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The Effect of the El Niño-Southern Oscillation on Stock Indices

Evidence for Developed Stock Market Indices and United States Sector Indices

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Abstract

This paper examines the effect of El Niño-Southern Oscillation (ENSO) events on eleven stock market indices and eleven US sector stock indices. I found that ENSO events do not significantly affect major stock market indices but do affect four US sector indices. I attribute this to increasing GDP growth and fewer hurricanes. Investors can benefit from a trading strategy by, at the right time, going long in 'winners' and shorting 'losers', caused by ENSO events resulting in 0.014% to 0.025% excess returns per day. Further research is needed to examine whether more extreme results emerge in subsectors to benefit from.

JEL Classification: G12, Q54

Keywords: Stock market returns; El Niño-Southern Oscillation cycle

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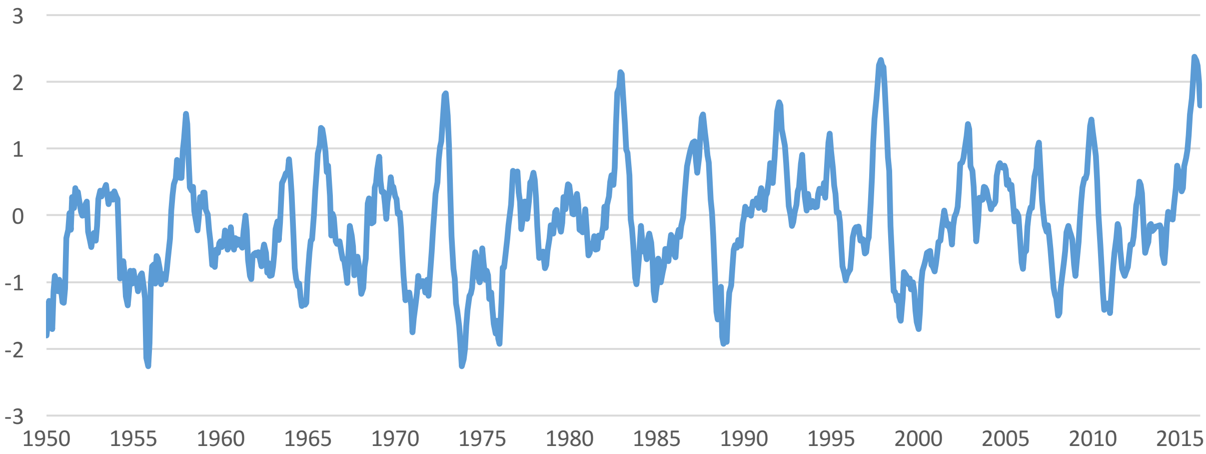
1 Introduction

In this paper the effect of different El Niño-Southern Oscillation (ENSO) events on the performance of eleven major stock market indices spread over eight developed countries and eleven sector stock indices in the United States (US) is examined. ENSO events emerge from abnormal sea surface temperatures (Rasmusson & Carpenter, 1982) and atmospheric pressure around the equator in the Pacific Ocean resulting in large global weather anomalies (Rasmusson & Wallace, 1983). These sea surface temperature and atmospheric pressure differences determine the intensity of an ENSO event. Naturally, more intense events go along with more extreme global weather consequences. These weather consequences consist of changes in the amount of daily sunshine and precipitation, temperature (Yulaeva & Wallace, 1994) and even the amount of hurricanes occurring in a specific year is influenced by ENSO (Bove, O'Brien, Eisner, Landsea, & Niu, 1998). According to the National Drought Mitigation Center, tropical regions like Africa, the Asia-Pacific and Latin America are primarily affected; enormous droughts could be the result of a highly intense event. Judging the peaks in Figure 1, it is clear that last year had one of the most intense El Niño events in recent history. The consequences of this event were enormous, since it even caused severe famine in regions like Somalia and Ethiopia.

Additionally, ENSO events also cause many diverging financial consequences around the globe (Changnon, 1999; Cashin, Mohaddes, & Raissi, 2015). Some regions experience benefits, while other regions face huge damages caused by the adverse weather conditions that affect the harvest of a country or by the amount of hurricanes that occur in a specific year. Similarly, these consequences can possibly affect stock markets in potential, discernible patterns I aim to uncover. To my knowledge, no research has been executed concerning the effect of ENSO events on stock markets. By filling in this gap I aim to contribute to the existing literature.

Investors should incorporate all available information to accurately value assets. In order to value assets, investors can make use the Capital Asset Pricing Model (CAPM). This standard model incorporates the risk free rate, the market risk premium and the systematic risk. However, this model lacks other factors that could affect the value of assets. Although short-term weather effects do not change the fundamental value of assets, it can affect stock prices by influencing the mood of investors (Saunders, 1993; Romer, 2000; Cao & Wei, 2005). Long-term weather effects can influence commodity prices, real GDP or create industry specific consequences and this could also affect asset prices (Cashin et al., 2015). In this paper, the effects of ENSO events on stock prices are examined, in order to determine whether the US and other developed countries should apply an ENSO-extension in the CAPM. However, the uncertain long-term predictions of an upcoming ENSO event render it difficult to anticipate on. Nevertheless, in a study by Fedorov, Harper, Philander, Winter and Wittenberg (2003), the authors argue that ENSO events can be predicted about eight months in advance by taken the wind power into consideration. If one assumes that all investors are fully rational, the daily weather changes caused by ENSO events should not affect stock prices. In contrast, the aforementioned other consequences of ENSO events, like changing the real Gross

Figure 1: Sea Surface Temperature Anomaly Measure on El Niño 3.4



Notes. (1) Data retrieved from National Oceanic and Atmospheric Administration.
(2) Monthly Extended Reconstructed Sea Surface Temperature (ERSST) 1950-2016 with 1981-2010 as base period on area Niño 3.4 (5°North-5°South) (170-120°West). The three most intense El Niño events with an ERSST higher than 2°C occurred in 1982/1983, 1997/1998 and 2015/2016.

Domestic Product (GDP), commodity prices and the amount of hurricanes in the US, could affect stock prices.

If this anomaly appears to exist, there should be at least one stock market index positively or one negatively correlated with the ENSO intensity to obtain excess returns. Investors can benefit from predictable changes in stock prices due to ENSO events. Subsequently, the market can be outperformed by buying or selling stocks in different countries or sectors at the right time.

For the past 25 years, there has been a lot of research on the effect that weather has on stock markets, with widely diverging results. Some researchers state that the weather significantly affects stock markets (Saunders, 1993; Kamstra, Kramer & Levi, 2003; Hirshleifer & Shumway, 2003; Cao & Wei, 2005; Kamstra, Kramer & Levi, 2007; Kang, Jiang, Lee & Yoon, 2010; Lu & Chou, 2011) while others contradict these findings (Trombley, 1997; Krämer & Runde, 1997; Pardo & Valor, 2003; Tufan & Hamarat, 2004; Novy-Marx, 2014). While time periods and variables could attribute to these different findings, one can wonder how some stock markets are affected by weather effects, while other stock markets are not. Even among the multiple researchers who did find significant results, the identified effects are not consistent with each other. Hirshleifer and Shumway (2003) e.g. found that sunshine is positively correlated with daily stock returns and Cao and Wei (2005) and Floros (2008) found that temperature is negatively correlated with daily stock returns. Cao and Wei (2005) found that the effect of apathy dominates aggression when temperature is high, leading to lower returns. Since sunshine usually increases maximum temperature (Matuszko & Weglarczyk, 2015), one can state that these seemingly contradicting results are at least remarkable. Altogether, there still is uncertainty about the effects of the daily weather on stock returns.

Besides weather conditions directly affecting stock markets by influencing investors' moods, another possible way that the weather can influence stock markets is e.g. by real GDP or commodity prices (Brunner, 2002; Cashin et al., 2015). In contrast to daily weather conditions affecting investors' mood, these changes in real GDP and commodity prices may not be depending on the weather of one single day. However, when the weather of a whole season changes, changes in real GDP and commodity prices may occur. These studies found that ENSO events affect commodity prices and real GDP which in turn could affect stock markets. The macroeconomic effects explored by Cashin et al. (2015) differ significantly per region due to different weather effects per region.

Since former researches do not provide consistent results about weather effects, it is hard to predict the effect of weather changes caused by ENSO events on stock markets. Additionally, changes in countries' real GDP vary greatly and are relatively small (Cashin et al., 2015). Together with the finding that only changes in expectations of future growth could affect stock markets, makes it implausible that ENSO events affect stock markets merely through changes in real GDP. Another macroeconomic effect of ENSO events are changes in commodity prices. Non-fuel commodity price changes caused by ENSO events are probably too small to affect the stock market of a whole developed country or a specific US industry. In contrast, fuel commodities changes due to ENSO events could affect a specific US sector since ENSO events increase oil prices enormously (Cashin et al., 2015). While this could have a negative impact on manufacturing and transporting companies, it could also affect the Oil & Gas industry in a positive way. At last, the amount of hurricanes that is affected by ENSO events could also affect stock prices. While this effect is perhaps too small to affect a whole country, hurricanes could affect returns on the Real Estate Investment Trusts (REITs) sector by damaging buildings and increasing insurance costs. Therefore, the expectations of this study are that the eleven major stock market indices will not be affected by ENSO events, which can be ascribed on the one hand to the different companies within the indices and on the other hand to the relatively small diverging consequences of ENSO events. However, for the sector indices, where the companies within the indices are more alike, the probability that they will be affected by ENSO events is greater, especially for sectors that are influenced by the amount of hurricanes, like diverse REITs and Financials.

This study tried to answer the question whether ENSO events significantly affect major market indices and/or US sector indices. In order to obtain the desired results, different comparisons are made. First, the effect of ENSO intensities on daily returns of different major market indices was examined. By this way, one is able to assess the effect of ENSO within each country separately. Additionally, the effects of ENSO events on stock markets of different countries were compared to each other. Next to that, I examined the effect of the ENSO intensity on daily returns of eleven US sector indices to see whether there are industry-specific effects caused by ENSO events.

In this study, weather anomalies mostly have no significant effects on the price indices. However, if only the significant effects are assessed, it appears that more sunshine positively influences performance, while more precipitation negatively influences performance. This corresponds to findings that sunshine enhances investors' mood while precipitation deteriorate investors' mood. When the mood of investors is ameliorated, they overestimate future performance. Corresponding to previous research, there is no unanimous conclusion about the effect of temperature on performance.

The results of this study suggest that the effects of ENSO events are too small to affect the major market indices, probably because major market indices are too diversified due to the inclusion of a legion of companies from multiple sectors. When examining different US sector indices, significant results appear regarding the Consumer Goods, diverse REITs, and Financials and Utilities sectors. I speculate that the combination of the El Niño consequences consisting of the increase in real GDP together with fewer hurricanes, attribute to higher daily excess returns in these sectors.

To benefit from the uncovered anomaly a portfolio with "winners" or "losers" can be created. Thus, if the ENSO variable is high, one should go long in one of the four sector indices that are significantly affected by ENSO events and go short in a highly correlated set of stocks that are not affected by ENSO events. If the ENSO variable is highly negative, one should short one of those four indices and go long in the set of stocks unaffected by ENSO events. The results suggest that profits ranging from 0.014% to 0.025% per day can be achieved by this trading strategy. However, one should be aware of the increase in volatility that comes along in case of the ENSO variable being highly negative.

In Section 2 the existing literature will be reviewed. Next, Section 3 will elaborate on the methodology. Section 4 describes the data used in this study. In Section 5 the results will be discussed, followed by the robustness of the results in Section 6. At last, a conclusion will be drawn up in Section 7.

2 Literature Review

To begin with, it is important to understand what an El Niño-Southern Oscillation event is. An ENSO event is a recurring weather phenomenon arising from the east side of the tropical Pacific Ocean leading to large global consequences. Anomalies in sea surface temperatures and air pressure in the Pacific Ocean create these weather anomalies all around the world (Rasmusson & Wallace, 1983). To be more specific, an ENSO event is a cycle consisting of two phases; the warm phase is called El Niño, while the cold phase is called La Nina. In this study, the ENSO event will refer to the whole cycle, including El Niño and La Niña events. According to the National Oceanic and Atmospheric Administration (NOAA), such an event occurs on average once in two to seven years and lasts about nine to twelve months. Obviously, the larger the sea surface temperature and air pressure anomalies are, the larger the global consequences are.

In this section, the global weather effects of ENSO will be drafted in Section 2.1. After that, studies on weather effects on single and multiple stock markets will be discussed in Section 2.2. Next, studies on macroeconomic effects due to ENSO events will be examined in Section 2.3. If these effects are clear and point in the same direction, they will contribute to determining the prediction of the effect of an ENSO event on stock markets.

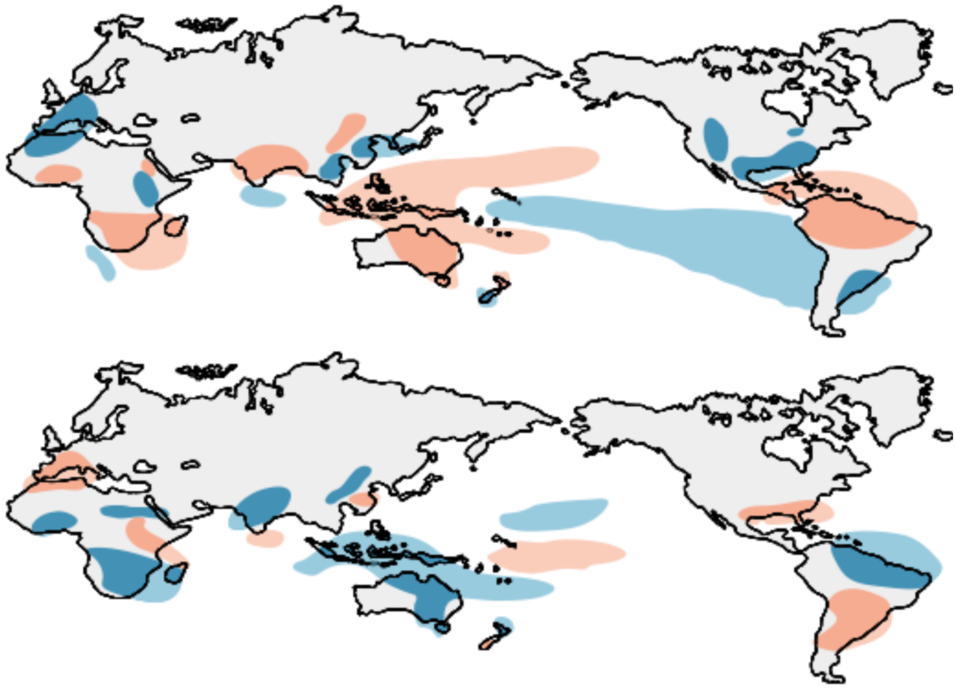
2.1 Weather consequences of ENSO

When ENSO events occur, some areas around the globe face very wet periods, while other areas face very dry periods; see Figure 2 for a concise overview. In the upper part of the figure the precipitation anomalies for El Niño events are displayed, whereas the bottom part displays the consequences of La Niña events. In the figure the blue parts represent wetter periods, while the orange parts represent drier periods. In some regions the amount of precipitation could be four to ten times as high as usual and the wet and dry periods could last about one year (Holmgren, Scheffer, Ezcurra, Gutiérrez, & Mohren, 2001).

For this study it is important to look at certain countries. Looking at Figure 2, it appears that Sydney faces relatively dry periods when El Niño events occur. In contrast, Paris, Frankfurt, Milan, Tokyo and Toronto face relatively wet periods while the precipitation in New York and London is practically unaffected by ENSO events. In a La Niña phase, precipitation increases in Sydney, while it is drier than usual in Paris and Milan.

Chiodi and Harrison (2013) examined several weather anomalies like temperature and precipitation, caused by El Niño events. In their study they focused on the weather consequences of four El Niño events (1982/83, 1986/87, 1991/92 and 1997/98) and five non-El Niño events (1987/88, 1994/95, 2002/03, 2004/05, 2006/07). When examining the individual December-February temperatures of the four El Niño years, they found that there is a large area in the US (consisting of the north to north-central part) where temperatures are more than 3°C higher than average in each of these four years. However, in the southern part of the US, cool anomalies are observed. On the other hand, when looking at the five non-El

Figure 2: Global precipitation levels during ENSO events



Note. Areas showing more precipitation (blue areas) and drier conditions (orange areas) during El Niño (upper part) and La Nina (lower part) periods of the ENSO phenomenon (Holmgren et al., 2001).

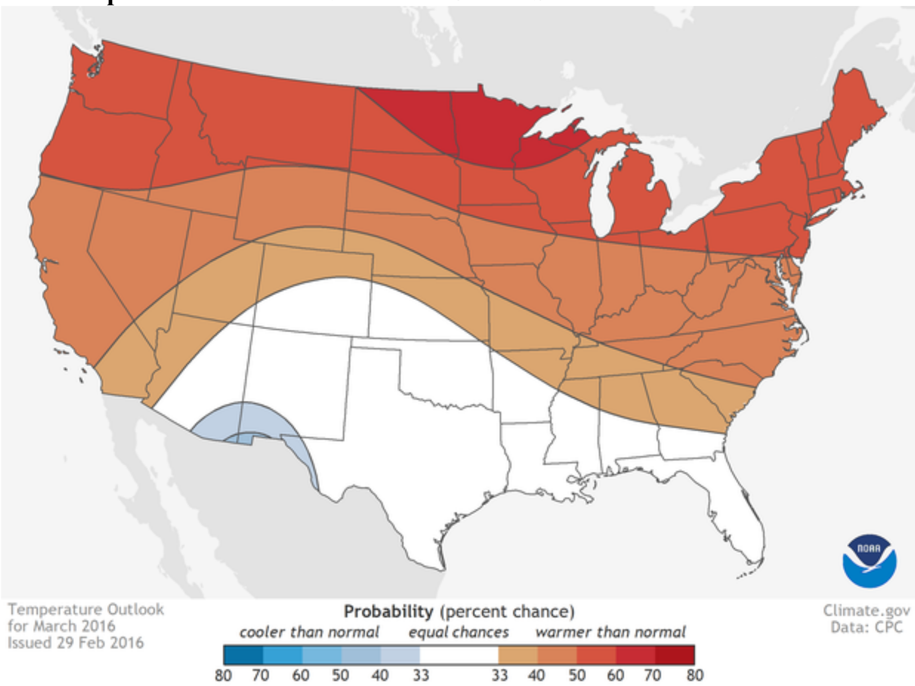
Niño events, the temperature differences vary greatly, so no conclusion can be drawn from this part of their study.

In a nutshell, according to both Holmgren et al. (2001) and Chiodi and Harrison (2013), El Niño events increase the mean temperature in the northern part of the US, which is consistent with Figure 3, showing weather forecasts for the US for March 2016. It shows higher than mean temperatures in the upperpart of the US to normal temperatures in the South.

Another important consequence of El Niño events is the amount of hurricanes occurring in the US. Bove et al. (1998) found that El Niño events, on average, result in fewer hurricanes while La Niña events bring along more hurricanes. In a neutral phase they found that during 1900-1997 the probability of two or more hurricanes in a single year in the US is 48%. During La Niña events the probability of two or more hurricanes in a single year appears to be 66% while during El Niño events, this is 28%. This means that increasing sea surface temperatures and air pressure in the specific period results in a decreasing amount of hurricanes.

While hurricanes decrease the economic growth rate in affected counties by 0.45 percent on an annual basis, the total US economic growth is unaffected (Strobl, 2011). However, between 2000 and 2010 fourteen major hurricanes were registered with estimated property damages ranging from one billion to 108 billion dollars (Blake & Gibney, 2011). Besides the damages concerning property, people will invest to protect their properties from hurricanes and insurance premiums on real estate will increase. This means that hurricanes are even more costly than the estimated property damages.

Figure 3: Predicted temperatures after El Niño in the United States.



Note. The National Oceanic and Atmospheric Administration (NOAA) predicts higher than mean temperatures for Northern areas of the US for March 2016 (after a big El Nino event), while they predict normal temperatures for the southern areas of the US (NOAA, 2016). The Figure shows varying effects of El Nino even within one country.

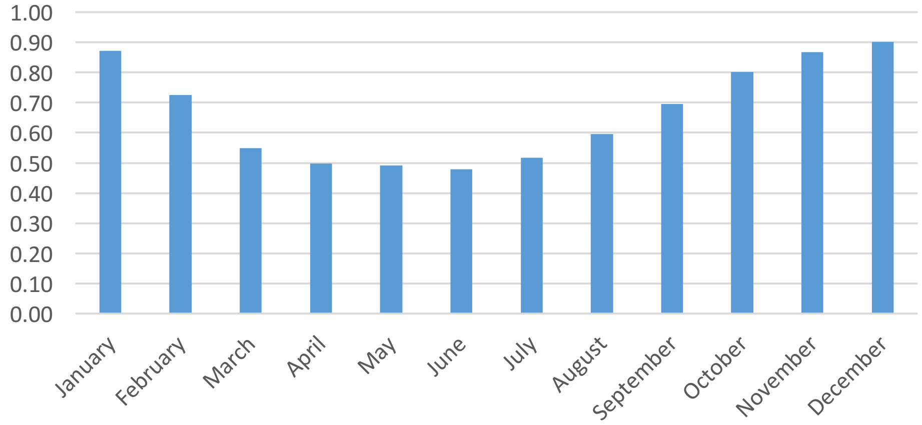
Besides looking at what happens to the weather due to ENSO events, it is also important to look when it happens. According to the NOAA, the weather changes caused by ENSO events are primarily observable during the end of the fall to the begin of the spring. The absolute values of the measured sea surface temperature anomalies are highest during the winter months and lowest during the summer months, which can be deduced from Figure 4, indicating that the weather effects do not come with a delay. However, the NOAA states that the amount of hurricanes that occur in the hurricane season, August-October, depend on the developing ENSO event. The development of the ENSO peak starts in the end of the summer and ends in the begin of the spring (Bove et al., 1998). The absolute values of the measured SST anomalies are highest after the hurricane season, indicating that the amount of hurricanes are a consequence of an upcoming ENSO event, even before the measured SST is at its maximum.

2.2 Meteorological effects on stock markets.

Several researchers found that investors tend to invest about 90% of their capital domestically (French & Poterba, 1991; Vanpée & De Moor, 2013). For this reason, one could state that weather conditions in a particular region affect the stock market in that region the most due to investors' home bias (Vanpée & De Moor, 2013). Hence, if one concludes that weather conditions indeed influence an investor's mood and therefore affect the stock market in that particular region, this will be amplified by the phenomenon called the home bias.

Since assets should be priced according to their underlying fundamental value, the price of assets should not be influenced by the daily weather, for the reason that daily weather does not drive company

Figure 4: Absolute values of monthly SST anomalies on El Niño 3.4



Notes. (1) Data retrieved from National Oceanic and Atmospheric Administration.
(2) Monthly Extended Reconstructed Sea Surface Temperature (ERSST) 1950-2016 with 1981-2010 as base period on area Niño 3.4 (5°North-5°South) (170-120°West).

performance over the long run. However, some literature suggests that daily weather conditions do affect stock markets, while other researchers contradict this. A reason for this could be that different time periods and variables attribute to these different findings.

Saunders (1993) was one of the first who examined the effect of the weather on stock markets and found that less cloud cover led to higher returns on the New York Stock Exchange (NYSE) in the period 1927-1989. Many other researchers followed Saunders to look into this phenomenon. Trombley (1997) reinvestigated the study done by Saunders and found that the results are not that significant as Saunders suggested; he states that the results are only observable for a few months per year. Next, the effects of cloudiness, humidity and atmospheric pressure on returns of the Frankfurt Stock Exchange were studied by Krämer and Runde (1997), who did not find any significant results for the period 1960-1990. Also Pardo and Valor (2003) did not find significant sunshine and humidity effects on the Madrid Stock Exchange for the period 1981-2000. Moreover, Tufan and Hamarat (2004) also did not find significant effects of cloudiness on the Istanbul Stock Exchange.

Kang et al. (2010) and Lu and Chou (2012) both examined the Shanghai Stock Exchange for the periods 1996-2007 and 2003-2008 respectively. Kang et al. (2010) examined the effects of temperature, humidity and sunshine and some other factors. They found that low temperatures in combination with a high amount sunshine is positively correlated with returns on the Shanghai Stock Exchange and high humidity in combination with low sunshine is negatively correlated with performance. Lu and Chou (2012) analyse the same stock exchange over another time period but did not find significant effects of weather variables on performance.

Besides only looking at the meteorological effects on one single stock market, other studies have been done examining the effects on multiple stock markets around the world. Kamstra et al. (2003) examined the effect of the length of days on stock market performance. They found that there is a significant positive effect on stock market returns when the moment arrives when days become longer. This is due to the seasonal affective disorder (SAD), which is a depressive disorder directly linked to a specific season. While some people experience SAD during the spring and summer months, most people experience SAD in the autumn and winter months. SAD could cause depressions leading to more risk-averse investors who then avoid risky assets. Although this SAD effect is quite a prolonged period that is certain to happen, it is consistent with the findings of Hirshleifer and Shumway (2003) who examined the effect of cloud cover on market performance. The latter found that cloud cover is negatively correlated with stock returns and relate this to the positive effect of sunshine on investors' moods and this finding is, in principle, similar to the finding of Kamstra et al. (2003). Subsequently, investors tend to overestimate future market performance when their mood is good and for this reason the returns on stock markets increase. However, these findings could be considered somewhat strange since sunshine is expected to increase the temperature (Matuszko & Weglarczyk, 2015) and Cao and Wei (2005) found in their study that temperature is negatively correlated with stock returns. They attribute this to investors' apathy when temperature is high, resulting in less risk-taking. Subsequently, less risk-taking leads to lower returns. Moreover, in three out of five European stock markets, a negative relationship between returns and temperatures appears (Floros, 2008). Considering the studies by Kang et al. (2010) in contrast to Cao and Wei (2005) and Floros (2008), the effect of temperature on stock market returns remain doubtful.

2.3 Macroeconomic effects caused by ENSO

Alongside stock market returns, the weather could also create macroeconomic effects. Studies by Brunner (2002) and, a more recently, by Cashin et al. (2015) examined the weather consequences of El Niño on commodity prices and real GDP. Brunner (2002) mainly focused on global growth and commodity prices caused by ENSO events. In contrast, Cashin et al. (2015) focused primarily on regions that were in fact directly affected by ENSO events. Brunner (2002) found that an increase in the level of intensity of ENSO leads to increasing commodity prices, stating that ENSO accounts for about one fifth of commodity price changes.

Growth expectations change over time and these appear to significantly affect equity returns. However, it is not the current growth in GDP that drives market returns, but the expectation of future growth (O'Neill, Stupnytska, & Wrisdale, 2011). Therefore, ENSO events could affect market returns by affecting the real GDP of a country. Since ENSO events are not completely predictable, this is considered to be a shock followed by changing the future expectations of the GDP.

Cashin et al. (2015) studied the consequences of ENSO events of 21 countries in the period 1979-2013. Their analysis revealed very diverging results depending on what the specific weather effects are on particular regions. For most countries that experience major droughts during the El Niño event, like Australia, Indonesia and South-Africa, the economic activity will decrease for a short period. For other countries, like the US, Mexico, Argentina and Canada, El Niño events boost their economy directly, resulting in GDP growths of 0.5% to 1.5% after an El Niño shock. Other countries that are not directly affected by these shocks, but do trade actively with countries that benefit from ENSO shocks, like the European region enjoy positive spillovers from doing business with these countries due to more trading activity, resulting in a GDP growth of 0.7% (Cashin et al., 2015). Remarkable is that a country like Japan experiences a short decline in the economy at first. However, after four quarters a siginificant increase in GDP is realized. The authors suggest that this is due to positive spillovers and a boost in the construction sector. Unfortunately, changes in GDP in case of La Niña events are not discussed in their paper.

Next to the effect of ENSO on real GDP, the effect of ENSO on (non-)fuel commodity prices is also studied by Cashin et al. (2015). After four quarters, less supply originating from the Asia-Pacific region of non-fuel commodities and more global demand did increase prices by about 5.3%. Also fuel prices increased due to more demand for water for irrigation purposes. Even after four quarters, oil demand stayed at high levels in order to keep production levels high. Four quarters after an ENSO event, oil prices increased by 13.9% (Cashin et al., 2015). Each of the changes in commodity prices will contain its own consequence for stock markets. Oil prices, in particular, will affect almost each company. Oil companies will experience stock price increases when oil prices increase but other companies will experience higher costs which in turn would decrease net income and therefore decrease stock prices (Nandha & Faff, 2008).

Non-fuel commodity price changes will, in general, only affect businesses that directly use these commodities. Changes in coffee prices will affect stock prices of coffee companies like Starbucks mostly. Therewith, changes in corn or wheat prices will affect companies similar to Kellogg's. In the Asia-Pacific region the effects of ENSO events on inflation are significant. Inflation of 0.1 to 0.6% was observed in most of the Asia-Pacific countries, while in New Zealand deflation of 0.6% was observed (Cashin et al., 2015). For the countries assessed in this study the inflation caused by ENSO events is negligible and the price changes affecting specific companies are expected to be insignificant on a whole sector or country.

In summary, changes in commodity prices and real GDP will probably affect specific stocks. This effect is sometimes immediately noticeable while the effects are also observable with a delay. Hence, ENSO events will affect stock prices, since it is suggested that ENSO events affect commodity prices and real GDP. However, it is doubtful whether these macroeconomic effects are sufficiently large that they will affect the major stock market indices.

3 Methodology

In this section two ways of examining the effect of ENSO events on stock markets are discussed. At first, standard multiple regression analyses are performed on each index. Next, ENSO intensities are subdivided into quintiles for each index in order to examine the relation between the ENSO intensities and the return on stock markets. In order to be able to benefit from the discovered results, a portfolio consisting of going long in so-called "winners" and shorting "losers" has to be created, which is described in the last subsection.

3.1 Standard Multiple Regression Analysis

In order to measure the effect of ENSO events on daily excess returns of different stock markets, two standard Mutiple Regression Analysis (MRAs) were performed. Since outliers influence MRA enormously, extreme values were eliminated in the MRA by using a 98% winsorization. Consequently, non-normality of the data is almost completely eliminated. This will further be explained in the data section, where the descriptive statistics tables are also displayed. One argument in favour of using winsorized data is that other factors (incidental events), which are not comprised in the MRA, are the main reason for these extreme outcomes (Kraft, Leone & Wasley, 2006). One recent example of such an extreme event that has nothing to do with ENSO events is the outcome of the referendum whether the UK leaves the European Union, which resulted in huge losses in most European financial markets.

These regressions control for several known anomalies. To begin with, residual autocorrelation is eliminated, due to the inclusion of lagged returns. This is suggested by Akgiray (1989), who found that the return of today is not completely independent of the return of prior days. In this MRA, the elimination of autocorrelation is only performed if the first-order autocorrelation appeared to be significant. Additionally, the MRA included dummies for several seasonality effects. First of all, the Monday effect is included. This effect has first been suggested by French (1980), who found significant negative returns on Mondays, which are caused primarily by the weekend effect instead of the other examined closed-market effect. Therefore, a dummy variable was only attached to trading days following the weekend and not on days following a holiday. Furthermore, the tax-loss selling effect appears to be related to stock market seasonalities (Gultekin & Gultekin, 1983; Brown, Keim, Kleidon & Marsh, 1983). Keim (1983) and Roll (1983) emphasized the influence of this effect of the last and first trading days of a tax year. For this reason, a dummy is attached to the last and first five trading days of the tax year. Additionally, the autumn dummy variable is included in the regression, since it is expected that investors shun risky assets due to seasonal depression, resulting in lower returns. Furthermore, the before mentioned SAD effect is also included in the regression because it is expected to influence the returns significantly, following the reasoning of Kamstra et al. (2003). They find that investors shun risky assets and rebalance their portfolio to relatively save assets in autumn, due to the seasonal affective disorder. Subsequently, length of days increase and investors start to resume their risky holdings leading to higher returns in winter. For clarification, all these independent variables are

Table 1: Independent variables

Independent variable	Measurement	Expected sign	Explanation
r_{t-1}	Return in basis points of the day before	+	Price adjusments delay factors and nonsynchronous trading[1]
D_t^{Monday}	1 if following a weekend, 0 otherwise	-	Monday effect is caused by investors' moods, whereas the mood in the first days of the week is more pessimistic than in the latter[2]
D_t^{Tax}	1 on last or first 5 trading days of tax year, 0 otherwise	+	Tax related pressure to sell stocks at the end of the year.
D_t^{Autumn}	1 if autumn, 0 otherwise	-	Seasonal depression causing investors to shun risky assets causing prices to drop.
SAD_t	12 minus the amount of hours between sunrise and sunset if >0, 0 otherwise.	+	Due to the seasonal affective disorder, investors shun risky assets and rebalance their portfolio to relatively safe assets in autumn. In winter, the length of days increase resulting in investors start resuming their risky holdings, leading to higher returns.
$ENSO_t$	SST anomaly in the El Niño 3.4 Region	?	Depends on region and sector.
$Sunshine_t$	Amount of sunshine in hours	+	Sunshine improves investors' moods causing investors to overestimate future performance.
$Temperature_t$	Max temperature measured on that day	-	Lower temperature leads to agression, increasing returns and higher temperature leads to apathy, decreasing returns.
$Precipitation_t$	Daily precipitation in mm.	-	Precipitation deteriorates investors' moods causing them to underestimate future performance.

Note. Table 1 shows all independent variables with its corresponding measurement, expected sign and explanation for the expected sign.

depicted in Table 1 together with their corresponding measurements, expectations, and explanations for the expectations.

To prevent that the consequences of ENSO events will be eliminated, equation (1) included the ENSO intensity, but excluded the environmental factors. Otherwise, the weather consequences caused by ENSO events are eliminated by controlling for these variables, consisting of sunshine, precipitation, and temperature. By this way, indirect causation is eliminated from the regression model. Additionally, it is expected that reverse causation is also not present. First, for the reason that the dummy variables are completely independent of stock returns. Second, the returns of yesterday are not affected by the returns of today. Lastly, the hours of daylight, hours of sunshine, maximum temperature, amount of precipitation, and the SST in the Niño 3.4 region will also not be influenced by stock returns.

$$(1)\quad r_t = u + p_1 r_{t-1} + u_{Monday} D_t^{Monday} + u_{Tax} D_t^{Tax} + u_{Autumn} D_t^{Autumn} + u_{SAD} SAD_t + u_{ENSO} ENSO_t + \varepsilon_t$$

[1] Atchison, Butler & Simonds (1987)
[2] Abu Bakar, Siganos & Vagenas-Nanos (2014)

In this equation, the daily excess return in period t on a particular index is $\mathrm{r_t}$[3]; the one day lagged daily excess return is included as $\mathrm{r_{t-1}}$. The dummy variable $\mathrm{D_t^{Monday}}$ equals one if the trading day is following a weekend and zero otherwise. For the same reason, the dummy variable $\mathrm{D_t^{Tax}}$ equals one if period t is in the last or first five trading days of the tax year and otherwise zero and $\mathrm{D_t^{Autumn}}$ equals one if period t is in the autumn and zero otherwise. SAD_t is a variable that includes the length of the day in period t which equals zero if the time between sunrise and sunset is larger than twelve hours. When the time between sunrise and sunset is shorter than twelve hours, the SAD variable equals twelve minus the actual amount of hours between sunrise and sunset.

All these variables are measured for the city where the exchange is located meaning that all these variables significantly differ per stock exchange. By this way, the effect of ENSO events can be measured separately for each country. On the subject of ENSO, it is the last variable to explain here. Instead of attaching a label of El Niño or La Niña to the sea surface temperature or air pressure, a continuous measure of the SST anomaly is used in the models, meaning that the Sea Surface Temperature (SST) anomaly in the Pacific Ocean in the Niño 3.4 region (5°N-5°S, 170°W-120°W) is used to measure the intensity. The historical mean of the SST is subtracted from the measured mean temperatures in a specific month, to obtain a clearer view of the contrast between La Niña and El Niño events. Moreover, the reason for the choice of a continuous measure is that highly intense events are expected to provide more pronounced results and for this reason a continuous measure is expected to provide more accurate results compared to an ENSO dummy.

Due to the many variables included in the regression model, a correlation matrix is displayed in Table 2 Panel A. This matrix provides the correlations between all the independent variables of the MRA of the Dow Jones Industrials between May 9, 1950 and March 31, 2016. It would be unnecessary to show the correlation matrices of all the indices, since they are quite similar. There are two reasons to depict the correlation matrix of the Dow Jones Industrials specifically. First, the Dow Jones Industrials index concerns the largest period relatively and second, most of its variables are identical to the variables of the other major US market and sector indices.

In Table 2 the correlations between the different independent variables of equation (1) are depicted. Underneath the correlations, the p-values of the t-tests of the correlations are displayed. According to Gunst and Mason (1980), correlations with a value higher than 0.70 or 0.80 should be further investigated because of the chance of multicollinearity. However, in this table the largest correlation is between the SAD measure and autumn dummy and equals only 0.4855; this is well below the alarming threshold of 0.7. Moreover, if the variance inflation factor (VIF) is taken as assessment to determine whether multicollinearity is present, no problems arise as can be deduced from Panel B of Table 2. The VIF measures by how much the variance of an estimated coefficient in the MRA is increased as a result of collinearity. Here, the largest VIF is the

[3] $r_t = \ln\left(\frac{p_t}{p_{t-1}}\right) - rfr$, where p_t is the closing index price on time t, p_{t-1} is the closing index price on time $t-1$ and rfr is the risk free rate on a daily basis in basis points, measured using 3-month T-Bills.

Table 2: Pearson Correlation Matrix and collinearity statistics equation (1)

Panel A: Pearson Correlation Matrix						
	r_{t-1}	D_t^{Monday}	D_t^{Tax}	D_t^{Autumn}	SAD_t	$ENSO_t$
r_{t-1}	1.0000					
D_t^{Monday}	0.0138	1.0000				
	(0.0712)					
D_t^{Tax}	0.0118	-0.0042	1.0000			
	(0.1222)	(0.5800)				
D_t^{Autumn}	0.0010	0.0001	0.1243*	1.0000		
	(0.8966)	(0.9947)	(0.0000)			
SAD_t	0.0173*	0.0001	-0.0843*	0.4855*	1.0000	
	(0.0231)	(0.9855)	(0.0000)	(0.0000)		
$ENSO_t$	-0.0013	0.0001	0.0078	0.0051	0.0183*	1.0000
	(0.8634)	(0.9910)	(0.3051)	(0.5065)	(0.0164)	
Panel B: Collinearity statistics						
Variance inflation factor	1.00	1.00	1.05	1.36	1.35	1.00

Notes. (1) Table 2 shows the Pearson correlation matrix of the different independent variables of equation (1) for the Dow Jones Industrials with 19743 observations.
(2) The p-values are presented beneath the correlation between brackets. Indicate statistical significance at the 5% level (two-sided test)

autumn dummy which is equalling 1.36 for the Dow Jones Industrials MRA. High VIFs may call the results of the MRA into question. While there are many rules of thump that the VIF should not exceed a certain threshold, it is not clearly defined. E.g. for the VIF of 1.36 the interpretation tells one that the variance of the coefficient is 36% larger than it would be without multicollinearity. Since most thresholds, suggested by diverse researchers[4], ought to be larger than four before multicollinearity becomes a problem, it suggests that near singularity is not present in the MRA.

In order to examine whether the ENSO effect happens through environmental factors, equation (2) will be executed. This MRA excludes the ENSO intensity and includes the weather variables.

$$(2)\quad r_t = u + p_1 r_{t-1} + u_{Monday} D_t^{Monday} + u_{Tax} D_t^{Tax} + u_{Autumn} D_t^{Autumn} + u_{SAD} SAD_t + u_{Sunshine} Sunshine_t + u_{Temperature} Temperature_t + u_{Precipitation} Precipitation_t + \varepsilon_t$$

In equation 2, the definitions of the variables r_{t-1}, D_t^{Monday}, D_t^{Tax}, D_t^{Fall}, SAD_t are identical to the ones of equation (1). Additionally, the regression includes three anomalies on environmental factors consisting of the following variables; $\mathrm{Sunshine_t}$, which includes the anomaly of the amount of hours of sunshine in period t, $\mathrm{Precipitation_t}$, which includes the anomaly of the amount of precipitation in millimetres, and $\mathrm{Temperature_t}$, which includes the anomaly of the temperature in degrees Celsius. In order

[4] Hair, Anderson, Tatham & Black (1995), Rogerson (2001), Pan & Jackson (2007), and Allen & Bennett (2010).

to calculate the daily sunshine, temperature, and precipitation anomalies, historical data on that specific day is used. As a complement, the four days before, together with the four days after the specific day are used to obtain a more general mean. To calculate the maximum temperature anomaly on the 10th of April 2015 for example, all of the maximum temperatures measured on the 6th to the 14th of April of all the years included in the dataset, are combined to calculate the mean. This mean is subtracted from the maximum temperature on the 10th of April 2015 to obtain the anomaly. This method to calculate the weather anomalies is used for all indices and all weather variables.

For equation (2) another Pearson correlation matrix is created and depicted in Table 3 Panel A with its corresponding variance inflation factors of the variables in Panel B of Table 3. Since the correlations between the variables already used in equation (1) do not change, they are omitted in this table. Moreover, the correlations between $\mathrm{Temperature_t}$ and $\mathrm{Precipitation_t}$ and the other variables are very small, whereas the highest measured correlation is 0.0322 between the $\mathrm{SAD_t}$ and $\mathrm{Temperature_t}$ variables and the largest negative correlation between the two weather variables which is equal to -0.0547. The VIFs of the newly attached variables are 1.00. Thus, one should not worry about near singularity in this MRA.

These two MRAs will be performed on both the stock market indices and US sector indices. For the stock market indices, only the ENSO variable is equal across all indices. Other variables show at least some divergence across the cities. Not even the Monday and autumn dummy is equal at all times across the cities. For the US sector indices all independent variables are equal, except for the lagged returns. For the stock market indices this means that next to macroeconomic effects, also the weather effects influence the stock market in another way compared to other major market indices. In contrast, the weather effects may influence the US sector indices, but since the weather is identical for all sector indices, due to all being exchanged in New York, there must be other factors that play a role if the effect of ENSO is differing across the industries.

3.2 Quintile creation

In order to examine the relationship between the ENSO intensities and the performance of the stock markets, a quintile analysis is performed on every major market index or sector index. In this analysis extreme values are eliminated by using a 98% winsorization. Once again, extreme positive and negative daily excess returns are not expected to be caused by ENSO events. Therefore, the observations of the 1% most positive and 1% most negative results will be deleted. Subsequently, the ENSO intensities will be divided into five quintiles together with their corresponding daily excess returns.

There are two ways to determine the importance of the quintiles. At first, the presence of a monotonic relationship will be examined. Increasing returns in combination with increasing SST anomaly or vice versa, would indicate a monotonic relationship. Next to that, an F-test is performed to examine the significance of the mean performance subject to different ENSO intensities, which are divided into five equally-sized bins. Moreover, to examine the significance of differences in the most extreme quintiles, t-tests are performed.

Table 3: Pearson Correlation Matrix and collinearity statistics equation (2)

Panel A: Pearson Correlation Matrix							
	r_{t-1}	D_t^{Monday}	D_t^{Tax}	D_t^{Autumn}	SAD_t	$Temperature_t$	$Precipitation_t$
$Temperature_t$	0.0036	0.0109	-0.0269*	0.0133	0.0322*	1.0000	
	(0.6404)	(0.1548)	(0.0004)	(0.0814)	(0.0000)		
$Precipitation_t$	0.0098	-0.0034	0.0038	-0.0023	-0.0004	-0.0547*	1.0000
	(0.1992)	(0.6603)	(0.6603)	(0.7600)	(0.9541)	(0.0000)	
Panel B: Collinearity statistics							
Variance inflation factor	1.00	1.00	1.05	1.36	1,35	1.00	1.00

Notes. (1) Table 3 shows the Pearson correlation matrix of the different independent variables of equation (2) with 19743 observations. The p-value is presented beneath the correlation between brackets.
(2) The correlations between the variables already included in Table 2 are omitted from this Table.
(3) The Sunshine variable is left out of the table because data on this variable was not available for the United States.
* Indicate statistical significance at the 5% level (two-sided test)

3.3 Portfolio creation

When the performance of indices appears to be significantly affected by the ENSO variable, one is able to compose a portfolio preferably with 'winners' and 'losers', regardless of the location of the stock exchange, since the ENSO variable is equal for all indices at a given point in time. Besides, it is also possible to create a portfolio with only one 'winner' or 'loser' in combination with an index that is not affected by ENSO events but highly correlated with this 'winner' or 'loser'. If ENSO intensity is positively correlated with performance, one should go long in the Exchange-Traded Fund of this index if the SST in the Niño 3.4 region is positive; one should short the index that is negatively correlated or uncorrelated with ENSO intensity. When the SST in the Niño 3.4 region is negative, one should go short in the ETF of the index that is positively correlated or uncorrelated with ENSO intensity and go long in the ETF of an index that is negatively correlated with ENSO intensity. This is one way to benefit from the newly uncovered anomaly. At the end of each section in the results, the possibility of creating such a portfolio is assessed.

4 Data

In this section a description of the data is provided. First, in Section 4.1, the data on price indices is discussed. Next, I continue by covering the data on weather conditions in Section 4.2. Finally, Section 4.3 describes the data on the ENSO measure, the SAD variable and risk-free rates.

4.1 Data on price indices

As this paper focuses on developed economies, the stock market indices of the G7 countries, (i.e. the United States, Canada, France, Germany, Italy, the United Kingdom, and Japan) were included in the dataset. In addition, one stock market index of Australia, which is also considered to be a developed country, is added to obtain a better view on the differences between direct and indirect effects of ENSO events. These eight countries represent large and wide economies and experience different direct climate effects caused by ENSO events. A trade-off has been made between a major stock market index or the MSCI Index of a country. In this study the dependent variable needed to have a large time range because the ENSO event occurs only once in two to seven years. Therefore, this paper includes the index for which DataStream contains most data. The descriptive statistics of these countries with corresponding indices are shown in Table 4. All the indices are price indices, focusing only on price movements of the securities. In the robustness section the results of the total return indices will be compared to the results of the price indices. Unfortunately, the time periods of the total return indices are shorter than the prices indices, therefore this paper mainly focuses on the price indices.

Furthermore, Table 4 shows similar statistics across the indices. For each index, there are two values displayed for each statistic. Considering the statistics of the raw data, which are presented in the first row of each cell, one can observe that these indices are negatively skewed and contain high levels of kurtosis, resulting in a non-normal distribution. Negatively skewed distributions indicate frequent small positive returns but the chance on extreme losses is higher compared to the chance on extreme positive returns. Consequently, the medians will be higher than the means. In the second row of cell in Table 4, the statistics are presented for the data that is winsorized on 98%. These statistics reveal that the non-normality is almost completely eliminated. Therefore, winsorization on 98% contributes to prepare the data for the MRA.

This paper considers only value-weighted returns of all indices for simplicity, since it would be a complex activity to calculate the equal-weighted returns for all the indices. The results are expected to be similar for both the equal- and value-weighted indices since this was also the case in the researches by e.g. Kamstra et al. (2003) and Cao and Wei (2005). They found similar results for equal- and value-weighted indices, when estimating their examined indices' returns depending on different variables.

DataStream provides eleven different sector price indices, which are used in this paper to examine different US industries. The sectors are subdivided into the following categories: Basic Materials, Consumer Goods, Consumer Services, Diverse REITs, Financials, Health Care, Industrials, Oil & Gas,

Table 4: Descriptive statistics on eleven major market indices.

Index and period	Country	City	Mean	SD	Min	Max	Skewness	Kurtosis
S&P500	United States	New York	0.024	1.01	-22.90	10.96	-1.03	27.86
02/01/1964-31/03/2016			0.027	0.81	-2.69	2.65	-0.09	0.80
NYSE	United States	New York	0.023	1.00	21.29	11.53	-1.03	25.76
03/01/1966-31/03/2016			0.028	0.80	-2.67	2.54	-0.13	0.79
Nasdaq	United States	New York	0.033	1.22	-12.05	13.25	-0.30	10.14
08/02/1971-31/03/2016			0.036	0.98	-3.68	3.34	-0.37	1.59
Dow Jones Industrials	United States	New York	0.026	0.95	-25.63	10.51	-1.25	38.97
05/05/1950-31/03/2016			0.028	0.77	-2.48	2.50	-0.08	0.69
S&P/TSX Comp.	Canada	Toronto	0.021	0.91	-11.79	9.37	0.79	13.71
03/01/1969-31/03/2016			0.027	0.73	-2.72	2.35	-0.31	1.24
MSCI France	France	Paris	0.025	1.24	-10.31	10.36	-0.22	5.89
05/01/1972-31/03/2016			0.030	1.04	-3.44	3.24	0.14	0.61
DAX30	Germany	Frankfurt	0.023	1.22	-13.71	10.80	-0.25	7.51
02/01/1965-31/03/2016			0.027	1.01	3.41	3.10	-0.14	0.65
MSCI Italy	Italy	Milan	0.022	1.38	-11.39	10.99	-0.24	4.76
05/01/1972-29-07-2014			0.029	1.17	-3.85	3.45	-0.10	0.53
FTSE100	United Kingdom	London	0.022	1.09	-13.03	9.38	-0.48	9.57
03/01/1984-31/03/2016			0.027	0.91	-3.03	2.81	-0.17	0.60
Nikkei225	Japan	Tokyo	0.017	1.22	-16.14	13.23	-0.40	10.19
05/01/1961-31/03/2016			0.023	1.01	-3.43	3.23	-0.26	0.99
MSCI Australia	Australia	Sydney	0.023	1.05	-25.92	8.43	-1.64	38.16
05/01/1972-31/03/2016			0.030	0.86	-2.65	2.57	-0.09	0.34

Notes. (1) In Table 4 the descriptive statistics on the major market indices are displayed. Columns 2 and 3 reveal in which country and city the exchange is located.
(2) The mean, standard deviation, minimum and maximum daily returns are displayed in percentages.
(3) For each index, the first row contains the value based on the raw data and the second row contains the data returns that are winsorized on 98%.

Technology, Telecom, and Utilities. The data provided by DataStream ranges from 1973 until today. This paper examines the daily excess returns in the MRA ranging from January 5, 1973 until March 31, 2016, since the data is complete for this period. Similar to all the US sector indices, New York is the city where the exchange of the stocks takes place and therefore all the corresponding variables are used to examine these sectors. In Table 5, similar results are obtained for the US sector indices compared to the major market indices. In the upper part of the cells the results from the raw data are displayed, where once again non-normality is observed. After a 98% winsorization of the data, most of the skewness and kurtosis disappears, making the data more applicable for the MRA.

4.2 Data on weather conditions

In order to gather the data on all the weather conditions from all these eight cities, many databases were consulted. In this paper three weather variables are taken into account for the return estimation: the amount of sunshine in hours, the maximum temperature in degrees Celsius and the amount of precipitation in millimetres. In Table 6 one can find the means and standard deviations of these weather variables per city. It is perhaps intuitive to think that the means differ a lot across the cities, but this is also true for the standard deviations, as can be deduced from Table 6. This means that a city like Tokyo with a very high standard

Table 5: Descriptive statistics on eleven sector price indices.

Sector	Mean	SD	Min	Max	Skewness	Kurtosis
Basic Materials	0.021	1.29	-21.43	11.36	-0.85	16.33
	0.029	1.04	-3.52	3.31	-0.06	0.71
Consumer Goods	0.018	1.13	-22.66	8.89	-0.81	18.54
	0.021	0.96	-2.99	2.93	-0.03	0.40
Consumer Services	0.028	1.15	-22.51	10.49	-0.77	18.69
	0.030	0.95	-2.98	3.09	-0.08	0.61
Diverse Real Estate	0.035	2.16	-23.83	27.35	0.72	17.07
Investment Trusts	0.019	1.61	-6.20	7.11	0.17	2.96
Financials	0.025	1.21	-17.05	12.16	-0.42	17.00
	0.028	0.93	-3.42	3.31	-0.13	1.29
Health Care	0.034	1.02	-18.89	11.41	-0.67	16.69
	0.038	0.85	-2.68	2.61	-0.07	0.49
Industrials	0.029	1.17	-21.30	9.11	-0.79	15.33
	0.035	0.97	-3.21	3.10	-0.11	0.74
Oil & Gas	0.024	1.33	-20.31	14.23	-0.66	13.50
	0.031	1.10	-3.54	3.46	-0.05	0.58
Technology	0.028	1.54	-23.25	15.64	-0.20	9.86
	0.028	1.29	-4.19	4.16	-0.06	0.68
Telecom	0.018	1.13	-19.85	11.97	-0.41	16.06
	0.021	0.92	-3.09	2.95	-0.05	0.70
Utilities	0.013	0.85	-13.99	12.44	-0.44	19.49
	0.018	0.68	-2.46	2.18	-0.15	1.03

Notes. (1) In Table 4 the descriptive statistics on the sector price indices are displayed of the period Jan 5, 1973 until May 31, 2016. Columns 2 and 3 reveal in which country and city the exchange is located.
(2) The mean, standard deviation, minimum and maximum daily returns are displayed in percentages.
(3) For each index, the first row contains the value based on the raw data and the second row contains the data returns that are winsorized on 98%.

Table 6: Data on the daily weather

City	Mean Sunshine (Hours)	SD Sunshine (Hours)	Mean Precipitation (mm)	SD Precipitation (mm)	Mean Max Temperature (°C)	SD Max Temperature (°C)
New York *(04/05/1950-03/05/2016)*	-	-	3.28	9.33	17.01	10.28
London *(01/04/1984-31/03/2016)*	4.41	4.05	1.66	3.73	15.39	6.48
Paris *(01/04/1972-31/03/2016)*	-	-	1.73	4.14	15.95	7.58
Milan *(01/04/1972-31/03/2014)*	-	-	3.13	8.89	18.42	9.15
Frankfurt *(01/04/1965-31/03/2016)*	4.47	4.27	1.73	4.06	14.68	8.71
Tokyo *(01/04/1961-31/03/2016)*	5.33	3.99	4.08	12.46	19.94	7.97
Toronto *(01/04/1969-31/03/2016)*	-	-	2.18	5.56	12.88	11.45
Sydney *(01/04/1972-31/03/2016)*	-	-	2.97	9.78	22.60	4.90

deviation in precipitation is more exposed to the precipitation effect compared to a city like London, for which the standard deviation is three times as small. Since the mean precipitation level will be subtracted from the daily precipitation level, it is the standard deviation that will determine the strength of the coefficient. Hence, the coefficient of the precipitation anomaly to estimate the daily excess return is three times as strong for Tokyo in comparison to London. Unfortunately, the amount of hours of sunshine is unavailable for most cities. Even the national meteorological institutes of these countries could not provide the data for this study. Besides, the means and standard deviations on full years are chosen to be displayed in Table 6, to eliminate seasonal differences in the weather.

The main supplier of the weather data is the National Climate Data Centre (NCDC) of the National Oceanic and Atmospheric Administration (NOAA). The environmental factors of the analysed period have been retrieved from this database, for the following cities: New York, Toronto, and Sydney, and partially Milan (1972-2008). The remaining data on Milan, for the period of 2008 to March 31, 2014 has been retrieved from the National Centers for Environmental Prediction (NCEP). To obtain the weather conditions in London the Library and Archive team of the National Meteorological Archive was consulted and they provided a spread sheet containing the required data. Additionally, the Japan Meteorological Agency[5] provided the weather data on Tokyo and the European Climate Assessment and Dataset (ECA&D) provided the data on Paris and Frankfurt.

4.3 ENSO, SAD and risk-free rates

While until now the data differed per region, the ENSO variable is equal for all cities, although it changes over time. In the Pacific Ocean, the Niño 3.4 region will determine the variable. It is the anomaly of Sea Surface Temperature (SST) in the Niño 3.4 region (5°N-5°S, 170°W-120°W) that will reflect the actual ENSO variable in this study. Thus, the historical average is subtracted from the measurement at a given point in time. This data is retrieved from the NCEP and is defined as the "Monthly Extended Reconstructed Sea Surface Temperature v4 (1981-2010 base period) Niño 3.4".

This paper includes the exact same Seasonal Affective Disorder measure as Kamstra, et al. (2003)[6]. In this formula there is one variable that differs per region, being the Latitude. Table 12 in Appendix A displays the latitude of the city where the exchange is located. The latitudes that correspond to the different cities were provided by the same sources who provided the data on the weather variables.

Lastly, as long as the T-Bill rates were positive, the excess return is calculated by subtracting the risk free rate from the index return. Investors will in general not invest in risk free assets with a negative return. Therefore, negative T-Bill rates were not subtracted from the index return. To calculate to excess return of different stock markets the 3-month Treasury Bill represents the risk free rate. Unfortunately, DataStream does not contain the same periods for T-Bills rates as it does for stock markets. Therefore, if the data for a certain T-Bill rate was unavailable, it had to be estimated. See Appendix B for an extended description of the data.

4.4 Monday, tax and autumn dummies

In this paper three dummy variables are used. At first, the Monday dummy equals one for every day following a weekend, which is usually a Monday.

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[5] Special thanks to Mr. Atsushi Minami who helped me gather the data on a Japanese website.
[6] See Kamstra et al. (2003) for the detailed description of the calculation.

Second, the tax dummy which equals one on the last and first five trading days of a tax year. Following the CIA World Factbook the fiscal year of the three European countries, Italy, France, and Germany, equals the calendar year. Conversely, the fiscal year for Japan and Canada starts at the first of April and ends at March 31. Similarly, the fiscal year in the UK is different as it starts at April 6 and the fiscal year of Australia too, since it starts at the first of July. Additionally, the US' fiscal year starts at the first of October, which is true from 1976 and on. Before 1976, the fiscal year started at the first of July and ended at June 30. From the first of July 1976 to September 30, 1976 there was a transition year in the US.

Lastly, the autumn dummy is equal for all countries except for Australia, which is located in the Southern Hemisphere. For MSCI Australia, the autumn dummy equals one on trading days between March 21 and June 22 and zero otherwise. For the other indices the autumn dummy equals one on trading days between September 21 and December 22.

5 Results

5.1 Standard Multiple Regression Analysis

Standard multiple regression analyses are performed to estimate the proportion of variance on stock market returns caused by multiple variables. In this MRA, the focus will be on the ENSO variable. Before the results can be interpreted, it is important to consider what data that is used. In this MRA the price indices are used, since the data covers a larger period compared to the total return indices. Moreover, this MRA does not consider the raw data on these price indices. Section 4 indicated that multivariate outliers were present in the dataset, resulting in non-normality. To overcome this problem, the data is winsorized on 98%. Moreover, many variables are used to estimate the stock market returns, which could lead to a multicollinearity problem. However, calculated variance inflation factors are relatively low, indicating that multicollinearity is not a problem. In Section 5.1.1. the results of the MRAs of the eleven major market indices will be assessed followed by the assessment of the eleven US sector indices in Section 5.1.2.

5.1.1 Results on the eleven major market price indices

In Table 7 the coefficient estimates of equation 1 and 2 are displayed for the eleven stock market indices of the aforementioned countries. Although there appear to be quite some significant variables, one should notice that the R^2 is very low for all MRAs, meaning that only 0.08% to 1.85% of the variability of the dependent variable is explained by the combination of the independent variables. Moreover, the adjusted R^2 ranges from 0.04% to 1.80%, meaning that the independent variables have almost no explanatory power on certain indices.

Most of the significant results correspond to the expectations. For instance, in line with the expectations, the significant estimates of the first-order autocorrelation and the tax and SAD effect show positive signs. Besides, the significant estimates on the Monday and autumn effect show negative signs, also as predicted. Additionally, although there are only few statistical significant results, the amount of sunshine increases daily excess returns while the amount of precipitation decreases daily excess returns. However, there is no unanimity on the direction of the maximum temperature variable. While there are only two significant results, they are in opposite directions.

Above all, the ENSO variable is what is most important in this study. Noteworthy is that no significant effects are observed of these eleven major market indices, meaning that the direct effects of ENSO events, consisting of changes in real GDP and its corresponding spillovers, commodity prices, weather conditions, and fewer hurricanes or any other consequences have no significant effects on these stock market indices.

Table 7: Multiple Regression Analysis results for eleven major market price indices

Model 1: $r_t = u + p_1 r_{t-1} + u_{Monday} D_t^{Monday} + u_{Tax} D_t^{Tax} + u_{Autumn} D_t^{Autumn} + u_{SAD} SAD_t + u_{ENSO} ENSO_t + \varepsilon_t$

Model 2: $r_t = u + p_1 r_{t-1} + u_{Monday} D_t^{Monday} + u_{Tax} D_t^{Tax} + u_{Autumn} D_t^{Autumn} + u_{SAD} SAD_t + u_{Precipitation} Precipitation_t + u_{Temperature} Temperature_t + \varepsilon_t$

	S&P 500 (02/01/1964-31/03/2016)		NYSE (03/01/1966-31/03/2016)		NASDAQ (08/02/1971-31/03/2016)		Dow Jones Industrials (05/05/1950-31/03/2016)		S&P/TSX COMP (03/01/1969-31/03/2016)	
Variable	*Model 1*	*Model 2*	*Model 1*	*Model 2*	*Model 1*	*Model 2*	*Model 1*	*Model 2*	*Model 1*	*Model 2*
u	*1.045* (1.06)	*1.005* (1.02)	*1.281* (1.30)	*1.291* (1.32)	*2.978*** (2.35)	*2.945*** (2.33)	*0.983* (1.17)	*1.133* (1.37)	*0.641* (0.69)	*0.623* (0.67)
p_1	*0.037*** (4.94)	*0.037*** (4.93)	*0.061*** (7.98)	*0.060*** (7.96)	*0.073*** (9.17)	*0.073*** (9.16)	*0.043*** (6.34)	*0.042*** (6.33)	*0.106*** (13.76)	*0.106*** (13.76)
u_{Monday}	*-5.597*** (-3.17)	*-5.612*** (-3.18)	*-7.212*** (-4.12)	*-7.246*** (-4.14)	*-13.792*** (-6.09)	*-13.806*** (-6.09)	*-5.929*** (-4.00)	*-5.922*** (-3.99)	*-6.610*** (-4.04)	*-6.611*** (-4.04)
u_{Tax}	*8.272** (1.70)	*8.328** (1.71)	*8.907** (1.84)	*8.955** (1.85)	*2.162* (0.34	*2.203* (0.35)	*10.748*** (2.68)	*10.714*** (2.67)	*2.904* (0.66)	*2.925* (0.67)
u_{Fall}	*-1.884* (-0.98)	*-1.880* (-0.98)	*-1.703* (0.89)	*-1.700* (0.89)	*-5.765** (-2.29)	*-5.738** (-2.28)	*-1.690* (-1.06)	*-1.715* (-1.07)	*-3.767** (-2.16)	*-3.757** (-2.16)
u_{SAD}	*2.051*** (2.69)	*2.051*** (2.69)	*2.036*** (2.68)	*2.036*** (2.69)	*3.787*** (3.83)	*3.782*** (3.83)	*2.123*** (3.31)	*2.105*** (3.29)	*2.708*** (4.32)	*2.712*** (4.33)
u_{ENSO}	*0.587* (0.70)	-	*0.350* (0.42)	-	*0.684* (0.65)	-	*-0.896* (-1.23)	-	*0.199* (0.26)	-
$u_{Temperature}$	-	*0.135* (0.91)	-	*0.059* (0.40)	-	*0.108* (0.57)	-	*0.259** (2.07)	-	*-0.001* (-0.01)
$u_{Precipitation}$	-	*-0.103* (-1.43)	-	*-0.154** (-2.17)	-	*-0.095* (-1.03)	-	*-0.143** (2.23)	-	*-0.114* (-0.98)
R^2	0.0033	0.0035	0.0070	0.0074	0.0117	0.0118	0.0044	0.0049	0.0185	0.0185
Adj. R^2	0.0029	0.0030	0.0066	0.0069	0.0112	0.0112	0.0041	0.0045	0.0180	0.0180

Table 7 (continued)

Model 1: $r_t = u + p_1 r_{t-1} + u_{Monday} D_t^{Monday} + u_{Tax} D_t^{Tax} + u_{Autumn} D_t^{Autumn} + u_{SAD} SAD_t + \ u_{ENSO} ENSO_t + \varepsilon_t$

Model 2: $r_t = u + p_1 r_{t-1} + u_{Monday} D_t^{Monday} + u_{Tax} D_t^{Tax} + u_{Autumn} D_t^{Autumn} + u_{SAD} SAD_t + u_{Sunshine} Sunshine_t + u_{Precipitation} Precipitation_t + u_{Temperature} Temperature_t + \varepsilon_t$

	MSCI France (05/01/1972-31/03/2016)		*DAX30 (02/01/1965-31/03/2016)*		*MSCI Italy (05/01/1972-31/03/2014)*		*FTSE 100 (03/01/1984-31/03/2016)*		*Nikkei 225 (05/01/1961-31/03/2016)*		*MSCI Australia (05/01/1972-31/03/2016)*	
Variable	*Model 1*	*Model 2*	*Model 1*	*Model 2*	*Model 1*	*Model 2*	*Model 1*	*Model 1*	*Model 1*	*Model 2*	*Model 1*	*Model 2*
u	*2.797**	*2.879**	*1.374*	*1.464*	*1.447*	*1.502*	*0.108*	*0.108*	*0.052*	*0.023*	*2.084**	*2.025**
	(2.05)	*(2.11)*	*(0.93)*	*(1.00)*	*(0.91)*	*(0.95)*	*(0.08)*	*(0.08)*	*(0.04)*	*(0.19)*	*(1.86)*	*(1.81)*
p_1	*0.051***	*0.051***	*0.021***	*0.021***	*0.082***	*0.082***	-	-	-	-	*0.094***	*0.094***
	(6.21)	*(6.23)*	*(2.45)*	*(2.45)*	*(9.73)*	*(9.70)*					*(11.70)*	*(11.71)*
u_{Monday}	*-11.383***	*-11.353***	*-10.529***	*-10.535***	*-14.504***	*-14.494***	*-6.214***	*-6.214***	*-0.102*	*-0.193*	*-5.077***	*-5.052***
	(-4.64)	*(-4.62)*	*(-3.99)*	*(-4.00)*	*(-5.17)*	*(-5.16)*	*(-2.49)*	*(-2.49)*	*(0.05)*	*(0.09)*	*(-2.52)*	*(-2.51)*
u_{Tax}	*1.887*	*1.799*	*9.835*	*9.807*	*-5.168*	*-5.134*	*8.723*	*8.723*	*10.501**	*10.384**	*7.978*	*7.991*
	(0.27)	*(0.26)*	*(1.30)*	*(1.30)*	*(-0.69)*	*(-0.69)*	*(1.27)*	*(1.27)*	*(1.84)*	*(1.82)*	*(1.39)*	*(1.40)*
u_{Fall}	*-5.548**	*-5.655**	*-1.883*	*-1.922*	*-5.959**	*-5.988**	*0.448*	*0.448*	*-3.780**	*-3.890**	*2.001*	*1.954*
	(-2.06)	*(-2.10)*	*(-0.65)*	*(-0.66)*	*(-2.01)*	*(-2.02)*	*(0.17)*	*(0.17)*	*(-1.69)*	*(-1.74)*	*(0.97)*	*(0.344)*
u_{SAD}	*1.682**	*1.681**	*1.543**	*1.537**	*3.250***	*3.263***	*1.517**	*1.517**	*3.027***	*3.022***	*-1.318*	*-1.325*
	(2.06)	*(2.06)*	*(1.84)*	*(1.83)*	*(3.26)*	*(3.27)*	*(2.16)*	*(2.16)*	*(2.75)*	*(2.74)*	*(-1.22)*	*(-1.12)*
u_{ENSO}	*-1.302*	-	*-0.976*	-	*-0.954*	-	*0.196*	-	*-0.846*	-	*1.449*	-
	(-1.14)		*(-0.78)*		*(-0.71)*		*(0.16)*		*(-0.83)*		*(1.54)*	
$u_{Sunshine}$	-	-	-	*0.378*	-	-	-	*0.795***	-	*1.047***	-	-
				(1.11)				*(2.62)*		*(4.07)*		
$u_{Temperature}$	-	*-0.233*	-	*-0.101*	-	*-0.145*	-	*-0.596**	-	*-0.479*	-	*0.104*
		(-0.93)		*(-0.37)*		*(-0.47)*		*(-1.88)*		*(-1.56)*		*(0.45)*
$u_{Precipitation}$	-	*-0.174**	-	*-0.098*	-	*-0.325*	-	*-0.315*	-	*-0.119*	-	*-0.036*
		(-1.83)		*(-0.35)*		*(-2.43)*		*(-1.15)*		*(-1.60)*		*(-0.43)*
R^2	*0.0060*	*0.0063*	*0.0023*	*0.0024*	*0.0121*	*0.0126*	*0.0017*	*0.0030*	*0.0008*	*0.0025*	*0.0130*	*0.0128*
Adj. R^2	*0.0055*	*0.0056*	*0.0018*	*0.0018*	*0.0115*	*0.0119*	*0.0011*	*0.0022*	*0.0004*	*0.0020*	*0.0124*	*0.0122*

Notes. (1) This table reports MRAs of eleven major market indices of both the MRA including the ENSO variable and excluding the weather variables (Model 1) and the MRA excluding the ENSO variable and including the weather variables (Model 2). To estimate the excess return in basis points r_t, this MRA controls for first-order autocorrelation (r_{t-1}), the Monday effect; a dummy following a weekend (D_t^{Monday}), the tax-loss effect; a dummy for the last and first five trading days of a fiscal (D_t^{Tax}), the autumn effect; a dummy for trading days in the autumn (D_t^{Autumn}), the seasonal affective disorder effect which is zero in the spring and summer and equals twelve minus the amount of hours daylight in the autumn and winter (SAD_t) in combination with the ENSO effect which equals the SST anomaly in the Niño 3.4 region ($ENSO_t$) in Model 1 or in combination with the anomaly in the amount of precipitation in mm ($Precipitation_t$), and in maximum temperature in degrees Celsius effect ($Temperature_t$) in Model 2.

(2) The cells containing a dash (-) represent cases for which the parameter is not estimated.

(3) The parameter estimates are presented in the table with corresponding t-statistic (in brackets) directly beneath the parameter.

(4) In the last row the R^2 for each regression is presented.

* Indicate statistical significance at the 5% level (one-sided test)

** Indicate statistical significance at the 1% level (one-sided test)

While temperatures in case of El Niño events usually increase in New York, this could affect the mood of investors as suggested by Cao and Wei (2005) who founds that higher temperature leads to lower returns due to apathy. In contrast, the results of this MRA suggest that increasing temperatures increase daily excess returns on the Dow Jones Industrials. This result increases the uncertainty about the effect of temperatures on equity returns even more. By way of contrast, temperature changes do not affect the other US stock market indices. Although El Niño events increase the mean temperatures in New York, the MRA indicates that this temperature effect is too small to suggest that ENSO events affect major market indices on its own. Considering the fact that temperatures are increased by El Niño especially in December, January and February, one could imagine that the changes in temperature caused by El Niño events, are not sufficiently large to affect such a large stock market on its own. Since precipitation in New York is not significantly affected by ENSO events, this cannot strengthen the effect of ENSO events on the particular market indices.

El Niño events are expected to increase the amount of precipitation in France, while La Niña events are expected to decrease the amount of precipitation. Since precipitation appears to significantly decrease daily excess return, it is expected that El Niño events, with its corresponding high positive ENSO intensities, decrease the daily excess return due increasing precipitation. In contrast, in case of a La Niña event, one would expect the opposite. Nevertheless, the precipitation effects of ENSO events are not sufficiently large to affect the MSCI France.

In conclusion, to be able to benefit from this research one needs at least one stock market index that is significantly affected by ENSO events. However, within the examined stock market indices, the ENSO variable appears to be insignificant on all of them. Therefore, it is impossible to create a portfolio with "winners" or "losers" as a result of ENSO events.

5.1.2 Results on United States sector price indices

Table 8 displays the parameter estimates of equation (1) and (2) for the eleven sector indices categorized by DataStream. Similar to the MRA on the eleven major market indices, the R^2 is also low for all indices, ranging from 0.03% to 1.30%. The Adjusted R^2 even ranges from 0.00% to 1.24%. Some of the adjusted R^2 were even negative but are reported as zero, meaning that the independent variables have no explanatory power at all. Unlike the MRA on the major market indices of the different countries, there are fewer significant results. Nevertheless, the signs of the significant coefficient estimates are similar. In this analysis, there are positive signs for the first-order autocorrelation and tax and SAD effect. While the negative signs still appear for the Monday and autumn coefficient estimates.

More importantly, the ENSO variable is significant at the 5% confidence level for four sector indices. It appears that the daily excess returns of the sectors: Consumer Goods, Diverse Real Estate Investment Trusts, Financials and Utilities are significantly affected by ENSO events. All of the significant ENSO coefficients positively influence daily excess returns. This indicates that the returns in case of El Niño events exceed the returns in La Niña events. The results suggest that daily weather variables in equation (2) do not significantly affect daily excess returns of these sector indices by influencing investors' mood. Consequently, there must be other factors, caused by ENSO events, affecting daily excess return. Also changes in real GDP, caused by ENSO events, are

Table 8: Multiple Regression Analysis results for eleven sector price indices

Model 1: $r_t = u + p_1 r_{t-1} + u_{Monday} D_t^{Monday} + u_{Tax} D_t^{Tax} + u_{Autumn} D_t^{Autumn} + u_{SAD} SAD_t + u_{ENSO} ENSO_t + \varepsilon_t$

Model 2: $r_t = u + p_1 r_{t-1} + u_{Monday} D_t^{Monday} + u_{Tax} D_t^{Tax} + u_{Autumn} D_t^{Autumn} + u_{SAD} SAD_t + u_{Precipitation} Precipitation_t + u_{Temperature} Temperature_t + \varepsilon_t$

	Basic Materials		*Consumer Goods*		*Consumer Services*		*Diverse Real Estate Investment Trusts*		*Financials*	
Variable	*Model 1*	*Model 2*	*Model 1*	*Model 2*	*Model 1*	*Model 2*	*Model 1*	*Model 2*	*Model 1*	*Model 2*
u	*1.582* *(0.92)*	*1.612* *(0.94)*	*-0.237* *(-0.15)*	*-0.369* *(-0.23)*	*2.240* *(1.42)*	*2.160* *(1.37)*	*2.175* *(0.82)*	*2.010* *(0.76)*	*1.145* *(0.74)*	*1.025* *(0.67)*
p_1	*0.090*** *(11.33)*	*0.090*** *(11.32)*	*0.043*** *(5.07)*	*0.043*** *(5.11)*	*0.070*** *(8.35)*	*0.070*** *(8.36)*	-	-	*0.085*** *(10.78)*	*0.085*** *(10.78)*
u_{Monday}	*-7.631*** *(-3.08)*	*-7.639*** *(-3.09)*	*1.430* *(0.63)*	*1.415* *(0.62)*	*-7.192*** *(-3.18)*	*-7.210*** *(-3.19)*	*-8.872*** *(-2.32)*	*-8.890*** *(-2.33)*	*-7.632*** *(-3.46)*	*-7.653*** *(-3.47)*
u_{Tax}	*7.402* *(1.13)*	*7.423* *(1.14)*	*10.262** *(1.71)*	*10.311** *(1.71)*	*14.791*** *(2.48)*	*14.838*** *(2.48)*	*9.861* *(0.98)*	*9.939* *(0.99)*	*4.833* *(0.83)*	*4.909* *(0.85)*
u_{Fall}	*-1.397* *(-0.54)*	*-1.387* *(-0.55)*	*-1.688* *(-0.71)*	*-1.679* *(-0.71)*	*-2.304* *(-0.98)*	*-2.287* *(-0.97)*	*-0.633* *(-0.16)*	*-0.609* *(-0.15)*	*1.174* *(0.51)*	*1.193* *(0.52)*
u_{SAD}	*1.845** *(1.78)*	*1.849** *(1.79)*	*1.224* *(1.28)*	*1.249* *(1.31)*	*1.215* *(1.28)*	*1.223* *(1.29)*	*0.382* *(0.24)*	*0.430* *(0.27)*	*1.665** *(1.80)*	*1.674** *(1.81)*
u_{ENSO}	*0.051* *(0.04)*	-	*1.826** *(1.70)*	-	*1.260* *(1.18)*	-	*2.996** *(1.67)*	-	*1.900** *(1.84)*	-
$u_{Temperature}$	-	*-0.027* *(-0.13)*	-	*0.051* *(0.27)*	-	*0.109* *(0.57)*	-	*0.014* *(0.04)*	-	*0.180* *(0.97)*
$u_{Precipitation}$	-	*-0.125* *(-1.24)*	-	*-0.059* *(0.68)*	-	*-0.082* *(-0.88)*	-	*-0.184* *(-1.18)*	-	*-0.107* *(-1.19)*
R^2	*0.0129*	*0.0130*	*0.0033*	*0.0031*	*0.0084*	*0.0084*	*0.0008*	*0.0007*	*0.0121*	*0.0120*
Adj. R^2	*0.0124*	*0.0124*	*0.0027*	*0.0024*	*0.0079*	*0.0077*	*0.0004*	*0.0002*	*0.0116*	*0.0114*

Table 8 (continued)

$$\text{Model 1: } r_t = u + p_1 r_{t-1} + u_{Monday} D_t^{Monday} + u_{Tax} D_t^{Tax} + u_{Autumn} D_t^{Autumn} + u_{SAD} SAD_t + u_{ENSO} ENSO_t + \varepsilon_t$$

$$\text{Model 2: } r_t = u + p_1 r_{t-1} + u_{Monday} D_t^{Monday} + u_{Tax} D_t^{Tax} + u_{Autumn} D_t^{Autumn} + u_{SAD} SAD_t + u_{Precipitation} Precipitation_t + u_{Temperature} Temperature_t + \varepsilon_t$$

	Health Care		*Industrials*		*Oil & Gas*		*Technology*		*Telecom*		*Utilities*	
Variable	*Model 1*	*Model 2*	*Model 1*	*Model 2*	*Model 1*	*Model 2*	*Model 1*	*Model 2*	*Model 1*	*Model 2*	*Model 1*	*Model 2*
u	*2.233* (1.59)	*2.111* (1.50)	*1.087* (0.68)	*1.067* (0.67)	*4.655*** (2.56)	*4.686*** (2.58)	*-3.141* (-1.47)	*-3.214* (-1.51)	*0.833* (0.54)	*0.885* (0.58)	*1.512* (1.35)	*1.402* (1.25)
p_1	*0.051*** (6.06)	*0.051*** (6.08)	*0.058*** (7.11)	*0.058*** (7.11)	*0.056*** (6.74)	*0.056*** (6.70)	*0.022*** (2.62)	*0.022*** (2.62)		-	*0.083*** (10.07)	*0.083*** (10.08)
u_{Monday}	*-2.681* (-1.33)	*-2.686* (-1.33)	*-4.222** (-1.84)	*-4.224** (-1.84)	*-5.917** (-2.27)	*-5.921** (-2.27)	*4.668* (1.52)	*4.662* (1.52)	*-2.815* (-1.28)	*-2.826* (-1.28)	*-4.535*** (-2.82)	*-4.539*** (-2.83)
u_{Tax}	*7.698* (1.45)	*7.749* (1.46)	*4.545* (0.75)	*4.556* (0.75)	*1.850* (0.27)	*1.867* (0.27)	*-3.044* (-0.38)	*-2.978* (-0.37)	*-1.984* (-0.34)	*-1.977* (-0.34)	*-6.965* (-1.63)	*-6.920* (-1.62)
u_{Fall}	*-0.521* (-0.25)	*-0.514* (-0.24)	*-0.726* (-0.30)	*-0.718* (-0.30)	*-4.590** (-1.69)	*-4.588** (-1.69)	*2.995* (0.94)	*3.032* (0.95)	*-0.505* (-0.22)	*-0.507* (-0.22)	*0.240* (0.14)	*0.235* (0.14)
u_{SAD}	*0.774* (0.91)	*0.788* (0.93)	*2.198** (2.28)	*2.192** (2.28)	*-0.779* (-0.71)	*-0.747* (-0.68)	*3.512*** (2.73)	*3.481*** (2.71)	*0.849* (0.92)	*0.857* (0.93)	*0.030* (0.04)	*0.073* (0.11)
u_{ENSO}	*1.524* (1.60)	-	*0.254* (0.24)	-	*0.217* (0.18)	-	*0.827* (0.57)	-	*-0.230* (-0.22)	-	*1.716** (2.28)	-
$u_{Temperature}$	-	*0.087* (0.51)		*0.101* (0.52)		*-0.261* (-1.19)		*0.446** (1.73)		*-0.110* (-0.59)	-	*-0.137* (-1.02)
$u_{Precipitation}$	-	*-0.013* (-0.16)		*-0.016* (-0.17)		*-0.142* (-1.33)		*-0.081* (-0.64)		*-0.096* (-1.07)	-	*-0.060* (-0.92)
R^2	*0.0041*	*0.0039*	*0.0056*	*0.0057*	*0.0048*	*0.0051*	*0.0016*	*0.0019*	*0.0003*	*0.0004*	*0.0105*	*0.0102*
Adj. R^2	*0.0035*	*0.0032*	*0.0051*	*0.0050*	*0.0043*	*0.0044*	*0.0010*	*0.0012*	*0.0000*	*0.0000*	*0.0099*	*0.0095*

Notes. (1) This table reports MRAs of eleven sector price indices of both the MRA including the ENSO variable and excluding the weather variables (Model 1) and the MRA excluding the ENSO variable and including the weather variables (Model 2). To estimate the excess return in basis points r_t, this MRA controls for first-order autocorrelation (r_{t-1}), the Monday effect; a dummy following a weekend (D_t^{Monday}), the tax-loss effect; a dummy for the last and first five trading days of a fiscal (D_t^{Tax}), the autumn effect; a dummy for trading days in the autumn (D_t^{Autumn}), the seasonal affective disorder effect which is zero in the spring and summer and equals twelve minus the amount of hours daylight in the autumn and winter (SAD_t) in combination with the ENSO effect which equals the SST anomaly in the Niño 3.4 region ($ENSO_t$) in Model 1 or in combination with the anomaly in the amount of precipitation in mm ($Precipitation_t$), and in maximum temperature in degrees Celsius effect ($Temperature_t$) in Model 2.
(2) The cells containing a dash (-) represent cases for which the parameter is not estimated.
(3) The parameter estimates are presented in the table with corresponding t-statistic (in brackets) directly beneath the parameter.
(4) In the last row the R^2 for each regression is presented.
* Indicate statistical significance at the 5% level (one-sided test)
** Indicate statistical significance at the 1% level (one-sided test)

unlikely to be the only factor of increasing the daily excess return in case of an El Niño event. If one sector index is affected by an increase in GDP, other sectors would probably also be affected by this. As well as changes in real GDP, changes in commodity prices caused by ENSO events are also unlikely to be main factor. Changes in non-fuel commodity prices would probably be too small to affect a whole sector. However, since El Niño events increase fuel prices significantly, it is expected that the Oil & Gas sector would benefit from it. However, these price changes appear not to be sufficiently large to suggest that ENSO events significantly affect the Oil & Gas sector, which can be deduced from Table 8.

Still, the question remains through what way these sector indices are influenced by ENSO events. As mentioned before, ENSO events can influence the amount of hurricanes in the US, where El Niño events usually decrease the amount of hurricanes and La Niña events usually increase the amount of hurricanes in a specific year. If one considers the possible economic damages caused by hurricanes, it can have a major impact on stock markets, especially in certain sectors. Take the sectors diverse REITs and Financials for example. Diverse REITs consists of many transport companies with vehicles and corresponding infrastructure, probably very vulnerable to hurricanes. Next to that, the Financials sector consists of, next to Financials Services, also of Insurance, Real Estate and Real Estate Investment Trusts (Office, Retail, Resident, Specialty, Mortgage, Hotel and Lodging). These last three components of the Financials sector are also expected to be vulnerable to hurricanes. This may be the reason that the performance of these two sectors, diverse REITs and Financials, are positively correlated with El Niño events.

However, the economic damages caused by hurricanes range from one to over one hundred billion dollars. With only a few hurricanes per year in difference between La Niña and El Niño events, this would probably not create such a significant impact on stock markets. In case of El Niño events, the growth in real GDP growth is 0.55% and fewer hurricanes occur in the US. It is likely that the combination of these consequences of El Niño events together, positively affect some sector indices in the US.

Growth in real GDP is closely related to the Consumer Goods and Utilities sector. When the inhabitants of the US have more money to spend, they are likely to spend more money on products within the Auto & Parts, Food & Beverages and Personal & Household Goods parts of the sector. Consequently, more utilities are needed to produce consumer goods. On the contrary, the warmer Winter months would decrease the amount of gas taken by the consumers heating their homes or companies heating their offices. This makes the reasons what caused ENSO events to affect the Utilities sector questionable.

Once again there is at least one “winner” or one “loser” needed to create a portfolio to achieve excess returns. In contrast to the major stock market indices, the results show significant ENSO coefficient estimates for four sector indices. All of the significant ENSO coefficient estimates are positively correlated with daily excess returns, meaning that one can go long in such a “winner” if there is an El Niño event and short a sector index that is not affected by ENSO events or vice versa, to outperform the market. One should be aware that these sector indices ought to be highly correlated to keep the risks as low as possible.

These results suggest the possibility of excess returns by making use of the ENSO effect. The ENSO coefficient estimates range from 1.71 to 3.00 basis points within the four sector indices. Next to that, the standard deviation of the ENSO intensity between 1950 and 2016 equals 0.82. Consequently, the one-standard deviation influence of the ENSO variable on the four sector indices' performance ranges from 0.014% to 0.025% per day. Therefore, the ENSO variable impact equals approximately one time the daily average return of these indices, on average.

5.2 Quintile analysis

Two methods will be analysed in this section: the presence of a monotonic relationships and the significance of the analyses. First, the presence of monotonic relationships is examined. In line with logical thinking, profits ought to be ascending when moving upwards from the smallest quintile or vice versa. This would indicate that there is some influence of ENSO events on daily excess returns. To be clear, the top 20% consist of the 20% highest ENSO intensities measures in the examined period and the bottom 20% consist of the 20% lowest, most negative, ENSO intensities. Although, due to different periods, the ENSO intensity boundaries of the quintiles are not equal for all indices, one should know that the difference between the boundaries within the quintiles are larger in the top and bottom quintiles compared to the middle three quintiles. Therefore, the differences between the middle three quintiles are not that important. Table 9 shows the mean performances of all eleven major market indices divided into quintiles of equal size, based on the ENSO intensity. As can be deduced from this table, the MSCI Australia shows quite a positive monotonic relationship indicating that negative SST anomalies go along with small negative daily excess returns. If the SST anomaly becomes positive, resulting in a weak or strong El Niño events, the mean daily excess returns increase considerably. In contrast, the MSCI France shows the opposite; highly negative SST anomalies result on average in relatively high daily excess returns compared to highly positive SST anomalies. Only the MSCI Italy shows similar results as France while the other stock market indices show basically no monotonic relationships.

Table 10 presents the results for the US sector indices. Four of the eleven sector indices show some monotonic relationships. Noticeable is that the returns of all these indices, Basic Materials, Diverse REITs, Financials and Health Care increase as the SST anomaly increases. Moreover, there are on average no negative returns when the ENSO variable is in the top 20%, while the mean returns are negative for five of the eleven sector indices in the bottom 20%.

However, it is important to examine the significance of these findings. A one-way analysis of variance (ANOVA) is performed to determine the significance of the effect of the ENSO intensity on daily excess returns. Although the data shows some heteroskedasticity across the quintiles, ANOVA is quite robust to this, especially when the number of observations are equal, which it approximately is.

For all of the major market and sector indices, the ANOVA is not statistically significant on the 5% confidence level since all the p-values, which are displayed in the second lowest rows of Table 9 and 10 respectively, of the F-tests are above 0.05. This means that at least one pair of average daily excess returns across the quintiles are not significantly different from each other.

Table 9: Major market index return quintiles based on ENSO intensities

ENSO Intensity	S&P 500	NYSE	NAS - DAQ	Dow Jones Ind.	S&P TSX Comp	MSCI France	DAX 30	MSCI Italy	FTSE 100	Nikkei 225	MSCI Australia
Top 20%	3.75	3.36	4.00	1.45	1.21	-2.10	1.69	-1.23	1.94	0.01	3.04
60-80%	0.73	0.81	1.99	0.96	3.28	0.88	0.99	-2.83	1.64	3.29	2.36
40-60%	-0.13	-0.43	1.86	1.20	-0.64	1.15	-2.41	1.25	-0.43	-0.40	-0.34
20-40%	-0.17	0.76	0.56	0.57	-1.04	5.14	4.53	4.79	1.27	1.75	-0.08
Bottom 20%	3.03	2.82	3.09	4.23	2.83	2.35	1.83	0.90	1.19	2.99	-0.23
p-value of F-test	0.249	0.401	0.801	0.302	0.339	0.286	0.124	0.261	0.954	0.492	0.524
p-value of t-test	0.797	0.874	0.783	0.152	0.450	0.133	0.954	0.496	0.844	0.305	0.209

Notes. (1) This table presents the mean, winsorized on 98%, returns in basis points of eleven major market indices as a function of ENSO intensities whereas the Top 20% reflects the 20% most positive ENSO intensities and Bottom 20% reflects the 20% most negative ENSO intensities.
(2) The second last row presents the p-values of the F-tests
(3) The bottom row displays the p-values of the t-test between the top and bottom quintiles.

Table 10: Sector index return quintiles based on ENSO intensities

ENSO Intensity	Basic Materials	Consumer Goods	Consumer Services	Diverse REITs	Financi als	Health Care	Industr ials	Oil & Gas	Technolo gy	Telec om	Utiliti es
Top 20%	3.42	3.42	3.85	1.77	3.81	4.11	3.16	1.95	4.74	0.78	1.63
60-80%	2.69	2.87	0.50	2.87	0.54	3.46	2.79	3.70	1.20	-0.41	0.97
40-60%	-0.48	-0.46	1.98	2.87	2.17	1.42	0.86	1.42	-0.22	-1.44	-0.70
20-40%	-3.22	-0.94	1.11	1.83	0.97	5.12	0.36	-0.10	-1.25	2.75	2.57
Bottom 20%	5.41	-0.63	1.18	-6.13	-0.10	-1.16	3.84	2.17	2.98	2.57	-1.97
p-value of F-test	0.051	0.370	0.802	0.286	0.656	0.107	0.708	0.848	0.540	0.484	0.172
p-value of t-test	0.628	0.203	0.391	0.089	0.140	0.057	0.821	0.899	0.738	0.460	0.124

Notes. (1) This table presents the mean, winsorized on 98%, returns in basis points of eleven United States sector price indices as a function of ENSO intensities whereas the Top 20% reflects the 20% most positive ENSO intensities and Bottom 20% reflects the 20% most negative ENSO intensities.
(2) The second last row presents the p-values of the F-tests
(3) The bottom row displays the p-values of the t-test between the top and bottom quintiles.

More importantly, t-tests are performed between the top and bottom quintile of the ENSO intensities. The corresponding p-values of the t-tests are displayed in the bottom rows of Table 9 and 10 respectively. Again, the differences in mean performance between the top and bottom quintiles, appear not to be significant, meaning that the differences in performance could be devoted to chance.

Although there are monotonic relationships present in some of the major and sector indices, the p-values of the F-tests and t-tests indicate that the differences in performance across ENSO intensities are not significant. Therefore, there is no reason to believe that creating a portfolio by going long in "winners" or going short in "losers" would provide excess returns.

6 Robustness

In this section the robustness of the executed analyses will be discussed. For some sector indices it appears that El Niño events on average increase daily excess return while La Niña events decrease daily excess return on average. Section 6.1 discusses what happens to the volatility in case of such events, in comparison to less extreme or neutral events. Besides, the analyses performed in this study are based on the major market price indices and US sector price indices, instead of the total return indices, which reinvest the paid out dividends. In Section 6.2, the results of the influence of the ENSO variable on daily excess returns on the total return indices will be compared to the effect on price indices.

6.1 Excess volatility

In this section the volatilities of the daily excess returns for the indices where the ENSO variable appears to be significant will be discussed. For these indices, it is logical to assess the volatility since one ought not use an anomaly if it results in excessive risks.

In order to assess the volatility of the returns, depending on the ENSO intensity, the standard deviations of the returns within the top and bottom quintile of the ENSO intensities will be compared to the total standard deviations of performance from January 1973 to March 2016. As can be deduced from Table 11, all standard deviations of the mean performance from the lowest 20% of the ENSO intensities are higher in comparison to the standard deviation of the total sample. In contrast, three out of four indices show standard deviations in the highest 20% of the ENSO intensities slightly higher in comparison to the total sample, while the standard deviation of the highest 20% of the ENSO intensities of the sector Diverse REITs is clearly lower in comparison to the total sample's standard deviation. To test the homogeneity of variances, a Bartlett's test is performed, of which the results are displayed in the bottom row of Table 11. As one could observe from the table, all p-values are less than 0.05, meaning that the quintiles do not have equal variances. Therefore, the null hypothesis that all quintiles have equal variances can be rejected.

As mentioned before, the Consumer Goods, Diverse REITs, Financials and Utilities sectors' performance are significantly affected by the ENSO intensity. However, volatility of these sectors increase when the SST anomaly is highly negative, while the volatility is similar when the SST anomaly is highly positive in comparison to the total sample.

Although the t-tests indicated that portfolios with "winning" and "losing" quintiles could not be created because the returns did not significantly differ from each other, volatility would be problematic too. By going long in "winners" and short in "losers" would significantly increase the volatility for at least three of the four sectors.

Table 11: Comparison of standard deviations between quintiles and total sample

Sector Index	Consumer Goods	Diverse REITs	Financials	Utilities
SD Bottom 20%	101.9	191.4	110.6	71.3
SD Top 20%	99.2	131.5	94.5	69.4
SD Total	95.9	160.6	93.2	67.8
Bartlett's test p-value	0.000	0.000	0.000	0.000

Notes. (1) Table 11 displays the standard deviation of the performance of the sector indices, displayed in Columns 2 to 5, of the lowest 20% and the highest 20% of the SST anomaly and of the total sample.
(2) The p-values of the Bartlett's test are depicted at the bottom row of the table.

6.2 Dividend distribution

Until now, the focus has been on price indices meaning that the paid out dividends by the companies were not reinvested in the concerning stock. The reason for this is the limited data available on total return indices, for which the distributed dividends were reinvested in the concerning stocks. In this section the results, which are displayed in Table 13 and Table 14 of Appendix C, of the MRA on total return indices are discussed.

Noticeable is that less variables appear to be significant, especially for the major market indices. This could be due to a smaller time period on which the regression is based, see Table 13 for the exact time period. Table 13 shows that for the major market indices there are still no significant ENSO-variables while Table 14 shows that for the sector indices, the ENSO variable is significant on the performance of two sectors, instead of four when examining the price indices. Financials is the only sector that appears to be significantly affected by the ENSO intensity in both the market price index as well as the total return index analysis. For the other three sectors, Consumer Goods, Diverse REITs and Utilities, the ENSO intensity does not significantly affect performance of the total return index. Instead, the ENSO variable appears to affect the performance of the total return index on Health Care. These differences may call the results of this study on price indices into question, since I cannot identify where these differences have emerged.

7 Conclusion

In this study, we examined the effect of ENSO events on different stock markets. Although ENSO events cause many meteorological and financial consequences around the globe, major stock market indices were not expected to be affected by ENSO events, due to the inclusion of companies from all sectors. However, it was expected that some United States sector indices were significantly affected by ENSO events. This study performed multiple MRAs on eleven major stock market indices and eleven US sector indices with a time period of at least 30 years. The MRA included lagged returns, various seasonality effects, and environmental factors, to estimate excess daily returns.

The performed analyses suggest that the examined major stock market indices, containing companies from all industries, are not significantly affected by ENSO events. When the industries were separated into sector indices it appeared that four out of the eleven examined sector indices were significantly affected by ENSO events, which accounted for 0.014% to 0.025% of the daily returns. This study did not provide the reasons for these findings. It is speculated that the combination of increasing expected growth in GDP and fewer hurricanes that comes along with El Niño events, increases the excess returns of these four sector indices. However, the results are not robust when examining the total return indices instead of the price indices. Unfortunately, I was not able to identify where these differences originate from.

Since all the coefficient estimates of the four sectors have equal signs it is only possible to go long in a 'winner' and go short in an index not affected by ENSO events but highly correlated with the winner, in order to minimize market and specific risk, or vice versa. In contrast, when the ENSO intensities were divided into quintiles, it appears that for all the indices at least two quintiles' performance were not significantly different, when subjected to a F-test. Moreover, the mean performances of the top and bottom quintiles were also not significantly different, when subjected to t-test, meaning that the few observed monotonic relationships have no significant importance. Even if there appeared significant differences between each quintile of the indices, a portfolio could only be created with higher levels of risk since the standard deviations of the most negative SST anomaly quintiles were considerably higher compared to the total sample.

Much research has been done on the effect of daily weather on various stock market indices. However, to my knowledge, the effects of this unique weather phenomenon, with corresponding large global consequences, on stock market indices has not been studied before. Furthermore, the previously studied weather effects were all on major market indices while it appears to be more likely that the effects of ENSO events are observable in more specified markets.

There are a number of ways to extend the research performed in this paper. First, this study considered the SST anomaly of the Niño 3.4 region as the ENSO variable, while using the Southern Oscillation Index is also a possibility. Moreover, in this study I used the SST anomaly in that month to predict returns within the same month. However, not all appreciable effects occur when the SST anomaly is at its highest point. In the first place, the changes in the amount of hurricanes is noticeable before the SST anomaly peak. Next to that, the changes in weather conditions are mostly visible when the SST anomaly is at its maximum while the growth in GDP is appreciable months after the peak. In a nutshell, these consequences do not occur at the same time. Therefore, it is hard to indicate whether the ENSO variable should be synchronized with the SST anomaly at a given point in time, as was done in this study. In theory, when the forecasts become more certain, the consequences of the upcoming ENSO event can be estimated and therefore, all the asset prices should adjust to this information, months before such an ENSO event occurs. Next, it is possible that a t-test would provide other results when comparing the two extreme deciles instead of quintiles, since this research performed a quintile analysis and did not find significant results after performing t-tests. Lastly, it is likely that these four sectors consist of a combination of stocks of 'winners', 'losers', and stocks not significantly affected by ENSO events. Further research needs to be done to examine whether this is true. If it is, creating a portfolio with 'winners' and 'losers' within one sector, will be less risky than creating such a portfolio with stocks from different sectors.

In conclusion, this study did provide the results needed to obtain excess return by creating a portfolio of 'winners' or 'losers'. It appeared that the US sector indices were more susceptible to ENSO events in comparison to the large diversified stock market indices. This offers hope to find more stocks within one sector index that are affected by ENSO events in order to reduces the risks and increase the returns of such a portfolio. Further research is needed to confirm the robustness of the results of this study and to reveal what the possibilities are for investors to create a portfolio with 'winners' and 'losers' within one sector.

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Appendix

Appendix A

Table 12: Cities with corresponding latitudes

City	Latitude
New York	40.77°N
Toronto	43.68°N
Paris	48.86°N
Frankfurt	50.11°N
Milan	45.47°N
London	51.48°N
Tokyo	35.69°N
Sydney	33.95°S

Appendix B

DataStream was the main supplier of the data of risk-free rates across the Globe. It accounted for the T-Bills of Canada, France, Australia, Japan and the UK. Next to that, the Federal Reserve Economic Data accounted for the T-Bills of Italy and the U.S.

For some countries the data on 3-month treasury bills were complete, concerning Italy, Canada, Australia, Germany, United Kingdom and the U.S. For this reason, it could immediately be applied to subtract it from the index returns to obtain the excess return. For France and Japan, a part of the period had to be estimated. The French T-Bill data was limited to 1973, while the year 1972 was included in the sample. To estimate the risk-free rate of 1972, the mean of the T-Bill rate of 1973 was taken. As was observed in the other T-Bills, this did not change a lot through these two years. At last, the Japanese T-Bill rate was unavailable on DataStream or anywhere else. However, the Japanese 3M Deposit from 1979-2016 was available on DataStream. Since interbank lending is riskier than lending to the state, deposit rates are expected to exceed T-Bill rates in that country. However, the mean Japanese 3M Deposit rate is significantly lower than all of the mean T-Bill rates of the other countries. Therefore, using the Japanese 3M Deposit rate is not expected to harm the results. Still, there are eighteen years of missing data. Since this rate is constantly very low, with very few peaks, the mean of the period 1979-2016 is used to estimate the period 1961-1978. This comes down to a mean of only 2.7% on an annual basis.

Appendix C

Table 13: Multiple Regression Analysis results for eleven major market total return indices

Model 1: $r_t = u + p_1 r_{t-1} + u_{Monday} D_t^{Monday} + u_{Tax} D_t^{Tax} + u_{Fall} D_t^{Fall} + u_{SAD} SAD_t + u_{ENSO} ENSO_t + \varepsilon_t$

Model 2: $r_t = u + p_1 r_{t-1} + u_{Monday} D_t^{Monday} + u_{Tax} D_t^{Tax} + u_{Fall} D_t^{Fall} + u_{SAD} SAD_t + u_{Precipitation} Precipitation_t + u_{Temperature} Temperature_t + \varepsilon_t$

	S&P 500 (07/01/1988-31/03/2016)		NASDAQ (30/09/2003-31/03/2016)		Dow Jones Industrials (05/10/1987-31/03/2016)		S&P/TSX COMP (06/01/1986-31/03/2016)	
Variable	*Model 1*	*Model 2*	*Model 1*	*Model 2*	*Model 1*	*Model 2*	*Model 1*	*Model 2*
u	1.704 (1.15)	1.716 (1.16)	4.034 (1.50)	3.971 (1.48)	1.311 (0.90)	1.324 (0.91)	1.057 (0.86)	1.151 (0.93)
p_1	-0.029** (-2.86)	-0.029** (-2.87)	-	-	-0.027** (-2.66)	-0.027** (-2.67)	0.055** (5.64)	0.055** (5.63)
u_{Monday}	1.984 (0.75)	1.971 (0.74)	-5.504 (-1.16)	-5.354 (-1.12)	5.450* (2.10)	5.440* (2.10)	-1.680 (-0.77)	-1.653 (-0.76)
u_{Tax}	1.399 (0.18)	1.386 (0.18)	3.679 (0.27)	3.736 (0.28)	-4.207 (-0.57)	-4.214 (-0.57)	5.530 (0.95)	5.583 (0.96)
u_{Fall}	1.617 (0.54)	1.608 (0.54)	5.256 (0.99)	5.335 (1.01)	2.715 (0.93)	2.670 (0.92)	-2.130 (-0.90)	-2.215 (-0.94)
u_{SAD}	0.967 (0.84)	0.975 (0.84)	-1.097 (-0.53)	-1.094 (-0.53)	0.593 (0.53)	0.693 (0.53)	2.222** (2.63)	2.251** (2.66)
u_{ENSO}	0.087 (0.07)	-	0.830 (0.53)	-	-0.649 (-0.53)	-	-0.570 (-0.55)	-
$u_{Temperature}$	-	-0.085 (-0.38)	-	-0.138 (-0.34)	-	-0.002 (-0.01)	-	-0.070 (-0.45)
$u_{Precipitation}$	-	-0.043 (-0.39)	-	0.178 (0.95)	-	-0.043 (-0.40)	-	-0.273 (-1.54)
R^2	0.0015	0.0015	0.0009	0.0012	0.0019	0.0019	0.0053	0.0056
Adj. R^2	0.0007	0.0006	0.0000	0.0000	0.0011	0.0010	0.0045	0.0047

Table 13 (continued)

Model 1: $r_t = u + p_1 r_{t-1} + u_{Monday} D_t^{Monday} + u_{Tax} D_t^{Tax} + u_{Fall} D_t^{Fall} + u_{SAD} SAD_t + u_{ENSO} ENSO_t + \varepsilon_t$

Model 2: $r_t = u + p_1 r_{t-1} + u_{Monday} D_t^{Monday} + u_{Tax} D_t^{Tax} + u_{Fall} D_t^{Fall} + u_{SAD} SAD_t + u_{Sunshine} Sunshine_t + u_{Precipitation} Precipitation_t + u_{Temperature} Temperature_t + \varepsilon_t$

	MSCI France (04/01/2001-31/03/2016)		*MSCI Italy (05/01/2001-31/03/2014)*		*FTSE 100 (06/01/1986-31/03/2016)*		*Nikkei 225 (09/01/2002-31/03/2016)*		*MSCI Australia (04/01/2001-31/03/2016)*	
Variable	*Model 1*	*Model 2*	*Model 1*	*Model 1*	*Model 1*	*Model 2*	*Model 1*	*Model 2*	*Model 1*	*Model 2*
u	*0.742* *(0.27)*	*1.094* *(0.39)*	*0.599* *(0.41)*	*0.599* *(0.41)*	*0.599* *(0.41)*	*0.716* *(0.49)*	*1.390* *(0.48)*	*2.015* *(0.68)*	*4.451** *(2.28)*	*4.238** *(2.16)*
p_1	-	-	-	-	-	-	*-0.041*** *(-2.85)*	*-0.041*** *(-2.85)*	*-0.030** *(-2.16)*	*-0.031** *(-2.18)*
u_{Monday}	*-2.652* *(-0.54)*	*-2.629* *(-0.53)*	*-1.395* *(-0.53)*	*-1.395* *(-0.53)*	*-1.395* *(-0.53)*	*-1.415* *(-0.54)*	*-3.285* *(-0.64)*	*-3.285* *(-0.64)*	*-3.562* *(-1.01)*	*-3.407* *(-0.97)*
u_{Tax}	*0.746* *(0.05)*	*0.697* *(0.05)*	*10.941* *(1.53)*	*10.941* *(1.53)*	*10.941* *(1.53)*	*10.759* *(1.50)*	*18.031* *(1.30)*	*18.058* *(1.30)*	*-3.917* *(-0.39)*	*-4.004* *(-0.40)*
u_{Fall}	*4.127* *(0.76)*	*3.920* *(0.72)*	*0.349* *(0.13)*	*0.349* *(0.13)*	*0.349* *(0.13)*	*0.222* *(0.08)*	*2.973* *(0.54)*	*2.607* *(0.48)*	*-0.382* *(-0.11)*	*-0.449* *(-0.12)*
u_{SAD}	*-0.848* *(-0.52)*	*-0.894* *(-0.55)*	*1.331** *(1.82)*	*1.331** *(1.82)*	*1.331** *(1.82)*	*1.341** *(1.83)*	*0.835* *(0.31)*	*0.635* *(0.24)*	*-2.588* *(-1.25)*	*-2.579* *(-1.25)*
u_{ENSO}	*0.195* *(0.07)*	-	*0.532* *(0.43)*	*0.532* *(0.43)*	*0.532* *(0.43)*		*-2.888* *(-1.08)*		*1.126* *(0.61)*	-
$u_{Sunshine}$	-	-	-	-	-	*0.738*** *(2.32)*	-	*0.570* *(0.90)*	-	-
$u_{Temperature}$	-	*-0.377* *(-0.74)*	-	-	-	*-0.540* *(-1.62)*	-	*-0.961* *(-1.25)*	-	*0.589* *(1.52)*
$u_{Precipitation}$	-	*-0.144* *(-1.21)*	-	-	-	*-0.387* *(-1.35)*	-	*-0.225* *(-1.37)*	-	*0.115* *(0.71)*
R^2	*0.0002*	*0.0008*	*0.0009*	*0.0009*	*0.0009*	*0.0021*	*0.0032*	*0.0040*	*0.0023*	*0.0028*
Adj. R^2	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0002*	*0.0012*	*0.0016*	*0.0018*	*0.0007*	*0.0010*

Notes. (1) This table reports MRAs of eleven major market total return indices of both the MRA including the ENSO variable and excluding the weather variables (Model 1) and the MRA excluding the ENSO variable and including the weather variables (Model 2). To estimate the excess return in basis points r_t, this MRA controls for first-order autocorrelation (r_{t-1}), the Monday effect; a dummy following a weekend (D_t^{Monday}), the tax-loss effect; a dummy for the last and first five trading days of a fiscal (D_t^{Tax}), the autumn effect; a dummy for trading days in the autumn (D_t^{Autumn}), the seasonal affective disorder effect which is zero in the spring and summer and equals twelve minus the amount of hours daylight in the autumn and winter (SAD_t) in combination with the ENSO effect which equals the SST anomaly in the Niño 3.4 region ($ENSO_t$) in Model 1 or in combination with the anomaly in the amount of precipitation in mm ($Precipitation_t$), and in maximum temperature in degrees Celsius effect ($Temperature_t$) in Model 2.

(2) The cells containing a dash (-) represent cases for which the parameter is not estimated.

(3) The parameter estimates are presented in the table with corresponding t-statistic (in brackets) directly beneath the parameter.

(4) In the last row the R^2 for each regression is presented.

* Indicate statistical significance at the 5% level (one-sided test)

** Indicate statistical significance at the 1% level (one-sided test)

Table 14: Multiple Regression Analysis results for eleven US sector total return indices

Model 1: $r_t = u + p_1 r_{t-1} + u_{Monday} D_t^{Monday} + u_{Tax} D_t^{Tax} + u_{Fall} D_t^{Fall} + u_{SAD} SAD_t + u_{ENSO} ENSO_t + \varepsilon_t$

Model 2: $r_t = u + p_1 r_{t-1} + u_{Monday} D_t^{Monday} + u_{Tax} D_t^{Tax} + u_{Fall} D_t^{Fall} + u_{SAD} SAD_t + u_{Precipitation} Precipitation_t + u_{Temperature} Temperature_t + \varepsilon_t$

	Basic Materials		*Consumer Goods*		*Consumer Services*		*Diverse Real Estate Investment Trusts*		*Financials*	
Variable	*Model 1*	*Model 2*	*Model 1*	*Model 2*	*Model 1*	*Model 2*	*Model 1*	*Model 2*	*Model 1*	*Model 2*
u	*2.469* *(1.44)*	*2.499* *(1.46)*	*1.137* *(0.72)*	*1.031* *(1.65)*	*2.980** *(1.89)*	*2.901** *(1.84)*	*3.198* *(1.20)*	*3.042* *(1.14)*	*2.378* *(1.55)*	*2.268* *(1.48)*
p_1	*0.126*** *(13.30)*	*0.125*** *(13.28)*	*0.063*** *(6.66)*	*0.063*** *(6.68)*	*0.083*** *(8.81)*	*0.084*** *(8.82)*	-	-	*0.116*** *(12.23)*	*0.116*** *(12.24)*
u_{Monday}	*-7.704*** *(-3.12)*	*-7.712*** *(-3.12)*	*1.032* *(0.45)*	*1.019* *(0.45)*	*-7.253*** *(-3.21)*	*-7.272* *(-3.21)*	*-9.271*** *(-2.42)*	*-9.294*** *(-2.43)*	*-7.923*** *(-3.60)*	*-7.940*** *(-3.61)*
u_{Tax}	*6.797* *(1.04)*	*6.818* *(1.05)*	*10.130** *(1.69)*	*10.173** *(1.69)*	*14.426*** *(2.42)*	*14.473*** *(2.42)*	*9.886* *(0.98)*	*9.966* *(0.99)*	*4.478* *(0.77)*	*4.546* *(0.78)*
u_{Fall}	*-1.193* *(-0.47)*	*-1.184* *(-0.56)*	*-1.666* *(-0.70)*	*-1.658* *(-0.70)*	*-2.293* *(-0.97)*	*-2.277* *(0.97)*	*-0.432* *(-0.11)*	*-0.403* *(-0.10)*	*1.074* *(0.47)*	*1.091* *(0.48)*
u_{SAD}	*1.830** *(1.77)*	*1.833** *(1.77)*	*1.225* *(1.28)*	*1.247* *(1.31)*	*1.174* *(1.24)*	*1.184* *(1.25)*	*0.601* *(0.38)*	*0.645* *(0.40)*	*1.755** *(1.70)*	*1.541** *(1.67)*
u_{ENSO}	*0.031* *(0.03)*	-	*1.522* *(1.42)*	-	*1.258* *(1.18)*	-	*2.891* *(1.61)*	-	*1.755** *(1.70)*	-
$u_{Temperature}$	-	*-0.016* *(0.08)*	-	*0.039* *(0.20)*	-	*0.093* *(0.49)*	-	*0.047* *(0.14)*	-	*0.161* *(0.87)*
$u_{Precipitation}$	-	*-0.120* *(-1.19)*	-	*-0.061* *(-0.66)*	-	*-0.087* *(-0.93)*	-	*-0.197* *(-1.26)*	-	*-0.097* *(-1.07)*
R^2	*0.0172*	*0.0173*	*0.0049*	*0.0047*	*0.0091*	*0.0091*	*0.0009*	*0.0008*	*0.0151*	*0.0150*
Adj. R^2	*0.0166*	*0.0167*	*0.0043*	*0.0041*	*0.0086*	*0.0085*	*0.0004*	*0.0002*	*0.0145*	*0.0144*

Table 14 (continued)

Model 1: $r_t = u + p_1 r_{t-1} + u_{Monday} D_t^{Monday} + u_{Tax} D_t^{Tax} + u_{Fall} D_t^{Fall} + u_{SAD} SAD_t + u_{ENSO} ENSO_t + \varepsilon_t$

Model 2: $r_t = u + p_1 r_{t-1} + u_{Monday} D_t^{Monday} + u_{Tax} D_t^{Tax} + u_{Fall} D_t^{Fall} + u_{SAD} SAD_t + u_{Precipitation} Precipitation_t + u_{Temperature} Temperature_t + \varepsilon_t$

	Health Care		*Industrials*		*Oil & Gas*		*Technology*		*Telecom*		*Utilities*	
Variable	*Model 1*	*Model 2*	*Model 1*	*Model 2*	*Model 1*	*Model 2*	*Model 1*	*Model 2*	*Model 1*	*Model 2*	*Model 1*	*Model 2*
u	*3.259*** (2.32)*	*3.127* (2.23)*	*2.191 (1.37)*	*2.177 (1.36)*	*6.047*** (3.33)*	*6.073*** (3.35)*	*-2.444 (-1.14)*	*-2.516 (-1.18)*	*2.755* (1.79)*	*2.810* (1.83)*	*2.036 (1.46)*	*2.001 (1.44)*
p_1	*0.074*** (7.84)*	*0.075*** (7.88)*	*0.086*** (9.08)*	*0.086*** (9.07)*	*0.079*** (8.29)*	*0.078*** (8.27)*	*0.031*** (3.28)*	*0.031*** (3.27)*	-	-	*0.088*** (9.42)*	*0.088*** (9.41)*
u_{Monday}	*-2.909 (-1.44)*	*-2.914 (-1.45)*	*-4.692* (-2.05)*	*-4.694* (-2.05)*	*-6.335*** (-2.43)*	*-6.339*** (-2.43)*	*4.692 (1.53)*	*4.686 (1.53)*	*-2.824 (-1.28)*	*-2.834 (-1.29)*	*-4.056* (-2.03)*	*-4.055* (-2.03)*
u_{Tax}	*7.481 (1.41)*	*7.533 (1.42)*	*4.317 (0.71)*	*4.327 (0.72)*	*0.130 (0.02)*	*0.150 (0.02)*	*-2.955 (-0.37)*	*-2.889 (-0.36)*	*-2.027 (-0.35)*	*-2.021 (-0.35)*	*-7.720 (-1.46)*	*-7.713 (-1.46)*
u_{Fall}	*-0.833 (-0.40)*	*-0.825 (-0.39)*	*-0.809 (-0.34)*	*-0.801 (-0.34)*	*-4.602* (-1.70)*	*-4.601* (-1.70)*	*2.977 (0.93)*	*3.013 (0.95)*	*-0.514 (-0.22)*	*-0.517 (-0.23)*	*1.878 (0.90)*	*1.867 (0.90)*
u_{SAD}	*0.687 (0.81)*	*0.701 (0.83)*	*2.034* (2.12)*	*2.026* (2.11)*	*-0.765 (-0.70)*	*-0.733 (-0.67)*	*3.477*** (2.70)*	*3.446*** (2.68)*	*0.838 (0.91)*	*0.846 (0.92)*	*0.780 (0.93)*	*0.810 (0.97)*
u_{ENSO}	*1.613* (1.70)*	-	*0.170 (0.16)*	-	*0.238 (0.19)*	-	*0.832 (0.58)*	-	*-0.272 (-0.26)*	-	*0.596 (0.64)*	-
$u_{Temperature}$	-	*0.102 (0.60)*	-	*0.102 (0.53)*	-	*-0.260 (-1.19)*	-	*0.439* (1.70)*	-	*-0.112 (-0.61)*	-	*-0.200 (-1.19)*
$u_{Precipitation}$	-	*-0.008 (-0.10)*	-	*-0.013 (-0.14)*	-	*-0.128 (-1.21)*	-	*-0.081 (-0.64)*	-	*-0.095 (-1.06)*	-	*-0.001 (-0.01)*
R^2	*0.0064*	*0.0062*	*0.0085*	*0.0085*	*0.0069*	*0.0072*	*0.0019*	*0.0022*	*0.0003*	*0.0004*	*0.0085*	*0.0085*
Adj. R^2	*0.0058*	*0.0055*	*0.0080*	*0.0079*	*0.0064*	*0.0065*	*0.0014*	*0.0016*	*0.0000*	*0.0000*	*0.0079*	*0.0079*

Notes. (1) This table reports MRAs of eleven sector total return indices of both the MRA including the ENSO variable and excluding the weather variables (Model 1) and the MRA excluding the ENSO variable and including the weather variables (Model 2). To estimate the excess return in basis points r_t, this MRA controls for first-order autocorrelation (r_{t-1}), the Monday effect; a dummy following a weekend (D_t^{Monday}), the tax-loss effect; a dummy for the last and first five trading days of a fiscal (D_t^{Tax}), the autumn effect; a dummy for trading days in the autumn (D_t^{Autumn}), the seasonal affective disorder effect which is zero in the spring and summer and equals twelve minus the amount of hours daylight in the autumn and winter (SAD_t) in combination with the ENSO effect which equals the SST anomaly in the Niño 3.4 region ($ENSO_t$) in Model 1 or in combination with the anomaly in the amount of precipitation in mm ($Precipitation_t$), and in maximum temperature in degrees Celsius effect ($Temperature_t$) in Model 2.
(2) The cells containing a dash (-) represent cases for which the parameter is not estimated.
(3) The parameter estimates are presented in the table with corresponding t-statistic (in brackets) directly beneath the parameter.
(4) In the last row the R^2 for each regression is presented.
* Indicate statistical significance at the 5% level (one-sided test)
** Indicate statistical significance at the 1% level (one-sided test)