	*-1.8117
4	0.65%	0.5920	-3.65%	-1.4612	-0.01%	-0.0216	-4.27%	*-1.8178
5	-0.29%	-0.2665	-3.94%	-1.5775	0.98%	1.4831	-3.28%	-1.3982
6	-3.68%	***-3.3770	-7.63%	***-3.0504	-0.01%	-0.0173	-3.29%	-1.4031
7	2.89%	***2.6529	-4.73%	*-1.8933	0.01%	0.0217	-3.28%	-1.3970
8	0.80%	0.7353	-3.93%	-1.5726	0.35%	0.5212	-2.93%	-1.2495
9	0.34%	0.3077	-3.60%	-1.4384	0.73%	1.0949	-2.21%	-0.9397
10	-0.35%	-0.3189	-3.94%	-1.5775	0.74%	1.1201	-1.46%	-0.6228
11	0.09%	0.0808	-3.86%	-1.5423	-1.22%	*-1.8362	-2.68%	-1.1423
12	0.33%	0.2988	-3.53%	-1.4120	-0.20%	-0.3033	-2.88%	-1.2282
13	-0.93%	-0.8552	-4.46%	-1.7850	-0.39%	-0.5882	-3.27%	-1.3946
14	-0.53%	-0.4886	-5.00%	*-1.9981	0.32%	0.4849	-2.95%	-1.2574

Note: *, **, and *: Statistically significant at 10%, 5%, and 1%, respectively.**

Source: Author's Construction

4.2.3 Impact of credit rating affirmation announcements on stock returns

The daily AARs and CAARs realized by investors during the event window surrounding the credit rating affirmation announcement date are presented in Table 4 for the overall time period, and in Tables 5 for the sub-periods.

The results indicate that neither AARs nor CAARs attain statistical significance in the context of credit rating affirmation announcements, both for the overall analysis period and the sub-periods. Consequently, there is no substantial statistical evidence to suggest that stock returns exhibit significant responses to credit rating affirmations. This implies a limited market reaction to such events, which aligns with the findings of Li, Nuttawat, and Puspakaran (2004), who similarly observed no significant share price response to affirmation announcements in both the short and long term. However, our findings contrast with those of Angeline and Ariff (2019) and Jung, Kausar, Kim, Park, and Zhou (2023), who report statistically significant positive abnormal returns around affirmation dates. This difference may be attributed to market-specific factors; their studies primarily focus on developed markets with higher liquidity and greater investor attention to credit ratings, whereas in the context of Sri Lanka, an emerging market, investor responses to affirmation announcements appear more muted, possibly due to lower market efficiency, limited transparency, and differing investor behavior.

Table 4 Daily AARs and CAARs for the affirmation announcements – Overall period

Day	Affirmation announcements			
	AAR	t-stat	CAAR	t-sat
-14	-0.47%	-1.0904	-0.01%	-0.0136
-13	0.43%	1.5929	0.41%	0.4310
-12	0.30%	1.3214	0.71%	0.7414
-11	0.16%	0.7305	0.87%	0.9130
-10	-0.34%	-1.4923	0.54%	0.5625
-9	-0.10%	-0.4346	0.44%	0.4604
-8	-0.23%	-1.0166	0.21%	0.2216
-7	0.04%	0.1768	0.25%	0.2631
-6	-0.11%	-0.4947	0.14%	0.1469
-5	0.12%	0.5496	0.26%	0.2760
-4	-0.09%	-0.4156	0.17%	0.1784
-3	-0.02%	-0.0954	0.15%	0.1560
-2	-0.28%	-1.2515	-0.13%	-0.1379
-1	-0.06%	-0.2757	-0.19%	-0.2027
0	**-0.31%**	**-1.3702**	**-0.50%**	**-0.5245**
1	-0.17%	-0.7567	-0.67%	-0.7022
2	-0.08%	-0.3386	-0.75%	-0.7817
3	0.44%	1.5701	-0.31%	-0.3190
4	0.05%	0.2026	-0.26%	-0.2714
5	-0.05%	-0.2356	-0.31%	-0.3268
6	-0.10%	-0.4365	-0.41%	-0.4293
7	-0.05%	-0.2225	-0.46%	-0.4816
8	0.30%	1.3253	-0.16%	-0.1703
9	-0.22%	-0.9940	-0.39%	-0.4038
10	-0.23%	-1.0221	-0.62%	-0.6438
11	-0.11%	-0.5102	-0.73%	-0.7636
12	0.09%	0.3921	-0.64%	-0.6716
13	0.15%	0.6555	-0.50%	-0.5176
14	-0.20%	-0.8767	-0.69%	-0.7235

Note: *, **, and *: Statistically significant at 10%, 5%, and 1%, respectively.**

Source: Author's Construction

Table 5 Daily AARs and CAARs for the affirmation announcements - Sub-periods

Analysis of the sub-periods – Affirmation announcements								
Day	**Period before COVID-19 pandemic**				**Period during COVID-19 pandemic**			
	AAR	**t-stat**	**CAAR**	**t-stat**	**AAR**	**t-stat**	**CAAR**	**t-stat**
-14	-0.32%	-1.0667	0.53%	1.2989	-0.30%	-0.7206	0.99%	0.6161
-13	-0.25%	-0.8333	0.28%	0.6809	0.08%	0.1898	1.07%	0.6660
-12	-0.22%	-0.7333	0.06%	0.1371	0.15%	0.3465	1.22%	0.7570
-11	0.06%	0.2028	0.12%	0.2875	0.07%	0.1701	1.29%	0.8016
-10	-0.12%	-0.3874	0.00%	0.0003	-0.56%	-1.3284	0.73%	0.4528
-9	-0.03%	-0.0854	-0.03%	-0.0630	-0.09%	-0.2109	0.64%	0.3974
-8	-0.31%	-1.0306	-0.33%	-0.8273	-0.28%	-0.6664	0.36%	0.2224
-7	0.17%	0.5711	-0.16%	-0.4038	-0.34%	-0.8088	0.02%	0.0100
-6	-0.26%	-0.8687	-0.42%	-1.0479	-0.06%	-0.1352	-0.04%	-0.0255
-5	0.22%	0.7338	-0.20%	-0.5037	-0.17%	-0.3947	-0.21%	-0.1292
-4	0.07%	0.2409	-0.13%	-0.3251	-0.35%	-0.8323	-0.56%	-0.3477
-3	0.05%	0.1644	-0.08%	-0.2032	-0.18%	-0.4260	-0.74%	-0.4596
-2	-0.27%	-0.9071	-0.35%	-0.8759	-0.22%	-0.5243	-0.96%	-0.5973
-1	0.25%	0.8234	-0.11%	-0.2652	-0.44%	-1.0509	-1.40%	-0.8733
0	**-0.46%**	**-1.5409**	**-0.57%**	**-1.4079**	**0.02%**	**0.0527**	**-1.38%**	**-0.8594**
1	0.25%	0.8333	-0.32%	-0.7899	-0.21%	-0.5019	-1.59%	-0.9912
2	0.25%	0.8480	-0.07%	-0.1611	-0.52%	-1.2335	-2.11%	-1.3152
3	0.24%	0.7990	0.17%	0.4313	0.63%	1.4855	-1.49%	-0.9251
4	0.26%	0.8734	0.44%	1.0790	-0.40%	-0.9578	-1.89%	-1.1766
5	-0.32%	-1.0786	0.11%	0.2792	0.14%	0.3416	-1.74%	-1.0869
6	-0.05%	-0.1667	0.06%	0.1556	-0.12%	-0.2927	-1.87%	-1.1638
7	-0.09%	-0.3000	-0.03%	-0.0669	0.10%	0.2359	-1.77%	-1.1018
8	0.29%	0.9776	0.27%	0.6581	0.25%	0.5898	-1.52%	-0.9469
9	0.08%	0.2568	0.34%	0.8485	-0.56%	-1.3284	-2.08%	-1.2958
10	-0.24%	-0.8000	0.10%	0.2553	0.52%	1.2335	-1.56%	-0.9718
11	0.00%	0.0000	0.10%	0.2553	-0.25%	-0.6046	-1.82%	-1.1306
12	0.28%	0.9226	0.38%	0.9394	-0.17%	-0.4150	-1.99%	-1.2396
13	-0.02%	-0.0719	0.36%	0.8861	0.30%	0.7182	-1.69%	-1.0510
14	-0.02%	-0.0725	0.34%	0.8323	-0.31%	-0.7257	-1.99%	-1.2416

Note: *, **, and *: Statistically significant at 10%, 5%, and 1%, respectively.**

Source: Author's Construction

5. Conclusion

In the volatile and dynamic financial world, credit rating announcements act as critical indicators of issuer creditworthiness, influencing investment decisions for a wide spectrum of market players. The current study aims to examine the response of stock returns following credit rating announcements, with particular attention to downgrade and affirmation announcements.The analysis is conducted across the period before and during the COVID-19 pandemic, utilizing the ESM, incorporating 214 credit rating announcements.

The results evidenced, negative market response to the credit rating downgrade announcements, which was particularly pronounced during the COVID-19 pandemic period.

The heightened sensitivity during the pandemic reflects investors' perception of downgrades as signals of deteriorating creditworthiness and increased financial risk, which are perceived as potential losses, often prompting selling behavior reinforced by heightened risk aversion (Khan, Fifield, & Power, 2024). Affirmations, in contrast, elicited no significant response, suggesting that neutral credit signals are generally perceived as less informative by investors, irrespective of market conditions.

These findings align with the theory of loss aversion, indicating that investors respond more strongly to negative information than to neutral signals, especially under situations of economic stress. Overall, the study provides evidence that credit rating downgrades convey valuable information in the Sri Lankan stock market and that investor responses are amplified during crises, challenging the semi-strong form of the Efficient Market Hypothesis. The insights will be important for investors, portfolio managers, fund managers, and policymakers seeking to make informed decisions in emerging market contexts.

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Annexure I: Summary of prior studies

Author, Year	Event	Sample size	Methodology	Expected Return Model	Window (Days)	
					Estimation Window	Event Window
Panel A: Credit ratings related event studies						
Weinstein (1977)	Bond rating	100	ESM	-	-	13 months (-7 to +6)
Griffin & Sanvicente (1982)	Bond rating	128	ESM	Market model	-	-11 months and during the month of a rating change
Glascock, Davidson, & Henderson (1987)	Bond rating	207	ESM	Market model	-	(-90 to +90)
Holthausen & Leftwich (1985)	Bond rating	1014	ESM	Marker model	300	(-300 to -61) (-60 to -1) (0 to +1)
Linciano (2003)	Credit rating	299	ESM	Market model	240	41 (-20 to +20)
Choy, Gray & Ragunathan (2006)	Credit rating	127	ESM	Market-adjusted returns	-	(-10 to +10) (-5 to +-5) (-1 to +1)
Freitas & Minardi (2013)	Credit rating changes Watch announcement	319	ESM	Mean-adjusted returns. Market-adjusted returns Market model	252	45 (-30 to +14)
Xie, Yang & Munir (2019)	Credit rating	101	ESM	CAPM	60	21 (-10 to +10)
Dawar, Bhatia & Bindal (2021)	Credit rating	72	ESM	Market model	250	15 (-7 to +7)
Panel B: Event studies other than credit ratings						

Keown & Pinkerton (1981)	Merger announcements	194	ESM	Market model	96	61 (-30 to +30)
Hackbarth & Morellec (2008)	Merger announcements	1086	ESM	Market model	90	-2years to +2 years
MacKinlay (1997)	Takeover announcements	600	ESM	Market model	250	41 (-20 to +20)
Brown & Warner (1980)	Dividend announcements	250	ESM	Mean adjusted returns. Market adjusted returns Market model	100 months	100 (-89 to +10)
Dissabandara (2000)	Dividend announcements	123	ESM	Market model	200	121 (-60 to +60)
Brown & Warner (1985)	-	250	ESM	Mean adjusted returns. Market adjusted returns Market model	239	11 (-5 to +5)
Hewage & Ediriwickrama (2021)	Auditor's report	1735	ESM	Market model	100	41 (-20 to +20)
Trueman, Wong, & Zhang, (2003)	Earnings announcements	1875	ESM	Fama and French (1993) Three-factor model	-	-
Fernando & Gunarathne (2008)	Bonus issue announcements	135	ESM	Mean adjusted returns. Market adjusted returns Market model	250	51 (-20 to +30)
Bandara (1997)	Right issue announcements	-	ESM	Market model	99	21 (-10 to +10)
Grinblatt et al., (1984)	Stock split announcements	1760	ESM	Market model		81 (-40 to +40)

Panel C: Event studies using methods other than ESM			
Poon & Chan (2008)	Credit Rating	160	Full information maximum likelihood (FIML) simultaneous equation system
Carter & Manaster (1990)	Reputed underwriting firms	501	Linear regression
Carter, Dark, & Singh (1998)	Reputed audit firms	1875	Ordinary Least Squares (OLS) regressions
Greenblatt & Hwang (1989)	management changes and IPOs	-	Two-parameter signaling model