Share returns and market efficiency :

Research on the Tokyo Stock Exchange

（株式収益率と市場の効率性：東京証券取引所に関する研究）

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Abstract

This thesis is based on research of share returns and the behavior of shares which are listed on the Tokyo Stock Exchange. It analyses share returns during different economic situations, to be specific, during share market crashes, in the post-crash period and in normal periods. By undertaking applied research on share prices and share returns, it provides an important insight into the issue of investor's behavior and is linked to the issue of share market efficiency. By examining returns on crash days and in the immediate post-crash period, we gain insight into the issue of investor's behavior and can see if the trading rules have an obvious effect on behavior. Some sections of the research examine if well-known theories occur in Japan, despite the existence of differing trading rules. To be specific, the flight-to-liquidity hypothesis is analyzed using data during a share market crash, and the lead-lag effect is studied in the immediate post-crash period. Studying share returns following the release of new information provides knowledge surrounding the rational of investors' behavior and touches on the issue of market efficiency.

Chapter one provides detailed background knowledge on the issues discussed in this thesis. A general explanation of Japanese share markets is presented together with information on the share market which was chosen to be the basis of this research, that is, the Tokyo Stock Exchange (TSE). One section conducts an empirical review of the most common asset pricing models for the Japanese share market and analyzes their robustness. This review is based on a paper titled *"An Empirical Review of Asset Pricing Models for the Japanese Share Market"*, which was published in the ***International Journal of Economics and Finance, Volume 8, No. 11.*** Based on the performance of the four common models for Japanese shares, it is concluded that the value factor is highly significant in Japan.

Chapter two analyses the performance of an asset pricing model recently developed by Hou *et al*. (2015), known as the q-factor model. This chapter is based on a paper titled *"Application of the q-factor Model to the Japanese Share Market"*, which has been published in the ***International***

Journal of Economics and Finance, Vol. 9, No. 6, and tests the performance of the q-factor model for shares listed on both the First Section and Second Section of the Tokyo Stock Exchange. The results in this paper suggest that the q-factor model does not adequately explain returns for shares listed on the Tokyo Stock Exchange. For comparison purposes the same ten year data sample is applied to the Fama French three-factor model, which leads to the conclusion that this model is more appropriate than the q-factor model for the Japanese share market. Despite evidence that there is a strong value effect in Japan, the factor which correlates to the value factor in the q-factor model is not significant, providing stronger support against the q-factor model as an adequate asset pricing model for Japan.

Chapter three explores the existence of the flight-to-liquidity phenomenon for shares which are traded on the Tokyo Stock Exchange during share market crashes. The flight-to-liquidity phenomenon is described as when investors sell less liquid investments and purchase more liquid assets during times of market uncertainty. This chapter is based on a paper titled *"Flight to Liquidity on the Tokyo Stock Exchange during the 2008 Share Market Crashes"*, which has been published in the ***International Journal of Economics and Financial Issues, Vol 5, No 3***. Using data from the First Section of the Tokyo Stock Exchange, the existence of a flight-to-liquidity during the 2008 share market crashes is clearly documented. The Tokyo Stock Exchange differs from other major exchanges as price limit rules restrict the daily price movements of shares. It provides a unique setting to test if a flight-to-liquidity occurs even when price limit rules may reduce market liquidity and delay price discovery. This research shows that despite having different trading rules, a flight-to-liquidity occurred during times of market uncertainty as investors were less willing to hold illiquid assets and rushed to sell these assets. The results are robust for smaller crash days and for different proxies of illiquidity.

Chapter four analyzes share return behavior following large one-day share market declines, otherwise known as market crashes. This chapter is based on a paper titled *"Japanese share returns* *in the immediate post-crash period"*, which has been published in the ***Osaka Economic Papers, Vol 64, No 4.*** This paper provides new evidence using recent data from 2008 to analyze share return behavior, and confirms that the results of Wang *et al*. (2009) are identical on the Japanese market, despite the trading rules being significantly different to the American market. Although the event days are limited, the overall results are consistent with previous research, and prove that there is a lead-lag relation with the returns of larger shares leading those of smaller shares. By analyzing dates with both subsequent positive reversals and continued negative declines, the conclusion is drawn that large firms respond faster to new information whether it be good news or bad news. Considering that the Japanese market and American market vary considerably with regards to trading rules, the fact that a lead-lag relation exists on both markets suggests that it is due to fundamental behavior of traders as opposed to institutional features.

The research in this thesis links to the issue of share market efficiency in several ways. Eugene Fama (1991) states that, "the cleanest evidence on market-efficiency comes from event studies, especially event studies on daily returns" (p.1607). Chapter three and four present evidence of share behavior around crash days, with the results showing that price adjustment is quick and there is predictability of share returns. A lead-lag effect is clearly documented in the post-crash period as large firms respond faster to new information, which suggests that prices are not independent. The research in this thesis provides evidence of inefficiencies on the Tokyo Stock Exchange, however without further information such as trading costs, we cannot state whether the market is efficient or not. The answer to the question, " Is the Japanese share market (semi-strong form) efficient? ", depends on whether a profit can be made from trading.

Chapter 1: Introduction

1.1 The issue of market efficiency and background of the thesis

The concept of market efficiency is probably one of the most debated issues in modern investment theory. It is an issue which is extremely important and interesting, leading many researchers to analyze the efficiency of share markets around the globe. The origins of the Efficient Market Hypothesis (EMH) can be traced back to the contributions of Bachelier (1900) and Samuelson (1965) (Campbell, Lo, MacKinlay, 1997). Samuelson (1965) summarized the issues raised by early researchers such as Bachelier, in his paper titled "Proof that Properly Anticipated Prices Fluctuate Randomly". The idea was that in an informationally efficient market, price changes must be unforecastable if they fully incorporate the expectations and information of all market participants (Campbell *et al*. 1997).

The notion of share market efficiency was described by Eugene Fama (1970) in his famous paper titled "Efficient Capital Markets: A Review of Theory and Empirical Work". He defined an efficient market to be, "a market in which prices always "fully reflect" available information is called 'efficient' (p.383)." Fama restated this theory in more detail in another famous paper "Efficient markets II" (1991), where he explains the idea as follows.

> "I take the market efficiency hypothesis to be the simple statement that security prices fully reflect all available information…. A weaker and economically more sensitive version of the efficiency hypothesis says that prices reflect information to the point where the marginal benefits of acting on information (the profits to be made) do not exceed the marginal costs" (p.1575).

Controversy exists over the exact definition of market efficiency, as the terms "fully reflect" and "available information" can be subjective.

According to the Present Value Model, the value of an asset is given by the stream of future expected cash flows discounted at the relevant cost of capital, in other words the expected required rate of return. Defining the expected cash flow in period t as E (C_t), and the expected required rate of return as E (r_t), the Present Value Model can be written as:

$$PV = \sum_{t=1}^{\infty} \frac{E(Ct)}{\prod_{i=1}^{t}[1+E(r\,i)]} \qquad (1)$$

In an efficient market, the price of an asset is equal to the value of the asset. When future expectations change, valuations and the price will also change. If investors are rational, then expectations and prices will change only when new information becomes available. This idea is the basis for the theory which the concept of market efficiency is formed on.

Fama described three different types of market efficiency, with varying definitions of "available information": weak form efficiency, semi-strong form efficiency and strong form efficiency. Weak form efficiency defines the information set as simply being past prices. For semi-strong form efficiency, the information set includes all publicly available information, and for strong form efficiency it includes all private information known by any market participant.

The research in this thesis is linked to the semi-strong form, which is concerned with whether current security prices 'fully reflect' all obviously publicly available information, and the speed of price adjustment to new publicly available information. As Fama (1991) stated, event studies can give a clear picture of the speed of adjustment of prices to information. He stated that, "the cleanest evidence on market-efficiency comes from event studies, especially event studies on daily returns" (1991, p.1607). The reason for this is that daily data allows precise measurement of the speed of the share-price response, which is the basis for tests on semi-strong market efficiency. Furthermore, the choice of daily data can help eliminate the joint-hypothesis problem, of testing market efficiency jointly with an asset-pricing model. The research in Chapters three and four are based on event studies of share market crashes and the post-crash period, respectively. A share market crash is defined as an abrupt decline in the value of securities (Garber, 1992). They are days when the share market has a sudden, sharp decline, and the prices of shares which are traded on the stock exchange decrease significantly in value. Both share market crashes and post-crash periods are ideal events to study to understand investor behavior following the release of new publicly available information, and to gain knowledge on the issue of market efficiency. In general, on a crash day the prices of shares decrease (negative returns) and in the immediate post-crash period, shares prices increase (positive returns). By analyzing share returns at these times, it can give insight into the rational of investors' behavior following the release of new information.

If new information is released in a random and independent manner, in an efficient market, share price changes should also be random and independent. If the share market is efficient, then it should not be possible to trade and make profits based on the information contained in the asset`s price history. In other words, share prices follow a random walk and are independent over time. If this does not hold and returns are not independent, it suggests that past prices can be used to predict future price changes. Many researchers have examined time series data to see if price changes are independent and if the random walk model holds. There are numerous studies which test for autocorrelation in price changes. Some research has produced evidence of a lead-lag relation based on share size (Lo and MacKinlay, 1990), some research has presented evidence of return reversals of prior winner and loser portfolios (De Bondt and Thaler, 1985), and some research has shown that returns have monthly patterns (Wachtel, 1942). If it is possible to make excess returns by using this knowledge gained from past returns, then it can be argued that the market is not efficient. Predictability of share returns from past returns is a topic which has received high interest since the publication of Eugene Fama`s famous paper in 1970, and is at the center of the controversy about market efficiency. The research presented in chapter four in particular, analyzes share returns in the post-crash period and the issue of return predictability.

Some researchers believe that crashes are detractors of the Efficient Markets Hypothesis, as share prices can seriously deviate from their fair values. It is common for a large daily price change to be followed by another large daily price change, however the sign of the successive changes are random. According to Fama (1970), the random walk models assumption that prices are independent is violated, indicating that the random walk model may not hold, however the market efficiency hypothesis still holds. His explanation for this is that when new information is released, sometimes the market cannot accurately evaluate it immediately, causing an initial over adjustment or under adjustment. While evidence shows that the sign of the price changes in the following days is random, the initial large change is an unbiased adjustment to the new information, and this is sufficient for the Efficient Market Hypothesis model.

The objectives of this thesis are two-fold, by examining the returns of shares listed on the Tokyo Stock Exchange it is hoped to gain knowledge regarding the issue of share market efficiency, plus to see if institutional features affect the behavior of investors. The Tokyo Stock Exchange has trading rules which differ from those in other share markets, with one prime example being the existence of price limits, which restrict daily price movements. Recently the New York Stock Exchange has introduced price bands, with the concept being similar to Japan`s price limit rules, however when the research in this thesis was conducted, they did not exist. The Tokyo Stock Exchange was chosen to be the basis of the research in this thesis for two main reasons. Firstly, the Tokyo Stock Exchange has a large market capitalization, making it an important and influential market in the world, yet financial literature is still limited to a certain degree. Secondly, the differing trading rules make it an ideal choice to see if investor behavior is affected by institutional features (i.e. price limits) or simply due to trader’s fundamental behavior.

The primary purpose of the research presented in this thesis is to examine returns of shares listed on the First Section of the Tokyo Stock Exchange. The application of asset pricing models to Japanese share returns is reviewed to determine which model describes share returns most accurately, and which characteristics have high explanatory power for returns. One asset pricing model which has been recently described in financial literature, known as the q-factor model, is applied to the Japanese share market to determine its robustness. Next, share returns on crash days and in the immediate post-crash period are analyzed to determine if there is predictability in returns, and to gain insight into the issue of investor's behavior and to see if the trading rules have an obvious effect on behavior. The methodology utilized in this research is a multivariate regression analysis, which depicts the relationship between share returns and the independent variables in the equation. The secondary purpose of this research is to study share returns during market crashes and during the post-crash period to see if predictability of returns exists, and if well-known theories occur in Japan, despite having different trading rules. To be specific, the flight-to-liquidity hypothesis is analyzed using data during a share market crash, and the lead-lag effect is studied in the immediate post-crash period. Studying share returns following the release of new information, can provide knowledge surrounding the rational of investors' behavior and touches on the issue of share market efficiency.

1.2 Background of the Japanese share market and the Tokyo Stock Exchange

Until recently, five regional stock exchanges existed in Japan: Tokyo, Osaka, Nagoya, Fukuoka and Sapporo. However, on the first of January 2013, the Japan Exchange Group, Inc (JPX) was established, which combined the Tokyo Stock Exchange and Osaka Securities Exchange (JPX Group). Currently there are four stock exchanges in Japan: JPX, Osaka, Nagoya and Fukuoka. The JPX is the third largest exchange in the world, with a market capitalization of 4,910 US billion, following the New York Stock Exchange (18,486 US billion) and the NASDAQ (7,449 US billion) (Desjardins, 2016). With a market capitalization of this magnitude, it is undoubtedly a very important and influential market in the global share market.

The JPX is combined of the Tokyo Stock Exchange, which is where listed securities are traded on equity markets, and the Osaka Exchange, which specializes in trading derivative instruments. Shares on the Tokyo Stock Exchange are separated into the First Section for large companies, the Second section for smaller companies, and the Mothers section which has high-growth and emerging shares listed. Basic information about the four exchanges, such as the number of companies listed and the market capitalization size are detailed in Table 1.

Table 1. The market capitalization and number of companies listed on the regional stock exchanges, as at September 2016.

Stock Exchange	Number of companies	Market capitalization (Sept. 2016)
Tokyo		
First Section	1,976	500,912.813 billion yen
Second Section	538	6,316.26 billion yen
Mothers	226	3,297.597 billion yen
Nagoya		
First Section	194	122,810,898 million yen
Second Section	86	1,183,098 million yen
Centrex	13	26.066 million yen
Fukuoka	112	49,207,900 yen
Sapporo	56	181,234,900 yen

Data sources: JPX Website, NSE Website, FSE Website, SSE Website.

Traditionally trading on the Tokyo Stock Exchange was conducted through floor-traders on the trading floor, however since the first of May 1999, all regular trades of shares are conducted through an electronic trading system, called arrowhead. Currently, following placement of orders by investors, the orders are processed and sorted according to factors such as the number of shares, whether it is a buy or sell order, the order price, the order type and the time of order acceptance, and then registered (JPX, 2015). After registration is complete, the registered orders are executed electronically according to the Tokyo Stock Exchange trading rules.

There are basically two types of orders available on the Tokyo Stock Exchange: limit orders and market orders. Limit orders are orders at specific prices, as investors state the lowest / highest price which they are willing to sell / buy at. If no orders match the specific price requirements, then orders will not be executed. In contrast to this, market orders are orders which do not indicate specific prices and are executed at the available price.

There are two trading sessions each day. There is a morning session from 9am to 11am, and an afternoon session from 12:30pm to 15:00pm. The Tokyo Stock Exchange, which is the focus of this thesis, is distinguished from other major foreign share markets by its trading rules. The Tokyo Stock Exchange applies two types of price limits: the maximum price variation and the daily price limit. The purpose of these rules is to prevent extreme price movements by setting a maximum and minimum in the range in which the price can move within a day. Limiting the daily movement of a share prevents high volatility, and investors making large financial losses. The daily price limits are decided based on the previous day`s closing price, otherwise known as the base price. Trading cannot occur outside of these limits, and limit orders cannot even be placed outside of these limits. The range which a share can trade in depends on the base price of the share. Shares with a small price have small price limits, whereas shares with a large price have significantly larger price limits. However, the size of the trading range is in proportion to the base price. The specific price limits and base prices are detailed in Table 1 in the Appendix.

1.3 Theoretical and literature review

1.3.1 Share market crashes and returns

What exactly is a share market crash? A share market crash is defined as an abrupt decline in the value of securities (Garber, 1992). To be specific, a crash is a large sudden drop in asset prices, typically accompanied by large selling pressures in the market, and followed by a slow recovery (Huang and Wang, 2009). The most famous market crashes are the 1929 crash, the 1987 crash, and the 2008 crashes. The biggest crash in history is undoubtedly the crash on October 19th 1987, otherwise known as "Black Monday". On this single day, the Dow Jones Industrial Average dropped 23%, and the Nikkei dropped 15%, making it the largest one day market decline in history. Share market crashes have serious repercussions for investors and incur large costs.

Literature on share market crashes tends to focus on the factors which cause a crash, and the co-movements of markets. The existing literature provides no clear consensus on the causes of a crash, however Kleidon (1995) details three possible explanations for share market crashes. One possible explanation is that share prices conform to rational expectations models and a large change in the external information about fundamentals, on which the models operate, causes a market crash. A common reason given as a change in information is new information about future cash flows (dividends or earnings) or discount rates. Another possible explanation is that share prices tend to conform to the rational expectations model, but changes in the trading environment can lead to temporary deviations from the model. If an event triggers a revision of beliefs about other traders then an abrupt change in prices may occur. A third explanation is based on irrationality of investors at the individual level. Barlevy and Veronesi (2003) suggest that crashes are caused by the behavior of uniformed traders, who panic and cause the price of shares to fall suddenly and drastically. This hypothesis can be linked to Kleidon`s (1995) explanation of irrational behavior. Regardless of the exact cause of a share market crash, a lack of liquidity has been blamed for intensifying the consequences (Huang and Wang, 2009).

A large proportion of financial literature which focuses on crashes, analyses the co-movement of share markets around the globe. The October 1987 crash is undoubtedly the largest share market crash to date. Almost all share markets dropped in value at the same time, despite different economic circumstances. Roll (1988) argues that the 1987 crash started in Asia, then spread to Europe, the US and Japan. Other researchers such as Yang *et al*. (2008) and Shiller *et al*. (1991) argue that the crash originated in America. The results of a questionnaire survey which asked Japanese institutional investors to recall what they thought and did during the worldwide stock market crash in October 1987, suggests that events in the United States were the proximate cause of the crash in Japan (Shiller *et al*. 1991). The results of this questionnaire suggest that the drop in American share prices was the primary factor on Japanese investors' minds, and other news stories in the United States dominated Japanese news stories (Shiller *et al*. 1991). There is no consensus as to the origin of the crash, however in the aftermath of "Black Monday", people started to realize the interconnectedness of share markets around the globe, leading many researchers to document the co-movement of markets around the globe.

Otherwise known as financial contagion, it is where different markets with different economic situations respond to share price changes in other markets. Research has been conducted on both data during normal market periods, and during crash periods. Yang and Bessler (2008) present empirical evidence for share market contagion during abnormal market times, that is, the 1987 share market crash. The idea of financial contagion is based on the theory that different countries are vulnerable to a possible share market crash originating from events in one country, and is possibly transmittable to other countries via financial market interactions (Shiller, Kon-Ya, Tsutsui, 1991). Research by Yang and Bessler (2008) is one example of a study which analyzes price fluctuation transmission, to illustrate the financial contagion pattern during a crash. To date, many researchers have studied the correlation between different share markets around the globe. The results show international evidence of cross-autocorrelation between Asian markets and the US market in long-term data (Chang, McQueen, Pinegar, 1999).

Share returns during share market crashes is an issue which has received interest in recent years. The volatility of share markets around the globe has been increasing in recent years, which has increased the need to further our understanding of crashes. Researchers such as Wang *et al*. (2009) have analyzed how a share market crash affects individual shares of US firms and if shares with different financial characteristics are affected differently during a crash. The results of their research show that shares with any of the following characteristics decrease more in value during a crash: high beta shares; large shares; high liquidity shares; and shares with high pre-crash volatility. Their research also suggests that shares with high debt ratios, shares with high levels of liquid assets, shares with low cash flow, and shares with low profitability tend to decrease in value on crash days.

It has been suggested that illiquidity plays a significant role during a share market crash. Amihud, Mendelson and Wood (1990) argue that the 1987 crash can be explained in light of the relationship between liquidity and share prices. They present the theory that a sharp decline in liquidity contributes significantly to the decline in share prices (Mendelson and Wood, 1990). They argue that recognition that the market is less liquid than had been previously thought, contributed to the decline of share prices. Similarly, Amihud (1990) showed that investors reallocated assets towards high-liquidity shares due to fear of another crash. Following the 2008 worldwide crashes, the role of liquidity during a crash again became a topic of interest, with a lack of liquidity being blamed for intensifying the consequences (Huang and Wang, 2009). Recent research by Wang *et al.* (2009) and Chang *et al.* (2010), has documented a positive relation between illiquidity and share returns during market downturns. During crashes, investors rush to sell illiquid assets and purchase more liquid assets, a phenomenon known as a flight-to-liquidity. This issue is discussed in section 1.3.3.

1.3.2 Empirical review of asset pricing models to the Japanese market

Researchers are continually striving to describe a model which explains share returns and market anomalies more accurately than current models. As new models are developed, researchers examine the performance and robustness of the model on different share markets around the world, to determine its effectiveness. Numerous researchers have tested the performance of asset pricing models on the Japanese share market, producing mixed results. Literature which examines the performance of common asset pricing models to the Japanese share market is reviewed.

<u>CAPM</u>

The Capital Asset Pricing Model (CAPM) was created in the 1960`s, and has received considerable attention over the decades. The Sharpe-Lintner version of the CAPM states that an asset`s excess return is explained by its average realized market risk premium. The model is expressed as follows.

$$R_{it} - R_{ft} = \alpha_i + \beta_i (R_{mt} - R_{ft}) + e_{it} \tag{1}$$

Where $R_{it} - R_{ft}$ is the realized excess return of asset *i* at time *t*, $(R_{mt} - R_{ft})$ is the excess market return, and β_i is beta, the coefficient to sensitivity of the expected excess asset returns to the expected excess market returns.

The general consensus in financial literature is that this model is not appropriate for the Japanese market. Yonezawa and Hin (1992) study long term data from January 1952 to December 1986 by forming sub-periods, and find that the CAPM is invalid for the Japanese market. Research based on recent data also gives the same result. Walid and Ahlem (2009b) analyze daily returns of shares listed on both the first and second section of the Tokyo Stock Exchange from the 1st of October 2002 to the 30th of September 2007, and find that the CAPM is not an appropriate model for the Japanese market. Bretschger and Lechthaler (2012) test the CAPM model for a significantly longer timeframe. They analyze monthly data for the period of 1984-2009, and draw the same conclusion as Walid and Ahlem, that is, that CAPM is not appropriate for the Japanese share market.

The Fama French Three-Factor Model

Research in the decades following the creation of CAPM suggested that variables other than beta have power to explain the cross-section of average returns. Fama and French (1992) found that combining the two variables; size and the ratio of book equity to market equity, captures most of the cross-section of average share returns in America. Following on from this, Fama and French (1993) identified three common risk factors in the returns on shares: an overall market factor, a factor relating to firm size, and a factor relating to book-to-market equity. This finding led to the development of the Fama French three-factor model, which is expressed as follows.

$$R_{it} - R_{ft} = \alpha_i + \beta_i (R_{mt} - R_{ft}) + s_i R_{SMB,t} + h_i R_{HML,t} + e_{it} \quad (2)$$

Where $R_{it} - R_{ft}$ is the realized excess return of asset *i* at time *t*, $R_{mt} - R_{ft}$ is the excess market return, $R_{SMB,t}$ is the realized return on the size-factor portfolio, and $R_{HML,t}$ is the return on the book-to-market factor portfolio.

Previous literature relating to this model has mixed results. Research by Kubota and Takehara (1997) showed that the Fama French three-factor model is appropriate for the Japanese market. Likewise, Bretschger and Lechthaler (2012) examine the model using data from July 1984 to July 2009, and find that the model captures common variation in share returns. In contrast to this, research by Daniel, Titman and Wei (2001) employs data from the Tokyo Stock Exchange for the period 1971 to 1997 to test the performance of the Fama French three-factor model. This analysis on Japanese share returns indicates that the value premium is strong, in fact it is substantially stronger in Japan than in America. Furthermore, the results reject the three-factor model for the Japanese market. Walid (2009a) replicates this analysis on the Japanese share market, by comparing the performance of the characteristics model and the Fama French three-factor model. He analyzes data from 2002 to 2007, and documents that size and book-to-market ratio are significantly related to average returns, and the characteristic model is more suitable for the Japanese market. A similar paper by Walid and Ahlem (2009b) presents new evidence on the applicability of the Fama French three-factor model to the recent timeframe of 2002 to 2007. This research reinforces the previous finding that both firm size and book-to-market ratio are significantly related to average returns, and have higher premiums than the market premium. It is clear that research results in financial literature have mixed results, which perhaps can be attributed to the timeframe chosen.

Carhart Four-Factor Model

Researchers such as Jegadeesh and Titman (1993) have documented that there is a momentum effect in share returns. The Fama French three-factor model`s inability to explain cross-sectional variation in momentum-sorted portfolio returns, motivated Carhart (1997) to create a four-factor model. Known as the four-factor Carhart-model, it is basically the Fama French three-factor model with a momentum factor (UMD) added on.

$$R_{it} - R_{ft} = \alpha_i + \beta_i (R_{mt} - R_{ft}) + s_i R_{SMB,t} + h_i R_{HML,t} + m_i R_{UMDt} + e_{it} \qquad (3)$$

Where $R_{it} - R_{ft}$ is the realized excess return of asset *i* at time *t*, $R_{mt} - R_{ft}$ is the excess market return, $R_{SMB,t}$ is the realized return on the size-factor portfolio, $R_{HML,t}$ is the return on the book-to-market factor portfolio and R_{UMDt} is the return on the momentum factor portfolio.

Many researchers have proven that momentum does not exist in the Japanese share market. Asness (2011) analyzed data from 1981 to 2010, and obtained a Sharpe ratio of 0.03, almost zero, which suggests that momentum does not exist in Japan. Bretschger and Lechthaler (2012) study monthly data for the time period 1984 to 2009, and find that the Carhart model performs reasonably well, and performs even better when the period is split into two periods around 1998. Fama and French (2012) test whether asset pricing models capture value and momentum patterns, by utilizing data for 23 countries for the timeframe of 1989 to 2011, with one of the countries being Japan. The results show no momentum in any of the size groups, however value premiums are evident in all size groups, with similar results for both small and large shares. It is results like this that have led many researchers to draw the conclusion that momentum does not exist in Japan.

The Fama French Five-Factor Model

Fama and French (2015a) created a five-factor model as other researchers stated that the three-factor model is an incomplete model. In particular, Novy-Marx (2013) and Titman, Wei and Xie (2004) say that it is an incomplete model because its three factors do not capture much of the variation in average returns related to profitability and investment. Based on this, Fama and French added the two factors of profitability and investment to the original Fama French three-factor model. This new model is expressed as follows.

$$R_{it} - R_{ft} = \alpha_i + \beta_i (R_{mt} - R_{ft}) + s_i R_{SMB,t} + h_i R_{HML,t} + r_i R_{RMW,t} + c_i R_{CMAt} + e_{it} \tag{4}$$

Where $R_{it} - R_{ft}$ is the realized excess return of asset *i* at time *t*, $R_{mt} - R_{ft}$ is the excess market return, $R_{SMB,t}$ is the realized return on the size-factor portfolio, $R_{HML,t}$ is the return on the book-to-market factor portfolio, $R_{RMW,t}$ is the return on the profitability factor and R_{CMAt} is the return on the investment factor. Both the profitability factor and investment factor are calculated using data from the annual financial statements.

Since the publication of this model in financial literature, it has receiving considerable attention from researchers, with many rushing to test the robustness of the model on various share markets around the world. Kubota and Takehara (2015) apply this model to shares on the Tokyo Stock Exchange to test if it works well on the Japanese market. They employ data with a long timeframe of 1977 to 2014 in their analysis. Contrary to results for the US market, the authors find that the return dispersions created by the two new factors of investment and profitability are small. Further tests show that these two factors are not statistically significant. Therefore, they concluded that this model is not a good benchmark pricing model for the Japanese share market. Fama and French (2015b) themselves test the effectiveness of their new five-factor model on four regions of the world, with one being Japan. They employ data with a long timeframe, from 1990 to 2015. With regards to Japan, the results show a strong positive relation between average returns and the book-to-market factor, but only very weak relations to profitability and investment. This research confirmed the existence of a strong value effect in Japan, but rejected the new model, and demonstrates that both the profitability factor and investment factor are not significant factors to explain share returns in Japan.

Summary of the empirical review of asset pricing models and significant variables

Financial literature which tests the robustness of these four models has mixed results, with some research supporting the model, and other research concluding that the specified model is not an accurate pricing model for the Japanese share market. Based on our empirical review of literature relating to the Japanese market, it appears that the Fama French three-factor model may be the most accurate model of the four models, in its ability to explain share returns. It is possible that the timeframe selected for the data analysis affects the results of the research, and whether the research supports the model as being appropriate for the Japanese share market or not.

While research regarding the robustness of asset pricing models is mixed, there is more consistency in the results which explain the important variables in Japan. Regardless of the timeframe chosen, numerous researchers have found evidence of a strong value effect in Japan. A value effect means that shares with high book-to-market ratios tend to have higher average returns than shares with lower book-to-market ratios. Research indicates that the value effect is substantially stronger in Japan than in other countries such as America. Chan, Hamao and Lakonishok (1992) analyze the relationship between share returns and the four variables: earnings yield, size, book to market ratio and cash flow yield. They find that the book to market ratio and cash flow yield have the most significant positive impact on share returns. Research by Walid (2009a) and Walid and Ahlem (2009b), utilizes a more recent data set, and concludes that book-to-market ratio and size are significantly related to average returns. Daniel, Titman and Wei (2001) analyze data with a long timeframe, and conclude that the value premium is strong in Japan. Likewise, Fama and French (2012) find evidence of value premiums in all size groups, both small shares and large shares. Further research replicates this finding, even though a different model is utilized in the analysis. In recent research on the new five-factor model, Fama and French (2015b) document a strong positive relation between average returns and the book-to-market factor.

There is no clear answer as to which model is most appropriate for the Japanese share market, and which characteristics are important, however research on share returns suggests that the value premium is strong, in fact it is substantially stronger in Japan than in other countries. This finding is consistent, regardless of the asset pricing model being analyzed, and provides strong evidence of the existence of a value effect. The reason for the value effect being significantly stronger in Japan than other countries is unclear, however it can be assumed that for an asset pricing model to be successful on the Japanese market, it needs to include the book-to-market factor as one of the variables.

1.3.3 Flight-to-liquidity

The flight-to-liquidity phenomenon is described as when investors sell less liquid investments and purchase more liquid assets during times of market uncertainty. Amihud (1990) was one of the first researchers to demonstrate that a decline in liquidity contributed significantly to the sharp decline in share prices in the 1987 crash. He showed that investors reallocated assets towards high-liquidity shares due to fear of another crash. In more recent research, Vayanos (2004) suggested that during volatile time's investors' effective risk aversion increases, and the risk premium demanded increases. Similarly, Watanabe (2008) also demonstrated that liquidity risk premium rises during times of high preference uncertainty.

Research by Chang, Faff and Hwang (2010) on the Japanese share market, and Wang *et al.* (2009) on the American share market, studies the relationship between liquidity and share returns. Both researchers found a positive relation between illiquidity and returns during market downturns. Chang *et al.* (2010) proved that the liquidity variable is statistically important in Japan even when the market is in the contracting phase. During times of market uncertainty investors are less willing to hold illiquid assets. This investor behavior is otherwise known as a flight-to-liquidity.

A share market crash is often caused by a large change in the external information about fundamentals, such as the release of new information about future cash flows (dividends or earnings) or discount rates. If the market is semi-strong efficient, share prices will quickly adjust to the release of new publicly available information and fully reflect all publicly available information. A flight-to-liquidity occurs when investors react to the new information by immediately selling illiquid assets.

1.3.4 Lead-lag effect

Lo and MacKinlay (1990) proved that returns of large-capitalization shares almost always lead those of smaller shares listed on the New York Stock Exchange. This size based lead-lag relation is known as a lead-lag effect. Their research documented a positive correlation in weekly returns of small firms and the lagged weekly returns of large firms, however no correlation exists when it is reversed. That is, there is no correlation between the returns of large shares and lagged small shares returns. Lo and MacKinlay (1990) argue that this size based lead-lag relation is important because it indicates the transmission of information from large firms to small firms. They suggest that this lead-lag effect may be the result of information flowing first to the prices of large market value firms and then to small market value firms.

Numerous researchers have conducted research on other share markets and presented evidence that a lead-lag effect exists. Mills and Jordanov (2000) documented that a lead-lag relation exists between portfolios of small firms and large firms for shares traded on the London stock exchange. Badrinath *et al.* (1995) analyze the process of information transmission between US firms and show that for size-based portfolios a one month lead-lag relation exists, and for institutional ownership-based portfolios, portfolios of high institutional ownership lead the returns on portfolios with lower institutional ownership by up to two months. Kanas and Kouretas (2005) analyze monthly data to extend the correlation-based short-run approach to the lead-lag effect to a cointegration-based long-run approach, and present evidence that large firm portfolio prices are long-run forcing variables for small firm portfolio prices, but not vice versa. Their results support Lo and MacKinlay`s (1990) findings.

While studies focusing on different share markets around the world have proved that a lead-lag relation exists, the exact cause of it is still unclear. If market imperfections do not exist, then it would be expected that information transmission is instantaneous. Therefore, researchers have attributed the lead-lag effect to the “thin trading” problem, noise traders, market liquidity, herd behavior, or as Jegadeesh and Titman (1995) suggest, to delayed reactions to common factors. Alternatively, Badrinath *et al.* (1995) suggest that firm size may proxy for the magnitude of information produced.

The majority of studies which examine the lead-lag effect are based on data from normal time periods, although some studies utilize data from crash periods. Wang *et al*. (2009) specifically examines returns on crash days and in the subsequent three-day post-crash period. They find that large firms react faster on crash days by gaining lower returns, and in the subsequent three-day post-crash period, they lead small firms with higher returns. In this study, large firms respond faster to new information and it is clear that a lead-lag effect exists.

On crash days the prices of shares suddenly decrease, in other words, shares have large negative returns. In the immediate post-crash period following a crash, the prices of shares often reverse back with shares having positive returns. Regardless of the direction of the price movement, if large firms respond faster to new information, there is a lead-lag effect. When large firms respond first with small firms following, it suggests that there is predictability of returns and that returns are not independent. If it is possible use this information to predict future price changes and make a profit, it suggests that the market may not be efficient.

1.4 Conclusion

Fama describes market efficiency as being when security prices fully reflect all available information to the point where the marginal benefits of acting on information do not exceed the marginal costs. He described three different types of market efficiency, however the research in this thesis is linked to the semi-strong form. This form of efficiency is concerned with whether current security prices 'fully reflect' all obviously publicly available information, and the speed of price adjustment to new publicly available information. If the market is efficient, share prices follow a random walk and are independent over time. Event studies can give a clear picture of the speed of adjustment of prices to new information. Share market crashes and the post-crash period are ideal events to study to gain knowledge on the issue of market efficiency. A share market crash, defined as an abrupt decline in the value of securities, is an ideal event to analyze to understand investor behavior following the release of new publicly available information.

The Tokyo Stock Exchange (TSE) was chosen to be the focus of the research in this thesis. The TSE is one of the largest stock exchanges in the world, with a market capitalization of 510,526.67 billion yen at September 2016 (JPX Website, 2016). It has trading rules which differ from those in other share markets, such as daily price limits, which prevent extreme price movements within a day by setting a maximum and minimum in the range in which trading can occur. This creates an ideal setting to see if institutional features affect the behavior of investors.

Numerous asset pricing models exist, and many researchers have tested the performance of these models on the Japanese share market. Previous research suggests that the Fama French three-factor model may be the most accurate model for the Japanese market in its ability to explain share returns. Furthermore, regardless of the timeframe chosen, researchers have continually found evidence of a strong value effect in Japan, meaning that the value factor is highly important in explaining returns of Japanese shares.

There are two well-known theories known as the flight-to-liquidity hypothesis and lead-lag effect, which can be linked to the issue of predictability of returns. During uncertain times such as a share market crash, a flight-to-liquidity can occur, which is when investors sell less liquid investments and purchase more liquid assets. A lead-lag effect is when large firms respond faster to new information, with small firms following. This size based lead-lag relation suggests that there is predictability of returns and that returns are not independent. The research in this thesis studies whether these phenomena exist in Japan, in order to gain knowledge on the efficiency of the Japanese share market.

Chapter 2: Application of the q-factor model to the Japanese Share Market

2.1 Introduction

Researchers are continually attempting to create a model which improves on the performance of past models, and is more accurate in explaining share returns. Recently Fama and French (2015) proposed a five-factor model, which adds the two new factors of investment and profitability onto the original three factor model. Similarly, Hou, Xue and Zhang (2015) proposed a four-factor model which includes a market factor, size factor, investment factor and a profitability factor. Research which applies data to test the performance of such models has shown that both models work well on the American share market.

It is well known that the Japanese share market differs from the American share market and other international share markets, especially with regards to the trading rules. Previous research which applies asset pricing models to the Japanese share market has often produced different results to research which focuses on other major markets. Research on the CAPM model has proved that this model is inappropriate for the Japanese market (Yonezawa and Hin, 1992; Walid and Ahlem, 2009b). While many researchers have drawn the conclusion that momentum does not exist in Japan, Bretschger and Lechthaler (2012) found that the Carhart four-factor model performs reasonably well. Research on the Fama French three-factor model has produced mixed results, however the Fama French three-factor model is often employed as the standard asset pricing model for Japanese shares. Research by Kubota and Takehara (1997) and Bretschger and Lechthaler (2012) showed that the model is appropriate for the Japanese market, whereas Daniel, Titman and Wei (2001) and Walid and Ahlem (2009b) present evidence which rejects the model.

Research which tests the performance of asset pricing models has produced mixed results, however evidence of a strong value effect in Japan has continually been documented. Chan, Hamao and Lakonishok (1992) found that the book to market ratio was one of two variables which has the most significant impact on share returns. More recent research by Walid (2009a) and Walid and Ahlem (2009b), showed that the book to market ratio is significantly related to average returns. Furthermore, Daniel, Titman and Wei (2001), Fama and French (2012), and Fama and French (2015b) have all documented that the value premium is strong in Japan.

Kubota and Takehara (2017) tested the plausibility of the Fama French five-factor model, recently proposed by Fama and French, to determine whether the model is appropriate for the Japanese share market. The research employs data from both the First section and Second section of the Tokyo Stock Exchange for the timeframe of January 1977 to December 2014. They conclude that the five-factor model is not a good benchmark pricing model for Japanese shares, and the two new factors of profitability (RMW) and investment (CML) are very weakly associated with the cross-sectional variation of share returns.

The main aim of this paper is to test the performance of the q-factor model, developed by Hou, Xue and Zhang (2015), on the Japanese share market. To the best of the authors' knowledge, there are no papers which test the performance of the q factor model on any Japanese market. Shares listed on both the First section and Second section of the Tokyo Stock Exchange are analyzed for the ten-year sample period of 2000 to 2010. At present, the Fama French three-factor model is generally considered to be the benchmark pricing model for Japanese shares. This model is also analyzed using the same data sample to compare the results to the q factor model and assist in determining if the q factor model is appropriate for the Japanese share market.

The remainder of the paper is organized as follows. Section 2.2 discusses the q-factor model and section 2.3 describes the data and the methodology used to calculate the factors and portfolios. Section 2.4 discusses the empirical results of the sorted portfolios. Section 2.5 examines the Fama French three-factor model and the test results from replicating the model, while Section 2.6 concludes the paper.

2.2 The q-factor model

Hou *et al*. (2015) proposed a q-factor model with four factors to explain share returns. They state that most of the anomalies that the Fama French three-factor model cannot explain, can be captured by this model. The model states that the expected excess return of an asset is described by the sensitivities of its returns to the market factor, size factor, investment factor and a profitability factor. The model is expressed as follows.

$$E[r^i] - r^f = \beta^i_{MKT}E\,[MKT] + \beta^i_{ME}E\,[r_{ME}] + \beta^i_{I/A}E\,[r_{I/A}] + \beta^i_{ROE}E\,[r_{ROE}] \tag{1}$$

in which E [MKT], E [r_{ME}], E [$r_{I/A}$], E [r_{ROE}] are the expected factor premiums, and β^i_{MKT}, β^i_{ME}, $\beta^i_{I/A}$ and β^i_{ROE} are the factor loadings on MKT, r_{ME}, $r_{I/A}$, and r_{ROE} respectively. The market factor (MKT) is the market excess return. The size factor (r_{ME}) is the difference between the return on a portfolio of small size shares and the return on a portfolio of big size shares. The investment factor ($r_{I/A}$) is the difference between the return on a portfolio of low investment shares and the return on a portfolio of high investment shares. Lastly, the profitability factor (r_{ROE}) is the difference between the return on a portfolio of shares with high return on equity and the return on a portfolio of shares with low return on equity. This model is partly inspired by investment-based asset pricing as the neoclassical q-theory of investment states that ROE forecasts returns to the extent that it forecasts future ROE.

2.3 Factors

2.3.1 Data description

This study examines monthly data for shares listed on both the First section and Second section of the Tokyo Stock Exchange, from October 2000 to September 2010 (10 years). The data comes from two sources. The monthly share prices, risk-free rate and all accounting data are collected from the Nikkei Economic Databank System database (NEEDS). The market returns for the universe of the First section and Second section of the Tokyo Stock Exchange are collected from "Kubota and Takehara`s Fama-French data related to the listed Japanese stocks". The returns for the universe are utilized as the market return, as this study combines shares from both the First section and Second section of the stock exchange.

The sample includes all shares listed on both sections of the Tokyo Stock Exchange, however financial firms and utilities have been excluded. Also, firms with data missing for any of the factors have been excluded from the sample.

The methodology of Hou *et al*. (2015) is followed by forming test portfolios based on size, the investment factor and profitability factor. Two adjustments were made from the original methodology to apply the model to the Japanese share market. Firstly, to ensure that the accounting data is publicly available at the time of portfolio formation, we formed portfolios at the beginning of October. Japanese companies have March as the end of their fiscal year, and release accounting information before September. Forming portfolios on the first of October ensures that all data is available. Other researchers such as Daniel, Titman and Wei (2001), and Walid (2009) have utilized this methodology when analyzing the Japanese share market. The portfolios are formed on the first of October and held for one year. The market size (size factor) is the market equity at the end of September. It is calculated as the share price times the number of shares issued, at the end of September. The second adjustment to the methodology of Hou *et al*. (2015) is the method used to calculate the profitability factor. Hou *et al*. (2015) utilized quarterly data, however most firms in Japan do not release quarterly figures. Due to data limitations, annual data is utilized for the return on equity (ROE) figures.

2.3.2 Factor construction

The size, investment and ROE factors are constructed from a triple sort (2 x 3 x 3) on size, investment-to-assets and ROE. Size is the market equity at the end of September. The investment factor (I/A) is the annual change in total assets divided by one-year-lagged total assets. The profitability factor (ROE) is the income before extraordinary items divided by lagged book equity.

At the end of September each year, shares are split into two groups, big and small, based on the market equity. Independently, at the end of September, shares are sorted into three groups based on the I/A data from the previous year, using the breakpoints of 30%, 40% and 30%. In addition, shares are sorted into three groups based on the ROE data for the previous year, using the breakpoints of 30%, 40% and 30%. Taking the intersections of the two size groups, 3 I/A groups and 3 ROE groups, creates 18 portfolios. The portfolios are constructed at the end of September and held for one year.

These portfolios are used to calculate the factor returns needed for the regressions. The size factor (r_{ME}) is the difference between the simple average of the 9 small portfolio returns and the simple average of the 9 big portfolio returns. The investment factor ($r_{I/A}$) is the difference between the simple average of the 6 low I/A portfolios and the simple average of the 6 high I/A portfolios. Similarly, the profitability factor (r_{ROE}) is the difference between the 6 high ROE portfolios and the 6 low ROE portfolios. The market portfolio contains all the shares.

2.4 Empirical Results

2.4.1 Return patterns of sorted portfolios

As previously explained, the q-factor model sorts shares based on size, investment and ROE, and forms 18 portfolios. The portfolios are created at the end of September and held for one year. The descriptive statistics for the 18 portfolios are detailed in Table 1. The number of shares in each portfolio varies and changes after the annual reconstruction. The two extreme portfolios, that is small size, low I/A, low ROE portfolio, and the big size, high I/A, high ROE portfolio have the largest average number of shares in the portfolio.

Table 1. Descriptive statistics for the 18 sorted portfolios formed on size, I/A and ROE: October 2000 to September 2010 (10 years).

Average of annual number of firms in the portfolio						
		Small			Big	
I /A	Low 1	2	3	Low 1	2	3
ROE						
Low 1	164.6	108.3	43.1	76	71	29.2
2	71.6	124.5	69.5	67.3	151.5	79.5
3	37.5	58.2	85	40.2	136.3	151.7
Average of annual averages of firm size for portfolio						
		Small			Big	
I /A	Low 1	2	3	Low 1	2	3
ROE						
Low 1	10171823740	10843793373	11339145224	2.06566E+11	2.14135E+11	3.34599E+11
2	11904466226	12856572823	12693273692	2.89155E+11	2.44278E+11	2.57158E+11
3	11611850827	12343528252	13501234233	4.61803E+11	4.278E+11	5.61842E+11
Average of annual ROE ratios for portfolio						
		Small			Big	
I /A	Low 1	2	3	Low 1	2	3
ROE						
Low 1	-19.11904	-6.15598	-8.52913	-15.37979	-3.26631	-8.24618
2	4.74111	4.80596	5.11897	4.79516	5.03537	5.31748
3	78.39574	13.85253	15.36731	14.82433	12.14065	14.98422
Average of annual I/A ratios for portfolio						
		Small			Big	
I /A	Low 1	2	3	Low 1	2	3
ROE						
Low 1	-0.10389	0.00500	0.17505	-0.08659	0.00623	0.16592
2	-0.07625	0.01213	0.15168	-0.06240	0.01118	0.13452
3	-0.09544	0.01335	0.20515	-0.07497	0.01642	0.19236

Table 2 presents the mean monthly excess returns for the 18 sorted portfolios for the ten year period. The mean monthly excess returns are all negative, which reflects the movement of the share market during the sample period. The movement of the indices for both the First section and Second section are shown in Figure 1. The return marginally decreases as the size and I/A values increase, with a maximum of a 0.009% lower return. In the q-factor model, the investment factor correlates to the value premium, and the profitability factor correlates to the momentum factor. A marginally decreasing return as I/A increases, suggests that a value effect may possibly exist.

Table 2. Mean Monthly Excess Returns (in percent) on the 18 Sorted Portfolios: October 2000 to September 2010 (120 months).

	Small			Big		
I/A	Low 1	2	3	Low 1	2	3
ROE						
Low 1	-0.116688	-0.117103	-0.115741	-0.11817	-0.11941	-0.121211
2	-0.117164	-0.118558	-0.11818	-0.119218	-0.119614	-0.122339
3	-0.119639	-0.117558	-0.120002	-0.121895	-0.122966	-0.124993

Size is price per share times shares outstanding. Investment-to-assets (I/A) is the annual change in total assets divided by lagged total assets. Return on equity (ROE) is income before extraordinary items divided by book equity. At the end of September of each year *t*, we use the median size at the end of September to split the shares listed on the First section and Second section into 2 groups, big and small. Independently, at the end of September of each year *t*, we also sort shares into 3 I/A groups, using the breakpoints of 30%, 40% and 30% based on the financial data for year *t-1*. In addition, we independently sort shares into 3 ROE groups using the breakpoints of 30%, 40% and 30% based on the financial data for year *t-1*. Taking the intersection of the 2 size groups, 3 I/A groups and 3 ROE groups, we form 18 portfolios. The monthly value-weighted returns for the 18 portfolios are calculated.

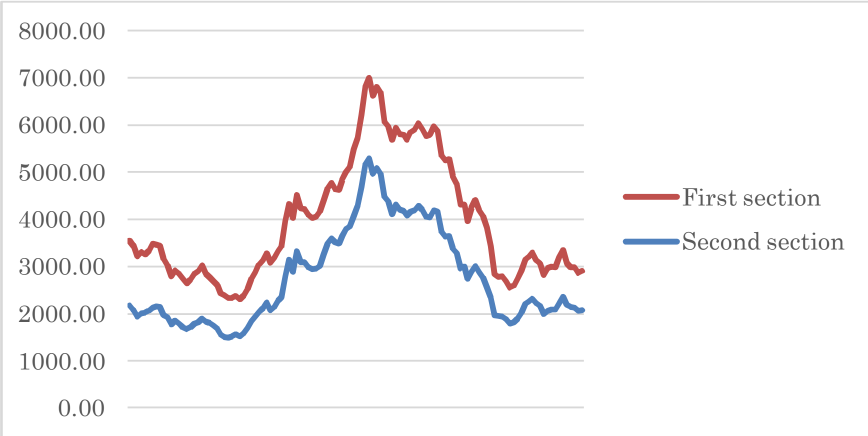

Figure 1: Movement of the Tokyo Stock Exchange Indices, October 2000 – September 2010

2.4.2 q-factor tests

To test the performance of the q-factor model on the Japanese share market, we construct factor returns and factor portfolios as explained in section 2.2. Table 3 reports the intercepts and t statistics for the 18 sorted portfolios. The average magnitude of the intercepts is -0.11526. The t statistics for all the portfolios is greater than 2, which suggests that this model is not appropriate to explain share returns on the Japanese share market. Research on the American share market by Hou *et al*. (2015) showed that the investment factor provided most of the model`s good performance. The results in Table 3 suggest that this is not the case in Japan. Furthermore, the investment factor earns an average return of 0.0838%, whereas the size factor earns 0.2918% and the profitability factor earns -0.312%. Overall the results suggest that neither the investment factor or the profitability factor as defined in the q-factor model are significant.

Table 3. Time Series Regression of the 18 Sorted Portfolios: October 2000 to September 2010 (120 months).

Panel A: Intercept Estimates from the q-factor model						
	Small			Big		
I/A	Low 1	2	3	Low 1	2	3
ROE						
Low 1	-0.11733	-0.11651	-0.11724	-0.11461	-0.11365	-0.11566
2	-0.11532	-0.11559	-0.11344	-0.1135	-0.11308	-0.11471
3	-0.11865	-0.11323	-0.11568	-0.11618	-0.11511	-0.11512
Panel B: t Statistics from the q-factor model						
	Small			Big		
I/A	Low 1	2	3	Low 1	2	3
ROE						
Low 1	-2.18403	-2.20445	-2.1829	-2.09431	-2.09254	-2.03711
2	-2.20229	-2.14049	-2.11981	-2.04447	-2.05792	-2.06388
3	-2.19688	-2.09684	-2.14539	-2.15205	-2.06815	-2.05839

The formation of the 18 sorted portfolios is described in Table 2. The construction of the size factor portfolio, the I/A factor portfolio, and the ROE factor portfolio is as follows. The size factor R_{me} is the difference each month between the simple average of the 9 small portfolio returns and the simple average of the 9 big portfolio returns. The investment factor, $R_{I/A}$, is the difference between the simple average of the 6 low I/A portfolios and the simple average of the 6 high I/A portfolios. Similarly, the profitability factor R_{roe} is the difference between the 6 high ROE portfolios and the 6 low ROE portfolios. A value-weighted portfolio Mkt is formed that contains all firms listed on the First section and Section of the TSE. This table presents the intercept estimates and t statistics from the q-factor model. The estimation method is ordinary least squares.

2.5 The Fama French Three-Factor Model

Previous research has produced mixed results regarding the performance of the Fama French three-factor model, however it is generally considered to be the benchmark asset pricing model for Japanese shares. In this study, the three-factor model is analyzed using the same data sample to compare the results to the q factor model and assist in determining if the q factor model is appropriate for the Japanese share market. The three-factor model is described as follows.

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,Mkt} (R_{Mkt,t} - R_{f,t}) + \beta_{i,SMB} (R_{SMB,t}) + \beta_{i,HML} (R_{HML,t}) + e_{i,t} \quad (2)$$

where $R_{i,t}$ is the return on asset I for month t, $R_{f,t}$ is the riskfree rate, $R_{Mkt,t} - R_{f,t}$ is the excess market return, $R_{SMB,t}$ is the realized return on the size-factor portfolio and $R_{HML,t}$ is the realized return on the book-to-market portfolio. We have followed the methodology of the q-factor model as much as possible, to ensure accurate comparisons between the models. At the end of September all shares are ranked on their book-to-market and size, independently, and the 20%, 40%, 60% and 80% breakpoints are used to sort the shares into five equal groups. Sorting shares into five size groups and five book-to-market groups, creates 25 portfolios. The portfolios are created at the end of September and held for one year.

Table 4 presents the mean monthly excess returns for the 25 size and book-to-market sorted portfolios. The bottom row and right-most column report the differences between the average returns of the smallest and largest shares, and the differences between the highest and lowest book-to-market shares. As size increases the average return decreases slightly, and as book-to-market increases the average return increases slightly. The average size effect across the five groups is -0.02428%, and the average book-to-market effect is -1.0636%. These results demonstrate the existence of a significantly strong book-to-market effect in the Japanese share market.

To replicate the Fama French tests we created factor portfolios. To form the portfolios, shares are ranked according to size and book-to-market values, and portfolios are constructed using the 30% and 70% breakpoints for book-to-market and 50% for size. Shares below the 30% breakpoint for book-to-market values are designated L, the middle 40% of firms are designated M, and the shares above the 70% breakpoint are designated H. Firms above the 50% size breakpoint are designated B and the remaining 50% are designated S. These rankings allow us to form six value-weighted portfolios: L/S, M/S, H/S, L/B, M/B and H/B. From these six portfolio returns, we calculate the HML factor portfolio returns, which are defined as $R_{HML} = (R_{HB} + R_{HS} - R_{LB} – R_{LS}) / 2$, and the SMB factor portfolio returns, which are defined as $R_{SMB} = (R_{HS} + R_{MS} + R_{LS} – R_{HB} – R_{MB} – R_{LB}) / 3$. A value-weighted portfolio Mkt is formed which contains all the firms in these six portfolios plus the excluded firms, in other words it contains all the shares listed on the First and Section sections of the Tokyo Stock Exchange. The regression results for the 25 portfolios are presented in Table 5, with the intercepts and t statistics from the Fama French three-factor model.

Table 4. Mean Monthly Excess Returns (in percent) on the 25 Size and Book-to-Market Sorted Portfolios: October 2000 to September 2010 (120 months).

	Book-to-Market					
	Low				High	H - L
Size						
Small	-1.021499	-1.056761	-1.055158	-1.041052	-1.026672	-1.055158
	-1.118407	-1.099575	-1.096864	-1.070634	-1.036591	-1.096864
	-1.142416	-1.08958	-1.094882	-1.07115	-1.036655	-1.094882
	-1.164054	-1.09864	-1.06324	-1.046522	-1.054147	-1.06324
Big	-1.072778	-1.019366	-1.007862	-0.961062	-1.018673	-1.007862
S - B	0.0512791	-0.037395	-0.047296	-0.07999	-0.007999	

We rank all TSE firms by their book-to-market at the end of March and their market capitalization (Size) at the end of September of year t. We form 20 percent, 40 percent, 60 percent and 80 percent breakpoints for book-to-market and size based on these rankings. At the beginning of October of year t, firms are placed into the five book-to-market groups and the five size groups based on these breakpoints. The firms remain in these portfolios from the beginning of October of year t to the end of September of year t+1.

The intercepts for all the portfolios are close to zero, and are lower than the intercepts in the q-factor model. Furthermore, none of the t statistics in Panel B are over 2, which suggests that it cannot be stated that this model does not do a good job of explaining returns. A comparison of the intercept estimates and t statistics from the Fama French three-factor model and the q-factor model, lead us to conclude that the Fama French model explains the cross-sectional variation of returns better.

Table 5. Time-Series Regressions of the 25 Size and Book-to-Market Sorted Portfolios: October 2000 to September 2010 (120 months).

Panel A: Intercept Estimates from the Fama French Three-Factor Model: $R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,Mkt}(R_{Mkt,t} - R_{f,t}) + \beta_{i,SMB}(R_{SMB,t}) + \beta_{i,HML}(R_{HML,t}) + e_{i,t}$					
	Book-to-Market				
	Low				High
Size					
Small	0.0034465	0.0030832	0.002254	0.001925	0.0034786
	-0.001739	0.0015197	-0.000767	-0.002193	-0.000788
	-0.002675	0.0025816	-0.000283	-0.002298	0.0009345
	-0.001128	0.0001087	0.004086	-0.000672	-0.003874
Big	0.0011182	0.0022444	0.0012473	-0.009209	-0.002029
Panel B: t Statistics from the Fama French Three-Factor Model					
Size					
Small	0.6170429	0.9950723	0.6433659	0.8168613	1.4698748
	-0.22698	0.3664862	-0.294656	-0.956644	-0.300556
	-0.380422	0.7493367	-0.076245	-0.584298	0.1997499
	-0.395389	0.0532685	0.8237679	-0.165855	-0.854676
Big	0.8651911	1.175267	0.495544	-1.445181	-0.353223

The formation of the 25 sorted portfolios is described in Table 4. The construction of the HML factor portfolio, SMB factor portfolio and the Mkt factor portfolio is as follows. Portfolios are constructed using the 30% and 70% breakpoints for book-to-market and 50% for size. Shares below the 30% breakpoint for book-to-market values are designated L, the middle 40% of firms are designated M, and the shares above the 70% breakpoint are designated H. Firms above the 50% size breakpoint are designated B and the remaining 50% are designated S. From these rankings, we form the six value-weighted portfolios L/S, M/S, H/S, L/B, M/B and H/B. From these portfolio returns, we calculate the HML factor portfolio return and the SMB factor portfolio return. This table presents the intercept estimates and t statistics for the Fama French three-factor model.

2.6 Conclusion

This study tests the performance of the q-factor model proposed by Hou *et al.* (2015) on the Japanese share market. It examines monthly data of shares listed on both the First section and Second section of the Tokyo Stock Exchange for the ten-year timeframe of October 2000 to September 2010.

The regression results on the portfolios sorted on the factors of size, investment and profitability, suggest that the q-factor model does not adequately explain share returns for the Japanese share market. In this model, the investment factor is correlated to value and the profitability factor is correlated to momentum. Previously numerous researchers have provided evidence that the value premium is significantly strong in Japan, however the analysis on the q-factor model shows that the investment factor, as defined in this model, is not significant. For comparison purposes, the same data sample and timeframe is utilized to test the performance of the Fama French three-factor model. While the analysis is limited, based on the results, we are not able to state that the model does not do a good job of explaining returns. Of the two asset pricing models, it appears that the Fama French model is more appropriate for the Japanese market.

Interestingly, the excess returns on the sorted portfolios demonstrate the existence of a significantly strong book-to-market effect, which is consistent with previous research. Daniel, Titman and Wei (2001), Walid (2009a), Walid and Ahlem (2009b), Fama and French (2012) and Fama and French (2015b), have all demonstrated the existence of a book-to-market effect for Japanese share returns. The regression results in this paper support previous research regarding a strong value premium, yet the factor which relates to value in the q-factor model is insignificant. This adds further support to the original portfolio regression results, that the q-factor model is not adequate for the Japanese market. The q-factor model calculates the factor based on the annual change in total assets, whereas the Fama French three-factor model defines the factor to be the book-to-market value. Interestingly, research by Kubota and Takehara (2017) which examines the Fama French five-factor model, also documents that the investment factor which is calculated the same as the value factor in the q-factor model, is not statistically insignificant. Future avenues for research may include extending the timeframe studied, or testing alternative calculation methods for the investment factor.

Chapter 3: Flight to liquidity on the Tokyo Stock Exchange during the 2008 share market crashes

3.1 Introduction

During times of financial crisis and market uncertainty such as a share market crash, it has been shown that both the flight-to-quality phenomenon and flight-to-liquidity phenomenon often occur. These phenomena occur because investors become increasingly risk averse when faced with market uncertainty, and endeavor to reduce risk by shifting their capital to safer assets. While these two phenomena are distinctly different, they often occur together as low risk assets tend to be more liquid. To be specific, a flight-to-quality refers to a sudden shift in investors' investment behavior during uncertain times as they seek to move their capital from risky assets to safe assets, whereas a flight-to-liquidity is when investors sell less liquid investments and purchase more liquid assets.

Amihud (1990) was one of the first researchers to demonstrate that a decline in liquidity contributed significantly to the sharp decline in share prices in the 1987 crash. He showed that investors reallocated assets towards high-liquidity shares due to fear of another crash. In more recent research, Vayanos (2004) suggested that during volatile time's investors' effective risk aversion increases, and the risk premium demanded increases. Similarly, Watanabe (2008) demonstrated that liquidity risk premium rises during times of high preference uncertainty. Research on the Japanese share market by Chang *et al*. (2010) analyzing the relationship between liquidity and share returns, proved that the liquidity variable is statistically important even when the market is contracting. Recently, Rosch and Kaserer (2013) examined the relationship between share market liquidity and credit ratings on the German market and found that liquidity costs increase with credit risk and is more pronounced in times of crisis, suggesting that a flight-to-liquidity holds for the share market.

This paper explores the flight-to-liquidity phenomenon for shares which are traded on the

Tokyo Stock Exchange during share market crashes. The main aim of this paper is to prove the existence of the flight-to-liquidity theory, which to the best of our knowledge has never been tested on the Japanese share market. Through our analysis of individual shares traded on the First section of the Tokyo Stock Exchange, we make a significant contribution to the existing literature on share market crashes by showing that the phenomenon does indeed exist. Secondly, this paper extends literature on share market crashes. The majority of papers on market crashes focus on the factors which cause a crash (Barlevy and Veronesi, 2003; Limmack and Ward, 1990; Kleidon 1995), and the co-movements of markets (Hon *et al.* 2004; Yang and Bessler, 2008). In this sense, this paper is rather unique. The volatility of share markets around the globe has been increasing in recent years, which has increased the need to further our understanding of crashes and the role of liquidity during a crash.

To the best of the authors' knowledge, there are no papers focusing on Japanese share returns for any share market crash. Yet the Japanese share market is a major international financial market, having a large market capitalization of 347,112,800 million yen in 2012, hence it is important that it receive greater attention (World Bank Group 2012). The Tokyo Stock Exchange (TSE), which is the focus of this paper, is the largest stock exchange in Japan with approximately 88% of the domestic trading value in 2012 (Tokyo Stock Exchange Fact Book 2012). The Tokyo Stock Exchange differs from other international exchanges especially with regards to the trading rules. The Tokyo Stock Exchange has price limit rules which restrict the maximum price variation and the daily price limit, meaning that the daily price movements of shares are limited. Critics of price limits argue that price limits reduce market liquidity, delay price discovery and weaken market efficiency. The possibility of reduced market liquidity due to price limits provides an important reason to research the flight-to-liquidity phenomenon on the Japanese share market.

This event study utilizes a multivariate regression analysis to examine the returns of individual shares on selected crash days. The six dates chosen all occur in October 2008, and are included in the list of the ten largest daily declines in the TOPIX (Tokyo Stock Exchange Fact Book 2010). To contrast against these large crash days, days with a smaller decline during October 2008 are also analyzed. It is believed that the reason the TOPIX crashed throughout October 2008 was due to concerns about a financial crisis and recession due to the New York share market depression (Tokyo Stock Exchange Fact Book 2010).

The variable of most interest in the regression is illiquidity. Many different proxies exist for illiquidity (or liquidity), all of which estimate the ease with which an asset can be traded. In this paper we follow the methodology of other researchers such as Wang *et al.* (2009) and Chang *et al.* (2010), and employ the illiquidity measure of Amihud (2002) as a proxy for illiquidity. This proxy measures the absolute price change per yen of daily trading volume.

The results prove the existence of a flight-to-liquidity during share market crashes. The illiquidity variable is positive and significant as predicted, which means that illiquid shares decrease more in value on crash days. This occurs as investors rush to sell illiquid assets and purchase more liquid assets, otherwise known as a flight-to-liquidity.

The remainder of this paper is organized as follows. In Section 3.2 the data and methodology used in this study is explained. The regression results are presented in Section 3.3 and robustness tests which support the findings are detailed in Section 3.4. In Section 3.5 the impact of price limit rules is considered, and the conclusions follow in Section 3.6.

3.2 Empirical Framework

3.2.1 Hypothesis Development

Amihud (1990) demonstrated that a decline in liquidity contributed significantly to the sharp decline in share prices in the 1987 crash, and showed that investors reallocated assets towards high-liquidity shares due to fear of another crash. Research specifically on the Japanese share market by Chang, Faff and Hwang (2010) analyzing the relationship between liquidity and share returns, proved that the liquidity variable is statistically important even when the market is in the contracting phase.

We hypothesis that a flight–to-liquidity occurs on days when the share market crashes, as investors rush to sell illiquid assets. In this study, we have followed the methodology of Wang *et al.* (2009) and utilized a multivariate regression, with the crash day return as the dependent variable and twelve independent variables which have explanatory effects on share returns. For the flight-to-liquidity phenomenon to hold, the illiquidity variable must be positive and statistically significant.

3.2.2 Data

Firstly, a "crash" as defined by Garber (1992) is an abrupt decline in the value of securities. A crash, as Kleidon (1995) states, can be caused by a change in external information about fundamentals. Another possible cause suggested by Barlevy and Veronesi (2003) is the behavior of uninformed traders who panic and cause the price of shares to fall suddenly and drastically.

For the purpose of our study, we have followed the methodology of Wang *et al.* (2009) and classified a crash date as a daily decrease in the TOPIX index of more than 5%. In the twelve year period from January 1998 to December 2009, there are thirteen days which are considered to be a share market crash. Ten of the thirteen occurred during 2008, and six occurred during the month of October 2008. This paper focuses on the six October 2008 dates. The reason for this limitation is primarily due to the fact that the October dates, listed in Table 1, have the highest daily decrease of all the crashes in the twelve year period, with the TOPIX daily return greater than -7%. These six dates are referred to as "large crash days" in the regression tables. Crash days with a daily return of between -2% and -5%, referred to as "small crashes", are also analyzed to determine if the results are applicable to crashes in general or only to large scale crashes.

Data on the TOPIX index, closing prices for all individual shares listed on the First section of the Tokyo Stock Exchange, plus all financial data, the price-to-book ratios and market capitalization data for all shares is obtained from the Nikkei Economic Electronic Databank System (NEEDS). The financial statements data is obtained from the firm`s annual financial statements in the NEEDS database for the previous financial year.

Following Fama and French (1992), utilities and financial firms are excluded from the analysis. Utilities are excluded because their financial decisions are affected by regulation and financial firms are excluded because their financial ratios are not comparable to those of industrial firms.

To be included in the data set, a firm must be listed on the First section, have a share price for both the crash date and the previous day, and have all other required data. That is, data on firm size, the market-to-book ratio and the daily trading volume for the year prior to October 1st, plus end of year financial statements for the previous year must be available with the required data on debt, liquid assets, cash flow, and earnings. In addition, shares prices must be available for the three years prior to October 1st 2008, and monthly close prices for the period January 2002 to December 2006 must be available for the calculation of beta. This period was selected to calculate beta because it is considered a relatively non-volatile period. Following Wang *et al.* (2009) monthly data was used to calculate the CAPM beta. Since monthly data is being utilized, a long timeframe of five years was selected to increase the accuracy of the beta calculation.

Firms with financial data missing for any of the requirements listed above are excluded from the sample. Some firms have no data for 2002 and 2003 which meant they failed the requirements needed to calculate beta. Due to the data requirements listed above and the exclusion of utilities and financial firms, the sample size is smaller than the number of shares listed on the Tokyo Stock Exchange. At the time of data collection there were 1702 shares listed in the First section, however as the sample size in the table below shows, a little over 500 shares have been excluded from the sample. The sample size varies slightly for each crash due to the fact that some of the shares have no price for either the crash day or the previous day, and hence the return cannot be calculated. Analysis of the trading volume data showed that on the days with no price there was no volume traded, and historically they tend to be thinly traded shares. The six large crash dates to be analyzed and their respective sample sizes are listed in Table 1.

Table 1. Crash days

Date	Daily decrease in TOPIX %	Sample size
8th October 2008	-8.04	1170
10th October 2008	-7.1	1171
16th October 2008	-9.52	1174
22nd October 2008	-7.05	1174
24th October 2008	-7.5	1173
27th October 2008	-7.4	1174

From here on, the 8th of October 2008 crash will be referred to as the 08/10 crash, the 10th of October 2008 crash will be referred to as the 10/10 crash, the 16th of October 2008 crash will be referred to as the 16/10 crash, the 22nd of October 2008 crash will be referred to as the 22/10 crash, the 24th of October 2008 crash will be referred to as the 24/10 crash and the 27th of October 2008 crash will be referred to as the 27/10 crash.

In the regression tables, "small crashes" refers to selected days when the TOPIX daily return was between -5% and -2%. The specific days analyzed are: 2nd of October 2008 (-2.19%), 3rd of October 2008 (-2.69%), 6th of October 2008 (-4.67%) and the 7th of October 2008 (-2.15%).

3.2.3 Methodology

A multivariate regression analysis is utilized in this event study to examine the returns of individual shares listed on the First section of the Tokyo Stock Exchange on the chosen crash days. The model and methodology follows that of Wang *et al.* (2009), except for the exclusion of the industry dummy variable. This variable was excluded because Wang found that overall it was not significant.

A one-day event window is used for each crash. The crash day share return (RET_{it}) is the dependent variable in the linear regression model. It is calculated as the realized daily return using the equation:

$$R_{it} = (P_{it} - P_{it-1}) / P_{it-1} \qquad (1)$$

Where R_{it} denotes the realized rate of return of share *i* at time *t*, P_{it} denotes the share price at time *t*, and P_{it-1} denotes the share price at time *t-1*. Since all the crash days occur during a very short time frame, that is October 2008, the independent variables are all calculated at the 1st of October for simplicity. Calculating the variables specifically for each single crash day gave the same overall results, however we have not included them in the paper. The linear regression model is:

$$RET_{it} = \beta_0 + \beta_1 BETA + \beta_2 SIZE + \beta_3 MVBV + \beta_4 ILLIQ + \beta_5 TDTA + \beta_6 LAR + \beta_7 CFPS$$
$$+ \beta_8 BEP + \beta_9 SDLR + \beta_{10} LR1 + \beta_{11} LR2 + \beta_{12} LR3 + e_t \qquad (2)$$

In this model the dependent variable RET_{it}, is the raw share return for the event day, and is calculated using equation (1). β_0 is the a constant and β_1, β_2 ... β_{12} are the regression coefficients. There are twelve independent variables included in the model. BETA is the CAPM beta of the share computed with monthly return data for the five year period from January 2002 to December 2006. SIZE is the logarithm of the firm's market capitalization, calculated as the average of the daily figures for the year directly prior to October 1st. MVBV is the market-to-book ratio, calculated as the average of the weekly market / book ratios for the year directly prior to October 1st. ILLIQ is the illiquidity ratio employed by Amihud (2002), calculated as:

$$ILLIQ = \frac{1}{Di} \sum_{t=1}^{Di} \frac{|Ri|}{VOLDi\ d} * 1000$$

where R_i is the share i`s daily returns, $VOLD_{id}$ is the daily volume, and D_i is the number of days in the period -252 to -30 days prior to October 1st for which it traded. We have following the methodology of Wang *et al.* (2009) and multiplied the Amihud ratio by 1000 to scale the figure. TDTA is the debt ratio (total debt / total assets) and LAR is the liquid assets ratio [(cash + marketable securities) / total assets], both calculated from the previous year's financial statements. CFPS is the cash flow per share, and BEP is the basic earning power ratio (EBIT / total assets). SDLR is the standard deviation of the lagged share returns from -252 to -30 days prior to October 1st. In addition three lagged returns are included in the model: LR1 (lagged return 1) which is the cumulative return from -7 to -2 days prior to October 1st, LR2 (lagged return 2) which is the cumulative return from -70 to -2 days prior to October 1st, and LR3 (lagged return 3) which is the cumulative return from -756 to -2 days prior to October 1st.

3.2.4 The Variables

The variable of most interest, illiquidity (ILLIQ), calculated as the average ratio of the daily absolute return to yen trading volume in the period -252 to -30 days prior to October 1st, is predicted to have a coefficient which is positive and significant. It is predicted to be positive as previous research has documented a positive relationship between illiquidity and share returns during both normal periods (Amihud, 2002; Chang *et al.* 2010) and during crashes (Wang *et al.* 2009). A positive sign during a share market crash shows that illiquid shares decrease more in value on crash days. This occurs as investors rush to sell illiquid assets and purchase more liquid assets during times of uncertainty, otherwise known as a flight-to-liquidity.

The other eleven variables in the model act as control variables in our research. We have employed the model of Wang *et al.* (2009), except for the exclusion of the industry dummy variable, as previous research has demonstrated that each of the eleven variables have a significant influence on share returns. Beta, size and market-to-book ratio, the variables in the Fama and French (1992) three factor model, have continually been shown over time to explain share returns. Based on the research by Wang *et al*. (2009) and other researchers, it is expected that beta will be statistically significant and negative in the regressions. It is reasonable to expect that since shares with high betas are more volatile, during a crash they will incur greater losses. Previous research regarding firm size has found that large firms lead small firms (Lo and MacKinlay, 1990). We expect that size will be significant and negative in the regression, implying that large firms incur more losses on the crash day. While Wang *et al.* (2009) found that the market-to-book ratio was not a significant variable during American share market crashes, due to the fact that the ratio is more closely linked to share returns in Japan, it is expected that it may be significant and negative.

Wang *et al.* (2009) included the debt ratio as a firm's debt ratio is likely to impact on the magnitude of the share price decrease during a crash. Based on Wang's results for the American market, the debt ratio variable is expected to be negative. The liquid cash ratio is included as this ratio is likely to impact on which firms are considered safer and favored. A high liquid asset level can be viewed in two ways, as a safe firm and as a firm with no profitable investment opportunities, causing difficulty in predicting the expected sign on this variable. Wang *et al.* (2009) found it to be negative for the American market, therefore it is expected to be negative in our regression on the Japanese market.

Previous research by Carpenter and Guariglia (2008) showed that cash flow helps determine a firm's share price, leading to the inclusion of this variable. Wang *et al.* (2009) argue that investors would be likely to favor firms with high cash flow levels during a crash. Based on this reasoning and the results of Wang *et al.* (2009), this variable is expected to be positive. Similarly, Pastor and Veronesi (2003) proved that firm profitability is closely related to share prices, therefore the basic earning power ratio is included as a variable. Based on the belief that profitable firms should lose less during a crash, and the findings of Wang *et al* (2009), this ratio is expected to be positive.

The standard deviation of lagged returns, considered to be a proxy for the volatility of share returns, will obviously impact on a shares return on a crash day. It is assumed that shares with more volatility prior to the crash are likely to have larger decreases during a share market crash. Hence it is expected that this variable will be significant and negative, as Wang`s research found.

Lastly, three lagged return variables are included in the regression to capture the short-term and long-term momentum effects. Over the last twenty years numerous papers have discussed momentum in returns. DeBondt and Thaler (1985) found long-term reversals of portfolio returns, and Li, Brooks and O`Sullivan (2008) found that “losers” react slower to negative shocks in the short term. It is difficult to predict the expected sign of these variables, as it will vary depending on the timeframe selected.

3.2.5 Descriptive Statistics and Correlations

The descriptive statistics of the variables used in the analysis are presented in Table 2. Overall, the descriptive statistics for the six crashes appear to have similar characteristics. The standard deviation, minimum and maximum figures have a wide range of values suggesting good regression results. There is a decreasing trend in skewness for returns from the 10/10 crash, which is in line with the findings by Wang *et al*. (2009) that skewness is negative on a crash day. One possible explanation for this gradual decrease is the existence of price limit rules on the TSE, which can limit the daily movement of a share and thus slow down the price discovery process. This issue and the implications for our research are considered in more detail in Section 3.5.

Kurtosis is higher than the normal figure of 3 for all days except 16/10, however distribution graphs of the returns suggest that there is not a problem of outliers. With regards to the variable of most interest, illiquidity, both high skewness and high kurtosis are evident.

The correlation coefficients between the variables used in the regression analysis for the six large crash dates are shown in Table 3. Correlations between the explanatory variables are generally not very high, suggesting that multicollinearity will not be an issue in the regressions.

Table 2. Summary statistics of the samples used in the regression analysis for the six share market crashes

Variables	Mean	Std. Dev	Skewness	Kurtosis	Maximum	Median	Minimum
October 8th (N =1170)							
RET	-0.0887776	0.0469064	0.1610891	4.11901	0.1398601	-0.0906977	-0.2594937
BETA	0.9957661	0.6091922	4.795033	58.85617	9.784703	0.9205934	-0.3875517
SIZE	24.82572	1.564781	0.6449326	2.997315	30.58525	24.59074	21.73332
MVBV	1.290229	0.8737826	2.725197	15.1957	8.383704	1.049051	0.25965
ILLIQ	0.0005801	0.0018772	9.512084	117.5535	0.0287334	0.0001126	3.42E-07
TDTA	0.5026445	0.1962375	-0.1170937	2.174867	0.9311291	0.5163914	0.0416077
LAR	0.1293834	0.097898	1.729436	7.578825	0.7321356	0.1068236	0.0005873
CFPS	1326.398	13914.54	15.77764	280.4415	280912.5	116.335	-2083.65
BEP	6.178897	5.275094	1.031102	9.918788	46.39	5.28	-25.34
SDLR	0.0270812	0.0079331	1.063759	6.340309	0.0819203	0.026287	0.00561
LR1	-0.039677	0.0717377	4.715422	73.80845	1.123457	-0.042362	-0.4321429
LR2	-0.165491	0.1704481	0.2582227	3.34474	0.6111111	-0.1641006	-0.7572519
LR3	-0.2498688	0.3676484	2.340844	17.06268	3.154762	-0.2922807	-0.9844444
October 10th (N =1171)							
RET	-0.0512642	0.0483252	0.3598551	4.947783	0.25	-0.0505166	-0.227758
BETA	0.9956066	0.6092755	4.788578	58.78019	9.784703	0.9219098	-0.3875517
SIZE	24.82825	1.566559	0.6433176	2.988443	30.58525	24.5908	21.73332
MVBV	1.291203	0.8736526	2.721419	15.18013	8.383704	1.049344	0.25965
ILLIQ	0.0005949	0.0019642	9.221306	107.6823	0.0287334	0.0001136	3.42E-07
TDTA	0.5027086	0.196158	-0.118059	2.176677	0.9311591	0.5169947	0.0416077
LAR	0.1293152	0.0978782	1.730824	7.583446	0.7321356	0.1068164	0.0005873
CFPS	1325.549	13908.62	15.78446	280.6825	280912.5	116.4	-2083.65
BEP	6.181734	5.274527	1.029442	9.912778	46.39	5.28	-25.34
SDLR	0.0270811	0.0079307	1.063571	6.34304	0.0819203	0.0262893	0.00561
LR1	-0.0396865	0.0717077	4.717701	73.87134	1.123457	-0.0424077	-0.4321429
LR2	-0.1653841	0.1703941	0.2559076	3.343921	0.6111111	-0.164	-0.7572519
LR3	-0.2499448	0.3675282	2.341931	17.07263	3.154762	-0.2933333	-0.9844444
October 16th (N =1174)							
RET	-0.0786378	0.0478468	0.1673933	2.801042	0.1115242	-0.0798936	-0.1931818
BETA	0.9951547	0.6085896	4.794592	58.90881	9.784703	0.9205934	-0.3875517
SIZE	24.8271	1.564879	0.645717	2.995644	30.58525	24.59074	21.73332

Continued from previous page							
MVBV	1.290054	0.8729118	2.724655	15.20763	8.383704	1.049232	0.25965
ILLIQ	0.0006057	0.0019737	9.076796	105.2207	0.0287334	0.0001137	3.42E-07
TDTA	0.5027445	0.1959473	-0.1186825	2.180626	0.9311291	0.5170425	0.0416077
LAR	0.1293205	0.097796	1.730973	7.589618	0.7321356	0.1067784	0.0005873
CFPS	1322.462	13890.96	15.80487	281.4047	280912.5	116.335	-2083.65
BEP	6.177036	5.270436	1.03078	9.923007	46.39	5.28	-25.34
SDLR	0.0270719	0.0079244	1.066144	6.352373	0.0819203	0.026287	0.00561
LR1	-0.0396762	0.0716443	4.717537	73.94092	1.123457	-0.042362	-0.4321429
LR2	-0.1649148	0.1704869	0.2517363	3.33271	0.6111111	-0.1629793	-0.7572519
LR3	-0.2496098	0.3672391	2.339737	17.07513	3.154762	-0.2922807	-0.9844444
October 22nd (N =1174)							
RET	-0.0541583	0.0321041	0.0304732	3.242571	0.0813008	-0.053998	-0.1814516
BETA	0.9952752	0.6085525	4.794933	58.91933	9.784703	0.9205934	-0.3875517
SIZE	24.82766	1.564647	0.6451216	2.996367	30.58525	24.59074	21.73332
MVBV	1.290176	0.8728138	2.725427	15.21265	8.383704	1.049232	0.25965
ILLIQ	0.000605	0.0019723	9.092891	105.5163	0.0287334	0.0001137	3.42E-07
TDTA	0.5025165	0.1959979	-0.1158146	2.178364	0.9311291	0.5163914	0.0416077
LAR	0.1292141	0.0977745	1.734804	7.603448	0.7321356	0.106585	0.0005873
CFPS	1322.506	13890.95	15.80487	281.4048	280912.5	116.335	-2083.65
BEP	6.182402	5.267807	1.030364	9.937436	46.39	5.29	-25.34
SDLR	0.0270758	0.0079261	1.064291	6.345096	0.0819203	0.026287	0.00561
LR1	-0.0396893	0.0716407	4.718749	73.95911	1.123457	-0.042362	-0.4321429
LR2	-0.1651848	0.1703598	0.2546324	3.341029	0.6111111	-0.163584	-0.7572519
LR3	-0.2496934	0.3672611	2.339949	17.07321	3.154762	-0.2922807	-0.9844444
October 24th (N =1173)							
RET	-0.0586465	0.0426697	-0.051948	3.566071	0.1333333	-0.0558824	-0.2033898
BETA	0.9958736	0.6084671	4.799402	58.98239	9.784703	0.9219098	-0.3875517
SIZE	24.82419	1.563122	0.6480277	3.005012	30.58525	24.59013	21.73332
MVBV	1.289143	0.8731142	2.727321	15.21754	8.383704	1.049119	0.25965
ILLIQ	0.0006024	0.0019702	9.125684	106.0865	0.0287334	0.0001136	3.42E-07
TDTA	0.5027402	0.1960669	-0.1189861	2.177665	0.9311291	0.5170902	0.0416077
LAR	0.1293477	0.0978326	1.729716	7.582788	0.7321356	0.1068164	0.0005873
CFPS	1323.294	13896.85	15.79805	281.1635	280912.5	116.23	-2083.65
BEP	6.173683	5.271112	1.032662	9.928584	46.39	5.28	-25.34
SDLR	0.0270883	0.0079246	1.062189	6.347766	0.0819203	0.0262938	0.00561

Continued from previous page							
LR1	-0.0396881	0.071667	4.717471	73.91349	1.123457	-0.0423163	-0.4321429
LR2	-0.1653549	0.1703291	0.2564493	3.345282	0.6111111	-0.164	-0.7572519
LR3	-0.2499689	0.3672297	2.343807	17.09957	3.154762	-0.2933333	-0.9844444
October 27th (N =1174)							
RET	-0.0606535	0.0465019	-0.0443986	3.995247	0.1706485	-0.060967	-0.2666667
BETA	0.9956526	0.6082547	4.801356	59.02139	9.784703	0.9205934	-0.3875517
SIZE	24.82428	1.562459	0.6481221	3.007395	30.58525	24.59041	21.73332
MVBV	1.288845	0.8728017	2.728893	15.23009	8.383704	1.049051	0.25965
ILLIQ	0.0006068	0.0019751	9.058736	104.9076	0.0287334	0.0001137	3.42E-07
TDTA	0.5026619	0.1960017	-0.1178915	2.178555	0.9311291	0.5170425	0.0416077
LAR	0.1293246	0.0977941	1.730975	7.589898	0.7321356	0.1067784	0.0005873
CFPS	1322.398	13890.96	15.80486	281.4045	280912.5	116.25	-2083.65
BEP	6.173739	5.268865	1.03307	9.937001	46.39	5.28	-25.34
SDLR	0.027083	0.0079233	1.063407	6.349756	0.0819203	0.0262915	0.00561
LR1	-0.0396568	0.0716444	4.716709	73.93535	1.123457	-0.042312	-0.4321429
LR2	-0.1651398	0.170416	0.2548269	3.338436	0.6111111	-0.163584	-0.7572519
LR3	-0.2496374	0.3672488	2.339749	17.07405	3.154762	-0.2922807	-0.9844444

The dependent variable is the return on the crash day. The explanatory variables are as follows. BETA is the CAPM beta calculated over a five year period. SIZE is the average logarithm of the firm`s market capitalisation for the year prior to October 1st. MVBV is the average of the market value/book value ratio for the year prior to October 1st. ILLIQ is Amihud`s illiquidity ratio based on the period -252 to -30 days prior to October 1st. TDTA is the debt ratio (total debt/total assets) for the previous financial year. LAR is the liquid assets ratio [(cash + marketable securities)/total assets] for the previous financial year. CFPS is the cash flow per share, and BEP is the basic earning power (EBIT/total assets) for the previous financial year. SDLR is the standard deviation of the lagged share returns for the period -252 to -30 days prior to October 1st. LR1 (lagged return) is the cumulative return for the period -7 to -2 days prior to October 1st, LR2 is the cumulative return for the period -70 to -2 days prior to October 1st, and LR3 is the cumulative return for the period -756 to -2 days prior to October 1st and e_t is the error term. Large crashes are defined as days where the TOPIX index decreased by more than -5%, and small crashes are when the decrease is less than -5%.

Table 3. Correlation coefficients between the variables used in the six share market crashes (t-statistics in parentheses)

	RET	BETA	SIZE	MVBV	ILLIQ	TDTA	LAR	CFPS	BEP	SDLR	LR1	LR2	LR3
													October 8^{th}
RET		-0.1385	-0.0528	-0.1370	0.1084	-0.1799	0.1066	0.0572	-0.0774	-0.3066	0.1665	0.2404	-0.0415
		(0.0000)	(0.0712)	(0.0000)	(0.0002)	(0.0000)	(0.0003)	(0.0503)	(0.0081)	(0.000)	(0.0000)	(0.0000)	(0.1560)
BETA	0.0531		-0.0125	0.0824	-0.0287	0.2154	-0.0682	-0.0298	0.0161	0.3746	-0.1271	-0.3128	-0.1258
	(0.0694)		(0.6694)	(0.0048)	(0.3263)	(0.000)	(0.0196)	(0.3088)	(0.5819)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
SIZE	-0.1858	-0.0143		0.4479	-0.1799	-0.0705	0.0422	0.1969	0.3780	-0.1444	0.0702	0.0515	0.3895
	(0.0000)	(0.6248)		(0.0000)	(0.0000)	(0.0158)	(0.1494)	(0.0000)	(0.0000)	(0.0000)	(0.0164)	(0.0783)	(0.0000)
MVBV	-0.0705	0.0813	0.4486		-0.0311	0.0800	0.1775	0.0598	0.5217	0.0862	0.0055	-0.0510	0.4259
	(0.0158)	(0.0054)	(0.0000)		(0.2884)	(0.0062)	(0.0000)	(0.0408)	(0.0000)	(0.0032)	(0.8516)	(0.0815)	(0.0000)
ILLIQ	-0.0525	-0.0238	-0.1696	-0.0279		-0.1305	0.0912	0.0565	0.0004	-0.0081	-0.0089	0.0032	-0.0825
	(0.0726)	(0.4167)	(0.0000)	(0.3393)		(0.0000)	(0.0018)	(0.0534)	(0.9887)	(0.7815)	(0.7616)	(0.9136)	(0.0047)
TDTA	0.0244	0.2156	-0.0710	0.0795	-0.1211		-0.5240	0.0369	-0.3484	0.2770	-0.0634	-0.1852	-0.0498
	(0.4049)	(0.0000)	(0.0150)	(0.0065)	(0.0000)		(0.0000)	(0.2067)	(0.0000)	(0.0000)	(0.0302)	(0.0000)	(0.0884)
LAR	0.0094	-0.0680	0.0413	0.1769	0.0819	-0.5240		-0.0619	0.2737	-0.0381	0.0319	0.0616	0.0138
	(0.7488)	(0.0199)	(0.1579)	(0.0000)	(0.0050)	(0.0000)		(0.0343)	(0.0000)	(0.1924)	(0.2751)	(0.0351)	(0.6381)
CFPS	-0.0738	-0.0297	0.1964	0.0597	0.0535	0.0369	-0.0618		0.0352	-0.0634	0.0635	0.0695	0.0645
	(0.0116)	(0.3094)	(0.0000)	(0.0411)	(0.0672)	(0.2067)	(0.0345)		(0.2291)	(0.0301)	(0.0298)	(0.0175)	(0.0273)
BEP	-0.0570	0.0152	0.3786	0.5220	-0.0007	-0.3486	0.2733	0.0351		-0.0151	-0.0153	-0.0981	0.2829
	(0.0510)	(0.6032)	(0.0000)	(0.0000)	(0.9817)	(0.0000)	(0.0000)	(0.2297)		(0.6048)	(0.6005)	(0.0008)	(0.0000
SDLR	0.1413	0.3750	-0.1456	0.0851	-0.0056	0.2770	-0.0380	-0.0634	-0.0158		-0.1428	-0.4262	-0.1541
	(0.0000)	(0.0000)	(0.0000)	(0.0036)	(0.8493)	(0.0000)	(0.1938)	(0.0301)	(0.5886)		(0.0000)	(0.0000)	(0.0000)
LR1	-0.0741	-0.1265	0.0698	0.0055	-0.0052	-0.0630	0.0318	0.0635	-0.0155	-0.1423		0.3405	0.0893
	(0.0112)	(0.0000)	(0.0169)	(0.8501)	(0.8578)	(0.0312)	(0.2762)	(0.0297)	(0.5957)	(0.0000)		(0.0000)	(0.0022)
LR2	-0.2398	-0.3127	0.0531	-0.0496	0.0107	-0.1846	0.0609	0.0694	-0.0975	-0.4259	0.3402		0.2564
	(0.0000)	(0.0000)	(0.0691)	(0.0899)	(0.7157)	(0.0000)	(0.0371)	(0.0175)	(0.0008)	(0.0000)	(0.0000)		(0.0000)
LR3	-0.1315	-0.1246	0.3883	0.4259	-0.0715	-0.0490	0.0136	0.0645	0.2824	-0.1530	0.0894	0.2558	
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0144)	(0.0938)	(0.6431)	(0.0272)	(0.0000)	(0.0000)	(0.0022)	(0.0000)	
October 10th													

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	RET	BETA	SIZE	MVBV	ILLIQ	TDTA	LAR	CFPS	BEP	SDLR	LR1	LR2	LR3
													October 16th
RET		-0.2554	-0.2786	-0.1412	0.1362	-0.1579	0.1168	0.0499	-0.1272	-0.3549	0.0893	0.3868	-0.0300
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0875)	(0.0000)	(0.0000)	(0.0022)	(0.0000)	(0.3038)
BETA	-0.1083		-0.0141	0.0817	-0.0253	0.2155	-0.0682	-0.0297	0.0156	0.3750	-0.1267	-0.3131	-0.1249
	(0.0002)		(0.6295)	(0.0051)	(0.3857)	(0.0000)	(0.0195)	(0.3098)	(0.5938)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
SIZE	-0.4194	-0.0143		0.4488	-0.1699	-0.0713	0.0409	0.1965	0.3789	-0.1454	0.0698	0.0523	0.3881
	(0.0000)	(0.6248)		(0.0000)	(0.0000)	(0.0145)	(0.1610)	(0.0000)	(0.0000)	(0.0000)	(0.0168)	(0.0733)	(0.0000)
MVBV	-0.1524	0.0815	0.4486		-0.0306	0.0792	0.1763	0.0598	0.5224	0.0854	0.0052	-0.0511	0.4252
	(0.0000)	(0.0052)	(0.0000)		(0.2946)	(0.0066)	(0.0000)	(0.0405)	(0.0000)	(0.0034)	(0.8582)	(0.0800)	(0.0000)
ILLIQ	0.1154	-0.0249	-0.1693	-0.0301		-0.1203	0.0815	0.0527	-0.0025	-0.0081	-0.0045	0.0169	-0.0687
	(0.0001)	(0.3945)	(0.0000)	(0.3031)		(0.0000)	(0.0052)	(0.0710)	(0.9311)	(0.7819)	(0.8784)	(0.5636)	(0.0186)
TDTA	-0.0595	0.2158	-0.0709	0.0801	-0.1224		-0.5233	0.0369	-0.3488	0.2771	-0.0631	-0.1842	-0.0494
	(0.0416)	(0.0000	(0.0151)	(0.0060)	(0.0000)		(0.0000)	(0.2065)	(0.0000)	(0.0000)	(0.0306)	(0.0000)	(0.0906)
LAR	0.0612	-0.0678	0.0415	0.1773	0.0795	-0.5233		-0.0618	0.2723	-0.0374	0.0323	0.0613	0.0131
	(0.0361)	(0.0202)	(0.1556)	(0.0000)	(0.0064)	(0.0000)		(0.0343)	(0.0000)	(0.2007)	(0.2692)	(0.0358)	(0.6528)
CFPS	0.0166	-0.0297	0.1965	0.0598	0.0528	0.0370	-0.0617		0.0352	-0.0633	0.0635	0.0691	0.0644
	(0.5708)	(0.3095)	(0.0000)	(0.0405)	(0.0706)	(0.2054)	(0.0345)		(0.2283)	(0.0302)	(0.0296)	(0.0179)	(0.0272)
BEP	-0.1723	0.0152	0.3786	0.5218	-0.0004	-0.3486	0.2732	0.0351		-0.0160	-0.0159	-0.0985	0.2822
	(0.0000)	(0.6033)	(0.0000)	(0.0000)	(0.9878)	(0.0000)	(0.0000)	(0.2293)		(0.5849)	(0.5869)	(0.0007)	(0.0000)
SDLR	-0.1233	0.3749	-0.1455	0.0850	-0.0073	0.2763	-0.0377	-0.0633	-0.0158		-0.1420	-0.4259	-0.1536
	(0.0000)	(0.0000)	(0.0000)	(0.0036)	(0.8020)	(0.0000)	(0.1963)	(0.0301)	(0.5893)		(0.0000)	(0.0000)	(0.0000)
LR1	0.0431	-0.1266	0.0699	0.0054	-0.0049	-0.0634	0.0320	0.0635	-0.0155	-0.1419		0.3403	0.0896
	(0.1404)	(0.0000)	(0.0165)	(0.8532)	(0.8663)	(0.0299)	(0.2740)	(0.0295)	(0.5954)	(0.0000)		(0.0000)	(0.0021)
LR2	0.1548	-0.3128	0.0532	-0.0498	0.0138	-0.1845	0.0605	0.0693	-0.0974	-0.4266	0.3401		0.2564
	(0.0000)	(0.0000)	(0.0686)	(0.0880)	(0.6376)	(0.0000)	(0.0382)	(0.0176)	(0.0008)	(0.0000)	(0.0000)		(0.0000)
LR3	-0.1433	-0.1249	0.3881	0.4253	-0.0690	-0.0490	0.0134	0.0645	0.2822	-0.1538	0.0896	0.2569	
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0180)	(0.0931)	(0.6469)	(0.0272)	(0.0000)	(0.0000)	(0.0021)	(0.0000)	
October 22nd													

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	RET	BETA	SIZE	MVBV	ILLIQ	TDTA	LAR	CFPS	BEP	SDLR	LR1	LR2	LR3
													October 24th
RET		-0.1343	-0.4094	-0.2367	0.1352	-0.0163	0.0337	0.0061	-0.2492	-0.1801	-0.0071	0.1571	-0.2032
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.5764)	(0.2493)	(0.8342)	(0.0000)	(0.0000)	(0.8093)	(0.0000)	(0.0000)
BETA	-0.1109		-0.0122	0.0826	-0.0237	0.2152	-0.0687	-0.0298	0.0164	0.3741	-0.1268	-0.3121	-0.1249
	(0.0001)		(0.6768)	(0.0046)	(0.4169)	(0.0000)	(0.0186)	(0.3082)	(0.5744)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
SIZE	-0.2226	-0.0122		0.4482	-0.1727	-0.0706	0.0419	0.1969	0.3783	-0.1443	0.0701	0.0506	0.3894
	(0.0000)	(0.6761)		(0.0000)	(0.0000)	(0.0156)	(0.1517)	(0.0000)	(0.0000)	(0.0000)	(0.0164)	(0.0829)	(0.0000)
MVBV	-0.0970	0.0828	0.4482		-0.0316	0.0800	0.1769	0.0599	0.5219	0.0854	0.0054	-0.0512	0.4263
	(0.0009)	(0.0045)	(0.0000)		(0.2795)	(0.0061)	(0.0000)	(0.0402)	(0.0000)	(0.0034)	(0.8531)	(0.0794)	(0.0000)
ILLIQ	0.1216	-0.0246	-0.1720	-0.0324		-0.1204	0.0822	0.0529	-0.0031	-0.0046	-0.0053	0.0120	-0.0715
	(0.0000)	(0.3997)	(0.0000)	(0.2674)		(0.0000)	(0.0049)	(0.0699)	(0.9144)	(0.8762)	(0.8572)	(0.6807)	(0.0143)
TDTA	-0.0596	0.2153	-0.0706	0.0801	-0.1211		-0.5232	0.0369	-0.3486	0.2759	-0.0631	-0.1831	-0.0488
	(0.0412)	(0.0000)	(0.0155)	(0.0060)	(0.0000)		(0.0000)	(0.2067)	(0.0000)	(0.0000)	(0.0307)	(0.0000)	(0.0948)
LAR	0.1015	-0.0686	0.0419	0.1770	0.0813	-0.5230		-0.0618	0.2727	-0.0382	0.0323	0.0623	0.0134
	(0.0005)	(0.0187)	(0.1517)	(0.0000)	(0.0053)	(0.0000)		(0.0343)	(0.0000)	(0.1908)	(0.2694)	(0.0328)	(0.6461)
CFPS	0.0439	-0.0297	0.1969	0.0599	0.0526	0.0369	-0.0618		0.0353	-0.0635	0.0635	0.0694	0.0646
	(0.1325)	(0.3085)	(0.0000)	(0.0401)	(0.0715)	(0.2062)	(0.0343)		(0.2276)	(0.0298)	(0.0296)	(0.0175)	(0.0270)
BEP	-0.0851	0.0164	0.3783	0.5219	-0.0031	-0.3486	0.2727	0.0353		-0.0152	-0.0158	-0.0995	0.2826
	(0.0035)	(0.5744)	(0.0000)	(0.0000)	(0.9153)	(0.0000)	(0.0000)	(0.2274)		(0.6024)	(0.5897)	(0.0006)	(0.0000)
SDLR	-0.1870	0.3742	-0.1443	0.0857	-0.0063	0.2762	-0.0380	-0.0634	-0.0152		-0.1418	-0.4251	-0.1536
	(0.0000)	(0.0000)	(0.0000)	(0.0033)	(0.8301)	(0.0000)	(0.1928)	(0.0299)	(0.6021)		(0.0000)	(0.0000)	(0.0000)
LR1	0.1432	-0.1270	0.0701	0.0052	-0.0041	-0.0633	0.0322	0.0635	-0.0158	-0.1420		0.3402	0.0891
	(0.0000)	(0.0000)	(0.0163)	(0.8578)	(0.8883)	(0.0301)	(0.2710)	(0.0297)	(0.5897)	(0.0000)		(0.0000)	(0.0023)
LR2	0.1191	-0.3123	0.0507	-0.0517	0.0153	-0.1835	0.0619	0.0692	-0.0994	-0.4256	0.3405		0.2560
	(0.0000)	(0.0000)	(0.0826)	(0.0766)	(0.6010)	(0.0000)	(0.0339)	(0.0177)	(0.0006)	(0.0000)	(0.0000)		(0.0000)
LR3	-0.1205	-0.1252	0.3893	0.4257	-0.0689	-0.0492	0.0132	0.0645	0.2825	-0.1541	0.0895	0.2570	
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0182)	(0.0920)	(0.6523)	(0.0272)	(0.0000)	(0.0000)	(0.0021)	(0.0000)	
October 27th													

3.3 Regression Results

The regression results are presented in Table 4, with Panel A showing the results for the pooled large crash days, Panel B lists the results for the individual days, and Panel C shows the results for the pooled small crash days. Overall, the results for both the large crash days and the small crash days are very similar. The most important result from Table 4 is that ILLIQ, the illiquidity variable, is positive and highly significant at the 5% level. To be specific, it is 0.682 for the pooled large crash days and 0.841 for the pooled small crash days. Analyzing the large crash days individually also showed that for five of the six days illiquidity is positive and highly significant at either the 1% level or the 5% level. The 10/10 crash is the only day which gave a negative sign for illiquidity. The 10^{th} is also the only day analyzed for which SDLR, a proxy for volatility, is not significant, reinforcing the proposition that on the 10^{th} investors reaction was abnormal. Nevertheless, pooling the six large crash days gave the result that illiquidity is positive and highly significant, and supports our hypothesis of a flight-to-liquidity on the Tokyo Stock Exchange.

The results for the size variable support our hypothesis of a flight-to-liquidity. On large crash days size is negative and highly significant at the 1% level, suggesting that large firms' shares are sold first during highly uncertain times. Our result is consistent with previous research by Lo and MacKinlay (1990) and Wang *et al.* (2009). This finding links to the flight-to-quality phenomenon as investors are shifting towards low risk assets such as cash. As previously mentioned, low risk assets tend to be more liquid, furthermore large firms tend to be more liquid, strengthening our proposition of the existence of a flight-to-liquidity.

Regarding the other variables, the results for the majority of the variables are consistent with our predictions and previous literature. Beta is negative and significant during a crash, as Limmack and Ward (1990) found during the 1987 crash, in addition to Ben-Zion *et al.* (1990) and Wang *et al.* (1990). The market-to-book ratio has mixed results for large and small crashes and the TDTA

Table 4. Share returns and the illiquidity level

INTERCEPT	BETA	SIZE	MVBV	ILLIQ	TDTA	LAR	CFPS
Panel A: Pooled regression for large crashes							
0.1470993***	-0.0024192**	-0.0075103***	0.0019403**	0.6823907**	-0.002697	0.0325401***	1.83e-07***
(13.69)	(-2.54)	(-18.20)	(2.28)	(2.47)	(-0.72)	(4.91)	(4.72)
Panel B: Individual large crash days							
Oct. 8th							
-0.0116999	(0.0011848)	-0.0010452	-0.0026804	1.908124***	-0.0153912*	0.037925**	1.62e-07*
(-0.45)	(0.51)	(-1.04)	(-1.30)	(2.73)	(-1.69)	(2.37)	(1.73)
Oct. 10th							
0.0769212***	-0.0021866	-0.0054366***	0.0011901	-2.147315***	-0.0135688	0.0080873	-4.75e-08
(2.78)	(-0.89)	(-5.11)	0.54	(-3.03)	(-1.40)	(0.47)	(-0.47)
Oct. 16th							
0.2364047***	-0.006032***	-0.0106418***	0.0039047**	1.317864**	-0.0026938	0.0445912***	2.92e-07***
(10.02)	(-2.88)	(-11.75)	(2.08)	(2.20)	(-0.33)	(3.07)	(3.43)
Oct. 22nd							
0.205881***	-0.0016198	-0.0098202***	0.0047356***	0.2862164	-0.0069568	0.0147137	2.19e-07***
(12.23)	(-1.09)	(-15.20)	(3.54)	(0.67)	(-1.18)	(1.42)	(3.60)
Oct. 24th							
0.2300704***	-0.0035567*	-0.0105909***	0.0018209	1.151947**	0.0093179	0.0332873**	2.20e-07***
(10.39)	(-1.81)	(-12.46)	(1.04)	(2.04)	(1.21)	(2.44)	(2.76)
Oct. 27th							
0.1450979***	-0.0022981	-0.0075315***	0.0027541	1.520921**	0.0129297	0.0564533***	2.53e-07***
(5.58)	(-1.00)	(-7.55)	(1.34)	(2.31)	(1.43)	(3.53)	(2.70)
Panel C: Pooled regression for small crashes							
-0.0641645***	-0.0051571***	0.0022006***	-0.0010005	0.8413923***	-0.0015199	0.0189865***	5.89e-08
(-5.41)	(-4.91)	(4.83)	(-1.06)	(2.64)	(-0.37)	(2.59)	(1.38)

Continued from previous page

INTERCEPT	BEP	SDLR	LR1	LR2	LR3	Adj. R^2	Obs
Panel A: Pooled regression for large crashes							
	-0.0004029***	-0.9502644***	0.0186572**	0.0143034***	-0.0069325***	0.1115	7036
	(-2.97)	(-12.06)	(2.40)	(3.77)	(-4.03)		
Panel B: Individual large crash days							
Oct. 8th							
	-0.0005343	-1.440429***	0.0648057***	0.0263954***	-0.0076302*	0.1590	1170
	(-1.63)	(-7.55)	(3.45)	(2.87)	(-1.83)		
Oct. 10th							
	-0.0004158	0.2266575	0.0120689	-0.06821***	-0.0007266	0.0991	1171
	(-1.19)	(1.11)	(0.60)	(-6.97)	(-0.16)		
Oct. 16th							
	-0.0002683	-1.594797***	-0.0225665	0.077485***	-0.0049917	0.3261	1174
	(-0.90)	(-9.21)	(-1.32)	(9.31)	(-1.32)		
Oct. 22nd							
	-0.0003929*	-0.5490391***	0.0047076	0.0199753***	-0.0047666*	0.2380	1174
	(-1.85)	(-4.44)	(0.39)	(3.36)	(-1.77)		
Oct. 24th							
	-0.000758***	-1.091298***	-0.0286794*	0.0268782***	-0.0118444***	0.2564	1173
	(-2.72)	(-6.73)	(-1.79)	(3.44)	(-3.34)		
Oct. 27th							
	-0.0000504	-1.254676***	0.0818031***	0.0029971	-0.011712***	0.1368	1174
	(-0.15)	(-6.59)	(4.36)	(0.33)	(-2.82)		
Panel C: Pooled regression for small crashes							
	0.0001254	-0.6409437***	0.0091329	0.045005***	-0.0013788	0.1083	4683
	0.84	(-7.38)	(1.07)	(10.76)	(-0.73)		

This table shows the regression results from the following model: $RET_t = \beta_0 + \beta_1 BETA + \beta_2 SIZE + \beta_3 MVBV + \beta_4 ILLIQ + \beta_5 TDTA + \beta_6 LAR + \beta_7 CFPS + \beta_8 BEP + \beta_9 SDLR + \beta_{10} LR1 + \beta_{11} LR2 + \beta_{12} LR3 + e_t$. The dependent variable is the return on the crash day. The explanatory variables are as follows. BETA is the CAPM beta calculated over a five year period. SIZE is the average logarithm of the firm`s market capitalisation for the year prior to October 1st. MVBV is the average of the market value / book value ratio for the year prior to October 1st. ILLIQ is Amihud`s illiquidity ratio based on the period -252 to -30 days prior to October 1st. TDTA is the debt ratio (total debt/total assets) for the previous financial year. LAR is the liquid assets ratio [(cash + marketable securities)/total assets] for the previous financial year. CFPS is the cash flow per share, and BEP is the basic earning power (EBIT/total assets) for the previous financial year. SDLR is the standard deviation of the lagged share returns for the period -252 to -30 days prior to October 1st. LR1 (lagged return) is the cumulative return for the period -7 to -2 days prior to October 1st, LR2 is the cumulative return for the period -70 to -2 days prior to October 1st, and LR3 is the cumulative return for the period -756 to -2 days prior to October 1st and e_t is the error term. Large crashes are defined as days where the TOPIX index decreased by more than -5%, and small crashes are when the decrease is less than -5%. The figures in parentheses are the corresponding t-statistics. ***, **, and * indicate 1%, 5% and 10% level of significance respectively.

variable is insignificant, suggesting that these two variables do not have an effect on share returns. Both the LAR and CFPS variables are positive and significant overall, and the BEP and SDLR variables are negative and significant. The results for the three lagged returns, LR1, LR2 and LR3, are mixed as would be expected. In summary, the results for the control variables are generally in line with previous research and do not diverge significantly from our predictions. Only the signs for BEP and LAR differ from our predictions.

BEP is negative for all individual days and when the large crash days are pooled. As previously explained, it is predicted that high profitability firms will lose less during a crash. However, the negative sign in the regression suggests that firms with higher profitability actually lose more value on crash days. Since this was an extended period of market uncertainty it is possible that the crashes were not unexpected, and investors purposely sold shares of profitable firms as a predetermined investment strategy.

Due to the difficulty in predicting the sign of the LAR variable, we predicted it to be negative in line with the results of Wang *et al.* (2009). However, as Table 4 shows, LAR is positive and highly significant for both large crashes and small crashes, meaning that firms with high liquid assets decreased less in value, signaling that investors regarded these assets as safer with lower bankruptcy risk.

3.4 Robustness Tests

The first robustness test replaces the illiquidity variable ILLIQ with a proxy for liquidity. The proxy chosen is DVOL, the natural logarithm of the average of yen trading volume over a specified period (Brennan *et al.* 1998). For consistency with the main regression, the same timeframe and methodology has been employed. That is, DVOL is calculated for the period -252 to -30 days prior to October 1st. The regression results with the DVOL variable replacing ILLIQ are presented in Table 5. The results are very similar to the original regression results presented in Table 4. The proxy for liquidity DVOL is negative and highly significant as expected for both the pooled large crash days and the pooled small crash days. It is also negative and highly significant for four of the individual crash days. This result reinforces the robustness of our regression results, and the existence of a flight-to-liquidity on the Tokyo Stock Exchange.

As a second robustness test, the original sample is trimmed to reduce the possibility of outliers biasing the regression results. Each variable is trimmed at the 1% and 99% levels to ensure that the possibility of large outliers biasing the results is eliminated. Wang *et al.* (2009) used a similar test in their research on American share market crashes, leading us to replicate it as a robustness test. The regression results with all variables trimmed are presented in Table 6. The results are similar to those of the full sample, with the main differences being in the significance levels.

Several other robustness checks were carried out however the tables have not been included in this paper. One test replaced ILLIQ with LN-ILLIQ, the logarithm of the illiquidity variable, and produced very similar results to Table 4. Another test replicated a robustness test of Wang *et al.* (2009) and replaced the SIZE variable which is defined as the logarithm of the firm`s market capitalization with the firm`s market capitalization SIZE-MC. In both results the illiquidity variable is positive and highly significant, further strengthening our results.

Table 5. Robustness test results for the ILLIQ variable

INTERCEPT	BETA	SIZE	MVBV	DVOL	TDTA	LAR	CFPS
Panel A: Pooled regression for large crashes							
0.1129886***	-0.0013195	-0.0050542***	0.0015792*	-0.0028298***	0.002024	0.0288072***	9.45e-08**
(9.20)	(-1.37)	(-8.59)	(1.85)	(-6.20)	(0.53)	(4.34)	(2.27)
Panel B: Individual large crash days							
Oct. 8th							
-0.0487775	0.0025995	0.0019227	-0.0029179	-0.0037414***	-0.0107148	0.0330979**	5.95e-08
(-1.63)	(1.11)	(1.34)	(-1.41)	(-3.34)	(-1.15)	(2.06)	(0.59)
Oct. 10th							
0.0717714**	-0.0025141	-0.0056488***	0.0008497	0.0008809	-0.0120533	0.0091089	-4.75e-08
(2.25)	(-1.00)	(-3.70)	(0.38)	(0.74)	(-1.21)	(0.53)	(-0.44)
Oct. 16th							
0.1588192***	-0.0035599*	-0.0051087***	0.0030485*	-0.0063214***	0.0080753	0.036193**	9.22e-08
(5.98)	(-1.70)	(-4.03)	(1.65)	(-6.43)	(0.97)	(2.52)	(1.02)
Oct. 22nd							
0.2004084***	-0.0014025	-0.0093799***	0.004698***	-0.0005585	-0.0062508	0.0140094	2.03e-07***
(10.41)	(-0.92)	(-10.20)	(3.51)	(-0.78)	(-1.04)	(1.34)	(3.11)
Oct. 24th							
0.1915755***	-0.0022413	-0.0077226***	0.0014718	-0.0034057***	0.0144744*	0.0287269**	1.18e-07
(7.58)	(-1.13)	(-6.38)	(0.84)	(-3.63)	(1.84)	(2.11)	(1.38)
Oct. 27th							
0.1066991***	-0.0009062	-0.0045751***	0.0024548	-0.0036121***	0.0179471*	0.0516684***	1.49e-07
(3.59)	(-0.39)	(-3.22)	(1.19)	(-3.29)	(1.94)	(3.22)	(1.48)
Panel C: Pooled regression for small crashes							
-0.0853256***	-0.0043862***	0.0038258***	-0.0011722	-0.0019879***	0.0013621	0.0165999**	1.87e-09
(-6.28)	(-4.11)	(5.87)	(-1.25)	(-3.91)	(0.32)	(2.26)	(0.04)

Continued from previous page	BEP	SDLR	LR1	LR2	LR3	Adj. R^2	Obs
Panel A: Pooled regression for large crashes							
	-0.0004639***	-0.7215125***	0.0189649**	0.0126504***	-0.0069708***	0.1155	7036
	(-3.42)	(-8.30)	(2.45)	(3.34)	(-4.06)		
Panel B: Individual large crash days							
Oct. 8th							
	-0.0006209*	-1.139922***	0.0649902***	0.024155***	-0.0079562*	0.1529	1170
	(-1.89)	(-5.40)	(3.46)	(2.63)	(-1.91)		
Oct. 10th							
	-0.0003842	0.1574363	0.01216	-0.0676711***	-0.0003363	0.0830	1171
	(-1.09)	(0.70)	(0.60)	(-6.87)	(-0.08)		
Oct. 16th							
	-0.0004045	-1.082698***	-0.0216641	0.073569***	-0.0049952	0.3466	1174
	(-1.38)	(-5.75)	(-1.29)	(8.95)	(-1.34)		
Oct. 22nd							
	-0.000406*	-0.5040474***	0.0047591	0.0196474***	-0.004798*	0.2381	1174
	(-1.91)	(-3.70)	(0.39)	(3.30)	(-1.78)		
Oct. 24th							
	-0.000833***	-0.816891***	-0.0283884*	0.0249397***	-0.0119749***	0.2622	1173
	(-2.99)	(-4.58)	(-1.78)	(3.20)	(-3.39)		
Oct. 27th							
	-0.0001321	-0.9638183***	0.0820776***	0.0009157	-0.0119168***	0.1408	1174
	(-0.40)	(-4.60)	(4.38)	(0.10)	(-2.87)		
Panel C: Pooled regression for small crashes							
	0.0000797	-0.4810917***	0.0093012	0.0438717***	-0.0014752	0.1099	4683
	(0.53)	(-5.01)	(1.09)	(10.48)	(-0.78)		

This table shows the regression results when Amihud's illiquidity ratio (ILLIQ) is replaced with DVOL, a proxy for liquidity. DVOL is defined as the logarithm of the average of yen trading volume over the period -252 to -30 days prior to Oct 1st. All the other variables in the regression are the same as those in the original regression (Table 3). The figures in parentheses are the corresponding t-statistics. ***, **, and * indicate 1%, 5% and 10% level of significance respectively.

Table 6. Share returns and the ILLIQ level for the trimmed sample

INTERCEPT	BETA	SIZE	MVBV	ILLIQ	TDTA	LAR	CFPS
Panel A: Pooled regression for large crashes							
0.1506076***	-0.0065414**	-0.007658***	0.0046975***	3.133279***	0.0024715	0.0255988***	-2.62e-07
(10.97)	(-4.43)	(-14.45)	(3.30)	(4.10)	(-0.58)	(3.06)	(-0.31)
Panel B: Individual large crash days							
Oct. 8th							
-0.0426384	-0.0058189*	-0.0001016	0.0003377	4.685341**	-0.0112174	0.0149317	-2.33e-06
(-1.29)	(-1.65)	(-0.08)	(0.10)	(2.41)	(-1.09)	(0.75)	(-1.14)
Oct. 10th							
0.1316859***	-0.0037656	-0.0077208***	0.0099394***	-3.653473*	-0.0221142*	-0.00007	1.59e-06
(3.79)	(-1.01)	(-5.77)	(2.76)	(-1.87)	(-2.04)	(-0.00)	(0.74)
Oct. 16th							
0.2511624***	-0.0161411**	-0.0112025***	0.0057754*	4.475764***	0.003193	0.0374837**	-3.11e-07
(8.35)	(-4.97)	(-9.64)	(1.85)	(2.75)	(0.34)	(2.04)	(-0.17)
Oct. 22nd							
0.2140707***	-0.0023682	-0.0099809***	0.0056755**	3.910365***	-0.0109797	0.0057843	9.50e-07
(9.83)	(-1.01)	(-11.87)	(2.51)	(3.21)	(-1.62)	(0.44)	(0.70)
Oct. 24th							
0.2383337***	-0.010226***	-0.0106011***	0.0016973	4.310359***	0.0037168	0.0226226	-9.86e-07
(8.37)	(-3.33)	(-9.64)	(0.57)	(2.77)	(0.42)	(1.30)	(-0.56)
Oct. 27th							
0.1169308***	-0.0010145	-0.0065388***	0.0050548	4.006983*	0.0218373**	0.0718263***	2.67e-07
(3.53)	(-0.28)	(-5.10)	(1.47)	(2.21)	(2.11)	(3.54)	(-0.13)
Panel C: Pooled regression for small crashes							
-0.0896535***	-0.0072102***	0.0031466***	-0.0004859	3.862431***	-0.0031609	0.0157949*	-1.80e-06*
(-5.93)	(-4.45)	(5.41)	(-0.31)	(4.39)	(-0.67)	(1.72)	(-1.92)

Continued from previous page	BEP	SDLR	LR1	LR2	LR3	Adj. R^2	Obs
Panel A: Pooled regression for large crashes							
	-0.0003309	-0.9873676**	0.0148579	0.0154561***	-0.009209***	0.1190	5746
	(-1.61)	(-9.34)	(1.27)	(3.24)	(-3.71)		
Panel B: Individual large crash days							
Oct. 8th							
	-0.0000684	-1.130355***	0.0437547	0.0436248***	-0.0118985**	0.1200	955
	(-0.14)	(-4.47)	(1.56)	(3.83)	(-1.99)		
Oct. 10th							
	-0.0007893	0.1149754	-0.0288019	-0.0777131***	-0.002127	0.1009	957
	(-1.52)	(0.43)	(-0.97)	(-6.44)	(-0.34)		
Oct. 16th							
	-0.000239	-1.585752***	-0.0044896	0.0803116***	-0.0072766	0.3597	959
	(0.53)	(-6.83)	(-0.17)	(7.67)	(-1.32)		
Oct. 22nd							
	-0.0006231*	-0.6442553***	0.0125341	0.017951**	-0.0044003	0.2668	957
	(-1.91)	(-3.85)	(0.68)	(2.38)	(-1.11)		
Oct. 24th							
	-0.0007798*	-1.045375***	-0.0255981	0.0218155**	-0.0084754	0.2650	959
	(-1.83)	(-4.77)	(-1.05)	(2.20)	(-1.63)		
Oct. 27th							
	0.0000371	-1.656603***	0.0910335***	0.0066216	-0.0218115**	0.1448	959
	(0.07)	(-6.48)	(3.21)	(0.57)	(-3.60)		
Panel C: Pooled regression for small crashes							
	0.0000245	-0.4815548***	0.0009014	0.0452452***	-0.0016139	0.0943	3847
	(0.11)	(-4.16)	(0.07)	(8.68)	(-0.59)		

This table shows the regression results when each variable is trimmed at the 1% and 99% levels to reduce the possibility of outliers biasing the regression results. The dependent variable and the explanatory variables are the same as those in the original regression (Table 4). The figures in parentheses are the corresponding t-statistics. ***, **, and * indicate 1%, 5% and 10% level of significance respectively.

3.5 The Price Limit Rule and the Possible Bias in Results

As previous explained, one feature of the Tokyo Stock Exchange which distinguishes it from other major share markets is the trading rules, in particular the price limit rules. The purpose of these rules is to prevent extreme price movements by setting a maximum and minimum in the range in which the price can move within a day. According to Nobanee *et al.* (2009a), critics of price limits argue that price limits reduce market liquidity, delay price discovery and weaken market efficiency. That is, they reduce the initial price loss, but have no effect on the long-run response (Lauterbach and Ben-Zion, 1993). They can also cause volatility to remain for longer because price limits prevent large one-day changes, and prevent an immediate bounce back. In the case of a share market crash when the prices of shares are falling suddenly and drastically, it is highly possible that a proportion of shares will hit the lower limit, and the daily movement will be limited. AlShattarat *et al.* (2009b) found in their analysis of price limit hits on the Tokyo Stock Exchange that shares of large firms, high beta shares, low market-to-book shares, high volatility shares and relatively less liquid shares tend to hit the lower limits.

Recalling the results of this paper (detailed in Section 3.3), it was found that illiquid shares decrease more in value on crash days, or in other words, that investors sell illiquid assets. This finding is in line with AlShattarat *et al*`s (2009b) result that less liquid shares tend to hit the lower limit, which led us to examine the possibility of bias in the regression results. The proportion of shares whose last ask price is affected by the price limit rules on each individual crash day are detailed in Table 7.

Table 7. Proportion of shares whose last price is affected by the price limit rules

Crash day	Number affected	Percentage of Sample
October 8th	31	0.027%
October 10th	26	0.022%
October 16th	46	0.039%
October 22nd	12	0.010%
October 24th	7	0.006%
October 27th	9	0.008%

On average, approximately 0.02% of shares traded on the first section of the Tokyo Stock Exchange hit the lower price limit on the six selected crash days. Based on these results, it can be concluded that only a small proportion of shares are affected by the price limit rules and the possibility of bias in the results is negligible. Another conclusion to be drawn is that the possibility of reduced market liquidity due to these rules does not appear to impact on investors' behavior, as a flight-to-liquidity is clearly documented. This result raises the question of whether price limit rules are actually effective or not, however that topic is out of scope of this paper.

3.6 Conclusions

In this paper, we explore the flight-to-liquidity phenomenon for shares which are traded on the First Section of the Tokyo Stock Exchange. Through a multivariate regression analysis of the returns of individual shares, we prove the existence of a flight-to-liquidity during share market crashes, specifically during the 2008 market crashes. The illiquidity variable is positive and significant as predicted, which means that illiquid shares decrease more in value on crash days. This occurs as investors rush to sell illiquid assets and purchase more liquid assets, otherwise known as a flight-to-liquidity. Further analysis proved that the results are robust for smaller crash days and when different proxies for illiquidity are employed.

The results are consistent with previous research by Wang *et al.* (2009) and Chang *et al.* (2010), who both found a positive relation between illiquidity and returns during market downturns. We make a significant contribution to the existing literature on share market crashes by examining the role of liquidity during a crash and proving that the flight-to-liquidity phenomenon does indeed exist. The Tokyo Stock Exchange provides a unique setting to test if a flight-to-liquidity occurs even when price limit rules may reduce market liquidity and delay price discovery. The results show that during times of market uncertainty investors are less willing to hold illiquid assets. The price limit rules which limit shares movements and possibly reduce market liquidity and delay price discovery do not appear to impact on the behavior of investors.

Chapter 4: Japanese share returns in the immediate post-crash period

4.1 Introduction

Numerous studies have analyzed share market rebounds and the behavior of shares in the period following a large one-day share market decline. Many papers focus on longer-term rebounds occurring over three to five years, however another group of researchers have analyzed reversals in the short term using weekly and monthly data. This paper focuses on short-run price rebounds that occur over the subsequent days immediately following a share market crash. Other papers in the same category include Cox and Peterson (1994), Bremer and Sweeney (1991) and Bremer *et al.* (1997).

The general finding on post-crash returns is that share prices reverse. Bremer and Sweeney (1991) and Atkins and Dyl (1990) found that price declines of at least 10% are followed by reversals. Specifically, Bremer and Sweeney (1991) document significant positive three-day abnormal returns following days with a price decline of 10% or more. Research by Bremer *et al.* (1997) specifically on the Japanese share market proved that returns for shares listed on the Nikkei 300 tend to be significantly positive after large price declines.

Another finding which has been well documented is a size based lead-lag effect. Research by Lo and MacKinlay (1990) proved that returns of large-capitalization shares almost always lead those of smaller shares listed on the New York Stock Exchange. In their paper, Lo and MacKinlay (1990) document a positive correlation in weekly returns of small firms and the lagged weekly returns of large firms. Their analysis found virtually no correlation between the returns of large shares and lagged small shares returns. They argue that this size based lead-lag relation is important because it indicates the transmission of information from large firms to small firms. Similarly, Mills and Jordanov (2000) documented a very similar pattern on the London stock exchange. Their research proved that a lead-lag relation exists between portfolios of small firms and large firms constructed from the London stock exchange. Badrinath *et al.* (1995) analyze the process of information transmission between firms and show that for size-based portfolios a one month lead-lag relation exists, and for institutional ownership-based portfolios, portfolios of high institutional ownership lead the returns on portfolios with lower institutional ownership by up to two months.

While studies based on different share markets have proved that a lead-lag relation exists, the exact cause of it is still unclear. If market imperfections do not exist, then it would be expected that information transmission is instantaneous. Therefore researchers have attributed the lead-lag effect to the "thin trading" problem, noise traders, market liquidity, herd behavior, or as Jegadeesh and Titman (1995) suggest, to delayed reactions to common factors. Alternatively, Badrinath *et al.* (1995) suggest that firm size may proxy for the magnitude of information produced.

The aim of this paper is to examine the behavior of shares listed on the First Section of the Tokyo Stock Exchange in the period immediately following a large one-day share market decline. The event days are limited making it a small event study, nevertheless the results prove that a lead-lag relation exists on the Japanese share market. The First Section of the Tokyo Stock Exchange lists the largest and most traded shares in the Japanese market. It is an appropriate choice for this study for two main reasons. Firstly, Japan is an important and large market which requires attention, and secondly because it provides a market with a significantly different structure and trading rules on which to investigate if the lead-lag relation is due to institutional features or fundamental behavior of traders.

This study follows the methodology of Wang *et al.* (2009), and utilizes a multivariate regression with the three day post-crash returns as the dependent variable. Wang *et al.* (2009) studied the returns of individual shares on the American market on crash days and during the post-crash period, and found that shares of large firms lead small firms on crash days, and also that large shares lead small shares in the immediate three-day post-crash period. In other words, the results show that large firms respond faster to new information. For the purpose of this study, a three day timeframe was selected to be the post-crash period, as other researchers such as Bremer and Sweeney (1991), in addition to Wang *et al.* (2009) have based their analysis on these days.

The results are consistent with previous literature, and reveal that a size based lead-lag relation exists. The sign for the size variable supports the finding that large firms respond faster to new information, whether it is good news or bad news. This paper contributes to financial literature in two ways. The first aim is to provide new evidence using recent data regarding share return behavior following large one-day share market declines on the Japanese market. Bremer *et al.* (1997) analyzed events during the 1980`s, while we have used events which occurred over twenty years later during 2008, meaning this study provides new evidence on share behavior. The second aim is to confirm that the results of Wang *et al.* (2009) are identical on the Japanese market, despite the trading rules being significantly different to the American market.

The remainder of this paper is as follows. Section 4.2 discusses the data utilized in this study and section 4.3 explains the methodology used. The empirical results and the robustness tests are discussed in section 4.4, and the results are summarized in section 4.5.

4.2 Data

This study specifically focuses on the individual shares listed on the First Section of the Tokyo Stock Exchange. The First Section comprises the largest shares on the Japanese share market, providing an ideal sample to test the existence of the lead-lag effect post large one-day share market declines.

We have followed the methodology of Wang *et al.* (2009) and classified a crash date as a daily decrease in the TOPIX index of more than 5%. The six specific dates selected to be analyzed are the 8^{th} of October, 10^{th} of October, 16^{th} of October, 22^{nd} of October, 24^{th} of October and the 27^{th} of October 2008. As detailed in Table 1, the daily decrease in the index on all of these dates is reasonably large, ranging between -7% and -10%. As previously stated, in order to analyze share behavior in the post-crash period, the cumulative return over the three days immediately following the crash is utilized as other researchers such as Wang *et al.* (2009) and Bremer (1991) have done. The cumulative three day return is calculated as:

$$RET_i = (P_{it+3} - P_{it}) / P_{it} \tag{1}$$

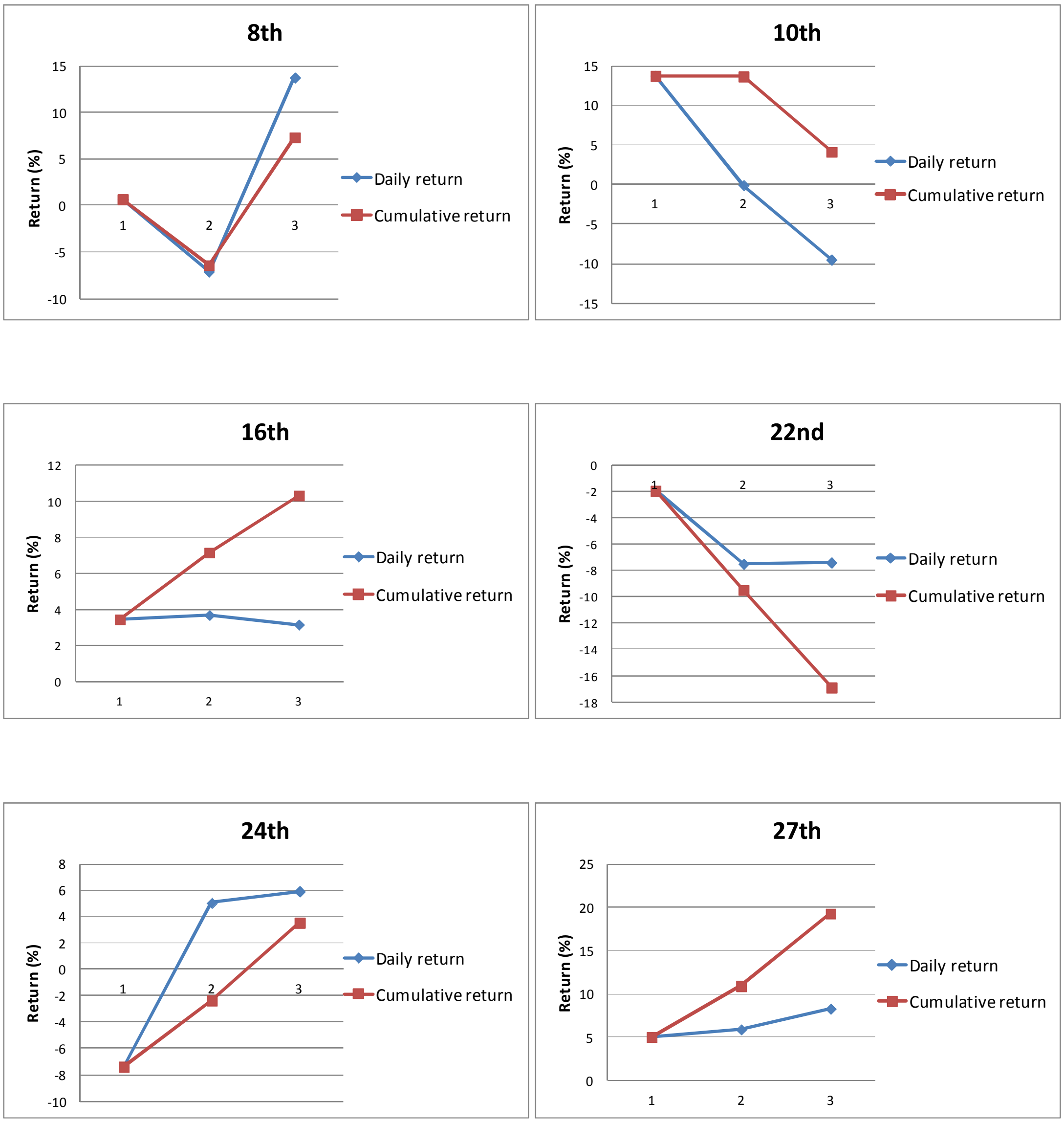
Where RET_i denotes the three day cumulative return of share *i*, P_{it+3} denotes the share price at time *t+3*, and P_{it} denotes the share price at time *t,* the crash day. Table 1 summarizes the selected dates and data employed in this event study.

Table 1. Crash days, crash day returns and post-crash returns

Date	Daily decrease in TOPIX %	Cumulative post-crash three day return %	Sample size
8th October 2008	-8.04	6.37	1170
10th October 2008	-7.1	2.81	1171
16th October 2008	-9.52	10.66	1174
22nd October 2008	-7.05	-16.06	1174
24th October 2008	-7.5	3.0	1173
27th October 2008	-7.4	20.48	1174

The magnitude of the three day post-crash cumulative return varies significantly depending on the date. As Figure 1 shows, the index had three consecutive days of positive returns for the 16th and 27th, three consecutive negative returns for the 22nd, and a combination of both positive and negative returns for the 8th, 10th and 24th. This variation in the pattern of returns is one reason why these six dates were selected, and it is promising that the analysis may produce interesting results.

Figure 1. Graphs of the three day cumulative returns and daily returns



Data on the TOPIX index, closing prices for individual shares, plus all financial data and ratios is obtained from the Nikkei Economic Electronic Databank System (NEEDS). The financial statements data is obtained from the firm`s annual financial statements in the NEEDS database for the previous financial year.

Following Fama and French (1992) and Wang *et al.* (2009), utilities and financial firms are excluded from the analysis. Utilities are excluded because their financial decisions are affected by regulation and financial firms are excluded because their financial ratios are not comparable to those of industrial firms. To be included in the data set, a firm must be listed on the First section, have a share price for both the crash date and the previous day, and have all other required data. Excluding shares which fail to meet the data requirements and utilities and financial firms reduced the sample size by approximately 500 shares, however the sample is still reasonably large at approximately 1174.

4.3 Methodology

4.3.1 Hypothesis

We hypothesize that the lead-lag relation documented by Lo and MacKinlay (1990) exists in the days immediately following a large one-day market decline. That is, that large share returns lead small share returns on the First Section of the Tokyo Stock Exchange. In this study, the post-crash three day cumulative return is the dependent variable in a multivariate regression, with twelve independent variables, all of which have explanatory effects on share returns.

If the share market experiences a reversal after the large decline, then for the lead-lag relation to hold, we predict that the size variable will be positive and significant in the regressions. A positive sign will indicate that larger firms have higher post-crash returns, and imply that large firms respond faster to new information. In other words, a positive sign will imply that a size-based lead-lag relation exists in the days immediately following a large market decline. In previous research by Wang *et al.* (2009) the sign variable is positive as reversals occurred.

If however the share market continues declining in the following days, then we predict that the size variable will be negative and significant as a negative sign will indicate that large firms decrease more in value than small firms. Wang *et al.* (2009) likewise found that size is negative on crash days.

Therefore, if our research proves that size is positive when the market is trending upward in the days following a large decline, and negative when the market is continuing to trend downward, it will imply that large firms respond faster to new information and a size-based lead-lag relation exists. To be specific, we predict that for the 10^{th} and 22^{nd} size will be negative as the cumulative return is trending down, and for the other four days it will be positive as it is generally trending upward, as depicted in the graphs in Figure 1.

4.3.2 The Model

For the purpose of our study, we have followed the methodology of Wang *et al.* (2009), with the only difference being the exclusion of the industry dummy variable. Wang *et al.* (2009) employed a multivariate regression analysis to determine how firm characteristics affect returns on both crash days and in the three day post-crash period.

As stated in section 3.1, this study employs a multivariate regression with the post-crash three day cumulative return as the dependent variable and twelve independent variables, all of which are believed to have explanatory effects on share returns. For simplicity, the independent variables are calculated as of the 1^{st} of October, 2008. The linear regression model:

$$RET_{it} = \beta_0 + \beta_1 BETA + \beta_2 SIZE + \beta_3 MVBV + \beta_4 ILLIQ + \beta_5 TDTA + \beta_6 LAR + \beta_7 CFPS + \beta_8 BEP + \beta_9 SDLR + \beta_{10} LR1 + \beta_{11} LR2 + \beta_{12} LR3 + e_t \quad (2)$$

In this model the dependent variable RET_{it}, is the cumulative share return for the three trading days immediately after the crash day. The cumulative three day post-crash share return RET_{it} is calculated using equation (1). β_0 is the a constant and β_1, β_2 ... β_{12} are the regression coefficients. There are twelve independent variables included in the model. *BETA* is the CAPM beta of the share computed with monthly return data for the five year period from January 2002 to December 2006. *SIZE* is the logarithm of the firm's market capitalization, calculated as the average of the daily figures for the year directly prior to October 1st. *MVBV* is the market-to-book ratio, calculated as the average of the weekly M/B ratios for the year directly prior to October 1st. *ILLIQ* is the illiquidity ratio employed by Amihud (2002), calculated as:

$$ILLIQ = \frac{1}{Di} \sum_{t=1}^{Di} \frac{|Ri|}{VOLDi\ d} *1000$$

Where R_i is the share i`s daily returns, $VOLD_{id}$ is the daily volume, and D_i is the number of days in the period -252 to -30 days prior to October 1st for which it traded. We have following the methodology of Wang *et al.* (2009) and multiplied the Amihud ratio by 1000 to scale the figure. *TDTA* is the debt ratio (total debt / total assets) and *LAR* is the liquid assets ratio [(cash + marketable securities) / total assets], both calculated from the previous year's financial statements. *CFPS* is the cash flow per share, and *BEP* is the basic earning power ratio (EBIT / total assets). *SDLR* is the standard deviation of the lagged share returns from -252 to -30 days prior to October 1st. In addition, three lagged returns are included in the model: *LR1* (lagged return 1) which is the cumulative return from -7 to -2 days prior to October 1st, *LR2* (lagged return 2) which is the cumulative return from -70 to -2 days prior to October 1st, and *LR3* (lagged return 3) which is the cumulative return from -756 to -2 days prior to October 1st.

4.3.3 Control Variables

In Section 4.3.1 our predictions regarding the size variable are explained. In this section, we detail our predictions for the other eleven control variables included in the regression. Since this event study contains both days which are followed by positive reversals and days with continued negative declines, both situations are considered.

For beta, since beta measures the volatility of a share compared to the market, it is predicted that when the share market is declining beta will be negative and when the market is reversing upward that beta will be positive. Market-to-book is not expected to be highly significant, reflecting the results of Wang *et al.* (2009). The illiquidity variable is predicted to be positive as Amihud (2002) documented a positive cross-sectional relationship between illiquidity and share returns, which signifies that illiquid shares reaction is smaller in magnitude compared to liquid shares. For the debt ratio we predict the sign to be negative during a market decline as firms with high debt are considered to have higher risk and be positive during a market reversal. The liquid assets variable is expected to be negative as Wang *et al.* (2009) found, however not highly significant. For cash flow, we predict it to be negative during a positive market reversal and positive during days when the market is trending down. The basic earning power ratio is expected to be positive as more profitable firms decrease less in value during crashes. Regarding the standard deviations of lagged returns variable, it is predicted that shares which are highly volatile prior to a market decline will continue to be more volatile after the decline. As such, we predict this variable to be negative if the market is continuing to decrease and positive if the market is reversing. For the three lagged return variables we cannot make justified predications as it will vary depending on the day.

4.3.4 Descriptive Statistics

The descriptive statistics of the variables used in the analysis are detailed in Table 2. The mean return figures in the table are lower than the figures for the TOPIX index, suggesting that larger firms have higher returns than small firms in the immediate post-crash period. Positive skewness is present in the majority of the variables, which is reasonable during volatile times.

Table 2. Descriptive statistics of the variables

Variables	Mean	Std. Dev	Skewness	Kurtosis	Maximum	Minimum
8th October						
RET	0.6766	12.0928	23.9320	578.7373	304.1948	-0.9965
BETA	0.9958	0.6092	4.7950	58.8562	9.7847	-0.3876
SIZE	24.8257	1.5648	0.6449	2.9973	30.5853	21.7333
MVBV	1.2902	0.8738	2.7252	15.1957	8.3837	0.2597
ILLIQ	0.0006	0.0019	9.5121	117.5535	0.0287	0.0000
TDTA	0.5026	0.1962	-0.1171	2.1749	0.9311	0.0416
LAR	0.1294	0.0979	1.7294	7.5788	0.7321	0.0006
CFPS	1326.3980	13914.5400	15.7776	280.4415	280912.500	-2083.6500
BEP	6.1789	5.2751	1.0311	9.9188	46.3900	-25.3400
SDLR	0.0271	0.0079	1.0638	6.3403	0.0819	0.0056
LR1	-0.0397	0.0717	4.7154	73.8085	1.1235	-0.4321
LR2	-0.1655	0.1704	0.2582	3.3447	0.6111	-0.7573
LR3	-0.2499	0.3676	2.3408	17.0627	3.1548	-0.9844
10th October						
RET	0.0569	0.0761	0.5620	4.8682	0.4759	-0.2894
BETA	0.9956	0.6093	4.7886	58.7802	9.7847	-0.3876
SIZE	24.8283	1.5666	0.6433	2.9884	30.5853	21.7333
MVBV	1.2912	0.8737	2.7214	15.1801	8.3837	0.2597
ILLIQ	0.0006	0.0020	9.2213	107.6823	0.0287	0.0000
TDTA	0.5027	0.1962	-0.1181	2.1767	0.9311	0.0416
LAR	0.1293	0.0979	1.7308	7.5834	0.7321	0.0006
CFPS	1325.5490	13908.6200	15.7845	280.6825	280912.500	-2083.6500
BEP	6.1817	5.2745	1.0294	9.9128	46.3900	-25.3400
SDLR	0.0271	0.0079	1.0636	6.3430	0.0819	0.0056
LR1	-0.0397	0.0717	4.7177	73.8713	1.1235	-0.4321
LR2	-0.1654	0.1704	0.2559	3.3439	0.6111	-0.7573
LR3	-0.2499	0.3675	2.3419	17.0726	3.1548	-0.9844
16th October						
RET	0.0957	0.0642	-0.3869	5.3376	0.3188	-0.3315
BETA	0.9952	0.6086	4.7946	58.9088	9.7847	-0.3876
SIZE	24.8271	1.5649	0.6457	2.9956	30.5853	21.7333
MVBV	1.2901	0.8729	2.7247	15.2076	8.3837	0.2597
ILLIQ	0.0006	0.0020	9.0768	105.2207	0.0287	0.0000
TDTA	0.5027	0.1959	-0.1187	2.1806	0.9311	0.0416
LAR	0.1293	0.0978	1.7310	7.5896	0.7321	0.0006
CFPS	1322.4620	13890.9600	15.8049	281.4047	280912.500	-2083.6500
BEP	6.1770	5.2704	1.0308	9.9230	46.3900	-25.3400
SDLR	0.0271	0.0079	1.0661	6.3524	0.0819	0.0056
LR1	-0.0397	0.0716	4.7175	73.9409	1.1235	-0.4321
LR2	-0.1649	0.1705	0.2517	3.3327	0.6111	-0.7573
LR3	-0.2496	0.3672	2.3397	17.0751	3.1548	-0.9844

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Variables	Mean	Std. Dev	Skewness	Kurtosis	Maximum	Minimum
22nd October						
RET	-0.1298	0.0740	-0.0735	3.0830	0.1542	-0.3682
BETA	0.9953	0.6086	4.7949	58.9193	9.7847	-0.3876
SIZE	24.8277	1.5646	0.6451	2.9964	30.5853	21.7333
MVBV	1.2902	0.8728	2.7254	15.2127	8.3837	0.2597
ILLIQ	0.0006	0.0020	9.0929	105.5163	0.0287	0.0000
TDTA	0.5025	0.1960	-0.1158	2.1784	0.9311	0.0416
LAR	0.1292	0.0978	1.7348	7.6034	0.7321	0.0006
CFPS	1322.5060	13890.9500	15.8049	281.4048	280912.500	-2083.6500
BEP	6.1824	5.2678	1.0304	9.9374	46.3900	-25.3400
SDLR	0.0271	0.0079	1.0643	6.3451	0.0819	0.0056
LR1	-0.0397	0.0716	4.7187	73.9591	1.1235	-0.4321
LR2	-0.1652	0.1704	0.2546	3.3410	0.6111	-0.7573
LR3	-0.2497	0.3673	2.3399	17.0732	3.1548	-0.9844
24th October						
RET	0.0454	0.0747	0.0381	4.8746	0.3687	-0.4051
BETA	0.9959	0.6085	4.7994	58.9824	9.7847	-0.3876
SIZE	24.8242	1.5631	0.6480	3.0050	30.5853	21.7333
MVBV	1.2891	0.8731	2.7273	15.2175	8.3837	0.2597
ILLIQ	0.0006	0.0020	9.1257	106.0865	0.0287	0.0000
TDTA	0.5027	0.1961	-0.1190	2.1777	0.9311	0.0416
LAR	0.1293	0.0978	1.7297	7.5828	0.7321	0.0006
CFPS	1323.2940	13896.8500	15.7981	281.1635	280912.500	-2083.6500
BEP	6.1737	5.2711	1.0327	9.9286	46.3900	-25.3400
SDLR	0.0271	0.0079	1.0622	6.3478	0.0819	0.0056
LR1	-0.0397	0.0717	4.7175	73.9135	1.1235	-0.4321
LR2	-0.1654	0.1703	0.2564	3.3453	0.6111	-0.7573
LR3	-0.2500	0.3672	2.3438	17.0996	3.1548	-0.9844
27th October						
RET	0.1867	0.1141	0.2149	3.1124	0.6278	-0.2216
BETA	0.9957	0.6083	4.8014	59.0214	9.7847	-0.3876
SIZE	24.8243	1.5625	0.6481	3.0074	30.5853	21.7333
MVBV	1.2888	0.8728	2.7289	15.2301	8.3837	0.2597
ILLIQ	0.0006	0.0020	9.0587	104.9076	0.0287	0.0000
TDTA	0.5027	0.1960	-0.1179	2.1786	0.9311	0.0416
LAR	0.1293	0.0978	1.7310	7.5899	0.7321	0.0006
CFPS	1322.3980	13890.9600	15.8049	281.4045	280912.500	-2083.6500
BEP	6.1737	5.2689	1.0331	9.9370	46.3900	-25.3400
SDLR	0.0271	0.0079	1.0634	6.3498	0.0819	0.0056
LR1	-0.0397	0.0716	4.7167	73.9354	1.1235	-0.4321
LR2	-0.1651	0.1704	0.2548	3.3384	0.6111	-0.7573
LR3	-0.2496	0.3672	2.3397	17.0741	3.1548	-0.9844

4.4 Empirical Results

4.4.1 Regression results

The regression results on the post-crash share returns for the six chosen dates are shown in Table 3. To ensure that multicollinearity between the variables is not an issue, variance inflation (VIF) tests are carried out. As shown in Table 3, the figures for the variance inflation tests are in the range of 1.0 and 2.0, which is significantly low indicating that multicollinearity is not a problem in the regressions.

As detailed in Table 3, the size variable is positive in the post-crash period for the 8^{th}, 16^{th}, 24^{th} and the 27^{th}, and highly significant for the 8^{th}, 24^{th} and 27^{th}. Size is negative and highly significant at the 1% level for the 10^{th} and 22^{nd}, as the cumulative return is trending downward over both of these three day periods. The results are in line with the predictions detailed in section 4.3.1, and imply that larger firms increase more than small firms when the market is trending upward in the days following a large decline, and decrease more in value when the market continues to trend downward. This result suggests that large firms respond faster to new information and a size-based lead-lag relation exists. Our results support previous research by Wang *et al.* (2009), which documented the existence of a lead-lag relation in the post-crash period on the American share market for seven out of eight crashes, and is consistent with research by Lo and MacKinlay (1990), which proved that returns of large shares lead those of smaller shares. Wang *et al.* (2009) specifically documented that on crash days the size variable is negative and in the post-crash period is positive.

The results for the eleven control variables are similar to our predictions in section 4.3.3 however significance is lower than that for the size variable, suggesting that in the period following a large market decline size has the highest influence on share returns. The results for the control variables can be summarized as follows. Beta has mixed results however only the 8^{th} has significance at the 10% level. Similarly, the sign for market-to-book variable is mixed and only highly significant for two of the eight days. The results for illiquidity are not as strong as expected, as the sign is positive for only two days and only one day has high significance. Overall the debt ratio is found to not be significant, which is similar to the findings in Wang *et al.* (2009), and the results for cash flow are mixed as the 10th and 22nd are positive and significant, and the 24th and 27th are negative and significant. For the basic earning power ratio, the sign is negative for four days however overall high significance is not evident. The results for the standard deviations of lagged returns variable is as expected, with a negative sign and high significance for the 10th, 16th, 22nd and 24th and for the 27th is positive and significant as the three day post-crash period contains three positive daily returns. The returns for the lagged variables are mixed and vary in the level of significance depending on the day.

The regression results indicate that larger firms respond faster to new information, and that a size based lead-lag relation exists in the days immediately following a large market decline on the Japanese share market. Previous studies focus on dates which are followed by positive reversals, and as such, they conclude that the size variable is positive and positive abnormal returns exist. This study analyses dates with both positive reversals and continued negative declines, meaning that the sign of the size variable depends on the trend of the share market. Nevertheless, the results imply that a size-based lead-lag relation exists with large firms responding faster to new information.

Table 3. Post-crash share returns

Explanatory variables	Oct. 8, 2008	VIF	Oct. 10, 2008	VIF	Oct. 16, 2008	VIF	Oct. 22, 2008	VIF	Oct. 24, 2008	VIF	Oct. 27, 2008	VIF
Intercept	-14.5406**		0.4882***		0.0926**		0.3470***		-0.1567***		-0.6917***	
	(7.26)		(0.043)		(0.038)		(0.037)		(0.044)		(0.056)	
BETA	-1.0624*	1.2	0.0019	1.2	0.0013	1.2	-0.0047	1.2	0.0008	1.2	0.0068	1.2
	(0.642)		(0.004)		(0.003)		(0.003)		(0.004)		(0.005)	
SIZE	0.6961**	1.5	-0.0172***	1.5	0.0012	1.5	-0.0174***	1.5	0.0087***	1.5	0.0328***	1.5
	(0.279)		(0.002)		(0.001)		(0.001)		(0.002)		(0.002)	
MVBV	0.8011	2.0	0.0170***	2.0	-0.0003	2.0	0.0054*	2.0	-0.0046	2.0	-0.0146***	2.0
	(0.575)		(0.003)		(0.003)		(0.003)		(0.003)		(0.004)	
ILLIQ	1.2233	1.0	-0.2604	1.0	-1.6265*	1.0	1.6854*	1.0	-1.5623	1.0	-4.2649***	1.0
	(194.716)		(1.100)		(0.974)		(0.953)		(1.120)		(1.42)	
TDTA	-3.2636	1.9	0.0139	1.9	-0.0160	1.9	0.0274**	1.9	0.0012	1.9	-0.0013	1.9
	(2.532)		(0.015)		(0.013)		(0.013)		(0.015)		(0.019)	
LAR	-6.7493	1.5	-0.0081	1.5	-0.0632***	1.5	0.0930***	1.5	-0.007	1.5	-0.1283***	1.5
	(4.465)		(0.027)		(0.024)		(0.023)		(0.027)		(0.034)	
CFPS	0.0000	1.0	0.0000**	1.0	-1.31e-07	1.0	0.0000***	1.0	-0.0000**	1.0	-0.0000***	1.0
	(0.000)		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)	
BEP	-0.0727	1.8	-0.0008	1.8	-0.0000	1.8	-0.0014***	1.8	0.0010*	1.8	0.0032***	1.8
	(0.091)		(0.001)		(0.000)		(0.000)		(0.000)		(0.001)	
SDLR	20.4406	1.4	-1.1746***	1.4	-0.5273*	1.4	-2.3448***	1.4	-0.5435*	1.4	2.3802***	1.4
	(53.123)		(0.316)		(0.281)		(0.275)		(0.322)		(0.411)	
LR1	2.1083	1.1	-0.0311	1.1	-0.0032	1.1	0.0228	1.1	0.0270	1.1	-0.0738*	1.1
	(5.237)		(0.031)		(0.028)		(0.027)		(0.032)		(0.041)	
LR2	1.5138	1.5	0.0269*	1.5	-0.0363***	1.5	0.0589***	1.5	-0.0165	1.5	-0.1079***	1.5
	(2.557)		(0.015)		(0.014)		(0.013)		(0.015)		(0.020)	
LR3	-2.6144**	1.4	-0.0178***	1.4	0.0089	1.4	-0.0314***	1.4	0.0030	1.4	0.0312***	1.4
	(1.160)		(0.007)		(0.006)		(0.006)		(0.007)		(0.009)	
Adjusted R-squared	0.0084		0.1163		0.0131		0.2903		0.0409		0.3322	
Number of firms	1170		1171		1174		1174		1173		1174	

This table shows the results when the three day post-crash cumulative returns are regressed on twelve explanatory variables. The variance inflation factor (VIF) test is used to test for multicollinearity. The figures in parentheses are the corresponding standard errors. ***, **, and * indicate 1%, 5% and 10% level of significance respectively.

4.4.2 Robustness tests

In this section of our study, several robustness tests on the multivariate regression are presented. The first robustness test reruns the regression with a different proxy for illiquidity. In the original regression the illiquidity variable was calculated as the Amihud ratio, however for this part of the analysis the natural logarithm of the average of yen trading volume over a specified period, DVOL, is employed as a proxy for liquidity (Brennan *et al.* 1998). The results are shown in Table 4.

The size variable is positive and highly significant at the 1% level for the 8th, 24th and 27th, and negative and highly significant at the 1% level for the 10th and 22nd. These results indicate that our findings in the three day post-crash period are robust to the use of a different proxy for illiquidity, or in this case, substituting with a proxy for liquidity. The main conclusion to be drawn from this is that a lead-lag relation exists in the period following a large share market decline. The results for the control variables are mixed and no distinct pattern in the sign or significant levels is evident, as was documented in the original regression in Table 3.

As a second robustness test, the original sample is trimmed to reduce the possibility of outliers biasing the regression results. Each variable is trimmed at the 0.05% and 99.5% levels to ensure that the possibility of large outliers biasing the results is eliminated. Wang *et al.* (2009) used a similar test in their research on American share market crashes, leading us to replicate it as a robustness test. The regression results with all variables trimmed are presented in Table 5. The results are virtually identical, with the only difference being that the significance level for size on the 8th has decreased.

As an additional robustness test the regression results including the DVOL variable as a proxy for liquidity were trimmed, and produced virtually the same results as Table 4, however they have not been included in this paper.

The three robustness tests all lead to the conclusion that the original regression results are robust, and that a size based lead-lag relation exists in the period following a large share market decline on the Tokyo Stock Exchange.

Table 4. Robustness test results for the ILLIQ variable

Explanatory variables	Oct. 8, 2008	Oct.10, 2008	Oct.16, 2008	Oct. 22, 2008	Oct. 24, 2008	Oct. 27, 2008
Intercept	-25.7498***	0.4385***	0.1247***	0.2936***	-0.1552***	-0.5899***
	(8.313)	(0.049)	(0.044)	(0.043)	(0.050)	(0.064)
BETA	-0.7506	0.0032	-0.0000	-0.0029***	0.0004	0.0031
	(0.651)	(0.004)	(0.003)	(0.003)	(0.004)	(0.005)
SIZE	1.4446***	-0.0139***	-0.0014	-0.0134***	0.0082***	0.0249***
	(0.400)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
MVBV	0.6541	0.0163***	-0.0000	0.0050*	-0.0048	-0.0138***
	(0.574)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)
DVOL	-0.7976**	-0.0034*	0.0032**	-0.0048***	0.0010	0.0097***
	(0.311)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
TDTA	-1.6377	0.0213	-0.020	0.0347**	0.0015	-0.0146
	(2.586)	(0.015)	(0.014)	(0.013)	(0.016)	(0.020)
LAR	-7.848*	-0.0126	-0.0590**	0.0869***	-0.0059	-0.1154***
	(4.473)	(0.027)	(0.024)	(0.023)	(0.027)	(0.035)
CFPS	0.0000	2.17e-07	-4.79e-08	4.49e-07***	-3.28e-07*	-6.54e-07***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
BEP	-0.0886	-0.0008	0.0001	-0.0015***	0.0010*	0.0034***
	(0.091)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)
SDLR	85.4761	-0.8971***	-0.7890**	-1.9568***	-0.6247*	1.5982***
	(58.746)	(0.349)	(0.310)	(0.302)	(0.356)	(0.452)
LR1	2.1968	-0.0306	-0.0035	0.0233	0.0270	-0.0745*
	(5.222)	(0.031)	(0.028)	(0.027)	(0.032)	(0.040)
LR2	1.0912	0.0250	-0.0344**	0.0561***	-0.0159	-0.1023***
	(2.555)	(0.015)	(0.014)	(0.013)	(0.016)	(0.020)
LR3	-2.589*	-0.0176**	0.0091	-0.0315***	0.0032	0.0317***
	(1.156)	(0.007)	(0.006)	(0.006)	(0.007)	(0.009)
Adjusted R-squared	0.0140	0.1189	0.0142	0.2940	0.0395	0.3367
Number of firms	1170	1171	1174	1174	1173	1174

This table shows the robustness test results when ILLIQ is replaced with a different proxy for illiquidity. That is, the results when ILLIQ (Amihud`s illiquidity ratio) is replaced with DVOL, a figure relating to trading volume. The figures in parentheses are the corresponding standard errors. ***, **, and * indicate 1%, 5% and 10% level of significance respectively.

Table 5. Post-crash share returns and the ILLIQ level for the trimmed sample

Explanatory variables	Oct. 8, 2008	Oct. 10, 2008	Oct. 16, 2008	Oct. 22, 2008	Oct. 24, 2008	Oct. 27, 2008
Intercept	-2.4600	0.4772***	0.0932**	0.3595***	-0.1299***	-0.6645***
	(8.292)	(0.049)	(0.043)	(0.043)	(0.050)	(0.064)
BETA	-1.8080**	-0.0110**	0.0058	-0.0093**	-0.0009	0.0120*
	(0.922)	(0.005)	(0.005)	(0.005)	(0.006)	(0.007)
SIZE	0.2653	-0.0170***	0.0011	-0.0175***	0.0078***	0.0316***
	(0.319)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
MVBV	1.4527*	0.0147***	-0.0039	0.0091**	-0.0075	-0.0211***
	(0.816)	(0.005)	(0.004)	(0.004)	(0.005)	(0.006)
ILLIQ	-1105.783***	-0.2345	-1.970	1.6689	-6.6372***	-12.2605***
	(401.613)	(2.394)	(2.071)	(2.033)	(2.406)	(3.015)
TDTA	-4.1837	0.0312*	-0.0170	0.0259*	0.0063	-0.0118
	(2.758)	(0.016)	(0.015)	(0.014)	(0.017)	(0.021)
LAR	-6.553	-0.0056	-0.0462*	0.0732***	-0.0036	-0.1153***
	(5.069)	(0.030)	(0.027)	(0.026)	(0.031)	(0.039)
CFPS	0.0013***	1.47e-06**	-1.47e-06**	-1.08e-06*	1.69e-06**	2.12e-06**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
BEP	-0.1254	-0.0001	-0.0001	-0.0013**	0.0012	0.0027***
	(0.121)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
SDLR	-10.2321	-1.0370***	-0.4791	-2.7056***	-0.6435*	2.9508***
	(64.071)	(0.378)	(0.336)	(0.330)	(0.386)	(0.490)
LR1	1.1406	0.0125	-0.0409	0.0737**	0.0092	-0.1472***
	(7.275)	(0.043)	(0.038)	(0.037)	(0.044)	(0.056)
LR2	0.4560	-0.0143	-0.0459***	0.0533***	-0.0178	-0.1056***
	(2.922)	(0.017)	(0.015)	(0.015)	(0.018)	(0.022)
LR3	-2.575*	-0.0248***	0.0186**	-0.0418***	0.0017	0.0425***
	(1.501)	(0.009)	(0.008)	(0.008)	(0.009)	(0.012)
Adjusted R-squared	0.1078	0.1164	0.0224	0.2927	0.0393	0.3377
Number of firms	1064	1064	1067	1067	1066	1067

This table shows the regression results when each explanatory variable is trimmed at the 99.5% and 0.5% levels to reduce the effect of outliers on the regression. The figures in parentheses are the corresponding standard errors. ***, **, and * indicate 1%, 5% and 10% level of significance respectively.

4.5 Conclusion

This paper investigates the returns of individual shares in the three day period following a large one-day market decline, otherwise known as a share market crash. The regression results show that large shares lead small shares, meaning that a lead-lag relation exists. The results are similar to those of Wang *et al.* (2009) using data on the American share market, and support previous research by Lo and MacKinlay (1990).

This event study is based on the data of approximately 1,174 shares listed in the First Section of the Tokyo Stock Exchange, meaning that the sample is composed of the largest and most frequently traded shares in the Japanese market. This study differs from other research as it analyses dates with both subsequent positive reversals and continued negative declines. Our analysis of six event days shows that when the share market is trending upward in the days following a large one-day decline the size variable is positive, and when the market is continuing to trend downward the size variable is negative. Larger firms have higher returns when the market is trending upward in the days immediately following a large decline, and decrease more in value when the market continues to trend downward. This result can be interpreted as the sign of the size variable in the regression being dependent on the trend of the share market. By analyzing dates with both subsequent positive reversals and continued negative declines, we can draw the conclusion that large firms respond faster to new information whether it be good news or bad news. Our research confirms that there is a definite relationship between firm size and share returns, and that a size-based lead-lag relation exists.

This paper contributes to financial literature by providing new evidence using recent data regarding share return behavior following large one-day share market declines on the Japanese market. Significant positive returns after large price declines are reported for the four events with an upward market trend, in line with the findings of Bremer *et al.* (1997). Furthermore, the analysis confirms that the results of Wang *et al.* (2009) are identical on the Japanese market. In other words, the data supports the existence of a lead-lag relation between large shares and small shares. As originally discovered by Lo and MacKinlay (1990), transmission of information from large firms to small firms occurs, with large firms responding faster to new information.

Our findings show that Japan has similar patterns regarding post-crash share returns to both America, as documented by Wang *et al.* (2009) and England, as replicated by Mills and Jordanov (2010). Considering that the Japanese market varies considerably to both of these markets with regards to trading rules, the fact that a lead-lag relation exists on all three markets suggests that it is due to fundamental behavior of traders as opposed to institutional features. Researchers are still unsure of the exact cause of the lead-lag relationship, however as Badrinath *et al.* (1995) suggests, it is possible that firm size may proxy for the magnitude of information produced.

Chapter 5: Conclusions

The research presented in this thesis is based on the analysis of share prices and returns of shares which are listed on the Tokyo Stock Exchange. Part of the research focuses solely on the First Section, which has the largest, frequently traded shares listed on it, and another part of the research focuses on shares listed on both the First Section and the Second Section of the exchange. The objectives of this thesis are two-fold, by examining the returns of shares listed on the Tokyo Stock Exchange it is hoped to gain knowledge on the efficiency of the share market, and to see if institutional features affect the behavior of investors.

Fama described market efficiency as being when security prices fully reflect all available information, to the point where the marginal benefits of acting on information do not exceed the marginal costs. The research in this thesis is linked to the semi-strong form, which is concerned with whether current security prices ‘fully reflect’ all obviously publicly available information, and the speed of price adjustment to new publicly available information. Fama states that “the cleanest evidence on market-efficiency comes from event studies, especially event studies on daily returns” (p.1607). For the purpose of this thesis, share market crashes and post-crash periods were selected as the events to be analyzed. A crash, as defined by Garber (1992) is an abrupt decline in the value of securities. Share market crashes are ideal events to study to gain knowledge on the issue of share market efficiency and investor behavior.

The trading rules on the Tokyo Stock Exchange differ from other countries, with one example being the price limit rules, which restrict daily movements of shares and can possibly impact on market efficiency. This setting makes it an ideal choice to study the returns of shares listed on the Tokyo Stock Exchange, as it indirectly examines if the trading rules have an obvious effect on behavior. As such, the objectives of this thesis are two-fold, to gain knowledge on the efficiency of the share market, and to see if institutional features, such as trading rules, affect the behavior of investors. First, the main results of the research can be summarized as follows:

Chapter two presents research which analyzes the performance of a relatively new asset pricing model, known as the q-factor model, developed by Hou *et al*. (2015). This research tests the performance of the model for shares listed on both the First Section and Second Section of the Tokyo Stock Exchange. The results suggest that the q-factor model does not adequately explain returns for shares listed on the Tokyo Stock Exchange. The Fama French three-factor model is generally considered to be the most appropriate model for Japan, hence for comparison purposes, the data sample is applied to the three-factor model. The results draw us to conclude that the Fama French three-factor model is more appropriate for the Japanese share market. Despite evidence that there is a strong value effect in Japan, the factor which correlates to the value factor in the q-factor model is not significant, providing stronger support against the q-factor model as an adequate asset pricing model for Japan.

Chapter three presents research which examines the behavior of shares during share market crashes and the existence of the flight-to-liquidity phenomenon during a crash. Data for shares which are traded on the First Section of the Tokyo Stock Exchange are studied, clearly documenting the existence of a flight-to-liquidity during the 2008 share market crashes. The trading rules on the Tokyo Stock Exchange differ from other major exchanges, with one difference being the price limit rules. Price limit rules restrict the daily price movements of shares, providing a unique setting to test if a flight-to-liquidity occurs even when price limit rules may reduce market liquidity and delay price discovery. The results of this research suggest that despite having different trading rules, a flight-to-liquidity occurred during times of market uncertainty as investors were less willing to hold illiquid assets and rushed to sell these assets.

Chapter four presents research which studies the behavior of shares following large one-day share market declines, otherwise known as a market crash. This research provides new evidence using data from 2008 and confirms the results of research on the American market, despite the trading rules being significantly different between the American market and Japanese market. The main conclusion drawn is that there is a lead-lag relation with the returns of large shares leading those of small shares, and large firms respond faster to new information whether it is good news or bad news. This result indicates that the lead-lag relation is due to the fundamental behavior of traders as opposed to institutional features.

How do these results link to the topic of share market efficiency? Is the Japanese share market (semi-strong form) efficient? If share prices reflect all publicly available information, then it is expected that the speed of the price adjustment to new publicly available information is relatively fast. In Chapter three and Chapter four, the movements of share prices during a share market crash and in the immediate post-crash period are studied. The results of the data analysis indicate that the price adjustment is quick, and there is evidence of predictability of share returns. In the post-crash period there is a lead-lag effect with large shares leading small shares. If the share market is efficient, share prices follow a random walk and are independent over time. It should not be possible to trade and make profits based on the information contained in the asset`s price history. The research in chapter four presents evidence of a lead-lag effect, which is consistent with research on other share markets by researchers such as Lo and MacKinlay (1990), and suggests that prices are not independent. According to the Efficient Market Hypothesis, share returns which are not independent and predictable suggest that the market is not efficient. However, according to Fama's weaker version of the hypothesis, a market is efficient when the marginal benefits of acting on information do not exceed the marginal costs. To answer the question, "Is the Japanese share market (semi-strong form) efficient?", we need information on the trading costs, which is out of scope of the research in this thesis. While there is evidence of some inefficiencies on the Tokyo Stock Exchange, in order to state if the market is efficient or not, further information is needed to make an accurate judgment.

Next, do institutional features, such as trading rules, affect the behavior of investors? Or is the behavior of investors similar to investors in other markets which have different features? The research in chapter three and four, present evidence of two well-known phenomena, known as a 'flight-to-liquidity' and a 'lead lag' relation. Previous research has shown that both of these phenomena exist on various foreign share markets, however the research in this thesis clearly shows that they exist on the Japanese market, despite the trading rules differing. In chapter three evidence of a 'flight-to-liquidity' on crash days is documented, and in chapter four evidence of a 'lead lag' relation in the immediate post-crash period is presented. There are price limit rules on the Tokyo Stock Exchange which limit daily price movements, yet the analysis in both chapters shows that despite having price limit rules which may reduce market liquidity, there is no obvious effect on investor's behavior. The results documented suggest that the movement of share prices is due to the fundamental behavior of traders as opposed to institutional features.

The issue of share market efficiency is probably one of the most debated issues in modern investment theory. It is also an issue which is highly important for investors and researchers. There are still many issues and share markets which have not been sufficiently studied, and future avenues for research are abundant. The focus of this thesis, the Tokyo Stock Exchange, is a highly important market yet literature is relatively limited. Future research could look at new asset pricing models in the hope of finding a model which explains share returns more accurately than the Fama French three-factor model. Also, different characteristics could be analyzed to find new factors which have high explanatory power for Japanese share returns. It is hoped that future research will shed light on the issue of market efficiency, and allow us to accurately answer the question, "Is the Japanese share market (semi-strong form) efficient?"

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Appendix

Table 1. The Price Limits of Stocks. Price limits are decided based on the previous day`s closing price, otherwise known as the base price. The range which trading can occur in is as follows.

Base Prices	Price Limits	
Less than 100 yen	Upward/Downward	30 yen
100 yen or more, but less than 200 yen		50 yen
200 yen or more, but less than 500 yen		80 yen
500 yen or more, but less than 700 yen		100 yen
700 yen or more, but less than 1000 yen		150 yen
1000 yen or more, but less than 1500 yen		300 yen
1500 yen or more, but less than 2000 yen		400 yen
2000 yen or more, but less than 3000 yen		500 yen
3000 yen or more, but less than 5000 yen		700 yen
5000 yen or more, but less than 7000 yen		1,000 yen
7000 yen or more, but less than 10,000 yen		1,500 yen
10,000 yen or more, but less than 15,000 yen		3,000 yen
15,000 yen or more, but less than 20,000 yen		4,000 yen
20,000 yen or more, but less than 30,000 yen		5,000 yen
30,000 yen or more, but less than 50,000 yen		7,000 yen
50,000 yen or more, but less than 70,000 yen		10,000 yen
70,000 yen or more, but less than 100,000 yen		15,000 yen
100,000 yen or more, but less than 150,000 yen		30,000 yen
150,000 yen or more, but less than 200,000 yen		40,000 yen
200,000 yen or more, but less than 300,000 yen		50,000 yen
300,000 yen or more, but less than 500,000 yen		70,000 yen
500,000 yen or more, but less than 700,000 yen		100,000 yen
700,000 yen or more, but less than 1,000,000 yen		150,000 yen
1,000,000 yen or more, but less than 1,500,000 yen		300,000 yen
1,500,000 yen or more, but less than 2,000,000 yen		400,000 yen
2,000,000 yen or more, but less than 3,000,000 yen		500,000 yen
3,000,000 yen or more, but less than 5,000,000 yen		700,000 yen
5,000,000 yen or more, but less than 7,000,000 yen		1,000,000 yen
7,000,000 yen or more, but less than 10,000,000 yen		1,500,000 yen
10,000,000 yen or more, but less than 15,000,000 yen		3,000,000 yen
15,000,000 yen or more, but less than 20,000,000 yen		4,000,000 yen
20,000,000 yen or more, but less than 30,000,000 yen		5,000,000 yen
30,000,000 yen or more, but less than 50,000,000 yen		7,000,000 yen
Where the price is more than 50,000,000 yen		10,000,000 yen