DOES CREDIT RATING ALONE ENOUGH FOR PROBABILITY OF DEFAULT: CDS MAY HELP FOR REAL TIME MEASUREMENT?

BY

MISS LALITA INNGERN

AN INDEPENDENT STUDY SUBMITTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF MASTER OF SCIENCE PROGRAM IN FINANCE (INTERNATIONAL PROGRAM) FACULTY OF COMMERCE AND ACCOUNTANCY THAMMASAT UNIVERSITY ACADEMIC YEAR 2016

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ABSTRACT

Credit risk of the counterparties is an important content that every institution needs to eliminate. In emerging market including Thailand, Malaysia and Philippines, CDS spread does have ability as a primary credit measurement to investors and credit analysts especially in case of actual Downgrade announcements. CDS market can fully anticipate the credit information 30 days before the announcements from credit rating agencies. This study also found that there's asymmetric reaction from CDS market between positive and negative credit events between actual Downgrade and Upgrade announcements. CDS market seems to under-react to the credit announcements which has reference entities in this region since we couldn't found significant anticipation in Outlook and CreditWatch reports. We're also studied predictability of CDS spread to the future credit announcements in order to introduce advantageous of this instrument in the credit analysis.

Keywords: Credit risk, Credit default swap, Credit Rating

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Miss Lalita Inngern

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CHAPTER 1
INTRODUCTION

Credit Default Swap (CDS) is the financial swap agreement for hedging credit risk of reference entities, widely used for protects the credit risk for corporates and financial institutions. The instrument was introduced widely in 2003. After 2007, the crisis has dishonored the reliability of U.S. credit derivative market especially in the Credit Derivative Collateralized Debt Obligation (CDO) which included the subprime mortgage as collateral. Nowadays, CDS has more roles in financial market other than hedging credit risk. It's also participates in funding and investing sections through financial institutions and hedge funds. Most of the credit analysis departments from financial institutions and corporates tend to consider credit ranking of the counterparties by referring to the CDS spread along with credit rating.

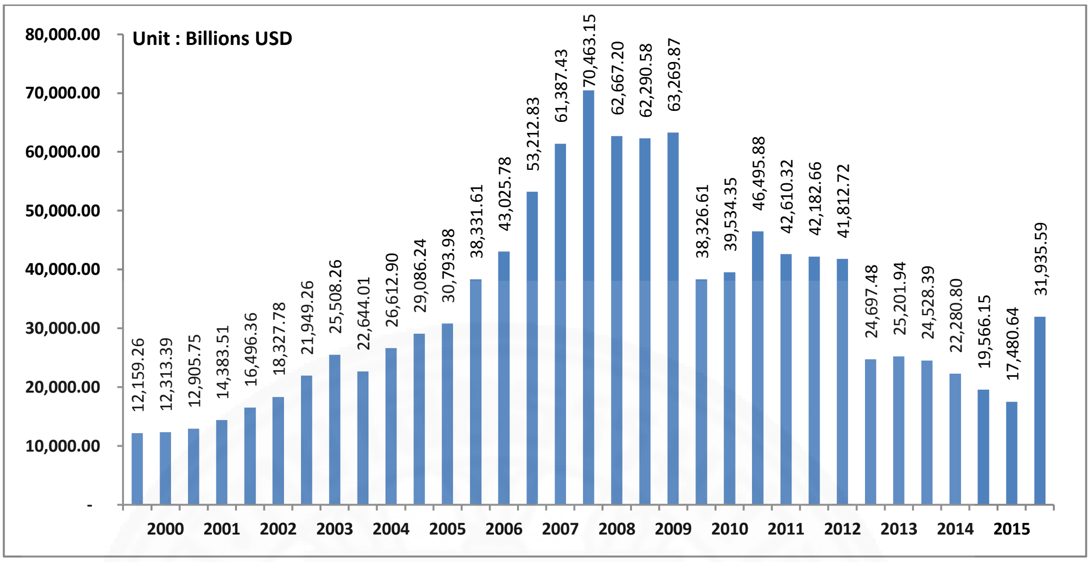
The mechanism for CDS is like an insurance contract. The purchaser or long position is the insurer who wants to protect themselves from default risk. They are willing to pay periodic premium for CDS contract. The seller of CDS is the seller of protection (CDS dealer) for default risk and receives this CDS spread as premium. In case that the underlying bonds in this contract defaults, the seller has to pay the purchaser in the amount they firstly negotiated which can be both in cash or physical assets. Hence, the payoff of the purchaser of CDS contract is like the short position in bonds while the payoff for the seller is the long position. Pricing method for CDS is based on the amount of credit risk associated with the reference entity and quantify this amount which an investor can follow different paths. One of the most important elements that CDS spread rely on is credit rating announced by Credit rating agencies that measure credit risk of the firms considering on their ability to service and repay debt. Credit rating agencies considers both sovereign and corporate credit ranking. A sovereign credit rating defines financial strength and probability of default of a country such as sovereign risk of Kingdom of Thailand. While a corporate credit rating defines probability of default and financial strength for a reference corporation. However, based on the financial crisis which occurred several times in 2000s, credit rating agencies were pressured to act more effectively on time. CDS spread is one of the alternative measurements for credit risk and probability of default to the reference entity. Its value contains information from credit rating itself and also reflects demand and supply of the market. Moreover, the spread can move more quickly than the credit rating since it is updated any time there is trade.

This study investigates the reaction of CDS spread to each of the credit events which consist of Outlook, CreditWatch, and Rating action. We also separately analyze positive and negative directions. This study mainly focused on corporates in developing countries in South-East Asia region including Thailand, Malaysia, and Philippines. Most of our observable corporates are likely to be the large corporates and have significant amount of outstanding bonds in USD currency. This type of the debt obligation would be interested by the foreign investors and they need to secure their investment by buying some hedging or insurance contracts. There are 16 corporations in this region who have CDS spread available in the market since 2007.

We employed Event study methodology for testing the first part to find if there is abnormal return in CDS spread around the event dates. The second part is to emphasize whether CDS spread could be a good predictor for the future changes of credit announcements using Logistic regression analysis. The results from Event study by t-test showed that there is no significant abnormal return in CDS spread for Outlook, CreditWatch and actual Upgrade announcements. However, the spread return is significantly related to actual Downgrade announcements since we found abnormal return in the pre-event period for actual Downgrade announcements. Moreover, Logistic regression could find predictability of CDS spread to the near-future credit events.

This report comprised of the following parts, section 2 is review of literature of the previous researches related to this study and section 3 described research methodology. Section 4 and 5 explained empirical results and conclusions from the test.

Figure 1.1: Outstanding Notional for all types of Credit Default Swap.



Sources: Bank of International Settlement

CHAPTER 2
REVIEW OF LITERATURE

2.1 Literature reviews

We've studied previous works related to the changes in Credit Default Swap Spread (CDSs) and credit rating announcements also the test for predictability of CDSs to credit rating announcements. These researches are our motivation and helpful for us to study in this topic. In the early of research, there were many papers had documented only for significant changes in actual downgrade on stock and bond prices. They found insignificant or weak reaction from the market to the actual upgrade events. This lead to the suggestion from the early researches that market anticipated only to negative events. We will explain the important papers in 2000s as followings.

Hull, Predescu and White (2004)

This paper studied about CDS spread changes, bond yield and effect of credit rating announcement to CDSs. The research used just CDSs and bond from investment-grade issuers since at that time there was less speculative-grade issuers which had their CDS traded in the market. In the first part, they tested the relationship between CDSs and bond yield by testing the distance between the implied risk free rate which is the swap zero curve and CDSs classified by credit rating. The result showed that CDSs and its reference entity's rating are comparable. Next, the paper used mean spread changes of CDS regress with the average CDSs from the same credit rating (based on Moody's). The test gave the result that all types of negative announcements are anticipated by the market but only the CreditWatch for downgrade contains significant information in the pre-event period. The final part did the estimation of probability that CDSs can examine negative credit events. The research employed Logistic regression model and PSM (Probability Sensitivity Measure) which measures the increasing in probability of a rating event for a basis point increase in the adjusted spread changes. The result of Logistic regression found that the spread changes from top quartile of all the credit spread changes contain helpful information for estimating all types of negative credit rating changes. However, they found insignificant of CDSs changes to the positive events and guested that the positive events were less sample sizes compared to the other one.

Lehnert and Neske (2006)

The paper studied return of CDSs using mean change in daily CDS spread compared to the control period. They employed Event study – Market Model method for data from European market and the market benchmark is Track-X Europe index of JP Morgan. The research designed time around event period into two parts which are control period and event period. The control period start from day -70 until -10 before the actual event. While the event period can be divided into 3 steps: first step is pre-event start from day -10 to -1, event date is -1 and 1 and post-event period around day 1 until day 10. This research used event news from Moody's as their solely rating agency and combined positive outlook and stable outlook as the same credit event since both of them hardly occurred during the test period. The results suggested that negative events have itself information to the market especially for the negative outlook report which impacted larger changes in CDSs than actual downgrade. Further, they found that difference types of announcements such as negative outlook report and actual downgrade are classified as independent events by the market. Moreover, this research could found significant CDSs changes in post-announcements for positive and stable outlook report.

Micu, Remolona and Wooldridge (2006)

This is working paper from BIS (Bank for International Settlements) analyzed all types of the credit events from all major credit rating agencies consist of Moody's, S&P and Fitch rating. The research had purpose to analyze which types and which rating agencies announced helpful information to the market and which one is not. They employed Event study based on Market Model benchmark from return on CDS spread with Trac-X and iBoxx using Standardized Z-Test or z_{BMP} to control for event-induced changes in variance. The research divided testing periods into Estimation period and event periods like those from *Lehnert and Neske (2006)*. They found that all types of credit events have significant impact on changes in CDSs both for positive and negative events. The market tends to consider each of the events separately and appreciate in CreditWatch and Outlook reports more than actual Rating action. Further, CDSs changes would be greater if the reference entities have more than one credit rating agencies and public the same announcements. Moreover, downgrade have a much greater impact to CDSs while upgrade impact more in case of lower-rating grade and downgrade impact much more in higher-ranking grade.

Finnerty, Miller and Chen (2013)

This paper used data from S&P and divided credit events into 3 types; Outlook (OL), Credit Watch (CW) and Rating change (RC). The methodology in this paper was developed from *Hull, Predescu and White (2004).* They used Event Study analysis which has Estimation window based on average of all CDSs (the paper claimed that both return on CDSs changes and the mean spread changes gave indifference results) written on the bonds from the same credit rating and industries with each of the reference entities. The research also tested predictability of CDSs using Logistic regression analysis and Regression analysis to find relationship between CDSs and credit events but adding some macroeconomic factor as controlled variables. They found a bit difference results from above researches. Similar to *Lehnert and Neske (2006)*, they found that not only negative news but positive news are also information anticipated by the market. The paper concluded that they found strongly signals from positive Outlook, CreditWatch and actual Upgrade to the CDS market which contradicted with the prior researches. They also suggested that credit rating agencies might adjusted methodologies for the positive announcements to be more real-time and align with CDS market. However, CDS market still anticipates actual Downgrade events better than actual Upgrade events. Moreover, in case of negative credit events, they found that CDSs from speculative-grade is also contains credit risk information just like the one from investment grade but they couldn’t found reaction from CDSs in case of positive events. Unlike the result from *Hull, Predescu and White (2004)*, by using Logistic model, the result showed that CDSs still can’t be a good predictor for the future rating change.

2.2 Theoretical Frameworks

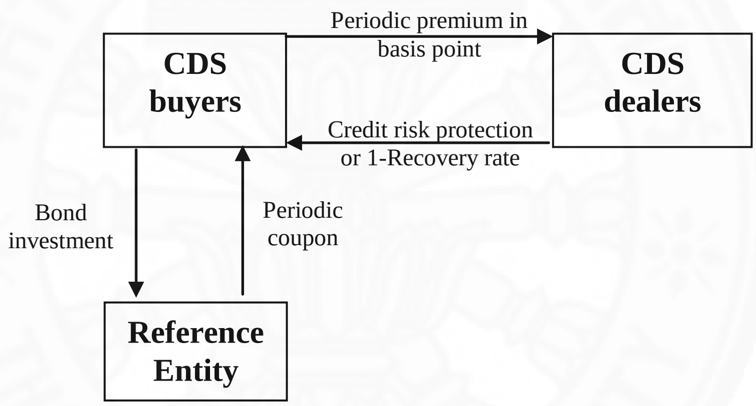
2.2.1 Credit risks

Credit risk implies to a risk that the borrower or the counter parties in any types of borrowing, investment and trading transactions. It's the probability that the borrower or the counter parties failed to make a repayment or a payment at due date due to their lacking in cash flows and financial performances. Unlike market risk which is a systematic risk and can't be diversified, credit risk can be diversified by doing a regular credit review procedures also require some guarantees or collateral from the borrowers and buyers. We can observe credit ranking in the funding market by compared to the risk-free government bond yield. The costs of the borrowers who have more widening spread implicate the higher credit risk they have. Credit risk can be measured by credit rating agencies, the agencies assigns credit ranking to the borrowers or issuers based on financial strength, ability to make the repayment reference to the outstanding debts and also the size of capital. Global rating agencies comprise of Moody's, S&P and Fitch rating, they have a bit difference methods to measure the issuer's credit risk. Nowadays, Moody's and S&P control 80% of the credit rating business while Fitch rating controls around 15% of the market share. Credit rating can be classified mainly into two types of credit ranking, investment grade and speculative grade. Most of the corporate and high-rated funds have limitations to invest in investment grade bonds although it has lower return. This condition was set to prevent investors from loss in case the issuers can't repay back. However, credit risk is currently used as a potentially arbitrage instrument along with Credit Default Swap (CDS) for financial institutions to funding from market more secure and lower cost than before. They construct an instrument named Credit Linked Note (CLN) as alternative investment for other financial institution and also corporates who seeking for higher return in the low-return market situation.

2.2.2 Credit Default Swap (CDS)

Credit Default Swap is a financial swap between two parties to trade credit risk of the reference entity with the cash premium in form of over the counter (OTC). CDS is the most popular credit derivatives in the market. It was introduced since 1990s by JP Morgan. CDS is traded at tenor of contracts between 1 to 10 years; the most liquid tenor is 5 year CDS contracts. CDS transactions is initiated from demand for hedging credit risk of bond holders who have long position in bond investment and need to protect the risks in case that the bond issuers can't make repayment and also interest payment at any due date. In order to hedge this credit risk, CDS sellers or "dealers" will quote CDS price in form of daily basis points. To measure credit risk of the reference entities, dealers need to construct probability of default for reference bonds which is calculated from financial strength, ability to repay and size of its capital. In exchange of that, dealer will receive the periodic premium from CDS buyers, the higher the credit risk, the higher in CDS spread.

Figure 2.1 Flows of bond investment and Credit Default Swap transaction.



Our study will focus on single-name CDS contract which rely on individual corporate credit risk. CDS contract is similar to an insurance contract for CDS buyers. For an example, if CDS buyers buy a protection in CDS contract maturity in 5 years, the buyers need to make periodic payments to CDS dealers and got the protection in case of default on reference entity. During the protection period, if there were no Event of Default defined in Terms and Conditions of the agreement, CDS dealers has no obligation to pay or take any action related to the agreement. On the other hand, if there were an Event of Default occurred as defined in the agreement, CDS dealers need to cover the loss by the face value of the reference entity equal to 1-Recovery rate. When there is a default on the reference entity, recovery rate is the percentage of the face value and accrued interest that the assets could be recovered from the default. If the bond holders didn't have any protection, they will get just the recovery rate or the physical bond that was already defaulted. On the contrary, if they have protection from CDS contract, they will get the recovery fund at 1-Recovery rate from CDS dealers.

In case of CDS valuation, dealers need to adjust the spread based on public information from the market. According to the paper work from *Micu, Remolona and Wooldridge (2006)*, they set assumptions for the period that can detect the abnormal spread changes into 3 cases. First, abnormal spread changes occurred in the pre-event period would be implied that the market fully anticipated with the publication of credit events. Next, for the abnormal changes at the event date, it can explain that the publication of credit events is not fully anticipated by the market. The last one is abnormality changes in the post-event period, they guested that this case might occur with the less-liquid names. As for the final case, we have more explainable assumption which refers to the asymmetry reaction by the market between positive and negative credit announcements.

CHAPTER 3
RESEARCH METHODOLOGY

To study this topic, our main sources of data are Reuters and Moody's official website.

3.1 Data

3.1.1 Credit Default Swap Spread

We collected daily single-name CDSs from corporates in Thailand, Malaysia and Philippines during 14 December 2007 – 31 March 2016 from Reuters. The spread used in this study is 5-year maturity contracts and have reference entity based on senior unsecured bond with USD quotation. We used mid-rate between bid and ask spread at ending of each day. CDSs is already a spread (basis point), it is comparable and the spread movements is also reflected by credit quality of the reference entity and the market. CDSs data are provided by Markit, a London-based distributor of credit pricing data. Markit provides the spread which are averaged by more than 20 dealers, they're also clean the inactive quoted and outliers from the data. Moreover, they construct the spread only when at least 3 dealers make the quotation. From historical information, dealers most frequently updates price for 5-year maturity contracts than the others, so this can confirm that 5-year CDSs has the most liquidity in the market.

Table 3.1 shows the final samples comprised of 16 issuers from 3 countries, 5 companies from Thailand, 7 companies from Malaysia and 4 companies from Philippines. Most of the companies are from Energy and Utility generating companies, Banking and Finance, Telecommunication and also Conglomerate sectors which have major role for income generation in the countries and have large market capital in their stock markets. These companies usually funding by debt financing for mega projects such as plant and refinery maintenance and construction, they need long-term and low price of funding which is local and foreign currency bond funding. Although most of them are considered as investment grade, their credit spread still has risk factors from uncertainty in their industries and countries. Hence, bond investors demand for a protection which is CDS for these bonds.

Table 3.1

Company data sample period from December 14, 2007 to March 31, 2016. Total 16 companies comprised of Thailand 5 companies, Malaysia 7 companies and Philippines 4 companies that could matched CDS spread with credit events.

Countries	Companies	Industries	Credit rating		
			S&P	Moody's	Fitch rating
Thailand	PTT PCL	Oil and Gas	BBB+	Baa1	BBB+
	Thai Oil PCL	Oil and Gas - Refiner	BBB	Baa1	N/A
	Kasikornbank PCL	Banking	BBB+	Baa1	BBB+
	Krung Thai Bank PCL	Banking	BBB	Baa1	BBB
	True Move Co Ltd	Telecommunications - Mobile, cellular	NR	N/A	N/A
Malaysia	Malayan Banking Bhd	Banking	A-	A3	A-
	Telekom Malaysia Bhd	Telecommunications	A-	A3	A-
	IOI Corporation Bhd	Conglomerate/diversified	BBB	Baa2	WD
	CIMB Bank Bhd	Banking	A-	A3	N/A
	Petroliam Nasional Bhd	Finance - Agency	A-	A1	A
	Tenaga Nasional Bhd	Utilities-Electric	BBB+	Baa1	BBB+
	MISC Bhd	Transportation	BBB	WR	N/A
Philippines	Globe Telecom Inc	Telecommunications	NR	WR	BBB-
	SM Investments Corp	Conglomerate/diversified	N/A	N/A	N/A
	Metropolitan Bank and Trust Co	Banking	NR	WR	BBB-
	National Power Corp	Utilities-Electric	BBB	Baa2	N/A

Credit rating as at 31 March 2016

Table 3.2 shows descriptive statistics for CDSs data. The spread from each of the companies were quoted in daily basis point in USD currency. Some reference entities have no outstanding senior unsecured bonds active in the market but naked investors still need to buy it even though they don’t have any risk exposure related to those bonds. Considered from the same credit ranking at BBB, MISC Bhd. had lower average CDSs than TOP, KTB, IOI Corporation Bhd. and National Power Corp. While CDSs from Tenaga Nasional Bhd. was lower than PTT and KBANK at the same credit rating at BBB+. The table demonstrates that CDSs from Malaysian companies are lower compared to the same rating from both Thailand and Philippines, for example, IOI Corporation Bhd. has the same credit spread as TOP and National Power Corp although they has much higher standard deviation.

Table 3.2

Descriptive statistic for CDS spread and matched credit events sample data from December 14, 2007 to March 31, 2016. For stable Outlook report, we assigned the direction of credit events to them compared to the previous report.

Countries	Companies	CDSs in basis point ($)		Number of matched credit events							
		Average	SD	OL+	OL-	OL stable	CW+	CW-	RA+	RA-	Total
Thailand	PTT PCL	123.55	48.69	1	3			2	2	2	10
	Thai Oil PCL	144.54	52.77					1			1
	Kasikornbank PCL	133.08	36.01	1					1	1	3
	Krung Thai Bank PCL	413.10	26.97	1						1	2
	True Move Co Ltd	744.28	214.62	1	2					1	4
Malaysia	Malayan Banking Bhd	118.84	35.01	1		1				1	3
	Telekom Malaysia Bhd	117.35	52.33			1	1				2
	IOI Corporation Bhd	148.41	108.67		1			1		1	3
	CIMB Bank Bhd	129.99	38.61			1				1	2
	Petroliam Nasional Bhd	112.15	48.43					1			1
	Tenaga Nasional Bhd	118.72	54.85			1					1
	MISC Bhd	123.16	51.68			1		1			2
Philippines	Globe Telecom Inc	153.64	86.35						1		1
	SM Investments Corp	347.65	37.03						2		2
	Metropolitan Bank and Trust Co	149.09	94.96	2			1	1		1	5
	National Power Corp	148.18	52.92	1			1		1		3
Total		**205.17**	**55.90**	**8**	**5**	**5**	**3**	**7**	**12**	**10**	**50**

The lowest average credit spread in our samples is 112.15 basis point from Petroliam Nasional Bhd. which has credit rating A- from S&P and highest credit spread is TRUE Move Co., Ltd. which has credit rating B from the same agency before it was withdrawn. Due to difference in spread levels and TRUE Move Co., Ltd. And IOI Corporation Bhd seems to have higher standard deviation than the others, we use return from spread changes to prevent the difference in spread level from each reference entity.

3.1.2 Credit rating announcements

As from Table 3.2, credit events mainly came from Moody's official website and we're also collected all the credit rating news announced by all rating agencies from Reuters. The period is also occurred during 14 December 2007 – 31 March 2016. We observed the events from Moody's first since they are the most effective source of credit news, and then compared the news with S&P and Fitch rating from Reuters. In case of duplication, we choose the first appearance event and also eliminated following event occurred during day [-120, +30] for event study analysis and we're also dropped the intervals containing another events for period [-150, -1] and [-365, -1] for Logistic regression analysis for making the data uncontaminated.

Among all credit rating agencies, Moody's published the most credit announcements for our sample companies around 90% of all credit events. This is the same as works from *Hull, Predescu and White (2004)* and *Lehnert and Neske (2006)* that analyzed based on Moody's credit rating. Announcements from credit rating agencies contains important information for financial strength and creditworthiness of the companies also the ability to repay debt. We can consider it as valuable information from the companies itself. There are 162 events observed along the period from 14 December 2007 – 31 March 2016, but after matching up with available CDSs and eliminating some of them for controlling our research, we have final credit events for 50 events. PTT from Thailand has the most credit events during our study which is 10 events totally. Hence, we have Actual Rating action for 22 events (Upgrade 12 events and Downgrade 10 events). Credit Outlook 18 events (positive Outlook 8 events, negative Outlook 5 events and stable Outlook 5 events) and the last one is CreditWatch for 10 events (positive CreditWatch 3 events and negative CreditWatch 7 events).

3.1.3 Credit events

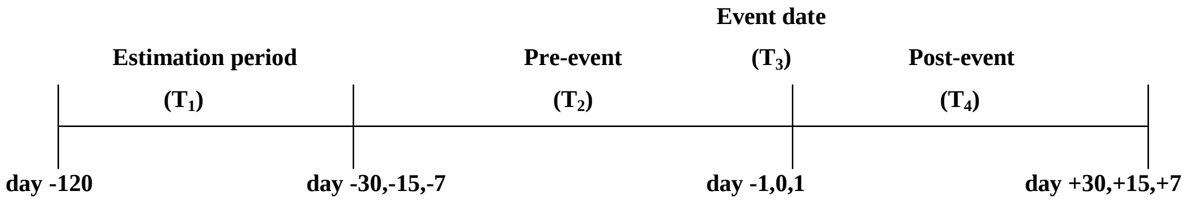
3.1.3.1 Rating Outlook: Rating Outlook is used to signal the potential direction of a rating movement over the intermediate term. It's classified into 4 types: Positive, Negative, Stable, and Developing (Contingent upon an event).

3.1.3.2 Rating review (CreditWatch): CreditWatch would be launched before rating change around 30 business days. They are the type of credit-alert, credit rating agencies used to identify issuers that is under surveillance. Moody's will conclude a formal review within 90 days.

3.1.3.3 Rating action: Rating action always occur after credit rating agencies could sum up all the information and make conclusion to change.

3.2 Event study analysis

Figure 3.1: Event Windows and Estimation Window for Event Study Analysis



In this study, we employ typical Event study analysis to test significant of abnormal spread return in Pre-event period day [-30, -2], At-event period day [-1, 0, 1] and Post-event period day [2, 30]. In order to find benchmark for this analysis, we employed Constant Mean Return Model that use historical daily average abnormal return from CDSs in Estimation period day [-120, -31] as a benchmark to measure the return in study periods. Since our data has insignificant portion in any CDS indexes, this method is the most suitable method. Constant Mean Return Model assumes constant expected return overtime but can be varied by event *i*. Because of this, the t-test statistic could be determined using ${\sigma^2}_i$ from Estimation period.

At the beginning, we need to find mean of daily spread return $\overline{S\,ret_i}$ for T_1 for day [-120, -31] in the calendar-day basis from historical CDSs from each of event *i*. For example, to find mean spread of PTT, we calculate $\overline{S\,ret_i}$ from historical CDSs of PTT during day [-120, -31] to be used as the benchmark for PTT's spread. From this step, we need to compute the ${\sigma^2}_i$ from the Estimation period.

$$\overline{S\,ret_i} = \frac{\sum S\,ret_i}{m_i} \tag{1}$$

$${\sigma^2}_i = \sqrt{\frac{\sum(S\,ret_{i,t} - \overline{S\,ret_i})^2}{n-1}} \tag{2}$$

Then, calculate daily Abnormal return $AR_{i,t}$ and $CAR_{i,T}$ (Cumulative Abnormal Return by event *i* and period T) for Pre-event period or T_2 day [-30, -2], At-event period or T_3 for day [-1, 0, 1] and Post-event period or T_4 for day [2, 30].

$$AR_{i,t} = S\,ret_{i,t} - \overline{S\,ret_i} \tag{3}$$

$$CAR_{i,T} = \sum_{t=1}^{n_i} AR_{i,t} \tag{4}$$

Where $\overline{S\,ret_i}$ = Average daily spread return of 5-year CDS contracts from event *i*

$S\ ret_i$ = Daily CDS spread return of 5-year CDS contracts from event *i*

m_i = Number of days available from event *i* in Estimation period or T_1

$n_{i,T}$ = Number of days available for period T

$\sigma^2{}_i$ = Variance calculated from AR in the Estimation period for event *i*

$AR_{i,t}$ = Daily abnormal return from event *i* for each of day t

$CAR_{i,T}$ = Cumulative Abnormal Return from event *i* for period T

Significance tests for Event study analysis

3.2.1 Event Study t-test

Brown and Warner (1980) showed that the Event Study t-test with $AR_{i,t}$ based on Constant Mean Return Model often gives the indifference results from the complicated model. Its null hypothesis tests the average of Cumulative Abnormal Return $\overline{CAR_T}$ equal to zero and variance from the Estimation period.

$$\overline{CAR_T} = \frac{1}{N}\sum_{i=1}^{N} CAR_{i,T} \quad (5)$$

$$\sigma^2{}_T = \frac{1}{N^2}\sum_i^N(\sigma^2{}_i \times n_{i,T}) \quad (6)$$

$$t - test_T = \frac{\overline{CAR_T}}{\sqrt{\sigma^2{}_T}} \quad (7)$$

Where $\sigma^2{}_T$= Variance for period T

N = Number of events

$n_{i,T}$= Number of days available for period T

3.3 Binary Logistic regression analysis

Despite the fact that event study analysis can detect CDSs movement in consistency with the publications of announcements related to such that credit events, we’re also explore further more in this study for the case that CDSs can be a suitable predictor for credit event or not. Previous studies such as *Hull, Predescu and White (2004)* and *Finnerty, Miller and Chen (2013)* employed Binary Logistic regression analysis to investigate this problem.

The previous papers constructed a set of non-overlapping interval each for 30 days and collected all of available intervals into the test. They used 2 types of calculation for independent variable, first were to use the last spread minus the first spread for each of the interval and second were to use average spread changes from each of interval. We adjusted the method to be beginning with the credit event dates and trace back for 150 days and 1 year before the events. We choose only events that have significantly abnormal return in the pre-event period testing by the event study analysis. Further, instead of using spread changes like the previous papers, we employed $CAR_{i,T}$ (Cumulative Abnormal Return) calculated from each of the 30 days-interval (days [-30, -1]) before the event date calculation based on CDSs from days [-150, -31] as the Estimation period. This method of $CAR_{i,T}$ calculation also applied to another interval by rolling the Estimation periods further back until 1 year.

We also dropped the intervals which contain another events, the intervals which has not contains CDSs at least 2 values and the intervals that have impact from earnings announcement periods. For the period that has a credit event occurred in the next interval period, we assign 1 for dichotomous variable and 0 for otherwise. The spread should be widening in the period before the events which the CDS seller should react asymmetrically with the market. In this case, dependent variable will have Bernoulli distribution since there are only 0 and 1.

Binary Logistic regression model is per below.

$$P = \frac{1}{1+e^{-z}} \tag{8}$$

$$z = \beta_0 + \beta_1 x \tag{9}$$

$$\frac{Probability(event)}{Probability(No\ event)} = e^{\beta_0+\beta_1 x} \tag{10}$$

$$Odd\ Ratio = \frac{e^{\beta_0+\beta_1(x+1)}}{e^{\beta_0+\beta_1 x}} = e^{\beta_1} \tag{11}$$

Where P = Probability of dependent variable in terms of Logistic function

z = Linear function of an explanatory variable x

x = Cumulative Abnormal Return ($CAR_{i,T}$) calculated from each interval T=30

β_i= Constant terms determined from Maximum Likelihood Estimation (MLE)

The Probability of dependent variable represent predicted probability of CDSs given changes of $\overline{CAR_T}$. Unlike the OLS regression analysis that estimates parameters manipulating the Least Square method, Logistic Regression analysis employs MLE (Maximum Likelihood Estimation) that recalculate the coefficient value (iterative algorithm). Iterative process starts from the model with empty-weighted coefficient model (no predictors-model) and gradually adjusts the weight of coefficient until stops when the process has converged so that we obtain the saturated model and get optimal β_i values. Since the relationship between independent and dependent variables in Logistic model can be explained in terms of *log odds* as describe in equation (10). Odd Ratio is used to determine how y changes when x changes by 1 unit as also described in equation (11). We can interpret relationship of y and x from Logistic model that as x changes by 1 unit, y will changes by e^{β_1} unit.

The goodness of fit test for Logistic model can be measured from Likelihood Ratio Test. It measures the difference between the empty model and the saturated model which equal to -2 log Likelihood.

$$D_{empty\ and\ saturated\ model} = -2ln\frac{Likelihood\ of\ the\ empty\ model}{Likelihood\ of\ the\ saturated\ model}$$

The Likelihood ratio test is also used for calculate the LR Chi-square test and p-value for goodness of fit test for the model.

CHAPTER 4
RESULTS AND DISCUSSION

4.1 Event study results

As referred in the earlier sections, we employed Event Study t-test in this study. First, we tested aggregated data defined as credit events including Outlook, CreditWatch and Rating action total 50 events. Outlook reports that were presented as Stable Outlook, we adjusted it by gave the direction referred to its previous announcements.

Table 4.1 displays results of the test. For aggregated data of positive and negative events, we absolute value of $CAR_{i,T}$ before we did the calculation. The results from aggregated data showed significant $\overline{CAR_T}$ for all the event periods at 1% confidential level. It might be biased since we used absolute value of $CAR_{i,T}$ before the test and it created over-abnormal return and made the results unreliable. We analyzed further by separating the events into positive and negative events for all the event types (Outlook, CreditWatch and Rating action), it gave more reliable results.

In case of positive events, there was no significant $\overline{CAR_T}$. As for the negative events, there was significant t-test for $\overline{CAR_T}$ at 5% confidential level for the pre-event period [-30, -2] and [-7, -2]. Overall, CDSs react to negative events before the announcement date since we can find the abnormal return since day -30 and the abnormal return appeared again in -7 days while in the positive event, there was no signal from CDS market. The result from Table 4.1 aligned with the prior works from *Hull, Predescu and White (2004)* and earlier papers which suggest that positive credit announcements didn't contained credit risk information in the market's view.

Table 4.1

$\overline{CAR_T}$ based on Event Study T-test from all types of credit events (Outlook, CreditWatch and Rating action) after controlling with contamination from other events occurred in period before the event date 120 days and after event date 30 days.

Event types	Periods	N	Event study t-test			
			$\overline{CAR_T}$	$\sum(\sigma_i^2 \times n_{i,T})$	t-test	p-value
Aggregated data between Positive and Negative events	[2,30]	50	0.1274	1.4689	5.26	**0.00** ***
	[2,15]	50	0.0646	0.7582	3.71	**0.00** ***
	[2,7]	50	0.0393	0.3280	3.43	**0.00** ***
	[-1,1]	50	0.0512	0.1430	6.77	**0.00** ***
	[-30,-2]	50	0.1438	1.5497	5.78	**0.00** ***
	[-15,-2]	50	0.0885	0.7534	5.10	**0.00** ***
	[-7,-2]	50	0.0543	0.3188	4.81	**0.00** ***
Positive events	[2,30]	25	0.0236	0.6745	0.72	0.48
	[2,15]	25	0.0171	0.3286	0.75	0.46
	[2,7]	25	0.0102	0.1333	0.70	0.49
	[-1,1]	25	0.0113	0.0886	0.95	0.35
	[-30,-2]	25	-0.0260	0.6636	-0.80	0.43
	[-15,-2]	25	-0.0260	0.3240	-1.14	0.27
	[-7,-2]	25	-0.0143	0.1345	-0.98	0.34
Negative events	[2,30]	25	-0.0041	0.7945	-0.11	0.91
	[2,15]	25	-0.0091	0.2176	-0.49	0.63
	[2,7]	25	0.0060	0.1947	0.34	0.74
	[-1,1]	25	0.0067	0.0935	0.54	0.59
	[-30,-2]	25	0.0934	0.8861	2.48	**0.02** **
	[-15,-2]	25	0.0359	0.4294	1.37	0.18
	[-7,-2]	25	0.0372	0.1843	2.16	**0.04** **

* Significance at 10%
** Significance at 5%
*** Significance at 1%
In case of Combination between Positive and Negative events, we absoluted $\overline{CAR_T}$ value before testing with both t-test

As described above that we've adjusted the direction of events by adding positive and negative direction for Outlook announcements in order to test along with other credit events. According to the fact that Outlook announcements are used by the credit rating agencies as potential status of the rating movements and are launched before the change for intermediate term, we considered them as non-active variable for our study's periods. In the next session, we considered to drop Outlook announcements from the tests and analyzed for CreditWatch and Rating action.

Table 4.2

$\overline{CAR_T}$ calculation based on Event Study T-test from CreditWatch and Rating action events after controlling with contamination from other events occurred in period before the event date 120 days and after event date 30 days.

Credit events	Periods	N	Event study t-test			
			$\overline{CAR_T}$	$\sum(\sigma_i^2 \times n_{i,T})$	t-test	p-value
	[2,30]	15	0.0418	0.5432	0.85	0.41
	[2,15]	15	0.0350	0.2647	1.02	0.33
	[2,7]	15	0.0185	0.1074	0.84	0.41
Positive events	[-1,1]	15	0.0162	0.0726	0.90	0.38
	[-30,-2]	15	-0.0767	0.5345	-1.57	0.14
	[-15,-2]	15	-0.0527	0.2604	-1.55	0.14
	[-7,-2]	15	-0.0212	0.1063	-0.97	0.35
	[2,30]	17	0.0160	0.4377	0.41	0.69
	[2,15]	17	-0.0121	0.2165	-0.44	0.67
	[2,7]	17	0.0102	0.0966	0.56	0.59
Negative events	[-1,1]	17	-0.0066	0.0487	-0.51	0.62
	[-30,-2]	17	0.1239	0.4465	3.15	**0.01 *****
	[-15,-2]	17	0.0590	0.2165	2.16	**0.05 ****
	[-7,-2]	17	0.0483	0.0928	2.70	**0.02 ****

* Significance at 10%
** Significance at 5%
*** Significance at 1%

The results shows in Table 4.2 confirmed that for positive case, there was still no significant abnormal return for the whole periods. However, the results from negative announcements were difference from Table 4.1. We can find significant abnormal return in the entire pre-event periods for [-30, -2] at 1% level, [-15, -2] and [-7, -2] at 5% confidential level. Our results were still implied that CDS market better anticipates negative news more than positive news. CDS market were fully anticipated to negative announcements before the event date for 30 days and the impact was still appeared approximately 7 days before the event date. This confirmed that credit Outlook reports had no significant impact to CDS market because after dropping it resulted in more significant abnormal return.

Table 4.3

$\overline{CAR_T}$ calculation based on Event Study T-test separately for Outlook, CreditWatch and Rating action after controlling with contamination from other events occurred in period before the event date 120 days and after event date 30 days.

Event types	Directions	Periods	N	Event study t-test			
				$\overline{CAR_T}$	$\sum(\sigma_i^2 \times n_{i,T})$	t-test	p-value
Outlook	**Positive**	[2,30]	10	-0.0038	0.1313	-0.10	0.92
		[2,15]	10	-0.0097	0.0639	-0.38	0.71
		[2,7]	10	-0.0021	0.0259	-0.13	0.90
		[-1,1]	10	0.0039	0.0160	0.31	0.76
		[-30,-2]	10	0.0501	0.1292	1.39	0.20
		[-15,-2]	10	0.0154	0.0636	0.61	0.56
		[-7,-2]	10	-0.0041	0.0282	-0.24	0.81
	Negative	[2,30]	8	-0.0466	0.3567	-0.62	0.55
		[2,15]	8	-0.0028	0.2130	-0.05	0.96
		[2,7]	8	-0.0028	0.0980	-0.07	0.95
		[-1,1]	8	0.0349	0.0448	1.32	0.23
		[-30,-2]	8	0.0285	0.4396	0.34	0.74
		[-15,-2]	8	-0.0133	0.2128	-0.23	0.82
		[-7,-2]	8	0.0135	0.0915	0.36	0.73
CreditWatch	**Positive**	[2,30]	3	0.1414	0.2256	0.89	0.47
		[2,15]	3	0.0269	0.1128	0.24	0.83
		[2,7]	3	0.0079	0.0468	0.11	0.92
		[-1,1]	3	0.0085	0.0305	0.15	0.90
		[-30,-2]	3	-0.2683	0.2201	-1.72	0.23
		[-15,-2]	3	-0.1223	0.1111	-1.10	0.39
		[-7,-2]	3	-0.0616	0.0434	-0.89	0.47
	Negative	[2,30]	7	0.0214	0.1545	0.38	0.72
		[2,15]	7	-0.0247	0.0759	-0.63	0.55
		[2,7]	7	-0.0127	0.0341	-0.48	0.65
		[-1,1]	7	-0.0212	0.0191	-1.07	0.32
		[-30,-2]	7	0.0870	0.1579	1.53	0.18
		[-15,-2]	7	0.0451	0.0759	1.14	0.30
		[-7,-2]	7	0.0090	0.0304	0.36	0.73

* Significance at 10%

** Significance at 5%

*** Significance at 1%

Table 4.3 (Continue)

$\overline{CAR_T}$ calculation based on Event Study T-test separately for Outlook, CreditWatch and Rating action after controlling with contamination from other events occurred in period before the event date 120 days and after event date 30 days.

Event types	Directions	Periods	N	Event study t-test			
				$\overline{CAR_T}$	$\sum(\sigma_i^2 \times n_{i,T})$	t-test	p-value
Rating action	**Positive**	[2,30]	12	0.0168	0.3176	0.36	0.73
		[2,15]	12	0.0334	0.1519	1.03	0.33
		[2,7]	12	0.0211	0.0606	1.03	0.33
		[-1,1]	12	0.0181	0.0421	1.06	0.31
		[-30,-2]	12	-0.0288	0.3143	-0.62	0.55
		[-15,-2]	12	-0.0353	0.1493	-1.10	0.30
		[-7,-2]	12	-0.0111	0.0629	-0.53	0.61
	Negative	[2,30]	10	0.0121	0.2833	0.23	0.82
		[2,15]	10	-0.0032	0.1406	-0.09	0.93
		[2,7]	10	0.0261	0.0626	1.04	0.32
		[-1,1]	10	0.0035	0.0297	0.21	0.84
		[-30,-2]	10	0.1498	0.2885	2.79	**0.02 ** **
		[-15,-2]	10	0.0688	0.1406	1.83	**0.10 * **
		[-7,-2]	10	0.0758	0.0625	3.03	**0.01 ** **

* Significance at 10%
** Significance at 5%
*** Significance at 1%

Table 4.3 displays the results when we conducted event study tests by classified much more to the type of credit events which are Outlook, CreditWatch and Rating action and separated it into positive and negative events to analyzed difference impact to CDSs.

Rating Outlook has 18 events (10 positive and 8 negative Outlook events after the stable Outlook adjustments). There was no significant $\overline{CAR_T}$ for credit Outlook events as we suspected. This aligned with our assumptions that Outlook events have long period of potential in intermediate term to gather vital information to a Rating change. Therefore, market will carefully price in these types of credit announcements into CDSs.

Similar to the Outlook reports, CreditWatch announcements (consist of 3 positive and 7 negative events), had no significant $\overline{CAR_T}$ in any event periods. These results from Outlook reports and CreditWatch announcements both unfamiliar with the prior studies that CDS market also anticipates with the report on these events.

In case of Rating action announcements (consist of 12 positive and 10 negative events), all of positive Rating action (actual Upgrade) had no significant reaction from CDS market. On the contrary, the results from Actual Downgrade had significant abnormal return with positive yield changes in the pre-event period [-30, -2] at 5% confidential level, [-15, -2] at 10% level and 5% confidential level in period [-7, -2]. The abnormal return could be found since 30 days before the event date and occurred along the time near the event date. This demonstrates that CDS market strongly anticipate to the actual Downgrade reports and also make the price adjustment until the time of event date.

Hence, for actual Rating action, the results confirm that CDS market asymmetry react between positive and negative events. CDS market fully anticipated in case of actual Downgrade but we can't find any reaction from the market for actual Upgrade events. The strongly significant abnormal return from Actual Downgrade events contradict with the prior studies since they suggested that Outlook and CreditWatch reports do contain credit information rather than Actual Rating action.

4.2 Logistic Regression results

Refers to results from event study analysis as described in Table 4.2 and 4.3, we analyzed further whether CDSs can be a good predictor for future credit events or not. There was only actual Downgrade event that have abnormal spread changes in the pre-event period for 30 days before the announcements. Hence, we can assume from the result that CDSs could have predictive ability only for actual Downgrade announcement. We employed Logistic regression for this analysis assigned dependent variable to be 0 and 1, the predictor came from $CAR_{i,T}$ calculation similar to the Event study analysis. $CAR_{i,T}$ used in this test determined from 30 days interval back date from an event study and estimated bases on its historical spread back date further to days [-150, -31] and rolling the estimation period until 1 year. After dropping the intervals which contains earnings announcements and contaminated credit events, we got 35 samples (with y=1 equal to 10 samples) for Estimation period back to 150 days and 81 samples (with y=1 equal to 10 samples) for Estimation period back to 1 year. The Logistic regression results are shown as per table 4.4 and 4.5 as below.

Table 4.4

Logistic Regression Analysis, the Logistic function is $P = \frac{1}{1+e^{-z}}$ in this model, independent variable came from absolute of Cumulative Abnormal Return (CAR) events from actual Downgrade with 30 day-intervals with Estimation period 150 days before the event date and track back for 150 days (track back for 5 intervals from the event date).

Outcome variable	Predictor variables	β_i	Std. Error β_i	Odd ratio e^{β}	z	p-value
Credit events	Constant	-1.674544	0.604592	0.187394	**-2.77**	**0.01** ***
	CAR	5.352912	3.121678	211.222500	**1.71**	**0.09** *

Number of obs.	35 *(with y=1 equal to 10 samples)*	* Significance at 10%
Pseudo R-square	0.0774	** Significance at 5%
Likelihood ratio (df=1)	3.24	*** Significance at 1%
p-value (Chi-square)	0.0718	
Predicted prob at y=1	35.75%	

Table 4.4 displays results of Logistic regression for $CAR_{i,T}$ that has Estimation period back to 150 days before the credit announcements. Likelihood ratio and goodness of fit tests show significant relationship between the coefficient of predictor and dependent variable at 10% confidential level. The predictor which is $CAR_{i,T}$ from historical 150 days each 30-day intervals has p-value equal to 0.09 which was rejected by null hypothesis at 10% confidential level. Further, Logistic regression could also computed the predicted probability of the future credit announcements based on CDS spread $CAR_{i,T}$ equal to 35.75%. As a result, we could imply that $CAR_{i,T}$ from historical 150 days can be a good predictor for the near-future actual Downgrade events.

Table 4.5

Logistic Regression Analysis, the Logistic function is $P = \frac{1}{1+e^{-z}}$ in this model, independent variable came from absolute of Cumulative Abnormal Return (CAR) events from actual Downgrade with 30 day-intervals with Estimation period 150 days and track back until 1 year (track back for 12 intervals from the event date).

Outcome variable	Predictor variables	β_i	Std. Error β_i	Odd ratio e^{β}	z	p-value
Credit events	Constant	-2.658822	0.558145	0.070031	**-4.76**	**0.00** ***
	CAR	4.687579	2.526688	108.589900	**1.86**	**0.06** *

Number of obs.	81 *(with y=1 equal to 10 samples)*	* Significance at 10%
Pseudo R-square	0.0540	** Significance at 5%
Likelihood ratio (df=1)	3.27	*** Significance at 1%
p-value (Chi-square)	0.0705	
Predicted prob at y=1	16.90%	

Table 4.5 shows Logistic regression results for the relationship between probability of credit events and its historical $CAR_{i,T}$ date back before the event for 1 year. The model has larger N here and z-test failed to reject null hypothesis as p-value of coefficient equal to 0.06 but the predictive ability was reduced to 16.90%. Hence, $CAR_{i,T}$ calculated from abnormal return of CDS spread using historical data for 1 year also can be a good predictor for the future actual Downgrade events.

We're also constructed Cumulative Average Abnormal Return (CAAR) to figure the level of changes in spread return from equation below.

$$CAAR = AAR_t + AR_{t+1} \tag{13}$$

Cumulative Average Abnormal Return (CAAR) is calculated from daily abnormal return average from each of corporate in the same event windows and we got daily Average Abnormal Return (AAR_t). Then we calculated for the CAAR from AAR_t.

Figure 4.1: Cumulative Average Abnormal Return (CAAR) from positive and negative credit Outlook reports.

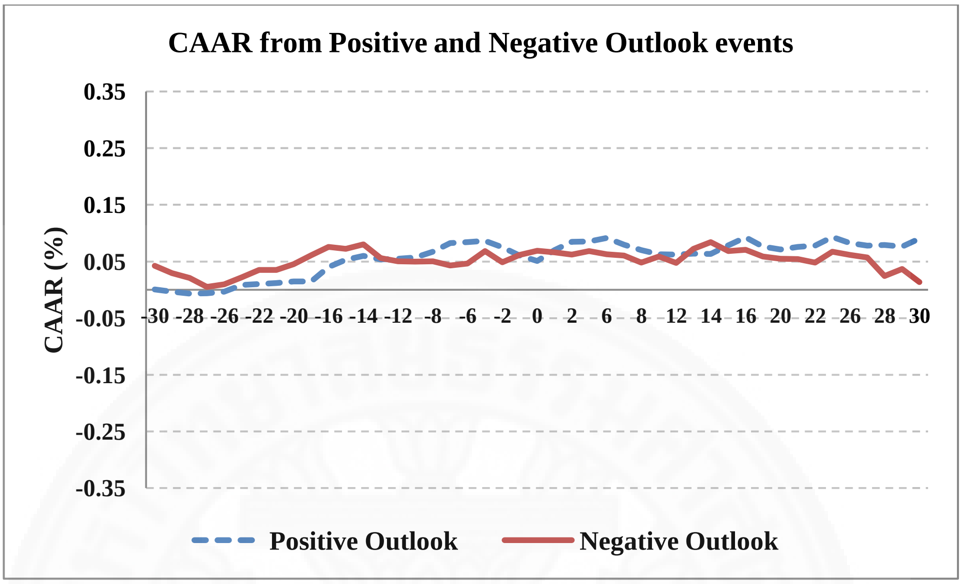


Figure 4.2: Cumulative Average Abnormal Return (CAAR) from positive and negative CreditWatch announcements.

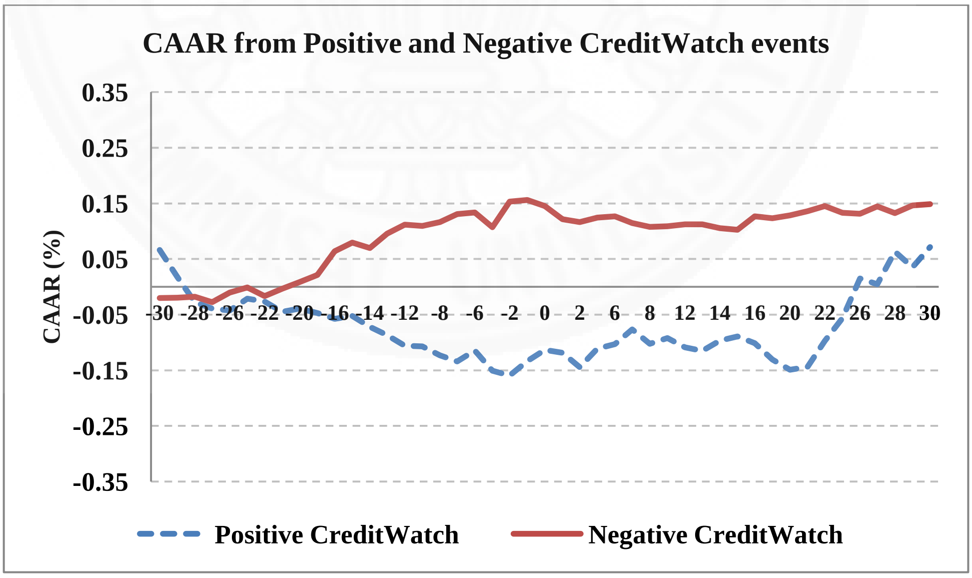


Figure 4.3: Cumulative Average Abnormal Return (CAAR) from actual Upgrade and Downgrade Rating Action announcements.

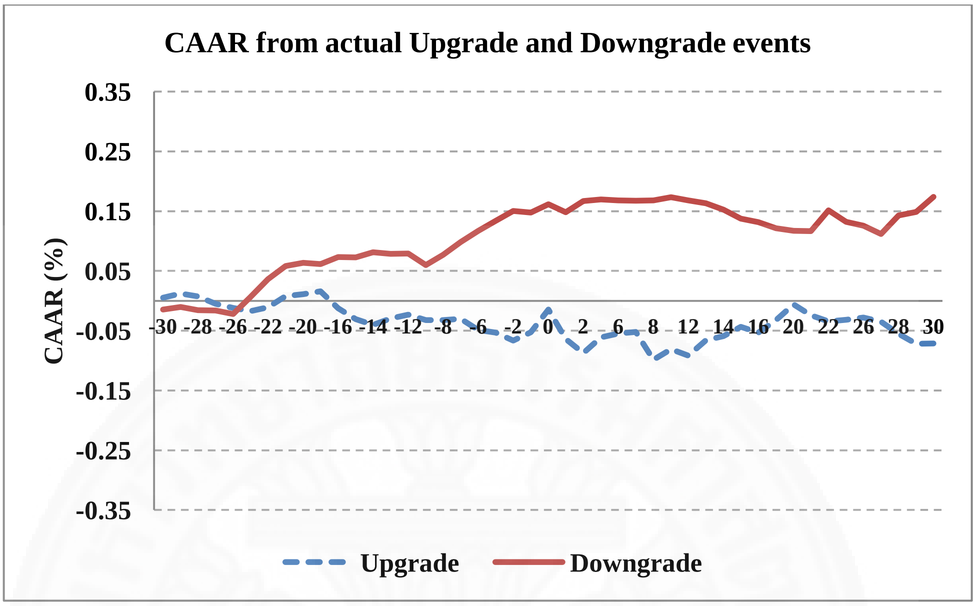


Figure 4.4: Impact from Outlook, CreditWatch and Rating Action to the absolute Cumulative Average Abnormal Return (absolute CAAR).

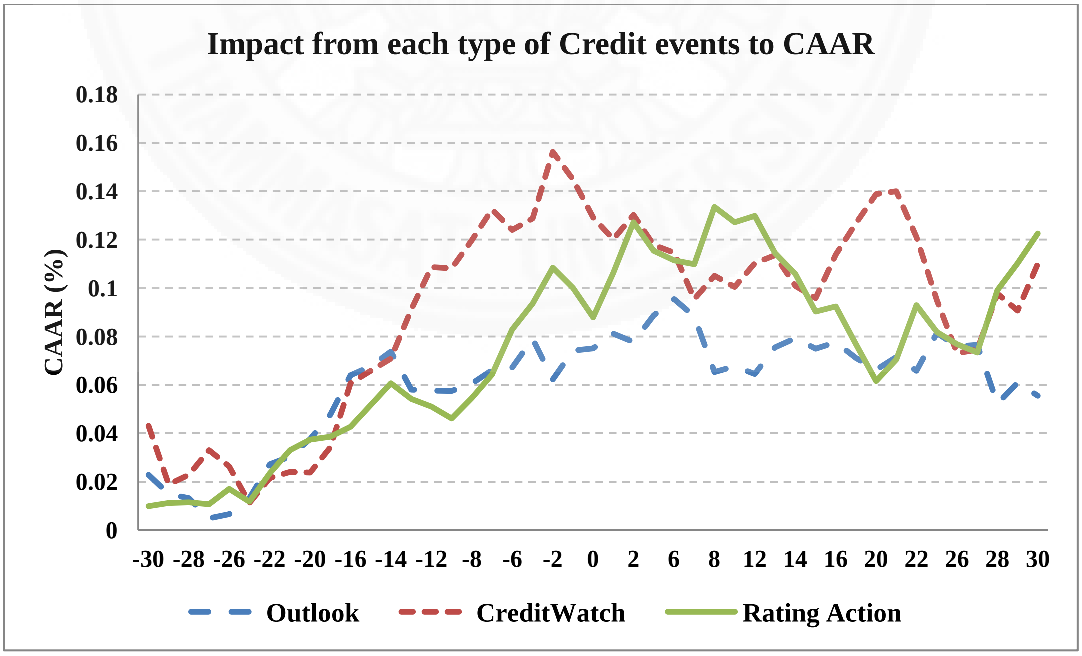
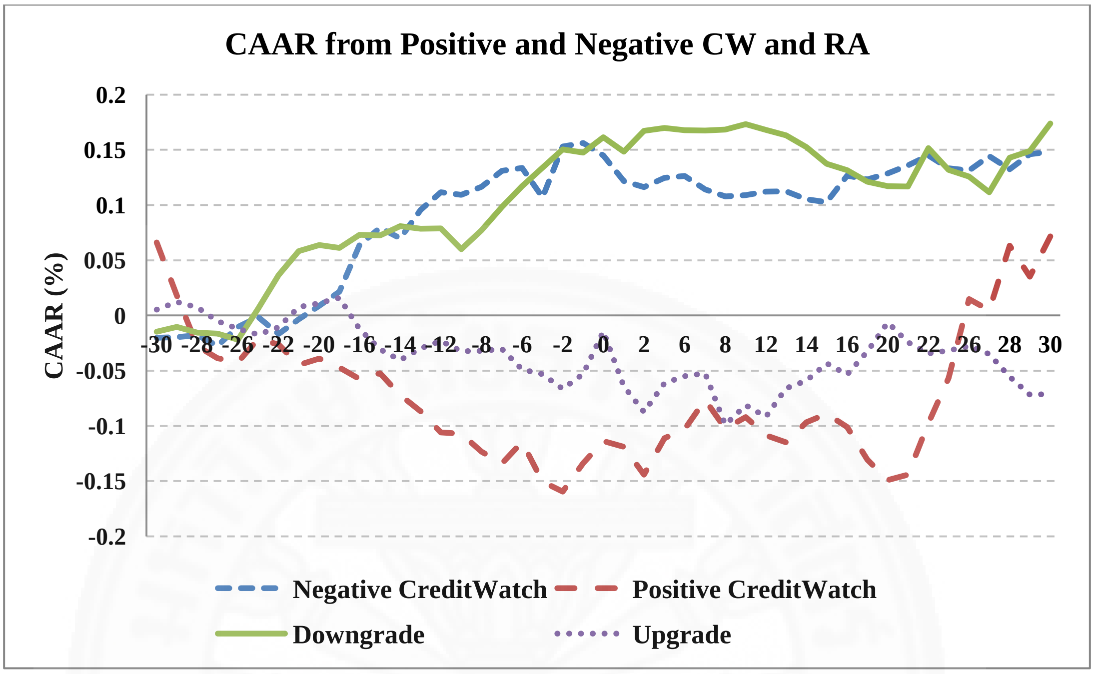


Figure 4.5: Cumulative Average Abnormal Return (CAAR) from CreditWatch and Rating Action classified into positive and negative events.[1]



[1] Since our t-test calculation from $t - test_T = \frac{\overline{CAR_T}}{\sqrt{\sigma^2{}_T}}$ and $\sigma^2{}_T = \frac{1}{N^2}\sum_i^N(\sigma^2{}_i \times n_{i,T})$, $t - test$ could not found abnormal return from CreditWatch which has lower N.

CHAPTER 5
CONCLUSIONS AND RECOMMENDATIONS

Our results from event studies can be explained that CDSs movement is relevance to credit events and the market does have ability to anticipate before the credit announcements for actual Downgrade event. On the other hand, they didn't perform in case of Outlook reports, CreditWatch and actual Upgrade events. The results differ from prior studies that most of them explored strongly significant abnormal return in case of Outlook reports and CreditWatch announcements since the market would price in these information before the actual Rating action. However, our results are still similar to some papers that the CDS market only anticipates for negative credit announcements as we can't find significant abnormal return in case of positive credit events.

Our studies focused on CDSs written on the bond of issuers from emerging market in South East Asia including Thailand, Malaysia and Philippines which we assumed that most of them are less-liquid names and CDS market could not anticipate them before the announcements. However, from results of Event Study analysis, we can conclude that our assumption was not correct. First, CDS market can anticipate for the actual Downgrade announcements 30 days prior to the event date. Secondly, we found that Credit Outlook and CreditWatch events weren't priced in to the spread around the time of events. Thirdly, the market asymmetry reacts to actual Rating action announcements between positive and negative events. They adjusted the spread before the actual Downgrade events whereas it's insignificantly reacts in spread adjustment in case of actual Upgrade events. Finally, CDS written on the issuers in emerging market can be considered as illiquid name in the CDS market.

Borrowers from emerging market are more difficult for investors and credit analysts to track their financial and credit risk information. The investors and analysts should rely more on the announcements from credit rating agencies especially for actual Downgrade to ensure the information before they can take any actions. The negative events that can ruin investment portfolios and counter-party trading transactions, are more focused than those from the positive news as we can see only the impact from actual Downgrade. Another point of differences is impact of Outlook and CreditWatch reports which are the intermediate-term signaling to CDS market. In developed market with higher liquidity, the Outlook or even CreditWatch reports are eventually used to consider for the spread adjustments rather than the Actual Rating action. On the contrary, the Outlook and CreditWatch reports will increase volatility in emerging market since they have smaller and less-liquidity compared to the developed market. However, our low number of N may result in insignificant abnormal return determined by t-test in some cases.

There were a few studies that employed Logistic regression to analyze predicted ability of CDSs to the credit events. Moreover, their results were not widely acknowledged in terms of used in academic matters. We altered methods for Logistic regression to use Cumulative Abnormal Return ($CAR_{i,T}$) instead of the spread changes. The Logistic regression gave us significant predicted probability of CDSs on actual Downgrade events which will occur in the next 30 days when collected Estimation window 150 days and one year before the event date.

To conclude, the parties who have direct and indirect obligations with the reference entities of CDS should consider on anticipation ability of CDSs especially in case of actual Downgrade. The spread can be used as the primary observation for changes in credit quality of the issuers prior to the credit rating announcements by 30 days. Investors and credit analysts should be aware of it in case the spread moves significantly.

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