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Measuring the Impact of Recurring Events on Financial Assets

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Abstract

I documented the impact of recurring events on financial assets using a new event study methodology. The new methodology follows the overall structure of a typical event study, but it also objectively identifies a unique duration of each event to be used for cumulative average abnormal return. Moreover, 2 simple criteria are proposed to objectively detect the direction of price movement. To conduct an event study with the new methodology, I developed an algorithm that has 2 user-defined variables according to the needs of the user. The algorithm measures the impact before, during, and after an event, and conducts significance tests at 90%, 95%, and 99% level. Market indices, stocks, and ETFs were evaluated from 2009 to 2019. The algorithm performed better for unexpected events than it did for expected events. I exposed shortcomings of the methodology and the algorithm, and provided directions for further research.

Keyword : Event Study, Research Methodology, Event Duration, Event Direction, Cumulative Average Abnormal Return

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Chapter 1. Introduction

1.1 Motivation

In modern portfolio theory and investment management, various pricing models are used to value financial assets to meet investment objectives. The effectiveness of the models varies depending on how close the assumptions in the model match the environment where the asset is to be priced. For example, market inefficiency (RayBall, 1994), expense fees to the portfolio manager (Cornell and Roll, 2005), transaction costs (Mayshar, 1981), restrictions on transaction (Gkillas and Longin, 2018), and other factors could cause empirical price to deviate from the price determined by theoretical models.

Unforeseen events, or even expected events that are not well understood, could also affect pricing models that can work well in the usual times. Geopolitical events, for instance, could give a shock to the financial market (Pastor, 2011). In recent time, Brexit Referendum contributed to a depreciation of GBP, while global uncertainty during the Covid-19 pandemic contributed to an increase of gold price. Thus, understanding the impact of events on financial markets can be a relevant topic for researchers (Dyckman et al., 1984; Dimson and Marsh, 1986; McWilliams et al., 1999; Chau et al., 2011).

Active investors attempt to capture arbitrage from inefficient market (Froot et al., 1992; Petajistro, 2017). Particularly after certain events, the price of associated financial assets fluctuate because investors do not have sufficient information to determine fair price of assets (Baker and Savasoglu, 2001; Heron and Lie, 2007). Thus, a better understanding of events' impact on financial assets can be resourceful to the investors who want to rebalance their portfolio composition during the turbulent times.

Given that assets can be mispriced following events, I analyze in this paper how different assets react to different events. Rather than conducting an event study on a single specific impact of a huge shock on the financial market, I focus on recurring events with the intent to identify any potential patterns of recurring event – financial asset pairs. Investors can learn from the patterns, accumulated from the past data, to respond as the newest recurring event unfolds.

Impact from an event refers to cumulative average abnormal return, which is commonly used in any event study to assess the magnitude of the event on a financial asset of interest. Unlike previous studies that chose the event window at researchers' discretion, which consequently affect the number of days to be used in cumulative return of the event, I assess the impact of recurring events using a newly developed algorithm.

The algorithm, inspired from a polar science research (Park et al., 2019), provides two benefits compared to the traditionally used methodology in event study. First, it objectively determines the duration of each event, instead of applying the same duration for all events. Finding the precise duration for each event is of relevance because there is a lack of standard practice to do so, leading to arbitrarily set event duration (Gim and Jang, 2020). Second, the algorithm detects the direction of return, which is not often explored but is of relevance to the researchers (Park, 2004; Curran and Moran, 2007).

The algorithm also returns other pertinent information that investors may find useful in an event study, including post-event return analysis, significance test at 90%, 95%, and 99% confidence levels, and the number of events in each direction.

This new method can be especially useful for the researchers who want to remove their subjectivity in choosing the event duration, and for those who want to easily identify the direction of return following the event. It may not better or appropriate than the alternative in every aspect, as sometimes human element can be an important factor in interpreting abnormal returns; however, it is at least a new tool for researchers to use in their event study.

1.2 Background

The field of event study began in 1969 (Binder, 1998), and since has been used in finance and beyond: earnings announcement (Patell, 1976; Syed and Bajwa, 2017), factor model (Brown and Weinstein, 1985), innovation (Austin, 1993), stock splits (RayBall et al., 1994; Armitage, 1995), sports events (Berman et al., 2000; Veranos et al., 2004; Scholtens and Peenstra, 2009; Dick and Wang, 2010), investment (Im et al., 2001), natural disasters (Ewing et al., 2006), corporate social governance (Curran and Moran, 2007), elections (Pastor, 2011), political uncertainty and terrorist attacks (Chau et al., 2014), IPO (Irshaid and Al-Ghusain, 2014), climate policy (Han et al., 2019), and online news (Yu and Huarng, 2020). Perhaps the broad scope of event study's applicability has been the contributing factor to the increasing volume of its literature.

Despite some limitations of the event study (McWilliams et al., 1999), literature notes the effectiveness of the methodology when reviewing an event's financial impact (Curran and Moran, 2007; Duso et al., 2010). Depending on the needs of the specific research or the characteristics of the data, slight modification is commonly made on the traditional approach.

An algorithm using a different set of rules than the ones to be described in this research, was developed (Inclan and Tiao, 1994) and used (Cheng and Lee, 2008) to determine the appropriate event window. As a contrast, the algorithm developed and used in this research only determines the event duration, which would be equivalent to the event window past the event date in other research.

To verify the effectiveness of the algorithm, this study will compare each analysis of an event on an asset: classic method versus the output of the algorithm. This comparison does not disregard the effectiveness of the well-established event study methodology; rather, this exercise is intended to demonstrate for which purpose the algorithm can work as intended. Further, the comparison can reveal the limitations of the algorithm.

1.2.1 Traditional approach

First, a security' s return is adjusted relative to the general market condition, to find the abnormal return. Then, the average of the abnormal return during the event window can be interpreted as the average deviation of the return during the event relative to the market condition. Cumulating this average abnormal return is, then, the cumulative average deviation of the return during the event relative to the market condition. (Fama et al., 1969). In a way, cumulative average abnormal return could be thought of as a difference-in-difference estimator that reveals the difference between actual and counterfactual return (Johannesen and Larsen, 2016). Event study typically finishes with a significance test of the abnormal returns (Armitage, 1995).

Other subsequent studies have also solved for cumulative abnormal return before solving for cumulative average abnormal return, and arrive at the same conclusion. This paper takes the second approach, as the duration of the event is unique to each event; cumulative abnormal return can give the total effect of each event - asset pair.

Chapter 2. Data

2.1 Study Period

Study period ranges from 2009 January 1 to 2019 December 31. This range was specifically chosen to avoid 2 major recent financial crisis that would undoubtedly have an effect on relatively smaller impact of recurring events. This selection is motivated by a previous study that conducts event study for each primary market trend (Asgharian et al., 2011). The 2 major financial crisis avoided are Global Financial Crisis during 2007-2008, and Covid-19 Crash in 2020.

Financial data were only collected within the aforementioned study period, while event dates were collected from 2009 to 2018, to allow a maximum of 1 year window to be investigated, following the last possible event date in 2018.

2.2 Financial Data

I collected 2 specific stocks and 5 market indices, as well as ETFs of different sectors, commodities, and more. These assets were split into 3 groups as listed below: (1) Stock indices, (2) Sector ETFs & Stocks, and (3) Uncorrelated financial assets. (1) Stock indices enables investors to evaluate the overall market situation, whereas (2) Sector

ETFs & Stocks has a narrower focus on specific portions of the market. (3) Uncorrelated financial assets can be used to analyze the effectiveness of diversification effect that many investors seek. All available daily close data of the financial assets listed below were collected from Refinitiv Eikon.

Stock indices

Symbol	Name of financial asset	Characteristics
KOSPI200	The Korea Composite Stock Price Index	Market index of Korea Stock Exchange
KOSDAQ	Korean Securities Dealers Automated Quotations	Korea SMEs and venture focused
DJI	Dow Jones Industrial Average	30 US large cap companies
SPX	S&P 500 Index	500 US large cap companies, reflecting overall US market
RUT	Russell 2000 Index	Represents US small cap

Sector ETFs & Stocks

Symbol	Name of financial asset	Characteristics
005930	Samsung Electronics Co Ltd	Samsung Electronics stock
AAPL	Apple Inc	Apple stock
XLK	Technology Select Sector SPDR Fund	Technology ETF
IYZ	iShares U.S. Telecommunications ETF	Telecommunications ETF
JETS	US Global Jets ETF	Airline industry ETF

Uncorrelated financial assets

Symbol	Name of financial asset	Characteristics
DJP	iPath Dow Jones-UBS Commodity ETN	Broadly diversified commodities
IAU	iShares Gold Trust	Gold
VNQ	Vanguard Real Estate Index Fund	Diversified real estate
XLU	Utilities Select Sector SPDR Fund	Broadly diversified utilities
EMB	iShares J.P. Morgan USD Emerging Markets Bond ETF	Broadly diversified emerging markets bonds
MNA	IQ Merger Arbitrage ETF	Mimics hedge funds' merger arbitrage strategy

2.2.1 Exchange Traded Fund (ETF)

ETFs were first introduced in 1993, and continue to grow in asset value, trading volume, and diversity, as well as numbers (Chau et al., 2011; Madhavan, 2014; Lettau and Madhavan, 2018; Sherrill and Stark, 2018; Glosten et al., 2021). ETF’s popularity is attributed to its several characteristics that is attractive to the investors. Therefore, these characteristics also make it a worthwhile type of asset to collect and investigate in this paper.

Like stocks, ETFs can be traded throughout the trading hours. ETFs are also considered to be cost and tax efficient, and many of them also provide diversification benefit (Poterba and Shoven, 2002; Lopez et al., 2015; Lettau and Madhavan, 2018; Miralles-Quiros et al., 2018; Sherrill and Stark, 2018; Xu et al., 2020; Glosten et al., 2021). Moreover, the exact ETF composition and strategy are usually outlined by the ETF issuers (Miralles-Quiros et al., 2018; Lettau and Madhavan, 2018). This implies that ETFs can be a sensible asset to trade if an investor were to quickly respond to an ongoing event (Madhavan, 2014; Miralles-Quiros et al., 2018).

Each ETF that is to represent an asset class was chosen with a preference to large total asset and average trading volume. Exact breakdown of ETF composition updates frequently, and it is available online (https://etfdb.com/ for instance).

2.3 Recurring Events

Recurring events were chosen based on 3 factors: (1) same type of event can repeat, (2) such an event can affect associated financial assets, and (3) event can be determined on a "yes or no" basis. While these were the criteria for this paper, event study methodology in general can analyze any events that meet the second criteria. The third criteria could be removed in future research to include events that falls under the "grey area", such as strikes or political approval, perhaps by using natural language processing (Yu and Huarng, 2020), but this is beyond the scope of this research. Then, I collected the dates of these recurring events from the aforementioned time range.

Taking advantage of the effectiveness of event study in analyzing essentially any events, the events analyzed in this paper are: North Korea missile test, North Korea nuclear weapons test, Chuseok, Korean New Year, iPhone release, Plane crash, and Black Friday. Other possible recurring events that could be worth investigating, other than those already mentioned in Section 1.2 are: sports events (franchise relocation, European Championship League announcement, Olympics, Olympics announcement, World Cup, etc), climate meetings, automobile announcement, satellite launch, military training (Korea & US joint training), Easter, gaming console release, major gaming franchise (Call of Duty series, Football Manager series, and NHL series, etc), climate action pledge announcement (for the GCF, GEF, etc), and more.

Events analyzed in this paper can be subdivided into expected and unexpected events. As the name implies, expected events are the events that can be predicted ahead of the occurrence. Expected events are: Chuseok, Korean New Year, iPhone release, and Black Friday. Logically, unexpected events are unpredictable. Unexpected events are: North Korea missile test, North Korea nuclear weapons test, and plane crash.

2.4 Recurring Event – Financial Asset Pairs

The following table summarizes recurring events and financial asset pairs that were analyzed. The pairs were based on my judgement that the event can have the potential to affect the asset price. Uncorrelated assets were also analyzed to see how they respond, perhaps differently than the first 2 groups.

Table 1: Recurring event – financial asset pairs to be analyzed. Shaded background denote output shown in Appendix C, as well as the additional analysis done, as explained in Chapter 5.

	NK missile test	NK nuclear weapons test	Chuseok	Korean New Year	iPhone release	Plane crash	Black Friday
KOSPI200	O	O	O	O			
KOSDAQ	O	O	O	O			
DJI							O
SPX	O	O				O	O
RUT							O
005930	O	O	O	O	O		
AAPL					O		
XLK					O		O
IYZ					O		
JETS						O	
DJP	O	O	O	O		O	
IAU	O	O	O	O		O	
VNQ						O	
XLU						O	
EMB						O	
MNA						O	

Chapter 3. Methodology

The spirit of the algorithm is to ignore minor fluctuations while looking for the time index when the greatest cumulative deviation, the local optimum, occurred away from the usual return trend. To do so, the algorithm evaluate each trading day following the event to see if the deviation returned back enough to the "normal" return. Once this point is detected, the maximum deviation between the event date and this return date is identified, which gives duration and cumulative abnormal return an event.

Figure 1: Flowchart of the event study algorithm.

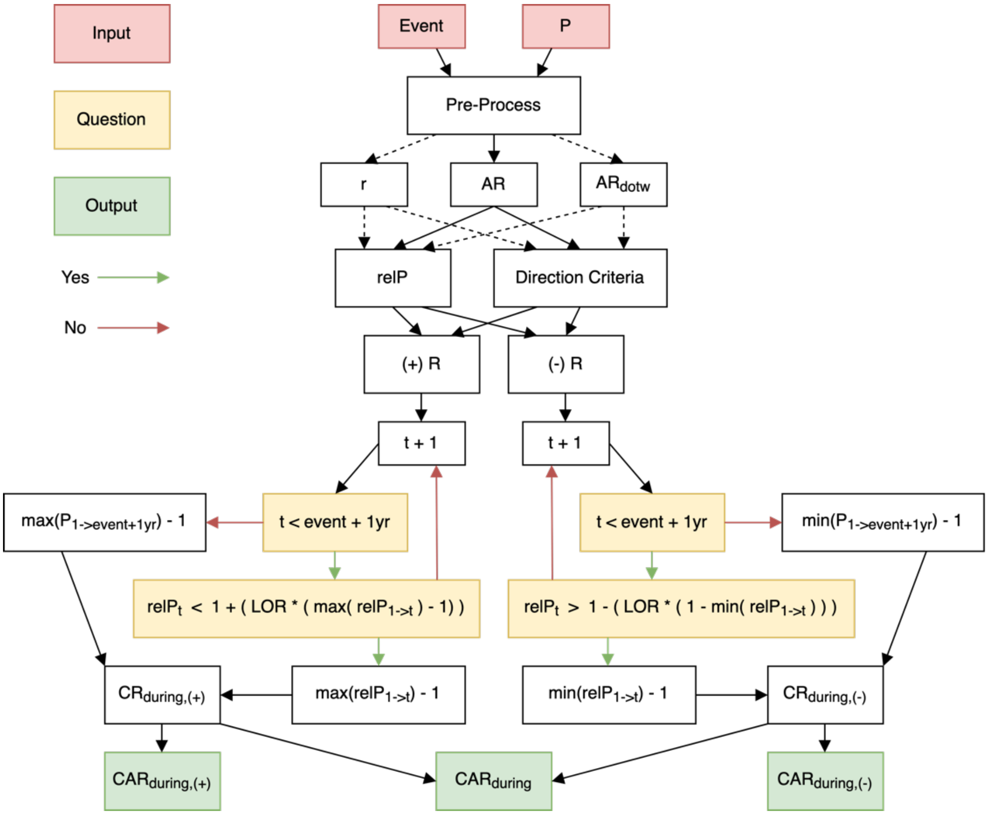
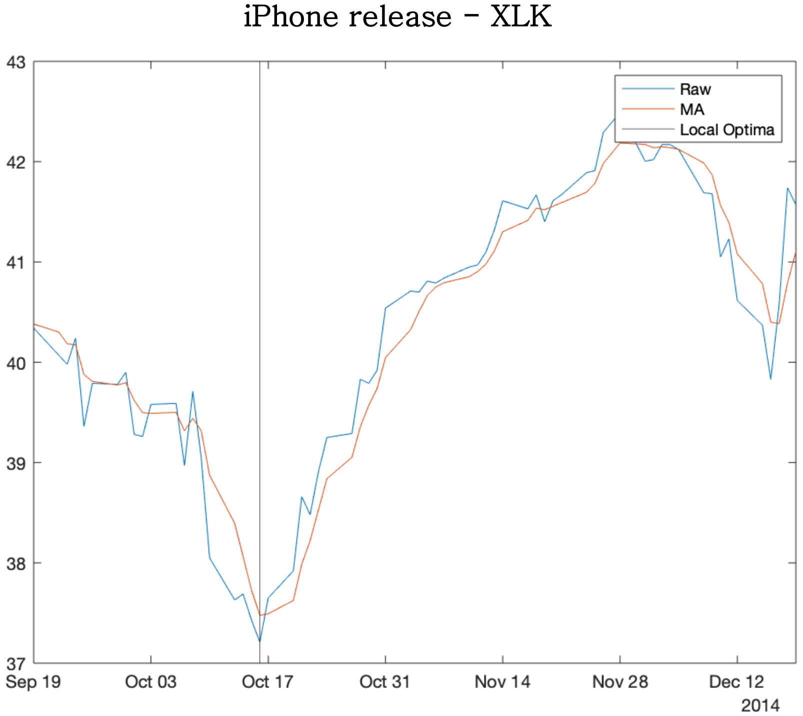


Figure 1 illustrates the essence of the algorithm used to conduct new methodology that can objectively detect direction and duration of each event on cumulative return. Figure 2 is XLK (technology ETF)' s response to one of the iPhone releases: on 2014 September 19. Feeding the algorithm with the event date and 5 day weighted moving average of XLK spot price r results in a negative cumulative return. The algorithm would repeat the procedure for all other release dates, to produce cumulative average returns for total, positive, and negative cumulative returns. Returns can be simple return, abnormal return, and day-of-the-week adjusted abnormal return.

Figure 2: iPhone release - XLK (Technology ETF). Event on 2014 September 19 (on y axis). Local optimum on 2014 October 16 (vertical line). Y axis is in USD.



The algorithm follows Section 3.2 to Section 3.5, as 3.1 isn' t a necessary component of the algorithm itself. Nevertheless, smoothing the data according to Section 3.1 can facilitate the algorithm in returning expected outputs.

There are 3 dimensions of cumulative return to be analyzed in this research. First is the type of return, as discussed in Section 3.3. Second is the direction of return, as discussed in Section 3.4. Third is the criteria for the direction of return, as discussed in Section 3.4. These additional factors, as well as the specific duration for each event, extend on a typical event study analysis.

Table 2: Comparison of analysis in event study.

Event study	Classic	Additional element
Return	CAAR	CAr, CAAR, $CAAR_{dotw}$
Duration	Arbitrary	Rule based
Direction	Total	Total, (+), (-)
Criteria for direction	NA	Sign, Standard deviation

Chapter 3 emphasizes each step of the algorithm to conduct the event study using the new method. Appendix B describes the mathematics without describing the algorithm.

3.1 Moving Average

Close price on its own is subject to daily volatility that can defer the analysis absence of the randomness. Thus, moving average (MA) can be applied to smooth the data. 3 types of moving average are often used in finance: (1) simple moving average, (2) weighted moving average, and (3) exponentially weighted moving average (Tsokos, 2010).

There is no MA that is generally applicable to all situations. Rather, the right MA and the number of periods is used on a case by case basis. While I calculated MAs using 3, 5, and 10 day periods, I analyzed the events using 5 day period to include every day in a trading week, as factor models demonstrates that the day of the week can have an effect on asset price (Kohli and Kohers, 1992; Patterson and Brorsen, 1993; Aggarwal and Schatzberg, 1997; Gayaker et al., 2020).

WMA was chosen because SMA puts too much emphasis on lagged data, while EMA puts too much emphasis on the recent data. Lagged data can distort the current evolution of the market, while too much emphasis on the recent data in a way nullifies the intention to smooth the data.

3.1.1 Simple moving average

Simple moving average (SMA), as its name implies, simply takes the simple average of all data from a given period. SMA can be solved as the follows:

(1) $SMA_t = \frac{(P_t + P_{t-1} + \dots + P_{t-I})}{\#}$

P_t -> price of an asset at time t
t -> time
t = 0 -> refers to the trading day that is either on or immediately follows the event day
i -> trading day relative to t
I -> highest i. −I would be the furthest trading days prior to t
= I + 1 -> total number of t in a period (+1 is needed because i starts at 0)

Equation (1) can be rewritten as:

(2) $SMA_t = \frac{1}{\#}\sum_{i=0}^{I} P_{t-i}$

3.1.2 Weighted moving average

Weighted moving average (WMA) simply takes the weighted average of all data from a given period. There are different ways to assign weight, but 1 common way is to assign linearly decreasing weight, moving away from t. This type of WMA can be solved as the follows:

(3) $$WMA_t = \frac{(w{=}\#)P_t + (\#-1)P_{t-1} + \ldots + (\#-I)P_{t-I}}{\# + (\#-1) + \ldots + (\#-I)}$$

w -> weight

Equation (3) can be rewritten as:

(4) $$WMA_t = \frac{1}{n(n+1)/2}\sum_{i=0}^{I}(w-i)P_{t-i}$$

3.1.3 Exponentially weighted moving average

Exponentially weighted moving average (EMA) is a special type of WMA, that takes exponential weight moving away from t. The exponential rate is determined by the smoothing factor α, and calculated iteratively as the follows:

(5) $$EMA_t = \alpha P_t + (1-\alpha)EMA_{t-1}$$

(6) $$\alpha = \frac{n}{t+1}$$

n = 2 is often used in EMA

EMA_{t-I} by definition is impossible to calculate because I is the furthest trading day away from EMA to be included in a moving average calculation. Thus, EMA_{t-I} is either replaced by SMA according to Equation (2), or simply P_{t-I}. With the first. Then, Equation (5) can be rewritten as:

(7) $EMA_t = \alpha \sum_i^{I-1}[(1-\alpha)^i P_{t-i}] + (1-\alpha)^I SMA_I$

With the later, Equation (5) can be rewritten as:

(8) $EMA_t = \alpha \sum_i^{I-1}[(1-\alpha)^i P_{t-i}] + (1-\alpha)^I P_{t-I}$

3.2. Temporal Data Pre-processing

3.2.1 Removing data 1 year beyond the event date

First, I excluded the events from the final year of study period. This is necessary because I limited the analysis of the returns following the event to be within 1 year. Thus, removing 1 year worth of the most recent trading dates from the study period ensures that the final trading date within the remaining can have a maximum of 1 year for analysis.

I analyzed up to 1 year following each event date because the analysis in this paper focuses on immediate impact of the event. 1 year is more than enough buffer to focus the immediate impact.

3.2.2 Matching event date with trading date to set t = 0

Unlike normal calendar days when an event can happen, financial market is not always open. The market typically opens on the weekdays, with some exception (example: New Year public holiday). Thus, I matched the event date with the closest following trading day. For example, if an event were to occur on Saturday or Sunday, the likely t = 0 is the following Monday.

3.2.3 Data range for analysis of each event

With the exact trading date known, the algorithm selects data range for the analysis of each event:

(9) $Trading\ date_{t=0-\mathrm{BAE}} < P_t < Event\ date_{t=0+1year}$

BAE -> before and after event, in trading days. This variable can be set in the algorithm

BAE in previous event study is the event window. In this paper, BAE is used to analyze before and post event returns, which is often ignored in the literature, but is of relevance because a short term response to an event may contrast a long term impact (Oler et al., 2008; Kaniel et al., 2012). For the main analysis in this paper, BAE = 20 was used, and for the extension work, BAE = 5 and 50 were used.

Exact value of event window is usually arbitrarily set, according to the needs of the research. There can be some reasoning in setting the window, by evaluating the cumulative average abnormal return over some period of time around the event date. Various range of event window has been used: -20 to +20 (Mackinlay, 1997), -15 to +15 (Lepetit et al., 2004), -10 to +10 (Syed and Bajwa, 2017), -9 to +9 (Irshaid and Al-Ghusain, 2014), -7 to +7 (Lepetit et al., 2004; Yu and Huarng, 2020), -5 to +5 (Brown and Warner, 1985), and 0 to +50 (Asgharian et al., 2011). For this paper, I selected BAE = 20, as it would give sufficient time to evaluate before and after each event.

For the remainder of this paper, event date would mean both event date and trading date, as the two terms are similar in the calendar date and identical in the data index.

3.3 Returns

3.3.1 Relative to 0%

Daily return relative to the previous day was solved as follows:

$$(10)\ r_t = \frac{P_t - P_{t-1}}{P_t}$$

Output using this daily return alone does not give any information on performance relative to the expected return, but on a short term basis, investors could be interested in simply knowing the raw change in spot price. Thus, I included r_t in the algorithm for analysis, as if it were an abnormal return.

3.3.2 Relative to $\bar{R}$

While knowing the simple return following the event can already be practical, investors can also be interested in return relative to the study period that can be a benchmark to compare (Zhu and Zhu, 2013; Nguyen, 2018; Farshadfar and Prokopczuk, 2019).

Abnormal return is the foundation of any event study. It can be solved by subtracting the expected return $E(r_t)$ from r_t. There are many models to solve for expected return, including market model, index model, average return model, CAPM, Fama-MacBeth model, and

Control portfolio model; average model performs worse if the same event date is used, but otherwise more complicated models do not yield better results (Armitage, 1995). Given that the purpose of this paper is not to compare different results of abnormal return solved using different expected returns, I follow through the simplest model, which is average return model:

$$(11)\ \bar{R} = \frac{\ln\left(\frac{P_{last}}{P_{first}}\right)}{(t_{last} - t_{first})}$$

$\bar{R}$ -> average return with continuous compounding, which approximates daily return
first -> first value in the study period after pre-processing
last -> last value in the study period after pre-processing

The length of the estimation window to solve for $\bar{R}$ can vary in the literature, as does the event window; typically, estimation window would be under 1 year. For this research, I selected the entire study period to be the estimation window, similar to the research that analyzed the entire bull and bear markets, which used the entire primary market trend to find the prevailing market condition (Asgharian et al., 2011).

With $\bar{R}$, abnormal return can be solved as follows:

(12) $AR_t = r_t - \bar{R}$

AR_t -> abnormal return at time t

3.3.3 Relative to day-of-the-week

I also analyzed abnormal return relative to each day of the week, which was not often included in previous research because the results are similar to the usual abnormal return (Dick and Wang, 2010). Nevertheless, this exercise could verify whether there is any significant improvement to taking account of the day-of-the-week effect. To find return relative to day-of-the-week, the following equation gives geometric mean return for each day-of-the-week:

(13) $\bar{R}_{dotw} = \prod_{t=first\ dotw}^{last\ dotw}(1 + r_t) - 1$, for each dotw

dotw -> day-of-the-week

Using Equation (13), return relative to day-of-the-week can be solved as follows:

(14) $AR_{dotw,t} = r_t - \bar{R}_{dotw}$, for each dotw

3.4 Direction

2 separate approaches were used to detect the direction, as defined as the increase or the decrease in the spot price immediately following the event. Accordingly, the algorithm returns output for each approach. Typically, researchers would have subjective expectation on the direction of their research (Patell, 1976), so they do not often distinguish the returns for both directions; instead, both increase and decrease are combined in their analysis. With my approach, total, positive, and negative returns for a recurring event are analyzed. Other research proposed different criteria, such as using intraday data, to determine the direction (Asgharian et al., 2011). Furthermore, other new event study methodology also shows the relevance of understanding direction (Yu and Huarng, 2020).

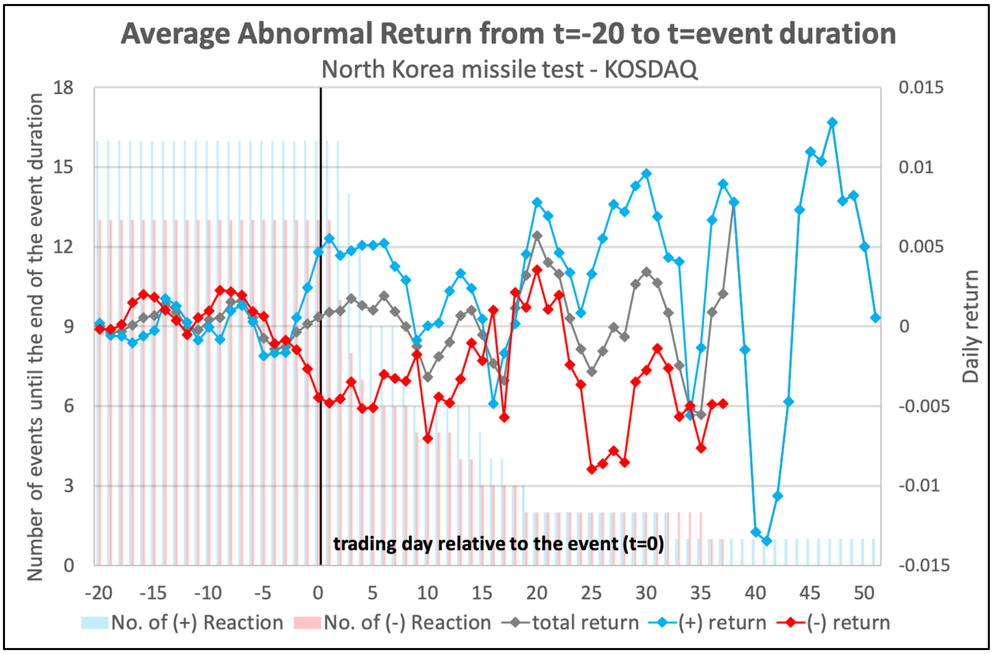
3.4.1 Sign criteria

The first criteria to identify the direction is very simple: the direction is the polarity of the event date' s and the subsequent date' s returns, described as follows:

$$(15)\ direction_{sign} = \begin{cases} up\,, if\ return_{t=0} + return_{t=1} > 0 \\ down\,, if\ return_{t=0} + return_{t=1} < 0 \end{cases},$$

$return$ -> returns as described in Equation (10), Equation (12), and Equation (14)

Figure 3: Daily average abnormal return of KOSDAQ for total, positive, and negative reaction to North Korea missile test, using the sign criteria to determine the direction.



3.4.2 Standard deviation criteria

The second criteria is relatively more complicated than the sign criteria, but is still quite simple. Essentially, this criteria assess whether the return following the event exceeds 1 standard deviation from the mean return of the study period. To do so, upper and lower boundaries are first set as follows:

$$(16)\ \ Upper\ boundary = UB = \overline{return} + \sigma_{return}\ ,$$

(17) $Lower\ boundary = LB = \overline{return} - \sigma_{return}$,

σ -> standard deviation

$\overline{return}$ is geometric return, as shown below:

(18) $\overline{return} = \prod_{t=first}^{last}(1 + return_t) - 1$

Knowing the upper and lower boundaries as threshold, the following describes the criteria to identify the direction:

(19) $direction_{std} = up\ , if \begin{pmatrix} return_{t=0} > UB \\ return_{t=1} > UB \\ return_{t=0} + return_{t=1} > UB \end{pmatrix}$

(20) $direction_{std} = down\ , if \begin{pmatrix} return_{t=0} < LB \\ return_{t=1} < LB \\ return_{t=0} + return_{t=1} < LB \end{pmatrix}$

(21) $direction_{std} = no\ , if \begin{pmatrix} direction_{std} = up = down \\ direction_{std} \neq up \neq down \end{pmatrix}$

If $direction_{std}$ is no (neither up or down for the event date), then the algorithm stops from proceeding with this event date, and moves to the next event.

3.5 Cumulative Average Return

3.5.1 During an event

From each event, relative price to the price on the day of the event was laid out as follows:

(22) $relP_t = \prod_{t=1}^{event\ date+1\ year}(1 + return_t)$

$relP_t$ -> relative price at t, versus the price on the event date
$relP_{t=0} = P_{t=0} = 1$ -> relative price at t = 0, set as 1

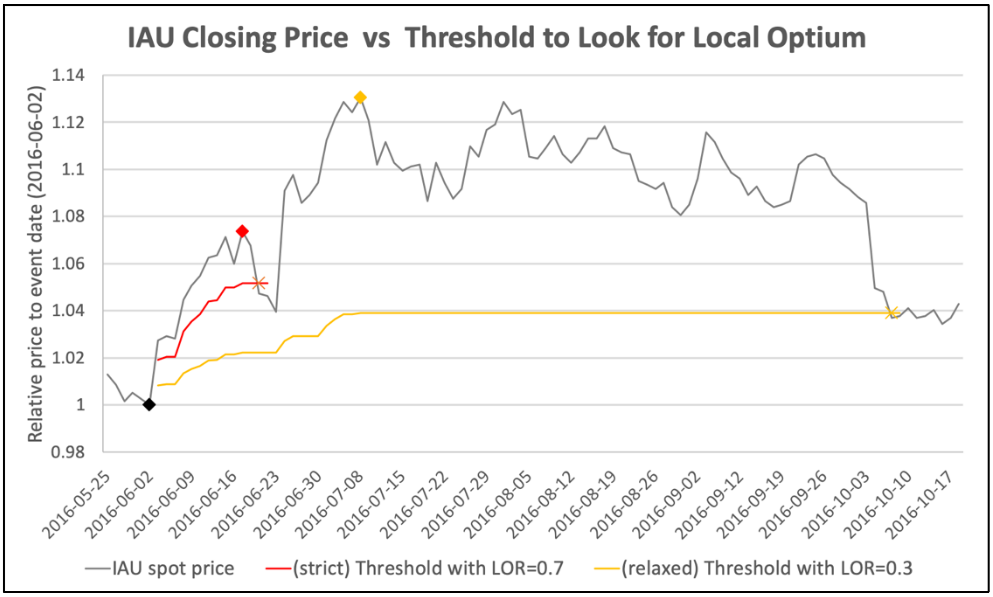
Then, $relP_t$ at each t is inspected according to Equation (23) or Equation (25) until the equation holds true:

(23) $relP_t < 1 + (LOR * (\max(relP_{1\rightarrow t}) - 1))$,

if $direction$ = up for each direction criteria

$\max(relP_{1\rightarrow t}) - 1$ -> distance between maximum price (from t =1 to t = t) and $relP_{t=0} = 1$
$LOR * (\max(relP_{1\rightarrow t}) - 1)$ -> distance away from $relP_{t=0}$, according to LOR
$0 \leq LOR < 1$ -> local optima ratio. This variable can be set in the algorithm
LOR = 0 -> no distance away from $relP_{t=0}$
LOR = 1 -> maximum distance away from $relP_{t=0}$
$1 + (LOR * (\max(relP_{1\rightarrow t}) - 1))$ -> threshold relative price, below of which stops t from advancing to next t to reinspect Equation (23)

Figure 4: IAU close price with a hypothetical event date on June 2, 2016. 2 thresholds using different LORs are shown according to Equation (23), resulting in different cumulative returns. Algorithm proceeds until "x", at which point "◆" − 1 is the cumulative return.



Naturally, setting high LOR means the algorithm will record the local optima at smaller recovery back towards the price at the event, and low LOR means the otherwise. Knowing Equation (22), cumulative $return$ is the maximum relative spot price minus 1, described as follows:

(24) $C\,return_{during} = \max(relP_{1\to t}) - 1$,

if $direction$ = up for each direction criteria

C -> cumulative

Equation (23) considered incidents when event caused a positive reaction. The following equation deals with negative reactions:

(25) $relP_t > 1 - (LOR * (1 - \min(relP_{1\to t})))$,

if $direction$ = down for each direction criteria

$1 - \min(relP_{1\to t})$ -> distance between minimum price (from t=1 to t=t) and $relP_{t=0} = 1$
$LOR * (1 - \min(relP_{1\to t}))$ -> distance away from $relP_{t=0}$, according to LOR
$1 - (LOR * (1 - \min(relP_{1\to t})))$ -> threshold relative price, above of which stops t from advancing to next t to replace Equation (25)

Same logic is used for Equation (25) as its counterpart, when identifying the threshold to stop advancing to the next t. Knowing this point, cumulative $return$ is the minimum relative spot price minus 1, described as follows:

(26) $C\,return_{during} = \min(relP_{1\to t}) - 1$,

if $direction$ = down for each direction criteria

In a rare case when the price following the event never returns to the threshold set by LOR within 1 year from the event date, then maximum or minimum relative price for positive or negative direction, respectively, is used to find the cumulative return. Equation (27) and

Equation (28) describes this incident:

(27) $C\,return_{during} = \max\left(relP_{1 \rightarrow event\ date+1\ year}\right) - 1$,

if $direction$ = up for each direction criteria

(28) $C\,return_{during} = \min\left(relP_{1 \rightarrow event\ date+1\ year}\right) - 1$,

if $direction$ = down for each direction criteria

Knowing the date of $C\,return_{during}$, number of trading days until local optima for each individual event can be found. In classic event study, number of days used to solve for $C\,return_{during}$ would be same across all events (or across all securities for a single event).

3.5.2 Before and after an event

Cumulative return before and after an event is as follows:

(29) $C\,return_{before} = \prod_{t=-BAE}^{-1}(1 + return_t) - 1$

(30) $C\,return_{after} = \prod_{t=\mathrm{during}+1}^{during+BAE}(1 + return_t) - 1$

3.5.3 Cumulative average return of a recurring event

Cumulative average return of a recurring event is as follows:

(31) $\overline{C\,return_T} = \frac{1}{E}\sum_{e=1}^{E} C\,return_{T,e}$,

for total, positive, or negative $C\,return_T$

T -> before, during, or after an event
e -> an event
E -> total number of events

3.5.4 Significance test

Setting the null hypothesis as described in Equation (32), I conduct a two-tailed cross-sectional t-test (Boehmer et al., 1991; Armitage,1995; Asgharian et al., 2011) for $\overline{C\,return_T}$ at 90%, 95%, and 99% confidence levels. This approach is often used for event study using cross-sectional data, that enables researchers to evaluate multiple securities over a single event. Despite the temporal element of events at different times, this study focuses on the impact of a recurring event, as if it were a single event; multiple responses of a same security to the same recurring event are analyzed, to evaluate the impact of a recurring event. Significance test is conducted as follows:

(32) Null : $\overline{C\ return_T} = \mathrm{E}(return_T) = \begin{cases} \bar{R}_T\ , for\ r \\ 0\ , for\ AR\ \&\ AR_{dotw} \end{cases}$

E(return) -> expected return

(33) $\mathrm{E}(r_T) = \begin{cases} \bar{R}_{during} = (1+\bar{R}_{/day})^{\overline{during}} - 1 \\ \bar{R}_{before} = \bar{R}_{after} = (1+\bar{R}_{/day})^{BAE} - 1 \end{cases}$

(34) test statistic : $\boldsymbol{test_T} = \sqrt{E}\,\frac{\overline{C\ return}_T - \mathrm{E}(return_T)}{\sigma_{\mathrm{T}}}$

(35) $\sigma_T = \sqrt{\frac{1}{E-1}\sum_{e=1}^{E} C\ return_T - \overline{C\ return}_T)^2}$

Chapter 4. Results and Discussions

4.1 Expected Events

Overall, Korean public holidays resulted in more frequent abnormal returns than the American did. Interestingly, KOSPI200 responded as people can expect, but KOSDAQ did not. Major US stock indices, however, was not affected by Black Friday, which could be thought of as counterintuitive.

iPhone release resulted in somewhat expected outcome for the producer Apple and its rival Samsung. As the public would have already incorporated their expectation well before the days leading up to the release, and spot price of Apple and Samsung were virtually unaffected before, during, and after the iPhone release. The release’s impact on technology and telecommunications sectors were significant in both directions.

4.1.1 Public holidays

(Korean New Year, Chuseok, and Black Friday)

Korean New Year - KOSPI200

Korean New Year showed statistical significance during the event for positive return, which doubled the frequency of negative return. For the negative return, the rebound post event was statistically significant, with higher cumulative return than that of the statistically insignificant fall. There was no statistical significance prior to the event for any directions. Overall positive return is sensible, considering that family gathering can lead to greater spending.

Korean New Year – KOSDAQ

Korean New Year showed no statistical significance, except 1 incident: during the event for abnormal return using classic event study methodology. For this pair, new event study methodology was provided no benefit.

Korean New Year – Other securities

Korean New Year had no effect for Samsung, DJP, and IAU. This is to be expected for the commodities, but surprising for Samsung, given the prominence of this conglomerate.

Chuseok – KOSPI200

This pair yielded interesting results that are sensible. For total and positive return, there was statistical significance for positive return prior to the event. Additionally, positive return during the event also showed significance at 90% level. This could be attributed to increased purchase prior to Chuseok. Positive return outnumbered negative return by twofold.

Chuseok – Other securities

Interestingly, Chuseok did not affect KOSDAQ or Samsung, which is peculiar given the results of KOSPI. DJP and IAU was not at all affected by Chuseok, which is to be expected.

Black Friday – US market indices

Black Friday essentially does not affect US market indices analyzed (Dow Jones, S&P500, Russell 2000). There is some significance for negative return prior to the positive return in S&P500; this is the most notable phenomenon out of the 3 indices. This is a counterintuitive result, and if reality is different, then this is a limitation of the algorithm.

Black Friday – XLK

Black Friday does not seem to affect technology sector. There is a slight hint of positive return following Black Friday, using sign criteria, but overall, no meaningful conclusion can be drawn.

4.1.2 iPhone release

iPhone release – 005930

Samsung did not respond to iPhone strongly in neither direction, shown by a lack of statistically significant return during most returns. Results are somewhat unexpected: Apple’s smartphone rival Samsung does not suffer from Apple’s newest product release. Concurrently, one could argue this is reasonable, as Samsung itself did not intrinsically change. Finally, there was a little bit of sign that Samsung security yielded a positive return prior to the release.

iPhone release - APPL

iPhone release did not affect Apple in neither direction, shown by a lack of statistically significant return for any returns using the new method. Using the classic method, Apple stock dropped at 90% significance level. Perhaps the lack of significance before, during, and after the release could be attributed to the idea that the public may have already been exposed to critical information about the new phone.

iPhone release - XLK

Technology sector responded in a peculiar way that is difficult to decipher. Overall, negative return was more common for both direction criteria, but both directions were statistically significant. When there was a positive return with significance prior to the release, then return was also positive. When there was no significant return prior to the event, then the return was negative but had a rebound post event. Using the sign criteria, the overall return was negative with significance at 95% level, which is an improvement over the classic event study methodology that resulted in no statistical significance.

iPhone release - IYZ

Telecommunications sector showed statistical significance at 90% level for positive direction and at 95% for the negative. The frequency of the 2 directions was similar. The significance was higher for negative direction. There was no statistical significance prior to the event, implying that iPhone release has an effect on the telecommunications sector, whichever direction it heads.

4.2 Unexpected Events

North Korean missile activity showed great results for almost all securities investigated, but 5 nuclear weapon test sample size was likely too small to assemble any insights. Often times, incorporating direction uncovered hidden information.

Algorithm successfully illustrated the impact on airplane crash on various securities analyzed. There was little correlation prior to the crash, which makes sense because investors cannot possibly have the information to forecast the airplane crash. Once the crash happened, the airline industry resulted in positive direction twice more frequent for the sign criteria and three times more frequent for the standard deviation criteria, compared to the negative return. This information would was not revealed using the traditional event study methodology, that showed some significance prior to the crash and no significance after. Assets that are typically used for diversification also responded strongly in both directions.

4.2.1 North Korea military weapons test

Missile Test - KOSPI200

Missile test shows a contrasting result, depending on the direction. For positive return, there was already a positive return with significance prior to the event while for negative return, there no statistical significance leading up to the event. From this, it could be possible that when North Korea conducted missile test while KOSPI was on the rise, it did not affect the trend. However, when there was no significance prior to the event, then the missile test lead to a negative return. Concurrently, only sign criteria showed any significance while standard deviation criteria did not.

Missile Test - KOSDAQ

Nothing can be revealed from total return, but the algorithm was highly effective when direction was taken into account. There was no statistical significance for returns prior to the event, whereas there was statistical significance for both directions using both criteria. Moreover, rebound post event was also statistically significant. Positive return showed higher significance.

Missile Test - SPX

The algorithm showed mixed results for S&P500. Negative direction, that had no statistical significance prior to the event, but significant after, was as expected. However, positive direction had significance prior to the event. The direction was evenly split.

Missile Test - 005930

Total return showed no notable information, but the analysis with direction revealed interesting information. For positive return, there was high statistical significance of positive return prior to the event, while significance at only 90% level accompanied positive return after the event. For negative return, there was no statistical significance prior to the event and significance after the event. This implies that even if positive direction shows significance, the relative decrease in significance for positive direction and increase for negative direction show that North Korea’ s missile test negatively affect Samsung stocks.

Missile Test - DJP

Results were not as expected for diversified commodities. There was no statistical significance for total or positive return at any time; there was statistical significance during the event and post event for negative return. Given that North Korean military activity could be perceived as a security threat to many nations, it is sensible that increase in uncertainty leads to an increase in an uncorrelated asset, such as diversified commodities. However, only negative return was statistically significant.

Missile Test - IAU

Results were somewhat as expected for gold. Total return revealed no statistical significance. However, taking account of direction revealed statistical significance after the event for both directions that were evenly split. There was no statistical significance prior to the event, bolstering the effectiveness of the algorithm.

Nuclear Weapon Test

Given only 5 nuclear weapon test, sample size was likely too small to yield any notable impact of the event. Of the results with statistical significance, negative return of KOSPI, negative return of Samsung, and positive return of IAU had statistical significance, all of which is reasonable.

4.2.2 Airplane crash

Plane Crash – SPX

Overall, there was little significance prior to the event and high significance after the event when direction was taken into account. For positive return, which was slightly more common than the alternative, rebound effect post event was also statistically significant at 95% level. Duration for both criteria in negative return hovered around 5 days, yet there was a huge discrepancy between the criteria for positive return. Standard deviation criteria, which is more strict, resulted in about 30 day duration while sign criteria resulted in around 7 day duration. Perhaps attributed to longer time frame, standard deviation criteria for positive return showed around threefold the cumulative average return. Interestingly, cumulative average return for rebound was very similar for both criteria for positive return.

Plane Crash – JETS

This pair may have shown the most interesting result out of all pairs investigated. Cumulative average return prior to the crash was mostly insignificant, validating the notion that investors cannot predict airplane crashes. Positive return was twice more frequent for sign criteria and three times more frequent for standard deviation criteria than the negative return. Positive return had significance for both direction criteria at 99% level during and post event, except for abnormal return’ s rebound using sign criteria that had 95%. For negative return, only sign criteria showed statistical significance. Change in price in terms of magnitude was similar for both directions. Total return after the event had no significance, except for simple return using sign criteria. Event study using the traditional approach shows no insights.

Plane Crash – DJP & IAU

Plane crash affected the uncorrelated commodity assets similarly. Total return using neither classical nor new event study methodology shows no information, yet analyzing the impact using direction does. For both commodity ETFs, both positive and negative cumulative average returns were significant for all return types. Despite their similarities, plane crash had a tendency to decrease the price of gold. Rebound effect post-event was also prominent for both assets.

Plane Crash – Other securities

Other securities exhibited similar behaviour as that shown by DJP and IAU. The algorithm successfully explains how the assets typically used for diversification respond to plane crashes.

Chapter 5. Extension

5.1 Robustness

Robustness check to the algorithm was conducted, by changing BAE and LOR values. The overall message from Chapter 4 was consistent despite changing these parameters. Moreover, each financial asset were assigned randomly sampled dates from the study period to evaluate the lack of effectiveness of the algorithm for random dates.

5.1.1 BAE

In addition to BAE = 20, BAE = 5 and 50 were used, and results were almost identical. BAE = 20 seemed to have affected the cumulative average return of some expected events, while unexpected events were unaffected.

I suspected that the investor expectation could have already been taken into account prior to the iPhone release, and this is why there was a lack of statistical significance. Unlike BAE = 20 used in the main analysis that had no statistical significance leading up to the event, BAE = 50 did for positive direction at 90% significance level. Perhaps this slight increase 50 to 20 trading days prior to the release indicate that this is when APPL could have incorporated available information.

KOSDAQ using BAE = 50 also show statistical significance for positive direction, prior to Korean New Year. This phenomenon can be sensible, given that the public could be spending more leading up to the special occasion.

5.1.2 LOR

Main analysis used LOR = 0.5. In this portion of extension analysis, I set LOR = 0.3, which means that the algorithm would allow greater price fluctuation before looking for local optima. The overall pattern did not change, aside from an increase in the magnitude of cumulative average returns and the average duration. The amount of increase from the expected return varied across different pairs.

5.1.3 Random sampling

10 and 100 dates were randomly selected and fed into the algorithm to verify its effectiveness. For 10 samples, there was random low significance in different timing and return types, showing the randomness of using random dates. However, using 100 samples revealed the algorithm’s weakness. First, the algorithm detects local optima by design. Thus, it will detect them no matter which dates are fed, and with enough of them, the results showed false positive (type 1 error). For some securities, overall market trend affected significance level before the event dates as well.

5.2 Limitations

(1) Sample size can hurt the effectiveness of the algorithm. If it is too small, then it does not have enough outcome to accurately determine the true trend. If it is too large, then it is subject to false positives.

(2) Algorithm picks up local optima regardless of the minimum days or return at local optima. Thus, it is prone to picking up noise instead of a larger local optima that investors and researchers may be more interested in.

(3) Event study often excludes event window from estimation window. For the new methodology proposed here, that is only possible with iteration.

(4) Idiosyncratic risk of the securities was not taken into account, which would have led to different expected return according to CAPM.

(5) Macroeconomic factors were ignored. Although they are not typically used in event study, they certainly can affect asset pricing regardless of the event.

(6) Event dates could be close enough with one another that event window can overlap. Moreover, event date does not always exactly

align with the trading date.

(7) In some cases, human judgement can be valuable.

5.3 Further Research

Given that this is a new approach to solve for cumulative average return, there is a great need and potential for further research.

(1) Natural language processing could assist event selection and analysis. Specifically, text mining can find qualitative events that cannot be classified as a simple “yes” or “no”. In the algorithm, sentiment analysis could be incorporated to better understand the variations within a recurring event.

(2) Correlation between a combination of securities could be used as another input to determine whether a return is abnormal. This is an entirely different approach than the typical way to solve for the abnormal return in an event study. Since correlation is associated with the magnitude and the direction of securities, it could also be used to aid or replace LOR as a threshold to solve for the cumulative return. Analyzing correlation during estimation window versus event duration has a potential to be a versatile tool.

(3) Criteria to include or reject a cumulative return of each event, as a part of average cumulative return, can lead to an analysis of truly abnormal returns. For instance, it could be as simple as setting a minimum duration or a magnitude threshold. It could be more sophisticated as well: for each individual event' s cumulative return on an asset, significance test could be conducted as a requirement.

(4) Different models could be used to find the expected return. This research used mean return across the primary market trend as the expected return. Incorporating secondary market trend to this approach could lead to a more accurate expected return, and consequently a more accurate abnormal return. Otherwise, any of the previously used models, such as the frequently used market model, can be valid.

(5) Optimal LOR could be determined using random sampling. LOR could be experimented for a given sample size, until significance of abnormal return from randomly sampled dates subsides.

(6) Post event analysis could take place, after price returns to the threshold set by (maximum deviation from $P_{t=0}$ * LOR). In this research, post event analysis was conducted from (1 trading day after the local optima) to (1 trading day after the local optima + BAE days).

(7) Methodology developed from this research could be applied across many financial assets of a single event. This research, instead, used many events on a single asset.

(8) Instead of using a user-defined variable LOR to determine when the reaction of an event has subsided enough to look for the cumulative return, setting a fixed rule can add to the objectivity. Statistically insignificant abnormal return could be a criteria, for instance.

(9) Applying the methodology developed in this research to intraday response to a recurring event could be relevant to researchers and traders alike.

Chapter 6. Conclusion

I analyzed how different assets react to different recurring events using a new event study methodology. The new method is similar in a sense that it still follows the overall structure of the event study methodology to arrive at cumulative average abnormal return. The new method also differs from the previous method in 2 ways: (1) unique duration of each event is objectively determined, and (2) 2 criteria are proposed to automatically detect the immediate polarity following an event.

An advantage of first difference is that the analysis of cumulative abnormal return is exclusive to each event’s unique event duration. Previously, same event window length was set for all events for a single security (or all securities for a single event), so the cumulative abnormal return can include return that is no longer abnormal and relevant.

A second advantage is the separate analysis of abnormal returns in each direction. Algorithm’s output demonstrates that both traditional and new event study methodology without taking account of direction can show mere insignificant abnormal returns. Indeed, direction reveals market response that would have been unknown otherwise.

I developed an algorithm to conduct the research using the new methodology. The algorithm produces cumulative average return, cumulative average abnormal return, cumulative average day-of-the-week adjusted abnormal return for total, positive, and negative returns according to 2 separate criteria. Additionally, it conducts significance test of all cumulative average returns before, during, and after a recurring event. Finally, it provides average duration and number of events for each associated cumulative average return. To produce these output, the algorithm requires daily price and event dates. BAE and LOR are 2 user-defined variables to accommodate the needs of the user. BAE is used to analyze returns on the days leading up to the event, in addition to the post event analysis. LOR is used to determine the range, local optima of which falls under. The input and the output of the algorithm are summarized as follows:

$$(36)\quad \begin{bmatrix} \overline{C\ return}_{T,} \\ significance\ test \\ \overline{duration}\ of\ E \\ number\ of\ events \end{bmatrix} = algorithm(price, event\ dates, BAE, LOR)\ ,$$

for total, positive, and negative returns

I used this algorithm to study and document the relationship between various financial asset – recurring event pairs. Type of return did not matter much, in terms of the statistical significance and the overall impact of an event. However, direction criteria mattered: (1)

sign criteria, and (2) standard deviation criteria. Standard deviation criteria is more strict, and consequently selected impact with larger cumulative abnormal return and duration until local optima. The tradeoff was that sign criteria tended to show higher statistical significance, likely attributed to higher sample size.

There are many patterns identified from the analysis. KOSPI responded to Korean holidays as expected, but major US market indices was unaffected from Black Friday. Perhaps a micro-level analysis using individual stocks can be worthwhile. Apple and Samsung did not respond to iPhone release, but technology and telecommunications ETFs did. Missile tests from North Korea led to clear and expected outcome for Korean securities, as well as commodity ETFs. Perhaps most interestingly, airplane crashes that are near impossible, if not entirely impossible, to predict led to positive return for the airline industry. All assets often used for diversification showed sigh significance for both directions, during and post event.

In most cases, the new method outperformed the classic method when direction was taken into account. In a few incidents, classic method still proved to be very useful: Korean New Year - KOSDAQ, for example.

Overall, the new methodology worked better for unexpected events, but it was useful at times even for expected events.

Specifically, unexpected events resulted in more frequent statistically significant cumulative average abnormal return during the event than they did before the event. As for the expected events, results are mixed for the pairs analyzed in this research, perhaps because investors already have the information that they need to assess the financial assets of interest. Consequently, investors could have adjusted their portfolio prior to the event, reflected in the market value.

I verified the effectiveness of the algorithm in the extension analysis. The algorithm was robust to different BAE and LOR, but random sampling at 100 dates identified its shortcoming: cumulative average return of an event can easily be significant by the design of the algorithm. To offset this weakness, additional criteria should be integrated in further research.

Active investors interested in using the findings of this research or the algorithm should note that the most critical time for this methodology is the trading date and the day after the trading date of an event because the asset price from these 2 days determines the direction.

Users of the algorithm should also keep in mind of its limitations. The new method does not work for every asset – event pair, especially for the expected events. Indeed, the classic method is still a very reliable technique.

The new method can be useful in a sense that it removes subjectivity when setting the event duration. Moreover, the 2 direction criteria enable separate analysis of total, positive, and negative returns. At the very least, this method offers researchers a new technique to conduct an event study.

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Appendix A
Recurring Event Dates

Recurring events are listed in the following format:

Recurring event
Year1 Month1 Day1
Year2 Month2 Day2
…

Korean New Year
2010 02 14
2011 02 03
2012 01 23
2013 02 10
2014 01 31
2015 02 19
2016 02 08
2017 01 28
2018 02 16

Chuseok (beginning dates)
2009 10 02
2010 09 21
2011 09 11
2012 09 29
2013 09 18
2014 09 08
2015 09 27
2016 09 15
2017 10 04
2018 09 24

iPhone release
2009 06 19
2010 06 24
2011 10 14
2012 09 21
2013 09 20
2014 09 19
2015 09 25
2016 03 31
2016 09 16
2017 09 22
2017 11 03
2018 09 21
2018 10 26

Black Friday
2009 11 27
2010 11 26
2011 11 25
2012 11 23
2013 11 29
2014 11 28
2015 11 27
2016 11 25
2017 11 24
2018 11 23

Commercial aircraft crash

2015 08 16
2015 09 05
2015 09 08
2015 10 02
2015 10 29
2015 10 31
2015 11 04
2015 11 22
2015 12 24
2016 01 08
2016 02 02
2016 02 24
2016 02 26
2016 03 09
2016 03 19
2016 03 29
2016 04 04
2016 04 13
2016 04 29
2016 05 18
2016 05 19
2016 05 27
2016 08 03
2016 08 05
2016 08 27
2016 10 28
2016 10 28
2016 10 31
2016 11 28
2016 12 07
2016 12 20
2016 12 23
2017 01 16
2017 03 20
2017 03 28
2017 04 29
2017 05 27
2017 07 07
2017 09 30
2017 10 14
2017 11 15
2017 12 13
2017 12 31
2018 01 13
2018 02 11
2018 02 18
2018 03 11
2018 03 12
2018 04 17
2018 05 14
2018 05 18
2018 06 28
2018 07 28
2018 07 31
2018 08 04
2018 08 10
2018 08 16
2018 09 01
2018 09 09
2018 09 28
2018 10 29
2018 11 09

North Korea missile test

2009 04 05
2009 07 04
2012 04 13
2012 12 12
2013 05 18
2014 06 30
2014 07 02
2015 05 09
2016 02 07
2016 04 09
2016 08 24
2016 10 15
2016 10 19
2017 02 11
2017 03 06
2017 04 04
2017 04 15
2017 04 28
2017 05 13
2017 05 21
2017 05 29
2017 06 08
2017 06 23
2017 07 04
2017 07 28
2017 08 26
2017 08 29
2017 09 15
2017 11 28

North Korea nuclear weapons test

2009 05 25
2013 02 12
2016 01 06
2016 09 09
2017 09 03

Appendix B
New Event Study Methodology

Chapter 3. Methodology focused on describing the algorithm. This section simplifies Chapter 3 down to the mathematics behind the proposed methodology. Out of 3 returns analyzed in the paper, only AR is to be written as it is the most typical return examined in an event study.

Equation (12) is rewritten in a more general form for ease of comparison with other studies, as there are many models used to estimate the expected return to find abnormal return:

$$AR_t = r_t - \mathrm{E}(\mathrm{r}_t)$$

Using abnormal return, the algorithm can find the duration that is unique to each event, using relative price to $P_{t=0,e} = 1$ as described in Equation (22):

$$relP_{t,e} = \prod_{t=1}^{event\ date\ +\ 1\ year} (1 + AR_{t,e})$$

$$relP_{during(e)} = algorithm(relP_{t,e})$$

t,e -> t index away from the event, for each event e
during(e) -> duration of an event as a function of each event e

Knowing $relP_{during(e)}$ from the algorithm, cumulative return of each event is found using one of Equation (24), (26), (27), or (28). In a more general form:

$$CAR_{during(e)} = relP_{during(e)} - 1$$

Equation (31) can be rewritten to solve for cumulative average abnormal return across all events:

$$\overline{CAR}_{during} = \frac{1}{E}\sum_{e=1}^{E} \mathrm{CAR}_{during(e)}$$

Appendix C
Algorithm Output

This section lists output of the algorithm described in Chapter 3, with LOR = 0.5 and BAE = 20. All returns are Cumulative Average. Acronyms used in the table is listed below:

Top

RT	Return Type
DC	Direction Criteria
D	Duration
R	Return
t-s	t-statistics
E	Events

Left

ARprev	Previous Abnormal Return
r	(simple) Return
AR	Abnormal Return
ARdotw	Day-of-the-week adjusted Abnormal Return

Stars

***	Significance at the 1% level
**	Significance at the 5% level
*	Significance at the 10% level

North Korea Missile Test – KOSPI200

Total		Before					During					After			
RT	DC	D	R		t-s	E	D	R		t-s	E	D	R	t-s	E
ARprev	NA	20	0.0191	**	2.43	29	20	0.0139	**	2.1	29				
r	Sign	20	0.0238	**	2.43	29	17.93	0.0193		1.38	29	20	0.0128	0.93	29
r	Std	20	0.0332		1.75	11	18.45	0.0148		0.6	11	20	0.0167	0.73	11
AR	Sign	20	0.0191	**	2.43	29	9.41	0.0057		1.05	29	20	0.0099	1.14	29
AR	Std	20	0.0284		1.75	11	11.45	0.006		0.5	11	20	0.0135	0.84	11
ARdotw	Sign	20	0.0191	**	2.42	29	9.41	0.0057		1.04	29	20	0.0098	1.12	29
ARdotw	Std	20	0.0307		1.72	10	12.2	0.0061		0.46	10	20	0.0181	1.06	10

North Korea Missile Test – KOSPI200

(+)		Before					During					After			
RT	DC	D	R		t-s	E	D	R		t-s	E	D	R	t-s	E
r	Sign	20	0.0323	**	2.5	19	24.44	0.0374	*	2.1	19	20	0.0024	-0.21	19
r	Std	20	0.0442		1.59	7	21.86	0.0362		1.31	7	20	0.0074	0.12	7
AR	Sign	20	0.0282	**	2.43	18	10.17	0.0195	***	3.03	18	20	0.0015	0.14	18
AR	Std	20	0.0394		1.59	7	10.86	0.0239		1.73	7	20	0.0051	0.23	7
ARdotw	Sign	20	0.0281	**	2.42	18	10.22	0.0195	***	3.03	18	20	0.0014	0.13	18
ARdotw	Std	20	0.045		1.57	6	12	0.027		1.7	6	20	0.0116	0.45	6

North Korea Missile Test – KOSPI200

(–)		Before					During					After			
RT	DC	D	R	t-s	E		D	R	t-s	E		D	R	t-s	E
r	Sign	20	0.0078	0.42	10		7.27	-0.0151 ***	-3.73	10		20	0.0327 *	2	10
r	Std	20	0.0138	1.18	4		12.5	-0.0226 *	-2.58	4		20	0.0328	1.29	4
AR	Sign	20	0.0043	0.62	11		8.18	-0.0168 ***	-3.57	11		20	0.0236	1.64	11
AR	Std	20	0.0092	1.18	4		12.5	-0.0254	-2.25	4		20	0.0281	1.29	4
ARdotw	Sign	20	0.0043	0.62	11		8.09	-0.0169 ***	-3.58	11		20	0.0235	1.64	11
ARdotw	Std	20	0.0091	1.18	4		12.5	-0.0254	-2.23	4		20	0.0278	1.27	4

North Korea Missile Test – KOSDAQ

Total		Before					During					After			
RT	DC	D	R	t-s	E		D	R	t-s	E		D	R	t-s	E
ARprev	NA	20	0.005	0.47	29		20	0.0065	0.81	29					
r	Sign	20	0.0097	0.47	29		13.21	0.0125	0.71	29		20	0.0057	0.09	29
r	Std	20	0.0166	0.65	16		17.06	0.0243	0.92	16		20	0.0052	0.03	16
AR	Sign	20	0.005	0.47	29		11.38	0.0072	0.55	29		20	0.0029	0.25	29
AR	Std	20	0.0119	0.65	16		13.75	0.0162	0.76	16		20	0.0039	0.21	16
ARdotw	Sign	20	0.0049	0.46	29		11.41	0.0071	0.55	29		20	0.0028	0.24	29
ARdotw	Std	20	0.0119	0.65	16		13.75	0.0161	0.75	16		20	0.004	0.22	16

North Korea Missile Test – KOSDAQ

(+)		Before					During						After				
RT	DC	D	R	t-s	E		D	R		t-s	E		D	R		t-s	E
r	Sign	20	0.0015	-0.19	17		15.81	0.048	**	2.77	17		20	-0.0289	**	-2.86	17
r	Std	20	0.0081	0.15	11		18.36	0.0605	**	2.35	11		20	-0.0295	**	-2.48	11
AR	Sign	20	-0.0031	-0.19	17		12	0.0413	**	2.71	17		20	-0.0296	**	-2.5	17
AR	Std	20	0.0034	0.15	11		12.82	0.0514	*	2.23	11		20	-0.0282	*	-2.01	11
ARdotw	Sign	20	-0.0012	-0.08	18		12	0.0389	**	2.68	18		20	-0.0276	**	-2.43	18
ARdotw	Std	20	0.0034	0.15	11		12.82	0.0513	*	2.23	11		20	-0.0282	*	-2	11

North Korea Missile Test – KOSDAQ

(–)		Before					During						After				
RT	DC	D	R	t-s	E		D	R		t-s	E		D	R		t-s	E
r	Sign	20	0.0212	1.28	12		10	-0.0378	**	-3.02	12		20	0.0547	***	3.23	12
r	Std	20	0.0354	1.05	5		14.2	-0.0555	**	-2.88	5		20	0.0815	*	2.47	5
AR	Sign	20	0.0165	1.28	12		10.62	-0.0412	**	-3	12		20	0.0491	**	3.06	12
AR	Std	20	0.0306	1.05	5		15.8	-0.0612	**	-3.09	5		20	0.0746	*	2.24	5
ARdotw	Sign	20	0.015	1.07	11		10.69	-0.0449	**	-3.1	11		20	0.0526	**	3.06	11
ARdotw	Std	20	0.0306	1.05	5		15.8	-0.0613	**	-3.11	5		20	0.0747	*	2.24	5

North Korea Missile Test – DJP

Total		Before				During				After			
RT	DC	D	R	t-s	E	D	R	t-s	E	D	R	t-s	E
ARprev	NA	20	0.0059	1.06	29	20	-0.0075	-1.17	29				
r	Sign	20	0.0025	1.06	29	18.03	-0.0254	-1.41	29	20	0.0062	1.07	29
r	Std	20	-0.0003	0.4	15	31.53	-0.0448	-1.31	15	20	0.0177	1.49	15
AR	Sign	20	0.0059	1.06	29	18.17	-0.0224	-1.48	29	20	0.0088	0.97	29
AR	Std	20	0.0032	0.44	16	29.75	-0.0378	-1.4	16	20	0.0184	1.36	16
ARdotw	Sign	20	0.0059	1.06	29	18.24	-0.0224	-1.48	29	20	0.0087	0.96	29
ARdotw	Std	20	0.0032	0.44	16	29.75	-0.0378	-1.4	16	20	0.0183	1.35	16

North Korea Missile Test – DJP

(+)		Before				During				After			
RT	DC	D	R	t-s	E	D	R	t-s	E	D	R	t-s	E
r	Sign	20	-0.0001	0.38	15	5	0.0143	1.46	15	20	-0.0188	-1.76	15
r	Std	20	-0.0042	-0.06	5	9.17	0.0373	1.27	5	20	-0.0321	-1.8	5
AR	Sign	20	0.0032	0.38	15	5	0.0162	1.49	15	20	-0.0169 *	-1.88	15
AR	Std	20	0.0001	0.01	6	8.29	0.0335	1.25	6	20	-0.0278 *	-2.11	6
ARdotw	Sign	20	0.0032	0.38	15	5.13	0.0163	1.51	15	20	-0.0171 *	-1.89	15
ARdotw	Std	20	0.0001	0.01	6	8.29	0.0335	1.25	6	20	-0.0279 *	-2.11	6

North Korea Missile Test – DJP

(−)		Before				During				After			
RT	DC	D	R	t-s	E	D	R	t-s	E	D	R	t-s	E
r	Sign	20	0.0054	1.19	14	32	-0.0679 **	-2.31	14	20	0.0329 **	2.91	14
r	Std	20	0.0017	0.53	10	46.44	-0.0858 *	-2.13	10	20	0.0426 **	3.23	10
AR	Sign	20	0.0087	1.19	14	34.38	-0.0638 **	-2.53	14	20	0.0363 **	2.91	14
AR	Std	20	0.005	0.53	10	46.44	-0.0806 **	-2.37	10	20	0.0461 **	3.23	10
ARdotw	Sign	20	0.0087	1.19	14	34.38	-0.0638 **	-2.53	14	20	0.0363 **	2.9	14
ARdotw	Std	20	0.005	0.53	10	46.44	-0.0806 **	-2.37	10	20	0.0461 **	3.24	10

North Korea Missile Test – IAU

Total		Before				During				After			
RT	DC	D	R	t-s	E	D	R	t-s	E	D	R	t-s	E
ARprev	NA	20	0.0012	0.2	29	20	-0.0062	-1.22	29				
r	Sign	20	0.0051	0.2	29	10.28	0.0024	0.07	29	20	-0.0116 *	-1.92	29
r	Std	20	0.0053	0.16	16	13.56	0.0029	0.02	16	20	-0.0031	-0.57	16
AR	Sign	20	0.0012	0.2	29	17.34	-0.0102	-0.83	29	20	-0.0156 *	-1.97	29
AR	Std	20	0.0047	0.54	15	13.53	-0.0015	-0.15	15	20	-0.0014	-0.12	15
ARdotw	Sign	20	0.0012	0.2	29	17.38	-0.0102	-0.83	29	20	-0.0155 *	-1.95	29
ARdotw	Std	20	0.0046	0.54	15	13.67	-0.0015	-0.15	15	20	-0.0008	-0.07	15

North Korea Missile Test – IAU

(+)		Before				During				After			
RT	DC	D	R	t-s	E	D	R	t-s	E	D	R	t-s	E
r	Sign	20	0.0013	-0.28	14	9.63	0.026 ***	3.53	14	20	-0.0398 ***	-4.47	14
r	Std	20	0.0064	0.18	8	13.63	0.032 **	2.63	8	20	-0.0369 **	-2.7	8
AR	Sign	20	-0.0006	-0.06	13	9.4	0.0239 ***	3.67	13	20	-0.0438 ***	-4.31	13
AR	Std	20	0.0096	0.7	7	13.57	0.0297 **	2.63	7	20	-0.0334 **	-2.47	7
ARdotw	Sign	20	-0.0005	-0.05	13	9.53	0.0239 ***	3.66	13	20	-0.0431 ***	-4.1	13
ARdotw	Std	20	0.0096	0.7	7	13.86	0.0296 **	2.62	7	20	-0.0322 *	-2.24	7

North Korea Missile Test – IAU

(–)		Before				During				After			
RT	DC	D	R	t-s	E	D	R	t-s	E	D	R	t-s	E
r	Sign	20	0.0087	0.62	15	11.08	-0.0197 ***	-4.55	15	20	0.0147	1.31	15
r	Std	20	0.0043	0.03	8	13.5	-0.0262 ***	-4.2	8	20	0.0307 **	2.74	8
AR	Sign	20	0.0026	0.35	16	25.86	-0.0379 *	-1.97	16	20	0.0073	0.89	16
AR	Std	20	0.0004	0.03	8	13.5	-0.0287 ***	-3.57	8	20	0.0267 **	2.74	8
ARdotw	Sign	20	0.0026	0.35	16	25.79	-0.0378 *	-1.97	16	20	0.0069	0.84	16
ARdotw	Std	20	0.0003	0.03	8	13.5	-0.0287 ***	-3.58	8	20	0.0266 **	2.72	8

North Korea Nuclear Weapon Test – KOSPI200

Total		Before					During					After			
RT	DC	D	R	t-s	E		D	R	t-s	E		D	R	t-s	E
ARprev	NA	20	-0.008	-0.48	5		20	-0.0047	-0.41	5					
r	Sign	20	-0.0034	-0.48	5		6.6	-0.0105	-0.83	5		20	0.018	0.9	5
r	Std	20	-0.0034	-0.48	5		6.6	-0.0105	-0.83	5		20	0.018	0.9	5
AR	Sign	20	-0.008	-0.48	5		5.4	-0.012	-0.85	5		20	0.0113	0.7	5
AR	Std	20	-0.008	-0.48	5		5.4	-0.012	-0.85	5		20	0.0113	0.7	5
ARdotw	Sign	20	-0.008	-0.49	5		5.4	-0.012	-0.85	5		20	0.0112	0.7	5
ARdotw	Std	20	-0.008	-0.49	5		5.4	-0.012	-0.85	5		20	0.0112	0.7	5

North Korea Nuclear Weapon Test – KOSPI200

(+)		Before					During					After			
RT	DC	D	R	t-s	E		D	R	t-s	E		D	R	t-s	E
r	Sign	20	-0.0323		1		15	0.043		1		20	-0.0204		1
r	Std	20	-0.0323		1		15	0.043		1		20	-0.0204		1
AR	Sign	20	-0.0368		1		9	0.0397		1		20	-0.0349		1
AR	Std	20	-0.0368		1		9	0.0397		1		20	-0.0349		1
ARdotw	Sign	20	-0.0368		1		9	0.0397		1		20	-0.035		1
ARdotw	Std	20	-0.0368		1		9	0.0397		1		20	-0.035		1

North Korea Nuclear Weapon Test – KOSPI200

(−)		Before				During				After			
RT	DC	D	R	t-s	E	D	R	t-s	E	D	R	t-s	E
r	Sign	20	0.0039	-0.04	4	4.5	-0.0239 **	-3.53	4	20	0.0276	1.57	4
r	Std	20	0.0039	-0.04	4	4.5	-0.0239 **	-3.53	4	20	0.0276	1.57	4
AR	Sign	20	-0.0007	-0.04	4	4.5	-0.0249 **	-3.33	4	20	0.0228	1.57	4
AR	Std	20	-0.0007	-0.04	4	4.5	-0.0249 **	-3.33	4	20	0.0228	1.57	4
ARdotw	Sign	20	-0.0008	-0.04	4	4.5	-0.0249 **	-3.32	4	20	0.0227	1.57	4
ARdotw	Std	20	-0.0008	-0.04	4	4.5	-0.0249 **	-3.32	4	20	0.0227	1.57	4

North Korea Nuclear Weapon Test – KOSDAQ

Total		Before				During				After			
RT	DC	D	R	t-s	E	D	R	t-s	E	D	R	t-s	E
ARprev	NA	20	0.005	0.18	5	20	-0.0052	-0.21	5				
r	Sign	20	0.0097	0.18	5	23.4	0.0024	-0.07	5	20	-0.0057	-0.29	5
r	Std	20	0.029	0.53	3	14	-0.0483	-1.31	3	20	0.0337	1.11	3
AR	Sign	20	0.005	0.18	5	23.4	-0.0033	-0.08	5	20	-0.0103	-0.29	5
AR	Std	20	0.0243	0.53	3	14	-0.0512	-1.23	3	20	0.0289	1.11	3
ARdotw	Sign	20	0.005	0.18	5	23.4	-0.003	-0.07	5	20	-0.0104	-0.3	5
ARdotw	Std	20	0.0328	0.42	2	20	-0.0738	-1.22	2	20	0.0402	1	2

North Korea Nuclear Weapon Test – KOSDAQ

(+)		Before					During					After			
RT	DC	D	R	t-s	E		D	R	t-s	E		D	R	t-s	E
r	Sign	20	-0.0208		1		37.5	0.1574		1		20	-0.1306		1
r	Std				0					0					0
AR	Sign	20	-0.0254		1		37.5	0.1378		1		20	-0.1346		1
AR	Std				0					0					0
ARdotw	Sign	20	-0.0254		1		37.5	0.1386		1		20	-0.1349		1
ARdotw	Std				0					0					0

North Korea Nuclear Weapon Test – KOSDAQ

(−)		Before					During					After			
RT	DC	D	R	t-s	E		D	R	t-s	E		D	R	t-s	E
r	Sign	20	0.0173	0.37	4		14	-0.0364	-1.31	4		20	0.0256	1.04	4
r	Std	20	0.029	0.53	3		14	-0.0483	-1.31	3		20	0.0337	1.11	3
AR	Sign	20	0.0126	0.37	4		14	-0.0386	-1.21	4		20	0.0208	1.04	4
AR	Std	20	0.0243	0.53	3		14	-0.0512	-1.23	3		20	0.0289	1.11	3
ARdotw	Sign	20	0.0125	0.37	4		14	-0.0385	-1.2	4		20	0.0207	1.03	4
ARdotw	Std	20	0.0328	0.42	2		20	-0.0738	-1.22	2		20	0.0402	1	2

North Korea Nuclear Weapon Test – DJP

Total		Before					During					After			
RT	DC	D	R	t-s	E		D	R	t-s	E		D	R	t-s	E
ARprev	NA	20	0.0207	0.9	5		20	0.001	0.08	5					
r	Sign	20	0.0173	0.9	5		8.2	-0.0024	-0.05	5		20	-0.0198	-0.62	5
r	Std	20	-0.0048	-0.07	3		9	-0.0279	-1.27	3		20	-0.0011	0.15	3
AR	Sign	20	0.0207	0.9	5		8.2	-0.0011	-0.05	5		20	-0.0165	-0.62	5
AR	Std	20	-0.0015	-0.07	3		9	-0.0265	-1.3	3		20	0.0022	0.15	3
ARdotw	Sign	20	0.0208	0.9	5		8.2	-0.0012	-0.05	5		20	-0.0164	-0.62	5
ARdotw	Std	20	-0.0012	-0.06	3		9	-0.0267	-1.3	3		20	0.0021	0.15	3

North Korea Nuclear Weapon Test – DJP

(+)		Before					During					After			
RT	DC	D	R	t-s	E		D	R	t-s	E		D	R	t-s	E
r	Sign	20	0.037	1.33	3		5.33	0.0278	1.33	3		20	-0.0381	-0.82	3
r	Std	20	0.01		1		2	0.0116		1		20	-0.0187		1
AR	Sign	20	0.0405	1.33	3		5.33	0.0287	1.29	3		20	-0.0349	-0.82	3
AR	Std	20	0.0134		1		2	0.012		1		20	-0.0155		1
ARdotw	Sign	20	0.0404	1.33	3		5.33	0.0287	1.3	3		20	-0.0347	-0.82	3
ARdotw	Std	20	0.0134		1		2	0.0119		1		20	-0.0154		1

North Korea Nuclear Weapon Test – DJP

(–)		Before					During					After			
RT	DC	D	R	t-s	E		D	R	t-s	E		D	R	t-s	E
r	Sign	20	-0.0122	-0.27	2		12.5	-0.0477	-3.98	2		20	0.0076	0.58	2
r	Std	20	-0.0122	-0.27	2		12.5	-0.0477	-3.98	2		20	0.0076	0.58	2
AR	Sign	20	-0.0089	-0.27	2		12.5	-0.0457	-3.85	2		20	0.011	0.58	2
AR	Std	20	-0.0089	-0.27	2		12.5	-0.0457	-3.85	2		20	0.011	0.58	2
ARdotw	Sign	20	-0.0086	-0.26	2		12.5	-0.0459	-3.87	2		20	0.0109	0.58	2
ARdotw	Std	20	-0.0086	-0.26	2		12.5	-0.0459	-3.87	2		20	0.0109	0.58	2

North Korea Nuclear Weapon Test – IAU

Total		Before					During					After			
RT	DC	D	R	t-s	E		D	R	t-s	E		D	R	t-s	E
ARprev	NA	20	0.0142	1.22	5		20	-0.0212	-1.09	5					
r	Sign	20	0.0182	1.22	5		47.8	-0.048	-0.99	5		20	-0.0039	-0.3	5
r	Std	20	0.0237	1.48	4		58	-0.0558	-0.91	4		20	0.0059	0.06	4
AR	Sign	20	0.0142	1.22	5		47.4	-0.0549	-0.86	5		20	-0.0076	-0.29	5
AR	Std	20	0.0197	1.48	4		57.5	-0.064	-0.79	4		20	0.0023	0.07	4
ARdotw	Sign	20	0.0143	1.23	5		47.8	-0.0548	-0.86	5		20	-0.0079	-0.3	5
ARdotw	Std	20	0.0199	1.5	4		58	-0.064	-0.79	4		20	0.0019	0.06	4

North Korea Nuclear Weapon Test – IAU

(+)		Before				During				After			
RT	DC	D	R	t-s	E	D	R	t-s	E	D	R	t-s	E
r	Sign	20	0.0312	1.75	3	4.33	0.0183 **	4.75	3	20	-0.0075	-0.29	3
r	Std	20	0.0312	1.75	3	4.33	0.0183 **	4.75	3	20	-0.0075	-0.29	3
AR	Sign	20	0.0272	1.75	3	3.67	0.0175 **	5.04	3	20	-0.011	-0.28	3
AR	Std	20	0.0272	1.75	3	3.67	0.0175 **	5.04	3	20	-0.011	-0.28	3
ARdotw	Sign	20	0.0274	1.79	3	4.33	0.0175 **	4.96	3	20	-0.0114	-0.29	3
ARdotw	Std	20	0.0274	1.79	3	4.33	0.0175 **	4.96	3	20	-0.0114	-0.29	3

North Korea Nuclear Weapon Test – IAU

(–)		Before				During				After			
RT	DC	D	R	t-s	E	D	R	t-s	E	D	R	t-s	E
r	Sign	20	-0.0014	-2.21	2	113	-0.1476	-1.3	2	20	0.0014	-0.06	2
r	Std	20	0.001		1	219	-0.2781		1	20	0.0461		1
AR	Sign	20	-0.0053	-2.21	2	113	-0.1634	-1.13	2	20	-0.0026	-0.06	2
AR	Std	20	-0.0029		1	219	-0.3084		1	20	0.0421		1
ARdotw	Sign	20	-0.0053	-2.16	2	113	-0.1633	-1.13	2	20	-0.0027	-0.06	2
ARdotw	Std	20	-0.0028		1	219	-0.3084		1	20	0.0417		1

Chuseok – KOSPI200

Total		Before				During				After			
RT	DC	D	R	t-s	E	D	R	t-s	E	D	R	t-s	E
ARprev	NA	20	0.0156 *	2.03	10	20	-0.0108	-0.61	10				
r	Sign	20	0.0203 *	2.03	10	6.6	0.0139	1.24	10	20	-0.0231	-1.82	10
r	Std	20	0.0157	1.42	7	8.86	0.0197	1.27	7	20	-0.0318	-1.86	7
AR	Sign	20	0.0156 *	2.03	10	6.6	0.0123	1.32	10	20	-0.0282 *	-1.84	10
AR	Std	20	0.0111	1.42	7	9	0.0175	1.34	7	20	-0.0367	-1.87	7
ARdotw	Sign	20	0.0156 *	2.02	10	6.6	0.0123	1.32	10	20	-0.0283 *	-1.85	10
ARdotw	Std	20	0.011	1.41	7	9	0.0175	1.34	7	20	-0.0367	-1.88	7

Chuseok – KOSPI200

(+)		Before				During				After			
RT	DC	D	R	t-s	E	D	R	t-s	E	D	R	t-s	E
r	Sign	20	0.0266 **	2.84	7	9.83	0.0245	1.87	7	20	-0.0245	-1.47	7
r	Std	20	0.0234 ***	6.15	4	14	0.0426 *	2.53	4	20	-0.0407	-1.5	4
AR	Sign	20	0.0197 *	2.25	6	9.67	0.0262 *	2.13	6	20	-0.0251	-1.09	6
AR	Std	20	0.0187 ***	6.15	4	14	0.0392 *	2.73	4	20	-0.0451	-1.5	4
ARdotw	Sign	20	0.0197 *	2.25	6	9.67	0.0262 *	2.14	6	20	-0.0251	-1.1	6
ARdotw	Std	20	0.0187 ***	6.15	4	14	0.0393 *	2.75	4	20	-0.0451	-1.5	4

Chuseok – KOSPI200

(–)		Before					During					After			
RT	DC	D	R	t-s	E		D	R	t-s	E		D	R	t-s	E
r	Sign	20	0.0055	0.05	3		1.75	-0.0109	-1.54	3		20	-0.0199	-0.9	3
r	Std	20	0.0055	0.05	3		2	-0.0109	-1.54	3		20	-0.0199	-0.9	3
AR	Sign	20	0.0094	0.62	4		2	-0.0086	-1.44	4		20	-0.033	-1.56	4
AR	Std	20	0.0009	0.05	3		2.33	-0.0114	-1.54	3		20	-0.0254	-0.91	3
ARdotw	Sign	20	0.0094	0.61	4		2	-0.0086	-1.43	4		20	-0.0331	-1.57	4
ARdotw	Std	20	0.0008	0.04	3		2.33	-0.0114	-1.51	3		20	-0.0255	-0.92	3

Chuseok – KOSDAQ

Total		Before					During					After			
RT	DC	D	R	t-s	E		D	R	t-s	E		D	R	t-s	E
ARprev	NA	20	0.0014	0.12	10		20	-0.0166	-0.77	10					
r	Sign	20	0.006	0.12	10		15.6	0.0323	0.59	10		20	-0.0156	-1.37	10
r	Std	20	-0.0049	-0.54	5		19.8	0.0896	1.06	5		20	-0.0315	-1.88	5
AR	Sign	20	0.0014	0.12	10		15.6	0.028	0.6	10		20	-0.0201	-1.37	10
AR	Std	20	-0.0095	-0.54	5		19.8	0.0837	1.11	5		20	-0.0359	-1.88	5
ARdotw	Sign	20	0.0013	0.12	10		15.3	0.0279	0.6	10		20	-0.0209	-1.41	10
ARdotw	Std	20	-0.0096	-0.55	5		19.2	0.0835	1.11	5		20	-0.0375	-1.95	5

Chuseok – KOSDAQ

(+)		Before				During				After			
RT	DC	D	R	t-s	E	D	R	t-s	E	D	R	t-s	E
r	Sign	20	-0.0018	-0.39	5	25	0.1135	1.43	5	20	-0.0412 **	-3.29	5
r	Std	20	-0.013	-0.65	3	31	0.158	1.21	3	20	-0.0556 **	-5.7	3
AR	Sign	20	-0.0064	-0.39	5	25	0.1062	1.5	5	20	-0.0457 **	-3.29	5
AR	Std	20	-0.0175	-0.65	3	31	0.1485	1.26	3	20	-0.06 **	-5.7	3
ARdotw	Sign	20	-0.0064	-0.39	5	24.4	0.1061	1.5	5	20	-0.0472 **	-3.41	5
ARdotw	Std	20	-0.0175	-0.65	3	30	0.1482	1.26	3	20	-0.0625 **	-7.65	3

Chuseok – KOSDAQ

(−)		Before				During				After			
RT	DC	D	R	t-s	E	D	R	t-s	E	D	R	t-s	E
r	Sign	20	0.0138	0.56	5	6.2	-0.0489	-1.19	5	20	0.01	0.25	5
r	Std	20	0.0072	0.1	2	3	-0.013	-4.39	2	20	0.0048	0	2
AR	Sign	20	0.0091	0.56	5	6.2	-0.0501	-1.17	5	20	0.0054	0.25	5
AR	Std	20	0.0026	0.1	2	3	-0.0136	-4.39	2	20	0.0002	0	2
ARdotw	Sign	20	0.009	0.55	5	6.2	-0.0502	-1.17	5	20	0.0055	0.26	5
ARdotw	Std	20	0.0022	0.09	2	3	-0.0137	-4.45	2	20	0	0	2

Korean New Year – KOSPI200

Total		Before					During					After			
RT	DC	D	R	t-s	E		D	R	t-s	E		D	R	t-s	E
ARprev	NA	20	-0.0152	-1.13	9		20	0.0192	1.86	9					
r	Sign	20	-0.0107	-1.13	9		12.44	0.0074	0.37	9		20	0.0176	1.15	9
r	Std	20	-0.0202	-1.58	7		14	0.0065	0.21	7		20	0.0207	1.11	7
AR	Sign	20	-0.0152	-1.13	9		9.44	0.0042	0.36	9		20	0.0162	1.49	9
AR	Std	20	-0.0247	-1.58	7		10.71	0.0028	0.18	7		20	0.0205	1.49	7
ARdotw	Sign	20	-0.0152	-1.13	9		9.44	0.0041	0.35	9		20	0.0162	1.48	9
ARdotw	Std	20	-0.0247	-1.58	7		10.71	0.0028	0.18	7		20	0.0204	1.48	7

Korean New Year – KOSPI200

(+)		Before					During						After			
RT	DC	D	R	t-s	E		D	R		t-s	E		D	R	t-s	E
r	Sign	20	-0.0085	-0.67	6		15.17	0.0256	*	2.38	6		20	-0.0008	-0.59	6
r	Std	20	-0.024	-1.07	4		19.25	0.0334	*	2.4	4		20	-0.0046	-0.66	4
AR	Sign	20	-0.013	-0.67	6		10.67	0.0216	**	2.61	6		20	-0.0005	-0.05	6
AR	Std	20	-0.0285	-1.07	4		13.5	0.0279	*	2.53	4		20	-0.0014	-0.09	4
ARdotw	Sign	20	-0.013	-0.67	6		10.67	0.0216	**	2.58	6		20	-0.0006	-0.06	6
ARdotw	Std	20	-0.0285	-1.07	4		13.5	0.028	*	2.51	4		20	-0.0015	-0.1	4

Korean New Year – KOSPI200

(–)		Before					During					After			
RT	DC	D	R	t-s	E		D	R	t-s	E		D	R	t-s	E
r	Sign	20	-0.0151	-1.21	3		7	-0.0292	-1.68	3		20	0.0545 **	5.5	3
r	Std	20	-0.0151	-1.21	3		7	-0.0292	-1.68	3		20	0.0545 **	5.5	3
AR	Sign	20	-0.0197	-1.21	3		7	-0.0307	-1.6	3		20	0.0497 **	5.5	3
AR	Std	20	-0.0197	-1.21	3		7	-0.0307	-1.6	3		20	0.0497 **	5.5	3
ARdotw	Sign	20	-0.0197	-1.21	3		7	-0.0308	-1.59	3		20	0.0497 **	5.5	3
ARdotw	Std	20	-0.0197	-1.21	3		7	-0.0308	-1.59	3		20	0.0497 **	5.5	3

Korean New Year – KOSDAQ

Total		Before					During					After			
RT	DC	D	R	t-s	E		D	R	t-s	E		D	R	t-s	E
ARprev	NA	20	-0.0075	-0.51	9		20	0.0264 **	2.47	9					
r	Sign	20	-0.0029	-0.51	9		24.22	0.049	1.25	9		20	-0.0138	-0.7	9
r	Std	20	-0.0215	-0.9	4		34.5	0.0703	0.86	4		20	-0.0193	-0.51	4
AR	Sign	20	-0.0075	-0.51	9		22.22	0.0398	1.28	9		20	-0.0122	-0.46	9
AR	Std	20	-0.026	-0.9	4		30	0.0549	0.82	4		20	-0.01	-0.21	4
ARdotw	Sign	20	-0.0074	-0.51	9		22.22	0.0399	1.28	9		20	-0.0123	-0.47	9
ARdotw	Std	20	-0.0176	-0.73	5		24.2	0.0445	0.85	5		20	-0.0117	-0.32	5

Korean New Year – KOSDAQ

(+)		Before					During					After			
RT	DC	D	R	t-s	E		D	R	t-s	E		D	R	t-s	E
r	Sign	20	-0.0083	-0.71	7		35	0.0736	1.66	7		20	-0.0403	-1.81	7
r	Std	20	-0.0287	-0.84	3		44.67	0.1161	1.33	3		20	-0.0611	-2.11	3
AR	Sign	20	-0.0129	-0.71	7		32	0.062	1.75	7		20	-0.0368	-1.4	7
AR	Std	20	-0.0332	-0.84	3		38.67	0.0958	1.29	3		20	-0.047	-1.11	3
ARdotw	Sign	20	-0.0128	-0.71	7		32	0.0621	1.75	7		20	-0.0369	-1.41	7
ARdotw	Std	20	-0.0208	-0.68	4		29.25	0.0726	1.26	4		20	-0.0399	-1.3	4

Korean New Year – KOSDAQ

(−)		Before					During					After			
RT	DC	D	R	t-s	E		D	R	t-s	E		D	R	t-s	E
r	Sign	20	0.0161	0.71	2		2.67	-0.0371	-1.26	2		20	0.079	2.73	2
r	Std	20	0		1		4	-0.0671		1		20	0.1062		1
AR	Sign	20	0.0114	0.71	2		2.67	-0.0379	-1.26	2		20	0.074	2.73	2
AR	Std	20	-0.0046		1		4	-0.068		1		20	0.1011		1
ARdotw	Sign	20	0.0114	0.71	2		2.67	-0.0379	-1.26	2		20	0.0739	2.74	2
ARdotw	Std	20	-0.0046		1		4	-0.068		1		20	0.1009		1

iPhone Release – 005930

Total		Before				During				After			
RT	DC	D	R	t-s	E	D	R	t-s	E	D	R	t-s	E
ARprev	NA	20	0.031	1.73	13	20	0.0033	0.16	13				
r	Sign	20	0.044	1.73	13	5	-0.0012	-0.36	13	20	0.034	0.83	13
r	Std	20	0.0443	1.11	6	1.5	-0.0006	-0.42	6	20	0.0113	-0.03	6
AR	Sign	20	0.031	1.73	13	5.92	-0.0067	-0.52	13	20	0.0242	0.98	13
AR	Std	20	0.0259	0.76	5	1.8	-0.0024	-0.49	5	20	0.0207	0.45	5
ARdotw	Sign	20	0.0308	1.72	13	5.69	-0.0065	-0.51	13	20	0.0246	0.99	13
ARdotw	Std	20	0.0259	0.77	5	1.8	-0.0023	-0.48	5	20	0.0207	0.45	5

iPhone Release – 005930

(+)		Before				During				After			
RT	DC	D	R	t-s	E	D	R	t-s	E	D	R	t-s	E
r	Sign	20	0.0532 *	2.09	8	4.14	0.0206	1.56	8	20	0.0249	0.3	8
r	Std	20	0.064 *	2.8	4	1	0.0046	2.07	4	20	-0.0079	-0.32	4
AR	Sign	20	0.039	1.76	7	4.67	0.0208	1.8	7	20	-0.0072	-0.18	7
AR	Std	20	0.0487	1.11	2	1	0.0072 *	8.44	2	20	-0.0627	-0.92	2
ARdotw	Sign	20	0.0387	1.76	7	4.67	0.021	1.84	7	20	-0.0071	-0.18	7
ARdotw	Std	20	0.0487	1.11	2	1	0.0073 **	14.2	2	20	-0.0625	-0.93	2

iPhone Release – 005930

(−)		Before				During				After			
RT	DC	D	R	t-s	E	D	R	t-s	E	D	R	t-s	E
r	Sign	20	0.0294	0.44	5	6	-0.0362 *	-2.25	5	20	0.0485	1.56	5
r	Std	20	0.0049	-0.09	2	2	-0.0111	-2.76	2	20	0.0496	1.43	2
AR	Sign	20	0.0216	0.7	6	7	-0.0387 *	-2.32	6	20	0.0609 **	2.83	6
AR	Std	20	0.0108	0.2	3	2.33	-0.0087	-1.63	3	20	0.0762	1.94	3
ARdotw	Sign	20	0.0215	0.7	6	6.57	-0.0385 *	-2.31	6	20	0.0616 **	2.85	6
ARdotw	Std	20	0.0108	0.2	3	2.33	-0.0087	-1.64	3	20	0.0761	1.95	3

iPhone Release – AAPL

Total		Before				During				After			
RT	DC	D	R	t-s	E	D	R	t-s	E	D	R	t-s	E
ARprev	NA	20	0.0146	0.99	13	20	-0.036 *	-1.79	13				
r	Sign	20	0.0375	0.99	13	22.15	-0.0178	-1.09	13	20	-0.0129	-1.44	13
r	Std	20	0.0351	0.59	9	9.11	0.0215	0.42	9	20	-0.0308	-1.75	9
AR	Sign	20	0.0146	0.99	13	24.46	-0.0429	-0.95	13	20	-0.0167	-0.58	13
AR	Std	20	0.0066	0.29	8	14.38	0.0037	0.13	8	20	-0.0477	-1.17	8
ARdotw	Sign	20	0.0145	0.99	13	24.62	-0.0431	-0.96	13	20	-0.0175	-0.61	13
ARdotw	Std	20	0.0065	0.28	8	14.63	0.0034	0.12	8	20	-0.0489	-1.2	8

iPhone Release – AAPL

(+)		Before				During				After			
RT	DC	D	R	t-s	E	D	R	t-s	E	D	R	t-s	E
r	Sign	20	0.0357	0.57	7	11.43	0.0503	1.34	7	20	-0.0318	-1.84	7
r	Std	20	0.0387	0.6	6	11.83	0.0506	1.13	6	20	-0.0289	-1.48	6
AR	Sign	20	0.0128	0.57	7	11	0.0313	1.66	7	20	-0.0439	-1.51	7
AR	Std	20	0.0074	0.24	5	13	0.0433	1.74	5	20	-0.0724 *	-2.52	5
ARdotw	Sign	20	0.0127	0.57	7	11.33	0.031	1.65	7	20	-0.0453	-1.56	7
ARdotw	Std	20	0.0072	0.24	5	13.4	0.0429	1.73	5	20	-0.0743 *	-2.62	5

iPhone Release – AAPL

(–)		Before				During				After			
RT	DC	D	R	t-s	E	D	R	t-s	E	D	R	t-s	E
r	Sign	20	0.0396	0.8	6	34.67	-0.0972	-2.01	6	20	0.0091	-0.32	6
r	Std	20	0.0281	0.13	3	3.67	-0.0369	-1.85	3	20	-0.0347	-0.8	3
AR	Sign	20	0.0166	0.8	6	36	-0.1295	-1.51	6	20	0.015	0.29	6
AR	Std	20	0.0053	0.13	3	16.67	-0.0623	-1.37	3	20	-0.0065	-0.06	3
ARdotw	Sign	20	0.0167	0.8	6	36	-0.1296	-1.52	6	20	0.0149	0.28	6
ARdotw	Std	20	0.0053	0.13	3	16.67	-0.0623	-1.38	3	20	-0.0066	-0.06	3

iPhone Release – XLK

Total		Before				During				After			
RT	DC	D	R	t-s	E	D	R	t-s	E	D	R	t-s	E
ARprev	NA	20	0.0106	1.12	13	20	-0.0198	-1.77	13				
r	Sign	20	0.0235	1.12	13	8.92	-0.0219 **	-2.44	13	20	0.0255	0.74	13
r	Std	20	0.0267	0.91	8	2.75	-0.0118	-1.57	8	20	0.0311	0.92	8
AR	Sign	20	0.0106	1.12	13	15.62	-0.0283 **	-2.24	13	20	0.0226	1.39	13
AR	Std	20	0.0143	1.06	9	18.56	-0.0283	-1.69	9	20	0.0263	1.37	9
ARdotw	Sign	20	0.0104	1.1	13	15.62	-0.0282 **	-2.23	13	20	0.0226	1.39	13
ARdotw	Std	20	0.0137	0.9	8	3	-0.0134	-1.5	8	20	0.0206	1	8

iPhone Release – XLK

(+)		Before				During				After			
RT	DC	D	R	t-s	E	D	R	t-s	E	D	R	t-s	E
r	Sign	20	0.0349	1.87	5	6.2	0.01 **	3.93	5	20	-0.033 *	-2.44	5
r	Std	20	0.0524 **	5.5	3	2.33	0.0076 **	7.47	3	20	-0.0147	-1.63	3
AR	Sign	20	0.0219	1.87	5	2	0.004 **	2.97	5	20	-0.0325 *	-2.35	5
AR	Std	20	0.0392 **	5.5	3	2.33	0.0061 **	9.87	3	20	-0.0271	-1.63	3
ARdotw	Sign	20	0.0218	1.85	5	2	0.0042 **	3.14	5	20	-0.0324 *	-2.34	5
ARdotw	Std	20	0.0391 **	5.55	3	2.33	0.0063 ***	11.28	3	20	-0.027	-1.63	3

iPhone Release – XLK

(−)		Before				During				After			
RT	DC	D	R	t-s	E	D	R	t-s	E	D	R	t-s	E
r	Sign	20	0.0163	0.26	8	10.63	-0.0418 **	-3.38	8	20	0.0622 **	3.37	8
r	Std	20	0.0113	-0.06	5	3	-0.0235 *	-2.34	5	20	0.0586	2.01	5
AR	Sign	20	0.0035	0.26	8	24.13	-0.0486 **	-2.84	8	20	0.057 ***	3.75	8
AR	Std	20	0.0019	0.11	6	26.67	-0.0456 *	-2.05	6	20	0.0529 **	2.66	6
ARdotw	Sign	20	0.0033	0.24	8	24.13	-0.0485 **	-2.83	8	20	0.057 ***	3.75	8
ARdotw	Std	20	-0.0016	-0.07	5	3.4	-0.0252 *	-2.22	5	20	0.0492	2.06	5

Plane Crash – JETS

Total		Before				During				After			
RT	DC	D	R	t-s	E	D	R	t-s	E	D	R	t-s	E
ARprev	NA	20	0.0146 *	1.77	62	20	0.0046	0.63	62				
r	Sign	20	0.0192 *	1.77	62	9.42	0.0158 **	2.11	62	20	-0.0113 *	-1.77	62
r	Std	20	0.01	0.47	28	10.29	0.0183	1.45	28	20	-0.0117	-1.24	28
AR	Sign	20	0.0146 *	1.77	62	7.77	0.0091	1.49	62	20	-0.0073	-0.81	62
AR	Std	20	0.0054	0.47	28	9.82	0.016	1.48	28	20	-0.0168	-1.27	28
ARdotw	Sign	20	0.0146 *	1.77	62	8.45	0.0106	1.66	62	20	-0.0092	-1.04	62
ARdotw	Std	20	0.0055	0.47	28	9.79	0.016	1.47	28	20	-0.0171	-1.3	28

Plane Crash – JETS

(+)		Before				During				After			
RT	DC	D	R	t-s	E	D	R	t-s	E	D	R	t-s	E
r	Sign	20	0.0229 *	1.87	40	11.12	0.0367 ***	4.91	40	20	-0.0321 ***	-3.59	40
r	Std	20	0.0224	1.47	21	10.29	0.0374 ***	3.47	21	20	-0.0404 ***	-4.26	21
AR	Sign	20	0.0183 *	1.87	40	8.55	0.0293 ***	4.8	40	20	-0.028 **	-2.69	40
AR	Std	20	0.0178	1.47	21	9.67	0.0349 ***	3.7	21	20	-0.0457 ***	-4.22	21
ARdotw	Sign	20	0.0183 *	1.88	40	9.44	0.0316 ***	4.84	40	20	-0.031 ***	-3.06	40
ARdotw	Std	20	0.0178	1.48	21	9.62	0.0349 ***	3.7	21	20	-0.0461 ***	-4.28	21

Plane Crash – JETS

(–)		Before				During				After			
RT	DC	D	R	t-s	E	D	R	t-s	E	D	R	t-s	E
r	Sign	20	0.0126	0.52	22	6.1	-0.0223 **	-2.78	22	20	0.0265	1.56	22
r	Std	20	-0.0273	-1.29	7	10.29	-0.0387	-1.92	7	20	0.0746 ***	3.97	7
AR	Sign	20	0.008	0.52	22	6.54	-0.0275 ***	-2.96	22	20	0.0304 **	2.25	22
AR	Std	20	-0.0317	-1.29	7	10.29	-0.0407	-1.81	7	20	0.0697 ***	3.97	7
ARdotw	Sign	20	0.008	0.53	22	6.78	-0.0275 ***	-2.97	22	20	0.0303 **	2.24	22
ARdotw	Std	20	-0.0316	-1.28	7	10.29	-0.0408	-1.81	7	20	0.0697 ***	3.98	7

Plane Crash – DJP

Total		Before				During				After			
RT	DC	D	R	t-s	E	D	R	t-s	E	D	R	t-s	E
ARprev	NA	20	0.0019	0.42	62	20	0.0047	1.03	62				
r	Sign	20	-0.0014	0.42	62	6.87	0	0.24	62	20	0.0074 **	2.18	62
r	Std	20	0.0018	0.74	29	8.79	-0.007	-0.62	29	20	0.013 **	2.35	29
AR	Sign	20	0.0019	0.42	62	6.76	0.0011	0.24	62	20	0.0103 **	2.07	62
AR	Std	20	0.0051	0.74	29	8.83	-0.0056	-0.63	29	20	0.0161 **	2.27	29
ARdotw	Sign	20	0.0019	0.42	62	6.76	0.0012	0.24	62	20	0.0103 **	2.07	62
ARdotw	Std	20	0.0047	0.7	30	8.57	-0.0055	-0.65	30	20	0.0166 **	2.41	30

Plane Crash – DJP

(+)		Before				During				After			
RT	DC	D	R	t-s	E	D	R	t-s	E	D	R	t-s	E
r	Sign	20	-0.0054	-0.31	34	6.48	0.0196 ***	4.13	34	20	-0.0132 *	-1.75	34
r	Std	20	0.0052	0.85	15	7	0.0208 **	2.57	15	20	-0.0095	-1	15
AR	Sign	20	-0.0021	-0.31	34	6.34	0.0207 ***	3.93	34	20	-0.0102 *	-1.78	34
AR	Std	20	0.0086	0.85	15	7.07	0.022 **	2.43	15	20	-0.0068	-1.04	15
ARdotw	Sign	20	-0.0013	-0.21	36	6.34	0.0195 ***	3.89	36	20	-0.009	-1.64	36
ARdotw	Std	20	0.0086	0.85	15	6.67	0.022 **	2.44	15	20	-0.0068	-1.04	15

Plane Crash – DJP

(−)		Before				During				After			
RT	DC	D	R	t-s	E	D	R	t-s	E	D	R	t-s	E
r	Sign	20	0.0034	1.12	28	7.26	-0.0238 ***	-3.46	28	20	0.0324 ***	6.33	28
r	Std	20	-0.0019	0.14	14	10.47	-0.0369 **	-3.01	14	20	0.0372 ***	4.39	14
AR	Sign	20	0.0067	1.12	28	7.2	-0.0226 ***	-3.59	28	20	0.0351 ***	6.11	28
AR	Std	20	0.0014	0.14	14	10.47	-0.0352 ***	-3.13	14	20	0.0406 ***	4.39	14
ARdotw	Sign	20	0.0063	0.98	26	7.2	-0.0243 ***	-3.65	26	20	0.0369 ***	6.12	26
ARdotw	Std	20	0.0008	0.09	15	10.47	-0.0331 ***	-3.11	15	20	0.0399 ***	4.61	15

Plane Crash – IAU

Total		Before				During				After			
RT	DC	D	R	t-s	E	D	R	t-s	E	D	R	t-s	E
ARprev	NA	20	-0.0069	-1.43	62	20	-0.0041	-0.93	62				
r	Sign	20	-0.003	-1.43	62	11.79	0.0012	-0.19	62	20	0.0036	-0.06	62
r	Std	20	0.004	0.02	27	14.15	-0.0064	-0.85	27	20	0.0126	0.96	27
AR	Sign	20	-0.0069	-1.43	62	10.95	-0.004	-0.8	62	20	0.0031	0.55	62
AR	Std	20	-0.0011	-0.22	28	14.82	-0.0127	-1.47	28	20	0.0131	1.4	28
ARdotw	Sign	20	-0.0069	-1.44	62	10.97	-0.0039	-0.8	62	20	0.0031	0.55	62
ARdotw	Std	20	-0.0011	-0.22	28	14.82	-0.0127	-1.46	28	20	0.013	1.4	28

Plane Crash – IAU

(+)		Before					During					After			
RT	DC	D	R		t-s	E	D	R		t-s	E	D	R		t-s	E
r	Sign	20	0.0052		0.15	27	17.16	0.0306	**	2.73	27	20	-0.0225	***	-3.3	27
r	Std	20	0.0085		0.44	8	21.13	0.0473		1.8	8	20	-0.0255		-1.5	8
AR	Sign	20	0.0013		0.15	27	11.75	0.024	***	3.7	27	20	-0.0278	***	-3.48	27
AR	Std	20	0.0045		0.44	8	15.38	0.0356	**	2.47	8	20	-0.0356		-1.81	8
ARdotw	Sign	20	0.0019		0.21	26	11.75	0.025	***	3.74	26	20	-0.0286	***	-3.46	26
ARdotw	Std	20	0.0045		0.43	8	15.38	0.0357	**	2.47	8	20	-0.0357		-1.82	8

Plane Crash – IAU

(−)		Before					During					After				
RT	DC	D	R		t-s	E	D	R		t-s	E	D	R		t-s	E
r	Sign	20	-0.0094	**	-2.56	35	8.16	-0.0215	***	-5.31	35	20	0.0237	***	3.91	35
r	Std	20	0.0022		-0.3	19	11.21	-0.029	***	-4.54	19	20	0.0287	***	3.3	19
AR	Sign	20	-0.0132	**	-2.56	35	10.45	-0.0255	***	-5.55	35	20	0.027	***	5.38	35
AR	Std	20	-0.0034		-0.59	20	14.6	-0.032	***	-4.56	20	20	0.0326	***	4.84	20
ARdotw	Sign	20	-0.0133	**	-2.64	36	10.47	-0.0248	***	-5.48	36	20	0.026	***	5.22	36
ARdotw	Std	20	-0.0033		-0.58	20	14.6	-0.032	***	-4.56	20	20	0.0325	***	4.83	20

Black Friday – SPX

Total		Before				During				After			
RT	DC	D	R	t-s	E	D	R	t-s	E	D	R	t-s	E
ARprev	NA	20	-0.0032	-0.33	10	20	0.0056	0.47	10				
r	Sign	20	0.0059	-0.33	10	7.5	0.0118	0.81	10	20	0.011	0.13	10
r	Std	20	-0.0154	-1.25	4	5.5	0.0083	0.73	4	20	0.01	0.03	4
AR	Sign	20	-0.0032	-0.33	10	8.3	0.0071	0.84	10	20	0.0028	0.2	10
AR	Std	20	-0.0243	-1.25	4	5.5	0.0058	0.99	4	20	0.0008	0.03	4
ARdotw	Sign	20	-0.0032	-0.32	10	8.3	0.0073	0.86	10	20	0.0028	0.2	10
ARdotw	Std	20	-0.0243	-1.25	4	5.5	0.0059	1.02	4	20	0.0008	0.03	4

Black Friday – SPX

(+)		Before				During				After			
RT	DC	D	R	t-s	E	D	R	t-s	E	D	R	t-s	E
r	Sign	20	-0.0132	-1.62	5	21.33	0.0268	0.9	5	20	0.0008	-0.3	5
r	Std	20	-0.0342 **	-5.27	3	19	0.0117	0.29	3	20	0.0055	-0.08	3
AR	Sign	20	-0.0336	-1.93	3	21	0.0343	1.52	3	20	0.0121	0.39	3
AR	Std	20	-0.0511 ***	-162.1	2	19	0.0126	1.2	2	20	0.0413	2.22	2
ARdotw	Sign	20	-0.0319 *	-2.55	4	21	0.0257	1.43	4	20	-0.0143	-0.42	4
ARdotw	Std	20	-0.043 **	-5.25	3	19	0.0085	1.16	3	20	-0.0036	-0.08	3

Black Friday – SPX

(–)		Before				During				After			
RT	DC	D	R	t-s	E	D	R	t-s	E	D	R	t-s	E
r	Sign	20	0.0251	1.9	5	1.57	-0.0033 **	-3.89	5	20	0.0213	1.05	5
r	Std	20	0.041		1	1	-0.0016		1	20	0.0235		1
AR	Sign	20	0.0098	1.18	7	2.86	-0.0045	-1.81	7	20	-0.0011	-0.07	7
AR	Std	20	0.0025	0.08	2	1	-0.0011	-1.06	2	20	-0.0396	-0.74	2
ARdotw	Sign	20	0.016 *	2.35	6	2.86	-0.0051	-1.8	6	20	0.0143	1.45	6
ARdotw	Std	20	0.0316		1	1	-0.0019		1	20	0.0143		1

Black Friday – XLK

Total		Before				During				After			
RT	DC	D	R	t-s	E	D	R	t-s	E	D	R	t-s	E
ARprev	NA	20	-0.0082	-0.63	10	20	-0.0005	-0.05	10				
r	Sign	20	0.0045	-0.63	10	3.7	0.0041	0.57	10	20	0.0083	-0.38	10
r	Std	20	-0.0047	-0.88	6	5.17	0.0076	0.96	6	20	0.0055	-0.39	6
AR	Sign	20	-0.0082	-0.63	10	2.4	0.0019	0.87	10	20	-0.0049	-0.43	10
AR	Std	20	-0.0369	-1.6	4	2.25	0.0043	0.94	4	20	-0.0088	-0.31	4
ARdotw	Sign	20	-0.0081	-0.63	10	2.4	0.0021	0.97	10	20	-0.005	-0.44	10
ARdotw	Std	20	-0.022	-0.94	5	2.2	0.0045	1.26	5	20	-0.0102	-0.46	5

Black Friday – XLK

(+)		Before				During				After			
RT	DC	D	R	t-s	E	D	R	t-s	E	D	R	t-s	E
r	Sign	20	-0.0119	-1.41	6	6.2	0.0085	1.08	6	20	0.0001	-0.77	6
r	Std	20	-0.0146	-1.3	5	9.33	0.0096	0.75	5	20	-0.0037	-0.85	5
AR	Sign	20	-0.0243	-1.41	6	3.6	0.0053 *	2.05	6	20	-0.0134	-0.83	6
AR	Std	20	-0.0596 ***	-11.75	3	6	0.0068	1.25	3	20	-0.0245	-0.73	3
ARdotw	Sign	20	-0.0243	-1.41	6	3.6	0.0055 *	2.13	6	20	-0.0135	-0.84	6
ARdotw	Std	20	-0.0353	-1.43	4	4	0.0063	1.62	4	20	-0.0224	-0.94	4

Black Friday – XLK

(−)		Before				During				After			
RT	DC	D	R	t-s	E	D	R	t-s	E	D	R	t-s	E
r	Sign	20	0.029	1.15	4	1.2	-0.0025	-2	4	20	0.0205	0.48	4
r	Std	20	0.0446		1	1	-0.0025		1	20	0.0518		1
AR	Sign	20	0.016	1.15	4	1.2	-0.0033	-1.85	4	20	0.0077	0.48	4
AR	Std	20	0.0314		1	1	-0.0031		1	20	0.0386		1
ARdotw	Sign	20	0.0161	1.15	4	1.2	-0.0031	-1.75	4	20	0.0077	0.48	4
ARdotw	Std	20	0.0315		1	1	-0.0029		1	20	0.0385		1