The El Niño-Southern Oscillation

A Natural Force to be Reckoned With?

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Abstract This study investigates the explanatory power of the El Niño-Southern Oscillation (ENSO) on the monthly stock returns of 22 global stock indices and 12 U.S. business sector indices over the period January 1950 to September 2017. The findings indicate that no direct 'El Niño effect' is present on the stock performance of the 22 global indices when using sea surface temperature anomalies, an indicator of an ENSO phase, to explain stock returns. Concerning the U.S. sector performance, I find that El Niño has a statistically significant seasonal effect, both positive and negative, on 6 out of the 12 studied sector indices. Finally, by using the 'El Niño surprise', the difference between forecasted- and actual El Niño intensity, I find that investors account for a positive El Niño effect based on forecasts.

Keywords El Niño Southern-Oscillation · International stock markets · International business sectors · Sea Surface Temperature anomalies

JEL Classification C32 · G10 · G15 · Q54

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Abbreviations:

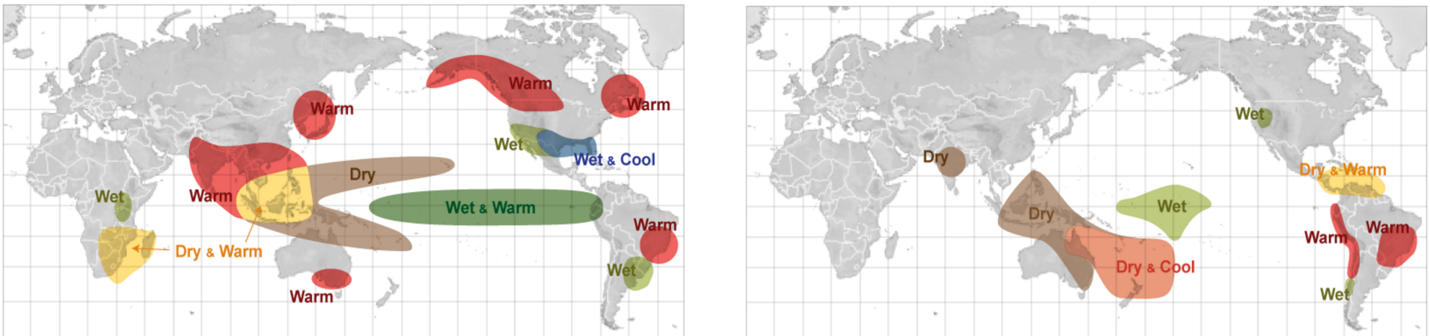
AR	Autoregressive
BG	Breusch-Godfrey
BP	Breusch-Pagan
DJIA	Dow Jones Industrial Average
ENSO	El Niño-Southern Oscillation
GDP	Gross Domestic Product
GHCN	Global Historical Climatology Network
MSPE	Mean Squared Prediction Error
NASDAQ	National Association of Securities Dealers Automated Quotation
NOAA	National Oceanic and Atmospheric Administration
NYSE	New York Stock Exchange
ONI	Oceanic Niño Index
RW	Random Walk
S&P 500	Standard & Poor's 500
SAD	Seasonal Affective Disorder
SST	Sea Surface Temperature
U.S.	United States

1. Introduction

"A strong El Niño is in place and should exert a strong influence over our weather this winter," said Mike Halpert, deputy director of the National Oceanic and Atmospheric Administration (NOAA, 2015). During 2015/16 we experienced one of the most powerful El Niño's in recorded history. In the United States, rainfall was heavier and drought was more severe. The warmer-than-average weather is caused by the presence of 'El Niño', a natural phenomenon in the equatorial Pacific Ocean that involves fluctuating ocean temperatures. The presence of El Niño affects weather all around the world.

El Niño is a phase of a naturally occurring global climate cycle and is also known as the El Niño-Southern Oscillation (ENSO). El Niño disrupts normal weather patterns across the globe and can lead to more intense storms in some places and droughts in others, affecting many lives and (local) economies for a period that lasts 6 to 18 months. The global climatological impact of El Niño is illustrated in Figure 1. According to Cashin et al. (2017), the changes in weather patterns (caused by El Niño) have a significant effect on agriculture, fishing and construction industries, as well as on national and global commodity prices.

Figure 1 Global climate impact El Niño



This figure shows the impact of El Niño on the weather worldwide. During the summer (left image) the climate is affected differently than during the winter (right image). Source: NOAA Climate.gov (2016)

As shown in Figure 1, the impact of an ENSO cycle varies during different seasons. ENSO is the world's most influential natural climate pattern (NOAA, 2016). El Niño warms large areas of the tropical part of the Pacific Ocean which significantly influences where and how much it rains there. Due to atmospheric jet streams[1] temperature and precipitation can be affected across the globe.

The effect of weather (amount of sunshine, temperature and precipitation anomalies) on the economy are well documented in financial literature (Kamstra et al., 2003), (Hirshleifer &

[1] Relatively strong winds concentrated in a narrow stream in the atmosphere, normally referring to horizontal, high-altitude winds. <https://forecast.weather.gov/glossary.php?word=jet%20stream>

Shumway, 2003). However, the amount of studies on the effects of El Niño on the economy or the stock market is very limited. One of these studies is the one of Cashin, Mohaddes, and Raissi (2017), who studied the effect of El Niño on the economic performance of 21 countries over the period 1979-2013. They found that El Niño episodes have both a statistically and economically significant effect on different economies around the world (effect on economic growth, inflation, and commodity prices). The impact of El Niño on the real economy varies between countries, some countries benefit (for example the U.S.) whereas other countries face an adverse effect on their economy. The effect of El Niño weather episodes on worldwide equity prices has not yet been studied, but one could argue that, if El Niño affects economies around the world, it might also impact the performance of equity markets.

Furthermore, climatologists are still studying the impact of global warming on the frequency and magnitude of El Niño-related weather events. Cai et al. (2014) studied the relationship between extreme El Niño events and global warming. During the last four decades, extreme El Niño events have occurred more frequently. Since the 1970' clear and increasing worldwide temperature anomalies are measured, which which raises the question whether or not this is related to global warming. In a successive study, Cai et al. (2015) found that greenhouse warming leads to a significant increase in the frequency of between extreme El Niño events. If the effects of El Niño are indeed more extreme, the research on the effects of El Niño on the stock market might be more relevant than ever.

Besides looking at the market as a whole, it might be interesting to look at individual stocks or stocks of a similar sector. As already stated, the presence of El Niño affects the weather around the world in different ways. The weather in the United States is affected in three different ways: a warmer north, a wetter west and a wetter/cooler south-east. One might expect that these temporary changes in the U.S. climate can affect its business sectors in different ways. Cashin et al. (2017) found that the United States benefits from the El Niño-related weather events. Examples of U.S. sectors that directly benefit are the agricultural sector and the insurance sector. The agricultural sector is affected via the increased rainfall in the south and the west, benefiting crops. Due to diminished tornado and hurricane activity in the Midwest/East Coast, the insurance sector benefits. Different U.S. sectors might also be affected indirectly. An example of an indirect effect is a higher oil price. Cashin et al. (2017) found that the higher temperatures and droughts following an El Niño event increases the price of oil as well as non-fuel commodities prices. The U.S. economy is affected by El Niño in different ways, but which business sectors' stock performance is affected has not yet been studied.

In this study, I will elaborate on the effect of an El Niño episode on stock performance. The empirical research is split into two parts. First, I study the impact of El Niño on equity markets around the world. In the second part I study the impact of El Niño on U.S. business sectors. The research questions are formulated as follows:

1. How do El Niño-related events affect the equity markets around the world?
2. How do El Niño-related events affect U.S. business sectors?

This thesis is structured as follows: in section 2, I discuss related literature, followed by the theoretical framework of my research. Next, I describe the data (in section 3) and methodology (in section 4) used in my empirical research for examining the relationship between El Niño and stock performance. Section 5 provides the findings of my empirical analysis as well as a discussion on the results. In the last part of this thesis, I conclude my findings (in section 6) and discuss the limitations along with recommendations for future research (in section 7).

2. Theoretical Framework

In the first part of the theoretical framework I focus on previous studies on the macroeconomical impact of El Niño. Secondly, I study whether these macroeconomical effects could affect stock performance. Finally, I study the effect of weather/climate on investor behaviour.

2.1 The Macroeconomic Impact of El Niño

Cashin et al. (2017) studied the effects of El Niño shocks on GDP, inflation, energy and commodity prices in a selection of countries from around the world. They found that Australia, Chile, Indonesia, India, Japan, New Zealand and South Africa face a short-lived fall in economic activity in response to El Niño-related events. The United States and Canada however, experience GDP growth due to El Niño shocks. Cashin et al. also found evidence for (positive) spillover effects on major trading partners in Europe. Furthermore, they found a positive, significant effect on global energy and non-fuel commodity prices. These findings are similar to those of Brunner (2002). He studied the effects of the ENSO cycle on world primary commodity prices, he found both statistically and economically significant evidence for a positive effect of an ENSO cycle on commodity prices.

Both the studies of Brunner (2002) and Cashin et al. (2017) refer to the 1997/98 El Niño episode as the one with the biggest impact on the global economy. Changnon (1999) did a more in-depth analysis on the impact of the 1997/98 El Niño on the U.S. economy; major economic losses were made due to property/crop damages (caused by storms) and the loss of business by snow-removal equipment manufacturers. Major economic benefits were primarily found in the U.S.'s northern states and included record seasonal sales of retail products and homes, substantial savings in highway & airline transportation and record construction levels. Due to an abnormally warm winter, the net economic effect of El Niño was further improved by the major reductions in heating costs experienced by most U.S. companies. Changnon (1999) also reported that the lack of Atlantic hurricanes and the subsequent losses was favorable for insurers. Overall, the net economic effect of the 1997/98 El Niño episode was positive; the estimated losses were $4 billion while the benefits were approximately $19 billion. The net economic effect was partially realized through the response on the (highly accurate) long-range predictions issued by NOAA's Climate Prediction Center. Due to these predictions, the government and different industries could account for an 'El Niño effect' whereby they mitigated the negative effects of the ENSO cycle and/or enhanced the positive effects. For example, several utility companies in the northern United States used the forecasts to change their strategy for purchasing natural gas and oil, which ultimately led to major savings.

2.2 The Effects of Macroeconomics on Stock Performance

In the previous paragraphs I discussed how El Niño related weather/climate anomalies affect the real economy. For my study it is relevant whether this is also reflected in the performance of equity markets around the globe. Subsequently, in the next paragraphs I discuss if/how GDP growth, energy/oil price fluctuations and other macroeconomic shocks might affect stock performance.

The high temperatures and droughts caused by an ENSO cycle (particularly in Asia-Pacific countries) are followed by increasing in oil prices. This is a consequence of a higher demand for crude oil (and coal) as lower electricity output is generated from both thermal power plants and hydroelectric dams (Cashin et al., 2017). An extensive set of literature is available on the effects of oil price fluctuations on stock performance. Miller and Ratti (2009) studied the relationship between world price of crude oil and international stock markets. They found a statistically significant negative relationship between the oil price and stock returns. These findings contribute to the theory that an increase in crude oil price raises the input costs for most industries (and their companies) and thereby reducing their earnings. Similar results are observed by Nandha and Faff (2008), they found that increasing energy prices negatively impact stock market returns for all sectors except the mining, oil and gas sector.

According to Brunner (2002), the presence of El Niño could account for approximately 10% to 20% of the variation in GDP growth and inflation in the G-7 countries.[2] Cashin et al. (2017) studied the effect of El Niño on real GDP more extensively. Their results indicate that an El Niño event has a statistically significant effect on real GDP growth for 17 out of 21 countries in their sample. They found that the magnitude as well as the direction (negative or positive) of GDP growth varies across countries, this variation can be partially explained by different climatological effects of El Niño across continents (and countries).

The effect of GDP growth on equity returns is an intensively investigated topic in financial literature. However, the findings on the impact of GDP on stock return are dispersed. Among others, Fama (1990), Schwert (1990) and Cornell (2010) find a positive correlation between output growth and stock return. According to these studies, the correlation between real economic activity and (lagged) real stock return is positive and both statistically and economically significant. These findings are explained by the link between earnings growth and long-run stock performance; as earnings growth is positively correlated with GDP growth. Not all studies find evidence for the existence of a relationship between growth and stock prices, Ritter (2005) and David et al. (2015) only found weak evidence for a relationship between stock performance and economic growth (measured as real GDP growth). They emphasize the understanding that “It is

[2] The Group of Seven (G-7) is a forum of the seven most industrialized countries in the world. The G-7 is composed of the following countries: Canada, France, Germany, Italy, Japan, the United Kingdom and the United States.

not unreasonable for an investor to associate rapid economic growth with strong stock market returns", but in their sample of 46 countries the evidence is weak and inconsistent.

Rapach (2001) studied the impact of non-fundamental macroeconomic shocks on U.S. stock prices. He identified different types of shocks including aggregate demand and aggregate supply shocks. The results indicate that each of these two shocks have a statistically and economically significant effect on the stock price. According to Rapach (2001), the aggregate supply shock is the most influential macro shock for explaining long-run fluctuations in real stock prices. A positive supply shock decreases the price level and increases the real output in both the short-run and the long-run causing stock prices to increase. Cashin et al. (2017) show that El Niño-related events affect the aggregate supply side as well as the aggregate demand side. The extreme weather conditions resulting from El Niño can constrain the supply of weather-driven agricultural commodities. Besides a demand shock in oil prices, excess demand also rises for non-fuel commodities (especially for food, beverages, metals, and agricultural raw materials).

2.3 The Effect of Weather on Investor Behaviour

Besides the studies on El Niño in particular, there has been a rapid growth in studies which examine the relationship between climate (temperature, amount of sun-hours, storms and other aspects of the weather) and economic performance (agricultural production, commodity prices, GDP growth and stock performance). Different studies found evidence for the existence of a direct effect of the climate/weather on the economy as well as an indirect effect (via investor's behaviour). Kramer, Kamstra and Levi (2003) studied the role of the Seasonal Affective Disorder (SAD) in the seasonal fluctuations of stock market returns. SAD is a type of depression that is related to changes in seasons, the shortness of days in the fall and winter may cause a depression for many people. They found that the impact of SAD on investor sentiment predicts market performance in all the studied countries with the exception of Australia.

In a similar research, Saunders (1993) examined the relationship between the New York City weather and daily stock returns on the New York Stock Exchange (NYSE) and/or the Dow Jones Industrial Average (DJIA). He found evidence for a significantly negative relationship between the level of cloud-cover and stock returns. According to his hypothesis, the negative mood effects of 'bad weather', defined as cloudy days, result in relatively lower stock returns. On the other hand, positive mood effects of 'good weather', defined as clear days, result in higher stock returns. The findings of Saunders (1993) are supported by those of Hirshleifer and Shumway (2003), who studied whether stock performance could be explained by the amount of daily sunshine-hours. Subsequently, they found a positive relationship between sunshine and stock returns. Hirshleifer and Shumway assign these findings to the positive effect of sunshine on someone's mood, investors with a good mood tend to evaluate future prospects more optimistically than investors who are in a bad mood. Based on the same data used in the research of Hirshleifer and Shumway (2003), Symeonidis et al. (2010) studied the impact of weather on stock market volatility. Their findings indicate that sunny weather affects volatility due to an increasing diversity of opinions amongst traders regarding the true value of assets. Instead of sunshine and clouds, Cao and Wei (2005) studied the effect of temperature on stock returns. Their analysis revealed that lower temperatures are related to higher stock returns during winter, whereas higher temperatures are related to lower stock returns. They suggest that lower temperatures lead to aggression (and higher stock returns), while higher temperature lead to apathy (and lower stock returns).

In contrast to the studies discussed in the paragraph above, not all research confirms that weather actually affects the stock market. Trombley (1997) revised the earlier study of Saunders (1993) on the correlation between New York City weather and stock market return. Trombley used an alteration of the approach used by Saunders and found that the results of Saunders are not robust to alternative types of stock returns and other sample periods. Overall, Trombley did not find evidence for a difference in stock return on sunny days and cloudy/rainy days. Kramer and Runde (1997) also did not find any evidence for stock markets in Germany to be affected by the weather. They addressed the possibility that data-mining could have influenced the results of Saunders (1993).

Kim (2017) discussed the validity of the statistical significance reported in various studies of weather effects on stock returns. The main finding in this paper is that statistically significant weather effects reported in previous studies are highly likely to be spurious due to a Type I error (the error that occurs when a null hypothesis is rejected although it is true). Furthermore, he questioned the sample size of the majority of the reviewed studies. Kim (2017) also emphasized the relationship between sample size and explanatory power (R^2). He found that a relatively large sample size is often accompanied with a low R^2. When a explanatory weather variable has a low R^2, the variable's contribution to the total variation of index return is also low.

3. Data

For my thesis, the following data is required for the analysis:

- Data on indicators of an El Niño period.
- Stock performance of indices based in developed countries in 1950-2015
- Stock performance of U.S. business sectors in 1950-2015.

3.1 International Stock Market Returns

I make use of a large dataset of stock market indices to identify the impact of an El Niño-period on international stock market returns. Datastream provides the monthly closing prices for the leading stock indices in the countries reported in Table 1. This table reports the descriptive statistics of the stock returns of all countries in my sample.

Table 1 Descriptive statistics country indices

Country	Index	City	Starting date	Number of observations	Mean monthly log return	Std. dev. monthly log return	Augmented Dickey Fuller test
Argentina	MERVAL	Buenos Aires	11/89	336	0.92	6.71	0.000
Australia	S&P / ASX 200	Sydney	6/92	305	0.17	1.72	0.000
Brazil	IBOV	Sao Paulo	1/93	298	1.36	5.34	0.000
Canada	S&P / TSX	Toronto	1/50	814	0.23	1.88	0.000
Chile	IPSA	Santiago	2/90	333	0.54	2.61	0.000
China	SZSE	Shanghai	2/92	309	0.34	5.45	0.000
France	CAC 40	Paris	8/87	363	0.15	2.54	0.000
Germany	DAX 30	Frankfurt	1/65	634	0.23	2.44	0.000
Hong Kong	Hang Seng	Hong Kong	8/64	639	0.38	3.97	0.000
Italy	FTSE MIB	Milan	1/98	238	-0.01	2.83	0.000
Japan	Nikkei 225	Tokyo	4/50	811	0.29	2.53	0.000
Mexico	MEXBOL	Mexico City	2/88	357	0.72	3.42	0.000
Netherlands	AEX	Amsterdam	2/83	418	0.26	2.60	0.000
Norway	OSEAX	Oslo	1/83	418	0.43	2.81	0.000
Singapore	MSCI	Singapore	1/70	574	0.21	3.25	0.000
South Africa	JSE / FTSE 40	Johannesburg	7/95	268	0.40	2.38	0.000
South-Korea	KOSPI 200	Seoul	2/75	514	0.30	3.06	0.000
Spain	IBEX 35	Madrid	2/87	369	0.17	2.79	0.000
United Kingdom	FTSE 100	London	1/84	406	0.22	2.01	0.000
United States	S&P 500	New York City	1/64	646	0.24	1.88	0.000
United States	NASDAQ	New York City	3/71	560	0.32	2.67	0.000
United States	Dow Jones	New York City	6/50	809	0.25	1.82	0.000

This table reports the descriptive statistics of all countries in the sample. The 2nd and 3rd column show the index from which the data is obtained and in which city this index is located. The mean and standard deviation are noted in percent. Monthly returns are calculated according to equation (1). In the last column, the p-values are shown of the augmented Dickey Fuller test.

The monthly logarithmic stock returns (R_t) are calculated by the following formula:

(1) $$R_t = 100 \times (\ln P_t - \ln P_{t-1})$$

Where P_t is the index closing price at the last day of month t. The countries that I include in my sample are selected by the criterion that they are likely to be (in)directly affected by El Niño events. The countries likely to be directly affected are located in: North America, South America, Africa and Asia. Like the sample used by Cashin et al. (2017), I will also add countries who might be indirectly affected by El Niño (via trade, financial channels commodity prices, etc.). These countries are mainly located in Europe. From Table 1 can be deducted that the leading stock indices in the developing countries, such as Argentina, Brazil, Chile and Mexico, experience a relatively high mean stock return in relation to the developed countries. Finally, as my research deals with time series in a regression analysis, stationarity is required. The Augmented Dickey-Fuller test is used on the stock return variable. The test, shown in Table 1, indicates that all returns are stationary and a unit root can be rejected.

3.2 U.S. Business Sector Returns

The data used in the study on the impact of El Niño on U.S. business sectors are also sourced from DataStream. From within the U.S. stock markets, stocks are allocated to sectors using the Thomson Reuters Business Classification chart[3], after which sector indices are calculated. The Thomson Reuters Business Classification breaks each market index down into five levels: Economic Sector, Business Sector, Industry Group, Industry and Activity. I use the Business Sector level, which divides the market into 41 sectors. Subsequently, I make a selection of these sectors to be used as my sample. The sectors are selected based on the Theoretical Framework (section 2) and my expectation of which sectors are likely to be affected by climate anomalies. Eventually I include the following 12 sectors in my sample: Oil & Gas Producers, Construction & Materials, Aerospace & Defense, Industrial Transportation, Food producers, Household Goods & Home Construction, Tobacco, Health Care, Travel & Leisure, Electricity, Utilities and Non-Life Insurance. The descriptive statistics of these sector indices are presented in Table 2 where all returns are calculated as monthly logarithmic stock returns according to equation (1). The average monthly returns vary across sector indices from 0.12% for Electricity to 0.43% for Tobacco. The monthly standard deviations of the indices point out the difference in volatility across the sectors. The highest volatilities are observed for Travel & Leisure (3.17%), Construction & Materials (3.03%) and Tobacco (3.0%), while the lowest volatility is observed for the Electricity sector stock returns, 1.87%. The stock indices of U.S. business sectors are also tested on stationarity. Similar

[3] Link to the Thomson Reuters Business Classification chart: <http://financial.thomsonreuters.com/content/dam/openweb/documents/pdf/financial/trbc-fact-sheet.pdf.>

to the international country indices (Table 1), the Augmented Dickey Fuller tested (shown in **Table 2**) the sector index returns to be stationary.

Table 2 Descriptive statistics U.S. sector indices

Sector	Number of observations	Starting date	Mean monthly log return	Std. dev. monthly log return	Augmented Dickey Fuller test
Oil & Gas Producers	538	1/73	0.24	2.45	0.000
Construction & Materials	538	1/73	0.28	3.03	0.000
Aerospace & Defense	538	1/73	0.37	2.72	0.000
Industrial Transportation	538	1/73	0.30	2.70	0.000
Food Producers	538	1/73	0.32	1.89	0.000
Household Goods & Home Construction	538	1/73	0.25	2.15	0.000
Tobacco	538	1/73	0.43	3.00	0.000
Health Care Equipment & Services	538	1/73	0.35	2.21	0.000
Travel & Leisure	538	1/73	0.34	3.17	0.000
Electricity	538	1/73	0.12	1.87	0.000
Gas, Water & Multiutilities	538	1/73	0.20	2.17	0.000
Non-Life Insurance	538	1/73	0.30	2.30	0.000

This table reports the descriptive statistics of the selected sectors in my sample. The mean and standard deviation are noted in percent. Monthly returns are calculated according to equation (1). In the last column, the p-values are shown of the augmented Dickey Fuller test.

3.3 The El Niño Variable

In order to measure whether El Niño influences stock return, an indicator for an ENSO cycle is necessary. The Oceanic Niño Index (ONI) is used by the NOAA as the primary tool for monitoring El Niño. NOAA considers El Niño conditions to be present when the Oceanic Niño Index is +0.5°C or higher than the seasonal norm for five consecutive overlapping 3-month periods, indicating that the east-central tropical Pacific is significantly warmer than usual. The ONI is calculated by measuring the running 3-month mean SST (Sea Surface Temperature) in the so-called 'El Niño 3.4 region' against the values of previous and following months. The Niño 3.4 region is a section in the Pacific Ocean that runs parallel to the equator (170°W - 120°W, 5°S - 5°N, see Figure A.1 in Appendix A). According to Barnston et al. (1997), the SST anomaly in this region is the most ENSO-related indicator of the whole Pacific Ocean. NOAA records data on El Niño since 1950 so the sample period I use in both models is 1950-2017. Each running 3-month mean SST anomaly is categorized by the last observed month. Table A.1 in Appendix A displays historical anomalies of the SSTs in the El Niño 3.4 region during the period 1950-2017, all ENSO periods are marked red. The monthly SST anomaly is implemented into the models as an independent variable.

3.4 Control Variables

In order to improve the accurateness of my models (introduced in section 4), several control variables are added. In this section I discuss the following implemented control variables: (absolute) change in interest rate, one-month lagged stock returns, January dummy, seasonality dummies, temperature anomaly and precipitation anomaly.

3.4.1 Change of Interest Rate

Among many others, Flannery and James (1984) studied the impact of interest rate changes on stock returns. They found that interest rate changes have a significantly negative effect on stock returns via three different levels; (i) an interest rate rise increases interest expenses for companies, lowering their earnings. (ii) Interest changes affect market value of assets and liabilities. Lastly, (iii) interest fluctuations have an impact on the opportunity costs of equity investments. The effect of interest rate changes is controlled by adding the control variable $\Delta I_{i,t-1}$, which is defined as the monthly change in the 3-month Treasury Bill rate (or other country's equivalent). I expect that this variable has a negative effect on the stock performance as higher interest rates are correlated with lower stock prices.

3.4.2 Lagged Stock Market Return

In order to control for (residual) autocorrelation, a one-month lagged stock market return is implemented into the model. The problem of autocorrelation is that the error terms are correlated over time. Because the error terms partly determine how you can interpret the results of the regressions, the Newey-West estimator is used to overcome autocorrelation and heteroscedasticity in the error terms (discussed more extensively in section 4.3).

3.4.3 January Dummy

Cooper et al. (2006) found that stock returns in the month of January are relatively high compared to the returns of other months. A possible explanation for the existence of this effect is tax-loss selling. A year with negative market returns may result in more end-of-the-year tax-loss selling of stocks such that the following month (January) is more likely to be positive. Another explanation is that managers use their year-end bonuses to buy stocks in the following month. In order to control for the January effect, a January dummy variable is added to the model.

3.4.4 Seasonality Dummies

As illustrated in Figure 1, the effect of an ENSO cycle on the climate varies during different seasons. The effects of El Niño on the weather are more widely spread across the globe during the summer than during the winter. To test whether different seasons indeed have different impact on stock returns, four dummies are created: Winter (December, January, February), Spring (March, April, May), Summer (June, July, August) and Autumn (September, October, November).

3.4.5 Weather Variables

As the described in the Theoretical Framework (section 2), local weather variables, such as sunshine hours, precipitation, cloud cover and temperature, can significantly affect stock market returns in the city in which the index is located (Cao & Wei, 2005), (Saunders, 1993). El Niño can effect temperatures as well as precipitation levels worldwide (NOAA, 2016). As I am studying whether the 'El Niño effects' on the real economies are also reflected into the stock markets, possible effects of El Niño on investor behaviour are undesirable. In order to control for local investor behaviour altered by the weather, I include two weather anomaly variables into my models, a monthly temperature anomaly variable and a monthly precipitation anomaly variable. The weather data is mainly being obtained from the Global Historical Climatology Network (GHCN) of NOAA. The GHCN is an integrated database of climate summaries from land surface stations across the globe. Besides the observed monthly average temperature and precipitation, this database also publishes the monthly anomalies. Both these variables are measured for the city in which the stock market is located. If no weather station is available in a city, another weather station is used within a 50 kilometer proximity. The temperature is measured in degrees Celsius (°C) and precipitation is measured in millimeters (mm).

3.5 Multicollinearity

Before starting the regression analysis, I study the correlation between independent variables. Multicollinearity posses a possible problem when estimating linear or generalized linear models. It arises when there exists high correlation among independent variables, which might lead to inaccurate and unreliable regression coefficients. The correlation between the independent variables in my model are presented in the Pearson correlation matrix in Table B.1 in Appendix B. As can be observed from this table, the correlation coefficient never exceeds the range -0.335 to 0.086. Correlation coefficients of these magnitudes do not impose restraints on the models. The correlation matrix in this table contains the stock return variable of the Dow Jones Industrial Average (DJIA) because I also use this index as a benchmark in my U.S. sector analysis. I do not include the correlation matrices of all studied indices in my thesis but the coefficients observed in these matrices are largely similar.

4. Methodology

As already stated in the Introduction, the empirical research is split in two parts:

1. Time-series analysis of El Niño on international stock markets
2. Time-series analysis of El Niño on U.S. business sector stock portfolios

For both analysis, the sample period of 1950-2017 is used.

4.1 Multiple Regression Analysis International Stock Markets

4.1.1 Basic Model

To examine a possible El Niño effect on international stock market returns I use a multiple regression analysis. The dependent variable is the monthly logarithmic stock return of 22 different national stock indices. I include the same control variables (absolute change in interest rate, one-month lagged stock returns, January dummy, precipitation anomaly and temperature anomaly) in all models. These control variables are implemented into the models in order to eliminate 'noise' and to improve the predictive power of the regression models. The regression equations in sections 4.1 – 4.2 are the estimated models which test the relationship between El Niño and stock market returns. I start with the following basic regression:

$$R_{i,t} = \beta_0 + \beta_1 SST_t^{An} + \beta_2 \Delta I_{i,t-1} + \beta_3 D_t^{Jan} + \beta_4 R_{i,t-1} + \beta_5 Precip_t^{An} + \beta_6 Temp_t^{An} + \varepsilon_{i,t} \quad (2)$$

$R_{i,t}$ is the dependent variable defined as the monthly logarithmic index return for index i at time t and $R_{i,t-1}$ represent the one-month lagged return for the same index. The variable SST_t^{An} takes on the SST anomaly at time t. $\Delta I_{i,t-1}$ measures the lagged change in interest rate for country i. The January dummy variable (D_t^{Jan}) will take on the value 1 for during the month of January and a value of 0 otherwise. $Precip_t^{An}$ and $Temp_t^{An}$ denote the deviations of the rain precipitation and temperatures from their (normal) average monthly values for the city in which the studied stock index is located. Finally, $\varepsilon_{i,t}$ is the error term in the regression. The coefficient β_1 in this regression represents the effect of SST anomalies (an indicator of an El Niño period) on monthly logarithmic returns, a positive value can be interpreted as a positive impact of the ENSO cycle.

4.1.2 Seasonality

As stated in section 1 of this thesis, El Niño affects the weather in large parts of the world. Ropelewski and Halpert (1992) were the first to make a robust analysis of regional shifts of precipitation and temperature distribution on a global scale during an ENSO cycle. They found that the effect of El Niño on the climate depends strongly on the location and the season. For example, the effects on precipitation are strongest in the western Pacific Ocean and South-East Asia during the months of September – November, while the effects on temperature is the most substantial during the boreal winter months (December – March) in the Americas.

In order to study the impact of seasonality in combination with El Niño, I implement interaction dummy variables into the previous model (2). The new regression is the following:

$$R_{i,t} = \beta_0 + \beta_1\, D_t^{Winter} \times SST_t^{An} + \beta_2\, D_t^{Spring} \times\; SST_t^{An} + \beta_3\, D_t^{Summer} \times SST_t^{An}$$

(3)

$$+ \beta_4\, D_t^{Autumn} \times SST_t^{An} +\; \beta_5 \Delta I_{i,t-1} \;+ \beta_6 D_t^{Jan} + \beta_7 R_{i,t-1}$$

$$+ \beta_8 Precip_t^{An} + \beta_9 Temp_t^{An} + \varepsilon_{i,t}$$

Where $R_{i,t}$ is the dependent variable and represents the monthly logarithmic index return for index i at time t and $\varepsilon_{i,t}$ is defined as the error term. All independent variables are the same as those in equation (2) with the exception of the seasonal dummies and the SST anomaly variable. The variable $D_t^{Season} \times SST_t^{An}$ takes on the SST anomaly at time t during the corresponding season and the value of 0 otherwise. By combining these variables, I can study the impact of El Niño during different seasons. Positive coefficients $\beta_1, \beta_2, \beta_3$ and β_4 can be interpreted as a positive effect of El Niño on monthly stock returns.

4.1.3 Time Variance

Cashin et al. (2017) studied the impact of El Niño shocks on the real economy and also categorize time windows within an El Niño period. They found, for example, that some economies are affected more in the first quarter of an El Niño period than in the last quarter and visa versa. It is possible that investors need time to integrate new El Niño-related market information into equity prices. If so, then an El Niño effect might not be observable immediately. Kumar and Levi (2003) found a delayed atmospheric response on the rising SST's in the El Niño region. The peak of this lagged response (and the additional weather anomalies) lies several seasons after the warming of the SST's. The most notable effects on the weather are temperature and precipitation anomalies. In order to check when/if El Niño affects the weather in different parts of the globe I've constructed a (Pearson) correlations matrix for every country studied in this thesis. I found that El Niño has a significant lagged effect on the global weather for up to 24 months. Table B.2 in Appendix B shows the correlation matrix for weather in China, El Niño has a significant effect on the precipitation between 12 and 24 months after the high SST anomalies in the El Niño 3.4 region. This finding gives rise to my third regression in which I study the impact of lagged SST anomalies on the return of international stock indices. The model is noted in the following equation (4):

$$R_{i,t} = \beta_0 + \beta_1 SST_t^{An} +\; \beta_2 SST_{t-4}^{An} \;+ \beta_3 SST_{t-8}^{An} +\; \beta_4 SST_{t-12}^{An} + \beta_5 SST_{t-16}^{An} +\; \beta_6 SST_{t-20}^{An}$$

(4)

$$+\; \beta_7 SST_{t-24}^{An} + \sum \beta_i C_{i,t} + \varepsilon_{i,t}$$

In essence this model is the same as the one noted in section 4.1.1, I still study the impact of SST anomalies on stock returns. This effect is controlled by the same set of control variables, these control variables are represented by $\sum \beta_i C_{it}$. In addition to equation (2) I've added six lagged SST variables in an attempt to find evidence for a lagged effect on stock returns after an ENSO cycle.

The lagged SST anomalies are represented by SST_{t-x}^{An}. I've chosen 4-months intervals between the lagged SST's to prevent autocorrelation among independent variables. The maximum lag of 24 months is chosen because 24 months is the longest period for SST anomalies to have an effect on temperature or precipitation. Finally, $\varepsilon_{i,t}$ is the error term in the regression. The coefficients β_2 - β_7 in this regression represent the lagged effect of SST anomalies on monthly logarithmic returns, a positive value indicates a positive impact of an ENSO cycle on stock performance.

4.1.4 The El Niño Surprise

Besides analyzing the direct effect of SST anomalies on stock returns, an alternative approach to study the impact of El Niño is to look at El Niño forecasts. During previous ENSO cycles, multiple U.S. companies/sectors used the forecasts issued by the NOAA to profit from El Niño effects (Changnon, 1999). On a short-term basis, the ENSO cycle is an accurately predictable phenomenon. It could be possible that, in addition to U.S. companies, (international) investors also account for the impact of an ENSO cycle using forecasting models of El Niño. I construct my own model for forecasting El Niño using previous SST anomaly values. In order to assess the direction and strength of the linear relationship between SST anomaly and lagged values I use a partial autocorrelation function. The partial autocorrelation function in Figure B.1 in Appendix B shows that the two previous 3-months running average SST values are highly correlated with the SST anomaly at time t. Using the t-1 and t-2 lagged values, I constructed the following (AR) time series forecasting model:

(5) $$SST_t^{An} = \beta_1 SST_{t-1}^{An} + \beta_2 SST_{t-2}^{An} + \varepsilon_t$$

The possible ability to forecast SST anomalies makes that stock markets can adjust to SST fluctuations relatively easy. Although a forecast could be accurate, it is not perfect. In order to study whether investors actually adept to El Niño forecasts, I study the difference between actual- and forecasted SST anomalies, the 'El Niño Surprise'. For clarity this is also noted in equation (6). First I test whether the surprise affects international stock returns without the use of any control variables (equation 7). Subsequently the El Niño surprise is implemented into the same equation as the SST anomaly in section 4.1.1, this is noted in equation (8).

(6) $$SST_t^{Surp} = SST_t^{Forecast} - SST_t^{An}$$

(7) $$R_{i,t} = \beta_0 + \beta_1 SST_t^{Surp} + \varepsilon_{i,t}$$

(8) $$R_{i,t} = \beta_0 + \beta_1 SST_t^{Surp} + \sum \beta_i C_{i,t} + \varepsilon_{i,t}$$

Where $R_{i,t}$ is the dependent variable and represents the monthly logarithmic index return for index i at time t. SST_t^{Surp} is the difference between forecasted- and actual SST anomaly as described in equation (6). In model (8), the surprise effect is controlled by the same set of control variables as equations (2) and (4). These control variables are noted by $\sum \beta_i C_{it}$ and represent the lagged change of interest, January effect dummy, lagged stock market return, precipitation anomaly and the temperature anomaly. Finally, $\varepsilon_{i,t}$ is the error term in the regressions. Coefficient β_1 represents the the effect of the El Niño surprise on the stock market at time t. Following Gilbert et al. (2012), I standardize the surprise to have unit variance to facilitate easy interpretation of coefficient β_1. All returns are in percent so a regression coefficient of 0.5 implies that there is a return response of 50 basis points (Bps) to a one standard deviation positive (forecasted SST anomaly > actual SST anomaly) El Niño surprise. A positive coefficient indicates that investors react negatively on an ENSO cycle.

4.2 Multiple Regression Analysis U.S. Sector Indices

As already discussed in the Theoretical Framework, the economical effect of El Niño differs per industry (Brunner, 2002), (Cashin et al., 2017), (Changnon, 1999). In this section I study the impact of an ENSO cycle on 12 U.S. business sector indices for the period 1973 to 2017. I prefer to study national industry indices over global industry indices because El Niño affects the global climate in different ways (see Section 1). By constructing global sector indices, the effects on different sectors might be mitigated due to less (or differently) affected nations.

4.2.1 Basic Model

To examine possible El Niño effects on U.S. sector returns I use a multiple regression analysis. The dependent variable is the monthly stock return of U.S. sector indices. In addition to the models in section 4.1, I include the Dow Jones Industrial Average (DJIA) stock return into the models as a proxy for market sentiment, as I assume that sector indices are primarily influenced by the national stock market(s). I've chosen the DJIA for its variety of enlisted companies and the fact that it is a price-weighted average. Furthermore, I include the same control variables (one-month lagged stock returns, January effect dummy, precipitation anomaly and temperature anomaly) in all models. These control variables are implemented into the models in order to improve the predictive power of the regression and to eliminate noise. I start with the following regression which is largely a combination of equation (2) and (4):

$$R_{s,t} = \beta_0 + \beta_1 SST_t^{An} + \beta_2 SST_{t-4}^{An} + \beta_3 SST_{t-8}^{An} + \beta_4 SST_{t-12}^{An} + \beta_5 R_{s,t-1} + \beta_6 R_t^{DJIA} + \beta_7 D_t^{Jan} + \beta_8 Precip_t^{An} + \beta_9 Temp_t^{An} + \varepsilon_{s,t} \tag{9}$$

Where $R_{s,t}$ is defined as the monthly logarithmic stock return for sector s at time t. The (lagged) SST anomalies are represented by SST_{t-x}^{An} where x is defined as the lagged number of months. The January dummy variable (D_t^{Jan}) will take on the value 1 for during the month of January and a value of 0 otherwise. The two weather variables, $Precip_t^{An}$ and $Temp_t^{An}$ represent the monthly deviations of precipitation and temperatures from the average values in New York City. Finally,

$\varepsilon_{i,t}$ is the error term in the regression. As already stated, I use DJIA returns as a control variable for market sentiment and expect its coefficient (β_7) to be high and statistically significant. In other words, I expect that each business sector is highly influenced by the national stock market(s). In my model I capture potential effect of El Niño on sector returns with the variable SST_{t-x}^{An}. The coefficients β_1 - β_4 in this regression represent the (lagged) effect of SST anomalies on monthly logarithmic returns, a positive value indicates a positive impact of an ENSO cycle on stock performance in sector s.

4.2.2 Seasonality

In order to check for the combination of seasonality with El Niño to have an effect on sector returns, I run the same regression as for the international stock markets in section 4.1.2. This is denoted in the following equation (10):

$$\begin{aligned} R_{s,t} = \beta_0 &+ \beta_1\, D_t^{Winter} \times SST_t^{An} + \beta_2\, D_t^{Spring} \times SST_t^{An} + \beta_3\, D_t^{Summer} \times SST_t^{An} \\ &+ \beta_4\, D_t^{Autumn} \times SST_t^{An} + \beta_5 R_t^{DJIA} + \beta_6 D_t^{Jan} + \beta_7 R_{s,t-1} \\ &+ \beta_8 Precip_t^{An} + \beta_9 Temp_t^{An} + \varepsilon_{s,t} \end{aligned} \tag{10}$$

Where $R_{s,t}$ is the dependent variable and represents the monthly logarithmic index return for sector s at time t and $\varepsilon_{s,t}$ is defined as the error term. Regarding to equation (3) all independent variables are the same with the exception of the return of the DJIA at time t. Again, I interact the seasonal dummy variables with the SST anomaly variable in order to detect possible effects on stock returns due to seasonal El Niño influences. Positive coefficients $\beta_1, \beta_2, \beta_3$ and β_4 can be interpreted as a positive effect of El Niño on monthly stock returns.

4.2.3 El Niño Surprise

As explained in section 4.1.4, the ENSO cycle is predictable. I use the El Niño surprise variable defined in equation (6) to study whether investors respond on deviations between the actual SST anomaly and the forecasted anomaly, the new model is described in the following equation (11):

$$R_{s,t} = \beta_0 + \beta_1 SST_t^{Surp} + \sum \beta_i C_{s,t} + \varepsilon_{s,t} \tag{11}$$

$R_{s,t}$ is defined as the monthly logarithmic return for sector s at time t. The El Niño surprise variable is described in equation (6) and like section 4.1.4, the variable is standardized to have unit variance for convenience in the interpretation. The control variables are noted as $\sum \beta_i C_{s,t}$ and represent the DJIA market returns, January dummy, lagged sector index return, precipitation anomaly and temperature anomaly. Finally, $\varepsilon_{i,t}$ is the error term in the regression. I focus on the coefficient β_1 from which a positive value in combination with a positive surprise effect (forecasted SST anomaly > actual SST anomaly) can be interpreted as an negative effect of El Niño on sector index returns.

4.3 Testing the Error Terms

The analysis of the error terms forms a crucial part of any regression model. The error is the difference between the expected and observed value. In order to get the most accurate estimates from a regression model the error term must be stochastic, which means that it is random and unpredictable. Non of de predictive/explanatory information should be in the error term because that would mean that the predictor variables are missing some of the predictive information. In order to get the most accurate estimates out of my OLS regressions I perform multiple tests on the errors in these regressions and correct them if necessary.

First, I check for possible autocorrelations in the errors of my models. Correlation in the error terms is an indicator of a mis-specified model which in turn might lead to biased estimates. Because I use a lagged value of the dependent variable as a control variable in my models, I perform the Breusch-Godfrey test for correlation in the residuals; the null hypothesis suggests that there is no correlation between the errors. Next, the issue of heteroscedasticity in the residuals is addressed. If heteroscedasticity is present, the variance of the error term is scattered differently when the independent variable changes. Violations of homoscedasticity results in an inaccurate standard deviation of the errors. A violation might also affect the accurateness of the estimated coefficients because too much weight is given to a small subset of the data (where the variance was largest/smallest). The Breusch-Pagan test is employed to detect the issue of heteroscedasticity in the residuals in the regression. The null hypothesis in the Breusch-Pagan test states homoscedasticity across error terms, which means that variance of error terms is constant if the independent variables changes. The results of both these tests (described in this section) are noted at the bottom of each table in which the results of my regression are noted. If I find significant ($p < 0.05$) evidence for heteroscedasticity or (auto)correlation in the error terms, I adjust the model by using Newey-West standard errors.

Finally, I check whether the residuals are distributed normally. If the residuals are not normally distributed this might create problems for determining if the coefficients in the regression are significantly different from zero. Sometimes the residual distribution is offset by a few large outliers. The estimations of confidence intervals are based on the assumption of normally distribution among errors. If not, confidence intervals may be too narrow or too wide. In order to test the normality of the residuals (calculated by deducting the estimated stock return from the observed stock return) I use the test for skewness and kurtosis described by D'Agostino et al. (1990). The null hypothesis of this test states that the data is distributed normally. The results of this test is also noted at the bottom of each table in which the results are displayed.

5. Results

The results of the tests and regressions stated in section 3 and 4 of this thesis are presented and examined in this chapter. The results regarding the international stock markets are discussed in section 5.1 and the results regarding the U.S. business sectors are discussed in section 5.2.

5.1 Analysis of International Stock Markets

5.1.1 Basic Model

In Table 3 the coefficients are shown (as well as their corresponding p-values) of the basic model noted in equation (2) for 22 international stock indices. Looking at the effect of SST anomalies on the stock market I observe that they do not have a significant impact on any of the observed stock markets, except for the stock market of South Africa (JSE / FTSE 40) which is significantly negatively effected at a 10% significance level (p-value of 0.063). As can be derived from these results, the SST anomalies at time t do not have an impact on international stock market returns. Furthermore, the low adjusted R-squared values are noticeable, the highest one is only 0.073. I've chosen to display the adjusted R-squared instead of the regular R-squared because it adjusts for the number of predictors in my model(s). A low (adjusted) R-squared means that little of the models' variations is explained by the linear model. For the interpretation of the results this is not problematic, regardless of the R-squared, a significant coefficient still represents the mean change of the dependent variable for one unit of the predictor (all else equal).

The tables in section 5 also show the results for the test on residuals for heteroscedasticity, autocorrelation and normal distribution. BG represents the Breusch-Godfrey test, BP represents the Breusch-Pagan test and the skewness/kurtosis test for normality is noted as Skew. From Table 3 can be derived that the residuals of most countries are heteroskedastic and/or autocorrelated. The results noted in the table are already adjusted (if heteroscedasticity or autocorrelation is present) by using Newey-West standard errors. Although I shall not mention it in the rest of the thesis, this is done for all tables in section 5.

In Table 3, all residuals are tested as non-normally distributed. When handling relatively large sample sizes, the normal distribution is often violated because some data points are far bigger than the standard deviation, which causes the normality test to reject normal distribution. So rather than solely rely on the quantitative test, I also visually check the residuals using a normal quantile plot. The violations of the normal distributions in my results are all being caused by a few outliers and therefore I proceed with my model without transforming any variables.[4]

[4] Transforming variables is a way (among others) to meet the assumption of normality.

Table 3 Estimates of returns regressions – Eq. (2)

Model: $R_{i,t} = \beta_0 + \beta_1 SST_t^{An} + \beta_2 \Delta I_{i,t-1} + \beta_3 D_t^{Jan} + \beta_4 R_{i,t-1} + \beta_5 Precip_t^{An} + \beta_6 Temp_t^{An} + \varepsilon_{i,t}$

	β_0	SST_t^{An}	ΔI_{t-1}	D_t^{Jan}	R_{t-1}	$Precip_t^{An}$	$Temp_t^{An}$	$\bar{R}^2$	BG	BP	$Skew$
Argentina MERVAL	0.326 (0.302)	0.029 (0.933)	-0.158** (0.027)	1.953* (0.060)	0.089 (0.121)	0.004 (0.392)	-0.040 (0.866)	0.027	0.522	0.994	0.001***
Australia S&P / ASX 200	0.137 (0.319)	-0.067 (0.597)	0.568 (0.465)	-0.175 (0.652)	-0.003 (0.970)	-0.002 (0.230)	0.108 (0.317)	0.016	0.305	0.013**	0.002***
Brazil IBOV	0.724 (0.139)	-0.112 (0.696)	-0.346*** (0.000)	0.447 (0.598)	-0.016 (0.801)	0.000 (0.919)	-0.203 (0.378)	0.094	0.564	0.003***	0.000***
Canada S&P / TSX	0.171** (0.017)	-0.050 (0.576)	-0.400** (0.026)	0.309 (0.216)	0.090* (0.061)	-0.003 (0.152)	0.031 (0.366)	0.021	0.418	0.010**	0.000***
Chile IPSA	0.334** (0.032)	0.023 (0.895)	-0.060 (0.723)	0.685 (0.318)	0.213*** (0.004)	-0.005 (0.283)	-0.022 (0.899)	0.037	0.020**	0.282	0.016**
China SZSE	-0.104 (0.814)	-0.020 (0.953)	-1.965** (0.049)	-0.360 (0.720)	-0.019 (0.712)	0.006 (0.198)	0.250 (0.264)	0.008	0.994	0.1442	0.000***
France CAC 40	0.048 (0.780)	-0.225 (0.222)	-0.202 (0.638)	-0.169 (0.729)	0.629 (0.368)	-0.004 (0.398)	0.067 (0.397)	0.000	0.722	0.000***	0.000***
Germany DAX 30	0.215** (0.036)	-0.088 (0.453)	0.076 (0.488)	0.554 (0.121)	0.044 (0.285)	-0.002 (0.538)	0.059 (0.265)	0.001	0.017**	0.177	0.000***
Hong Kong Hang Seng	0.497*** (0.006)	-0.145 (0.466)	-0.485** (0.021)	-0.591 (0.357)	0.011 (0.828)	-0.001 (0.579)	-0.241 (0.159)	0.011	0.954	0.906	0.001***
Italy FTSE MIB	-0.255 (0.270)	-0.133 (0.555)	-0.982 (0.327)	-0.220 (0.748)	0.061 (0.362)	0.000 (0.907)	0.295 (0.051)	0.000	0.698	0.957	0.012**
Japan Nikkei 225	0.282** (0.019)	-0.094 (0.390)	-0.251 (0.562)	0.682** (0.034)	0.064* (0.081)	-0.001 (0.817)	-0.111 (0.136)	0.002	0.786	0.000***	0.000***
Mexico MEXBOL	0.796** (0.011)	-0.038 (0.842)	-0.284** (0.042)	0.288 (0.728)	-0.083 (0.442)	0.002 (0.554)	-0.430* (0.052)	0.064	0.866	0.000***	0.000***
Netherlands AEX	0.225 (0.132)	-0.101 (0.523)	0.863 (0.122)	-0.097 (0.840)	0.062 (0.228)	-0.002 (0.504)	0.061 (0.405)	0.021	0.902	0.004***	0.000***
Norway OSEAX	0.289* (0.063)	-0.207 (0.225)	-0.992*** (0.003)	0.248 (0.621)	0.155** (0.022)	-0.005 (0.236)	0.039 (0.447)	0.073	0.073	0.000***	0.000***
Singapore MSCI Singapore	0.046 (0.754)	-0.080 (0.679)	-0.628** (0.045)	1.010* (0.030)	0.081* (0.068)	-0.001 (0.585)	0.008 (0.977)	0.014	0.012**	0.083*	0.000***
South Africa JSE / FTSE 40	0.041 (0.864)	0.349* (0.063)	-0.505* (0.092)	1.251** (0.029)	-0.067 (0.330)	-0.005 (0.156)	0.209 (0.180)	0.038	0.570	0.115	0.000***
South Korea KOSPI 200	0.326* (0.061)	-0.244 (0.181)	-0.150 (0.307)	0.108 (0.838)	0.103** (0.025)	0.000 (0.979)	-0.094 (0.354)	0.008	0.146	0.117	0.000***
Spain IBEX 35	0.105 (0.563)	0.028 (0.891)	0.655* (0.062)	0.452 (0.452)	0.071 (0.319)	0.000 (0.960)	0.088 (0.362)	0.005	0.883	0.000***	0.000***

Table 3 Continued

	β_0	SST_t^{An}	ΔI_{t-1}	D_t^{Jan}	R_{t-1}	$Precip_t^{An}$	$Temp_t^{An}$	$\bar{R}^2$	BG	BP	$Skew$
United Kingdom FTSE 100	0.224** (0.042)	-0.039 (0.748)	-0.236 (0.340)	0.086 (0.812)	-0.017 (0.730)	-0.005 (0.171)	0.002 (0.983)	0.008	0.882	0.177	0.000***
United States S&P 500	0.186** (0.021)	-0.024 (0.790)	-0.495*** (0.001)	0.189 (0.485)	0.033 (0.395)	-0.001 (0.485)	0.077* (0.082)	0.018	0.328	0.262	0.000***
United States DJIA	0.201 (0.131)	0.023 (0.876)	-0.632*** (0.003)	0.761* (0.069)	0.100 (0.113)	-0.002 (0.209)	0.092 (0.146)	0.032	0.706	0.002***	0.000***
United States NASDAQ	0.219*** (0.001)	-0.059 (0.474)	-0.512*** (0.000)	0.092 (0.693)	0.017 (0.622)	-0.001 (0.521)	0.056 (0.149)	0.029	0.310	0.314	0.000***

This table reports the OLS regression denoted in equation (2) with Newey-West standard errors. The dependent variable is R_{i,t}, the stock return of country I at time t. In this table, the dependent variable is noted as the county in which the stock index is located. SST_t represents the SST anomalies in the El Niño region. I_t represents the change in the national 3-months T-Bill, R_{t-1} the lagged monthly return of the stock return of country i at time t-1. The precipitation anomaly (Precip_t) is measured in mm and the temperature anomaly (Temp_t) is in degrees Celsius. The p-values are reported in the parentheses. The adjusted R-squared is noted as R^2. BG represents the Breusch-Godfrey test, BP represents the Breusch-Pagan test and Skew represents the skewness/kurtosis test, the values displayed in these three columns are p-values.

*Significant at the 10% level; **significant at the 5% level; ***significant at the 1% level

5.1.2 Seasonality of El Niño

Next, the issue of seasonality is discussed. Before I test whether different seasons in combination with El Niño affect international stock markets, I study if these variables actually differ from each other. As described in equation (3), I implement the following interaction dummy variable(s) into the original model (2): $D_t^{Season} \times SST_t^{An}$; which takes on the value of the SST anomaly at time t during the corresponding season and the value of 0 otherwise. I test whether these four variables differ from one another by deploying an F-test while they are implemented in equation (3), with the null hypothesis that the coefficients are equal ($\beta_1 = \beta_2 = \beta_3 = \beta_4$). The results of this test are shown in Table 4. In the column denoted with an F, the p-values of the F-test are displayed. According to these results, I can assume that in non of the 22 indices in my sample, a seasonal impact of El Niño exists. Hence it does not seem logical to insert the results of the actual regression as it is roughly the same as the results of equation (2) (displayed in Table 3). Another argument for excluding the results is the fact that due to the distribution of the total number of observations across four different variables (instead of one), possible evidence for an El Niño effect is less robust.

Table 4 F-Test for difference – Eq. (3)

Model: $R_{i,t} = \beta_0 + \beta_1 D_t^{Winter} \times SST_t^{An} + \beta_2 D_t^{Spring} \times SST_t^{An} + \beta_3 D_t^{Summer} \times SST_t^{An} + \beta_4 D_t^{Autumn} \times SST_t^{An} + \beta_5 \Delta I_{i,t-1} + \beta_6 D_t^{Jan} + \beta_7 R_{i,t-1} + \beta_8 Precip_t^{An} + \beta_9 Temp_t^{An} + \varepsilon_{s,t}$

$H_0: \beta_1 = \beta_2 = \beta_3 = \beta_4$	F	$\bar{R}^2$	BG	BP	$Skew$
Argentina	0.849	0.019	0.849	0.704	0.001*
Australia	0.907	-0.015	0.363	0.006*	0.003*
Brazil	0.876	-0.023	0.173	0.402	0.000*
Canada	0.949	0.017	0.381	0.011*	0.000*
Chile	0.514	0.032	0.471	0,013*	0.019*
China	0.469	0.005	0.718	0.047*	0.000*
France	0.890	-0.010	0.969	0.000*	0.000*
Germany	0.548	0.000	0.040*	0.891	0.000*
Hong Kong	0.761	0.005	0.984	0.530	0.002*
Italy	0.205	0.007	0.703	0.713	0.008*
Japan	0.890	0.005	0.804	0.000*	0.000*
Mexico	0.634	-0.008	0.094	0.554	0.003*
Netherlands	0.882	-0.005	0.022*	0.000*	0.000*
Norway	0.398	0.028	0.053	0.000*	0.000*
Singapore	0.839	0.011	0.022*	0.530	0.000*
South Africa	0.830	0.029	0.485	0.783	0.000*
South-Korea	0.123	0.017	0.566	0.229	0.000*
Spain	0.958	-0.002	0.916	0.000*	0.000*
United Kingdom	0.671	-0.006	0.514	0.000*	0.000*
United States / S&P500	0.556	0.017	0.400	0.484	0.000*
United States / NASDAQ	0.755	0.029	0.927	0.008*	0.000*
United States / DJIA	0.692	0.017	0.115	0.071	0.000*

This table reports the F-test in the regression denoted in equation (3) with Newey-West standard errors; for the following null hypothesis: Beta_1=Beta_2=Beta_3=Beta_4. The values reported in column F represent the p-values of the F-test. The dependent variable is R_{i,t}, the stock return of country I at time t. In this table, the dependent variable is noted as the county in which the stock index is located. SST_t x D^season represent the dummy interaction variable between a seasonal dummy and the SST anomaly; which takes on the value of the SST anomaly at time t during a specific season and the value of 0 otherwise. I_t represents the change in the national 3-months T-Bill, R_{t-1} the lagged monthly return of the stock return of country i at time t-1. The precipitation anomaly (Precip_t) is measured in mm and the temperature anomaly (Temp_t) is in degrees Celsius. The p-values are reported in the parentheses. The adjusted R-squared is noted as $\bar{R}^2$. BG represents the Breusch-Godfrey test, BP represents the Breusch-Pagan test and Skew represents the skewness/kurtosis test, the values displayed in these three columns are p-values.

*Significant at the 5% level.

5.1.3 The Lagged El Niño Effect

As can be derived from the results in section 5.1.1 and 5.1.2, El Niño does not have an immediate effect on international stock markets. Meaning that SST anomalies do not influence the stock market in the same month as in which they are observed. However, based on the findings of Kumar and Levi (2003) (also described in section 4.1.3) it is possible that the impact of El Niño will only follow in the months/years after the initial El Niño presence. In order to test this, I add several lagged SST anomaly variables with 4-month time intervals into the basic model, as can be noted in equation (4). Table C.1 in Appendix C displays the results of the OLS regression when the lagged SST anomaly variables are added.

Focusing on the coefficients of the lagged SST anomalies, I detect few significant effects. The most noticeable are those of China, were ENSO has a significant lagged effect from between 12 and 24 months after the SST anomaly value is observed (With p-values between 0.082 and 0.026). The coefficients seem to reverse every 4 months as it alternates between negative and positive values. A possible explanation could be seasonality but as I ruled out the seasonal influence in section 5.1.2 (Value of F-test China is 0.469) this cannot be the case. Next to China, the following countries are also slightly affected by the lagged El Niño: Brazil, Chile, Japan and Singapore. As these 4 countries are only marginally influenced by the lagged SST anomalies, at a 10% significance level and only one significant variable, no clear conclusion can be deducted from these coefficients.

Concerning the control variables, they correspond with the dependent variable as could be expected of them. Almost all indices are significantly negatively affected by a positive change in interest rate. As investors invest more in government bonds (and less in stocks) when the interest goes up, this is certainly not a strange finding. The effects of both the January effect and the 1-month lagged stock return are also like I expect them to be, positive, although not as significant as the change of interest rate.

5.1.4 The El Niño Surprise Effect

Finally, I conclude the analysis of international stock markets with the impact of the El Niño surprise on the stock market. Before I run the OLS regression regarding model (7) and (8) I study whether the autoregressive (AR) time series forecasting model (denoted in model 5) is actually capable of accurately predicting the 1-month SST anomalies. The results of implementing equation (5) in a simple time series OLS regression are shown in Table 5.

Table 5 Estimates of returns regressions — Eq. (5)

Model: $SST_t^{An} = \beta_1 SST_{t-1}^{An} + \beta_2 SST_{t-2}^{An} + \varepsilon_t$

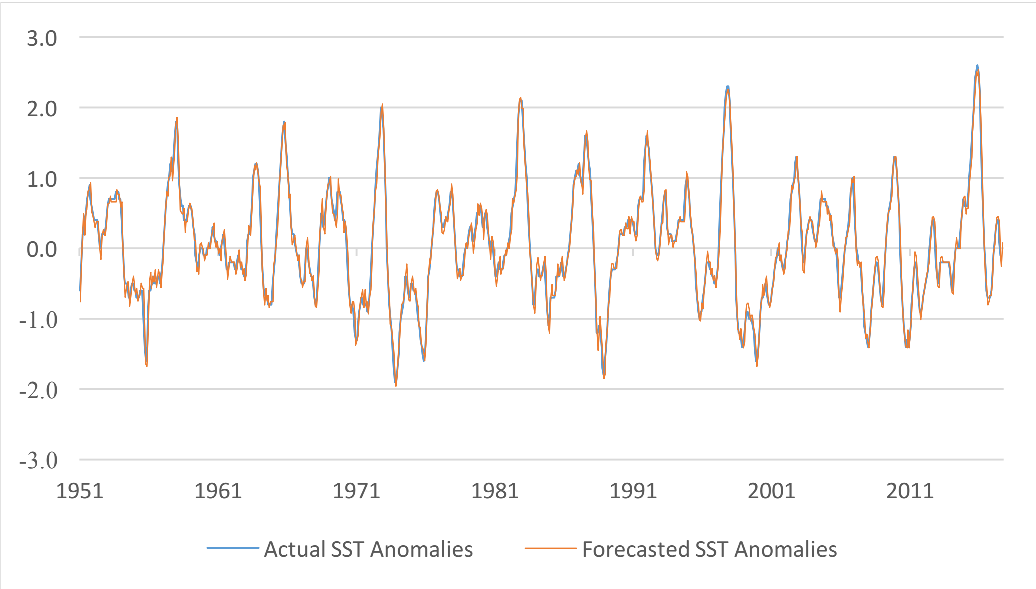
	SST_{t-1}^{An}	SST_{t-2}^{An}	$\bar{R}^2$
SST_t^{An}	1.7308*** (0.000)	-0.7823*** (0.000)	0.9778

This table reports the OLS regression denoted in equation (5). Dependent variable is SST_t, the 1-month forecasted Sea Surface Temperature anomaly. SST_{t-1} and SST_{t-2} represent the lagged SST anomalies in the El Niño region. In the last row the adjusted R-squared is noted.

*Significant at the 10% level; **significant at the 5% level; ***significant at the 1% level

From Table 5 can be deducted that both variables are statistically very significant (with p-values of 0.000) and their corresponding coefficients (1.7308 and -0.7823) are economically significant as well, meaning that they both have a relatively big impact on the dependent variable. With an adjusted R-squared of 0.9778 I can also assume that the model fits the data very well. The forecasted SST anomalies are displayed in the line chart in Figure 2, next to the actual SST anomalies. Note that the actual and the forecasted SST anomalies follow almost identical paths.

Figure 2 The actual SST anomaly vs the forecasted SST anomaly



The blue line represents the actual measured SST anomalies in the El Niño 3.4 region. The orange line represent the 1-month forecasted SST anomaly using equation (5) and (6). The SST anomalies are displayed on the y-axis while the time scale is displayed on the x-axis. Source: NOAA (2017)

In order to test the robustness of my forecasting model I've compared it against a random walk model by measuring both their mean squared prediction errors (MSPE). The MSPE measures the expected (squared) distance between the predicted value and the actual value. A relatively low

MSPE is an indicator of an accurate prediction model. The random walk (RW) forecasting model is noted as the following:

(12) $$SST_t^{RW\_Forecast} = \beta_1 SST_{t-1}^{An} + \varepsilon_t \text{ assuming } \varepsilon \sim N\ (1,0)$$

By setting $\beta_1 = 1$ and assuming that the errors are normally distributed I've created a random walk which is entirely dependent of the error. I extract the MSPE for both equations (5) and (6) by the following formula:

(13) $$\text{MSPE} = \frac{1}{T}\sum_{t=1}^{T}(SST_t^{An} - SST_t^{Forecast})^2$$

Where $SST_t^{Forecast}$ denotes the forecasted SST of both the AR and the RW model. Subsequently, the MSPE of the RW model is 0.036 and the MSPE of the AR model is 0.014. From these results can be derived that my AR forecasting model is more than 2.5 times more accurate than a random walk model.

Given the results of the tests in the previous paragraphs, I conclude that my forecasting model is able to predict the 1-month SST anomalies accurately. By using this model, investors are able to account for future El Niño effects. This might cause the effects of the actual SST anomaly to be priced into the markets before it is actually observed. I study whether this is indeed the case by constructing and implementing the El Niño surprise variable (equation 6) into two different models, (7) and (8).

In Table 6 the estimates of equation (7) are noted. As can be derived from this table, the El Niño surprise has a significantly negative impact on stock markets. A negative surprise coefficient indicates that investors initially accounted for a positive El Niño effect on stock returns and thereafter respond negatively when it turns out that the forecasted SST anomaly was higher than the observed SST anomaly. In 8 of the 22 indices in the sample, the impact was significant at a 5% or 10% significance level. The economically significant impact is the greatest in Hong Kong and Singapore with coefficients of -0.357 (p-value of 0.033) and -0.321 (p-value of 0.027). For interpretation, the stock market in Hong Kong has a return response of -0.357% to a one-unit standard deviation of the El Niño surprise. Noticeable is that the El Niño surprise only affect countries in the Americas (Canada, Chile and the U.S.) and Asia (Hong Kong, Japan, and Singapore), this rules out the significant spillover effects to the European countries found by Cashin et al. (2017). A final note on the results in Table 6 is the observation that all countries in my sample are negatively affected by the El Niño surprise. This is noteworthy because El Niño affects the weather differently in different parts of the world. A possible explanation for this is that, although not significant, some spillover effects are still present.

Table 6 Estimates of the returns regressions – Eq. (7)

Model: $R_{i,t} = \beta_0 + \beta_1 SST_t^{Surp} + \varepsilon_{i,t}$

	β_0	SST_t^{Surp}	$\bar{R}^2$	BG	BP	$Skew$
Argentina MERVAL	0.914** (0.013)	-0.567 (0.118)	0.003	0.008***	0.009***	0.000***
Australia S&P / ASX 200	0.173* (0.080)	-0.022 (0.838)	-0.003	0.934	0.498	0.000***
Brazil IBOV	1.369*** (0.000)	-0.464 (0.141)	0.003	0.000***	0.409	0.002***
Canada S&P / TSX	0.207*** (0.002)	-0.154** (0.023)	0.006	0.002***	0.018**	0.000***
Chile IPSA	0.543*** (0.000)	-0.261* (0.097)	0.006	0.002***	0.010**	0.000***
China SZSE	0.340 (0.275)	-0.145 (0.670)	-0.003	0.716	0.884	0.000***
France CAC 40	0.155 (0.133)	-0.148 (0.294)	0.000	0.202	0.357	0.000***
Germany DAX 30	0.225** (0.020)	-0.019 (0.843)	-0.002	0.066*	0.076*	0.000***
Hong Kong Hang Seng	0.004** (0.014)	-0.357** (0.033)	0.006	0.124	0.013**	0.000***
Italy FTSE MIB	-0.003 (0.988)	-0.160 (0.420)	-0.002	0.261	0.644	0.013**
Japan Nikkei 225	0.278*** (0.002)	-0.155* (0.078)	0.003	0.063*	0.948	0.000***
Mexico MEXBOL	0.728*** (0.000)	-0.216 (0.276)	0.001	0.725	0.000***	0.000***
Netherlands AEX	0.259** (0.042)	-0.076 (0.569)	-0.002	0.123	0.272	0.000***
Norway OSEAX	0.431*** (0.002)	-0.220 (0.131)	0.003	0.005***	0.001***	0.004***
Singapore MSCI Singapore	0.221 (0.102)	-0.321** (0.027)	0.007	0.000***	0.067*	0.000***
South Africa JSE / FTSE 40	0.400*** (0.006)	-0.050 (0.747)	-0.003	0.697	0.009***	0.000***
South Korea KOSPI 200	0.304** (0.025)	-0.188 (0.154)	0.002	0.013**	0.392	0.000***
Spain IBEX 35	0.167 (0.250)	-0.251 (0.104)	0.005	0.104	0.705	0.000***

Table 6 Continued

	β_0	SST_t^{Surp}	$\bar{R}^2$	BG	BP	$Skew$
United Kingdom FTSE 100	0.215** (0.031)	-0.091 (0.385)	0.000	0.946	0.053*	0.000***
United States S&P 500	0.239*** (0.001)	-0.178** (0.023)	0.007	0.493	0.014**	0.000***
United States NASDAQ	0.326*** (0.004)	-0.287** (0.013)	0.009	0.023**	0.003***	0.000***
United States DJIA	0.244*** (0.000)	-0.126** (0.056)	0.004	0.703	0.025**	0.000***

This table reports the OLS regression denoted in equation (7) with Newey-West standard errors. The dependent variable is R_{i,t}, the stock return of country I at time t. In this table, the dependent variable is noted as the county in which the stock index is located. SST_t represents the SST surprise in the El Niño region calculated according equation (6). The p-values are reported in the parentheses. The adjusted R-squared is noted as R^2. BG represents the Breusch-Godfrey test, BP represents the Breusch-Pagan test and Skew represents the skewness kurtosis test, the values displayed in these three columns are p-values.

*Significant at the 10% level; **significant at the 5% level; ***significant at the 1% level

In Table C.2 in Appendix C the results are shown of model (8), when I add different control variables to model displayed in Table 6 in order to make my findings more robust. Comparing both tables I note that adding control variables does not change the initial results much. Again, the coefficients of all countries in my sample are negative, with the exception of South Africa (coefficient of 0.037 with p-value 0.854). The countries which are significantly influenced by the El Niño surprise changed a bit, 7 out of the 22 indices in my sample are affected. These countries are predominantly located in the Americas (Argentina, Canada, Chile and the U.S.) and also one in Europe (Spain). The fact that Spain is affected is somewhat surprising, as Europe in general is only modestly affected by the ENSO cycle (Brönnimann, 2007). The most noticeable difference between the results noted in Table 6 and C.2 is that adding control variables partially offsets the significance of the El Niño surprise effect on the Asian stock markets. According to Table C.2, non of the Asian indices is affected by the surprise. The significance of the surprise effect in all Asian countries went down in model (8) relative to model (7).

Lastly, a note on the adjusted R-squared values. As could be expected, very low and even negative adjusted R-squared values are noted in both Table 6 and Table C.2 in Appendix C, meaning that SST surprise has almost no explanatory power on the international stock markets. In term and magnitude, the R-squareds are similar to those of Kamstra et al. (2003) and Cao and Wei (2005), who also predicted stock market returns using climate (anomaly) variables. An explanation for the low R-squared values could be that climate anomalies only have a small impact on the monthly stock market returns.

5.2 Analysis of U.S. Sector Indices

5.2.1 Basic Model

My analysis of U.S. sector indices follows a similar path to the analysis of the international stock markets. In Table 7 the results are shown of the basic model noted in equation (9) for the 12 selected U.S. sector indices. The sectors are selected based on the Theoretical Framework (section 2) and my expectation of which sectors could be affected by climate anomalies.

From Table 7 can be deducted that at time t the SST anomaly has a significant positive effect on household goods & home construction, with a coefficient of 0.267 (and a p-value of 0.039), implicating that a 1.0°C increase of the SST anomaly leads to a 0.267% increase of the corresponding sector index return. This finding is in line with the study of Changnon (1999) who found record seasonal sales of retail products and homes during the, relatively intense, El Niño episode of 1997/98. According to him this was due to high temperatures during the winter in most of the U.S., caused by El Niño. The 12-month delayed impact of El Niño on the (industrial) construction & materials (coefficient of -0.339 and p-value of 0.036) could also be explained by the study of Changnon (1999), where abnormal storm & tornado activity caused billions in property damage.

Comparing the results between U.S. sector returns and the returns of the three major U.S. stock indices (studied in section 5.1.3), one might note that they behave in a rather similar way regarding the impact of (lagged) SST anomalies. The S&P 500, NASDAQ and DJIA are not significantly affected by El Niño and the same goes for almost all sector indices. Looking at the R-squared values however, I observe a difference between the two models. The adjusted R-squareds displayed in Table 7 are substantially higher (between 0.171 and 0.606) than those in Table C.1 in Appendix C (0.033 at most). This difference can easily be explained by the fact that the DJIA return variable is included into the model used in Table 7, since sector returns are largely (and significantly) affected by a major national stock market.

Table 7 Estimates of the returns regressions – Eq. (9)

Model: $R_{s,t} = \beta_0 + \beta_1\, SST_t^{An} + \beta_2\, SST_{t-4}^{An} + \beta_3\, SST_{t-8}^{An} + \beta_4\, SST_{t-12}^{An} + \beta_5 R_{s,t-1} + \beta_6 D_t^{Jan} + \beta_7 R_t^{DJIA} + \beta_8 Precip_t^{An} + \beta_9 Temp_t^{An} + \varepsilon_{i,t}$

	β_0	SST_t^{An}	SST_{t-4}^{An}	SST_{t-8}^{An}	SST_{t-12}^{An}	R_{t-1}	D_t^{Jan}	R_t^{DJIA}	$Precip_t^{An}$	$Temp_t^{An}$	$\bar{R}^2$	BG	BP	$Skew$
Oil & Gas	0.128 (0.173)	-0.154 (0.356)	0.199 (0.423)	-0.055 (0.824)	0.000 (0.999)	-0.048 (0.164)	-0.452 (0.145)	0.756*** (0.000)	-0.001 (0.391)	-0.054 (0.280)	0.361	0.855	0.845	0.231
Construction & Materials	-0.065 (0.477)	0.073 (0.655)	0.044 (0.855)	0.338 (0.163)	-0.339** (0.036)	0.011 (0.696)	0.344 (0.256)	1.189*** (0.000)	-0.001 (0.541)	0.050 (0.301)	0.604	0.895	0.498	0.000***
Aerospace & Defense	0.097 (0.239)	0.054 (0.710)	-0.156 (0.474)	0.161 (0.464)	-0.106 (0.465)	0.049 (0.072)	0.257 (0.344)	1.066*** (0.000)	-0.001 (0.266)	-0.015 (0.734)	0.596	0.208	0.336	0.000***
Industrial Transportation	0.120 (0.148)	0.057 (0.700)	-0.192 (0.382)	0.349 (0.112)	-0.110 (0.449)	-0.042 (0.129)	-0.292 (0.286)	1.042*** (0.000)	-0.004*** (0.004)	-0.015 (0.727)	0.583	0.332	0.236	0.008***
Food Producers	0.235*** (0.001)	-0.106 (0.399)	0.238 (0.192)	-0.266 (0.131)	-0.004 (0.969)	0.003 (0.934)	-0.547** (0.023)	0.648*** (0.000)	0.000 (0.584)	-0.037 (0.259)	0.445	0.194	0.522	0.000***
Household Goods & Home Construction	0.128* (0.076)	0.267** (0.039)	-0.014 (0.940)	0.232 (0.224)	0.145 (0.252)	0.001 (0.987)	-0.573** (0.017)	0.784*** (0.000)	-0.001 (0.379)	-0.040 (0.303)	0.506	0.325	0.000***	0.000***
Tobacco	0.321** (0.013)	-0.151 (0.508)	0.156 (0.644)	0.006 (0.985)	-0.187 (0.405)	0.000 (0.996)	-0.660 (0.119)	0.713*** (0.000)	0.000 (0.988)	-0.026 (0.703)	0.207	0.800	0.025**	0.000***
Health Care Equipment & Services	0.163* (0.053)	0.053 (0.680)	0.112 (0.532)	-0.050 (0.786)	-0.109 (0.407)	-0.010 (0.766)	0.089 (0.760)	0.783*** (0.000)	0.000 (0.994)	0.014 (0.735)	0.474	0.177	0.030**	0.003***
Travel & Leisure	-0.063 (0.515)	0.153 (0.392)	-0.055 (0.824)	0.104 (0.690)	-0.143 (0.403)	0.064* (0.070)	0.407 (0.279)	1.237*** (0.000)	0.010 (0.484)	0.093* (0.053)	0.606	0.657	0.027**	0.000***

Table 7 Continued

	β_0	SST_t^{An}	SST_{t-4}^{An}	SST_{t-8}^{An}	SST_{t-12}^{An}	R_{t-1}	D_t^{Jan}	R_t^{DJIA}	$Precip_t^{An}$	$Temp_t^{An}$	$\bar{R}^2$	BG	BP	$Skew$
Electricity	-0.197 (0.449)	0.027 (0.847)	0.146 (0.459)	-0.096 (0.633)	-0.060 (0.662)	0.000 (0.362)	-0.036 (0.903)	0.404*** (0.000)	0.001 (0.537)	-0.043 (0.331)	0.171	0.868	0.003***	0.005***
Gas, Water & Multiutilities	0.084 (0.333)	-0.070 (0.651)	0.170 (0.457)	-0.173 (0.451)	0.116 (0.445)	0.043 (0.237)	-0.035 (0.903)	0.618*** (0.000)	0.000 (0.733)	-0.080* (0.084)	0.302	0.094	0.000***	0.000***
Non-Life Insurance	0.135* (0.082)	-0.066 (0.631)	0.234 (0.255)	-0.124 (0.544)	0.008 (0.950)	0.033 (0.275)	-0.562** (0.029)	0.816*** (0.000)	0.000 (0.834)	0.005 (0.897)	0.494	0.036**	0.823	0.000***

This table reports the OLS regression denoted in equation (9) with Newey-West standard errors. The dependent variable is R_{s,t}, the stock return of sector s at time t. In this table, the dependent variable is noted as the sector of which Datastream constructed a stock index. SST_t represent the (lagged) SST anomalies in the El Niño region. R^DJIA represents the stock return of the Dow Jones Industrial Average at time t and R_{t-1} the lagged monthly return of the stock return of sector s at time t-1. The precipitation anomaly (Precip_t) is measured in mm and the temperature anomaly (Temp_t) is in degrees Celsius. The p-values are reported in the parentheses. The adjusted R-squared is noted as R^2. BG represents the Breusch-Godfrey test, BP represents the Breusch-Pagan test and Skew represents the skewness kurtosis test, the values displayed in these three columns are p-values.

*Significant at the 10% level; **significant at the 5% level; ***significant at the 1% level

5.2.2 Seasonality of El Niño

Similar to the model used in Table 4, I study whether the seasonal SST variables differ from each other before I test if the seasonal SST variables affect U.S. sector returns. I test whether these four variables differ from one another by deploying an F-test while they are implemented in equation (10), with the null hypothesis that their coefficients are equal ($\beta_1 = \beta_2 = \beta_3 = \beta_4$). The results of this test are displayed in Table 8 where I primarily focus on the p-values of the F-test. In contrast to the F-test in Table 4, I found that a seasonal impact of El Niño exist in multiple cases within the sample. The observed p-values (of the F-test) for both the tobacco- and the travel & leisure sector are significantly low, causing them to reject the null hypothesis. Subsequently, the sectors aerospace & defense, household goods & home construction and health care equipment & services also display relatively low (but insignificant) p-values. As for the combination of these results I have chosen to run an OLS regression on all sectors.

The results of the regression are shown in Table C.3 in Appendix C in which 6 of the 12 studied sectors noted at least one significant seasonal SST variable. The household[5] sector is significantly positive affected by SST anomalies during the winter (p-value of 0.001) which is in line with my findings in section 5.2.1 and those of Changnon (1999), who stated that the relatively warm winter caused record seasonal sales of retail products and homes. The tobacco sector is negatively affected during the spring but shows a reversal during the summer. This is partially in line with the study of Hansen et al (1998), they found that ENSO cycles significantly influence corn and tobacco yields during winter and/or spring. Finally, the last noteworthy finding is related to the travel & leisure sector. During autumn, this sector is significantly positively influenced by SST anomalies. A climate map, published by the NOAA, could provide a possible explanation for this finding (NOAA, 1997). On this map the average October-December temperature rankings during ENSO events are displayed, from which can be derived that autumn temperatures during El Niño are relatively higher. Warmer temperatures during fall could make the travel & leisure sector prosper. Outdoor tourism in many North American parks is constrained by cool conditions, warmer temperatures are likely to result in increased visitation (Richardson & Loomis, 2004). This theory is strengthened by the temperature anomaly coefficient (p-value of 0.051), which indicates that the stock return in this sector increases with 0.099% per 1.0°C anomaly.

While analyzing the control variables in Table C.3 in Appendix C one can note that the January effect does not hold as some coefficients are (significantly) negative, indicating a decrease in stock return during the month of January. Just like the results in Table 7, the DJIA return variable is by far the most influencing variable with both high coefficients (between 0.403 and 1.239) and low p-values (all 0.000). The inclusion of this variable is also the logic behind the relatively high

[5] Short for: household goods & home construction

adjusted R-squared values. The proportion of the variability in the monthly stock return can reasonably well be explained by the model as the DJIA is a substantial influencer of most sectors.

Table 8 F-Test for difference – Eq. (10)

Model: $R_{s,t} = \beta_0 + \beta_1 D_t^{Winter} \times SST_t^{An} + \beta_2 D_t^{Spring} \times SST_t^{An} + \beta_3 D_t^{Summer} \times SST_t^{An} + \beta_4 D_t^{Autumn} \times SST_t^{An} + \beta_5 R_t^{DJIA} + \beta_6 D_t^{Jan} + \beta_7 R_{s,t-1} + \beta_8 Precip_t^{An} + \beta_9 Temp_t^{An} + \varepsilon_{s,t}$

$H_0 : \beta_1 = \beta_2 = \beta_3 = \beta_4$	F	$\bar{R}^2$	BG	BP	$Skew$
Oil & Gas Producers	0.589	0.362	0.881	0.938	0.218
Construction & Materials	0.659	0.599	0.877	0.846	0.000*
Aerospace & Defense	0.230	0.598	0.153	0.300	0.000*
Industrial Transportation	0.546	0.582	0.346	0.413	0.000*
Food Producers	0.394	0.443	0.163	0.393	0.001*
Household Goods & Home Construction	0.209	0.505	0.375	0.000*	0.000*
Tobacco	0.005*	0.220	0.949	0.017*	0.000*
Health Care Equipment & Services	0.138	0.477	0.189	0.023*	0.005*
Travel & Leisure	0.043*	0.611	0.465	0.076	0.000*
Electricity	0.806	0.170	0.908	0.004*	0.004*
Gas, Water & Multiutilities	0.445	0.302	0.060	0.000*	0.000*
Non-Life Insurance	0.367	0.496	0.029*	0.629	0.000*

This table reports the F-test in the regression denoted in equation (10) with Newey-West standard errors; for the following null hypothesis: Beta_1=Beta_2=Beta_3=Beta_4. The values reported in column F represent the p-values of the F-test. The dependent variable is R_{s,t}, the stock return of sector s at time t. In this table, the dependent variable is noted as the sector of which Datastream constructed a stock index. SST_t x D^season represent the dummy interaction variable between a seasonal dummy and the SST anomaly; which takes on the value of the SST anomaly at time t during a specific season and the value of 0 otherwise. R^DJIA represents the stock return of the Dow Jones Industrial Average at time t and R_{t-1} the lagged monthly return of the stock return of sector s at time t-1. The precipitation anomaly (Precip_t) is measured in mm and the temperature anomaly (Temp_t) is in degrees Celsius. The p-values are reported in the parentheses. The adjusted R-squared is noted as R^2. BG represents the Breusch-Godfrey test, BP represents the Breusch-Pagan test and Skew represents the skewness kurtosis test, the values displayed in these three columns are p-values.

*Significant at the 5% level.

5.2.3 El Niño Surprise

In order to analyze whether the El Niño surprise affects the stock performance of U.S. sectors, I use only one model (11), contrasting the analysis of the international stock markets in which I use two models (7 and 8). I exclude a basic model similar to equation (7) after considering the results noted in Table 6 and C.2 in Appendix C, which indicate that the three major U.S. stock markets are significantly affected by the El Niño surprise. In turn, the stock markets largely influence the underlying business sectors (see the DJIA return variable in Table 7). From these findings I derive my expectation that, using a basic model with El Niño surprise as the only predictor, would generate biased, inaccurate results. By adding the DJIA variable into model (11), I try to control for trends and investor sentiment in the stock market as a whole. The results of equation (11) are shown in Table 9.

From the results can be derived that the SST surprise has a significantly negative effect on only one of the sectors in my sample, the aerospace & defense sector. The interpretation of this coefficient is as follows, per one-unit positive standard deviation of the the El Niño surprise variable, the aerospace & defense sector has a decrease in stock return of -0.185%. As explained in section 5.1.4, a negative surprise coefficient indicates that investors initially accounted for a positive effect of El Niño on stock return. This finding can be explained by the study of Changnon (1999). He found that, due to a decreased number of delays (caused by the weather), the profits of the airline transportation industry increased with an estimated 3% - 8%.

Although not significant (p-value of 0.110), one other sector is also negatively affected by the surprise, the oil & gas sector. No clear explanation for this finding is present. They higher oil prices caused by an ENSO cycle (Cashin et al., 2017) do not directly cause the stock performance of oil companies to improve. The relationship between the oil price and the stock prices in the oil & gas sector is complex as oil plays the role of both cost and profit for the companies in this sector (Diaz & Gracia, 2017). Furthermore, when looking at the p-values (between 0.496 and 0.980) of all other sectors in my sample I can conclude that these sectors are not directly affected by the El Niño surprise. This does not necessarily mean that non of the companies within these sectors are affected by the El Niño surprise. However, if the affected companies only make up for a fraction of the total sector, then this shall probably not be translated into the results.

Table 9 Estimates of return regressions – Eq. (11)

Model: $R_{s,t} = \beta_0 + \beta_1 SST_t^{Surp} + \beta_2 R_{s,t-1} + \beta_3 D_t^{Jan} + \beta_4 R_t^{DJIA} + \beta_5 Precip_t^{An} + \beta_6 Temp_t^{An} + \varepsilon_{i,t}$

	β_0	SST_t^{Surp}	R_{t-1}	D_t^{Jan}	R_t^{DJIA}	$Precip_t^{An}$	$Temp_t^{An}$	$\bar{R}^2$	BG	BP	$Skew$
Oil & Gas	0.133 (0.153)	-0.144 (0.110)	-0.048 (0.157)	-0.433 (0.161)	0.751*** (0.000)	-0.001 (0.431)	-0.060 (0.230)	0.367	0.772	0.962	0.238
Construction & Materials	-0.070 (0.447)	0.014 (0.871)	0.020 (0.453)	0.321 (0.294)	1.192*** (0.000)	0.000 (0.513)	0.061 (0.219)	0.592	0.809	0.743	0.000***
Aerospace & Defense	0.105 (0.201)	-0.185** (0.019)	0.046* (0.090)	0.277 (0.304)	1.057*** (0.000)	-0.001 (0.320)	-0.026 (0.552)	0.602	0.235	0.407	0.000***
Industrial Transportation	0.122 (0.143)	-0.054 (0.496)	-0.039 (0.161)	-0.291 (0.288)	1.041*** (0.000)	-0.003*** (0.005)	-0.011 (0.801)	0.583	0.411	0.382	0.008***
Food Producers	0.234*** (0.001)	-0.030 (0.644)	0.004 (0.891)	-0.542** (0.016)	0.646*** (0.000)	0.000 (0.636)	-0.045 (0.212)	0.443	0.116	0.728	0.000***
Household Goods & Home Construction	0.132* (0.070)	-0.036 (0.606)	0.008 (0.789)	-0.570 (0.018)	0.779*** (0.000)	-0.001 (0.438)	-0.047 (0.238)	0.499	0.612	0.000***	0.000***

Table 9 Continued

	β_0	SST_t^{Surp}	R_{t-1}	D_t^{Jan}	R_t^{DJIA}	$Precip_t^{An}$	$Temp_t^{An}$	$\bar{R}^2$	BG	BP	$Skew$
Tobacco	0.316**	-0.012	0.002	-0.662	0.714***	0.000	-0.028	0.208	0.734	0.035**	0.000***
	(0.020)	(0.927)	(0.970)	(0.102)	(0.000)	(0.938)	(0.653)				
Health Care Equipment & Services	0.162**	-0.032	-0.007	0.087	0.781***	0.000	-0.016	0.472	0.239	0.050*	0.002***
	(0.037)	(0.664)	(0.813)	(0.713)	(0.000)	(0.988)	(0.684)				
Travel & Leisure	-0.064	0.002	0.067**	0.399	1.237***	0.001	0.094**	0.606	0.722	0.042**	0.000***
	(0.494)	(0.980)	(0.014)	(0.203)	(0.000)	(0.468)	(0.065)				
Electricity	-0.197	-0.043	0.000	-0.025	0.402***	0.001	-0.046	0.171	0.966	0.003***	0.003***
	(0.450)	(0.564)	(0.358)	(0.931)	(0.000)	(0.535)	(0.292)				
Gas, Water & Multiutilities	0.086	-0.034	0.043	-0.027	0.616***	0.000	-0.082*	0.305	0.064*	0.000***	0.000***
	(0.317)	(0.679)	(0.234)	(0.924)	(0.000)	(0.759)	(0.077)				
Non-Life Insurance	0.134*	0.024	0.035	-0.565	0.818	0.000	-0.008	0.495	0.029**	0.743	0.000***
	(0.085)	(0.747)	(0.251)	(0.028)	(0.000)	(0.804)	(0.833)				

This table reports the OLS regression denoted in equation (11) with Newey-West standard errors. The dependent variable is R_{s,t}, the stock return of sector s at time t. In this table, the dependent variable is noted as the sector of which Datastream constructed a stock index. SST_t represents the SST surprise in the El Niño region calculated according equation (6). R^DJIA represents the stock return of the Dow Jones Industrial Average at time t and R_{t-1} the lagged monthly return of the stock return of sector s at time t-1. The precipitation anomaly (Precip_t) is measured in mm and the temperature anomaly (Temp_t) is in degrees Celsius. The p-values are reported in the parentheses. The adjusted R-squared is noted as R^2. BG represents the Breusch-Godfrey test, BP represents the Breusch-Pagan test and Skew represents the skewness kurtosis test, the values displayed in these three columns are p-values.

*Significant at the 10% level; **significant at the 5% level; ***significant at the 1% level

5.3 International Sector Analysis

Additional to the U.S. sector analysis, which was the initial focus of section 5.2, I expand the sector study beyond the national borders of the United States. Based on the combined results of the international market- and the U.S. sector analysis, it seems reasonable to assume that the business sectors of other countries are also affected by ENSO. In order to study this, I create a sub-sample (out of my original sample of 22 countries) for which I analyze the sectors. This sub-sample consist of four countries (other than the U.S.) that are most affected by the El Niño (surprise): Canada, Chile, Singapore and Hong Kong. As I found most significant results studying the seasonality of the ENSO cycle in combination with sector returns, I use a similar model (10) to study the international sectors. For comparability reasons I study the same 12 sectors as in section 5.2. The results of these regressions are presented in Tables 10 – 13. Note that, since not all 12 sectors are available in Datastream for all countries, the results of some sectors are absent.

First, I discuss the findings of the Canadian sector analysis. The most notable results are those of the (non-life) insurance sector and the health care sector. From Table 10 can be derived that the insurance sector experiences an increase in stock return during winter and summer of 0.404% and 0.757% (p-values of 0.045 & 0.042) per 1.0°C SST anomaly. A possible explanation for this result is the reduction in the amount of storms that hit Canada during an ENSO phase.[5] According to Changnon et al. (1997) the performance of the property insurance industry is substantially influenced by the amount and severity of storms. In contrast to all other significantly affected sectors, the health care sector is negatively influenced by El Niño during all seasons. As the health care sector is very complex, no real conclusions can be drawn from these results. Furthermore, it shows that the electricity, aerospace and construction sector are all positively affected (at a 10% significance level) during winter. That El Niño affects stock returns notably during the winter is due to the impact of the ENSO on the Canadian climate. Historically, Canada is mostly affected by El Niño in the course of winter and spring, during which the climate is milder and drier than normal in most parts of the country.[6] In comparison with their neighboring country (the U.S.) I do not examine a lot of similarities among the results, which is remarkable since both countries are similarly influenced by the ENSO cycle.

Next, I review the results of the sector analysis for both Hong Kong and Singapore, noted in Table 11 and 12. The results of Singapore show that the construction (autumn) and travel & leisure (winter) sector are very significantly (positively) impacted, with p-values of 0.003 and 0.008. Looking at the influence of El Niño these results can be explained by drier conditions during the monsoon season. The affected sectors in Hong Kong are completely different, the transport (winter & spring), food (summer) and electricity (winter & summer) sectors are the most influenced. Although both located in South-East Asia, their climate is influenced differently (see Figure 1), this could illustrate the contrasting affected sectors.

I conclude the international sector analysis with the study of Chile. As Chile is located close to the El Niño region, one might expect that the sector returns are relatively heavily impacted. However, looking at the sector analysis presented in Table 13, this is not the case. Three out of the studied nine Chilean sectors are influenced by El Niño, the insurance, construction and Utilities sector. No clear conclusion can be drawn from the results as all three sectors are only impacted at a 10% significance level, during different seasons and both positive and negative.

Overall, the results of the international sector analysis show almost no resemblance to the findings of the U.S. sector. Moreover, the results of all five studied countries show little parallels between one another. This might be due to the fact that the global impact of the ENSO cycle is different in all parts of the world and this is partly translated into the results of sector performances, which are also affected differently. A final note on the international sector analysis is that the results are in line with those of the El Niño surprise in section 5.1.4. All five countries are affected positively by El Niño (surprise) and this is also (partly) translated into their business sectors which are predominantly positively affected.

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[6] From the website of the Government of Canada: < https://www.canada.ca/en/environment-climate-change/services/el-nino.html#ENImpacts >

Table 10 Estimates of returns regressions – Eq. (10) Canada

Model: $R_{s,t} = \beta_0 + \beta_1\, D_t^{Winter} \times SST_t^{An} + \beta_2\, D_t^{Spring} \times\ SST_t^{An}\ \ + \beta_3\, D_t^{Summer} \times SST_t^{An}\ + \beta_4\, D_t^{Autumn} \times SST_t^{An} +\ \beta_5 R_t^{TSX} +\ \beta_6 D_t^{Jan} + \beta_7 R_{s,t-1} + +\beta_8 Precip_t^{An} + \beta_9 Temp_t^{An} + \varepsilon_{s,t}$

	β_0	$D_t^{Winter} \times SST_t^{An}$	$D_t^{Spring} \times SST_t^{An}$	$D_t^{Summer} \times SST_t^{An}$	$D_t^{Autumn} \times SST_t^{An}$	R_{t-1}	D_t^{Jan}	R_t^{TSX}	$Precip_t^{An}$	$Temp_t^{An}$	$\bar{R}^2$	BG	BP	$Skew$
Oil & Gas	0.052 (0.613)	-0.049 (0.783)	-0.055 (0.828)	0.074 (0.824)	-0.057 (0.801)	0.004 (0.882)	-0.540 (0.120)	1.026*** (0.000)	-0.002 (0.280)	-0.025 (0.591)	0.470	0.142	0.442	0.000***
Construction & Materials	-0.006 (0.953)	0.452* (0.065)	-0.662 (0.007)	0.495 (0.144)	-0.166 (0.512)	0.030 (0.420)	0.401 (0.339)	0.971*** (0.000)	-0.001 (0.720)	0.106 (0.056)	0.421	0.021**	0.369	0.000***
Aerospace & Defense	0.184 (0.354)	0.553* (0.068)	-0.236 (0.597)	-0.520 (0.406)	-0.149 (0.675)	-0.097 (0.097)	-0.001 (0.932)	0.466*** (0.000)	-0.002 (0.097)	-0.323 (0.492)	0.263	0.861	0.174	0.004***
Industrial Transportation	0.446*** (0.003)	0.301 (0.253)	-0.278 (0.447)	0.065 (0.894)	0.065 (0.844)	-0.042 (0.274)	0.252 (0.607)	0.905*** (0.000)	-0.002 (0.587)	-0.104 (0.120)	0.262	0.600	0.380	0.000***
Food Producers	0.309 (0.004)	0.236 (0.197)	-0.065 (0.800)	-0.196 (0.561)	-0.042 (0.854)	-0.026 (0.489)	0.176 (0.617)	0.596*** (0.000)	-0.002 (0.397)	0.020 (0.673)	0.224	0.088	0.585	0.001***
Household Goods & Home Construction	0.014 (0.978)	-0.159 (0.841)	-0.615 (0.571)	2.381 (0.148)	0.669 (0.459)	-0.046 (0.703)	0.197 (0.902)	1.001*** (0.006)	-0.016 (0.298)	0.205 (0.278)	0.037	0.787	0.180	0.019**
Tobacco	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Health Care Equipment & Services	0.016 (0.913)	-0.336 (0.194)	-0.616* (0.093)	-0.474 (0.321)	-0.549* (0.095)	0.112*** (0.005)	1.383*** (0.006)	0.673*** (0.000)	0.001 (0.700)	-0.109 (0.113)	0.184	0.629	0.000***	0.000***

Table 10 Continued

	β_0	$D_t^{Winter} \times SST_t^{An}$	$D_t^{Spring} \times SST_t^{An}$	$D_t^{Summer} \times SST_t^{An}$	$D_t^{Autumn} \times SST_t^{An}$	R_{t-1}	D_t^{Jan}	R_t^{TSX}	$Precip_t^{An}$	$Temp_t^{An}$	$\bar{R}^2$	BG	BP	$Skew$
Travel & Leisure	0.453*** (0.003)	0.145 (0.561)	0.246 (0.484)	-0.019 (0.967)	-0.346 (0.262)	0.031 (0.476)	-2.441*** (0.000)	0.816*** (0.000)	-0.001 (0.686)	-0.030 (0.656)	0.291	0.162	0.511	0.006***
Electricity	0.124 (0.117)	0.222* (0.094)	-0.139 (0.498)	0.166 (0.507)	0.177 (0.400)	-0.080 (0.162)	-0.404* (0.091)	0.444*** (0.000)	0.000 (0.968)	-0.028 (0.405)	0.224	0.002***	0.823	0.000***
Gas, Water & Multiutilities	0.082 (0.342)	0.098 (0.518)	0.007 (0.972)	0.364 (0.195)	0.218 (0.254)	-0.079** (0.040)	0.014 (0.961)	0.466*** (0.000)	-0.002 (0.436)	0.013 (0.735)	0.204	0.178	0.187	0.000***
Non-Life Insurance	0.303*** (0.008)	0.404** (0.045)	0.055 (0.842)	0.757** (0.042)	-0.295 (0.243)	0.139*** (0.004)	-0.209 (0.576)	0.551*** (0.000)	-0.001 (0.565)	-0.069 (0.175)	0.217	0.633	0.573	0.000***

This table reports the OLS regression denoted in equation (10) with Newey-West standard errors. The dependent variable is R_{s,t}, the stock return of sector s at time t. In this table, the dependent variable is noted as the sector of which Datastream constructed a stock index. SST_t x D^season represent the dummy interaction variable between a seasonal dummy and the SST anomaly; which takes on the value of the SST anomaly at time t during a specific season and the value of 0 otherwise. R^TSX represents the stock return of the S&P / TSX index at time t and R_{t-1} the lagged monthly return of the stock return of sector s at time t-1. The precipitation anomaly (Precip_t) is measured in mm and the temperature anomaly (Temp_t) is in degrees Celsius. The p-values are reported in the parentheses. The adjusted R-squared is noted as R^2. BG represents the Breusch-Godfrey test, BP represents the Breusch-Pagan test and Skew represents the skewness kurtosis test, the values displayed in these three columns are p-values.

*Significant at the 10% level; **significant at the 5% level; ***significant at the 1% level

Table 11 Estimates of returns regressions – Eq. (10) Singapore

Model: $R_{s,t} = \beta_0 + \beta_1\, D_t^{Winter} \times SST_t^{An} + \beta_2\, D_t^{Spring} \times\ SST_t^{An}\ +\ \beta_3\, D_t^{Summer} \times SST_t^{An}\ + \beta_4\, D_t^{Autumn} \times SST_t^{An} +\ \beta_5 R_t^{MSCI} +\ \beta_6 D_t^{Jan} + \beta_7 R_{s,t-1} + +\beta_8 Precip_t^{An} + \beta_9 Temp_t^{An} + \varepsilon_{s,t}$

	β_0	$D_t^{Winter} \times SST_t^{An}$	$D_t^{Spring} \times SST_t^{An}$	$D_t^{Summer} \times SST_t^{An}$	$D_t^{Autumn} \times SST_t^{An}$	R_{t-1}	D_t^{Jan}	R_t^{MSCI}	$Precip_t^{An}$	$Temp_t^{An}$	$\bar{R}^2$	BG	BP	$Skew$
Oil & Gas	0.035 (0.229)	0.009 (0.842)	0.123 (0.164)	-0.009 (0.926)	0.132** (0.029)	0.071 (0.339)	0.133 (0.139)	-0.006 (0.539)	0.000 (0.758)	-0.052 (0.416)	0.005	0.732	0.000***	0.000***
Construction & Materials	-0.115 (0.433)	0.489* (0.076)	-0.082 (0.837)	-0.069 (0.891)	1.005*** (0.003)	-0.007 (0.797)	0.751 (0.140)	1.175*** (0.000)	-0.003** (0.021)	-0.220 (0.465)	0.594	0.625	0.984	0.000***
Aerospace & Defense	0.184 (0.354)	0.553* (0.068)	-0.236 (0.597)	-0.520 (0.406)	-0.149 (0.675)	-0.097* (0.097)	-0.001 (0.999)	0.466*** (0.000)	-0.001 (0.750)	-0.323 (0.492)	0.263	0.861	0.174	0.005***
Industrial Transportation	0.012 (0.899)	0.241 (0.186)	-0.180 (0.486)	0.200 (0.543)	0.021 (0.924)	0.074** (0.017)	0.433 (0.197)	0.835*** (0.000)	0.000 (0.931)	-0.010 (0.960)	0.639	0.765	0.626	0.000***
Food Producers	-0.003 (0.974)	0.315 (0.165)	-0.121 (0.713)	-0.286 (0.493)	-0.068 (0.807)	0.005 (0.850)	0.685 (0.102)	0.929*** (0.000)	-0.001 (0.341)	0.119 (0.629)	0.569	0.718	0.924	0.000***
Household Goods & Home Construction	0.289 (0.289)	0.119 (0.119)	-0.018 (0.968)	0.776 (0.111)	-0.622 (0.171)	-0.094* (0.074)	0.172 (0.803)	0.575*** (0.000)	0.001 (0.336)	-0.433 (0.291)	0.244	0.710	0.000***	0.000***
Tobacco	0.297 (0.162)	0.144 (0.639)	-0.176 (0.718)	0.898 (0.117)	-0.588 (0.216)	-0.102 (0.048)	0.187 (0.788)	0.593*** (0.000)	0.001 (0.299)	-0.345 (0.415)	0.237	0.649	0.000***	0.000***
Health Care Equipment & Services	0.055 (0.503)	0.212 (0.170)	0.110 (0.625)	0.025 (0.928)	-0.068 (0.721)	0.042* (0.090)	0.833*** (0.004)	0.814*** 0.000()	-0.001 (0.431)	0.112 (0.508)	0.689	0.623	0.981	0.001***

Table 11 Continued

	β_0	$D_t^{Winter} \times SST_t^{An}$	$D_t^{Spring} \times SST_t^{An}$	$D_t^{Summer} \times SST_t^{An}$	$D_t^{Autumn} \times SST_t^{An}$	R_{t-1}	D_t^{Jan}	R_t^{MSCI}	$Precip_t^{An}$	$Temp_t^{An}$	$\bar{R}^2$	BG	BP	$Skew$
Travel & Leisure	0.124 (0.236)	0.528*** (0.008)	-0.446 (0.122)	-0.266 (0.464)	-0.022 (0.925)	0.057* (0.071)	-0.570 (0.119)	0.723*** (0.000)	-0.001 (0.468)	-0.305 (0.158)	0.516	0.065*	0.009***	0.000***
Electricity	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Gas, Water & Multiutilities	0.596 (0.129)	-0.024 (0.969)	1.457 (0.127)	1.367 (0.318)	0.620 (0.398)	-0.046 (0.447)	0.868 (0.425)	1.184*** (0.000)	-0.004 (0.250)	-1.514 (0.111)	0.332	0.754	0.451	0.000***
Non-Life Insurance	0.280* (0.090)	0.179 (0.560)	0.087 (0.840)	0.170 (0.756)	-0.186 (0.619)	0.022 (0.612)	0.118 (0.832)	0.678*** (0.000)	-0.002 (0.225)	-0.248 (0.487)	0.286	0.165	0.072*	0.000***

This table reports the OLS regression denoted in equation (10) with Newey-West standard errors. The dependent variable is R_{s,t}, the stock return of sector s at time t. In this table, the dependent variable is noted as the sector of which Datastream constructed a stock index. SST_t x D^season represent the dummy interaction variable between a seasonal dummy and the SST anomaly; which takes on the value of the SST anomaly at time t during a specific season and the value of 0 otherwise. R^MSCI represents the stock return of the Morgan Stanley Capital International Singapore index at time t and R_{t-1} the lagged monthly return of the stock return of sector s at time t-1. The precipitation anomaly (Precip_t) is measured in mm and the temperature anomaly (Temp_t) is in degrees Celsius. The p-values are reported in the parentheses. The adjusted R-squared is noted as R^2. BG represents the Breusch-Godfrey test, BP represents the Breusch-Pagan test and Skew represents the skewness kurtosis test, the values displayed in these three columns are p-values.

*Significant at the 10% level; **significant at the 5% level; ***significant at the 1% level

Table 12 Estimates of returns regressions – Eq. (10) Hong Kong

Model: $R_{s,t} = \beta_0 + \beta_1\, D_t^{Winter} \times SST_t^{An} + \beta_2\, D_t^{Spring} \times SST_t^{An} + \beta_3\, D_t^{Summer} \times SST_t^{An} + \beta_4\, D_t^{Autumn} \times SST_t^{An} + \beta_5 R_t^{HS} + \beta_6 D_t^{Jan} + \beta_7 R_{s,t-1} + +\beta_8 Precip_t^{An} + \beta_9 Temp_t^{An} + \varepsilon_{s,t}$

	β_0	$D_t^{Winter} \times SST_t^{An}$	$D_t^{Spring} \times SST_t^{An}$	$D_t^{Summer} \times SST_t^{An}$	$D_t^{Autumn} \times SST_t^{An}$	R_{t-1}	D_t^{Jan}	R_t^{HS}	$Precip_t^{An}$	$Temp_t^{An}$	$\bar{R}^2$	BG	BP	$Skew$
Oil & Gas	0.147 (0.702)	-0.065 (0.931)	0.778 (0.403)	0.836 (0.644)	-0.764 (0.295)	0.239* (0.062)	-2.726** (0.028)	0.968*** (0.000)	0.004 (0.103)	-0.006 (0.984)	0.227	0.115	0.000***	0.000***
Construction & Materials	-0.098 (0.611)	0.446 (0.243)	-0.015 (0.975)	0.186 (0.727)	-0.311 (0.520)	-0.021 (0.740)	1.019 (0.125)	0.801*** (0.000)	-0.002* (0.075)	-0.027 (0.870)	0.391	0.033**	0.913	0.000***
Aerospace & Defense	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Industrial Transportation	-0.071 (0.493)	0.345** (0.039)	-0.605** (0.020)	0.306 (0.374)	-0.326 (0.260)	0.030 (0.366)	-0.012 (0.973)	0.770*** (0.000)	0.000 (0.642)	-0.039 (0.678)	0.669	0.000***	0.738	0.000***
Food Producers	0.112 (0.619)	0.008 (0.982)	-0.490 (0.364)	-1.729** (0.029)	-0.207 (0.662)	0.059 (0.333)	-0.977 (0.212)	0.450*** (0.000)	0.000 (0.959)	-0.217 (0.320)	0.178	0.351	0.091*	0.018**
Household Goods & Home Construction	0.115 (0.836)	-0.398 (0.504)	1.606* (0.096)	1.400 (0.464)	1.739 (0.175)	0.044 (0.623)	-1.620 (0.210)	0.816*** (0.000)	0.003 (0.172)	-0.451 (0.363)	0.085	0.021**	0.063*	0.000***
Tobacco	0.107 (0.572)	0.514 (0.136)	-0.349 (0.397)	-0.422 (0.573)	-0.500 (0.469)	0.156** (0.001)	1.215** (0.051)	0.370*** (0.000)	-0.001 (0.312)	0.146 (0.383)	0.144	0.100	0.024**	0.023**
Health Care Equipment & Services	0.931** (0.021)	-0.540 (0.445)	0.302 (0.762)	-0.837 (0.609)	0.837 (0.368)	0.183** (0.021)	-0.542 (0.684)	0.452*** (0.002)	-0.002 (0.377)	0.050 (0.890)	0.076	0.187	0.955	0.007***

Table 12 Continued

	β_0	$D_t^{Winter} \times SST_t^{An}$	$D_t^{Spring} \times SST_t^{An}$	$D_t^{Summer} \times SST_t^{An}$	$D_t^{Autumn} \times SST_t^{An}$	R_{t-1}	D_t^{Jan}	R_t^{HS}	$Precip_t^{An}$	$Temp_t^{An}$	$\bar{R}^2$	BG	BP	$Skew$
Travel & Leisure	-0.027 (0.813)	0.322 (0.115)	-0.153 (0.594)	-0.165 (0.660)	0.011 (0.966)	0.030 (0.213)	-0.270 (0.499)	0.881*** (0.000)	-0.001* (0.080)	-0.161 (0.124)	0.680	0.247	0.756	0.000***
Electricity	0.158 (0.282)	0.481** (0.047)	-0.279 (0.124)	0.519* (0.054)	0.326 (0.112)	-0.044 (0.148)	0.153 (0.671)	0.760*** (0.000)	0.001 (0.172)	0.005 (0.959)	0.705	0.039**	0.000***	0.000***
Gas, Water & Multiutilities	0.457*** (0.001)	0.265 (0.288)	-0.212 (0.607)	-0.174 (0.720)	0.510* (0.066)	-0.001 (0.969)	-0.595 (0.135)	0.753*** (0.000)	-0.001 (0.300)	-0.218 (0.102)	0.538	0.003***	0.340	0.000***
Non-Life Insurance	0.633* (0.050)	0.031 (0.957)	-1.083 (0.194)	-0.931 (0.485)	1.351* (0.066)	-0.048 (0.455)	-2.018* (0.068)	1.016*** (0.000)	-0.002 (0.316)	0.227 (0.449)	0.342	0.309	0.117	0.006***

This table reports the OLS regression denoted in equation (10) with Newey-West standard errors. The dependent variable is R_{s,t}, the stock return of sector s at time t. In this table, the dependent variable is noted as the sector of which Datastream constructed a stock index. SST_t x D^season represent the dummy interaction variable between a seasonal dummy and the SST anomaly; which takes on the value of the SST anomaly at time t during a specific season and the value of 0 otherwise. R^HS represents the stock return of the Hang Seng index at time t and R_{t-1} the lagged monthly return of the stock return of sector s at time t-1. The precipitation anomaly (Precip_t) is measured in mm and the temperature anomaly (Temp_t) is in degrees Celsius. The p-values are reported in the parentheses. The adjusted R-squared is noted as R^2. BG represents the Breusch-Godfrey test, BP represents the Breusch-Pagan test and Skew represents the skewness kurtosis test, the values displayed in these three columns are p-values.

*Significant at the 10% level; **significant at the 5% level; ***significant at the 1% level

Table 13 Estimates of returns regressions – Eq. (10) Chile

Model: $R_{s,t} = \beta_0 + \beta_1\, D_t^{Winter} \times SST_t^{An} + \beta_2\, D_t^{Spring} \times SST_t^{An} + \beta_3\, D_t^{Summer} \times SST_t^{An} + \beta_4\, D_t^{Autumn} \times SST_t^{An} + \beta_5 R_t^{IPSA} + \beta_6 D_t^{Jan} + \beta_7 R_{s,t-1} + +\beta_8 Precip_t^{An} + \beta_9 Temp_t^{An} + \varepsilon_{s,t}$

	β_0	$D_t^{Winter} \times SST_t^{An}$	$D_t^{Spring} \times SST_t^{An}$	$D_t^{Summer} \times SST_t^{An}$	$D_t^{Autumn} \times SST_t^{An}$	R_{t-1}	D_t^{Jan}	R_t^{IPSA}	$Precip_t^{An}$	$Temp_t^{An}$	$\bar{R}^2$	BG	BP	$Skew$
Oil & Gas	-0.042 (0.799)	0.194 (0.504)	-0.311 (0.432)	-0.093 (0.868)	-0.164 (0.652)	-0.031 (0.467)	-0.638 (0.256)	0.951*** (0.000)	0.003 (0.448)	-0.099 (0.557)	0.482	0.072*	0.100	0.000***
Construction & Materials	-0.538** (0.039)	0.198 (0.649)	-0.452 (0.470)	1.255* (0.066)	1.021 (0.094)	0.0t03 (0.957)	-0.001 (0.999)	0.954*** (0.000)	-0.004 (0.555)	-0.159 (0.570)	0.243	0.208	0.009***	0.000***
Aerospace & Defense	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Industrial Transportation	-0.479 (0.110)	0.412 (0.439)	0.475 (0.511)	-0.763 (0.569)	0.137 (0.838)	0.065 (0.228)	-0.733 (0.475)	0.925*** (0.000)	0.003 (0.678)	-0.160 (0.624)	0.202	0.134	0.191	0.000***
Food Producers	0.032 (0.836)	0.207 (0.483)	0.425 (0.414)	0.087 (0.859)	0.494 (0.120)	-0.026 (0.652)	-0.260 (0.635)	0.753*** (0.000)	0.002 (0.560)	0.155 (0.359)	0.367	0.028**	0.039**	0.000***
Household Goods & Home Construction	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Tobacco	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Health Care Equipment & Services	-0.048 (0.824)	-0.274 (0.459)	0.111 (0.880)	0.915 (0.354)	0.083 (0.865)	-0.068 (0.263)	0.390 (0.591)	0.777*** (0.000)	-0.003 (0.621)	0.428* (0.082)	0.243	0.001***	0.004***	0.000***

Table 13 Continued

	β_0	$D_t^{Winter} \times SST_t^{An}$	$D_t^{Spring} \times SST_t^{An}$	$D_t^{Summer} \times SST_t^{An}$	$D_t^{Autumn} \times SST_t^{An}$	R_{t-1}	D_t^{Jan}	R_t^{IPSA}	$Precip_t^{An}$	$Temp_t^{An}$	$\bar{R}^2$	BG	BP	$Skew$
Travel & Leisure	0.546*	0.672*	0.714	-1.307	-0.401	-0.041	-2.534**	0.826***	0.016	-0.131	0.114	0.476	0.000***	0.000***
	(0.083)	(0.065)	(0.460)	(0.427)	(0.582)	(0.513)	(0.031)	(0.000)	(0.257)	(0.773)				
Electricity	-0.028	0.031	-0.071	0.339	0.046	0.030	-0.126	0.935***	0.002	0.137	0.756	0.941	0.965	0.059**
	(0.755)	(0.844)	(0.743)	(0.275)	(0.819)	(0.309)	(0.681)	(0.000)	(0.282)	(0.162)				
Gas, Water & Multiutilities	-0.289	0.015	-0.100	-0.636	0.789*	-0.046	1.407	0.693***	-0.006	0.424**	0.231	0.395	0.000***	0.000***
	(0.193)	(0.969)	(0.851)	(0.403)	(0.061)	(0.561)	(0.195)	(0.000)	(0.198)	(0.047)				
Non-Life Insurance	0.082	-0.521*	-0.143	1.166	-0.147	0.122*	-1.104*	0.539***	0.004	-0.541***	0.182	0.041**	0.606	0.056*
	(0.650)	(0.089)	(0.790)	(0.230)	(0.752)	(0.087)	(0.096)	(0.000)	(0.421)	(0.009)				

This table reports the OLS regression denoted in equation (10) with Newey-West standard errors. The dependent variable is R_{s,t}, the stock return of sector s at time t. In this table, the dependent variable is noted as the sector of which Datastream constructed a stock index. SST_t x D^season represent the dummy interaction variable between a seasonal dummy and the SST anomaly; which takes on the value of the SST anomaly at time t during a specific season and the value of 0 otherwise. R^IPSA represents the stock return of the Indice de Precio Selectivo de Acciones at time t and R_{t-1} the lagged monthly return of the stock return of sector s at time t-1. The precipitation anomaly (Precip_t) is measured in mm and the temperature anomaly (Temp_t) is in degrees Celsius. The p-values are reported in the parentheses. The adjusted R-squared is noted as R^2. BG represents the Breusch-Godfrey test, BP represents the Breusch-Pagan test and Skew represents the skewness kurtosis test, the values displayed in these three columns are p-values.

*Significant at the 10% level; **significant at the 5% level; ***significant at the 1% level

6. Concluding Remarks

This study aims to identify the influence of the El Niño Southern-Oscillation on international stock markets and business sectors. It follows the conclusions drawn from a study by Cashin et al. (2017), who found evidence for El Niño to have a significant effect on worldwide economic growth, inflation and commodity prices. The assumption that El Niño affects the real economy gives rise to the concept that it might also affect stock performance around the world. By examining the monthly stock returns of 22 stock indices and 12 business sectors I have investigated the subject summarized in the following two research questions:

1. How do El Niño-related events affect the equity markets around the world?
2. How do El Niño-related events affect U.S. business sectors?

The empirical findings indicate that Sea Surface Temperature (SST) anomalies, an indicator of an El Niño episode, only have a marginal effect on international stock markets. First, I did not find consistent evidence to confirm that the presence of an ENSO cycle directly impacts equity market returns, at time t. Only 1 of the studied 22 countries was (positively) affected by El Niño (at a 10% significance level). Following the assumption that El Niño could have a delayed effect on the climate and/or stock market, I studied the lagged effects of an ENSO cycle. Again, I did not find sufficient evidence for a (significant) relationship between El Niño and stock market returns.

The results of the U.S. sector analysis provide a clearer picture of a significant effect of El Niño on the performance of certain sectors. From the studied sectors, 6 out of 12 are affected, from whom 5 directly (at time t). In contrast to the international stock markets I found evidence for the ENSO to be seasonally influenced. The most notable results are those of the household sector during winter, and the travel & leisure sector during autumn, both sectors are positively affected at a significance level of 1%. Across the different sectors, a slightly predominant positive effect of El Niño is found, which might be an explanation for the fact that the stock market as a whole is not significantly influenced. These results are in line with the international business sector analysis which were also mostly positive.

Finally, I constructed a SST anomaly forecasting model and tested whether the difference between forecasted anomalies and observed anomalies, the 'El Niño surprise', could explain the stock returns of business sectors and/or stock markets. The overall impact of the surprise on the international stock market is negative when the forecasted SST anomaly is higher than the observed anomaly, indicating that investors initially account for a positive effect of El Niño (based on forecasts) and respond negatively if the observed SST anomaly is lower than expected. The negative response is between -0.150% and -0.578% to a one-unit standard deviation of the El Niño surprise.

Overall, I conclude that El Niño-related events do have a significant effect on the monthly stock returns of international stock markets as well as international business sectors. In my view this is foremost due to the finding that investors use forecasts to account for El Niño effects in advance. Not all country/sector equity indices in my samples are affected by El Niño related events. However, those who are, are all located in the Americas or South-East Asia. Unsurprisingly, the climate in these geographical areas are also identified to be the most affected by the ENSO cycle (Figure 1). One final remark is on the comparison of my results with those of Cashin et al. (2017). In both studies, evidence is found for the ENSO cycle to have an (predominantly positive) effect on the countries which's climate is also directly affected by El Niño, although, no spillover effect to European countries is found in my study.

7. Limitations & Recommendations for Future Research

I have encountered some limitations and shortcomings while writing this thesis. In the coming section I discuss these issues after which I make suggestions for future research.

Although I found significant evidence for the existence of a relationship between El Niño and stock performance, I still expect that this study did not capture the whole impact of the ENSO cycle on stock returns. As can be derived from the sector analysis, the impact of El Niño varies between sectors and perhaps even between companies. If the affected companies only make up for a fraction of the total sector, then this shall probably not be translated into the results. Another similar limitation is that large-cap companies are overly represented in the studied indices. Large companies are becoming more and more diversified, on a vertical, horizontal and even conglomerate level. In my view, an El Niño-related effect is less detectable when studying these types of companies. In order to overcome these issues, future researchers should investigate the impact of El Niño (surprise) on relatively small cap index funds. By doing this I expect that a possible effect becomes better visible in certain Indices.

Regarding the study on the stock markets of South American countries, I have encountered a limitation that could be assigned to the unavailability of data. I could not include all the South American countries I initially wanted as the dataset was largely incomplete. The data on weather anomalies was full of holes and the historical stock index data was too volatile and/or had too little observations to get reliable results. This is unfortunate as these countries' climate is impacted by the ENSO cycle in a variety of ways.

For more accurate and complete results, I have a couple of recommendations regarding my own thesis. Firstly, a new model with lagged seasonal SST anomalies. As stated earlier in my thesis, the actual effect of El Niño on the local climate could be delayed for multiple seasons. By implementing lagged seasonal SST anomalies, it could be possible to capture those effects. Next, I based my sector analysis on a selection of sectors. By including all 54 sectors (created by Datastream) the results will be more complete. Lastly, my (forecasting) models could be made more accurate by using multiple El Niño indicators. Examples of other ENSO indicators are: The Southern Oscillation Index (based on air pressure), Outgoing Longwave Radiation (based on electromagnetic radiation) and sea level anomalies.[7]

Finally, a look into the future. A future where the climate plays an increasingly substantial role in the economy. According to Cai et al. (2015), it is likely that El Niño will intensify extreme weather conditions worldwide on a more frequent basis. For future research It might be interesting to study whether there is also an observable trend in stock market performance. For example, one could use the same models on different time frames. It could be possible that investors in the present adapt immediately to (forecasted) SST anomalies while their predecessors awaited the actual effect of El Niño on the weather. Considering the increased frequency and intensity of ENSO cycles, I would say that in the near future, El Niño is certainly a natural force to be reckoned with.

[7] NOAA, < https://www.ncdc.noaa.gov/teleconnections/enso/indicators/ >.

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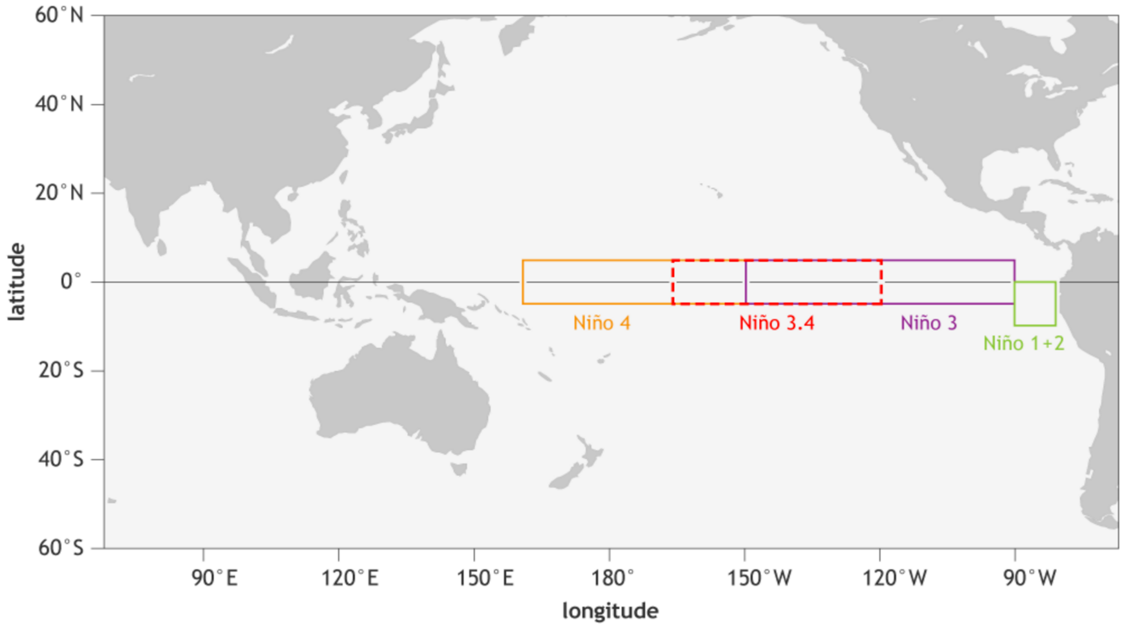
Appendices

Appendix A El Niño Tables and Figures

Figure A.1 The El Niño 3.4 region



This figure shows the the El Niño 3.4 region. The Oceanic Niño Index (ONI) is based on SST departures from average in this region, and is a measure for monitoring, assessing, and predicting ENSO. Source: NOAA (2017)

Table A.1 The 3-month running mean SST anomalies in Niño 3.4 region

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
1950	-1.4	-1.2	-1.1	-1.2	-1.1	-0.9	-0.6	-0.6	-0.5	-0.6	-0.7	-0.8
1951	-0.8	-0.6	-0.2	0.2	0.2	0.4	0.5	0.7	0.8	0.9	0.7	0.6
1952	0.5	0.4	0.4	0.4	0.4	0.2	0.0	0.1	0.2	0.2	0.2	0.3
1953	0.5	0.6	0.7	0.7	0.7	0.7	0.7	0.7	0.8	0.8	0.8	0.7
1954	0.7	0.4	0.0	-0.4	-0.5	-0.5	-0.5	-0.7	-0.7	-0.6	-0.5	-0.5
1955	-0.6	-0.6	-0.7	-0.7	-0.7	-0.6	-0.6	-0.6	-1.0	-1.4	-1.6	-1.4
1956	-0.9	-0.6	-0.6	-0.5	-0.5	-0.4	-0.5	-0.5	-0.4	-0.4	-0.5	-0.4
1957	-0.3	0.0	0.3	0.6	0.7	0.9	1.0	1.2	1.1	1.2	1.3	1.6
1958	1.8	1.7	1.3	0.9	0.7	0.6	0.6	0.4	0.4	0.4	0.5	0.6
1959	0.6	0.6	0.5	0.3	0.2	-0.1	-0.2	-0.3	-0.1	0.0	0.0	0.0
1960	-0.1	-0.1	-0.1	0.0	0.0	0.0	0.1	0.2	0.3	0.2	0.1	0.1
1961	0.0	0.0	-0.1	0.0	0.1	0.2	0.1	-0.1	-0.3	-0.3	-0.2	-0.2
1962	-0.2	-0.2	-0.2	-0.3	-0.3	-0.2	-0.1	-0.2	-0.2	-0.3	-0.3	-0.4
1963	-0.4	-0.2	0.1	0.2	0.2	0.4	0.7	1.0	1.1	1.2	1.2	1.1
1964	1.0	0.6	0.1	-0.3	-0.6	-0.6	-0.7	-0.7	-0.8	-0.8	-0.8	-0.8
1965	-0.5	-0.3	-0.1	0.1	0.4	0.7	1.0	1.3	1.6	1.7	1.8	1.5
1966	1.3	1.0	0.9	0.6	0.3	0.2	0.2	0.1	0.0	-0.1	-0.1	-0.3
1967	-0.4	-0.5	-0.5	-0.5	-0.2	0.0	0.0	-0.2	-0.3	-0.4	-0.4	-0.5
1968	-0.7	-0.8	-0.7	-0.5	-0.1	0.2	0.5	0.4	0.3	0.4	0.6	0.8
1969	0.9	1.0	0.9	0.7	0.6	0.5	0.4	0.5	0.8	0.8	0.8	0.7
1970	0.6	0.4	0.4	0.3	0.1	-0.3	-0.6	-0.8	-0.8	-0.8	-0.9	-1.2
1971	-1.3	-1.3	-1.1	-0.9	-0.8	-0.7	-0.8	-0.7	-0.8	-0.8	-0.9	-0.8
1972	-0.7	-0.4	0.0	0.3	0.6	0.8	1.1	1.3	1.5	1.8	2.0	1.9
1973	1.7	1.2	0.6	0.0	-0.4	-0.8	-1.0	-1.2	-1.4	-1.7	-1.9	-1.9
1974	-1.7	-1.5	-1.2	-1.0	-0.9	-0.8	-0.6	-0.4	-0.4	-0.6	-0.7	-0.6
1975	-0.5	-0.5	-0.6	-0.6	-0.7	-0.8	-1.0	-1.1	-1.3	-1.4	-1.5	-1.6
1976	-1.5	-1.1	-0.7	-0.4	-0.3	-0.1	0.1	0.3	0.5	0.7	0.8	0.8
1977	0.7	0.6	0.4	0.3	0.3	0.4	0.4	0.4	0.5	0.6	0.8	0.8
1978	0.7	0.4	0.1	-0.2	-0.3	-0.3	-0.4	-0.4	-0.4	-0.3	-0.1	0.0
1979	0.0	0.1	0.2	0.3	0.3	0.1	0.1	0.2	0.3	0.5	0.5	0.6
1980	0.6	0.5	0.3	0.4	0.5	0.5	0.3	0.2	0.0	0.1	0.1	0.0
1981	-0.2	-0.4	-0.4	-0.3	-0.2	-0.3	-0.3	-0.3	-0.2	-0.1	-0.1	0.0
1982	0.0	0.1	0.2	0.5	0.6	0.7	0.8	1.0	1.5	1.9	2.1	2.1
1983	2.1	1.8	1.5	1.2	1.0	0.7	0.3	0.0	-0.3	-0.6	-0.8	-0.8
1984	-0.5	-0.3	-0.3	-0.4	-0.4	-0.4	-0.3	-0.2	-0.3	-0.6	-0.9	-1.1
1985	-0.9	-0.7	-0.7	-0.7	-0.7	-0.6	-0.4	-0.4	-0.4	-0.3	-0.2	-0.3
1986	-0.4	-0.4	-0.3	-0.2	-0.1	0.0	0.2	0.4	0.7	0.9	1.0	1.1
1987	1.1	1.2	1.1	1.0	0.9	1.1	1.4	1.6	1.6	1.4	1.2	1.1
1988	0.8	0.5	0.1	-0.3	-0.8	-1.2	-1.2	-1.1	-1.2	-1.4	-1.7	-1.8
1989	-1.6	-1.4	-1.1	-0.9	-0.6	-0.4	-0.3	-0.3	-0.3	-0.3	-0.2	-0.1
1990	0.1	0.2	0.2	0.2	0.2	0.3	0.3	0.3	0.4	0.3	0.4	0.4
1991	0.4	0.3	0.2	0.2	0.4	0.6	0.7	0.7	0.7	0.8	1.2	1.4

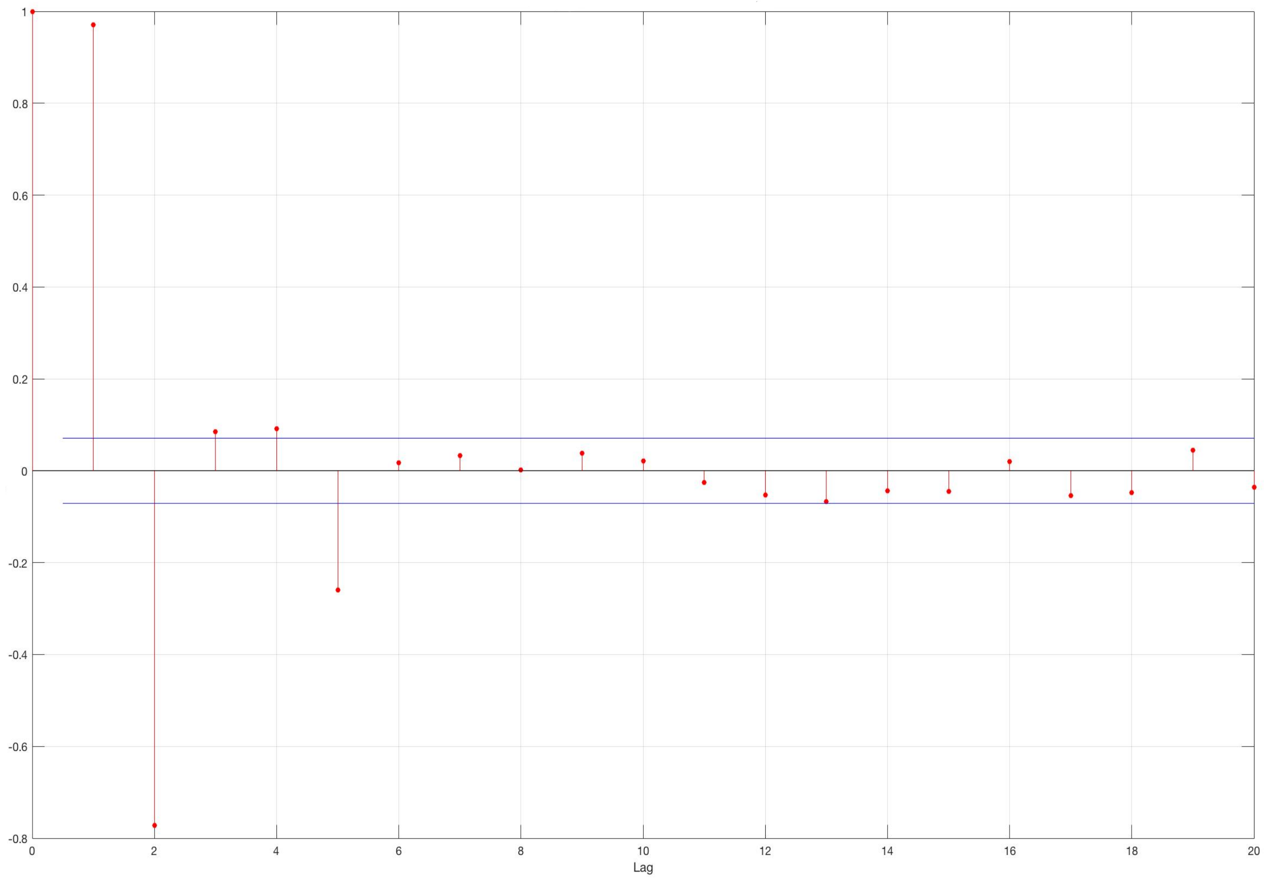
Table A.2 Continued

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
1992	1.6	1.5	1.4	1.2	1.0	0.8	0.5	0.2	0.0	-0.1	-0.1	0.0
1993	0.2	0.3	0.5	0.7	0.8	0.6	0.3	0.2	0.2	0.2	0.1	0.1
1994	0.1	0.1	0.2	0.3	0.4	0.4	0.4	0.4	0.4	0.6	0.9	1.0
1995	0.9	0.7	0.5	0.3	0.2	0.0	-0.2	-0.5	-0.7	-0.9	-1.0	-0.9
1996	-0.9	-0.7	-0.6	-0.4	-0.2	-0.2	-0.2	-0.3	-0.3	-0.4	-0.4	-0.5
1997	-0.5	-0.4	-0.2	0.1	0.6	1.0	1.4	1.7	2.0	2.2	2.3	2.3
1998	2.1	1.8	1.4	1.0	0.5	-0.1	-0.7	-1.0	-1.2	-1.2	-1.3	-1.4
1999	-1.4	-1.2	-1.0	-0.9	-0.9	-1.0	-1.0	-1.0	-1.1	-1.2	-1.4	-1.6
2000	-1.6	-1.4	-1.1	-0.9	-0.7	-0.7	-0.6	-0.5	-0.6	-0.7	-0.8	-0.8
2001	-0.7	-0.6	-0.5	-0.3	-0.2	-0.1	0.0	-0.1	-0.1	-0.2	-0.3	-0.3
2002	-0.2	-0.1	0.1	0.2	0.4	0.7	0.8	0.9	1.0	1.2	1.3	1.1
2003	0.9	0.6	0.4	0.0	-0.2	-0.1	0.1	0.2	0.3	0.4	0.4	0.4
2004	0.3	0.2	0.1	0.1	0.2	0.3	0.5	0.7	0.7	0.7	0.7	0.7
2005	0.6	0.6	0.5	0.5	0.4	0.2	0.1	0.0	0.0	-0.1	-0.4	-0.7
2006	-0.7	-0.6	-0.4	-0.2	0.0	0.1	0.2	0.3	0.5	0.8	0.9	1.0
2007	0.7	0.3	0.0	-0.1	-0.2	-0.2	-0.3	-0.6	-0.8	-1.1	-1.2	-1.3
2008	-1.4	-1.3	-1.1	-0.9	-0.7	-0.5	-0.3	-0.2	-0.2	-0.3	-0.5	-0.7
2009	-0.8	-0.7	-0.4	-0.1	0.2	0.4	0.5	0.6	0.7	1.0	1.2	1.3
2010	1.3	1.1	0.8	0.5	0.0	-0.4	-0.8	-1.1	-1.3	-1.4	-1.3	-1.4
2011	-1.3	-1.1	-0.8	-0.6	-0.3	-0.2	-0.3	-0.5	-0.7	-0.9	-0.9	-0.8
2012	-0.7	-0.6	-0.5	-0.4	-0.3	-0.1	0.1	0.3	0.4	0.4	0.2	-0.2
2013	-0.4	-0.5	-0.3	-0.2	-0.2	-0.2	-0.2	-0.2	-0.2	-0.2	-0.2	-0.3
2014	-0.5	-0.6	-0.4	-0.2	0.0	0.0	0.0	0.0	0.2	0.4	0.6	0.7
2015	0.6	0.6	0.6	0.8	1.0	1.2	1.5	1.8	2.1	2.4	2.5	2.6
2016	2.5	2.2	1.7	1.0	0.5	0.0	-0.3	-0.6	-0.7	-0.7	-0.7	-0.6
2017	-0.3	-0.1	0.1	0.3	0.4	0.4	0.1	-0.1				

This Table reports the 3-month running mean SST anomalies in the Niño 3.4 region. The values are noted in degrees Celsius. Values above 0.5 are coloured red and represent an El Niño period.

Appendix B Data Checks

Figure B.1 Partial autocorrelation function of SST anomalies in the El Niño 3.4 region



The red lines represent the partial autocorrelation of SST anomalies in the El Niño 3.4 region. The blue lines represent the 5% significance limit for the partial autocorrelations. On the x-axis the 20 lags are noted.

Table B.1 Pearson's correlation matrix for independent variables in the U.S.

	SST_t^{An}	ΔI_{t-1}	D_t^{Jan}	R_{t-1}	D_t^{Winter}	D_t^{Spring}	D_t^{Summer}	D_t^{Autumn}	$Precip_t^{An}$	$Temp_t^{An}$
SST_t^{An}	1									
ΔI_{t-1}	0.020 (0.568)	1								
D_t^{Jan}	0.000 (0.997)	-0.045 (0.209)	1							
R_{t-1}	-0.013 (0.715)	0.021 (0.600)	0.075** (0.034)	1						
D_t^{Winter}	0.004 (0.9037)	-0.007 (0.843)	0.523*** (0.000)	0.086** (0.015)	1					
D_t^{Spring}	-0.014 (0.686)	-0.023 (0.524)	-0.173*** (0.000)	0.066* (0.061)	-0.332*** (0.000)	1				
D_t^{Summer}	0.001 (0.974)	0.048 (0.177)	-0.173*** (0.000)	-0.053 (0.138)	-0.332*** (0.000)	-0.335*** (0.000)	1			
D_t^{Autumn}	0.009 (0.801)	-0.018 (0.607)	-0.173*** (0.000)	-0.099*** (0.005)	-0.332*** (0.000)	-0.335*** (0.000)	-0.335*** (0.000)	1		
$Precip_t^{An}$	0.029 (0.399)	-0.026 (0.467)	-0.058* (0.099)	0.008 (0.810)	0.045 (0.204)	0.059* (0.096)	-0.048 (0.172)	-0.056 (0.116)	1	
$Temp_t^{An}$	0.011 (0.748)	0.037 (0.297)	-0.016 (0.650)	-0.025 (0.465)	-0.023 (0.511)	0.023 (0.516)	-0.029 (0.403)	0.030 (0.397)	-0.049 (0.159)	1

This table reports the Pearson correlation matrix of the different independent variables of equations (2), (3), (4) and (10) for New York City (U.S.). I_t represents the change in U.S. 3-months T-Bill, R_{t-1} the lagged monthly return of the DJIA. The seasonal dummy variables are noted as D^season and takes on the value of 1 during the corresponding season and 0 otherwise. The precipitation anomaly (Precip_t) is measured in mm and the temperature anomaly (Temp_t) is in degrees Celsius. The p-values are reported in the parentheses.

*Significant at the 10% level; **significant at the 5% level; ***significant at the 1% level

Table B.2 Pearson's correlation matrix for (lagged) SST anomalies and weather variables in China

	SST_t^{An}	SST_{t-4}^{An}	SST_{t-8}^{An}	SST_{t-12}^{An}	SST_{t-16}^{An}	SST_{t-20}^{An}	SST_{t-24}^{An}	SST_{t-28}^{An}	$Precip_t^{An}$	$Temp_t^{An}$
SST_t^{An}	1									
SST_{t-4}^{An}	0.684*** (0.000)	1								
SST_{t-8}^{An}	0.206*** (0.000)	0.6842*** (0.000)	1							
SST_{t-12}^{An}	-0.087** (0.014)	0.206*** (0.000)	0.686*** (0.000)	1						
SST_{t-16}^{An}	-0.192*** (0.000)	-0.088** (0.014)	0.208*** (0.000)	0.686*** (0.000)	1					
SST_{t-20}^{An}	-0.238*** (0.000)	-0.192*** (0.000)	-0.089** (0.013)	0.213*** (0.000)	0.693*** (0.000)	1				
SST_{t-24}^{An}	-0.243*** (0.000)	-0.240*** (0.000)	-0.202*** (0.000)	-0.082** (0.023)	0.232*** (0.000)	0.697*** (0.000)	1			
SST_{t-28}^{An}	-0.148*** (0.000)	-0.244*** (0.000)	-0.249*** (0.000)	-0.199*** (0.000)	-0.073** (0.043)	0.226*** (0.000)	0.686*** (0.000)	1		
$Precip_t^{An}$	0.076** (0.035)	0.050 (0.171)	-0.015 (0.671)	-0.060* (0.097)	-0.102*** (0.005)	-0.153*** (0.000)	-0.082** (0.024)	-0.039 (0.288)	1	
$Temp_t^{An}$	0.007 (0.848)	0.052 (0.156)	0.0457 (0.214)	-0.013 (0.724)	-0.042 (0.260)	-0.041 (0.270)	-0.016 (0.673)	0.026 (0.490)	-0.069* (0.060)	1

This table reports the Pearson correlation matrix of the monthly (lagged) SST anomaly variables as well as the monthly temperature and precipitation anomaly variables in Shanghai (China). The precipitation anomaly is measured in mm and the temperature anomaly is in degrees Celsius. The p-values are reported in the parentheses.

*Significant at the 10% level; **significant at the 5% level; ***significant at the 1% level

Table B.3 Pearson's correlation matrix for SST and weather variables in in the U.S.

	SST_t^{An}	SST_{t-4}^{An}	SST_{t-8}^{An}	SST_{t-12}^{An}	$Precip_t^{An}$	$Temp_t^{An}$
SST_t^{An}	1					
SST_{t-4}^{An}	0.684*** (0.000)	1				
SST_{t-8}^{An}	0.206*** (0.000)	0.684*** (0.000)	1			
SST_{t-12}^{An}	-0.088** (0.014)	0.206*** (0.000)	0.686*** (0.000)	1		
$Precip_t^{An}$	0.011 (0.748)	-0.024 (0.507)	-0.021 (0.557)	-0.008 (0.825)	1	
$Temp_t^{An}$	0.030 (0.399)	0.075** (0.034)	0.089** (0.013)	0.029 (0.417)	-0.050 (0.159)	1

This table reports the Pearson correlation matrix of the monthly (lagged) SST anomaly variables as well as the monthly temperature and precipitation anomaly variables in New York City (U.S.). The precipitation anomaly is measured in mm and the temperature anomaly is in degrees Celsius. The p-values are reported in the parentheses.

*Significant at the 10% level; **significant at the 5% level; ***significant at the 1% level

Appendix C Statistical Analysis

Table C.1 Estimates of returns regressions – Eq. (4)

Model: $R_{i,t} = \beta_0 + \beta_1\, SST_t^{An} + \beta_2\, SST_{t-4}^{An} + \beta_3\, SST_{t-8}^{An} + \beta_4\, SST_{t-12}^{An} + \beta_5\, SST_{t-16}^{An} + \beta_6\, SST_{t-20}^{An} + \beta_7\, SST_{t-24}^{An} + \beta_8 \Delta I_{i,t-1} + \beta_9 D_t^{Jan} + \beta_{10} R_{i,t-1} + \beta_{11} Precip_t^{An} + \beta_{12} Temp_t^{An} + \varepsilon_{i,t}$

	β_0	SST_t^{An}	SST_{t-4}^{An}	SST_{t-8}^{An}	SST_{t-12}^{An}	SST_{t-16}^{An}	SST_{t-20}^{An}	SST_{t-24}^{An}	ΔI_{t-1}	D_t^{Jan}	R_{t-1}	$Precip_t^{An}$	$Temp_t^{An}$	$\bar{R}^2$	BG	BP	$Skew$
Argentina	0.294	-0.071	-0.101	0.676	-0.818	0.764	-0.322	-0.173	-0.153**	1.919*	0.084	0.003	0.006	0.011	0.487	0.920	0.000***
MERVAL	(0.361)	(0.899)	(0.904)	(0.468)	(0.391)	(0.423)	(0.715)	(0.769)	(0.034)	(0.068)	(0.147)	(0.516)	(0.981)				
Australia	0.118	0.035	-0.247	0.430	-0.209	0.176	0.218	0.223	0.482	-0.158	-0.011	-0.001	0.122	-0.012	0.205	0.017**	0.002***
S&P / ASX 200	(0.390)	(0.862)	(0.414)	(0.203)	(0.548)	(0.607)	(0.485)	(0.301)	(0.319)	(0.676)	(0.853)	(0.264)	(0.292)				
Brazil	0.496	-0.260	0.099	0.629	-0.564	0.769	-0.431	0.767*	0.077	0.504	0.039	-0.001	-0.035	-0.017	0.011**	0.132	0.000***
IBOV	(0.348)	(0.591)	(0.888)	(0.430)	(0.494)	(0.347)	(0.559)	(0.089)	(0.279)	(0.581)	(0.567)	(0.855)	(0.907)				
Canada	0.167**	-0.052	0.038	0.286	-0.157	0.085	-0.084	0.181	-0.413***	-0.330	0.084**	-0.003	0.031	0.022	0.646	0.019**	0.000***
S&P / TSX	(0.020)	(0.702)	(0.848)	(0.191)	(0.472)	(0.696)	(0.681)	(0.206)	(0.005)	(0.182)	(0.020)	(0.124)	(0.367)				
Chile	0.331**	0.153	-0.419	0.903*	-0.712	0.558	-0.236	0.151	-0.048	0.688	0.201***	-0.003	-0.033	0.033	0.328	0.025**	0.018**
IPSA	(0.047)	(0.609)	(0.345)	(0.070)	(0.165)	(0.260)	(0.603)	(0.632)	(0.826)	(0.229)	(0.001)	(0.444)	(0.858)				
China	-0.260	-0.068	-0.267	1.051	-1.677*	1.713*	-1.638**	1.193**	-2.177**	-0.265	-0.029	0.007*	0.275	0.012	0.635	0.000***	0.000***
SZSE	(0.563)	(0.901)	(0.739)	(0.255)	(0.082)	(0.063)	(0.048)	(0.036)	(0.026)	(0.791)	(0.570)	(0.087)	(0.231)				
France	0.037	-0.193	-0.073	0.454	-0.426	0.511	-0.298	0.367	-0.193	-0.167	0.051	-0.003	0.061	-0.007	0.820	0.000***	0.000***
CAC 40	(0.827)	(0.476)	(0.857)	(0.315)	(0.351)	(0.265)	(0.492)	(0.223)	(0.609)	(0.746)	(0.360)	(0.491)	(0.487)				
Germany	0.220**	-0.125	0.029	0.238	-0.375	0.243	-0.310	0.405*	-0.040	0.532	0.030	-0.002	0.057	0.003	0.030**	0.644	0.000***
DAX 30	(0.037)	(0.608)	(0.930)	(0.467)	(0.221)	(0.417)	(0.276)	(0.035)	(0.780)	(0.180)	(0.572)	(0.399)	(0.253)				
Hong Kong	0.477	-0.039	-0.219	0.486	-0.174	0.043	0.187	0.058	-0.501**	-0.568	0.006	-0.001	-0.234	0.000	0.864	0.697	0.000***
Hang Seng	(0.008)	(0.907)	(0.661)	(0.381)	(0.763)	(0.939)	(0.717)	(0.869)	(0.018)	(0.359)	(0.891)	(0.612)	(0.175)				
Italy	-0.268	0.012	-0.405	0.710	-0.252	0.242	-0.327	0.259	-0.867	-0.175	0.045	0.000	0.320**	-0.011	0.910	0.614	0.010**
FTSE MIB	(0.255)	(0.973)	(0.440)	(0.222)	(0.666)	(0.677)	(0.549)	(0.489)	(0.398)	(0.799)	(0.501)	(0.914)	(0.038)				
Japan	0.276	-0.039	-0.183	0.482*	-0.357	0.236	-0.120	0.204	-0.532	0.705**	0.055	0.000	-0.112*	0.008	0.857	0.000***	0.000***
Nikkei 225	(0.012)	(0.831)	(0.475)	(0.082)	(0.209)	(0.415)	(0.687)	(0.297)	(0.242)	(0.027)	(0.239)	(0.801)	(0.097)				

Table C.1 Continued

	β_0	SST_t^{An}	SST_{t-4}^{An}	SST_{t-8}^{An}	SST_{t-12}^{An}	SST_{t-16}^{An}	SST_{t-20}^{An}	SST_{t-24}^{An}	ΔI_{t-1}	D_t^{Jan}	R_{t-1}	$Precip_t^{An}$	$Temp_t^{An}$	$\bar{R}^2$	BG	BP	$Skew$
Mexico	0.892***	-0.209	0.211	0.333	-0.084	0.136	-0.002	0.138	-0.286**	-0.302	-0.093	0.002	-0.469*	0.054	0.487	0.000***	0.001***
MEXBOL	(0.007)	(0.550)	(0.678)	(0.546)	(0.879)	(0.797)	(0.997)	(0.728)	(0.039)	(0.718)	(0.381)	(0.566)	(0.051)				
Netherlands	0.182	-0.375	0.451	0.003	-0.001	0.139	-0.061	0.246	-0.680	-0.190	0.072	-0.002	0.069	0.001	0.034**	0.000***	0.000***
AEX	(0.225)	(0.156)	(0.241)	(0.993)	(0.999)	(0.742)	(0.877)	(0.362)	(0.222)	(0.693)	(0.156)	(0.413)	(0.341)				
Norway	0.270*	-0.281	0.111	0.346	-0.460	0.539	-0.408	0.417	-1.007***	0.244	0.145***	-0.004	0.034	0.070	0.003***	0.000***	0.000***
OSEAX	(0.065)	(0.298)	(0.779)	(0.434)	(0.299)	(0.220)	(0.318)	(0.139)	(0.000)	(0.623)	(0.003)	(0.204)	(0.554)				
Singapore	0.043	-0.408	0.587	0.029	-0.499	0.844*	-0.569	0.287	-0.585*	1.067**	0.073*	-0.001	-0.128	0.016	0.078*	0.765	0.000***
MSCI	(0.768)	(0.154)	(0.157)	(0.949)	(0.294)	(0.072)	(0.183)	(0.313)	(0.063)	(0.035)	(0.099)	(0.487)	(0.669)				
South Africa	0.083	-0.191	-0.204	0.352	-0.386	0.322	0.332	0.102	-1.523***	0.945*	-0.016	-0.005*	0.159	0.136	0.884	0.000***	0.000***
JSE / FTSE 40	(0.719)	(0.529)	(0.634)	(0.423)	(0.432)	(0.514)	(0.463)	(0.713)	(0.007)	(0.064)	(0.819)	(0.057)	(0.253)				
South Korea	0.290	-0.339	-0.058	0.461	-0.082	-0.362	-0.150	-0.164	-0.160	0.127	0.082	0.000	-0.088	0.015	0.145	0.315	0.000***
KOSPI 200	(0.096)	(0.257)	(0.895)	(0.345)	(0.868)	(0.464)	(0.738)	(0.593)	(0.276)	(0.809)	(0.078)	(0.947)	(0.383)				
Spain	0.076	0.015	0.055	0.043	0.167	-0.072	0.234	-0.079	-0.655**	0.400	0.066	0.000	0.090	-0.007	0.646	0.000***	0.000***
IBEX 35	(0.668)	(0.960)	(0.899)	(0.929)	(0.739)	(0.866)	(0.619)	(0.807)	(0.026)	(0.476)	(0.228)	(0.939)	(0.379)				
United Kingdom	0.218**	-0.182	0.208	0.082	-0.220	0.300	-0.118	0.044	-0.235	0.068	-0.022	-0.005	0.003	-0.015	0.879	0.009***	0.000***
FTSE 100	(0.049)	(0.367)	(0.483)	(0.803)	(0.507)	(0.359)	(0.695)	(0.828)	(0.347)	(0.851)	(0.659)	(0.169)	(0.967)				
United States	0.184**	-0.045	0.001	0.194	-0.132	0.086	-0.081	0.145	-0.508***	0.191	0.030	-0.001	0.071	0.013	0.225	0.115	0.000***
S&P 500	(0.023)	(0.759)	(0.995)	(0.426)	(0.587)	(0.724)	(0.718)	(0.346)	(0.000)	(0.479)	(0.445)	(0.527)	(0.109)				
United States	0.213*	-0.048	0.084	0.360	-0.293	0.251	-0.150	0.322	-0.657***	0.763*	0.089**	-0.002	0.076	0.033	0.594	0.000***	0.000***
NASDAQ	(0.085)	(0.828)	(0.801)	(0.334)	(0.433)	(0.502)	(0.662)	(0.165)	(0.001)	(0.061)	(0.034)	(0.230)	(0.249)				
United States	0.210***	-0.098	0.052	0.097	-0.049	0.054	-0.011	0.044	-0.533***	0.107	0.018	-0.001	0.056	0.012	0.148	0.086**	0.000***
DJIA	(0.003)	(0.461)	(0.789)	(0.647)	(0.815)	(0.797)	(0.955)	(0.747)	(0.000)	(0.654)	(0.607)	(0.578)	(0.155)				

This table reports the OLS regression denoted in equation (4) with Newey-West standard errors. The dependent variable is R_{i,t}, the stock return of country I at time t. In this table, the dependent variable is noted as the county in which the stock index is located. SST_t represent the (lagged) SST anomalies in the El Niño region. I_t represents the change in the national 3-months T-Bill, R_{t-1} the lagged monthly return of the stock return of country i at time t-1. The precipitation anomaly (Precip_t) is measured in mm and the temperature anomaly (Temp_t) is in degrees Celsius. The p-values are reported in the parentheses. The adjusted R-squared is noted as R^2. BG represents the Breusch-Godfrey test, BP represents the Breusch-Pagan test and Skew represents the skewness kurtosis test, the values displayed in these three columns are p-values.

*Significant at the 10% level; **significant at the 5% level; ***significant at the 1% level

Table C.2 Estimates of returns regressions – Eq. (8)

Model: $R_{i,t} = \beta_0 + \beta_1 SST_t^{Surp} + \beta_2 \Delta I_{i,t-1} + \beta_3 D_t^{Jan} + \beta_4 R_{i,t-1} + \beta_5 Precip_t^{An} + \beta_6 Temp_t^{An} + \varepsilon_{i,t}$

	β_0	SST_t^{Surp}	ΔI_{t-1}	D_t^{Jan}	R_{t-1}	$Precip_t^{An}$	$Temp_t^{An}$	$\bar{R}^2$	BG	BP	$Skew$
Argentina	0.330	-0.578*	-0.147**	2.158**	0.084	0.004	-0.071	0.039	0.319	0.596	0.002***
MERVAL	(0.294)	(0.063)	(0.038)	(0.038)	(0.140)	(0.391)	(0.741)				
Australia	0.144	-0.003	0.545	-0.172	-0.002	-0.002	0.096	0.000	0.350	0.014**	0.002***
S&P / ASX 200	(0.290)	(0.976)	(0.480)	(0.658)	(0.981)	(0.241)	(0.348)				
Brazil	0.770	-0.322	0.063	0.527	0.049	-0.001	-0.217	0.000	0.072*	0.099*	0.000***
IBOV	(0.122)	(0.240)	(0.376)	(0.564)	(0.471)	(0.849)	(0.372)				
Canada	0.167**	-0.150**	0.388**	0.332	0.089*	-0.002	0.028	0.027	0.426	0.001***	0.000***
S&P / TSX	(0.018)	(0.026)	(0.027)	(0.188)	(0.060)	(0.158)	(0.408)				
Chile	0.311*	-0.311*	-0.070	0.816	0.215***	0.005	0.021	0.050	0.377	0.077*	0.010**
IPSA	(0.059)	(0.061)	(0.748)	(0.150)	(0.000)	(0.250)	(0.904)				
China	-0.351	-0.322	-2.079	-0.164	-0.015	0.008	0.325*	0.010	0.768	0.000***	0.000***
SZSE	(0.384)	(0.933)	(0.297)	(0.905)	(0.785)	(0.212)	(0.091)				
France	0.008	-0.171	-0.004	0.203	-0.015	0.006	0.058	0.000	0.680	0.000***	0.000***
CAC 40	(0.958)	(0.264)	(0.989)	(0.716)	(0.811)	(0.253)	(0.466)				
Germany	0.208**	-0.091	-0.049	-0.558	0.045	-0.002	0.057	0.001	0.040**	0.145	0.000***
DAX 30	(0.045)	(0.384)	(0.732)	(0.171)	(0.390)	(0.483)	(0.262)				
Hong Kong	0.480***	-0.262	-0.491**	-0.573	0.010	-0.001	-0.255	0.050	0.934	0.524	0.008***
Hang Seng	(0.007)	(0.191)	(0.019)	(0.348)	(0.841)	(0.540)	(0.133)				
Italy	-0.220	-0.142	-0.964	-0.162	0.060	0.000	0.264*	0.003	0.942	0.917	0.017**
FTSE MIB	(0.339)	(0.488)	(0.334)	(0.813)	(0.366)	(0.934)	(0.079)				
Japan	0.289**	-0.127	-0.490	0.718**	0.062*	0.000	-0.123*	0.010	0.944	0.000***	0.000***
Nikkei 225	(0.016)	(0.150)	(0.254)	(0.025)	(0.088)	(0.829)	(0.096)				
Mexico	0.823***	-0.284	-0.271**	-0.214	-0.077	0.002	-0.436*	0.073	0.312	0.000***	0.000***
MEXBOL	(0.008)	(0.139)	(0.048)	(0.792)	(0.454)	(0.548)	(0.050)				
Netherlands	0.201	-0.080	-0.674	-0.169	0.083	-0.002	0.065	-0.001	0.056*	0.000***	0.000***
AEX	(0.191)	(0.577)	(0.351)	(0.682)	(0.257)	(0.464)	(0.327)				
Norway	0.278*	-0.198	-0.983***	0.306	0.150***	-0.005	0.039	0.073	0.005**	0.000***	0.000***
OSEAX	(0.056)	(0.166)	(0.000)	(0.538)	(0.002)	(0.154)	(0.494)				
Singapore	0.037	-0.236	-0.667**	1.154**	0.076*	-0.001	-0.054	0.019	0.126	0.783	0.000***
MSCI Singapore	(0.797)	(0.111)	(0.033)	(0.023)	(0.084)	(0.613)	(0.813)				
South Africa	0.171	0.037	-1.582***	0.862*	-0.005	-0.005*	0.084	0.151	0.792	0.000***	0.000***
JSE / FTSE 40	(0.443)	(0.854)	(0.004)	(0.092)	(0.934)	(0.038)	(0.476)				

Table C.2 Continued

	β_0	SST_t^{Surp}	ΔI_{t-1}	D_t^{Jan}	R_{t-1}	$Precip_t^{An}$	$Temp_t^{An}$	$\bar{R}^2$	BG	BP	$Skew$
South Korea KOSPI 200	0.313 (0.066)	-0.212 (0.165)	-0.175 (0.230)	0.148 (0.780)	0.111** (0.015)	0.000 (0.983)	-0.114 (0.277)	0.009	0.524	0.210	0.000***
Spain IBEX 35	0.117 (0.518)	-0.246* (0.093)	0.609* (0.066)	0.438 (0.390)	0.063 (0.371)	0.000 (0.962)	0.069 (0.470)	0.012	0.887	0.001***	0.000***
United Kingdom FTSE 100	0.221 (0.063)	-0.141 (0.148)	-0.274 (0.333)	0.119 (0.747)	-0.020 (0.764)	-0.005 (0.146)	0.000 (0.996)	-0.003	0.878	0.042**	0.000***
United States S&P 500	0.188** (0.019)	-0.160** (0.034)	-0.487*** (0.001)	0.233 (0.386)	0.026 (0.498)	-0.001 (0.511)	0.068 (0.120)	0.025	0.250	0.153	0.000***
United States NASDAQ	0.207 (0.115)	-0.241** (0.033)	-0.618*** (0.003)	0.795* (0.056)	0.093 (0.140)	-0.002 (0.242)	0.080 (0.194)	0.039	0.685	0.001***	0.000***
United States DJIA	0.217 (0.002)	-0.113* (0.078)	-0.507*** (0.000)	0.108 (0.641)	0.014 (0.680)	-0.001 (0.560)	0.050 (0.194)	0.019	0.169	0.095*	0.000***

This table reports the OLS regression denoted in equation (8) with Newey-West standard errors. The dependent variable is R_{i,t}, the stock return of country I at time t. In this table, the dependent variable is noted as the county in which the stock index is located. SST_t represents the SST surprise in the El Niño region calculated according equation (6). I_t represents the change in the national 3-months T-Bill, R_{t-1} the lagged monthly return of the stock return of country i at time t-1. The precipitation anomaly (Precip_t) is measured in mm and the temperature anomaly (Temp_t) is in degrees Celsius. The p-values are reported in the parentheses. The adjusted R-squared is noted as R^2. BG represents the Breusch-Godfrey test, BP represents the Breusch-Pagan test and Skew represents the skewness kurtosis test, the values displayed in these three columns are p-values.

*Significant at the 10% level; **significant at the 5% level; ***significant at the 1% level

Table C.3 Estimates of returns regressions – Eq. (10) U.S.

Model: $R_{s,t} = \beta_0 + \beta_1\, D_t^{Winter} \times SST_t^{An} + \beta_2\, D_t^{Spring} \times\ SST_t^{An}\ \ + \beta_3\, D_t^{Summer} \times SST_t^{An}\ + \beta_4\, D_t^{Autumn} \times SST_t^{An} +\ \beta_5 R_t^{DJIA} +\ \beta_6 D_t^{Jan} + \beta_7 R_{s,t-1} + +\beta_8 Precip_t^{An} + \beta_9 Temp_t^{An} + \varepsilon_{s,t}$

	β_0	$D_t^{Winter} \times SST_t^{An}$	$D_t^{Spring} \times SST_t^{An}$	$D_t^{Summer} \times SST_t^{An}$	$D_t^{Autumn} \times SST_t^{An}$	R_{t-1}	D_t^{Jan}	R_t^{DJIA}	$Precip_t^{An}$	$Temp_t^{An}$	$\bar{R}^2$	BG	BP	$Skew$
Oil & Gas	0.129	-0.056	0.188	0.097	-0.210	-0.048	-0.451	0.757***	-0.001	-0.054	0.362	0.881	0.938	0.218
	(0.169)	(0.725)	(0.408)	(0.743)	(0.300)	(0.162)	(0.146)	(0.000)	(0.347)	(0.280)				
Construction & Materials	-0.073	0.219	0.067	0.531*	0.115	0.017	0.331	1.189***	-0.001	0.059	0.599	0.877	0.846	0.000***
	(0.426)	(0.161)	(0.763)	(0.070)	(0.560)	(0.533)	(0.276)	(0.000)	(0.527)	(0.227)				
Aerospace & Defense	0.094	0.106	-0.354*	0.199	-0.031	0.047*	0.256	1.063***	-0.001	-0.011	0.598	0.153	0.300	0.000***
	(0.252)	(0.447)	(0.076)	(0.446)	(0.860)	(0.082)	(0.344)	(0.000)	(0.304)	(0.792)				
Industrial Transportation	0.120	0.046	0.075	0.193	-0.209	-0.039	-0.296	1.042***	-0.003	-0.009	0.582	0.346	0.413	0.000***
	(0.149)	(0.741)	(0.711)	(0.465)	(0.246)	(0.145)	(0.279)	(0.000)	(0.004)	(0.827)				
Food Producers	0.232***	0.104	-0.205	0.149	-0.054	0.002	-0.543**	0.646***	0.000	-0.041	0.443	0.163	0.393	0.001***
	(0.001)	(0.367)	(0.211)	(0.486)	(0.713)	(0.945)	(0.015)	(0.000)	(0.661)	(0.246)				
Household Goods & Home Construction	0.131*	0.345***	0.144	0.214	-0.004	0.001	-0.569**	0.781**	-0.001	-0.048	0.499	0.612	0.000***	0.000***
	(0.067)	(0.001)	(0.634)	(0.370)	(0.977)	(0.985)	(0.015)	(0.000)	(0.370)	(0.249)				
Tobacco	0.310**	0.180	-0.604**	0.875**	-0.321	0.002	-0.657*	0.706***	0.000	-0.021	0.220	0.949	0.017**	0.000***
	(0.023)	(0.377)	(0.048)	(0.017)	(0.326)	(0.961)	(0.100)	(0.000)	(0.956)	(0.740)				
Health Care Equipment & Services	0.160*	0.278**	-0.009	0.413*	-0.128	-0.011	0.090	0.781***	0.000	-0.016	0.477	0.189	0.023**	0.005***
	(0.054)	(0.028)	(0.954)	(0.073)	(0.374)	(0.750)	(0.757)	(0.000)	(0.955)	(0.689)				

Table C.3 Continued

	β_0	$D_t^{Winter} \times SST_t^{An}$	$D_t^{Spring} \times SST_t^{An}$	$D_t^{Summer} \times SST_t^{An}$	$D_t^{Autumn} \times SST_t^{An}$	R_{t-1}	D_t^{Jan}	R_t^{DJIA}	$Precip_t^{An}$	$Temp_t^{An}$	$\bar{R}^2$	BG	BP	$Skew$
Travel & Leisure	-0.069 (0.463)	0.072 (0.652)	-0.163 (0.476)	-0.064 (0.830)	0.616*** (0.003)	0.063** (0.019)	0.403 (0.195)	1.239*** (0.000)	0.001 (0.407)	0.099* (0.051)	0.611	0.465	0.076*	0.000***
Electricity	0.031 (0.707)	0.161 (0.281)	-0.029 (0.891)	0.149 (0.566)	0.197 (0.294)	-0.008 (0.841)	0.018 (0.950)	0.403*** (0.000)	0.001 (0.514)	-0.037 (0.395)	0.170	0.908	0.004***	0.004***
Gas, Water & Multiutilities	0.084 (0.349)	-0.025 (0.885)	0.032 (0.842)	0.279 (0.296)	-0.099 (0.632)	0.041 (0.439)	-0.028 (0.939)	0.616*** (0.000)	0.000 (0.745)	-0.081 (0.113)	0.302	0.060*	0.000***	0.000***
Non-Life Insurance	0.134 (0.110)	0.180 (0.146)	-0.069 (0.764)	0.326 (0.220)	-0.117 (0.470)	0.033 (0.411)	-0.558** (0.047)	0.815*** (0.000)	0.000 (0.818)	0.006 (0.873)	0.496	0.029**	0.629	0.000***

This table reports the OLS regression denoted in equation (10) with Newey-West standard errors. The dependent variable is R_{s,t}, the stock return of sector s at time t. In this table, the dependent variable is noted as the sector of which Datastream constructed a stock index. SST_t x D^season represent the dummy interaction variable between a seasonal dummy and the SST anomaly; which takes on the value of the SST anomaly at time t during a specific season and the value of 0 otherwise. R^DJIA represents the stock return of the Dow Jones Industrial Average at time t and R_{t-1} the lagged monthly return of the stock return of sector s at time t-1. The precipitation anomaly (Precip_t) is measured in mm and the temperature anomaly (Temp_t) is in degrees Celsius. The p-values are reported in the parentheses. The adjusted R-squared is noted as R^2. BG represents the Breusch-Godfrey test, BP represents the Breusch-Pagan test and Skew represents the skewness kurtosis test, the values displayed in these three columns are p-values.

*Significant at the 10% level; **significant at the 5% level; ***significant at the 1% level