Making Profit out of Airplane Crashes

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สืบเนื่องมาจากทฤษฎีทางเศรษฐศาสตร์พฤติกรรม เมื่อนักลงทุนมีอารมณ์ที่เป็นด้านลบ จะส่งผลกระทบต่อการลงทุนของพวกเขา ในรายงานการวิจัยฉบับนี้เราได้ทำการวิจัยผลกระทบของอุบัติเหตุเครื่องบินตกต่อการเคลื่อนไหวของผลตอบแทนของหุ้นทั้งผลตอบแทนของหุ้นของสายการบินที่ประสบอุบัติเหตุและผลตอบแทนของหุ้นที่เป็นคู่แข่งของสายการบินที่ประสบอุบัติเหตุ เป็นระยะเวลา ๕๐ ปี ทั้งนี้เพื่อศึกษาการเคลื่อนไหวของผลตอบแทนของหลักทรัพย์เมื่อนำหุ้นทั้งสองฝั่งมาทำการซื้อขาย นอกจากนี้แล้วรายงานวิจัยฉบับนี้ยังศึกษาเพิ่มเติมเกี่ยวกับปัจจัยที่จะส่งผลกระทบต่อหลักทรัพย์ที่นำหุ้นทั้งสองฝั่งมาทำการซื้อขายกันแล้ว จากผลการศึกษาในรายงานการวิจัยฉบับนี้ เราได้พบว่า อัตราผลตอบแทนที่ผิดปกติสะสม (cumulative abnormal return, CAR) ของหุ้นของสายการบินที่ประสบอุบัติเหตุนั้น มีการเคลื่อนไหวไปในทางที่ลดลงอย่างต่อเนื่องและเคลื่อนขึ้นไปในทิศทางที่กลับคืนสู่สภาวะปกติ ในด้านของอัตราผลตอบแทนที่ผิดปกติสะสมของหุ้นฝั่งคู่แข่ง รายงานวิจัยฉบับนี้พบว่าอัตราผลตอบแทนที่ผิดปกติสะสมของหุ้นฝั่งคู่แข่งมีการเคลื่อนไหวโดยรวมไปในทางที่เพิ่มขึ้นอย่างต่อเนื่องไปในระยะเวลาหนึ่งก่อนที่จะมีการเคลื่อนไหวไปในทางที่กลับเข้าสู่สภาวะปกติ นอกจากนี้แล้วเรายังพบอีกว่าอัตราผลตอบแทนที่ผิดปกติสะสมของหลัทรัพย์ที่ทำการซื้อขายตามการซื้อขายตามการขึ้นลงของอัตราผลตอบแทนที่ผิดปกติสะสมนั้น มีการเพิ่มขึ้นเมื่ออุบัติเหตุเครื่องบินตกนั้นเกิดไกลจากตลาดหุ้นที่หุ้นของสายการบินที่ตกนั้นจดทะเบียนอยู่มากขึ้น ฉะนั้นนี่ถือเป็นการค้นพบที่ตรงกับทฤษฎีทางเศรษฐศาสตร์พฤติกรรม ที่ชื่อว่า Heuristic Theory ที่นักลงทุนจะตอบสนองน้อยลงเมื่อเหตุการณ์ที่มีผลกระทบต่ออารมณ์นักลงทุน เช่นอุบัติเหตุเครื่องบินตกนั้น เกิดขึ้นไกลจากนักลงทุนเหล่านั้นมากขึ้น

ภาควิชา	การธนาคารและการเงิน	ลายมือชื่อนิสิต	....
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According to behavioral finance, negative emotions drives negative sentiment that affects the decision to invest and may affect asset pricing. In this study we examine the effect of aviation disasters on the movement of the stock return of both the crashing airline and the competitor of the crashing airline over 50 years period, in order to detect the significant movement to form a profitable portfolio right after the crash happens. Moreover, we also study how the cumulative abnormal return of the portfolio and the crashing airline's stock would change due to various conditions. From the evidence, we find that there is a significant decrease in the cumulative abnormal return of the crashing airline and a significant increase in the cumulative abnormal return in the competitors' airline's stocks. Moreover, we also found an evidence that there is an increase in the cumulative abnormal return of the crashing airline as the crash happens further away from the stock market that the crashing airline's stock is listed. This could be inferred that people feel less emotional as the aviation crash happens further away from them. Thus, the Heuristc Theory also applies to this study.

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Student's Signature ....

Advisor's Signature ....

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CHAPTER 1

Introduction

1.1 Background and motivation

Normally when any disaster happens, people get panic and keep on shorting the stocks, which makes their prices as well as the overall financial market to go down. But in the case of airplane crashes, the effect is 60 times larger than the normal disruption from other shocks that affects the financial market (Kaplanski and Levy, 2010). Thus, this scenario interests us to study the correlation of the aviation disaster event and the stock movement in the financial market, especially the parties that are directly affected, which in this case are the crashing airline's stock and the competing airlines' stocks. When people are in negative mood, they usually perform some negative things, they also tend to be negative about the future, which leads them to take less risk at the current time. Thus, it is expected that people are afraid to hold the crashing airline's stock when they know that the crash had already happened recently. According to (Ho et al., 2013), there is a switching effect when the number of death in the crash is less than 10, which people would switch form holding the crashing airline's stock to the competing airlines' stocks. Thus, this would make the stock price of the competing airline to rise as soon as the investors know the news. This assumption leads us to study the movement of the stock prices of both the crashing airline and the competing airline. In this study, we find the evidence that there is a 19 days continuous decrease in the cumulative abnormal return (CAR) of the crashing airline's stock, with an evidence of a reverse trend right after that. On the competing airline's side, we find the evidence of a decreasing trend in the CAR of the competing airlines' stocks for 16 days before a reverse back down right after that. This movement leads us to detect an evidence of switching effect from holding the crashing airline's stock to holding the competing airlines' stocks. As there is an evidence of a reversal effect in movement of both the crashing airline's stock and the competing airlines' stocks, it could be implied that the stock movement of both sides has an event effect which people react to it through their negative emotion. This is because if the effect has a real economic loss, there wouldn't be a reversal trend of the return of the stock in such a short period of time.

The movement of the CAR in both sides of the stocks found in this study confirms Kaplanski and Levy (2008) research that the crashing airline stock really drops and reverse back up, and this result suggests that there is a room for profit making, which is to short when the stock price is falling and to long when the stock price is increasing. However, the reversal point is not exactly on the same date as theirs. In fact, the pattern of movements on each day is hardly significant across crashing events. Thus, there is no trivial rules for trading these stocks to the best make profit. Hence, we suggest several ways to form potential portfolios to retrieve some profits.

We also conduct an analysis to study the factors that affect the magnitude of the crashing airline's and the portfolio's abnormal return in different ways. Here, we include 5 factors to our analysis which are the financial market structure, the number of recent crashes, distance of the crash from the stock market, type of the flight, and number of death per crash. We test these factors because we want to know what makes the price moves when the crash happens, to find a theoretical explanation for the stock movement which could be helpful for investors to set priors in forming portfolios to gain profit from such crashing events in the future.

In particular, severity of incidents and some characteristics of the crashes may affect degree of panic and, thereby, have consequence on the movement of stock prices and abnormal returns. Moreover, according to the behavioral finance theory suggested by Tversky and Kahneman (1977), the size of panic or market reaction is lower when people experiences similar events more often as suggested in prospect theory. Therefore, it is interesting to examine if the behavioral finance theory can be applied in this case. More precisely, we will examine whether the abnormal returns diminish with an increase in the number of recent airplane crashes in the past twelve months. Also, there is an interesting theory called Heuristic Theory which is proposed by the same person, in which people have a bounded rationality, where they form some rationality which sometimes don't match the reality by their own experience or other factors. This leads us to think about the distance of the crash from the stock market that the stock of the crashing airline is listed, where people usually have home biased for holding the stocks available in their nation anyway, whether people would react more if the crash happens close to them. Thus, this could make a new finding about new type of Heuristic Theory for Behavioral Finance which could be developed further in the future.

The evidence from our study shows that there are only two variables that are statistically significant when run the regression against the cumulative abnormal return of both portfolio and the crashing airline's stock. These two factors are the distance between the crashing location and the stock market that the crashing airline is listed in and the number of death per crash. The distance factor seems to have a positive relationship with the cumulative abnormal return of the crashing airline's stock. This could be inferred that people pays less attention to the crash relative to the cases that happens closer to them. Thus, it would mean that the heuristic theory applies to the airplane crashing event as well. The number of death per crash affects negatively to the cumulative abnormal return of the crashing airline's stock. This means that people do get more depressed when the airplane crashes gets more severe.

The factor of the frequency of the crash seems to not have any significant effect to the mind of the investors and the result in this study shows no statistically significant coefficient of this factors. Thus, the Prospect Theory seems not to apply with the number of recent crashes and the mind of investors in this study.

1.2 Research Questions

This study have 3 main research questions as followed.

1.2.1 Research Question 1: Can profit be made out of crash?

As when the airplane crashing happens, people would be in panic and have a high level of anxiety. Thus, from this event the investors would react to the event by switching from holding the crashing airline's stock to holding the competing airlines' stocks. Thus, it is interesting to know if the investors really react as we expected. Moreover, as a result of this action, the stock price of the crashing airline would be moving up and the stock price of the competing airlines would be moving down after the investor perceive this news from the media. Thus, if we short the crashing airline's stock and long the competing airlines' stocks, it is interested to know if we could make a profit out of it.

1.2.2 Research Question 2: Is the cumulative abnormal return of the portfolio affected when the number of recent crashes changes?

As normally when we feel something painful up to one point, we would be numb and indifferent of any marginal increase in the level of pain from that. Thus, it is interesting to know if this concept also applies to the financial investing behavior as well. The period that we collect the number of crashes is 12 months before the considering crash, which we expect that people would be indifferent by then. Thus, it is expected that the cumulative abnormal return of the portfolio decreases a lot as the number of recent crashes increaseท up to one point. Then it would reaches a plateau at the bottom where people do not react to the airplane crashing event anymore.

1.2.3 Research Question 3: Is the cumulative abnormal return of the portfolio affected when the distance between crashing location and the crashing airline's stock market changes?

Normally, people would be less interested to things that happens further away from them. This applies with both the literal distance and the subjective area of interest or area of knowledge that we normally perceive in each day of our lives. Thus, it is interesting to know that if the investing behavior in the financial industry also has this kind of behavior acts upon the shocking event that happens further away from them as well. As a result, it is expected that the cumulative abnormal return of the crashing airline is higher as the distance gets further. It would also be inferred that the cumulative abnormal return of the portfolio would be lower as the distance gets longer when we short the crashing airline's stock.

1.3 Objectives & Contributions

1.3.1 Objectives

The objective is to investigate stock price and return movement around airplane crashes, in order to form portfolios that could make profit. More importantly, this study aims to examine the reasons of why such profit could be made, by investigating more deeply on characteristics of the market, crashes, and involving airlines. The ultimate goals are to provide sensible investing strategies for investors and to provide regulators with empirical facts that could be helpful for policy implementation to promote market stability.

1.3.2 Contributions

The finding of this study contributes to the financial world in the area of behavioral finance. This study concerns about two areas about the behavioral finance, which are Heuristic Bias and Prospect Theory. The part of the report that we concern about these two areas of behavioral finance are in the hypothesis II and III. In Hypothesis II, we state that the abnormal return of the crashing airline's stock will decline with the number of recent crashes. The reason behind this is that we expect people to be indifferent to the feeling of loss up to one point, like the utility movement of the investors when they face the loss in their investment. In the Prospect Theory, the utility of the investment decreases significantly when they face a little amount of loss. However, as the loss grows bigger and bigger, the marginal utility that drops down tends to be smaller and smaller, until those investors feel indifferent to the loss. If this hypothesis is true, it would imply that the utility of the loss in investment also applies to the utility of loss in the actual life story, which will in turn affects the investment decision.

For Hypothesis III, it concerns about the Heuristic Theory issue in Behavioral Finance. As there are many types of heuristics biased exists already, such as the heuristic that happens with likelihood, frequency and prediction. However, there is still no heuristic type that is clearly about the distance and the feeling of a person. In this study, we expect that the distance between crashing location and the market in which the crashing airline stock listed has impact on abnormal return of the crashing airline, which in turn affects the cumulative abnormal return of the portfolio. We expected that people would feel that the accident that happens closer to them are more relevant to them, which make them to aware more about it and react to it more intensely than the one that happens further away from them. Thus, the answer from this hypothesis will an evidence for the further research to propose a new type of Heuristic, which would include a deeper and more actual psychological experiment in the future time for confirmation.

CHAPTER 2

Literature Review

In the work of (Ho et al., 2013), it projects that there are two investors' behaviors following the airplane crashing, which are contagion effect and switch effect. The contagion effect happens when the number of death in the crash is exceeding 2 digit number. This is when people would perceive that this is a major crash in which will pull down every crashing airplane stocks' market value down. The switch effect happens when the fatality rate in the airplane crash is not exceeding 1 digit number as people would perceive it as minor, and would switch to the other competitors as their substitutes. This paper uses AR, AAR, and CAR of airplane stocks both of the crashing and the competitor airline's stocks to project the trend, which for our research we also use this method. The death rate also inspire us to study the factors that affect abnormal return as well, which in our report we include the distance of the crash and the frequency of the crash as the factors to be studied in our report here too, as they are able to be explained by the Heuristic and Prospect Theory of Tversky and Kahneman (1977).

According to Tversky and Kahneman (1977), each heuristic was associated with a set of biases. Use of the availability heuristic leads to error whenever member retrieval is a bias cue to actual truth. This is because individuals tend to seek out and remember dramatic cases or because the broader world tends to call attention to some particular type of examples. They could be aware of something that happens close to them or something that is available for them to see from the everyday living source of news. Some of these biases were defined as deviations from some true or objective value. However, most of it violates the basic laws of probability that it will really happen like the way we thought it would be. For example, when there is an airplane crash happens in their country or very close to their home country, they could probably feel that it is more relevant to them and would dangerous to their lives more than the ones that happens further away. They would feel that there might be a high chance that it will occur again in a near time than the case that happens further away. Most of these heuristic bias are formed irrationally to make a quick and dirty solution due to a person's overload of information. Most of the decision making due to heuristic bias are about the likelihood, frequency, and prediction.

The prospect theory also comes to attention when we make profits and make losses in the investment. According to Tversky and Kahneman (1977), when people make a little profit, the utility of the investor increases enormously. However, when the profit level reaches to one point, the marginal utility of the investor tends to decrease, it becomes less and less as the profit grow higher and higher, until they feel indifference to the marginal increase in the profit of their portfolio. This also applies to the loss side of the investment. When people make a small amount of loss in their investment, their utility from trading will enormously drop. However, as the marginal of loss in the investment goes on, the marginal utility that the investor obtains from the investment tends of be smaller and smaller. Nevertheless, up to one point the investor would feel indifferent to the marginal increase in the loss that occurs to them. Thus, it is interesting to know if the feeling of loss in the investment applies to the feeling of loss in the aviation crash when it comes to trading the airline's stocks as well.

In the work of Kaplanski and Levy (2010), it studies the event effect and the reversal effect. It depicts these effects though the projection of cumulative average abnormal return (CARs) around the dates when aviation disaster occurred. It projects that when the airplane crash happens, when the media are flooded with disturbing pictures about the crash and the horrible stories about it, the CARs goes down very significantly in the first day after the crash. This decline is almost 10 times larger in absolute terms than the average daily rates of return during the observed period. However, the market fully reverts back in 10 days after the decline. The reason that was given in their paper was that when people have anxiety, they would be more risk averse in trading risky stocks. And then when the sophisticated investors exploited the effect, the reversal effect occurs. Such movements would occur more to the stocks that are highly subjective and difficult to arbitrage and belong to the less stable industries. We use the event effect and reversal effect to exploit the profit from the price trend.

Moreover, there are several studies that show that mood and anxiety affect asset pricing. The work of Saunders (1993) and Hirshleifer and Shumway (2003) shows that sunshine associates with the person's mood and correlates positively with the daily stock returns. The work of Kamstra, Kramer, and Levi (2003) also confirm this effect. It shows that when the daylight period is shorter due to seasonal characteristic, there is a significant lower return on risky asset. Thus, it is interesting to know if the aviation disaster increases investors' fear and anxiety, which will then negatively affect the stock prices. The effect also depends on the media coverage of disasters, the fear and anxiety that the aviation disasters provoke, and the reduced in the willingness of investors to take risks when dear and anxiety increases. According to Singer and Endreny (1987), there is a heuristic bias that explain the tendency in media to cover aviation disasters. It said that "*a rare hazard is more newsworthy than a common one, other things being equal; a new hazard is more newsworthy than an old one; and a dramatic hazard—one that kills many people at once, suddenly or mysteriously—is more newsworthy than a long-familiar illness*". Barnett (1990) also show the evidence of the disproportionate media coverage regarding to the aviation disasters. He finds that the news about the aviation disaster in US occupied most of the area of the front page of famous newspapers, comparing to any other kind of loss of life news. He also projects that on per capita death basis, the number of stories about the aviation disaster is about 60 times higher than stories about AIDS, about 80 times higher than homicide stories, and several thousand times higher than articles relating to automobile accidents, suicide, and cancer. Anzur (2000) also summarize the public health officials' criticisms of media coverage of disaster. It accuses the media of being media of being ''*dominated by sensational images that may frighten rather than inform the public; having a potential for psychological damage to viewers when frightening images are shown repeatedly in the days and weeks of the disaster; and placing too much emphasis on crime, property damage, and loss of life, giving a relatively low priority to disaster preparedness and to public health issues in the aftermath of a disaster*'' (p. 196). Slovic (1987) also shows the evidence that anxiety affect the perceived of risk. It projects that the kind of risk that affect the risk perception the most is the risk that is called "Dread Risk", which is the risk that is perceived to be uncontrollable, involuntary, and has catastrophic potential or fatal consequences. As the aviation disaster incorporate these characteristics and using the service of the airline is almost a necessity when people has to travel to somewhere in a long distance, the fear of flying effect would affect a large proportion of the population relative to any other phobia.

CHAPTER 3

Data Description

3.1 Hypothesis Development

We expected that people would react negatively to the crashing airline's stock and to react positively to the competing airlines' stocks. Thus, it is expected that the CAR of the crashing airline's stock should drop down after the crash and the CAR of the competing airlines' stocks to increase. Thus, if we short the crashing airline's stock and long the competing airlines' stocks right after the crash happens, we would probably could create a profit out of the event.

For the factors that we want to test if they affect the CAR of the portfolio that we will make, the development of the hypothesis explanation is as followed.

The market structure (**MS**) in this case is the developed stock market and the emerging stock market. As emerging market would have less of professional traders, more of amateur traders, less information flows, and more of insiders. This would deteriorate the market to operate efficiently, the price doesn't reflect the information instantly. Thus, there would be more of cumulative abnormal return of the portfolio due to lots of amateur traders are not able to capture the abnormal profit. Thus, there would be more room to capture more of the abnormal profit in a short period of time in the emerging market.

From the Dow Jones as of September 2014, it classifies 26 countries as developed market which are Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Hong Kong, Iceland, Ireland, Israel, Italy, Japan, Luxembourg, Netherlands, New Zealand, Norway, Portugal, Singapore, South Korea, Spain, Sweden, Switzerland, United Kingdom, and United States. From the same source the Emerging Countries include Brazil, Chile, China, Colombia, Czech Republic, Egypt, Greece, Hungary, India, Indonesia, Malaysia, Mexico, Peru, Philippines, Poland, Qatar, Russia, South Africa, Taiwan, Thailand, Turkey, and United Arab Emirates.

Frequency of the crash (**FRQ**) as a factor that affects the abnormal return on portfolio. According to the prospect theory of behavioral in finance, when the gain or loss exceeds a certain level, people would feel indifferent with the marginal absolute increase in each of them. This would apply to the feeling of loss too. When there is too much pain from receiving the bad news, people would feel almost indifferent about such loss after a while. Thus, if there are a lot of airplane crashing news flowing to the investors many times in a specific period that people hasn't forgot the feeling about the last one, people would also feel almost indifferent to the airplane crashing news after a while.

Distance of the crash from where stock is listed (**DIST**) matters. People might have the Heuristic Biased, in which they are more aware of things that happens close to them. As a result, such bias could make the investors react more to the crash that happens not so far away from their country (where the crashing airline's stock is listed).

The flight (**FLGT**) has an effect on the investors' concern. When it comes to an international flight, there would be more alternatives for the international customers to switch to use the service from other airlines as they feel safer. Thus, the alternatives make the market to be more efficient as people have more options to trade. As a result, there would be less abnormal return for the shock from the aviation disaster i.e. less abnormal return for crashing

The number of death per crash (**DTH**) also matters for the abnormal return of the portfolio. The According to the work of (Ho et al., 2013), when the number of death per crash is less than one digit number, the customers will switch from using the crashing airlines to use the competitor airlines. This phenomena is called the "switch effect" as stated in the paper. However, if the number of death per crash is more than two digits number, there will be a "contagion effect" where the price of the stocks in the market all goes down as reflected by CARs.

3.2 Research Hypothesis

3.2.1 Hypothesis I: Profit can be made out of Airplane Crashing event

The condition behind this is that when an airplane crash happens the stock of the crashing airline will drop down significantly and bounce back up. Moreover, if the investor switch to buy the competitor stocks due to expected higher demand from customers' substitution from the crashing to safer airlines, the price of the competitor stocks would be pushed up. This suggests that if shorting the crashing airline stocks and longing the competitor stocks on the day of the crash and readjusting portfolio position at an appropriate time when the stock prices start to revert to their equilibrium price level, decent profit could be made out of the crashing events.

For the crashing stock Kaplanski and Levy (2010) suggests that investors close the short position 2 days later when the stock started to bounce back up. Here, there is a theory called “Availability Bias” of Behavioral Finance Theory explaining this movement. According to the availability bias concept, people tend to heavily weight their decisions toward the more recent information, which this could happen in real life all the time as well, such as when one sees an accident on one road that one regularly uses, he will begin to drive very cautiously after that even though the road is no more dangerous than it has ever been. Thus, seeing the accident make people overreact. However, people will be back to their own driving habits very soon after they don’t see any more accidents after that time for a while. Nevertheless, if the stocks continue to drop down without bouncing up in 25 days period like in (Ho et al., 2013) work, it is quite hard to make a profit out of that, and might not do anything much about it but suggesting the holder to sell those stocks and rebuying when the price starts to recover in a later time. Nevertheless, (Ho et al., 2013) work include the terrorist case into the analysis, which the case affects has a larger economic value as it affects the confidence of the investors of that country too, thus; this might be the reason that makes the CAR movement of the crashing airline of (Ho et al., 2013) different from the work of Kaplanski and Levy (2010).

However, movement of the competitor airline stocks have still be unclear. If there is no significance increase in the price of the competitor stocks but there is a drop and bounce up of the crashing airline stock, shorting the crashing airline stocks and close the position 3 days after the crash when the stocks started to bounce back up, would be enough to make a decent profit.

3.2.2 Hypothesis II: The cumulative abnormal return of the portfolio decreases as the number of recent crashes gets higher.

Due to the idea of prospect theory, the portfolio should not be able to make much profit as the number of recent crashes increases up to one point. Thus, the cumulative abnormal return of the crashing airline should increase as the number of recent crashes gets higher. At the same time, the cumulative abnormal return of the portfolio should then decrease as the number of the recent crashes gets higher.

3.2.3 Hypothesis III: The cumulative abnormal return of the portfolio decreases when the distance between crashing location and the crashing airline's stock market gets higher.

According to the Heuristic theory, the theory that is proposed by Tversky and Kahneman (1977), people usually use a short cut for making decision, especially when they have cognitive loads, they usually form their own rationality based on their old experiences or other factors. According to Familiarity Heuristic, where people are more aware of things they are familiar with, it implies that people are willing to hold more of the homeland listed stocks than international listed stocks as they feel familiar with the name and things around. They are more willing to go with what they know and easily to understand. This Heuristic Theory could be applied even further. People may react differently regard to the distance of the accident that happened from them. In other words, people are more aware if the accident happens close to them. This suggests that if an airplane crash occurs in the place that is not so far from where the crashing airplane stock is listed, investors may be able to relate the crash event back to their old experience more easily, and thus they will react to it more than if the crash that happens far away from their homeland. As a result, it would make the cumulative abnormal return of the crashing airline to increase as the distance is longer. Consequently, when we short the crashing airline's stock it would make the cumulative abnormal return of the portfolio to decrease as the distance is longer.

3.3 Data description

These are the variables that will be used in order to select the competitors' stocks and to test the factors that affects the abnormal return of the portfolio.

Variables	Description	Source
Crash Dates	The date that the airplane crashes	The Aviation Safety Network of the Flight Safety Foundation database
r_i	Return on Stock	Datastream Database
r_m	Market Return	Datastream Database
r_f	Risk-free Rate	Datastream Database
P/E	Price to Earning ratio	Datastream Database
P/S	Share price / sales per share	Datastream Database
EV/Sales	Enterprise value / net sales	Datastream Database
EV/EBITDA	Enterprise value / Earnings before Interest, Tax, Depreciation & Amortization. Also excludes movements in non-cash provisions and exceptional items	Datastream Database
ROA	Return on Asset	Datastream Database
ROE	Return on Equity	Datastream Database
Market Capital	Market Capital	Datastream Database
MS	Market Structure, whether the stock is listed in the emerging market or developed market. It is a dummy variable, which take a value of 1 when it is an emerging country and value of 0 when it is a developed country.	The Aviation Safety Network of the Flight Safety Foundation database
FRQ	Frequency of the crash in the past 12 months for each crash	The Aviation Safety Network of the Flight Safety Foundation database and manually count
DIST	Distance between where the plane crashed and how far from where the stock is listed	The Aviation Safety Network of the Flight Safety Foundation database and google earth
FLGT	International flight or domestic flight. It is a dummy variable which takes value of 1 when the crash happens with the domestic flight	The Aviation Safety Network of the Flight Safety Foundation database

	and 0 when the crash happens with the internal flight.	
DTH	Number of death per crash	The Aviation Safety Network of the Flight Safety Foundation database

Table 4: *Variables explanation*

The scope of the study is to include the event of the crash in 50 years period time, which is from 1965-2015. The reason that we choose this period is because it is the most recent period and most of the emerging markets and the IPO happens just in the past 50 years, before that would not have the samples to use anyways. Our samples contains the passenger flights from all over the world only. The terrorist attack case and other mysterious case such as lost airplane will be excluded. The reason is that we believe that it really affects the real economics value, which will affect the economy of the whole country in overall negatively and would create no reversal effect to the stock price of the crashing airline. Moreover, the event used only if the crashed airline stock has already listed in the country that already has stock market in that period. The countries that are included in this study are classified to the emerging and the developed stock market as listed by Down Jones. Also, the event are used only if the accounting data P/E, P/S, Market Cap, EV, EBITDA, ROA, and ROE of the crashing airline stocks and its competitor's stocks are available in the period.

The data used in this study include the accounting data for selecting the competitors' stocks, the stock prices of the crashing and competitor, the market rate, and the risk free rate. For the accounting data, it includes P/E, P/S, Market Cap, EV, EBITDA, ROA, and ROE of both crashing airline and the competitors' airlines in the period of the crash. The competitors' ratio will be used to compare with the crashing airline by giving the range of 5 percent interval. If the competitors' ratio falls within the interval, then they will be selected to further analysis. To add, the competitors' stock must also be listed in the same capital market as the crashing one.

For the stock prices of the crashing and the competitors' airline, the period of data that will be used is 46 to 255 trading days before the crashing happens and 25 trading days.

For the market rate, it will be used to calculate the market return for the CAPM model. In each particular stock market will have different indicator of market return. For example, in Thailand would be SET100. In other countries would be other different ones. Also, the period of data that will be used is 46 to 255 trading days before the crashing happens and 25 trading days.

For risk-free rate, it will also be used to form a CAPM model. In different countries will also have different risk-free rate indicator, which one for each country will be stated on Datastream database. The period of data that will be used is also 46 to 255 trading days before the crashing happens and 25 trading days since the day of the crash. The Table 6 summarize all the data that will be used in this study.

3.4 Data Screening

3.4.1 Crashing airline

We first obtain the data from The Aviation Safety Network of the Flight Safety Foundation database. Then we screen out the hi-jacked, non-commercial airlines, and the missing cases. After that, we select just the crash that has the stocks trading publicly for the airline. Then we cut off the crashing cases that do not have the risk free rate and the market index and the stock prices in that period. This leaves us with only 111 airplane crashing cases for our analysis in this study.

3.4.2 Competing Airline

We select the competing airline of the crashing airline through looking at the business nature and its service along with the accounting ratios which include P/E, PBV, P/S, ROA, ROE, Market Cap, and EV/EBITDA, and EV/Sales. If it is within 20 percent range, we will select it for our analysis. Then we cut off the cases that does not have the risk free rate and the market index and the stock prices in that period. Thus, there are only 156 competing airline stocks left for our analysis in this study.

3.4.3 Factors

For market structure, we classify if the stock is in Emerging or Developed country though using the information from Dow Jones, FTSE, IMF, and S&P. For the frequency of the crash, we obtain the information by counting all the airplane crashing cases, that happens before the considering case in the period of 12 months before the considering crash, in the Aviation Safety

Network database. For the Distance between the crash and the country that the crashing airline's stock is listed, we use Google Earth to measure it by plugging in the starting point and the destination location, which are the country that the stock is listed and the country that the crash happens in. For the Type of the Flight and the number of Death per Crash, we obtain the information directly from the Aviation Safety Network database.

CHAPTER 4

Methodology

4.1 Methodology

In order to answer Hypothesis I, we must investigate the patterns of the crashing and competitor airline's stock abnormal return first. Then, based on the patterns we found, an appropriated portfolio can be constructed to gain a decent profit.

4.1.1 Identifying the Airline Competitors

To select the competitor of the crashing airline, we pick the competitors through using the method of "Comparable Company Analysis". It is a process that is used to evaluate the value of the company for comparing other businesses with similar size and in the same industry (Meitner, 2006). It starts with establishing the peer group that consists of similar companies that have similar size that are in the same industry and in the same region. This will use the accounting information of the firms to calculate the ratios to compare with each other, this include P/E, PBV, P/S, ROA, ROE, Market Cap, and EV/EBITDA, and EV/Sales. Then select the stocks that have these ratios within the range of $\pm 20\%$ of the ratios of the crashing airline's stocks.

4.1.2 Finding Abnormal Returns

In this study, we estimate abnormal returns based on the Capital Asset Pricing Model (CAPM). The period used to estimate the CAPM model for each event covers trading days 255 days to 46 prior to the crashing date. We use CAPM for this study because it could form a capital asset pricing model without much complications (Bodie et al., 1996). Although CAPM might not be a perfect model because of its strict assumption, we allow the constant term α into our model to accept the flaw of this model. In the case that CAPM was perfect model, the α would be zero.

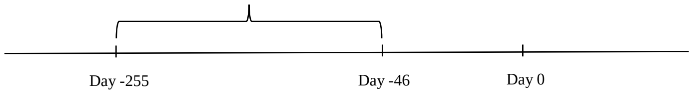

Figure A: Estimation window

As we can see from Figure 4.1.2, the estimation window that we use for this study is from 255 to 46 trading days before the event date, which is the crashing date at Day 0. For example, suppose the Delta airline crashing was in Lebanon on the 17^{th} July 2014, we will use the data of the stock returns, risk-free rates and the market return of the New York Stock Exchange during 46-255 days to run the following regression to get the estimated $\hat{\alpha}$ and $\hat{\beta}$ of this crash event.

$$(r_{i,t} - r_{f,t}) \quad = \alpha_i + \beta_i(r_{m,t} - r_{f,t}) + \varepsilon_t$$

where $r_{i,t}$ is the daily return of the stock i in period t, r_f is the risk free rate, r_m is the market return, and ε is the error term.

After we find the estimated CAPM equations for each individual crash, i.e. $\hat{\alpha}_i$ and $\hat{\beta}_i$, the abnormal return (AR) of each day during the event window of 25 days after the crash happens will be estimated as follows:

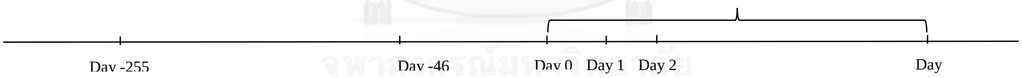

Figure B: Event window

$$AR_{i,t} = R_{i,t} - \hat{R}_{i,t} = R_{i,t} - \left(\hat{\alpha}_i + \hat{\beta}_i(r_{m,t} - r_{f,t})\right); \;\; t = 1, 2, \dots, 25$$

After that, we calculate CAR for each of the crashing airline's stock with the equation below

$$CAR_{i,N} = \sum_{t=0}^{N} AR_{i,t}$$

where N is the number of days that we want to find cumulative abnormal returns.

In fact, in order to examine the average patterns of CAR, we will, for each crash *i*, calculate CAR up to 25 periods after the crash, i.e. $CAR_{i,1}, CAR_{i,2}, CAR_{i,3}, \dots, CAR_{i,25}$.

4.1.3 Testing Hypothesis I

In testing Hypothesis I, we first run regression of CAR of the stock with the dummy variable from Day 0 to Day 25 in equation 1&2 to test the significant movement of the stock after the crash.

Crashing airline stock movement

$$CAR_{i,N} = \beta_0 + \beta_1 D_{0,i,N} + \beta_2 D_{1,i,N} + \beta_3 D_{2,i,N} \ldots\ldots + \beta_{25} D_{24,i,N} + \varepsilon_{i,N} \qquad (1)$$

where $D_{M,i,N}$ are dummy variables taking value 1 if $M = N$. We can then conduct hypothesis tests to see if there are significant changes in the mean of CARs across the 25 days since the crash happens.

Then for each of the stocks of the competitor's airlines, we calculate the CAR of each stocks like all the process above. Then run regression through this equation again to find the $\hat{\alpha}$ and $\hat{\beta}$ and get the pattern of the competitor airlines' stocks of how they react to the crash.

To prove if the stock really falls in Day 1, it must be $\beta_0 + \beta_1 > \beta_0 + \beta_2$, which will make $\beta_2 - \beta_1 < 0$. From this, we can get the null hypothesis and alternative hypothesis as,

$$H_0: \beta_2 - \beta_1 \geq 0, \qquad H_1: \beta_2 - \beta_1 < 0$$

To prove if the other days drop further than in previous days

$$H_0: \beta_{n+i} - \beta_n \geq 0, \qquad H_1: \beta_{n+i} - \beta_n < 0$$

To prove if the CAR bounces back up from the previous days

$$H_0: \beta_{n+i} - \beta_n \leq 0, \qquad H_1: \beta_{n+i} - \beta_n > 0$$

Competing Airline stock movement

First, we will have to select the competitors of the crashing airline. Here, we use the method of comparable company analysis (Meitner, 2006), which we is a process that is used to evaluate the value of the company for comparing other businesses with similar size and in the same industry and same region, alongside with comparing its accounting ratios, which include P/E, PBV, P/S, ROA, ROE, Market Cap, and EV/EBITDA, and EV/Sales. Then we select the stocks that have these ratios within the range of ±20% of the ratios of the crashing airline's stocks (See Table 1).

Then we use the same formula as the crashing airlines' case to test the movement of the competitor airlines on the day that the crash happens and 25 days since the crash happens.

$$CAR_{i,N} = \beta_0 + \beta_1 D_{0,i,N} + \beta_2 D_{1,i,N} + \beta_3 D_{2,i,N} \ldots . + \beta_{25} D_{24,i,N} + \varepsilon_{i,N} \qquad (2)$$

where $D_{M,i,N}$ are dummy variables taking value 1 if $M = N$. We can then conduct hypothesis tests to see if there are significant changes in CAR across the 25 days after crashes. We can then conduct hypothesis tests to see if there are significant changes in CAR across the 25 days since the crash happens.

To prove if the stock really falls in Day 1, it must be $\beta_0 + \beta_1 > \beta_0 + \beta_2$, which will make $\beta_2 - \beta_1 < 0$. From this, we can get the null hypothesis and alternative hypothesis as,

$$H_0: \beta_2 - \beta_1 \geq 0, \qquad H_1: \beta_2 - \beta_1 < 0$$

To prove if the other days drop further than in previous days

$$H_0: \beta_{n+i} - \beta_n \geq 0, \qquad H_1: \beta_{n+i} - \beta_n < 0$$

4.2 Testing Hypothesis II & III

After we get the significant movement of the CAR of both crashing airline's stock and the competing airlines' stocks, we then form strategies that could make profit out of the movement. We then test the effect of the five following factors to the CAR of both the crashing airline's stock and the portfolio. The regressions that we use to test this effect are

$$CAR_i = \emptyset_0 + \emptyset_1 MS_i + \emptyset_2 FRQ_i + \emptyset_3 DIST_i + \emptyset_4 FLGT_i + \emptyset_5 DTH_i \qquad (3)$$

$$CAR_i = \emptyset_0 + \emptyset_1 MS_i + \emptyset_2 FRQ_i + \emptyset_2 FRQ^2{}_i + \emptyset_3 DIST_i + \emptyset_4 FLGT_i + \emptyset_5 DTH_i \qquad (3.1)$$

where MS = Market Structure, whether it is emerging market or developed market. It is a dummy variable, FRQ = Frequency of the crash in the past 12 months for each crash, DIST = the distance of the crash from where the stock listed, which is measured in kilometers, FLGT = International flight or domestic flight, it is a dummy variable which takes a value of 1 when the crash happens with the domestic flight and 0 when the crash happens with the crash happens with the international flight, and DTH = Number of death per crash

CHAPTER 5

Empirical Results

After we have selected the samples, there are 111 samples for the crashing cases, and 156 cases for the competitors' cases as listed in Appendix in Table 3, 4, and 5.

5.1.1 Abnormal Return by *Non-Regression Method*

We first examine the AR, AAR, CAR, and CAAR of all the samples we have for 25 days and plot them into graphs as seen in Figure B&C to see a rough pattern before we run the regression in Equation 1&2. For the crashing airline, there is an evidence of a decrease in CAR. The other types of abnormal return has the unclear direction pattern.

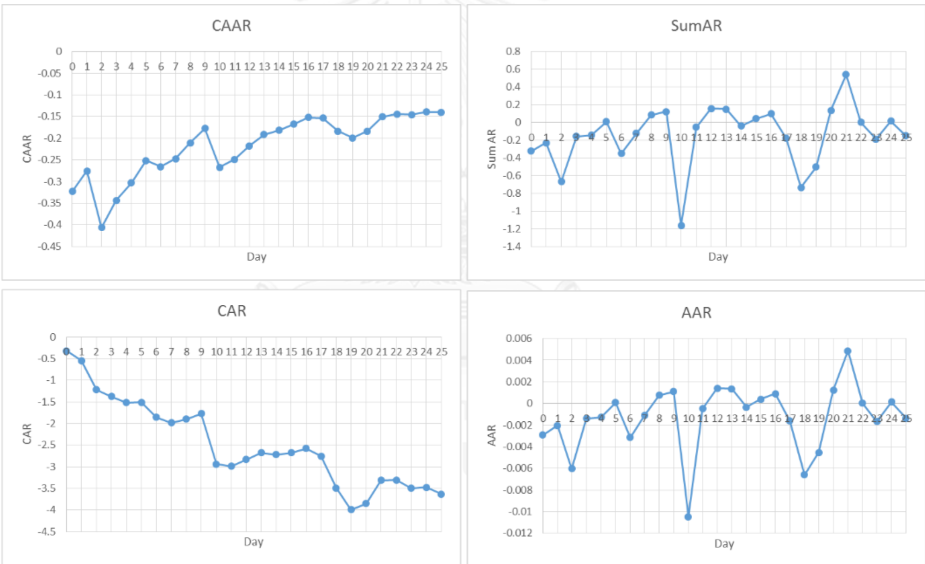

Figure C: *4 Types of Abnormal Returns of Crashing airline*

For the competing airline, there is no clear direction pattern in all types of the abnormal returns. However, there is an evidence of an increase of CAAR from Day 0 to Day 2, and then a bounce back down before it becomes quite stable. We use these patterns to guide and confirm our results in the following patterns that we found it from running the regression in Equation 1&2.

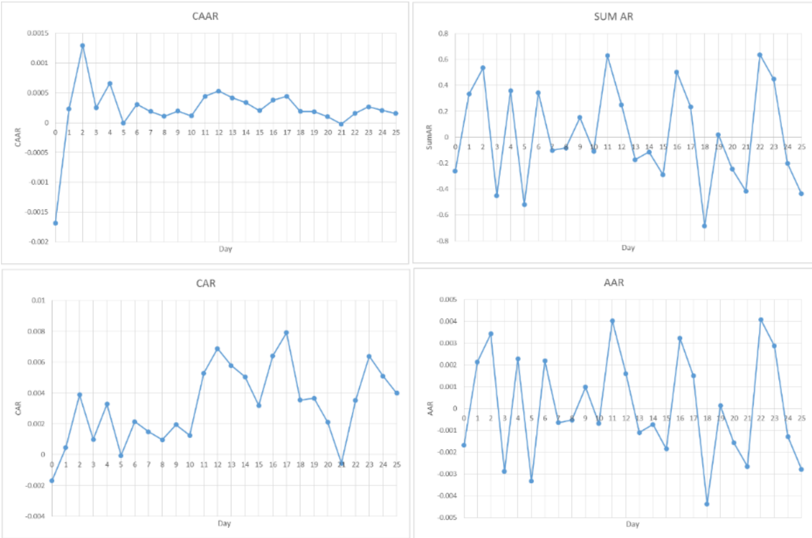

Figure D: *4 Types of Abnormal Returns of Competing Airline*

5.1.2 Abnormal Return of the crashing airline by Regression Method

After we run regression according to Equation 1 and Equation 2, we see an evidence of a continuing decrease in the CAR of the crashing airline's stock. It could be seen that the CAR drops the most on Day 19. Thus, the effective strategy according to this movement is to start shorting on Day 0 and close the position at the end of Day 19.

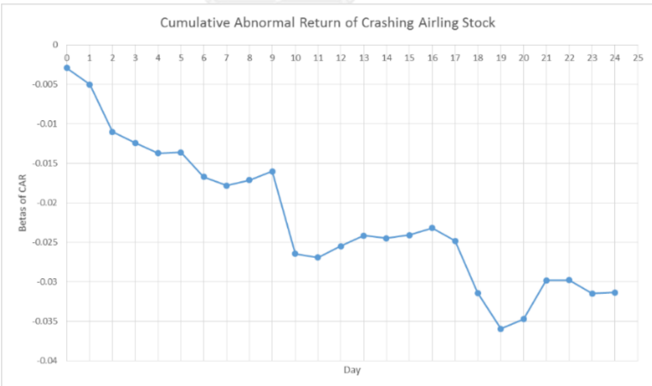

Figure 1.1: *Crashing airline Cumulative Abnormal Returns' Beta*

5.2.1 Abnormal Return of the crashing airline by Regression Method for the Case of 1 digit number of death per crash

We now try running regression of CAR in Equation 1 by using just the airplane crashing case that has 1 digit number of death per crash. As we can see from Figure 1.3.1, the CAR of the crashing airline's stock when the number of death per crash is a single digit number has similar patterns as the one with the overall pattern of CAR of the crashing airline's stock from the total sample. The pattern is that the CAR is continually dropping little by little until Day 19 and then starts to bounce back up after that.

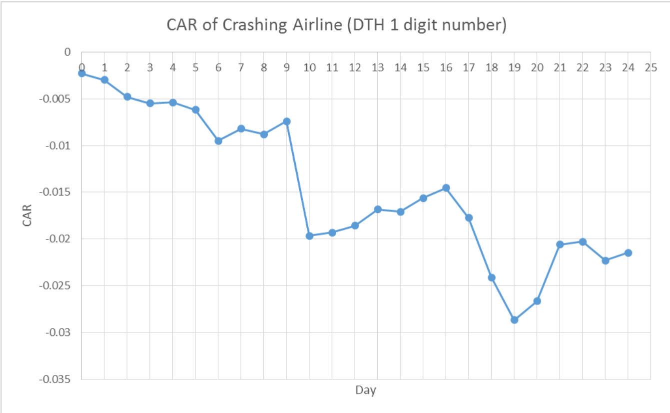

Figure 1.3.1: *Crash Airline Cumulative Abnormal Returns with DTH 1 digit number*

5.2.2 Abnormal Return of the crashing airline by Regression Method for the Case of 2 digits number of death per crash

After we run regression with Equation 1 for the case of the number of death per crash is a 2 digits number, we found that the CAR of the crashing airline's stock significantly drops from Day 0 to Day 4 with the T-Stat value of 1.99, which is significant at 95 percent confidence level. Then it continues dropping down with no evidence of an end until Day 24.

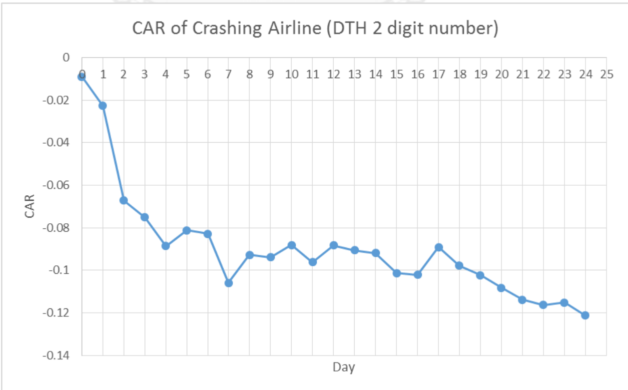

Figure 1.4.1: *Crash Airline Cumulative Abnormal Returns with DTH 2 digit number*

5.2.3 Abnormal Return of the competing airline by Regression Method

Considering the CAR of competing airlines' stocks from running the regression according to Equation 1 and Equation 2, there is an evidence of a trend of increasing in CAR until Day 16. Thus, the effective strategy according to this movement is to start longing the competing airlines' stocks on Day 1 and close the position on Day 16.

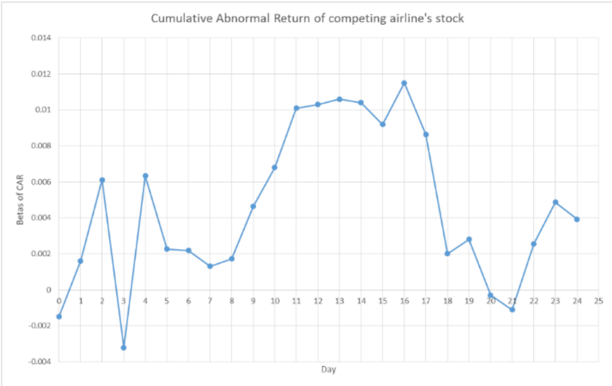

Figure 2.1: *Competing Airline Cumulative Abnormal Returns*

5.2.4 Abnormal Return of the competing airline considering all airlines that listed in the same stock market as the crashing airline

After considering the direct competitors of the crashing airline through comparable company analysis method, we try testing the movement of the other airlines that are listed in the same country as the crashing airline as well. The result turns out that the cumulative abnormal return of these airlines has a trend of decreasing from Day 0 to Day 10, then stay down for 12 days before bouncing back up on Day 23 (See the list of the airlines in Table 9).

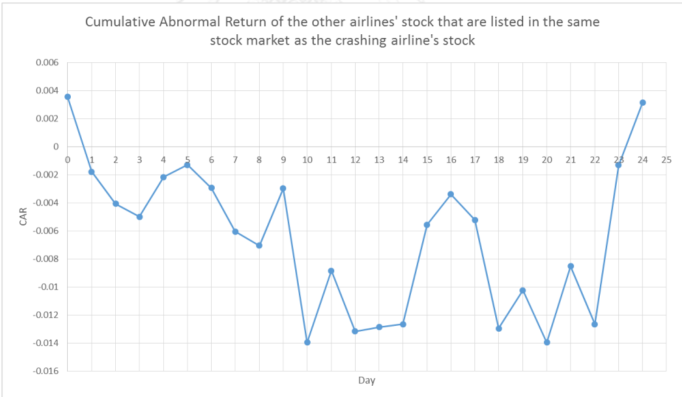

Figure 2.4: *the other airlines' stocks CAR movement that are listed in the same stock market as the crashing airline*

5.3.1 Portfolio Strategy I: Testing with CAR

According to the CAR movement of both Crashing airline's stock and Competing airlines' stocks, the strategy that would make a profit would be to short the crashing airline's stock on Day 0 and close the position at the end of Day 19 and to long the competing airlines' stocks on Day 0 and close the position on Day 16 (See Figure 1.1 and 2.1). Then we use the CAR that we got from this strategy to run regression in Equation 3 and 3.1, where we test the effect of the 5 factors to the CAR of the portfolio both linear function of the frequency of the crash alone and the parabola function.

For equation 3 and 3.1, the result turns out that there is no significant coefficient of any factors in the equation. However, for the market structure (See Figure 6.1 and 8.1).

In Strategy I, there are 58 cases that could make profit out of this strategy and 53 cases that make loss. The maximum profit from this strategy is 28%, while the maximum loss is -28% (See Figure 5.1).

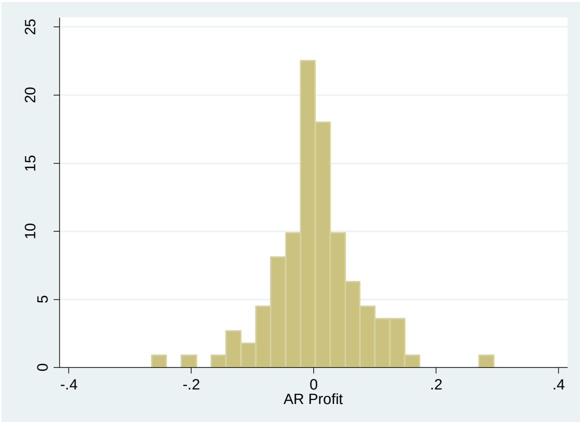

Figure 5.1: *Profit's Histogram Strategy I*

5.3.2 Portfolio Strategy II: Testing with CAR

As we run the regression from STATA for testing the movement of the stock 25 days after the crash, the result shows that there is no significant increase or decrease in the cumulative abnormal return in both crashing side and the competitors' side (See Figure 1, 1.1, 2, and 2.1). As a result, we try re-run the regression with the abnormal return instead of the cumulative abnormal return as we planned to see the absolute single divided value for each day. By using the equation

$$AR_{i,N} = \beta_0 + \beta_1 D_{0,i,N} + \beta_2 D_{1,i,N} + \beta_3 D_{2,i,N} ..... + \beta_{24} D_{25,i,N} + \varepsilon_{i,N} \qquad (4)$$

where $D_{M,i,N}$ are dummy variables taking value 1 if $M = N$ and we count the crash day as Day 0. We can then conduct hypothesis tests to see if there are significant changes in AR across the 25 days after crashes. This new equation is applied to both the crashing airline case and the competitor airline case.

The result turns out that there is an evidence of a decrease in the abnormal return of the crashing airline stock (See Figure 3 and 3.1). Although it is not in a clear pattern, we found that the abnormal return falls statistically significant on Day 10 at 96 percent confidence level with the T-Stat value of 2.21, then bounces back up significantly on Day 11 at 90 percent confidence interval with the T-Stat value of 1.9.

For the competitors' side, there is also no significant movement of the stock prices for running the regression with cumulative abnormal return (See Figure 2 and 2.1). However, when we use the abnormal return (AR) to run regression, we see some significant movement of the return of stock in each day (See Figure 4 and 4.1). According to the result from running the regression to test the significant movement from the dummy variable equation with the abnormal return as the regressand, there is an instant reaction to the crash (See Figure 4.1). There is an evidence of an increase in AR Day 1 and Day 2, followed by a significant decrease on Day 3, Day 5 and a significant increase on Day 19 with the T-Stat value of -1.72, -1.67 and 1.97. However, the increase of AR on Day 0 to Day 2 are not significant. We then use these movement of that AR to form the portfolio strategy.

On the crashing side, as we found that the movement of the crashing airline stock is significantly decreased on Day 10 and significantly increase on Day 11. Thus we could make a profit from this by start shorting on Day 9 where the stock price has not significantly decrease, and then close the position on Day 10 and long another crashing airline's stock at the same time where the stock price significantly drop, and then close the position by selling this crashing stock on Day 11 where the stock price increases the most on this day.

On the competitor side, we found that the movement of the competing airlines' stocks significantly decreases on Day 3 and Day 5, and then significantly increase on day 19. Thus, we make the strategy according to this significant movement by shorting on day 2 where the stock price of the competing airline hasn't significantly dropped and close the position on day 3. Then short another competing airline stock on day 4 and close the position on day 5. Lastly, we take a long position on day 18 and close the position on Day 19.

After we tested the factors against the portfolio's cumulative abnormal return in equation 3 and 3.1 for this strategy, we found no statistically significant coefficient in all of the factors that appears in the equation (See Figure 6.2 and 8.2)

5.3.3 Portfolio Strategy II: Testing with AR

We try running the regression by using AR of the portfolio to run regression against the 5 factors again. Then we got the result as in Figure 6.3 and 8.3. There is also still no evidence of any factors that are significantly affecting the AR of the portfolio (See Figure 6.3)

After we tested the factors against the portfolio's cumulative abnormal return in equation 3 and 3.1 for this strategy, we found no statistically significant coefficient in all of the factors that appears in the equation (See Figure 6.3 and 8.3)

In Strategy II, there are 59 cases that could make profit out of this strategy and 52 cases that make loss. The maximum profit from this strategy is 114%, while the maximum loss in this strategy is only 28% (See Figure 5.2).

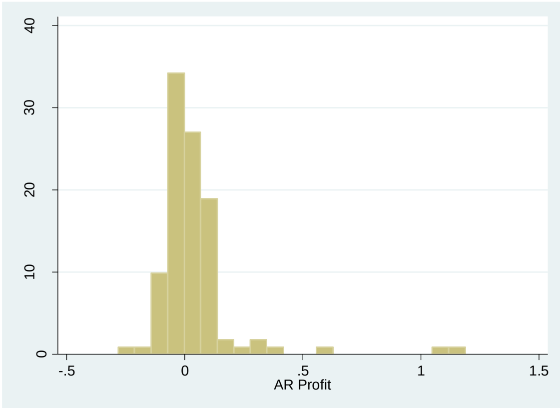

Figure 5.2: *Profit's Histogram Strategy II*

5.3.4 Portfolio Strategy III: Testing with CAR

After we look at the CAR graph of both case again, we notice that although the movement test is not significant, the CAR graph of crashing airline continues falling down from the crashing day on day 0 to the lowest amount of CAR on day 19 (See Figure 1.1). Thus, we tried testing the significance of the difference of the betas of day 0 and day 19, and we found out that it is really significant at T-Stat value of 2.54 (See Figure 1.1.1). However, we do not find any significant movement of the CAR on any day after the crash in the competing airline case, both by seeing form the eye and by testing statistically.

As a result, the strategy that suits this movement should be to start shorting just the crashing stock on the day that the airline crashes, and hold it until closing the position on day 19. After that, we tried running the regression to test the effect of the factors to the CAR of the portfolio that was made of this strategy with equation 3. Then we got the result as in Figure 6.4. From the result, we also found no significant coefficient of all the factors that appears in equation 3. However, after we tested the Portfolio's CAR against 5 factors in Strategy III with Equation 3.1, we found that the coefficient of the number of death per crash (DTH) is positive and statistically significant at 90 percent confidence level. In the case of Equation 3.1 result, when the number of death per crash is increase by 1 person, the cumulative abnormal return of the portfolio would increase by 0.000798 unit.

As we can see from the histogram in Figure 8.1, there is a very high chance that the investor cannot make a profit at all. There is also a very little chance in making a very high profit.

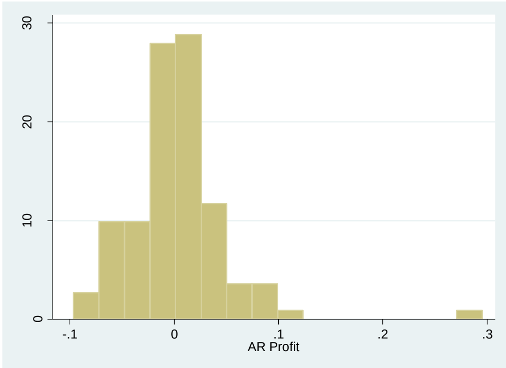

Figure 5.3: *Profit's Histogram Strategy III*

5.3.5 Portfolio Strategy IV: Testing with CAR

After that we tried another strategy to recheck the significance and the sign direction of the factors impact to the CAR profit of the portfolio. This time we tried using the strategy above that we short the crashing stock for 19 days, then we combine it with the strategy that we got from the significant movement of the competing stocks' AR (See Figure 4.1). As the AR movement of the competing airline stock is significantly decreasing on Day 3 and Day 5 and significantly increasing on Day 19, we short the competing stock on Day 2 then close the position on Day 3, and then short the competing stock on day 4 and close the position on day 5, then longing on Day 18 and close the position on Day 19. Then we use this strategy to form the portfolio and run regression of the 5 factors against the CAR of the portfolio in equation 3. The result turns out like to be in the same way as the last strategy that we short the crash airline for 19 days.

After that we test the cumulative abnormal return of the portfolio against the factors in Equation 3, we got the result as in figure 6.5. The number of death per crash is the only factor that is significant. When the number of death per crash is higher by 1 unit, there is a significant increase in CAR profit of the portfolio by 0.0009624 unit at the confidence level of 95 percent (See Figure 6.5). Moreover, after we tested Equation 3.1, we also found that the coefficient of the number of death per crash is positive and statistically significant at 90 percent confidence level. In the case of the result in Equation 3.1, when there is an increase in the number of death per crash by 1 person, there is an increase of the portfolio's cumulative abnormal return by 0.000931 unit.

In this strategy, there are 59 cases that could make abnormal return profit and 52 cases that make loss. The maximum profit in this strategy is 28%, while the maximum loss is -24%.

As we can see from the histogram in figure 9.2, there is a very high chance in making no profit at all and making loss. There is almost equal chance of making profit and making loss.

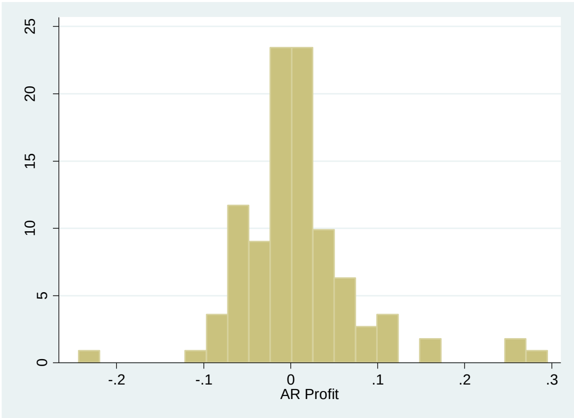

Figure 5.4: *Profit's Histogram Strategy IV*

5.3.6 Portfolio Strategy V: Testing with CAR and utilize major movement

From Strategy I, we made an additional shorting position after Day 16. Utilizing the movement of the CAR of both sides of the stock, we still see the bounce back down of the CAR of the competitors from Day 16 to Day 21 (See Figure 2.1). Thus, the additional strategy in here that we add from Strategy I is the short the competing airlines' stocks on Day 16 and close the position on Day 21 at the end of the day. After we use the CAR of the portfolio from this Strategy, we run regression with Equation 3. The result that we get is that there is no significance effects of the factors to the CAR of the portfolio. The factors that are almost significant at 90 percent confidence level are the market structure and the frequency of the crash. When the crash happens with the Airline's stock that is listed in the emerging country, there is a decrease in the CAR of the portfolio from this strategy by 0.0915 with the T-Stat Value of -1.54. When there is higher number of the crash happening before the considering crash by 1 unit, there is a higher CAR of the portfolio by 3.75e-06 with the T-Stat value of 1.28. In this strategy, there are only 54 cases that could make an abnormal profit and 57 cases that make lost. Its maximum abnormal profit is 33% and the maximum loss is -32%.

After we tested the cumulative abnormal return against the factors in equation 3 and 3.1, we found no statistically significant coefficients from this strategy as the results appeared in Figure 6.6 (See Figure 6.6 and 8.6).

As we can see from the Histogram below, there is the highest probability that the abnormal return profit is zero. Moreover, there is a higher chance that could make loss more than making profit.

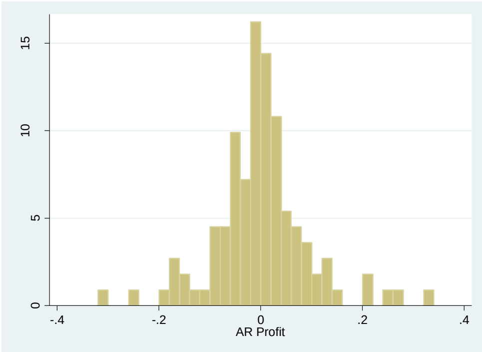

Figure 5.5: *Profit's Histogram Strategy V*

All of the Strategies above could really make an abnormal return profit. However, the strategy that has a very high frequency trading such as Strategy II could involve in a very high transaction fee. Thus, before trading the trader may need to consider the transaction fee which is vary from country to country, and see if it is not higher than the profit that we have predicted in here.

5.4 Test: The crashing airline with 5 Factors

After we tested the equation the cumulative abnormal return against the factors in equation 3, we found some statistically significant coefficient for the distance between the crashing place and the stock market that the crashing airline is listed (DIST) and the number of death per crash (DTH) (See Figure 7.5 and 7.6).

After we tested the cumulative abnormal return of the crashing airline against 5 factors on Day 19 in the case of number of death per crash is more than 1 digit number in Equation 3, we found that the coefficient of the distance factor (DIST) is positive and statistically significant at 90 percent confidence level. From figure 7.5, when the distance increases by 1 kilometers, the cumulative abnormal return of the crashing airline would increase by 1.97e-05 unit. For the number of death per crash (DTH), we found that the coefficient of the number of death per crash factor is positive and statistically significant at 90 percent confidence level. From figure 7.5, when there is an increase in the number of death per crash, there is an increase of the cumulative abnormal return of the crashing airline's stock by -0.00201 unit.

After we tested the CAR of the crashing airline against 5 factors on Day 21 in the case of the number of death per crash is more than 1 digit number in Equation 3, we also found statistically significant coefficients at 95 percent confidence level for both distance (DIST) and the number of death per crash factor (DTH) (See Figure 7.6). When the distance between the crashing location and the stock market that the crashing airline is listed in, there is an increase in the cumulative abnormal return of the crashing airline's stock by 1.91e-05 unit (See figure 7.6). Also, when the number of death per crash is higher by 1 person, the cumulative abnormal return of the crashing airline's stock decreases by -0.00226 unit.

5.5 Suggestions for applying the result to real life

All in all, from the result of the factors that have on the cumulative abnormal return of both portfolio and the crashing airline's stocks, we could tentatively form a future strategy according to the result of these factors. Firstly, considering the distance between the crashing location and the country where the crashing airline stock is listed (DIST). As there is an evidence that people react less negatively to the airplane crashing event when the crash happens further away, people should avoid shorting the crashing airline stock when the crash happens further away from where its stock is listed. Secondly, considering number of the death per crash (DTH). As the evidence appears that people react negatively to both the crashing airline's stock and the competing airline's stock when the number of death per crash is higher than one digit number, people should short the crashing airline stock and avoiding longing the competing airline's stock when the number of death per crash is more than one digit number.

Nevertheless, considering the effect of the airplane crashing event to the other airline's stocks that are also listed in the same stock market as the crashing airline's stock. The evidence appears that there is a decrease in the cumulative abnormal return of these airlines' stocks, and stays down for 4 weeks after bouncing back up. Thus, it is quite safe to avoid longing the non-direct competing airlines when the crash happens.

CHAPTER 6

Conclusion

Both crashing airline's stock and the competing airlines' stock have a significant direction of movement, which could create the profit from forming the portfolio. All the 5 strategies that we made from the significant movement of the CAR and AR of both sides of the stocks could really make an abnormal return profit as represented in Figure 11. Thus, Hypothesis I is confirmed to be true. We can make a profit through trading stocks from the airplane crashing event. However, there is almost equal chance of making profit and loss. Thus, trading with these strategies during the crashing event is very risky.

The crashing stock's abnormal return (AR) has a trend of decreasing in CAR and bouncing back as expected. Thus, it can be inferred that there is a reversal effect happening, which could further imply that people react to the aviation disaster through their emotions, not just what they see as the real economic value. This is because if the aviation disaster has a real economics value, there would not be a reversal effect in the falling of the crashing airline's abnormal return (AR).

However, when we look at the cumulative abnormal return (CAR) of the crashing airline's stock, there is an evidence of a continuous decrease in the CAR. Although there is no significant movement in each consecutive day after the crash, there is a significant decrease in the CAR from Day 0 to Day 19, which Day 19 is the day that the CAR drops the most. There is an evidence of a bouncing back up of the CAR after Day 19, however; not statistically significant. Thus, we cannot conclude that there is an evidence of a reversal effect in this study through using the CAR as the indicator.

The competing airlines' stocks also has an evidence of increasing in the abnormal return (AR) since the first day that the crash happens, however; not statistically significant. Yet, there is a statistical evidence that the abnormal return (AR) significantly falls on Day 3 and Day 5 and a significant increase on Day 19. Thus, it still can't be conclude that there is a statistically significant evidence that there is a switching effect from holding the crashing airline's stock to holding the competing airlines' stocks in the result of this study. However, this result can be used as a guidance to develop for further research, where there are more samples that could provide a statistical evidence to support this. Nevertheless, looking at the AR movement of the competing airline stock could barely tell the direction of the abnormal return movement in overall because the movements are quite random and there is no clear direction of which way it will move to.

Thus, we come to look at the cumulative abnormal return (CAR) of the competing airlines' stocks. Although there is no evidence of any statistical significant movement of the CAR in each of the consecutive day after the crash for the competing airlines' stocks, there is a trend of an increase in the CAR over 16 days after the crash. However, as the movement is not statistically significant, we still cannot really conclude that there is a switching effect from holding the crashing airline's stock to holding the competing airlines' stocks. Nevertheless, there is still a room for a further experiment on this in a future time when there are a more samples that have accounting information ready for conducting the analysis.

However, after we try testing the effect of the airplane crashing event to all of other airlines that are listed in the same stock market as the crashing airline, we found that the cumulative abnormal return of these airlines drops down and fluctuate around the bottom then increase instantly after 22 days after the crash. This could be imply that the airplane crashing accident also negatively affects the airlines that include the non-direct competing airlines in the same country that the stock is listed as well. Moreover, there is also a reversal effect of these airlines' stock returns from the event effect as well.

One thing that we notice from the movement of the CAR and AR of both the crashing airline's stock and the competing airlines' stocks is that there is a significant movement of both sides of the stocks on Day 19. For the crashing airline's side, the CAR drops the most on Day 19. For the competing airline's, there is a significant increase in the AR on Day 19. This could be implied that the event effect might end at this day. As when the crash happens, there would be some amount of people that abandon the holding position of the crashing airline's and choose to hold just the cash instead of switching to hold the alternative stocks. Thus, when they began to cool down the panic about the crashing event, they probably went back to hold the crashing airline's stock again.

In this study we only found two statistically significant result for the factors that affect the cumulative abnormal return of the crashing airline's stock and the cumulative abnormal return of the portfolio. The two factors are the distance between the crashing location and the stock market that the crashing airline is listed in (DIST) and the number of death per crash (DTH). Firstly, we consider the distance between the crashing location and the stock market location where the crashing airline's stock is listed (DIST). In the case of the number of death per crash is more than 1 digit number, the distance has significant correlation with the CAR of crashing airline and the CAR of the portfolio. When the distance has positive relationship with the CAR of the crashing airline. As when the distance gets further, the CAR of the crashing airline increases. This reflects that people may feel that the crash that happens further away are less related to them, which in turn would make them react less to the case that happens further away. This is also confirmed by the result of the portfolio's CAR that are negatively related to the distance as we short the crashing airline's stock. Thus, the heuristic theory really applies with the distance and mind of people.

Secondly, considering the death per crash (DTH), there is a significant evidence that when there is higher number of death per crash, there is less CAR of the crashing airline's stock. This also confirm with the portfolio's CAR that when we short the crashing airline's stock would flip the sign from negative to a positive abnormal return for the portfolio. This confirms the result in (Ho et al., 2013) work as well.

The number of recent crashes that we wanted to study turns out that there is no statistically significant evidence that it has an effect on neither the crashing airline's stock nor the portfolio.

Finally, this work leaves a room for a further study when there are more samples with more complete financial information for using in the analyses. Moreover, this study could be extended to the hi-jacked, terrorist, and missing cases to study the difference of the movement which could also make profit out of it.

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Figure A: *Estimation window*

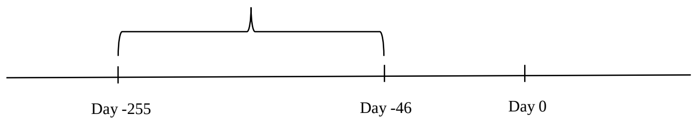


Figure B: Event window

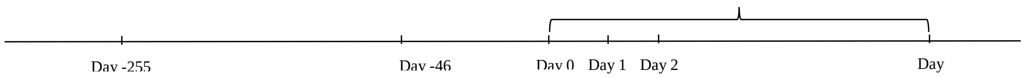


Figure C: *4 Types of Abnormal Returns of Crashing airline*

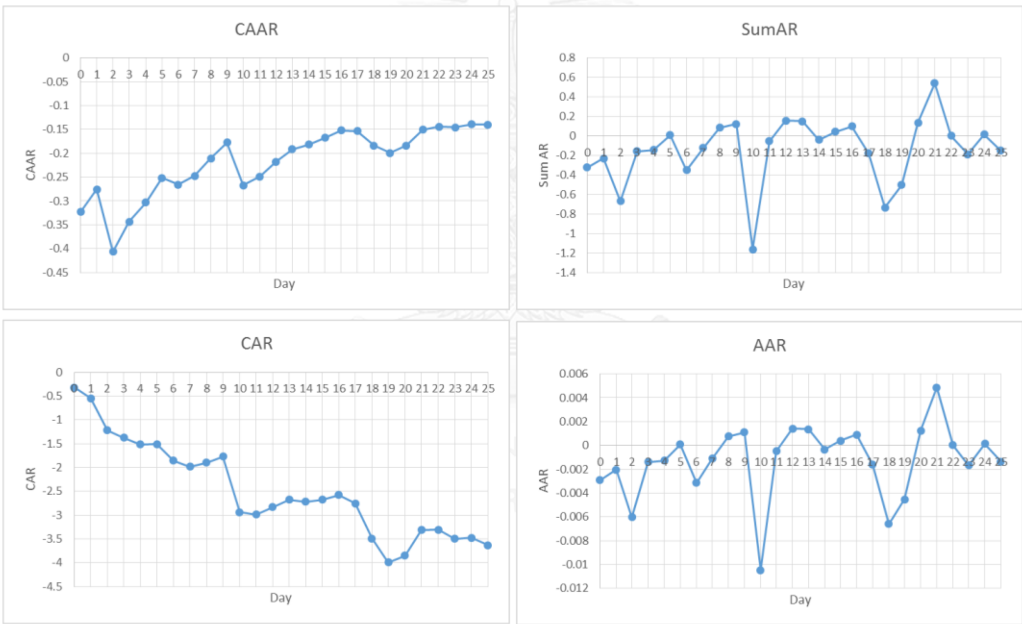


Figure D: *4 Types of Abnormal Returns of Competing Airline*

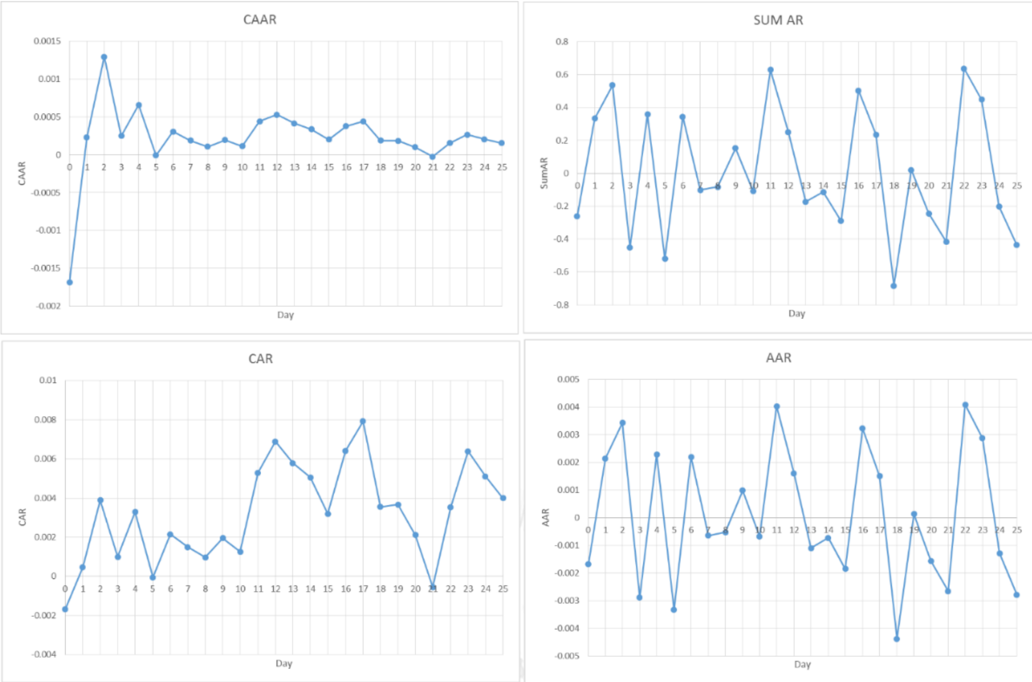


Figure 1: *Test the crashing airline's CAR movement*

	(1)
VARIABLES	car
d0	0.0298
	(0.0207)
d1	0.0277
	(0.0207)
d2	0.0217
	(0.0207)
d3	0.0203
	(0.0207)
d4	0.0190
	(0.0207)
d5	0.0191
	(0.0207)
d6	0.0160
	(0.0207)
d7	0.0149
	(0.0207)
d8	0.0156
	(0.0207)
d9	0.0167
	(0.0207)

d10	0.00626
	(0.0207)
d11	0.00579
	(0.0207)
d12	0.00720
	(0.0207)
d13	0.00856
	(0.0207)
d14	0.00821
	(0.0207)
d15	0.00861
	(0.0207)
d16	0.00950
	(0.0207)
d17	0.00788
	(0.0207)
d18	0.00128
	(0.0207)
d19	-0.00325
	(0.0207)
d20	-0.00201
	(0.0207)
d21	0.00287
	(0.0207)
d22	0.00290
	(0.0207)
d23	0.00122
	(0.0207)
d24	0.00136
	(0.0207)
Constant	-0.0327**
	(0.0147)
Observations	2,886
R-squared	0.003
Standard errors in parentheses	
*** p<0.01, ** p<0.05, * p<0.1	

Figure 1.1: *Crash Airline's Cumulative Abnormal Returns*

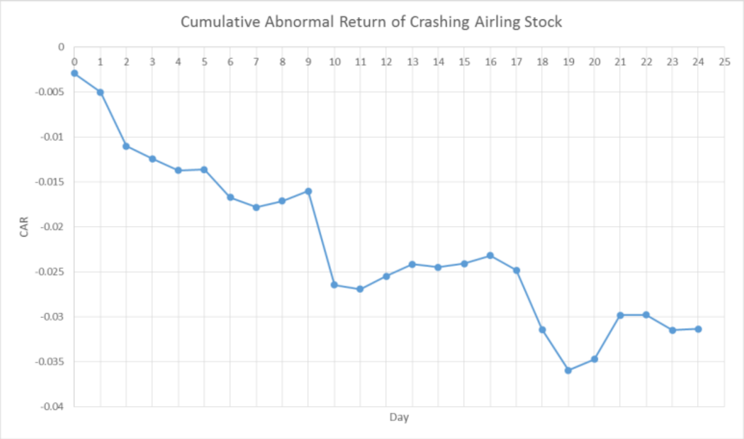


Figure 1.1.1: *Movement Testing result of CAR of Day 0 and Day 19 for crashing airline*

It is expected that		CAR Day 19	–	CAR Day 0 <0
CAR19	–	CAR0	<0	
$\beta_0 + \beta_{20}$	-	$\beta_0 + \beta_1$	<0	
β_{20}	-	β_1	<0	

Thus, we use the following command in STATA to test if they are significant from 0

```
. test d0=d19

 ( 1)  d0 - d19 = 0

       F(  1,  2860) =    2.54
            Prob > F =    0.1112
```

Figure 1.3: *Test the crashing airline's CAR movement with DTH 1 digit number*

	(1)
VARIABLES	car
d0	0.0207
	(0.0220)
d1	0.0200
	(0.0220)
d2	0.0182
	(0.0220)
d3	0.0175
	(0.0220)
d4	0.0176
	(0.0220)
d5	0.0168
	(0.0220)
d6	0.0135
	(0.0220)
d7	0.0148
	(0.0220)
d8	0.0142
	(0.0220)
d9	0.0156
	(0.0220)
d10	0.00334
	(0.0220)
d11	0.00369
	(0.0220)
d12	0.00441
	(0.0220)
d13	0.00616
	(0.0220)
d14	0.00593
	(0.0220)
d15	0.00739
	(0.0220)
d16	0.00847
	(0.0220)
d17	0.00525
	(0.0220)
d18	-0.00112

	(0.0220)
d19	-0.00566
	(0.0220)
d20	-0.00364
	(0.0220)
d21	0.00239
	(0.0220)
d22	0.00271
	(0.0220)
d23	0.000705
	(0.0220)
d24	0.00153
	(0.0220)
Constant	-0.0230
	(0.0155)
Observations	2,600
R-squared	0.002
Standard errors in parentheses	
*** p<0.01, ** p<0.05, * p<0.1	

Figure 1.3.1: *Crash Airline Cumulative Abnormal Returns with DTH 1 digit number*

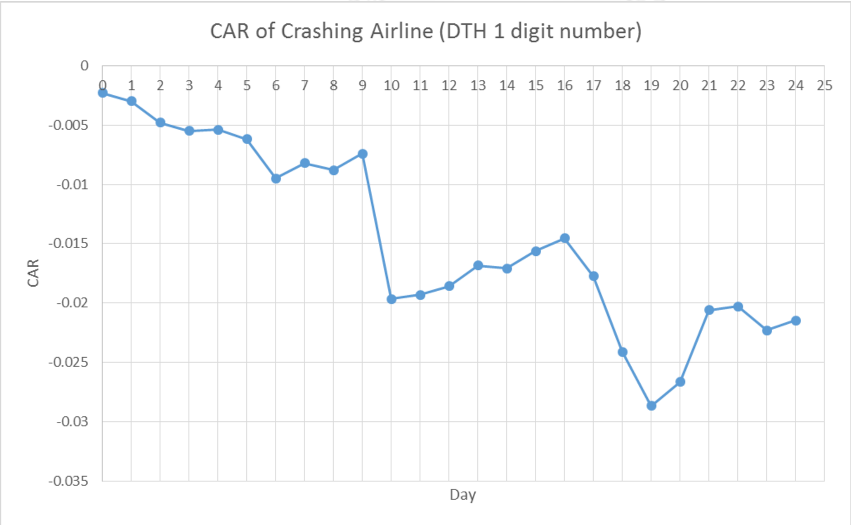


Figure 1.4: *Test the crashing airline's CAR movement with DTH 2 digit number*

	(1)
VARIABLES	car
d0	0.112**
	(0.0565)
d1	0.0983*
	(0.0565)
d2	0.0538
	(0.0565)
d3	0.0459
	(0.0565)
d4	0.0323
	(0.0565)
d5	0.0398
	(0.0565)
d6	0.0381
	(0.0565)
d7	0.0150
	(0.0565)
d8	0.0283
	(0.0565)
d9	0.0271
	(0.0565)
d10	0.0328
	(0.0565)
d11	0.0248
	(0.0565)
d12	0.0326
	(0.0565)
d13	0.0304
	(0.0565)
d14	0.0290
	(0.0565)
d15	0.0197
	(0.0565)
d16	0.0188
	(0.0565)
d17	0.0318
	(0.0565)
d18	0.0231
	(0.0565)

d19	0.0186
	(0.0565)
d20	0.0128
	(0.0565)
d21	0.00719
	(0.0565)
d22	0.00469
	(0.0565)
d23	0.00589
	(0.0565)
d24	-0.000224
	(0.0565)
Constant	-0.121***
	(0.0400)
Observations	286
R-squared	0.039
Standard errors in parentheses	
*** p<0.01, ** p<0.05, * p<0.1	

Figure 1.4.1: *Crash Airline Cumulative Abnormal Returns with DTH 2 digit number*

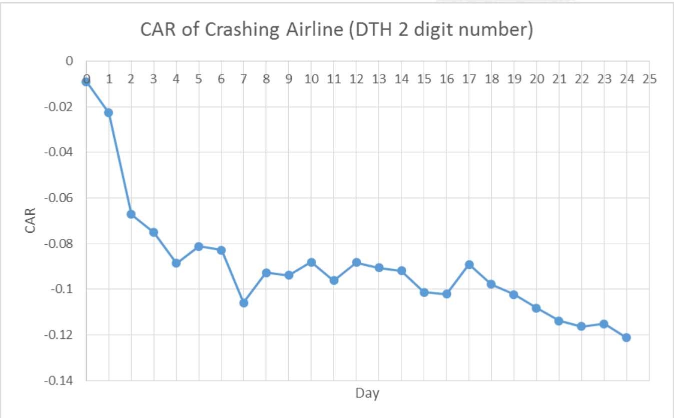


Figure 1.4.1.1: *Test the crashing airline's stock CAR movement direction with DTH 2 digit number for Day 0 and Day 4.*

```
. test d0=d4

 ( 1)  d0 - d4 = 0

       F(  1,   260) =    1.99
            Prob > F =    0.1591
```

Figure 2: *Test the competing airline's CAR movement*

	(1)
VARIABLES	car
d0	-0.00150
	(0.0160)
d1	0.00160
	(0.0160)
d2	0.00611
	(0.0160)
d3	-0.00322
	(0.0160)
d4	0.00633
	(0.0160)
d5	0.00226
	(0.0160)
d6	0.00218
	(0.0160)
d7	0.00131
	(0.0160)
d8	0.00172
	(0.0160)
d9	0.00464
	(0.0160)
d10	0.00680
	(0.0160)
d11	0.0101
	(0.0160)
d12	0.0103
	(0.0160)
d13	0.0106
	(0.0160)
d14	0.0104
	(0.0160)
d15	0.00919
	(0.0160)
d16	0.0115
	(0.0160)
d17	0.00864
	(0.0160)
d18	0.00201

	(0.0160)
d19	0.00280
	(0.0160)
d20	-0.000302
	(0.0160)
d21	-0.00111
	(0.0160)
d22	0.00256
	(0.0160)
d23	0.00486
	(0.0160)
d24	0.00392
	(0.0160)
Constant	0.00123
	(0.0113)
Observations	4,056
R-squared	0.001
Standard errors in parentheses	
*** p<0.01, ** p<0.05, * p<0.1	

Figure 2.1: *Competing Airline's Cumulative Abnormal Returns*

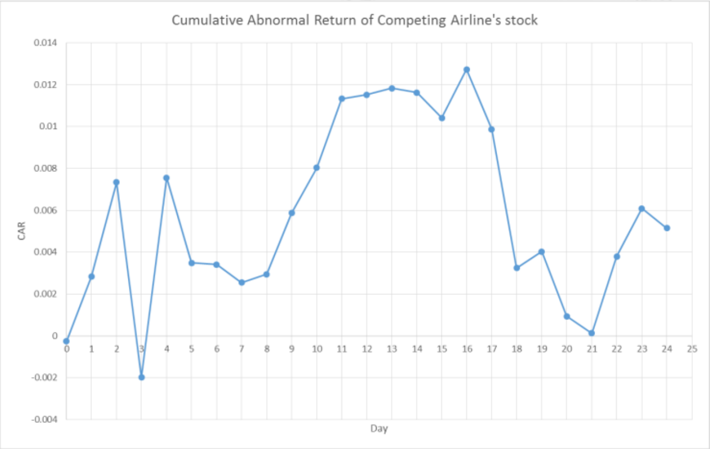


Figure 2.2: *Test the other airlines' stocks CAR movement that are listed in the same stock market as the crashing airline*

	(1)
VARIABLES	car
d0	0.00405
	(0.0194)
d1	-0.00132
	(0.0194)
d2	-0.00360
	(0.0194)
d3	-0.00453
	(0.0194)
d4	-0.00169
	(0.0194)
d5	-0.000825
	(0.0194)
d6	-0.00247
	(0.0194)
d7	-0.00559
	(0.0194)
d8	-0.00659
	(0.0194)
d9	-0.00251
	(0.0194)
d10	-0.0135
	(0.0194)
d11	-0.00837
	(0.0194)
d12	-0.0127
	(0.0194)
d13	-0.0124
	(0.0194)
d14	-0.0122
	(0.0194)
d15	-0.00510
	(0.0194)
d16	-0.00291
	(0.0194)
d17	-0.00475
	(0.0194)
d18	-0.0125

	(0.0194)
d19	-0.00977
	(0.0194)
d20	-0.0135
	(0.0194)
d21	-0.00805
	(0.0194)
d22	-0.0122
	(0.0194)
d23	-0.000850
	(0.0194)
d24	0.00362
	(0.0194)
Constant	-0.000463
	(0.0137)
Observations	4,446
R-squared	0.001
Standard errors in parentheses	
*** p<0.01, ** p<0.05, * p<0.1	

Figure 2.4: *the other airlines' stocks CAR movement that are listed in the same stock market as the crashing airline*

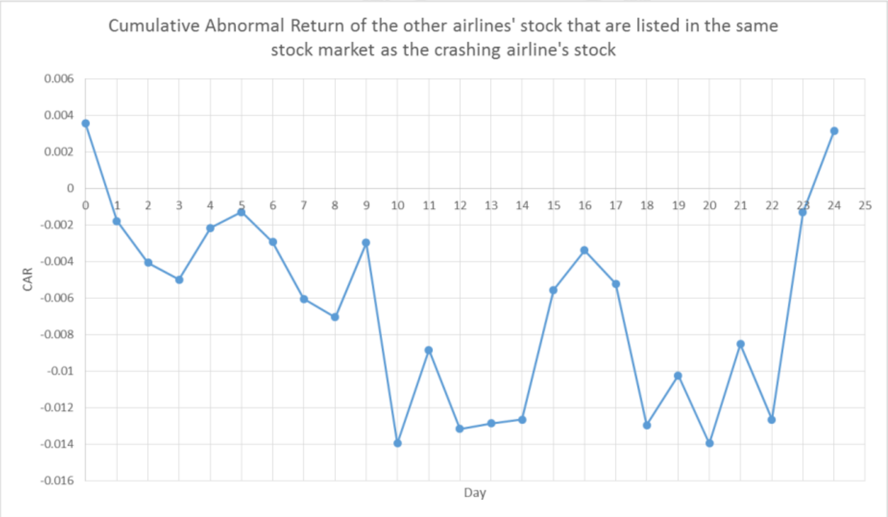


Figure 3: *Test the crashing airline's AR movement*

	(1)
VARIABLES	ar
d0	-0.00155
	(0.00524)
d1	-0.000693
	(0.00524)
d2	-0.00466
	(0.00524)
d3	-4.11e-05
	(0.00524)
d4	7.08e-05
	(0.00524)
d5	0.00144
	(0.00524)
d6	-0.00179
	(0.00524)
d7	0.000247
	(0.00524)
d8	0.00213
	(0.00524)
d9	0.00247
	(0.00524)
d10	-0.00911*
	(0.00524)
d11	0.000884
	(0.00524)
d12	0.00278
	(0.00524)
d13	0.00272
	(0.00524)
d14	0.00101
	(0.00524)
d15	0.00175
	(0.00524)
d16	0.00225
	(0.00524)
d17	-0.000256
	(0.00524)
d18	-0.00524

	(0.00524)
d19	-0.00317
	(0.00524)
d20	0.00261
	(0.00524)
d21	0.00624
	(0.00524)
d22	0.00139
	(0.00524)
d23	-0.000326
	(0.00524)
d24	0.00150
	(0.00524)
Constant	-0.00136
	(0.00370)
Observations	2,886
R-squared	0.006
Standard errors in parentheses	
*** p<0.01, ** p<0.05, * p<0.1	

Figure 3.1: *Crashing airline Abnormal Returns*

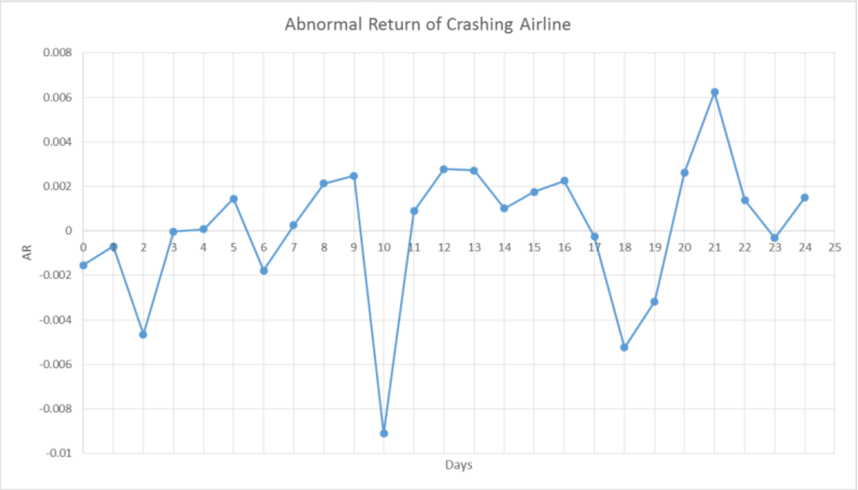


Figure 4: *Test the competing airline's AR movement*

	(1)
VARIABLES	ar
d0	0.00366
	(0.00376)
d1	0.00702*
	(0.00376)
d2	0.00843**
	(0.00376)
d3	0.00194
	(0.00376)
d4	0.00613
	(0.00376)
d5	-0.000155
	(0.00376)
d6	0.00384
	(0.00376)
d7	0.00306
	(0.00376)
d8	0.00433
	(0.00376)
d9	0.00684*
	(0.00376)
d10	0.00608
	(0.00376)
d11	0.00720*
	(0.00376)
d12	0.00414
	(0.00376)
d13	0.00425
	(0.00376)
d14	0.00367
	(0.00376)
d15	0.00274
	(0.00376)
d16	0.00622*
	(0.00376)
d17	0.00107
	(0.00376)
d18	-0.00271
	(0.00376)

d19	0.00472
	(0.00376)
d20	0.000821
	(0.00376)
d21	0.00312
	(0.00376)
d22	0.00759**
	(0.00376)
d23	0.00623*
	(0.00376)
d24	0.00298
	(0.00376)
Constant	-0.00392
	(0.00266)
Observations	4,056
R-squared	0.006
Standard errors in parentheses	
*** p<0.01, ** p<0.05, * p<0.1	

Figure 4.1: *Competing Airline Abnormal Returns*

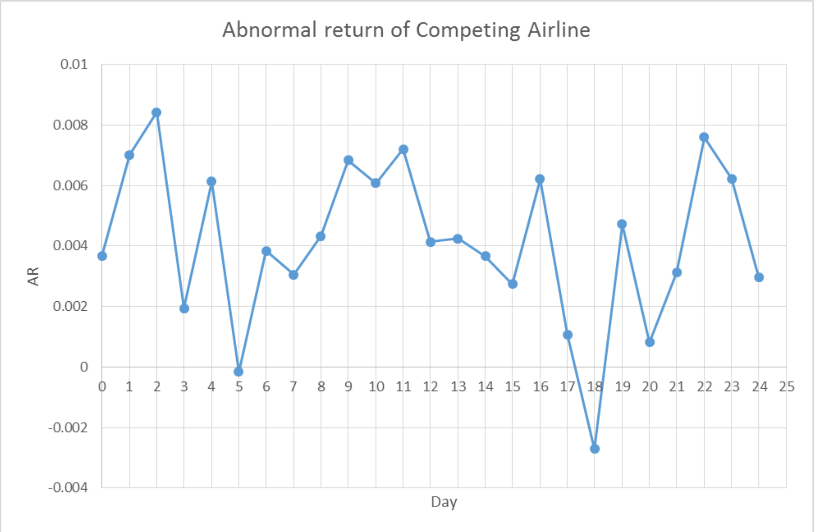


Figure 5.1: *Profit's Histogram Strategy I*

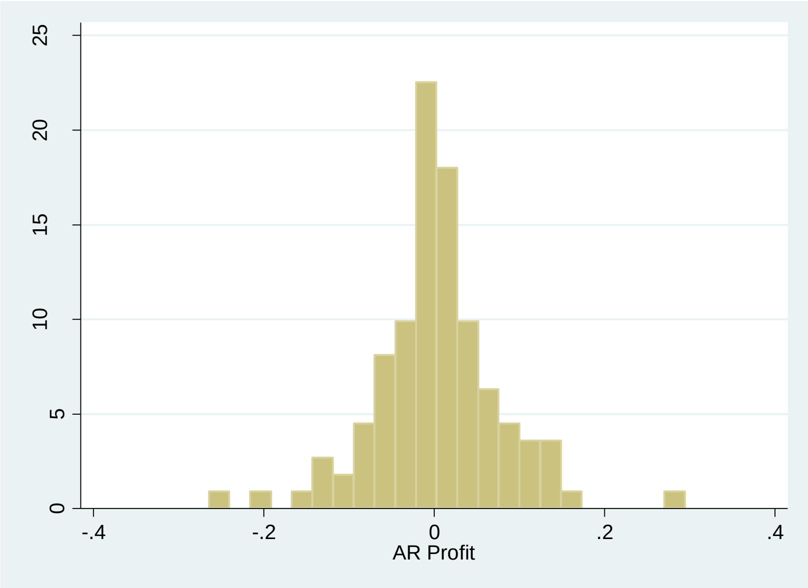


Figure 5.2: *Profit's Histogram Strategy II*

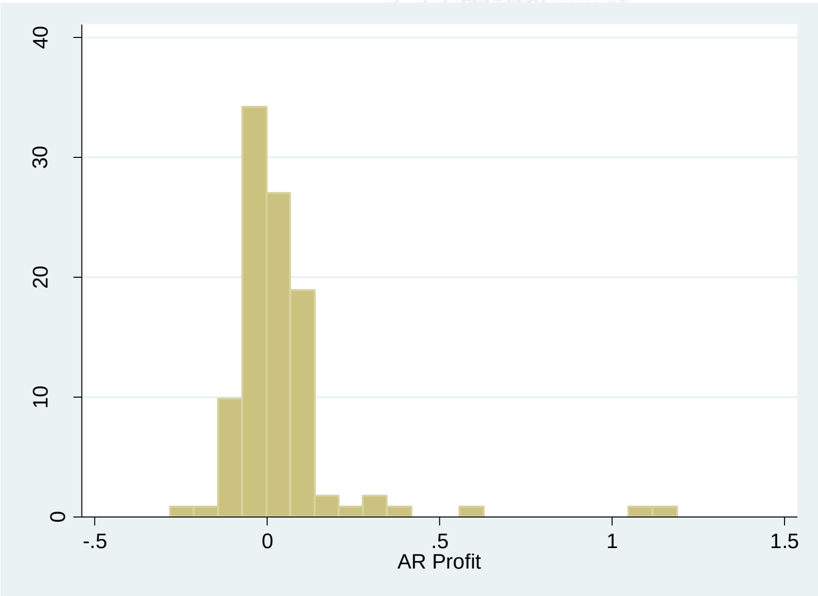


Figure 5.3: *Profit's Histogram Strategy III*

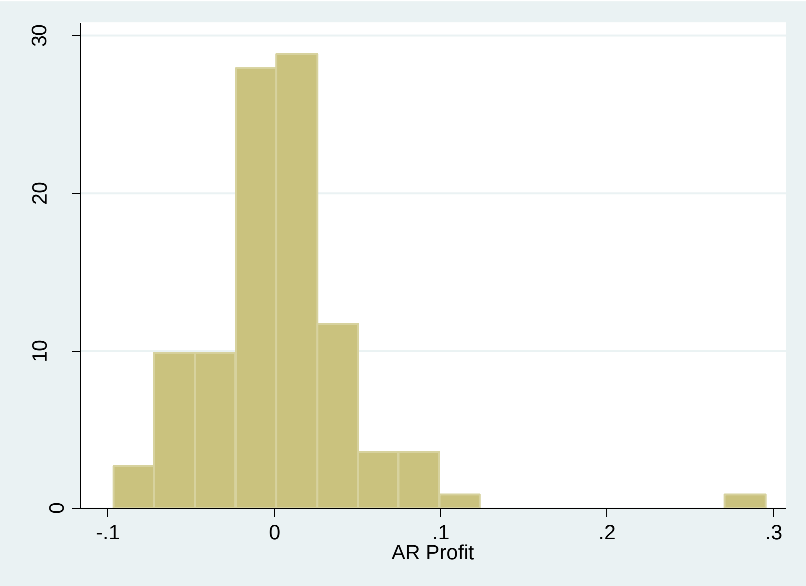


Figure 5.4: *Profit's Histogram Strategy IV*

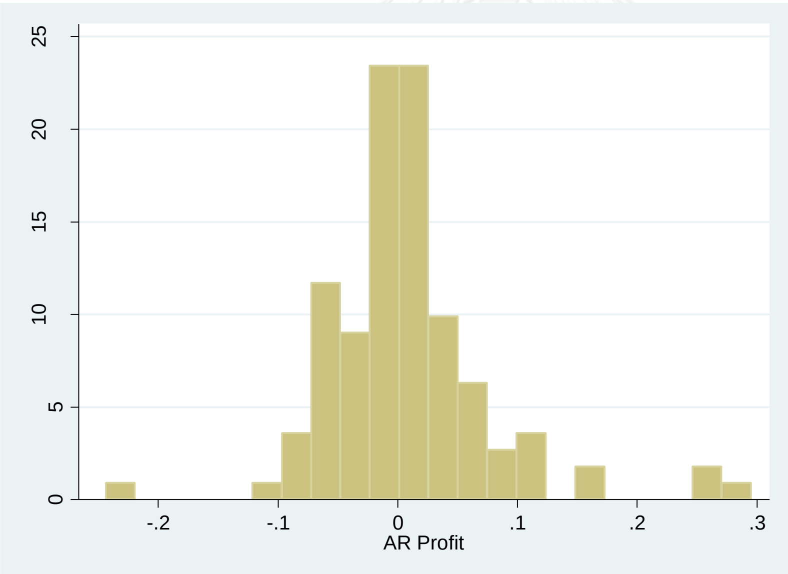
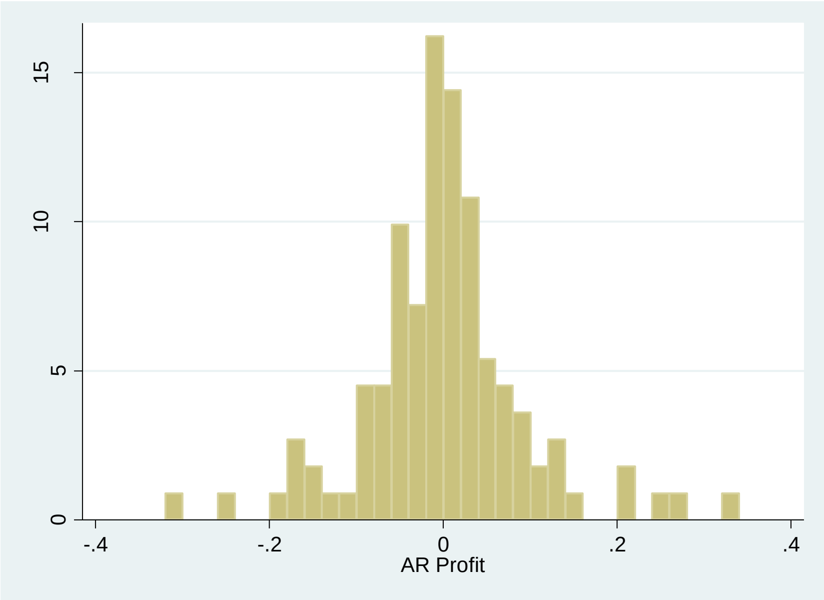


Figure 5.5: *Profit's Histogram Strategy V*



6.1 Test the Portfolio's CAR against 5 factors in Strategy I (Equation 3)

	(1)
VARIABLES	carport
ms	-0.0648074
	(0.0506095)
frq	0.0013948
	(0.0009762)
dist	2.79e-06
	(06.46e-06)
flgt	-0.0413412
	(0.056727)
dth	-0.0000872
	(0.0005374)
Constant	-0.1715625
	(0.187469)
Observations	110
R-squared	0.0420
Standard errors in parentheses	
*** p<0.01, ** p<0.05, * p<0.1	

6.2 Test the Portfolio's CAR against 5 factors in Strategy II (Equation 3)

	(1)
VARIABLES	carport
ms	-0.0091247
	(0.0093426)
frq	-5.02e-07
	(0.0001824)
dist	-4.31e-07
	(1.11e-06)
flgt	-0.0142291
	(0.0100014)
dth	-0.0000236
	(0.0001029)
Constant	-0.036656
	(0.03496)
Observations	278
R-squared	0.0133
Standard errors in parentheses	
*** p<0.01, ** p<0.05, * p<0.1	

6.3 Test the Portfolio's AR against 5 factors in Strategy II (Equation 3)

	(1)
VARIABLES	arport
ms	0.0030416
	(0.0029484)
frq	-1.67e-07
	(0.0000576)
dist	-1.44e-07
	(3.51e-07)
flgt	-0.004743
	(0.0031563)
dth	7.88e-06
	(0.0000325)
Constant	-0.0012219
	(0.0110328)
Observations	834
R-squared	0.0049
Standard errors in parentheses	
*** p<0.01, ** p<0.05, * p<0.1	

6.4 Test the Portfolio's CAR against 5 factors in Strategy III (Equation 3)

	(1)
VARIABLES	carport
ms	-0.0414642
	(0.0386122)
frq	-0.0002516
	(0.0007448)
dist	-4.56e-06
	(4.93e-06)
flgt	0.0391465
	(0.0432795)
dth	0.0008067
	(0.00041)
Constant	0.0709347
	(0.143282)
Observations	110
R-squared	0.0559
Standard errors in parentheses	
*** p<0.01, ** p<0.05, * p<0.1	

6.5 Test the Portfolio's CAR against 5 factors in Strategy IV (Equation 3)

	(1)
VARIABLES	carport
ms	0.005717
	(0.0452306)
frq	-0.0007142
	(0.0008725)
dist	-6.21e-06
	(5.77e-06)
flgt	0.022853
	(0.0506979)
dth	0.0009624**
	(0.0004803)
Constant	0.119429
	(0.1675441)
Observations	110
R-squared	0.0470
Standard errors in parentheses	
*** p<0.01, ** p<0.05, * p<0.1	

6.6 Test the Portfolio's CAR against 5 factors in Strategy V (Equation 3)

	(1)
VARIABLES	carport
ms	-0.0908695
	(0.0593007)
frq	0.0014397
	(0.0011439)
dist	-6.02e-06
	(7.57e-06)
flgt	-0.0537778
	(0.0664688)
dth	-0.0002506
	(0.0006297)
Constant	-0.1488268
	(0.2196631)
Observations	110
R-squared	0.0505
Standard errors in parentheses	
*** p<0.01, ** p<0.05, * p<0.1	

7.1 Test the CAR of the crashing airline against 5 factors on Day 19 (Equation 3)

	(1)
VARIABLES	car
ms	0.0657
	(0.0399)
frq	0.000239
	(0.000770)
dist	4.24e-06
	(5.10e-06)
flgt	-0.0641
	(0.0448)
dth	-0.000890**
	(0.000424)
Constant	-0.0728
	(0.148)
Observations	110
R-squared	0.082
Standard errors in parentheses	
*** p<0.01, ** p<0.05, * p<0.1	

7.2 Test the CAR of the crashing airline against 5 factors on Day 21 (Equation 3)

	(1)
VARIABLES	car
ms	0.0575
	(0.0389)
frq	0.000150
	(0.000751)
dist	4.25e-06
	(4.97e-06)
flgt	-0.0682
	(0.0436)
dth	-0.000990**
	(0.000413)
Constant	-0.0425
	(0.144)
Observations	110
R-squared	0.093
Standard errors in parentheses	
*** p<0.01, ** p<0.05, * p<0.1	

7.3 Test the CAR of the crashing airline against 5 factors on Day 19 in the case of DTH<10 (Equation 3)

	(1)
VARIABLES	car
ms	0.0628
	(0.0437)
frq	0.000367
	(0.000857)
dist	3.27e-06
	(6.53e-06)
flgt	-0.0661
	(0.0505)
dth	-0.0176
	(0.0199)
Constant	-0.0901
	(0.166)
Observations	99
R-squared	0.065
Standard errors in parentheses	
*** p<0.01, ** p<0.05, * p<0.1	

7.4 Test the CAR of the crashing airline against 5 factors on Day 21 in the case of DTH<10 (Equation 3)

	(1)
VARIABLES	car
ms	0.0553
	(0.0426)
frq	0.000235
	(0.000836)
dist	3.35e-06
	(6.37e-06)
flgt	-0.0679
	(0.0492)
dth	-0.0149
	(0.0194)
Constant	-0.0540
	(0.162)
Observations	99
R-squared	0.063
Standard errors in parentheses	
*** p<0.01, ** p<0.05, * p<0.1	

7.5 Test the CAR of the crashing airline against 5 factors on Day 19 in the case of DTH>9 (Equation 3)

	(1)
VARIABLES	car
ms	0.0654
	(0.0967)
frq	0.00150
	(0.00221)
dist	1.97e-05*
	(7.67e-06)
flgt	-0.204
	(0.130)
dth	-0.00201*
	(0.000809)
Constant	-0.184
	(0.496)
Observations	11
R-squared	0.686
Standard errors in parentheses	
*** p<0.01, ** p<0.05, * p<0.1	

7.6 Test the CAR of the crashing airline against 5 factors on Day 21 in the case of DTH>9 (Equation 3)

	(1)
VARIABLES	car
ms	0.0658
	(0.0923)
frq	0.00148
	(0.00211)
dist	1.91e-05**
	(7.32e-06)
flgt	-0.247
	(0.124)
dth	-0.00226**
	(0.000772)
Constant	-0.136
	(0.474)
Observations	11
R-squared	0.719
Standard errors in parentheses	
*** p<0.01, ** p<0.05, * p<0.1	

8.1 Test the Portfolio's CAR against 5 factors in Strategy I (Equation 3.1)

	(1)
VARIABLES	carport
ms	-0.0661
	(0.0511)
frq	6.80e-06
	(2.68e-05)
frq	-0.00126
	(0.0105)
dist	2.90e-06
	(6.50e-06)
flgt	-0.0419
	(0.0570)
dth	-9.79e-05
	(0.000541)
Constant	0.0823
	(1.016)
Observations	110
R-squared	0.043
Standard errors in parentheses	
*** p<0.01, ** p<0.05, * p<0.1	

8.2 Test the Portfolio's CAR against 5 factors in Strategy II (Equation 3.1)

	(1)
VARIABLES	carport
ms	0.00860
	(0.00934)
frq^2	6.89e-06
	(5.28e-06)
frq	-0.00264
	(0.00203)
dist	-3.80e-07
	(1.11e-06)
flgt	-0.0151
	(0.0100)
dth	1.94e-05
	(0.000103)
Constant	0.246
	(0.194)
Observations	278
R-squared	0.019
Standard errors in parentheses	
*** p<0.01, ** p<0.05, * p<0.1	

8.3 Test the Portfolio's AR against 5 factors in Strategy II (Equation 3.1)

	(1)
VARIABLES	arport
ms	0.00287
	(0.00295)
frq^2	2.30e-06
	(1.67e-06)
frq	-0.000881
	(0.000642)
dist	-1.27e-07
	(3.51e-07)
flgt	-0.00503
	(0.00316)
dth	6.48e-06
	(3.25e-05)
Constant	0.0820
	(0.0614)
Observations	834
R-squared	0.007
Standard errors in parentheses	
*** p<0.01, ** p<0.05, * p<0.1	

8.4 Test the Portfolio's CAR against 5 factors in Strategy III (Equation 3.1)

	(1)
VARIABLES	carport
ms	-0.0425
	(0.0390)
frq^2	5.85e-06
	(2.04e-05)
frq	-0.00253
	(0.00799)
dist	-4.46e-06
	(4.96e-06)
flgt	0.0386
	(0.0435)
dth	0.000798*
	(0.000413)
Constant	0.289
	(0.775)
Observations	110
R-squared	0.057
Standard errors in parentheses	
*** p<0.01, ** p<0.05, * p<0.1	

8.5 Test the Portfolio's CAR against 5 factors in Strategy IV (Equation 3.1)

	(1)
VARIABLES	carport
ms	0.00199
	(0.0455)
frq^2	2.01e-05
	(2.38e-05)
frq	-0.00855
	(0.00933)
dist	-5.87e-06
	(5.80e-06)
flgt	0.0211
	(0.0508)
dth	0.000931*
	(0.000482)
Constant	0.870
	(0.905)
Observations	110
R-squared	0.054
Standard errors in parentheses	
*** p<0.01, ** p<0.05, * p<0.1	

8.6 Test the Portfolio's CAR against 5 factors in Strategy V (Equation 3.1)

	(1)
VARIABLES	carport
ms	-0.0927
	(0.0598)
frq^2	1.01e-05
	(3.13e-05)
frq	-0.00249
	(0.0123)
dist	6.19e-06
	(7.62e-06)
flgt	-0.0547
	(0.0668)
dth	-0.000266
	(0.000634)
Constant	0.228
	(1.190)
Observations	110
R-squared	0.051
Standard errors in parentheses	
*** p<0.01, ** p<0.05, * p<0.1	

8.7 Test the CAR of Crashing Airline at Day 19 against 5 factors in the case of DTH<10 (Equation 3.1)

	(1)
VARIABLES	car
ms	0.0625
	(0.0439)
frq^2	2.74e-06
	(2.56e-05)
frq	-0.000683
	(0.00984)
dist	3.36e-06
	(6.62e-06)
flgt	-0.0662
	(0.0508)
dth	-0.0182
	(0.0208)
Constant	0.00850
	(0.937)
Observations	99
R-squared	0.065
Standard errors in parentheses	
*** p<0.01, ** p<0.05, * p<0.1	

8.8 Test the CAR of Crashing Airline at Day 21 against 5 factors in the case of DTH<10 (Equation 3.1)

	(1)
VARIABLES	car
ms	0.0552
	(0.0429)
frq^2	9.65e-07
	(2.50e-05)
frq	-0.000134
	(0.00960)
dist	3.38e-06
	(6.45e-06)
flgt	-0.0679
	(0.0495)
dth	-0.0151
	(0.0203)
Constant	-0.0193
	(0.914)
Observations	99

R-squared	0.063
Standard errors in parentheses	
*** p<0.01, ** p<0.05, * p<0.1	

8.9 Test the CAR of Crashing Airline at Day 19 against 5 factors in the case of DTH>9 (Equation 3.1)

	(1)
VARIABLES	car
ms	0.0673
	(0.109)
frq^2	1.55e-05
	(0.000106)
frq	-0.00555
	(0.0483)
dist	1.98e-05*
	(8.64e-06)
flgt	-0.210
	(0.150)
dth	-0.00206
	(0.000972)
Constant	0.618
	(5.509)
Observations	11
R-squared	0.687
Standard errors in parentheses	
*** p<0.01, ** p<0.05, * p<0.1	

9.1 Test the CAR of Crashing Airline at Day 21 against 5 factors in the case of DTH>9 (Equation 3.1)

	(1)
VARIABLES	car
ms	0.0744
	(0.0982)
frq^2	6.69e-05
	(9.58e-05)
frq	-0.0289
	(0.0436)
dist	1.99e-05*
	(7.80e-06)
flgt	-0.273
	(0.136)
dth	-0.00249**
	(0.000878)
Constant	3.319
	(4.976)

Observations	11
R-squared	0.749
Standard errors in parentheses	
*** p<0.01, ** p<0.05, * p<0.1	

9.2 Test the CAR of Crashing Airline at Day 19 against 5 factors (Equation 3.1)

	(1)
VARIABLES	car
ms	0.0661
	(0.0403)
frq^2	-2.38e-06
	(2.11e-05)
frq	0.00116
	(0.00826)
dist	4.20e-06
	(5.13e-06)
flgt	-0.0639
	(0.0450)
dth	-0.000886**
	(0.000427)
Constant	-0.162
	(0.802)
Observations	110
R-squared	0.083
Standard errors in parentheses	
*** p<0.01, ** p<0.05, * p<0.1	

9.3 Test the CAR of Crashing Airline at Day 21 against 5 factors (Equation 3.1)

	(1)
VARIABLES	car
ms	0.0578
	(0.0393)
frq^2	-1.71e-06
	(2.06e-05)
frq	0.000816
	(0.00805)
dist	4.22e-06
	(5.00e-06)
flgt	-0.0681
	(0.0439)
dth	-0.000987**
	(0.000417)
Constant	-0.106
	(0.781)

Observations	110
R-squared	0.093
Standard errors in parentheses	
*** p<0.01, ** p<0.05, * p<0.1	

Table 1: *Competitors Selections*

Crashing airline	Competing Airline	Date	Business Nature	PE_RATIO	PX_TO_BV_PER_WEIGHTED_DILUTED_SH	BEST_PX_SALES_RATIO	PX_TO_SALES_RATIO	RETURN_ON_ASSET	RETURN_COM_EQY	CUR_MKT_CAP	CURRENT_EV_TO_T12M_EBITDA	CURRENT_EV_TO_12M_SALES	AVERAGE_EV_TO_T12M_SALES	BEST_CURRENT_EV_BEST_SALES	BEST_CURRENT_EV_BEST_EBIT	CURRENT_EV_TO_T12M_EBIT
Aeroflot	British Airways	11/11/98	X													
Aeroflot	British Airways	9/21/01	X													
Aeroflot	British Airways	12/28/06	X													
Aeroflot	British Airways	6/30/08	X													
Aeroflot	British Airways	9/14/08	X													
Aeroflot	British Airways	6/3/09	X													
Aeroflot	Deutsche Lufthansa	11/11/98	X													
Aeroflot	Deutsche Lufthansa	9/21/01	X													
Aeroflot	Deutsche Lufthansa	12/28/06	X													
Aeroflot	Deutsche Lufthansa	6/30/08	X													
Aeroflot	Deutsche Lufthansa	9/14/08	X													
Aeroflot	Deutsche Lufthansa	6/3/09	X													
Aeromexico	COPA Airlline	4/16/13	X													
Aeromexico	American Airlines	10/15/97	X				X									
Aeromexico	American Airlines	10/6/00	X													
Aeromexico	American Airlines	10/31/02	X													

Aeromexico	American Airlines	4/16/13	X													
Aeromexico	LATAM Airlines	10/6/00	X													
Aeromexico	LATAM Airlines	10/31/02	X													
Aeromexico	LATAM Airlines	4/16/13	X													
Aeromexico	Avianca	4/16/13	X													
Air Berlin	Deutsche Lufthansa	9/19/15	X				X					X	X			
Air Berlin	Aeroflot	9/19/15	X													
Air Canada	American Airlines	3/29/15	X													
Air Canada	Delta Airlines	3/29/15	X													
Air Canada	WestJet Airlines	3/29/15	X							X					X	
Air France	American Airlines	2/12/99	X													
Air France	American Airlines	3/4/99	X													
Air France	American Airlines	7/25/00	X							X						
Air France	American Airlines	8/2/05	X													
Air France	American Airlines	6/1/09	X													
Air France	American Airlines	4/13/11	X													
Air France	American Airlines	9/12/11	X													
Air France	Deutsche Lufthansa	2/12/99	X													
Air France	Deutsche Lufthansa	3/4/99	X													
Air France	Deutsche Lufthansa	7/25/00	X													
Air France	Deutsche Lufthansa	8/2/05	X				X									
Air France	Deutsche Lufthansa	6/1/09	X				X					X	X			
Air France	Deutsche Lufthansa	4/13/11	X				X					X	X			
Air France	Deutsche Lufthansa	9/12/11	X				X					X	X			

Air France	International Consolidated Airline	2/12/99	X													
Air France	International Consolidated Airline	3/4/99	X													
Air France	International Consolidated Airline	7/25/00	X													
Air France	International Consolidated Airline	8/2/05	X							X						
Air France	International Consolidated Airline	6/1/09	X													
Air France	International Consolidated Airline	4/13/11	X				X					X	X			
Air France	International Consolidated Airline	9/12/11	X				X					X	X			
Air Asia	Tiger Airways	1/10/11	X													
Alitalia	Deutsche Lufthansa	8/19/94	X													
Alitalia	Deutsche Lufthansa	5/22/97	X													
Alitalia	Deutsche Lufthansa	1/28/99	X													
Alitalia	Deutsche Lufthansa	4/20/04	X							X						
Alitalia	Aeroflot	4/20/04	X							X						
American Airlines	Southwest Airlines	8/15/15	X							X						
American Airlines	Delta Airlines	8/15/15	X									X	X	X	X	
American Airlines	United Continental	8/15/15	X			X	X					X	X	X	X	
Asiana Airlines	Tiger Airways	4/16/13	X													

Asiana Airlines	Tiger Airways	7/6/13	X													
Asiana Airlines	Tiger Airways	4/14/15	X													
Asiana Airlines	Singapore Airlines	10/28/09	X									X	X			
Asiana Airlines	Singapore Airlines	4/16/13	X		X							X	X			
Asiana Airlines	Singapore Airlines	7/6/13	X		X											
Asiana Airlines	Singapore Airlines	4/14/15	X													
Asiana Airlines	Korean Airline	10/28/09	X													
Asiana Airlines	Korean Airline	4/16/13	X		X		X									
Asiana Airlines	Korean Airline	7/6/13	X		X		X									
Asiana Airlines	Korean Airline	4/14/15	X			X	X									
Asiana Airlines	Cathay Pacific Airways	10/28/09	X									X	X			
Asiana Airlines	Cathay Pacific Airways	4/16/13	X		X											
Asiana Airlines	Cathay Pacific Airways	7/6/13	X		X			X								
Asiana Airlines	Cathay Pacific Airways	4/14/15	X											X		
Austrian Airlines	SWISS Air	1/5/04	X													
Austrian Airlines	Air France	1/5/04	X													
Canadian Airlines International	American Airlines	10/19/95	X													
Canadian Airlines International	American Airlines	9/6/97	X													
Canadian Airlines International	America West Airline	10/19/95	X													

Canadian Airlines Internatio nal	America West Airline	9/6/97	X													
Cathay Pacific Airways	Singapore Airlines	4/13/10	X		X											
Cathay Pacific Airways	China Eastern Airlines	4/13/10	X													
Cathay Pacific Airways	China Southern Airlines	4/13/10	X							X						
Cebu Pacific Air	Singapore Airlines	6/2/13	X													
Cebu Pacific Air	Tiger Airways	6/2/13	X													
China Airlines	Singapore Airlines	4/26/94	X													
China Airlines	Singapore Airlines	2/16/98	X													
China Airlines	Singapore Airlines	8/22/99	X													
China Airlines	Singapore Airlines	5/25/02	X													
China Airlines	Singapore Airlines	8/20/07	X													
China Airlines	China Southern Airlines	8/22/99	X													
China Airlines	China Southern Airlines	5/25/02	X													
China Airlines	China Southern Airlines	8/20/07	X													
China Airlines	Eva Airways	5/25/02	X							X						
China Airlines	Eva Airways	8/20/07	X							X						
China Eastern Airlines	China Southern Airlines	9/11/98	X													
China Eastern Airlines	China Southern Airlines	6/7/13	X							X		X	X			

China Eastern Airlines	Cathay Pacific Airways	9/11/98	X													
China Eastern Airlines	Cathay Pacific Airways	6/7/13	X													
China Eastern Airlines	Air China	6/7/13	X													
China Southern Airlines	China Eastern Airlines	6/9/99	X									X	X			X
China Southern Airlines	China Eastern Airlines	3/7/08	X								X	X	X			
China Southern Airlines	Cathay Pacific Airways	6/9/99	X													
China Southern Airlines	Cathay Pacific Airways	3/7/08	X													
China Southern Airlines	Air China	3/7/08	X								X					
Delta Air Lines	American Airlines	12/22/03	X													
Delta Air Lines	American Airlines	6/13/13	X													
Delta Air Lines	United Continental	6/13/13	X				X					X	X			
Delta Air Lines	United Continental	12/5/13	X													
Delta Air Lines	United Continental	1/31/14	X												X	
Delta Air Lines	United Continental	10/22/14	X	X							X					
Delta Air Lines	United Continental	3/5/15	X											X		
Delta Air Lines	United Continental	6/17/15	X												X	
Delta Air Lines	Deutsche Lufthansa	12/22/03	X													

Delta Air Lines	Deutsche Lufthansa	6/13/13	X				X									
Delta Air Lines	Deutsche Lufthansa	12/5/13	X													
Delta Air Lines	Deutsche Lufthansa	1/31/14	X													
Delta Air Lines	Deutsche Lufthansa	10/22/14	X													
Delta Air Lines	Deutsche Lufthansa	3/5/15	X													
Delta Air Lines	Deutsche Lufthansa	6/17/15	X					X								
Easy Jet	British Airways	12/22/03	X													
Easy Jet	Ryanair	12/22/03	X													X
Easy Jet	Ryanair	2/14/12	X													
Eva Air	Cathay Pacific Airways	11/20/01	X													
Eva Air	China Airlines	11/20/01	X													
Eva Air	Singapore Airlines	11/20/01	X													
Hainan Airlines	China Southern Airlines	11/7/05	X													
Hainan Airlines	China Eastern Airlines	11/7/05	X													
Iberia	United Continental	8/20/07	X							X						
Iberia	United Continental	11/9/07	X							X						
Iberia	Deutsche Lufthansa	3/24/05	X					X				X	X			
Iberia	Deutsche Lufthansa	8/20/07	X				X									
Iberia	Deutsche Lufthansa	11/9/07	X									X	X			
Iberia	Air France	3/24/05	X								X					
Iberia	Air France	8/20/07	X													
Iberia	Air France	11/9/07	X													
Jet Airways	Malaysian Airline	7/1/07	X													
Jet Airways	Kingfisher Airlines	7/1/07	X													

Kenya Airways	British Airways	1/30/00	X													
Kenya Airways	British Airways	5/5/07	X				X									
Kingfisher Airlines	Malaysian Airline	11/10/09	X													
Korean Air	Singapore Airlines	7/27/89	X													
Korean Air	Singapore Airlines	11/25/89	X													
Korean Air	Singapore Airlines	6/13/91	X													
Korean Air	Singapore Airlines	8/10/94	X													
Korean Air	Singapore Airlines	8/6/97	X													
Korean Air	Singapore Airlines	8/5/98	X													
Korean Air	Singapore Airlines	3/15/99	X													
Korean Air	Cathay Pacific Airways	6/13/91	X													
Korean Air	Cathay Pacific Airways	8/10/94	X													
Korean Air	Cathay Pacific Airways	8/6/97	X													
Korean Air	Cathay Pacific Airways	8/5/98	X													
Korean Air	Cathay Pacific Airways	3/15/99	X													
Lufthansa	British Airways	9/14/93	X													
Lufthansa	British Airways	5/15/06	X				X			X						
Lufthansa	Air Berlin PLC	8/10/12	X				X					X	X			
Lufthansa	Air Berlin PLC	5/2/15	X				X					X	X			
Lufthansa	Air France	5/15/06	X				X					X	X			
Lufthansa	Air France	8/10/12	X				X					X	X			
Lufthansa	Air France	5/2/15	X				X					X	X			

Qantas	United Continental	7/25/08	X													
Qantas	United Continental	10/7/08	X													
Qantas	United Continental	11/4/10	X									X	X			
Qantas	Singapore Airlines	9/23/99	X													
Qantas	Singapore Airlines	7/25/08	X													
Qantas	Singapore Airlines	10/7/08	X		X							X	X			
Qantas	Singapore Airlines	11/4/10	X													
Qantas	Virgin Australia	7/25/08	X				X									
Qantas	Virgin Australia	10/7/08	X									X	X			
Qantas	Virgin Australia	11/4/10	X		X		X	X				X	X			
Ryanair	Easy Jet	3/21/08	X								X					
Ryanair	Easy Jet	11/10/08	X													
Ryanair	Easy Jet	6/28/14	X													
Ryanair	Easy Jet	7/29/14	X								X					
Ryanair	Easy Jet	4/1/15	X													
Ryanair	Aer Lingus	3/21/08	X													
Ryanair	Aer Lingus	11/10/08	X													
Ryanair	Aer Lingus	6/28/14	X													
Ryanair	Aer Lingus	7/29/14	X	X												
Ryanair	Aer Lingus	4/1/15	X													
Ryanair	International Consolidated Airline	3/21/08	X													
Ryanair	International Consolidated Airline	11/10/08	X													
Ryanair	International Consolidated Airline	6/28/14	X													
Ryanair	International	7/29/14	X							X						

	Consolidated Airline															
Ryanair	International Consolidated Airline	4/1/15	X							X						
Singapore Airlines	Japan Airlines	10/31/00	X													
Singapore Airlines	Malaysian Airline	10/31/00	X													
Singapore Airlines	Malaysian Airline	3/12/03	X													
Singapore Airlines	Cathay Pacific Airways	10/31/00	X													
Singapore Airlines	Cathay Pacific Airways	3/12/03	X													
Southwest Airlines	American Airlines	6/9/93	X													
Southwest Airlines	American Airlines	11/22/94	X													
Southwest Airlines	American Airlines	8/26/82	X													
Southwest Airlines	American Airlines	2/10/91	X													
Southwest Airlines	American Airlines	3/5/00	X							X						
Southwest Airlines	American Airlines	5/24/03	X													
Southwest Airlines	American Airlines	12/8/05	X													
Southwest Airlines	American Airlines	7/13/09	X									X	X			
Southwest Airlines	American Airlines	4/1/11	X													
Southwest Airlines	American Airlines	10/4/12	X													
Southwest Airlines	American Airlines	7/22/13	X													
Southwest Airlines	Delta Airlines	7/13/09	X									X	X			
Southwest Airlines	Delta Airlines	4/1/11	X									X	X			
Southwest Airlines	Delta Airlines	10/4/12	X				X				X	X	X			
Southwest Airlines	Delta Airlines	7/22/13	X				X					X	X			

Southwest Airlines	Delta Airlines	1/3/14	X		X		X				X	X	X			
Southwest Airlines	Delta Airlines	12/12/14	X													
Southwest Airlines	Delta Airlines	12/15/15	X													
SpiceJet	Jet Airways	3/8/15	X				X									
SpiceJet	Jet Airways	12/4/15	X													
Thai Airways	China Southern Airlines	12/11/98	X													
Thai Airways	China Southern Airlines	3/3/01	X													
Thai Airways	China Southern Airlines	9/8/13	X													
Thai Airways	Garuda	9/8/13	X													
Thai Airways	Cathay Pacific Airways	12/11/98	X													
Thai Airways	Cathay Pacific Airways	3/3/01	X													
Thai Airways	Cathay Pacific Airways	9/8/13	X													
Thai Airways	Singapore Airlines	3/3/01	X													
Thai Airways	Singapore Airlines	9/8/13	X													
Thai Airways	Qantas Airways	12/11/98	X							X						
Thai Airways	Qantas Airways	3/3/01	X													
Thai Airways	Qantas Airways	9/8/13	X													
Tower Air	British Airways	12/20/95	X													
US Airways	Delta Airlines	1/15/09	X				X									
US Airways	Southwest Airlines	2/17/08	X													
US Airways	Southwest Airlines	1/15/09	X													

US Airways	United Continental	2/17/08	X				X									
US Airways	United Continental	1/15/09	X				X									

Table 2: *List of crashing airlines in our sample*

List of the crashing airlines	Date of Crash
Aeromexico	10/15/97
Aeromexico	10/6/00
Aeromexico	10/31/02
Aeromexico	4/16/13
Air Asia	1/10/11
Air Berlin	9/19/15
Air Canada	3/29/15
Air France	2/12/99
Air France	11/12/99
Air France	7/25/00
Air France	8/2/05
Air France	6/1/09
Air France	4/13/11
Air France	9/12/11
Alitalia	1/28/99
Alitalia	4/20/04
America West Airlines	12/30/89
America West Airlines	10/15/99
America West Airlines	6/12/00
America West Airlines	8/25/01
America West Airlines	8/28/02
American Airlines	8/15/15
Asiana Airlines	10/28/09
Asiana Airlines	4/16/13
Asiana Airlines	7/6/13
Asiana Airlines	4/14/15
Austrian Airlines	1/5/04
Canadian Airlines International	10/19/95
Canadian Airlines International	9/6/97
Cathay Pacific Airways	4/13/10
Cebu Pacific Air	6/2/13
China Airlines	4/26/94

China Airlines	10/27/98
China Airlines	8/22/99
China Airlines	5/25/02
China Airlines	8/20/07
China Eastern Airlines	9/11/98
China Eastern Airlines	2/15/14
China Southern Airlines	6/9/99
China Southern Airlines	3/7/08
Delta Air Lines	6/13/13
Delta Air Lines	12/5/13
Delta Air Lines	1/31/14
Delta Air Lines	10/22/14
Delta Air Lines	3/5/15
Delta Air Lines	6/17/15
Easy Jet	12/22/03
Easy Jet	2/14/12
Eva Air	11/20/01
Hainan Airlines	11/7/05
Iberia	3/24/05
Iberia	8/20/07
Iberia	11/9/07
Jet Airways	7/1/07
Kingfisher Airlines	11/10/09
Korean Air	8/10/94
Korean Air	8/6/97
Korean Air	8/5/98
Korean Air	3/15/99
Lufthansa	5/15/06
Lufthansa	8/10/12
Lufthansa	5/2/15
MALAYSIAN AIRLINE SYSTEM BERHAD	5/23/92
MALAYSIAN AIRLINE SYSTEM BERHAD	9/2/92
MALAYSIAN AIRLINE SYSTEM BERHAD	9/15/95
MALAYSIAN AIRLINE SYSTEM BERHAD	1/8/98
MALAYSIAN AIRLINE SYSTEM BERHAD	3/15/00
Pakistan International Airlines - PIA	3/1/04
Pakistan International Airlines - PIA	6/16/04
Pakistan International Airlines - PIA	7/10/06

Pakistan International Airlines - PIA	5/30/09
Pakistan International Airlines - PIA	8/31/12
Pakistan International Airlines - PIA	2/11/13
Pakistan International Airlines - PIA	5/24/13
Pakistan International Airlines - PIA	6/24/14
Qantas	9/23/99
Qantas	7/25/08
Qantas	10/7/08
Qantas	11/4/10
Ryanair	3/21/08
Ryanair	11/10/08
Ryanair	6/28/14
Ryanair	7/29/14
Ryanair	4/1/15
Singapore Airlines	10/31/00
Singapore Airlines	3/12/03
Southwest Airlines	2/10/91
Southwest Airlines	6/9/93
Southwest Airlines	11/22/94
Southwest Airlines	3/5/00
Southwest Airlines	5/24/03
Southwest Airlines	12/8/05
Southwest Airlines	7/13/09
Southwest Airlines	4/1/11
Southwest Airlines	10/4/12
Southwest Airlines	7/22/13
Southwest Airlines	1/3/14
Southwest Airlines	12/12/14
Southwest Airlines	12/15/15
SpiceJet	3/8/15
SpiceJet	12/4/15
Thai Airways	12/11/98
Thai Airways	3/3/01
Thai Airways	9/8/13
Tower Air	12/20/95
Trans World Airlines - TWA	9/9/99
Trans World Airlines - TWA	8/9/01
US Airways	2/17/08
US Airways	1/15/09
Valujet Airlines	1/7/96
Valujet Airlines	5/11/96

Table 3: *List of competing airlines in our sample*

Competing Airlines	Date of Crashing
Air Berlin	5/2/15
Air Berlin	8/10/12
Air China	3/7/08
Air China	6/7/13
Air France	1/5/04
Air France	3/24/05
Air France	5/15/06
Air France	8/20/07
Air France	11/9/07
Air France	8/10/12
Air France	5/2/15
America West Airline	9/6/97
America West Airlines	10/19/95
American Airlines	2/10/91
American Airlines	6/9/93
American Airlines	11/22/94
American Airlines	9/6/97
American Airlines	2/12/99
American Airlines	3/4/99
American Airlines	3/5/00
American Airlines	7/25/00
American Airlines	10/6/00
American Airlines	5/24/03
American Airlines	12/22/03
American Airlines	8/2/05
American Airlines	12/8/05
American Airlines	6/1/09
American Airlines	7/13/09
American Airlines	4/1/11
American Airlines	4/13/11
American Airlines	9/12/11
American Airlines	10/4/12
American Airlines	3/29/15

American Airlines	10/31/02
American Airlines	2/10/91
British Airways	9/21/01
British Airways	12/22/03
British Airways	5/15/06
British Airways	12/28/06
British Airways	5/5/07
British Airways	6/30/08
British Airways	9/14/08
British Airways	6/3/09
British Airways	12/20/95
Cathay Pacific Airways	8/5/98
Cathay Pacific Airways	9/11/98
Cathay Pacific Airways	10/31/00
Cathay Pacific Airways	3/3/01
Cathay Pacific Airways	11/20/01
Cathay Pacific Airways	3/7/08
Cathay Pacific Airways	10/28/09
Cathay Pacific Airways	4/16/13
Cathay Pacific Airways	7/6/13
Cathay Pacific Airways	9/8/13
Cathay Pacific Airways	4/14/15
Cathay Pacific Airways	6/7/13
Cathay Pacific Airways	6/9/99
Cathay Pacific Airways	8/6/97
Cathay Pacific Airways	3/15/99
China Eastern Airlines	11/7/05
China Eastern Airlines	4/13/10
China Eastern Airlines	6/9/99
China Southern Airlines	3/3/01
China Southern Airlines	4/13/10
China Southern Airlines	8/22/99
COPA Airline	4/16/13
Delta Airlines	1/15/09
Delta Airlines	7/13/09
Delta Airlines	4/1/11
Delta Airlines	10/4/12

Delta Airlines	7/22/13
Delta Airlines	1/3/14
Delta Airlines	12/12/14
Delta Airlines	8/15/15
Delta Airlines	12/15/15
Delta Airlines	3/29/15
Deutsche Lufthansa	4/20/04
Deutsche Lufthansa	3/24/05
Deutsche Lufthansa	8/2/05
Deutsche Lufthansa	12/28/06
Deutsche Lufthansa	8/20/07
Deutsche Lufthansa	11/9/07
Deutsche Lufthansa	6/30/08
Deutsche Lufthansa	9/14/08
Deutsche Lufthansa	6/1/09
Deutsche Lufthansa	6/3/09
Deutsche Lufthansa	4/13/11
Deutsche Lufthansa	9/12/11
Deutsche Lufthansa	6/13/13
Deutsche Lufthansa	12/5/13
Deutsche Lufthansa	1/31/14
Deutsche Lufthansa	10/22/14
Deutsche Lufthansa	3/5/15
Deutsche Lufthansa	6/17/15
Deutsche Lufthansa	9/19/15
Easy Jet	3/21/08
Easy Jet	11/10/08
Easy Jet	6/28/14
Easy Jet	7/29/14
Easy Jet	4/1/15
Eva Airways	8/20/07
Eva Airways	5/25/02
International Consolidated Airline	8/2/05
International Consolidated Airline	3/21/08
International Consolidated Airline	11/10/08
International Consolidated Airline	6/1/09
International Consolidated Airline	6/28/14

International Consolidated Airline	7/29/14
International Consolidated Airline	4/1/15
Jet Airways	11/10/09
Jet Airways	3/8/15
Jet Airways	12/4/15
Kingfisher Airlines	7/1/07
Korean Air	10/28/09
Korean Air	4/16/13
Korean Air	4/14/15
LATAM Airlines	4/16/13
Malaysian Airline	11/10/09
Malaysian Airline	3/12/03
Qantas Airways	12/11/98
Qantas Airways	3/3/01
Qantas Airways	9/8/13
Ryanair	12/22/03
Ryanair	2/14/12
Singapore Airlines	10/28/09
Singapore Airlines	11/4/10
Singapore Airlines	4/16/13
Singapore Airlines	7/6/13
Singapore Airlines	4/14/15
Singapore Airlines	4/13/10
Singapore Airlines	6/2/13
Singapore Airlines	3/15/00
Southwest Airlines	2/17/08
Southwest Airlines	1/15/09
Southwest Airlines	8/15/15
Tiger Airways	1/10/11
Tiger Airways	6/2/13
United Continental	8/20/07
United Continental	11/9/07
United Continental	2/17/08
United Continental	7/25/08
United Continental	10/7/08
United Continental	1/15/09
United Continental	11/4/10

United Continental	6/13/13
United Continental	12/5/13
United Continental	1/31/14
United Continental	10/22/14
United Continental	3/5/15
United Continental	6/17/15
United Continental	8/15/15
Virgin Australia	7/25/08
Virgin Australia	10/7/08
Virgin Australia	11/4/10
WestJet Airlines	3/29/15

Table 4: *Variables explanation*

Variables	Description	Source
Crash Dates	The date that the airplane crashes	The Aviation Safety Network of the Flight Safety Foundation database
r_i	Return on Stock	Datastream Database
r_m	Market Return	Datastream Database
r_f	Risk-free Rate	Datastream Database
P/E	Price to Earnings ratio	Datastream Database
P/S	Share price / sales per share	Datastream Database
EV/Sales	Enterprise value / net sales	Datastream Database
EV/EBITDA	Enterprise value / Earnings before Interest, Tax, Depreciation & Amortization. Also excludes movements in non-cash provisions and exceptional items	Datastream Database

ROA	Return on Asset	Datastream Database
ROE	Return on Equity	Datastream Database
Market Capital	Market Capital	Datastream Database
MS	Market Structure, whether the stock is listed in the emerging market or developed market. It is a dummy variable, which take a value of 1 when it is an emerging country and value of 0 when it is a developed country.	The Aviation Safety Network of the Flight Safety Foundation database
FRQ	Frequency of the crash in the past 12 months for each crash	The Aviation Safety Network of the Flight Safety Foundation database and manually count
DTH	Number of death per crash	The Aviation Safety Network of the Flight Safety Foundation database
DIST	Distance between where the plane crashed and how far from where the stock is listed	The Aviation Safety Network of the Flight Safety Foundation database
FLGT	International flight or domestic flight. It is a dummy variable which takes value of 1 when the crash happens with the domestic flight and 0 when the crash happens with the internal flight.	The Aviation Safety Network of the Flight Safety Foundation database

Table 5: *List of the other Airlines that are listed in the same stock market as the Crashing Airlines*

Other Airlines in the same stock market as the Crashing Airlines	Day
Aer Lingus	3/21/08
Aer Lingus	11/10/08
Aer Lingus	6/28/14
Aer Lingus	7/29/14
Aer Lingus	4/1/15
Air China	6/7/2013
American Airlines	3/5/15
American Airlines	6/17/15
American Airlines	12/15/15
British Airways	12/22/03
China Airlines	11/20/01
China Eastern Airlines	11/7/05
China Southern Airline	11/7/05
China Southern Airline	6/7/2013
Delta Air Lines	1/15/09
Delta Air Lines	7/13/09
Delta Air Lines	4/1/11
Delta Air Lines	10/4/12
Delta Air Lines	7/22/13
Delta Air Lines	1/3/14
Delta Air Lines	12/12/14
Delta Air Lines	8/15/15
Delta Air Lines	12/15/15
Deutsche Lufthunsa	9/19/15
EVA Air	5/25/02
EVA Air	8/20/07
ExpressJet	12/8/05
ExpressJet	2/17/08
ExpressJet	1/15/09
ExpressJet	7/13/09
Far Eastern Air Transport	8/22/99
Far Eastern Air Transport	11/20/01
Far Eastern Air Transport	5/25/02
Far Eastern Air Transport	8/20/07
Flybe	2/14/12
Frontier Airlines	12/20/95
Frontier Airlines	1/7/96
Frontier Airlines	5/11/96
Frontier Airlines	9/9/99
Frontier Airlines	10/15/99

Frontier Airlines	3/5/00
Frontier Airlines	6/12/00
Frontier Airlines	8/9/01
Frontier Airlines	8/25/01
Frontier Airlines	8/28/02
Frontier Airlines	5/24/03
Frontier Airlines	12/8/05
Frontier Airlines	2/17/08
Frontier Airlines	1/15/09
Frontier Airlines	7/13/09
Gama Aviation	2/14/12
Hawaiian Airlines	9/9/99
Hawaiian Airlines	10/15/99
Hawaiian Airlines	3/5/00
Hawaiian Airlines	6/12/00
Hawaiian Airlines	8/9/01
Hawaiian Airlines	8/25/01
Hawaiian Airlines	8/28/02
Hawaiian Airlines	5/24/03
Hawaiian Airlines	12/8/05
Hawaiian Airlines	2/17/08
Hawaiian Airlines	1/15/09
Hawaiian Airlines	7/13/09
Hawaiian Airlines	4/1/11
Hawaiian Airlines	10/4/12
Hawaiian Airlines	6/13/13
Hawaiian Airlines	7/22/13
Hawaiian Airlines	12/5/13
Hawaiian Airlines	1/3/14
Hawaiian Airlines	1/31/14
Hawaiian Airlines	10/22/14
Hawaiian Airlines	12/12/14
Hawaiian Airlines	3/5/15
Hawaiian Airlines	6/17/15
Hawaiian Airlines	8/15/15
Hawaiian Airlines	12/15/15
HOP!	2/12/99
HOP!	3/4/99
HOP!	7/25/00
Jet Airways	11/10/09
Jet Airways	3/8/15
Jet Airways	12/4/15

JetBlue Airways	12/8/05
JetBlue Airways	2/17/08
JetBlue Airways	1/15/09
JetBlue Airways	7/13/09
JetBlue Airways	4/1/11
JetBlue Airways	10/4/12
JetBlue Airways	6/13/13
JetBlue Airways	7/22/13
JetBlue Airways	12/5/13
JetBlue Airways	1/3/14
JetBlue Airways	1/31/14
JetBlue Airways	10/22/14
JetBlue Airways	12/12/14
JetBlue Airways	3/5/15
JetBlue Airways	6/17/15
JetBlue Airways	8/15/15
JetBlue Airways	12/15/15
Malaysia Airlines	1/10/11
Mesa Airlines	12/30/89
Mesa Airlines	2/10/91
Mesa Airlines	6/9/93
Mesa Airlines	11/22/94
Mesa Airlines	12/20/95
Mesa Airlines	1/7/96
Mesa Airlines	5/11/96
Mesa Airlines	9/9/99
Mesa Airlines	10/15/99
Mesa Airlines	3/5/00
Mesa Airlines	6/12/00
Mesa Airlines	8/9/01
Mesa Airlines	8/25/01
Mesa Airlines	8/28/02
Mesa Airlines	5/24/03
Mesa Airlines	12/8/05
Mesa Airlines	2/17/08
Mesa Airlines	1/15/09
Mesa Airlines	7/13/09
Southwest Airlines	12/30/89
Southwest Airlines	12/20/95
Southwest Airlines	1/7/96
Southwest Airlines	5/11/96
Southwest Airlines	9/9/99

Southwest Airlines	10/15/99
Southwest Airlines	6/12/00
Southwest Airlines	8/9/01
Southwest Airlines	8/25/01
Southwest Airlines	8/28/02
Southwest Airlines	2/17/08
Southwest Airlines	1/15/09
Southwest Airlines	6/13/13
Southwest Airlines	1/31/14
Southwest Airlines	10/22/14
Southwest Airlines	3/5/15
Southwest Airlines	6/17/15
Southwest Airlines	8/15/15
SpiceJet	11/10/09
Spirit Airlines	10/4/12
Spirit Airlines	6/13/13
Spirit Airlines	7/22/13
Spirit Airlines	12/5/13
Spirit Airlines	1/3/14
Spirit Airlines	1/31/14
Spirit Airlines	10/22/14
Spirit Airlines	12/12/14
Spirit Airlines	3/5/15
Spirit Airlines	6/17/15
Spirit Airlines	8/15/15
Spirit Airlines	12/15/15
United Continental	2/17/08
United Continental	1/15/09
United Continental	7/13/09
United Continental	4/1/11
United Continental	10/4/12
United Continental	6/13/13
United Continental	7/22/13
United Continental	12/5/13
United Continental	1/3/14
United Continental	1/31/14
United Continental	10/22/14
United Continental	12/12/14
United Continental	3/5/15
United Continental	6/17/15
United Continental	8/15/15
United Continental	12/15/15

Virgin America	12/15/15

VITA

Ms. Nachanok Punyavirocha was born in August 20, 1990 in Chonburi, Thailand. She was graduated from Beijing BISS International School in 2009. Then she finished a Bachelor degree in 2012 from Faculty of Economics, International Program, Thammasat University. In her senior year, she was a Vice President of the Student Union of Thammasat University and a Teacher Assistant in a class called Man and Arts: Visual Art, Music and Performing Arts. She enjoyed being a political figure and wanted to pursue her career as a Prime Minister. Thus, she decided to pursue a Master Degree from Master of Science in Finance in 2014, in order to gain a strong knowledge base for developing the Thai society in the near future.