A Comprehensive Assessment of the Efficiency of the New Zealand Stock Market.

Daniel Jason Symons

July 25, 2018

Faculty of Business, Economics, and Law

Department of Finance

A dissertation submitted to Auckland University of Technology in partial fulfilment of the requirements for the degree of a Master of Business, specialising in Finance

Abstract

An efficient market is one in which the market price, at any point in time, reflects all relevant information available at that time. The three forms of efficiency are: weak form, which says that past prices are fully reflected in the current price; semi-strong form, where public information is fully reflected; and strong form, where insider knowledge is fully reflected. To determine whether the New Zealand market is weak form efficient, this paper uses an Augmented Dickey Fuller test for unit-roots to assess whether past prices can explain future returns in the NZX 50; and tests for seasonality in the NZX 50 through tests for a day-of-the-week effect, a week-of-the-year effect, a monthly effect, and a holiday effect to assess whether certain periods provide an exploitable return. To determine the efficiency of other information, and particularly insider information, a regression was run to measure the performance of managed funds compared to the NZX 50 New Zealand market benchmark. The results for the unit-root test are consistent with efficiency, with the market exhibiting a unit-root. The tests for seasonality show that there are a few anomalies that exist, but these do not entirely stand up as evidence against efficiency as there is no strategy that exists whereby excess risk-adjusted return could be made by trading around these periods, although investors may use them to time their trades. The analysis of the New Zealand funds show that they do outperform the market, but the evidence is not strong enough to confirm either efficiency nor inefficiency. This paper contributes to the literature by providing a broader analysis of the New Zealand stock market's efficiency after the impact of the Global Financial Crisis and formation of a 50-stock index. It also contributes to the industry by cautioning investors about using past price data to predict returns, although the results do show that there are opportunities for gain in the timing of trades. Furthermore, this paper shows that managed funds may be able to outperform the market using insider information.

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Acknowledgements

Primary Supervisor: Dr. Alexandre Garel
Secondary Supervisor: Dr. Bart Frijns

Attestation of Authorship

I hereby declare that this submission is my own work and that, to the best of my knowledge and belief, it contains no material previously published or written by another person (except where explicitly defined in the acknowledgements), nor material which to a substantial extent has been submitted for the award of any other degree or diploma of a university or other institution of higher learning.

Signed: ___________________________

1. Introduction

The hypothesis of an efficient market was first proposed by Eugene Fama in his paper titled *The Behaviour of Stock Market Prices* (1965). He begins the article with a brief summation of the two main differing beliefs at the time concerning the explanatory power of historical prices on the future prices of a stock. The first is that of the 'chartists' who believe that "History repeats itself in that 'patterns' of past price behavior will tend to recur in the future" (p. 34). Secondly, 'random walks' represent the belief that "a security is no more predictable than a series of cumulated random numbers" (p. 34). Fama purposes the paper to test the validity of the random walk theory and concludes that there is significant evidence in its support, noting "chart reading, though perhaps an interesting pastime, is of no real value to the stock market investor". The term 'efficient market' was coined within the conclusion where Fama writes the sentence:

> "…a situation where successive price changes are independent is *consistent with* the existence of an 'efficient' market for securities, that is, a market where, given the available information, actual prices at every point in time represent very good estimates of intrinsic values" (p. 90).

This sentence, along with the paper's findings, brought forth a wave of research that now forms one of the most prevalent and broadly tested academic financial theories. Fama himself has written a multitude of papers on the subject, usually with a focus on examining the research of others to show the researches development (Fama, 1970, 1976, 1991). In his first review, *Efficient capital markets: A review of theory and empirical work* (1970), Fama defines three subsets within the efficient market hypothesis (EMH). The first, known as weak form, can be summarised as a random walk, or that historic prices alone are 'fully reflected' in the current price. The second, or semi-strong form, goes further to say that all publicly available knowledge is included in the current price of a stock. The third, or strong form, says that even insider knowledge is included in the price (p. 383). Naturally, strong form efficiency is unlikely to be comprehensively proven due to its stringent conditions and Fama states that "We would not, of course, expect this model to be an exact description of reality" (p. 409). However, the other two forms are plausible for, at least, advanced stock markets such as in the United States, but also potentially for semi-advanced markets such as the large third world countries like India, and for smaller developed countries such as New Zealand.

The impact of the EMH, if determined to be true, is significant for the investment industry. Managed funds for years have sought to 'beat the market' by achieving returns greater than that of their chosen benchmark. Countless theories have been produced outlining exactly how to do this, many with academic backing, resulting in hordes of amateur investors pouring resources into the authors managed funds only for them to fail to achieve the benchmark return, let alone significantly surpass it. This outcome is inevitable if we believe the efficient market hypothesis to be true. Malkiel (1989) puts it best: "Indeed, a blindfolded chimpanzee throwing darts at the stock pages of The Wall Street Journal could, according to EMH, select a portfolio that performs as well as one carefully chosen by the experts" (p. 1313). In other words, investors can achieve similar gains, if not better, if they form a simple but well diversified-portfolio themselves while also avoiding a large management fee; or investing in the now common exchange traded funds (ETFs), which mimic the market return with much smaller fees than actively managed funds. This follows what Malkiel (2003b) later said: "Of course, the advice was not to literally throw darts, but instead to throw a towel over the stock pages" (p. 60). The reason for this is intuitive in the definition of an efficient market. If all relevant information is already and always priced into the value of a stock then there is no method of knowing which way the stock will move, or of having any certainty of gains. 'Stock-picking' merely becomes gambling, and any superior returns a result of chance; not something that is repeatable over the long-term. The maximum long-term return is, therefore, the return of the market. This makes matching a portfolio to the market the best option.

Although it is still not fully accepted, there has been a lot of industrial impact caused by the EMH. Fama (1991) mentions this about the impact of the research: "One result is the rise of passive investment strategies that simply buy and hold diversified portfolios (e.g., the many S&P 500 funds). Professional managers who follow passive strategies (and charge low fees) were unheard of in 1960; they are now an important part of the investment-management industry." (p. 1608). Since then, ETFs and other index-hugging funds have been developed around this idea, with the

New Zealand market receiving its first ETF in 1996. Initially released by Smartshares Limited, a subsidiary of the NZX stock exchange, that ETF fund developed into five different funds by 2013, and then to 23 by 2016, indicating a still growing appetite for passive investment funds in the nation (Smartshares Limited, 2016).

With many examples and years of evidence suggesting that beating the market is not a sustainable long-term goal, why then do so many still follow it? The reason is that there are many inconsistencies and occurrences that, rightfully or not, cause us to question the validity of the efficiency hypothesis. One is that there does appear to be people, companies, and funds that have consistently beaten the market return over long periods. Probably the most notable example is Warren Buffet and his investment firm Berkshire Hathaway. The firm had an average annual return on investments of 19.1% from 1965 to 2017, while the S&P500 managed only 9.9% over the same period. More astonishingly, the company managed to beat the market 38 out of 43 years from 1965 to 2008, or 88.37% of the time, and only recorded negative gains twice from 1965 to 2017. (Buffet, 2018). Other irregularities that are often mentioned are market events such as the sharp drop that occurred on October 19, 1987, commonly known as Black Monday, when the Dow Jones Industrial Average fell 22.6% in a single day. This event is especially notable for the New Zealand market where the fall was a much larger 60% in a single day. (Bernhardt & Ecklad, 2013). The reason the efficient market falls short in this example is that, as Fama (1965) said, the "actual prices at every point in time represent very good estimates of intrinsic values." (p. 90). According to this definition, there must have been a true decrease in the intrinsic value of stocks by an average of 60% in a single day; or as Malkiel questioned in his 1989 paper, "Had fundamental information about the economic prospects of U.S corporations changed that much in the following 2 weeks to justify a drop in share valuations of almost one-third?" (p.1313). Naturally that is hard to believe. Therefore, the only plausible explanation is that the actual prices of the market were not good representatives of the intrinsic value before, and/or after, the crash, or even close to it.

Despite these arguments, the literature has largely been in favour of the efficiency hypothesis, particularly for developed markets. Many different tests have been produced to analyse this. One of the earliest of these is the unit-root test, which aims to determine whether a stock index's price follows that of a random walk whereby current returns are not affected by previous returns (Fama, 1965; Groenewald, 1997, Li & Xu, 2002; Narayan, 2005; Hasanov, 2009). Another wide-ranging method is to test for seasonality in the market's returns. Seasonality occurs when there is a change in returns due to a specific time period. This indicates inconsistency with the EMH because it implies mispricing during certain periods and therefore the opportunity to earn abnormal returns. Some of the most commonly tested forms of seasonality are the day-of-the-week effect (Cross, 1973; Dicle & Levendis, 2014), which tests for abnormal returns during specific days; the monthly effect (Rozeff & Kinney, 1976; Raj & Thurston, 1994), which tests for abnormal returns during specific months; the holiday effect (Fields, 1934; Cao, Premachandra, Bhabra, & Tang, 2009), which tests for abnormal returns around stock market holidays; and the newer week-of-the-year effect (Levy & Yagil, 2012), which tests specified weeks during the year for abnormal returns. Both the unit-root test and the seasonality tests are used to determine return predictability, thereby fitting under the weak-form of market efficiency. A common method used to test strong-form market efficiency involves directly testing whether funds manage to outperform their relative benchmark index (Jensen, 1968; Bauer, Otten, & Tourani-Rad, 2006; Frijns & Tourani-Rad, 2015). This method looks to see whether inside information, such as that expected to be obtained by professional fund managers, is capable of being used to obtain excess risk-adjusted returns.

This paper uses all three of these methods to analyse market efficiency in New Zealand. Using NZX 50 daily, weekly, and monthly returns from 2004 to 2017, an Augmented Dickey Fuller test is used to determine whether the market exhibits a unit root. The results are consistent with market efficiency, showing that market returns follow a random walk and that past prices do not have explanatory power for future returns. Seasonality is tested for using NZX 50 daily return data from 2004 to 2017 for a day-of-the-week effect and a Holiday effect, consistent NZX 50 weekly return data is used to determine whether seasonality exists in any particular weeks, and NZX 50 monthly return data is used to determine whether there appears to be any seasonality in specific months. The results show that there are potential inefficiencies in all four of these particular seasonal effects. However, the inability to exploit these anomalies mostly points towards market efficiency, even though traders may be able to exploit these days by timing their trades on them for additional return. Using a simple market model, fund performance is analysed by modelling the yearly return of various funds' New Zealand stock components from 2009 to 2017 to determine whether the selection or weighting of these stocks manage outperformance relative to the NZX 50. The results show that these funds, in general, are able to outperform this benchmark index. Whereas an analysis of the individual funds show that three manage to achieve significant excess risk-adjusted return. While this implies market inefficiency, it is concluded that the evidence is not strong enough to make a definite claim about this, particularly as a result of the model chosen. Instead, we can say that it does not support market efficiency. The reason for the choice of these three methods is that a unit-root and the seasonality tests are able to determine the return predictability of the New Zealand market and therefore its weak-form efficiency. On the other hand, the fund performance test is able to determine whether insider, and therefore non-public information, is efficiently priced into the market, determining whether any form of information will give investors an advantage over that of the market, potentially implying that index funds will result in superior long term performance than more actively managed funds (Jensen, 1968).

This paper looks to determine whether the New Zealand market exhibits efficiency, from a perspective not previously looked at for New Zealand. Often papers focus hard on one method of determining market efficiency and vigorously test the data using that method, concluding that the market does or does not show efficiency in a specific way. While this is not incorrect and in most cases is the best way of proceeding, it does tend to present a fairly narrow view. The market can display inefficiency in multiple ways, and so one method cannot possibly have the breadth to argue for total market efficiency. Instead of taking a high definition and zoomed image of market efficiency, this paper aims to take a wider shot of the market in an attempt to see whether the market exhibits the most basic signs of inefficiencies. It contributes to the literature by providing a multifaceted analysis of the New Zealand stock market to determine where breaks in efficiency may be taking place. This is done in light of changes to the environment of the New Zealand market following events such as the introduction of the NZX 50 in 2003, and the Global Financial Crisis (GFC) in 2008. It also contributes to the industry by showing that investors cannot use past prices to determine future returns, although seasonality could be taken advantage of through the timing of trades to provide them extra return. It also shows that it is not certain that investors cannot beat the market using inside information, meaning that managed funds may be able to earn an excess risk-adjusted return.

The rest of the paper is set out as follows. Section 2 reviews existing literature of the market hypothesis, gives a summary of key papers and, if relevant, their New Zealand counterparts. Section 3 outlines the data that will be used for each test. Section 4 describes the methodology for each area of efficiency being examined. Section 5 analyses the results of the tests and discusses them in relation to their implications for market efficiency. Section 6 concludes.

2. Literature Review

In 1965, Fama wrote *The behaviour of stock-market prices* to analyse the underlying theory of the random-walk model and to test empirical validity. It was in this paper that he concluded that successive price changes are independent of each other and that this independence is "consistent with the existence of an 'efficient market'" (p. 90). In the years following, multiple papers were written on the subject, leading Fama to write his 1970 paper *Efficient Capital Markets: A review of theory and empirical work* which summarised the findings and discussions of these papers. In this paper, Fama defines the three forms of market efficiency and examines the methods that are used to test these. The findings show that there is much evidence supporting the EMH, with most challenges being unexploitable for a profit either because of transaction costs or otherwise, such as evidence of dependence between daily returns which would result in vast amounts of transaction costs if exploited.

To respond to criticism of his 1970 paper, Fama wrote *Reply* in 1976, which provides new models and concludes that there are two common methods to test market efficiency. The first is to discover a trading rule which can result in abnormal expected returns, an occurrence which shouldn't exist if the papers definition of efficiency holds. The second is to test whether some form of information was capable of being used to identify deviations in the true and the expected return of a security.

In 1991 Fama presented a sequel to his 1970 paper, titled *Efficient Capital Markets II*. This paper starts of by defining what the EMH implies, which Fama initially states as “the simple statement that security prices reflect all relevant information”; but soon concedes that due to the presence of information and trading costs, a more reasonable definition is that “prices reflect information to the point where the marginal benefits of acting on information…do not exceed the marginal costs” (p. 1575). The paper then states that market efficiency literature should not be focused on inferring the specific degree of market efficiency but instead should focus on improving our understanding of the behaviour of security returns and should be judged in its ability to do so. The three categories of market efficiency, outlined previously, were then redefined to fit the evolution of the research more closely. The main changes occur with the previous category of ‘weak-form tests’, now defined as “tests for return predictability”, and includes tests of random-walks, seasonality, and asset-pricing models. The second and third categories had little changes other than their names, which are now “event studies” and “tests for private information”, respectively (p. 1577).

Written shortly after the aforementioned 1987 crash, Malkiel’s paper *Is the Stock Market Efficient?* (1989) looks to discuss the viability of the EMH in the wake of this damning event. The paper analyses the previous research into various methods for analysing efficiency, including some used by this paper. Random walk tests are found to generally support efficiency, although papers more recent to this 1989 found that the random walk model does not “strictly hold” (p. 1314). Nonetheless, Malkiel is not quick to dismiss the idea of weak-form efficiency. Seasonality, and in particular the January effect and the ‘week-end’ or Monday effect, are also examined. The author concludes that the transaction costs involved likely outweigh the returns, and even if they do not,the opportunity would be quickly priced out by the profit-maximising market. Malkiel finds that due to the existence of psychological factors, there is some doubt as to the exactness of market prices and their true value. Whilst hedoes concede that there is a significant volume of evidence indicating efficiency, and although an inefficiency may exist, it will soon be eliminated by the market. The paper then leaves us with a forecast of the future of market efficiency research. The author predicts that "with the passage of time and with the increasing sophistication of our databases and empirical techniques, we will document further departures from efficiency and understand their causes more fully" (p. 1318).

Malkiel's 2003a paper *Passive Investment Strategies and Efficient Markets*, petitions for the use of passive investment strategies. He also states that although there appears to be large errors in the valuation of some stocks historically, there was no clear arbitrage opportunity prior to the event which uncovers this mispricing – a fact which underpins his belief in the hypothesis. The paper then argues that market return is a "zero-sum game" (p. 2), whereby in the long-term over- and under-performance average out to the market return and so to maximise the mean of the returns an investor should minimise transaction costs and therefore follow an indexing strategy. Malkiel also uses this paper to show that fund managers fail to beat the market return over the long term.

Malkiel's 2003b paper *The Efficient Market Hypothesis and Its Critics*, similarly argues that inefficiency requires overperformance, concluding "the evidence is overwhelming that whatever anomalous behaviour of stock prices may exist, it does not create a portfolio trading opportunity that enables investors to earn extraordinary risk adjusted returns" (p. 60). Malkiel argues the market is efficient because of two key reasons: first, it successfully and rapidly reflects new information; and second, it does not allow investors to earn above-average risk-adjusted returns.

In 2005, Malkiel wrote *Reflections on the Efficient Market Hypothesis: 30 Years Later* to reflect the development of the EMH since he wrote *A Random Walk Down Wall Street* in 1973. In a similar vein to his 2003 papers, Malkiel argues that a strategy of indexing has and will consistently outperform the vast majority of investment funds. His main claim of the existence of an efficient market is premised on the fact that if the market was as inefficient as argued by critics, then surely actively managed funds would be able to outperform that of a passive fund following a buy and hold strategy. The evidence provided shows that this is not the case and therefore the market is efficient.

In Groenewold's 1997 paper *Share market efficiency: tests using daily data for Australia and New Zealand*, he analyses the weak-form efficiency of the New Zealand and Australia stock markets between 1975 and 1992 using a unit-root test for stationarity and an autocorrelation test on the daily log price for each countries' main indices. Using the NZSE-40 index for New Zealand and an Augmented Dickey-Fuller test, Groenewold found the presence of a unit-root in the data and therefore non-stationarity, which is consistent with weak-form efficiency. However, in examining the intertemporal structure of daily rates of return, he found that past returns do have some predictive power for current returns, which is inconsistent with weak-form efficiency.

In 2002, Li and Xu built upon Groenewold's findings in their paper titled *A note on New Zealand Stock Market efficiency*. Using data from 1993 to 2000, this paper used the New Zealand indices of the NZSE 10, NZSE 30, NZSE 40, and the NZSE SC to determine whether weak-form efficiency varied between the difference in the capitalisation of the stocks involved. This was done in the belief that an index consisting of larger stocks by capitalisation, such as the NZSE 10, would be more efficient than an index with a smaller average capitalisation, such as the NZSE 40 or the entirely small capitalisation stocks index, NZSE SC. The findings show that the NZSE 10 does not have a unit-root, leading to a conclusion that it is stationary with a drift. Combining these results with a high F-statistic and R-squared implying high explanatory power by past returns, the authors find that the large company index is therefore inefficient. While the NZSE SC creates ambiguity because of its high F-value, the other three indices all exhibit a unit-root and, with their low F-statistic and R-squared values, the NZSE 30 and NZSE 40 imply weak-form efficiency.

In 2005, Narayan similarly performed unit root tests on the Australian and New Zealand stock markets in his paper *Are the Australian and New Zealand stock prices nonlinear with a unit root?*. Testing NZSE 40 data from 1967 to 2003 using a threshold unit root test, Narayan found that the market prices are nonlinear and nonstationary, consistent with efficiency. This paper was contradicted by Hasanov (2009) who, in his paper *A note on efficiency of Australian and New Zealand stock markets*, argued that the model used by Narayan fails to properly take into account the dynamics of the stock market. Using a unit root test procedure with an exponential smooth transition autoregressive model, Hasanov found that the market fails to show a sign of a unit root and is therefore inconsistent with market efficiency.

The Holiday effect was first analysed in *Security prices and stock exchange holidays in relation to short selling* (Fields, 1934). In this, he compared the market price of the Dow Jones Industrial Average on Saturdays as well as the single day before and afterwards, to determine whether pre-holidays provided excess returns. Fields found that Saturdays' prices were significantly higher than those of the preceding and following days; significantly higher 51.3% of the time and significantly lower 33.7% of the time. This contrasted with the ordinary week days which were analysed in a similar way. Their results were closer to 45% significantly higher and 40% significantly lower, implying a form of pre-holiday effect. In 2008, Cao, Premachandra, Bhabra, and Tang tested the New Zealand market for a pre-holiday effect over the period 1967 to 2006 in their paper *Firm size and the pre-holiday effect in New Zealand*. Using the NZSE 40 and NZSE 50 (following its replacement of the former in 2003), they find a significant and increasingly stronger holiday effect over this period, with a mean return of almost ten times that of the other trading days and a similar standard deviation.

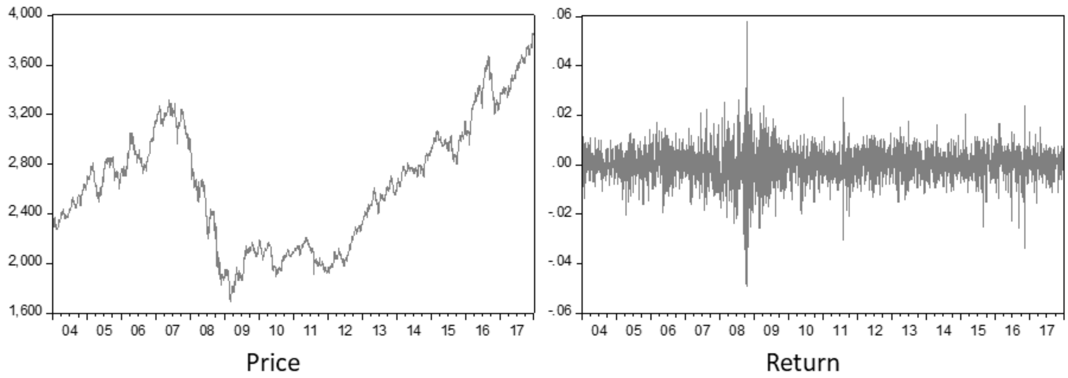
The Monday, or Weekend effect, was first analysed in *The Behaviour of Stock Prices on Fridays and Mondays* (Cross, 1973). Using data on the S&P Composite index over the period 1953 to 1970, this paper shows that 62% of Fridays produced positive gains, with a mean of 0.12%, while only 39.5% of Mondays produced positive gains, with a mean of negative 0.18%. The negative results for Monday were amplified when the previous Friday produced a negative return, with only 24% returning positive gains and a mean of negative 0.48%. This effect was highlighted by its comparison to the returns of other days which followed a negative return for the preceding day, with the percentage of positive returns being 49.0% and a mean of negative 0.02%. The Monday effect eventually evolved into the 'day-of-the-week effect'. In 2014, Dicle and Levendis tested multiple nations for a day of the week effect, including New Zealand, in their paper *The day-of-the-week effect revisited: international evidence*. Using the NZSE 40 and later the NZSE 50 between 2000 and 2007, the authors found that the equal-weighted returns implied a significantly negative return on Tuesdays and Fridays when close-to-close returns were used, and on Fridays when open-to-close returns were used (as was the case for most nations) indicating the existence of a day-of-the-week effect. There was no effect to be found for the value weighted returns, with the difference likely to be arising from large differences in weight between larger and smaller companies in the NZSE 40 and NZSE 50.

The January effect was first analysed in *Capital market seasonality: The case of stock returns* (Rozeff & Kinney, 1976). Using the monthly returns on the New York Stock Exchange from 1904 to 974, this paper finds that January exhibits significantly higher returns over the period than that of the other months and that there were other spreads in returns between the months. Raj and Thurston tested for this same effect in their 1994 paper *January or April? Tests of the turn-of-the-year effect in the New Zealand stock market*. At the time, this came to be known as the 'turn-of-the-year effect' due to a prevalent belief that excess return occurred due to January's position at the start of a new tax year in the United States. The reasoning behind this is that investors try to utilise the tax advantage gained by incurring losses from dumping underperforming stock in December, only to repurchase it in January. Raj and Thurston looked to see whether this hypothesis stood up in the New Zealand market where April signals the beginning of a new tax year, instead of January. Using NZSE 40 data from 1983 to 1993, this paper tested the mean return for January against that of the other months combined, finding that there is no significant evidence of a January effect, nor an April effect, in New Zealand.

The week-of-the-year effect was first analysed by Levy and Yagil in their 2012 paper, *The week-of-the-year effect: Evidence from around the globe*. In this paper, the authors recorded the weekly returns of different countries stock indices, with an average of 1277 recorded weeks for each. Using uniform weeks, they found that for 19 of the 20 countries, week 44 provided positive returns, 18 of which were significant, while the previous week 19 countries recorded negative returns, 11 of which were significant. The authors link this to the effect of the number of hours of daylight, a phenomenon known as Seasonal Affective Disorder.

One of the earliest papers to attempt to determine the success or performance of portfolios, at least in relation to some form of a benchmark, was Jenson's (1968) *The performance of mutual funds in the period 1945-1964*. Taking into account the new-found stock performance measures surrounding risk and return, Jenson expands on the Capital Asset Pricing Model (CAPM). The CAPM relates portfolio or asset performance to the market and the risk-free rate, such that its expected return is positively related to its riskiness in relation to the market return. To determine whether a portfolio outperformed the market, such that it earned more return than its riskiness implies, Jenson included a constant or alpha (Jenson's alpha) in the equation, whereby a positive alpha implied outperformance by the portfolio, while a negative value implied underperformance. Over time this model has been augmented to include additional explanatory variables, such as Fama and French's (1993) three factor model which included capitalisation size and book-to-market value, and the Carhart (1997) four-factor model which included a factor for persistence. Bauer, Otten, and Tourani-Rad (2006) examined mutual funds invested in New Zealand stocks to determine outperformance in their paper titled *New Zealand mutual funds: measuring performance and persistence in performance*. Using multiple models, including the CAPM model with Jenson's alpha and the Carhart four-factor model, the authors examined 143 survivor-bias free mutual funds over the period 1990 to 2003 and found no evidence of fund overperformance.

Figure 1: Plotted Price and Returns of the NZX 50 recorded daily.



3. Data

3.1 Random walk

In March 2003, the New Zealand stock exchange replaced its flagship index, the NZSE 40, with the larger NZSE 50 (later renamed NZX 50). Because of this, the data for the random walk and seasonality tests begin in January 2004, the first full year using the 50-company index, and continues to December 2017. The data used for the unit-root test is recorded daily, weekly, and monthly. The data for the daily and monthly simply follow as each day and each month respectively – each month beginning on the 1st of that month and finishing on the 1st of the following month. For weekly, the data does not follow a specified week of the year. Instead, it records the return over a seven-day period (including weekends when the market is closed, and so therefore five trading days). This means that not every week follows the conventional Monday-to-Friday format, in order to ensure equal periods. It also does not inhibit the results as the choice of weeks is purely for the length, as opposed to a conventional week. All three forms of returns are retrieved from Datastream, and analysis is performed using Eviews. Following Li & Xu (2002), the log prices were used by taking the natural log of the price at each time period, so that price changes are consistent. Figure 1 of the price data indicated that a trend should be used. The graph showed an upward trend from the start of 2004 to around the middle of 2007, where the price begins descending. This was followed by a sharp downward trend until the end of 2008 (the GFC), no trend until mid-2012, and then a steady upward trend until the end of 2017. Discounting the GFC, the data shows evidence of an upward trend. Lag length is selected using the Schwarz Information Criteria (SIC).

3.2 Seasonality

3.2.1 Daily

For the tests of seasonality in the days of the week, daily NZX 50 market values are used with either a log return or the natural logarithm of the result of the return at time t divided by the return at time t_{-1}. Because public holidays cause market closures and therefore have no returns, the number of observations for each day of the week are not exactly even. With the majority of public holidays falling on a Monday, there are only 664 observations for this day, while the other four vary from 703 for Friday and 722 for Thursday. Looking at the distribution of the returns, there is clearly evidence of heteroskedasticity. This means that the variance of the data is inconsistent over time which can bias the variance, and therefore the standard errors of the coefficient values, invalidating the results. Therefore Huber-White standard errors are used through all seasonality formats. All data for seasonality is collected from Datastream and analysis conducted using Eviews.

3.2.2 Weekly

Following Levy and Yagil (2012) for the weekly effect tests, specified weeks were used, where the first week of each year, or week one, begins at the close of the 31^{st} of December and ends at the close of the 7^{th} of January. The second week, or week two then begins at the close of the 7^{th} and ends at the close of the 14^{th}, and so on, such that each week corresponds to a certain period that is the same among all the years. The exception for this is leap years where the weeks after February 29^{th} were pushed forward a day to preserve the seven-day format. This method leaves a single day at the end of each year, other than leap years where there are two, and so this day(s) forms the final, or 53^{rd} week. For the returns, daily NZX 50 values are used for the end of the previous week and the end of the current week, and the log return of these are taken. This is so that the value of the index at the beginning of the week as well as the closing value at the end of the week, is captured.

3.2.3 Monthly

Monthly returns use the log returns of the NZX 50 at the 1st of each month to the 1st of the following month.

3.2.4 Holiday

For the holiday data, the choice of days follows that of Cao et al (2008) which uses days where the market is closed for trading. This includes: New Year's Day (two days), Waitangi Day, Easter (two days), ANZAC day, Queen's Birthday, Labour Day, and Christmas (two days). Dummy variables are created for the day before and after, two days before and after, each holiday, and the data set for the daily effect with log returns is used. Before 2014, if Waitangi Day and ANZAC day fell on a weekend, then no specific market closure would take place since the weekends were closed anyway and those days are excluded from the tests. However, from 2014 onwards, if these holidays fell on a weekend, then the market closure would take place on the following Monday and so those are the days used for the holiday.

3.3 Funds

The goal of the NZX 50 is to provide an index that best represents the New Zealand market and it does this by tracking the 50 largest listed companies in the New Zealand Stock Exchange by market capitalisation. Unfortunately, because of the similar market value for the companies within the 45 to 55 range, it would be difficult and costly for changes to be made for companies just entering the range. Therefore, there is a buffer in place for entry or exclusion from the list. This buffer is a high of 44th and a low of 56th, which means that even though one company is larger than the four lowest valued in the index, it will not be included (S&P/NZX, 2018). This decreases the accuracy of the index to the true value of the New Zealand Market. To get around this issue, a 'mock NZX 50' is formed at each yearly interval by taking the market capitalisation of the 50 largest NZX listed companies at that point in time and their returns over the period. This provides a better example of the New Zealand market return for comparison. The market capitalisation and price data are obtained through Datastream. Because of the size of the New

Zealand market, there are large differences between the top few listed stocks and the rest. This is especially evident with the companies of the Australia and New Zealand Banking Group (ANZ) and Westpac, both of which are two of the large ‘Big Four’ Australian banks. These two together account for close to 70% of the NZX 50’s weighting, which would heavily bias the market performance to these companies. As such, a cap of 5% is placed on the capitalisation of the NZX 50 constituents, such that no stock is responsible for more than 5% of the index’s weight. This results in up to nine companies being capped at 5% at each time period. This follows a similar methodology as the S&P/NZX 50 Portfolio Index but with inclusion that doesn’t follow their buffer system, but instead reweights yearly with the top 50 companies at that time (S&P/NZX, 2018).

The fund data is collected through Morningstar. 56 funds are found to have a notable number of New Zealand stocks and weighting between them. The constituent data for each funds stock portfolio from December 2009 to January 2017 at each recorded year is downloaded, and all New Zealand stocks and their weights are separated and formed into a synthetic New Zealand portfolio, where their weights are recalculated as a weighting of this separate portfolio. All weightings are recorded at the start of the year to avoid double counting any movement throughout the year. Comparison of these weights show that multiple funds, managed by the same company, have near identical synthetic portfolio weightings. Excluding these duplicates leaves 31 funds in the new portfolio. Although not a high number, this is believed to be sufficient for a market of New Zealand’s size. Returns are then recorded at each monthly period for each stock, using changes in the price between periods. Using the yearly synthetic weights, the monthly weighted returns are calculated and summed to form a monthly return for the synthetic portfolio. Unfortunately, the data from Morningstar is not as expansive as desired, with only 23 funds having data from between five and eight years. Following the previous literature (Bauer et al, 2006; Frijns & Tourani-Rad, 2015), the risk-free rate used is the 90-day bank bill rate obtained from the Reserve Bank of New Zealand (https://www.rbnz.govt.nz/statistics). Newey-West standard errors are used to correct for potential autocorrelation and heteroskedasticity in the residuals.

4. Methodology

4.1 Random Walk

A random walk follows the idea that changes in value from one observation to the next is random, such that the change in the next value from the current value is unrelated to the change from the current value from the previous one. The simplest formula for this is:

$$Y_t = Y_{t-1} + \varepsilon_t \tag{1}$$

Where Y_t represents the value of today's observation, Y_{t-1} is the value of the previous periods observation, and ε_t represents random errors such that as $\varepsilon_t \sim$ i.i.d.$(0, \sigma^2)$. This formula can be augmented to include a constant and a deterministic trend:

$$Y_t = \alpha + \beta t + Y_{t-1} + \varepsilon_t \tag{2}$$

Where α represents the constant and βt represents a time-based trend component. Because of the apparent trend shown by the data, this model of a random walk is tested for, and in the form of:

$$\ln P_t = \alpha + \beta t + \ln P_{t-1} + \varepsilon_t \tag{3}$$

Where, following the previous literature, lnP represents the natural logarithm of the price of the NZX 50 index. The use of the natural logarithm of the price is so that price changes of the same percentage magnitude are similar even though the magnitude of the price change may be different.

An Augmented Dickey-Fuller (ADF) test is chosen to test the hypothesis of a unit root. The formula for the ADF test of a unit root in the log price, including a constant and trend is:

$$\Delta \ln P_t = \alpha + \beta t + \rho \ln P_{t-1} + \sum_{t=0}^{m} \theta_t \Delta \ln P_{t-1} + \varepsilon_t \tag{4}$$

Where the null hypothesis of this test is H_0: $\rho = 0$, indicating that the data represents a unit root.

4.2 Seasonality

To test for seasonality, a simple regression is performed with each time period variable being included as a dummy variable. The formula for this is:

$$r_t = \sum_{i=1}^{n} \alpha_i D_{i,t} + \varepsilon_t \tag{5}$$

Where r_t is the return on the market index between period t-1 and 1, α_i is the coefficient of the average return over period i and D_i is the dummy which is equal to 1 during period i but 0 otherwise. This follows a similar methodology as Seif, Docherty, and Shamsuddin (2017), although dummy variables will be used for all time periods.

The formula for the day-of-the-week effect is:

$$r_t = \alpha_0 D_{Mon,t} + \alpha_1 D_{Tue,t} + \alpha_2 D_{Wed,t} + \alpha_3 D_{Thu,t} + \alpha_4 D_{Fri,t} + \varepsilon_t \qquad (6)$$

Where there are dummy variables for each day of the week.

The holiday effect follows a similar formula, just with added holiday dummy variables:

$$r_t = \alpha_0 D_{Mon,t} + \alpha_1 D_{Tue,t} + \alpha_2 D_{Wed,t} + \alpha_3 D_{Thu,t} + \alpha_4 D_{Fri,t} + \alpha_5 D_{Pre\text{-}Holiday,t} + \alpha_6 D_{Post\text{-}Holiday,t} + \varepsilon_t \qquad (7)$$

Where the holiday dummy variables represent the day before/after for one regression, and two days before/after with another. The values of the alphas in these equations is the evidence for or against seasonality with significantly non-zero values indicating a seasonal effect and potentially inefficiency while insignificant figures imply efficiency.

A similar formula is used for the Monthly effect where each dummy will represent a specific month.

$$r_t = \alpha_0 D_{Jan,t} + \alpha_1 D_{Feb,t} + \alpha_2 D_{Mar,t} + \alpha_3 D_{Apr,t} + \alpha_4 D_{May,t} + \alpha_5 D_{Jun,t} + \alpha_6 D_{Jul,t} + \alpha_7 D_{Aug,t} + \alpha_8 D_{Sep,t} + \alpha_9 D_{Octr,t} + \alpha_{10} D_{Nov,t} + \alpha_{11} D_{Dec,t} + \varepsilon_t \qquad (8)$$

The weekly effect follows this format but contains an intercept for all weeks of the year.
The formulas could be further expanded by replacing one of the dummy variables with a constant to determine the significance of the difference between the return of one of the seasonal observations and that of the other seasonal observations. This was excluded from this study because the focus is on the individual variables return and not its relationship with the others.

4.3 Fund performance

To determine the performance of funds relative to the New Zealand market, the CAPM model developed by Jensen (1968) is used due to its simplicity. The model is formed as such:

$$R_{it} - R_{ft} = \alpha_i + \beta_0(R_{mt} - R_{ft}) + \varepsilon_{ti} \tag{9}$$

Where R_{it} represents the return incurred by the fund i at time t, R_{mt} represents the market return, or return of the NZX 50, at time t, β_0 represents the riskiness of the fund in relation to the market where $\beta_0 > 1$ implies that the fund is riskier than the market, and $\beta_0 < 1$ implies less risky. The α_i represents Jenson's alpha, the determinant of whether the fund over- or underperforms the market, such that $\alpha_i > 0$ implies overperformance and $\alpha_i < 1$ implies underperformance.

5. Results

5.1 Random walk

Table 1 shows the results of the Augmented Dickey Fuller tests using the three time periods. A lag of one is chosen using the SIC for the Daily unit-root test, although 0 is chosen for each other test including the 1st difference of the daily price. As the table illustrates, each period is found to contain a unit root as each initial test was unable to reject the null hypothesis, while each 1st difference test is able. Interestingly, each test fails to find evidence of a drift or a trend in the data despite the graph of the plotted data indicating this. This is likely a result of the GFC which breaks what appears to be a trend by decreasing the NZX 50 price greatly and then stalling return for the following few years. It is likely that a test of the data from 2011 onwards would result in a significant trend but this cannot be said for certain unless tested. This means that, over this period, the New Zealand market follows a random walk without a trend or drift, as shown by Equation 1. These results are consistent with the bulk of previous studies on the New Zealand market which finds that the market exhibits a unit root. It also indicates that the past prices do not have explanatory power for future returns, a finding that is consistent with that of the weak-form efficiency hypothesis.

Table 1. Tests for a unit root

Series	*ADF*	*α*	*β*	*m*	*Adj. R²*
DailylnP	-0.627	0.608	1.286	1	0.005
ΔDailylnP	-56.19***	-0.389	1.146	0	0.464
WeeklylnP	-0.56	0.540	1.308	0	0.000
ΔWeeklylnP	-25.26***	-0.395	1.127	0	0.466
MonthlylnP	-0.704	0.687	1.203	0	- 0.003
ΔMonthlylnP	-11.28***	-0.309	0.921	0	0.432

Note: ADF is the ADF statistic. *α* is the constant t-statistic, and *β* is the trend t-statistic. *m* is the number of lags chosen by the SIC.

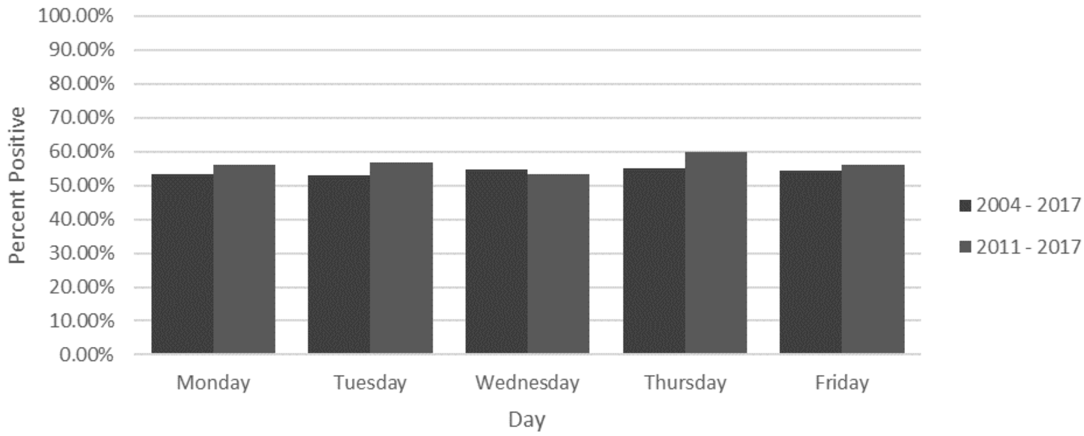
A potential limitation of this test is the choice of procedure. While simple to attempt and interpret, the Augmented Dickey-Fuller test does not have the same power as more recent models such as the exponential smooth transition autoregressive model developed into a unit-root test procedure by Kapetanios, Shin, and Snell (2003) and used by Hasanov (2009) which takes into account different regimes in the data, and so the results may not be an accurate representation of the true nature of the relationship between past and current prices. However, this limitation should not be an issue when considering the strength of the findings. Another limitation, as briefly mentioned earlier, could be the inclusion of the GFC which causes a large break in the pattern of the market price for a significant period of time. Clearly not part of the trend, this break at least skewed the results for the trend coefficient.

5.2 Seasonality

5.2.1 Day-of-the-week

Figure 1 shows the spread between positive and negative returns occurring for each day. The number of days with either a positive return or a negative return are very close for each of the weekdays, with the lowest being 53.1% of Tuesdays being positive and the highest being 55.12% of Thursdays. There are two things to note from this. First is that at this small ‘day’ period size, the slight trend upwards that is exhibited by the market can be seen. Each day has a very similar relationship such that it experiences a near 50/50 chance of a positive or negative return, with a slight skew towards the positive, which results in the upward trend. Another thing to note is that all of the days have a very similar ratio of positive to negative returns. This shows that, purely in number of positive returns, there is no day that is particularly favourable for

Figure 2. Number of positive observations



investment. This relationship changes little when considering data after the GFC, with the increase in the ratios of positive returns being expected, although there is a notable difference in the ratio between Wednesday, 53.48%, and that of Thursday, 59.89%. Wednesday is also the only day to have their ratio drop compared to the total data set.

To avoid the large impact of the GFC and to understand the data better, three regressions are performed each with different periods. The first is a regression on the whole period, from January 2004 to December 2017. This regression shows that most of the days are quite insignificant, with all but one having a p-value higher than 0.4770. That exception is Wednesday which had a p-value of 0.0342 and a coefficient of 0.000515, indicating with 95% confidence that returns on Wednesday will be positive over time, as shown by Table 2. This table includes the average and total returns for each weekday over this period. Total returns are used to show the total gain possible in the absence of transaction costs over each period, for comparison. When looking at the averages and total returns over this period it can be seen that Wednesday provides most of the positive returns, being larger than all the other periods combined. This indicates that, in the absence of transaction costs, a large and significant return in comparison to the rest of the market, could have been obtained by trading around this day. However, the costs that would accumulate from day trading upwards of 50 times a year would likely eliminate any profits made by this strategy. Using ANZ's brokerage costs as an indication, a single online trade incurs a transaction cost of 0.40% for the average investor

Table 2. Total and (average) daily return, and regression results

					Regression results		
Variable	Obs.	*04-17*	*04-10*	*11-17*	*04-17*	*04-10*	*11-17*
Monday	664	0.90%	- 9.98%	10.87%	0.000012	- 0.000273	0.000298
		(0.0014%)	*- (0.03%)*	*(0.0329%)*	*(0.9585)*	*(0.4631)*	*(0.3074)*
Tuesday	710	12.82%	2.33%	10.50%	0.000176	0.000064	0.000288
		(0.0181%)	*(0.0066%)*	*(0.0295%)*	*(0.4773)*	*(0.8798)*	*(0.2667)*
Wednesday	720	37.57%	23.71%	13.86%	0.000515**	0.000649*	0.000380
		(0.0522%)	*(0.0657%)*	*(0.0386%)*	*(0.0342)*	*(0.0714)*	*(0.2452)*
Thursday	722	9.74%	- 10.08%	19.82%	0.000133	- 0.000284	0.000543**
		(0.0135%)	*- (0.0278%)*	*(0.0552%)*	*(0.5757)*	*(0.4877)*	*(0.0268)*
Friday	703	- 9.59%	- 16.15%	6.56%	- 0.000131	- 0.000422	0.000180
		- (0.0136%)	*- (0.046%)*	*(0.0186%)*	*(0.5950)*	*(0.3050)*	*(0.5106)*
Adjusted R^2					- 0.000016	0.000419	- 0.001688

Note: This table shows the regression results for Eq. (6) alongside actual returns observed for the period. Obs. Is the number of observations over the full period. Total return was the sum of returns over the relevant period. Average return was achieved by dividing total return by the number of observations and are not the result of a regression. Coefficients for each day are reported with their associated P-values underneath in parentheses. * ,**, *** indicate significance at the 10%, 5%, and 1%, levels respectively.

(ANZ, n.d.). At almost ten times that of the expected daily gain, there is no potential profit from this strategy at this level of costs. However, this cannot be ruled out fully as evidence against efficiency because of the sheer size of the difference in return between it and the other days (37.57% for Wednesday vs. 13.87% combined for the other days) and that there may be investors capable of achieving transaction costs low enough to take advantage of this. New Zealand does not have a capital gains tax and so this is not a concern. Short-selling was not considered in this study as many New Zealand stocks are not able to be traded and so any conclusions determined assuming short-selling may be inconsistent with reality.

Also of interest to note is the negative returns on Friday. Although the regression coefficient on this day (-0.000131) is shown to be insignificant, it is still surprising to see that over this period Friday managed to produce -9.59%. A potential reason why Friday's results are so low is the one given by Fields (1934) in the first line of his paper testing the holiday effect, which mentions that the uncertainty of weekends may cause security traders to liquidate their positions on the Friday and then pick them up again on the Monday. While this paper was written over 80 years ago, a few years after the Great Depression and during a time when Saturdays weren't always closed, this idea might still hold in a weaker sense, whereby investors are more cautious around weekends and therefore are more likely to sell, causing the negative returns. This low return can also be seen for Monday, which although not negative, manages to only produce 0.90% over the 14-year period. One reason Monday could have such low return is that because Monday is the first day of the week back at work, investor moral may be lower on that day than other days and the prospect of working for five days before the weekend may instil a sense of pessimism, thereby causing bearish feelings. This may also point towards the Monday effect tested in Cross (1973) where returns from the previous Friday influence the following Monday. This would imply that Friday alone is the cause of the low returns of the weekend as the lower Monday returns are a result of that. The reason Wednesday might experience such high return is that the middle of the week might cause a development in investors of a sense of security. In an opposite vein to that of Fridays and Mondays, investors would be thick into their work with two days behind them, with the weekend close enough to cause a sense of optimism while also far enough away to keep out of the investors mind. This would be particularly effective during the GFC where the safer and more competent investors feel, the more bullish they are expected to be, and therefore more likely to push the market price up. These three observations could also point to some form of weekend effect, or middle of the week effect, whereby returns increase in the middle of the week and lessen around the weekend. This can be seen with the returns of Tuesday and Thursday being 12.82% and 9.74% respectively.

To further understand these potential relationships and to determine the effect of the GFC, a second regression is run over the period January 2004 to December 2010. The results in Table 2 show that once again Wednesday exhibits significance while the other days are statistically insignificant. The power of Wednesdays' returns decreased slightly, with the p-value increasing to 0.0714, but the magnitude of its returns increased, especially in comparison to the others which can be clearly seen in Table 2. Monday, Thursday, and Friday all experience large negative returns of -9.98%, -10.08%, and -16.15% respectively. Tuesday manages a positive return of 2.33%, but Wednesday achieved a total return over the period of 23.71%, dwarfing the others. The negative returns are clearly a result of the GFC which took place between 2007 and 2009 and decreased the NZX 50 value from 2305 at the beginning of 2004 to 2082 by the end of 2010, with a daily low of 1688. The results here show that Wednesdays large returns over 2004 to 2017 may come from this period and so not be of much significance outside of it. It also shows why Friday experienced a negative return over that period as it experienced a large loss over this period. The large returns from Wednesday during this period show that there could have been potentially been a trading strategy to earn excess return to that of the market. Also, with the market showing dismal results for each other day, there is little incentive to invest on them. Over this 7-year period, Wednesday's 23.71% return was 62.25% higher than the total return of all days excluding Wednesday, which was -38.54%. If transaction costs lower that the coefficient on Wednesday of 0.0649% could be achieved per transaction, then this would have represented a profitable opportunity much greater than that of the market over this time period. However, at a cost of 0.40% per transaction, this is not possible for anyone who could not negotiate very low transaction costs.

The comfortability of Wednesday's would have had a greater effect on investors during this time period as they wrestled with the GFC. This could potentially be the reason that such a high return is achieved on this day. The losses shown from Friday strengthen the possible reason mentioned previously that followed from Fields (1934). The GFC would have cause considerable 'fear' among investors in a similar way to the Great Depression and so they would have been more likely to sell at signs of market collapse, particularly on weekends when the market experiences two additional days' worth of changes prior to the opening bell on Monday. This would have exaggerated the losses on that day, which appears to be the case from our observations. The Monday effect is hard to analyse in this period because although there are large negative returns on Friday and Monday, there is also on Thursday and so it cannot be easily said that the negative returns on Monday is a result of Friday. The mid-week effect mentioned earlier breaks down slightly during this period. Although Wednesday and Tuesday still follow it to an extent as they are the only positive days, Thursday experiences a large negative return, lower even than Monday. This could be as a result of the increased losses on Friday and the reason for that, which could have crept over into Thursdays and so pushed the mid-week effect upwards so that Wednesday captures both it and Thursdays effect. In fact, it could be argued that the large return experienced by Wednesday is a result of the same cause of the poor return on Fridays. The fear of weekends experienced by investors is balanced out by optimism during the middle of the week, where negative news appears to come less often and when the investors are more prepared for it.

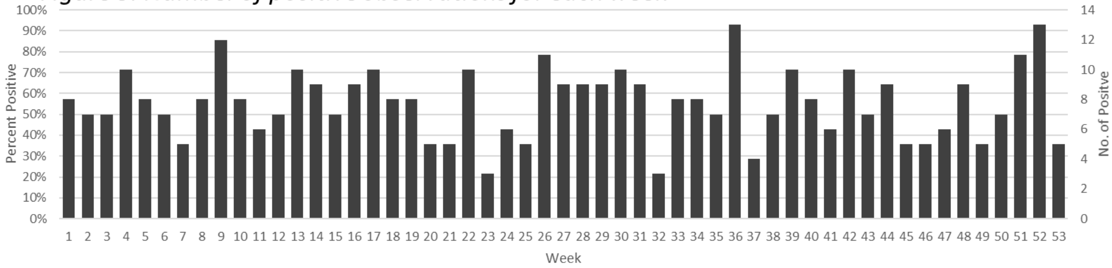
The third regression is over the period January 2011 to December 2017. The results of this show, as expected, that the majority of the power for Wednesday was a result of its performance from 2004 to 2010, with its coefficient no longer being statistically significant. Instead, Thursday has become significant with a coefficient of 0.000543 and a p-value of 0.0268. Unlike Wednesday, however, Thursday's significant return is not high enough to form a trading strategy around even with no transaction costs, with its 19.82% return being less than 5% higher than the nearest day, and with three of the four other days all experiencing returns of over 10%. This means that although its significant coefficient is higher than that of Wednesday over 2004 to 2017, a trading strategy around Thursday would miss out on much more return than it would lock in. The higher return experienced by Thursdays might follow a similar reasoning to that of Wednesdays in the previous period, specifically that it provides a sense of security for investors. The higher return on Wednesday can again be seen here, potentially again implying a form of mid-week effect with the high return on Thursday. This is strengthened by the low relative returns on Friday which also strengthens the 'Friday fear' hypothesis. The Monday effect appears to have little strength here as Monday fails to follow the lower returns on Friday.

There are a few potential challenges to market efficiency presented in the daily evidence. In a basic sense we could point to the enormous comparative gains experienced by Wednesday over the whole period and the first half of it. It is expected that if market efficiency was held to be true then a particular day's return should not be so much larger than the others. Another argument against efficiency can be made by the significance of the returns of Wednesdays over the whole period and by Thursdays over the most recent half of the period. This implies a high confidence that positive returns will occur over the long term on these two days. There is an issue with these two arguments though that Fama (1991) and Malkiel (2003b) argue implies market efficiency. Fama (1991) stated that for market inefficiency to be determined, the marginal gain from acting on a trading strategy must outweigh the marginal cost, while Malkiel (2003b) echoed the idea with one of his two requirements for market inefficiency being that it allows investors to earn above-average risk-adjusted returns. This easily diminishes the argument for Thursday's significant returns as it fails to enable above-average returns to be achieved. Wednesday's argument is harder to eliminate because of its large comparative return but it is unlikely that the return over the full period will outweigh the cost of the many transactions involved. The first half period though may well indicate market inefficiency, but only over that period. Clearly a trading strategy around Wednesday would not have resulted in superior gains over the 2011 to 2017 period and so we can comfortably say that this is no longer an exploitable break in efficiency. Therefore, based on these arguments we cannot confirm market inefficiency. Another argument could be formed around one of the reasons given for the pattern of return. If these were proven to be true, then they may offer opportunity for above-average returns. However, these hypotheses are not tested in this paper and cannot be given as evidence against efficiency until proven significant. These findings may provide other use to investors though. With Thursday's exhibiting higher returns than the other, prices would be higher as well. Therefore, to maximise the profit, or minimise the loss, from a sale, an investor should wait until Thursday to sell so as to get the highest sale price. The opposite could be said for buying, where an investor should avoid Thursdays and instead trade on a Friday when returns are expected to be at their lowest. This idea does not hold up too well with all the days producing positive returns though, as with each successive day the market is likely to increase. With only Thursday being found to be positive, investors at least can, with a high level of confidence, expect prices to increase and so sales should be planned for this day. This would only be possible in the short term, however, as the increase in sales on Thursday would decrease the returns on that day and bring the return over each week day towards an equilibrium.

5.2.2 Week-of-the-year

As can be seen from Figure 2, the ratio of positive to negative returns for each week vary a fair amount, which should be expected with only 14 observations each, but most weeks are between

Figure 3. Number of positive observations for each week



35% and 65% positive returns, with most of those being above 50%. This trend of positive returns continues with the more extreme months, with 12 of the 53 weeks having positive returns over 70% of the time, while only three weeks experience positive returns less than 30% of the time. This similarly follows the daily by exhibiting a positive skew, but shows much more variation, as expected with a lower number of observations. Something else to note here is that the weeks that experienced over 70% positive returns are quite spread out, almost in a uniform way. Until September these weeks fall on the last or near to last week in each month. This could imply a turn-of-the-month effect which may show up in the regression.

Like with the daily data, multiple regressions are run. The results of these can be seen in Table 3. The first is a regression over the 2004 to 2017 period. This shows that 15 weeks have significant coefficients, with six weeks being significant at the 10% level, a further four being significant at the 5% level, and another five being significant at the 1% level. Of these 15 weeks, only four have significantly negative coefficients, with the other 11 being positive. Some interesting features include the clumping of these values towards the middle of the year, with seven of the weeks being within week 21 and week 32. Also interesting is the significance of weeks 51 and 52. As we'd expect, most of the weeks which experience large amounts of positive or negative returns are found to have significant coefficients that matched, but interestingly there are some that are statistically significant but only experienced an average number of positive returns. This implies that they experienced larger returns, at least during the period they were found to be significant. There were also some that were not statistically significant but experienced a large number of positive (negative) returns, implying that their positive (negative) returns were small or their negative (positive) returns were large enough to overshadow these. Compared to daily returns which have roughly 250 observations in total every year, or 50 for

Table 3. Week-of-the-year test results

Variable	*Start date*	*04-17*	*11-17*
Week 4	*22-Jan*	0.005941**	
		(0.0329)	
Week 9	*26-Feb*	0.00682***	0.011742***
		(0.0093)	*(0.0000)*
Week 13	*26-Mar*	0.007277*	0.009156**
		(0.0554)	*(0.0174)*
Week 15	*9-Apr*		0.009156**
			(0.0136)
Week 17	*23-Apr*	0.007568**	
		(0.0215)	
Week 18	*30-Apr*		0.003563*
			(0.0781)
Week 19	*7-May*		0.006025**
			(0.0167)
Week 20	*14-May*		- 0.006692*
			(0.0554)
Week 21	*21-May*	- 0.009285**	
		(0.0111)	
Week 22	*28-May*	0.004502*	
		(0.0762)	
Week 23	*4-Jun*	- 0.009212***	- 0.006671***
		(0.0024)	*(0.0009)*
Week 25	*18-Jun*	- 0.006419*	- 0.009245***
		(0.0999)	*(0.0016)*
Week 26	*25-Jun*		0.006402***
			(0.0001)
Week 27	*2-Jul*		0.007203*
			(0.0925)
Week 29	*16-Jul*	0.008223*	
		(0.0981)	
Week 30	*23-Jul*	0.006854*	
		(0.0885)	
Week 32	*6-Aug*	- 0.006783**	
		(0.0380)	
Week 33	*13-Aug*		0.00899**
			(0.0118)
Week 36	*3-Sep*	0.005986***	0.006011***
		(0.0004)	*(0.0082)*
Week 43	*22-Oct*		0.006903*
			(0.0774)
Week 48	*26-Nov*	0.00553*	
		(0.0880)	
Week 51	*17-Dec*	0.00803***	0.008107*
		(0.0022)	*(0.0560)*
Week 52	*24-Dec*	0.008245***	0.009265***
		(0.0000)	*(0.0008)*
Week 53	*31-Dec*		- 0.002537**
			(0.0251)
Adjusted R^2		0.025068	0.67143

Note: This table shows the regression results for the weekly effect. Coefficients for each significant week are reported with their associated P-values underneath in parentheses. * ,**, *** indicate significance at the 10%, 5%, and 1%, levels respectively.

each weekday, weekly returns only have 53 observations each year, one for each week, and so offer a more likely chance of profit because of the decreased number of transactions that need to take place. Also, the return over a whole week is usually superior to that of a single day, therefore minimising the weight of the transaction cost to the profit taken. When we look at the returns over this period for each week there does appear to have been a profitable opportunity if the significant weeks were taken advantage of. Over the whole period from January 2004 to December 2017, the total return on all 53 weeks was 51.44%. If only the 11 significantly positive weeks were invested in, this number would almost double to 99.44%, as seen in Table 4. This is shown in the coefficient values for each week as well. If we take the values to be a true representation of the future, then by only investing in these 11 weeks, a yearly return of 7.49% is expected, whereas a yearly return of only 3.67% is expected if a buy and hold strategy of the market was undertaken. With transaction costs only being occurred nine times (twice two weeks followed each other) a year, this would have been quite a profitable strategy if favourable costs were achieved, or at least trading costs of less than 3.82% (7.49% - 3.67%) which amounts to 0.42% per trade. Using ANZ's costs, we can see that this strategy manages to just beat the 0.40% per transaction cost incurred and so the average investor may only make a slight return over the market from this, whereas investors who can incur lower costs would make a a larger return (ANZ, n.d.). A potentially even more profitable strategy could instead have been implemented. Obviously we'd expect that if the four weeks with significant negative coefficients were avoided then the return would be higher, but if this was done then a total return of 95.81% could have been achieved with only four transactions taking place. The reason for this is that the four weeks total returns over the period were -13.00%, -12.90%, -8.99%, and -9.50%. Naturally first thought goes to the GFC, and it is assumed that these large losses must have occurred over only a couple observations, but upon reviewing the data it can be seen that these weeks experienced fairly consistent losses over the period. Over the 14 observations, two weeks managed positive returns only four times and the other two only managed positive returns three times. There were notable losses in 2008 because of the GFC, with weeks 23 and 25 experiencing losses of roughly 3.7% which does contribute a large portion of their total losses, and without may not be significant, but weeks 21 and 31 experienced losses not very different

Table 4. Profit from weekly trading strategy

Trading strategy	*04-17*	*11-17*
Return from sig. positive weeks	99.45%	62.00%
Yearly Average'	7.49%	8.86%
Ret. without sig. negative weeks	95.82%	78.72%
Yearly Average'	6.84%	11.20%
Total Return- Buy and hold	51.44%	61.62%
Yearly Average	3.67%	8.80%

Note: ' Average return was achieved by taking the coefficient values of the regression for each week and summing them, whereas the total return was the sum of the actual return over the full period and so they may differ.

to their other observations. Week 31 did experience a loss of -3.10% in 2015 but so did week 33 which remained insignificant and even had a positive coefficient. The closeness of these two losses may indicate that a single or a few closely related events were to blame. The potential increase in return is shown by the coefficients, such that if we can expect them to be true, trading around these four weeks would result in a 6.84% annual return, 3.1% over the market, which easily out earns the transaction costs incurred.

One potential explanation for the significant weeks is the turn-of-the-month effect as mentioned previously, which is followed by quite a few of the weeks, particularly in the first eight months where most of the significant weeks occur at or near the end of a month. This 'turn-of-the-month' effect was first hypothesised in Ariel (1987) and was tested for New Zealand by McConnell and Xu (2008) who found that there was over performance around the ends of months from 1988 to 2006. The reason they give for this effect is what they call the 'payday hypothesis' which says that most investors receive their wages, dividends, and interest, at the end of months and the investment of this income pushes up the price of the market. Another interesting pattern is the concentration of significant values around the middle of the year. An explanation similar to the one used for the higher returns in the middle of the week could be used but there must be caution because that is also where all four of the significantly negative results occur. Three of the four negative results occur during the second half of May and June, which also happens to be the beginning of winter. As shown by Levy and Yagil (2012), the weather can have a negative effect on people, increasing pessimism and causing them to be more bearish. This could explain the concentration of these negative returns. And then, if these three significant weeks were removed, the rest of the significant returns in the middle of the year follow the end-of-the-month hypothesis in a similar fashion to returns in the beginning few months of the year, therefore explaining the concentration around the middle of the year. Another feature of the returns is that the final two full weeks of December are both significantly positive. This is likely caused by the coming of Christmas and New Years and all the joy and excitement associated with that, resulting in a bullish feeling among investors. It may also be a result of the coming of summer which begins in December and so has an opposite effect to that shown in May/June. It is also around the time where Christmas bonuses and other gifts are given and so this increase in funds may be invested into the market, raising the price.

The second regression is run over the period 2011 to 2017 so as to avoid the impact of the GFC and to get a better understanding of the current market. This regression's results are similar to the full period one, with 16 significant coefficients, four of which are negative, and a grouping of significance towards the middle of the year as well as the last few weeks of the year. Interestingly, many of the weeks that were significant over the full period are not significant over this period, while many that were not significant now are. This is likely the result of the GFC causing abnormal market conditions but may also be a result of traders realising the potential for profit and acting on it, causing the effect to dissipate. Unlike the full 14-year period, the returns for this period show that there is little gain to be made from trading around the weeks shown to be significantly positive, with the total returns of the market being 61.62%, compared to 62.00% for the significant weeks. While this is a slightly higher return, it is hardly large enough to overcome the transactions costs incurred by trading nine times a year. With a yearly average of 8.80% for the market and 8.86% for the significant months, unless transaction costs are less than 0.06% yearly then there is no profit to be made with this strategy. The strategy of avoiding significantly negative weeks may still provide excess return though, as the gain is large enough to overcome transaction costs. The total return of avoiding the four significantly negative months was 78.72%, 17.1% higher than the market, and the sum of its coefficients is 11.25%, nearly 2.4% more per year.

With the change in significance between the weeks, it appears as though the turn-of-the-month effect is less prevalent in the 2011 to 2017 period, with many weeks around the end of the month losing significance. There is, however, enough months that still appear to exhibit this effect and so I wouldn't rule it out entirely. The clumping around the middle of the year still takes place, although with slightly different weeks. June still exhibits two highly significant negative months, the same two from the whole period regression, and so the potential negative effect of weather cannot be ruled out. Weeks 51 and 52 still exhibit significantly positive returns and so idea behind those returns remain. The final one or two days of December, represented by Week 53, contradict these two weeks by being significantly negative. This may result because of a sort of Christmas hangover, whereby the high returns over the past two weeks are slightly corrected for, or may follow a similar reasoning we gave for Friday's slump in the daily data where investors are concerned about the potential volatility during extended holiday and so are more bearish regarding their investments. Another new feature is the clumping of significance during the beginning and middle of May. These are characterised by two positive weeks to begin May followed by one negative month. One reason why May could have experienced these negative returns is that there could be an influx of quarterly reports at this time. Although written for the first quarter of the year, the process of collecting all the data, reports, write-ups, as well as the process of auditing, the reports are released with a delay. If these reports tend to come out around May then this could be the result of both the significantly positive return that takes place at first, and then the significantly negative return that occurs as the market corrects any overreaction to the reports. A similar argument could be made for the sequence of returns in mid-July to early September during the 2004 to 2017 period, where two successive weeks of positive returns is followed shortly by a single week of negative returns, not long after the half year point of June.

The impact of these findings on the EMH is similar to that of the daily regressions. Many weeks show signs of significance and so an argument could be made that this indicates inefficiency. If the definition of efficiency requires excess returns to be made, then this argument has to be extended to whether investors can profitably undertake a strategy around this. From 2004 to

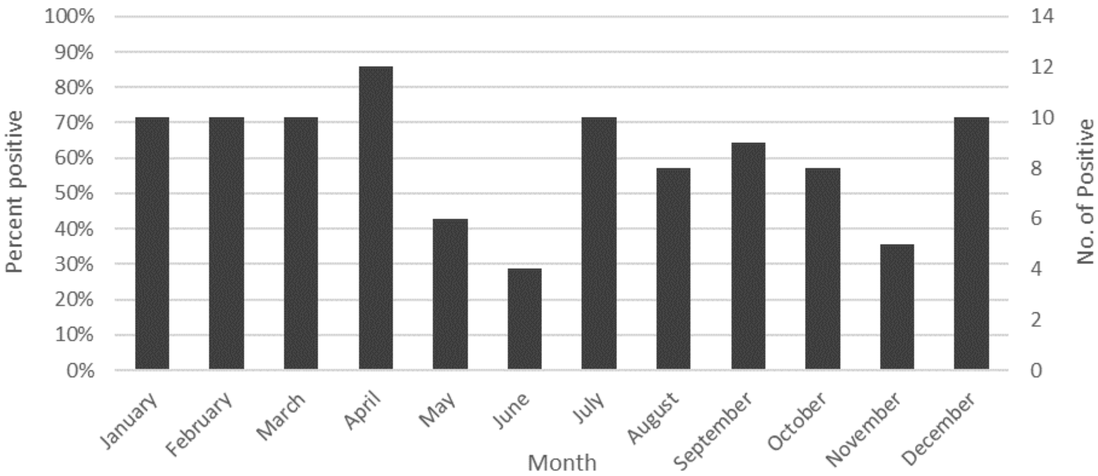
2010 there appears to have been big breaks from efficiency with large profits to be made by trading around significant weeks, implying inefficiency during this period. This weakens greatly in the following 7-year period though, with little to no profit to be made following a strategy around the significantly positive weeks. This is not so much the case for a strategy around avoiding the significantly negative weeks, where profits can be achieved and so a case could be made that this shows that the market is inefficient. Other potential breaks in efficiency include the significantly negative return at the start of winter, which could provide a profitable opportunity to an investor, as well as the significantly positive returns in the second half of December. Also, the turn-of-the-month effect may potentially be utilised if proved to be true, providing another break in efficiency. Again, these findings provide investors with information as to when they should time their buying or selling. With a week like Week 5, if a seller waits out the full week then they're expected to earn an additional 1.17%, or with Week 20 they should aim to sell just before May 14 so as to gain the positive returns from Week 19 and avoid the negative returns of Week 20. A buyer would follow the opposite.

5.2.3 Monthly

Figure 3 illustrates the difference between the number of positive and negative returns experienced by each month. This data also shows limited variation around the mean, which looks to be about 60%. The most common outcome for a month is ten positive returns out of the 14 observations. This occurs for five different months, which may be months where significantly positive returns are found. April stands out with 12 positive returns and will likely be found to have significant returns, while the same could be said for June which is found to have ten negative returns and so may be significantly negative.

Multiple regressions are run for the monthly returns, for the same reasons given for the week-of-the-year tests. The first regression takes place over the full 2004 to 2017 period. This regression finds that April, July, and December all exhibit highly significant positive returns, all with p-values below 0.0100. The significance of April was expected with the high number of positive returns it experiences. December was also expected to be positive because of the

Figure 4. Number of positive returns per month



two significantly positive weeks we find that occur around Christmas. Interesting though, June is not found to be significantly negative despite the large number of negative returns it experiences, and the fact that two of its weeks are found to be significantly negative. Although insignificantly, five months exhibit negative coefficients implying an average loss by these months over this time period, a somewhat surprising occurrence due the length of each observation and the number of them. To determine the significant months impact on the EMH, a strategy involving trading around them is formed, to determine whether this results in excess return. Over the 14-year period these three months return 74.84%, a whole 23.40% over that of the market return (51.44%). Incurring transaction costs of 0.40% only three times in a year, a strategy around investing only during these three months would result in more return than that of the market. The yearly average return from this strategy would be 5.35%, much larger than the market return of 3.67%, and provided investors with 1.38% more return yearly than a buy and hold strategy.

The reason why December has significantly positive returns would likely follow the same reasoning as for the two significantly positive weeks in December, i.e. that the combination of the psychological effect of the holidays and the beginning of summer, and the increase in investable funds, would drive the price up. April and July do not follow as intuitively. July does experience two significantly positive weeks over the period and so is likely significant as a result of that, although the reasoning is less clear. I could be that it occurs as a form of correction

Table 5. Monthly test results

Variable	*04-17*	*11-17*
January	0.004228	0.017065**
	(0.6261)	*(0.0414)*
February	- 0.003344	0.016111***
	(0.7384)	*(0.0000)*
March	0.012438	0.012586
	(0.1784)	*(0.1741)*
April	0.015811***	0.016842***
	(0.0013)	*(0.0021)*
May	- 0.010218	- 0.002548
	(0.1922)	*(0.7709)*
June	- 0.012999	- 0.011265**
	(0.2840)	*(0.0309)*
July	0.024832***	0.019161*
	(0.0024)	*(0.0518)*
August	- 0.004116	- 0.000531
	(0.5206)	*(0.9642)*
September	0.004879	- 0.003108
	(0.5273)	*(0.6899)*
October	0.000952	0.015713
	(0.9408)	*(0.3001)*
November	- 0.006628	0.000586
	(0.4109)	*(0.9418)*
December	0.012813***	0.00742
	(0.0057)	*(0.2486)*
Adjusted R^2	0.047856	0.047904

Note: This table shows the regression results for Eq. (8). Coefficients for each month are reported with their associated P-values underneath in parentheses. * ,**, *** indicate significance at the 10%, 5%, and 1%, levels respectively.

after the negative returns in June which is likely due to the onset of winter. This loses strength though when we see that June did not have significantly negative returns over this period and that multiple weeks pass before this correction occurs. This may follow a similar reasoning to that given for the results in the first few weeks of May, specifically that Quarterly reports are released during that time and overreaction ensues. The significance of April may also follow this reasoning, although to make that claim we'd have to renounce the same one on the significant weeks in May and I'm not sure that would be wise to do. The reasoning could be similar to that of December, whereby the Easter period inspires joy among investors and so they feel more bullish, driving up the price, although this lacks the power of December's argument because of the lack of increased funds by way of gifts and that it does not occur at the beginning of summer. Perhaps a combination of these two reasonings could be the case.

Table 6. Profit from monthly trading strategy

Trading strategy	*04-17*	*11-17*
Return from sig. positive months	74.84%	48.43%
Yearly Average'	5.35%	6.92%
Ret. without sig. negative months		69.51%
Yearly Average'		9.93%
Total Return- Buy and hold	51.44%	61.62%
Yearly Average	3.67%	8.80%

Note: ' Average return was achieved by taking the coefficient values of the regression, whereas the total return was the sum of the actual return and so they may differ.

The regression over the 2011 to 2017 period shows the market returning to a more even situation, as have shown the previous seasonal period regressions. April manages to stay highly significant over this period, indicating that it was not GFC conditions that caused its high returns. December proved the opposite, and despite the weeks within it remaining significant during this period, the month itself did not. July decreases in significance but remains so at the 10% level. The new comers are not without intrigue either, with the much-expected June being found to be significantly negative, while the positive significance of January and February oame with a surprise as their insignificant weeks failed to provide any hints. Four of the 12 months have negative coefficients, including the significant one of June as previously mentioned, and no coefficient comes close to being as large as July's 0.024832 from the full period regression. Again, a trading strategy is tested where the significantly positive months alone are held. Despite the addition of one more positive month and the effect of a significantly negative one, this strategy fails to outperform the market return of 61.62%, by returning 48.43%. This indicates that investors cannot earn excess returns from trading around the positive months. They can, however, by trading around the negative month, where the return of 69.51% would have beaten the market by 7.89% over the period, or by 1.13% per year, as sum that easily out earns the transaction costs involved.

The significance of June during this period is easily explained by the same reasoning given for the significance of the weeks within it. April and July remain significant, indicating that at least some of their return is caused by something other than GFC conditions. This is likely caused by some of the reasons given previously. January and February are interesting though because during this period, the only significant week that either showed was Week 9, beginning on the

26th of February, which is probably explained by the turn-of-the-month effect. The significance of these two months may imply some sort of beginning of the year effect, similar to that of the January effect explored in Rozeff and Kinney (1976) which found an increase in returns during the month of January. While that paper does not look to explain the existence of the effect, Raj and Thurston (1994) give the reason of "tax loss selling" (p. 81) whereby an increase in returns for January is caused by widespread selling in December, however they find that this is not the case in New Zealand. Perhaps there may be another reason for the significance of the two months, such as that the beginning of the year brings with it hope for investors and so they tend to be more bullish. Or perhaps the holidays usually taken around the end/start of the year rested investors, and so they feel better. Maybe this gain is a result of the summer weather, whereby the warmth and increased hours of daylight improve the emotions of investors, leading to higher gains.

The seasonal data over the 2004 to 2017 period provides evidence against the efficiency of the market because of the profit-making opportunities available to investors, but this fails to continue when the more reliable period of 2011 to 2017 is looked into. There is, however, a profitable opportunity in selling around June which would lead to excess risk adjusted returns. This is a similar finding to that of the weekly data but this one involves less transaction costs. There also appears to be breaks in efficiency by way of the significance of January and February which could indicate that the summer weather positively influences prices. Also, the significance of April and July leave questions as to the reaction of the market to earnings news. The findings from the monthly data would also provide an indication of when to sell or buy and when to avoid it, although to a lesser extent than the daily or weekly data because of the length of a month. Timing specific weeks would be easier and more fluid as they occur more regularly. We'd also expect their returns to be more consistent throughout, as shown by February where the month as a whole is expected to return 1.61% while the week beginning on the February 26 is expected to return 1.17%, over a period a quarter the size.

5.2.4 Holiday

Similar to the day-of-the-week effect, regressions are run on the three time periods of 2004 to 2017, 2004 to 2010, and 2011 to 2017. Two regressions are run for each of these periods with the dummy variables for one being a single day before/after the holiday (first regression), and the holiday dummy variables of the other being two days before/after (second regression). These are shown in Table 7. In the first period, the first regression finds no evidence of a holiday effect, although the coefficient for 'before' is close to being significant at the 10% level. It does change the value of the coefficients from the day-of-the-week regression though. We expect this of course, but it would be interesting to see what impact this effect has as we analyse more. For one, Wednesday has a smaller coefficient than before but is still significant at the 5% level. Friday is found to be more negative than before, likely because the 'before' coefficient is positive. 'Before' will more likely effect Fridays' returns because of the prevalence of holidays occurring on Monday. Thursday will be similarly affected for the second regression, while Tuesday and Wednesday will be affected by the 'after' variable. Not all holidays fall on a Monday though and so the two dummies' will have a slight effect on every day, including Monday, which now has a negative coefficient although is still very insignificant. The second regression over this period results in a further decrease in most of the weekday coefficients, with Wednesday falling out of significance at the 5% level but remaining so at the 10% level. This time 'before' is found to be significant at the 10% level, with a coefficient of 0.000828, implying a holiday effect. Unfortunately for investors, this return is far too small and occurs not nearly often enough to provide a trading strategy that relies solely on holidays. There could have be an opportunity if it was added to the Wednesday strategy from the day-of-the-week effect but as we can see, by comparing Table 2 and Table 7, the expected return from Wednesdays has decreased from the addition of the holiday variables, implying that some of Wednesdays' return can be explained by the holiday effect. This means that the returns we initially expected from Wednesday were over inflated and even as such were not able to produce viable excess returns when transaction costs were involved, therefore we can expect the same outcome with the addition of the holiday effect. Cao et al. (2008) investigate the pre-holiday effect in New Zealand and also find evidence supporting it. The reasons they give for why this

Table 7. Holiday test results

Variable	04-17		04-10		11-17	
Monday	- 0.000003	- 0.000009	- 0.000288	- 0.000293	0.000282	0.000276
	(0.9897)	*(0.9714)*	*(0.4401)*	*(0.4324)*	*(0.3350)*	*(0.3453)*
Tuesday	0.000139	0.000135	0.000047	0.000014	0.00023	0.000254
	(0.5765)	*(0.5859)*	*(0.9114)*	*(0.9739)*	*(0.3859)*	*(0.3320)*
Wednesday	0.000498**	0.000452*	0.00064*	0.000577	0.000356	0.000327
	(0.0405)	*(0.0685)*	*(0.0762)*	*(0.1176)*	*(0.2762)*	*(0.3258)*
Thursday	0.000096	0.000043	- 0.000323	- 0.000360	0.000501**	0.000445*
	(0.6892)	*(0.8620)*	*(0.4362)*	*(0.3887)*	*(0.0431)*	*(0.0803)*
Friday	- 0.000202	- 0.000199	- 0.000492	- 0.000498	0.0000965	0.000105
	(0.4214)	*(0.4265)*	*(0.2403)*	*(0.2323)*	*(0.7266)*	*(0.7045)*
One day before	0.001040		0.000160		0.001169	
	(0.1091)		*(0.3119)*		*(0.1036)*	
One day after	0.000394		0.001111		0.000587	
	(0.6412)		*(0.9149)*		*(0.4952)*	
Two days before		0.000828*		0.000670		0.000978*
		(0.0976)		*(0.4366)*		*(0.0652)*
Two days after		0.000317		0.000502		0.000134
		(0.5463)		*(0.5771)*		*(0.8133)*
Adjusted R^2	0.000109	0.000299	- 0.000184	- 0.000063	- 0.001364	- 0.00117

Note: This table shows the regression results for Eq. (7). Coefficients for each day are reported with their associated P-values underneath in parentheses. * ,**, *** indicate significance at the 10%, 5%, and 1%, levels respectively.

effect may occur include an extension of high returns for market closures, a closing of positions by short-sellers, and an increase in optimism brought about by the joy of the holiday. The first of these I find to be unlikely, considering the low return we see on Fridays, a day when the market closes. The short-seller hypotheses hold’s merit, although short-selling is not a common practice in the New Zealand market and so unlikely to cause a significant effect. The third suggestion seems to me to be the most plausible. For this to be the case though, that optimism must remain, or at least not turn into pessimism, after the holiday because the coefficients remain positive for the following days.

The regression over period two further damages the holiday effect’s influence on market efficiency. Unlike the previous seasonality test, it appears as though the GFC actually decreases the strength of the holiday effect. The first regression over this time period follows very similarly to that of the first regression over the whole period, with no indication of holiday significance and little change other than that of decreasing the coefficients of the weekdays. Friday in particular decreased, which is notable due to its large negative coefficient. This further strengthens the belief that there is some form effect that keeps Fridays returns so low compared to the others, although without significance in its coefficient this argument has little merit. The second regression is interesting because it has quite a large effect on Wednesday’s significance, or rather insignificance, as it falls out of the 10% confidence level. This implies that the second day either before or after a holiday has a large effect on it. This is more likely to be the second day after, which would be Wednesday if the holiday fell on a Monday. With no significance in any of the variables in this regression there is clearly no trading strategy that can produce gains superior to the market and, at least in respect to the holiday effect, there is no break in efficiency over this period. The trading strategy of combining Wednesday and the two days before the holiday is further discredited by these results. Clearly, while Wednesday is strongest during the years 2004 to 2010, the ‘pre-holiday effect’ is strongest in the years 2011 to 2017, and so neither would be providing significant returns at the same time.

The third period regressions also go against the trend shown by the other seasonality periods, with significance for the holiday effect increasing. The first regression over this period shows little significance, although with a p-value of 0.1036, ‘before’ is close to being significant at the 10% level. The second regression shows that ‘before’ is significant at the 10% level, as expected. Unfortunately, it is still too small to provide significant gains if exploited in a strategy and so is not much of an argument against efficiency. The regression also decreased the significance of Thursday, with its coefficient now only significant at the 10% level. This is likely due to the ‘before’ coefficient with most holidays occurring on a Monday. Something to note is the lack of significance of the holiday effect when only measured one day before/after the holiday, as opposed to two days. One reason for this may be that investors, taking advantage of the holiday effect, may increase their holdings two days before a holiday in the hope of picking up excess gain over the single day before a holiday. They may then follow suit with the second day after a holiday. The result of this would be a decreased gain on the single day before/after the holiday, and an increased gain two days before/after. Malkiel (1989) argues that this is the method the market takes to eliminate anomalies buy eventually spreading the effect out far enough that it no longer exists.

Unlike the other seasonal effects tested, the strength of the holiday effects argument for inefficiency increased over time, with a pre-holiday effect being apparent over the past seven years but not the seven years before that. Despite this, there is almost no way to profitably exploit this effect on its own for return and so there is little attack on the EMH. If anything, this effect seems to strengthen the EMH for daily data by diminishing the significance of Wednesdays and Thursdays, and therefore further discrediting the return potential of them. It does, however, provide investors with another period to use for selling though, with higher expected prices before holidays.

Table 8. Fund performance

Series	α	β	*Adjusted R^2*
All funds	0.001614*	0.986361***	0.6608
	(0.0536)	*(0.0000)*	
Fisher Funds NZ Growth Fund	0.006212***	0.774986***	0.5486
	(0.0003)	*(0.0000)*	
Mint Australia NZ Active Equity	0.002924***	0.969729***	0.8442
	(0.0055)	*(0.0000)*	
AMP Capital Strategic NZ Shares Fund	0.002382**	0.950284***	0.8608
	(0.0196)	*(0.0000)*	

Note: This table shows the regression results for Eq. (9). α (Jenson's Alpha) represents the constant and is used as the measure of outperformance. β represents the riskiness in relation to the maket. Coefficients are reported with their associated P-values underneath in parentheses. * ,**, *** indicate significance at the 10%, 5%, and 1%, levels respectively.

5.3 Fund performance

To determine the performance of investment funds in New Zealand, a regression of the grouped fund returns is performed on the NZX 50 returns data, as well as a regression of each fund with five or more years' worth of observations, on the NZX 50 over the same period. As shown by Table 8, the full fund regression on Equation 9 results in an α of 0.001614 and was found to be significant at the 10% level. This indicates that, with 90% confidence, manged funds in New Zealand are able to earn a risk adjusted premium to that of the market return. This amounts to a compounded risk adjusted return of 1.95% p.a. Three funds with over five years' worth of data also display evidence of outperformance. Mint Australia NZ Active Equity and AMP Capital Strategic Shares fund both have similar results, with a β of slightly under one indicating that it's slightly less risky than the market, an R^2 in the mid 0.80's, and a significantly positive α. The funds relatively low β is likely caused by a more equal weighting among their stock constituents than the NZX 50 which, even with a 5% cap per stock, exhibit large differences in size between the top end companies and the rest, as well as between industries with seven of the top 22 NZX 50 stocks being energy companies. The fairly high R^2 indicates that the model explains a large percentage of the return experienced by these funds, although the missing variables may be able to explain the excess returns better, or even remove it. Fisher Funds NZ Growth Fund is a more interesting case. The large and significant α indicates that this fund has earned a compounded risk adjusted return of 7.71% p.a. This is a very high number for a fund invested in similar stocks to that as the NZX 50. Looking at the funds constituents over time it can be seen that it is almost entirely invested in New Zealand stocks. The higher return therefore must come from successful asset selection, which is supported by the fairly small number of stocks held by the fund (11 New Zealand stocks at the lowest, 17 at the highest). The small number of stocks fails to explain the low β of 0.78 though, as fewer stocks should imply more risk due to less diversification. This, along with the low R^2 of 0.55, shows that caution should be taken before concluding outperformance by this fund. It could be that there is not enough data and so this excess return is just 'lucky' or, in other words, that the stocks they picked happened to be the ones that grew. This explanation does have some merit but because this fund has data for the full eight year tested period I wouldn't lean on it. A much more viable answer is that the model we use is not extensive enough to properly capture the returns experienced by this fund, with a more accurate model such as Fama and French's (1993) 3-factor model or Carhart's (1997) 4-factor model being able to better explain its high risk-adjusted returns. This argument could be extended to the full regression which also experiences a fairly small R^2 of 0.66 and so outperformance should be cautiously accepted until further analysis is undertaken.

To determine whether investing in a managed fund provides better gains for an investor than forming a diversified portfolio, the funds fees need to be compared. With an excess return of 7.71% p.a., Fisher Funds easily outperforms the 1.54% p.a. plus performance fees charged by the managers (Fisher Funds, 2018). Mint charges a similar fee of 1.52% p.a. plus performance, which is fairly easily beaten by its compounded excess return of 3.57% p.a. (Mint Asset Management, 2017). The same could be said for the slightly lower compounded excess return of AMP which, at 2.90% p.a., largely exceeds the 0.79% p.a. it charges (AMP Capital, 2017). Instead, these fees pose a bigger threat to the 1.95% p.a. compounded excess return experienced by the market. If AMP's structure is determined to be around the average charged by funds, then the true compounded excess return experienced by investors would be closer to 1.15% p.a., and worth undertaking by an investor. If the return is closer to that of the 1.54% p.a. charged, then the compounded excess return would be 0.41% p.a., a much smaller value but still worthwhile. A question could be made for the other funds individually. With only three of the 23 funds with five or more years of data failing to significantly outperform the market, it is unlikely that the fees they charge are lower than their risk adjusted performance. Also working in the funds favour is that the methods used to isolate the New Zealand stock returns resulted in any fees incurred by the funds in the management of the fund, such as transaction costs, being excluded and so their true returns may be lower. Working against the funds though is that the methods used also excluded any movement in the funds portfolio throughout the year and so any attempt to take advantage of season effects or otherwise was not included, and therefore so was any potential returns achieved by this.

In a very basic way we could say that by finding a significantly positive α we also find evidence against the EMH, although this wouldn't be entirely accurate. There is uncertainty in the results because of the methods used to collect and analyse the data, particularly with the model which is too simply to fully explain the return. Also, the lack of pure New Zealand invested portfolios means that the New Zealand stocks in a fund may simply be part of a broader strategy, and so analysis of these on their own as a designed strategy may be presumptuous. Our results then cannot be used as definitive evidence for inefficiency but can be used to show that there may be inefficiencies in the performance of managed funds and that the market is not necessarily efficient in this area.

6. Conclusion

This paper analyses market efficiency in New Zealand by testing whether past prices have explanatory power for future return, whether seasonal anomalies exist and are exploitable, and whether funds are capable of outperforming the market. These three methods are chosen so that a fuller picture could be formed of the use of information in the market, particularly with past prices for the first two, and insider information for the third. An Augmented Dickey Fuller test using NZX 50 daily, weekly, and monthly returns shows that the market exhibits a unit root. This implies that the market prices follow a random walk, consistent with market efficiency. Day-of-the-week effect, Holiday effect, Week-of-the-year effect, and a Monthly effect are tested for to determine the seasonality of the NZX 50. The results show that while there are potential inefficiencies, these are mostly unexploitable for profit, consistent with market efficiency. The analysis of New Zealand fund performance finds that funds in general are able to outperform the benchmark index, while an analysis of the individual funds show that three manage to achieve significant excess risk-adjusted return. Little can be said about these results' impact on efficiency because the evidence is not strong enough to make a claim either way. This paper contributes to the literature by providing a broader analysis of the New Zealand stock market's efficiency after the impact of the GFC and formation of a 50-stock index. It also contributes to the industry by cautioning investors about using past price data to predict returns, although does show that there are opportunities for gain in the timing of trades. It also shows that managed funds may be able to outperform the market using insider information. Of the limitations for the unit-root test was the choice of the fairly simple ADF test procedure, although it is not believed that a more complicated model would have reversed our findings on efficiency, and the inclusion of the GFC period in the data. There were a few limitations to our tests of fund outperformance. Of the biggest, the first was that the methods used to collect and manage the data opened it up to errors, as well as leaving out valuable information, while the second was our choice of model which was not specific enough to strongly capture the returns of the funds leading to uncertainty in the results.

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