The effect of El Niño on Stock Markets

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Abstract

This paper is about the relationship between El Niño Southern Oscillation (ENSO) and world-wide stock markets. We start by reviewing available ENSO data sources and find the Oceanic Niño Index to be most suitable. As previous researches conclude relationships between ENSO and macroeconomic indicators, we study the possible effects on stock markets of 21 countries globally. We find no significant results for any of the countries in the time-series dimension. We do find that an El Niño trading strategy is able to generate money in the long-run, but suspect the outperformance to be caused by luck, rather than skill. Furthermore, we study the possible relationship between ENSO and the S&P500 throughout time and conclude that the intensity of the event magnifies the results.

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1. Introduction

Extreme weather events like El Niño that cause hurricanes, drought and rainfall in the tropical pacific region are likely to have environmental and societal impact; during El Niño Southern Oscillation (ENSO) cycles, the eastern pacific is dominated by abnormally cold sea-surface temperatures, while the far western Pacific is haunted by very warm conditions (Hoerling et al., 1997). Next to this, Cashin et al. (2014) show that the consequences of weather phenomena like El Niño can be economical either. They investigate the macroeconomic effects of El Niño shocks and find varying results. Expectedly, these severe conditions directly affect countries in the western pacific like Australia, Indonesia and New Zealand; rain-driven agricultural export is strained by sustained periods of drought, causing commodity prices to rise. Furthermore, fishery is limited along the coast of Peru by warm nutrient-poor water. On the other hand, there are also countries along the equatorial coast of South America that benefit due to an increased amount of rain and lower temperatures.

According to Brunner (2002), inflation and GDP of advanced G-7 economies are significantly impacted ENSO-cycles. They state that over the period 1963 to 1997, 20% of the deviation in GDP growth and inflation is explained by these cycles. Moreover, they find explanatory power for non-oil commodity prices.

Although El Niño (in)directly impacts world-wide economies through commodity prices, changes in economic growth and inflationary upticks, the resulting damage done to and/or benefits to affected companies (i.e. El Niño winners/losers) are heavily under-studied. The urge to understand the impact at a company-specific level raises naturally following one of the strongest El Niño events measured during 2014-2016. Adams et al. (1995) studied the US agricultural sector and found the economic value of an imperfect ENSO forecast to be $96 million. Solow et al. (1998) highlight the urge by estimating the annual value of perfect forecasting to be $323 million.

Despite the economic damage done by ENSO to specific sectors like agriculture seems significant, the relationship between El Niño events and stock returns is yet to be investigated into further detail. Since the real economy is clearly impacted, one might expect similar results for stock prices. In a broader sense, the relationship between the weather and stock markets has indeed been studied before. More specifically, researches like Saunders (1993), Hirschleifer and Schumway (2003), and Cao and Wei (2005) support the idea of irrational markets that are affected by local weather. The traditional view of efficient markets seems far but relevant in the existence of extreme weather events like El Niño. Let aside the psychological effect of temperature on mood (thereby creating the possibility of over-optimizing future prospects), weather deviations are likely to affect weather-related firms through the mere absence of sunlight or rain (i.e. agriculture).

On the other hand, researches like Jacobsen and Marquering (2007) and Novy-Marx (2014) have posed a more skeptical view. They claim that several weather induced anomalies found to explain stock returns are possibly data-driven and/or caused by insufficient methods of research respectively. Moreover, they argue that the commonly used methodology of citing several psychological studies, linking the mood change to risk aversion and/ or misattribution and finally testing the hypothesized relations is possibly not sound enough. Due to overlapping causes and small differences, the possible explanations are possibly premature.

Taking into account the diverse conclusions mentioned above, we dedicate this research to further identifying possible effects of El Niño on stock markets world-wide. The main research question for that reason is:

"How do El Niño events affect stock markets?"

Now, to answer the main question we split it up into several sub questions. First of all, to intensively study the different results we are likely to find across countries:

"Do El Niño influences on stock markets differ across countries?"

Secondly, these extreme weather events occur once every 3 to 7 years and are closely followed by governments world-wide. Moreover, the most recent El Nino of 2014-2016 is known to be amongst the top three strongest events ever measured and as global warming leads to changing weather conditions, stakeholders might be curious how the effects on stock markets change through time.

"How does the relationship between El Niño events and stock markets change through time?"

We answer the first sub question by studying 21 countries in a time-series dimension. We find no significant result for any of the countries used in our dataset. We do however conclude that the stock indices are, to a large extent, affected in the same direction as the macroeconomic indicators used in previous studies. The second is answered by studying the U.S. stock market throughout time using rolling-windows of 10 years. We find that the intensity of ENSO is related to the size of the impact on the S&P500 Index. Lastly, we construct a portfolio based on an El Niño trading strategy, that invests when the Oceanic Niño Index triggers a sea-surface temperature trigger. The strategy can be profitable if trading costs are excluded, but the outperformance may at the same time be caused by mere luck, rather than skill.

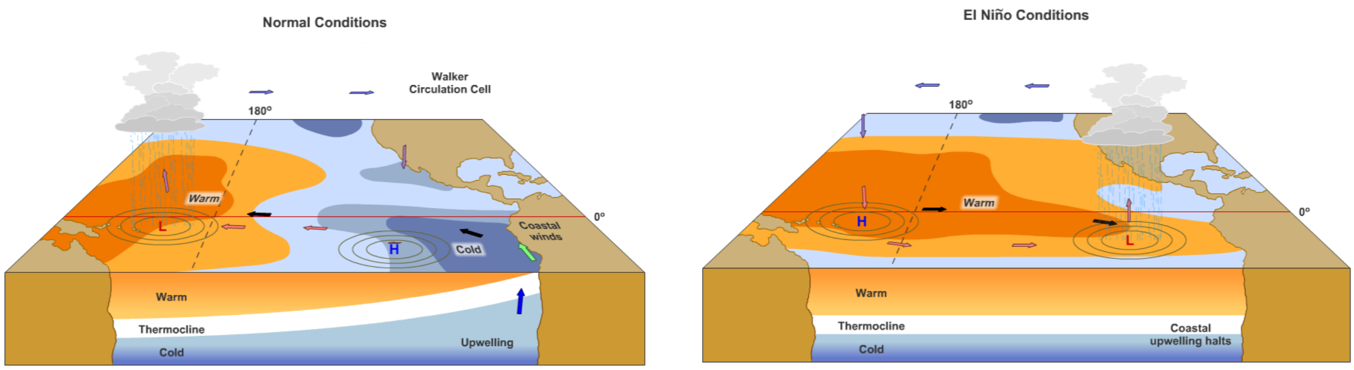
The remainder of this paper is as follows: in section 2 we review the possible ENSO data sources. In section 3 we describe the relevance of the data we use. Section 4 addresses the models used in our regressions and section 5 included the results. Finally, we conclude our findings in section 6.

2. El Niño Southern Oscillation

On average, every 3 to 7 years the pacific is home to El Niño Southern Oscillation, changing weather events significantly. The schematic picture on the left of Figure 1 displays the 'normal' scenario, where warm water flows across the equatorial line from west to east. The water is blown by wind into this direction as a result of high pressure areas in the east (displaying the eastern Pacific Ocean, near South America) and low pressure areas in the west (displaying the western Pacific Ocean, near Asia). As the surface water is warmer and evaporates more quickly, rainfall hits Australia and Indonesia. Oppositely, due to ocean surface currents and coastal winds, the thermocline (approximately the location of water that is about 20ºC) is pushed upward along the coast of South America. An upwelling of colder, nutrient-rich water thereby offers fishermen opportunities.

The alternative scenario[1] is the occurrence of an El Niño; due to high pressure and low pressure zones shifting around, the equatorial counter current accumulates warm surface water from west to east. The result of a declined thermocline slope is less upwelling of cold, nutrient-rich water. This directly impacts fishing. Next to this, extreme rainfall circles around the equatorial region of South America and extreme drought haunts the western Pacific. Agriculture and commodity prices are affected as a result either. Not only are the effects local, but reach as far as 8000 km across the equatorial region of the pacific through teleconnections. Examples of these connections are found amongst others in precipitation: lower than normal activity across western Oceania, southeastern Africa, northeastern South America and India, and higher than normal activity in western South America and eastern equatorial Africa (Rosenzweig & Hillel, 2008).

Figure 1: Southern Oscillation



Source: National Oceanic and Atmospheric Administration (NOAA) United States Department of Commerce

[1]A second alternative phase, La Niña, to a certain extent mirrors the El Niño phase. But, as the focus of this study is connected to the effects of El Niño activity, we exclude further details regarding the mirroring phase.

As EL Niño events usually last several months and occur quasi-periodically, data is available in abundance. However, as the impact of the event is global, variability exists within the way of measuring both the occurrence and the intensity. As a means of clarifying what data is available and to motivate what we find suitable to this research, we investigate multiple data sources in this section.

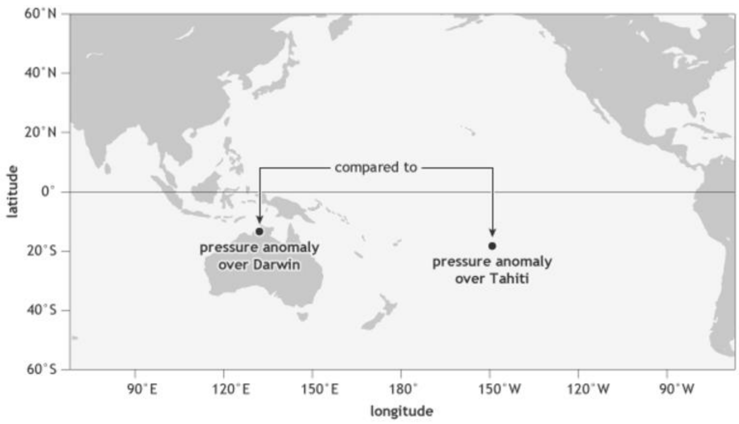
Southern Oscillation Index (SOI)

One of the most widely known and oldest ways of measuring El Niño activity is through the Southern Oscillation Index. It uses air pressure differences at sea level between Tahiti (French Polynesia) and Darwin (Australia), and hereby studies the atmospheric conditions associated with ENSO (Walker & Bliss, 1932). As air pressure rises above average in Darwin and below average in Tahiti during El Niño events, sustained negative values of the SOI indicate it's occurrence. Furthermore, to exclude seasonal influences and short-term deviations, the index is standardized in the following matter:

$$SOI = 10\frac{[Pdiff - \mu_{Pdiff}]}{\sigma_{Pdiff}}$$

where: $Pdiff = \mu_{\text{Mean Sea Level Pressure in Tahiti}} - \mu_{\text{Mean Sea Level Pressure in Darwin}}$, and the multiplication by 10 is applied to have whole numbers. The data is measured on a monthly basis.

Figure 2: SOI (Geographical)



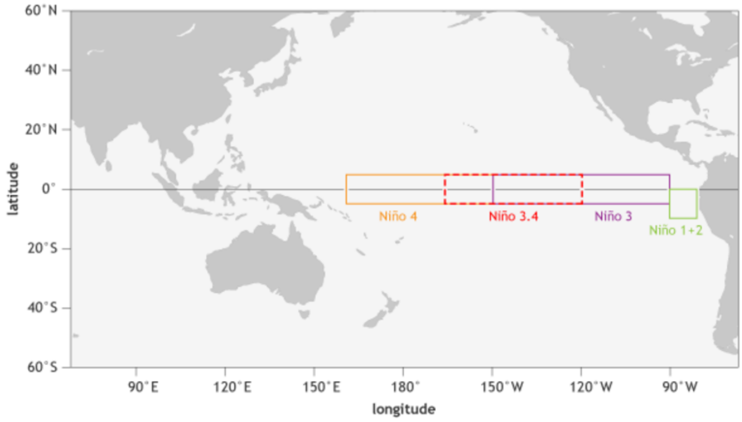
Source: National Oceanic and Atmospheric Administration (NOAA) United States Department of Commerce

A weakness of this index is the location of Tahiti and Darwin: 18°S and 12°S respectively, while the largest component of El Niño activity is located along the equator. The Equatorial Southern Oscillation Index is not exposed to this problem, as the regions are located at 5°S to 5°N. However, this index started in 1949, while in contrast, the regular SOI started in the late 1800s (Barnston, 2015).

Oceanic Niño Index (ONI)

Another way of measuring the intensity and occurrence of El Niño events is through the Oceanic Niño Index. It studies sea surface temperatures in the eastern and central pacific ocean. NOAA uses the region presented in figure 3 as Niño 3.4: 120˚W to 170˚W longitude, as it was shown to be the most representative for ENSO-activity[2] (Barnston et al., 1997).

Figure 3: ONI (Geographical)



Source: National Oceanic and Atmospheric Administration (NOAA) United States Department of Commerce

To investigate sea surface anomalies, the ONI tracks running 3-month averages and compares these with 30-year averages. El Niño events are indicated by values significantly higher than 0.5. As expected by the increased thermocline during these events, the water temperature increases significantly as one goes further east in the observed are. The data goes back to 1950.

Outgoing Longwave Radiation Indexes (OLR)

A third method for measuring ENSO-activity is by studying outgoing radiation from cloud tops. It is an indicator of thunderstorm activity across the tropical Pacific. Regions with above-average sea surface temperatures are usually home to above-average amounts of thunderstorm activity and rainfall. Because of reliable satellite data becoming available in 1979, this source of information contains less observations. There are several other ways to study ENSO activity, for example through wind indexes, but as these only sometimes have significant impact in triggering an El Niño event, we leave these out of scope.

[2] Region 3.4 is formed by parts of (and overlapping) regions 3 and 4. Regions 1 and 2 were removed to accurately study the deviations in sea surface temperature.

Multivariate ENSO Index (MEI)

Next to the individual methodologies mentioned above, the variables correlated with ENSO activities are often combined to form a composite index. NOAA compresses six variables that they believe are most associated with ENSO: sea-level air pressure (SOI), sea surface temperature (ONI), cloudiness fraction of the sky (OLR), surface wind (zonal, as well as meridional) and surface air temperature. Sustained positive values indicate El Niño activity. A strength of this method is that the ENSO effects are caused by aggregated sources. This, at the same time, poses a shortfall: by using multiple indices, which use data from different geographical regions, tracing back ENSO activity to a specific region is not allowed. For this reason, keeping the indices separated is often preferred when studying the effect of one variable on a specific region, i.e. one might prefer using the ONI rather than the SOI when studying activity around the equator. (Barnston, 2015).

3. Data

To answer the main research question and study the effects of El Niño on worldwide stock markets, we gather data from several sources. First of all, we include all countries used in Cashin et al. (2014) and take monthly closing prices from the corresponding stock indices. Figure 3 displays what conclusions were made based on how shocks to the Southern Oscillation Index anomaly affected the countries both in the short-term (first and second quarter following a shock) as well as in the long-term (third and fourth quarter). As inflation-based influences are subject to expectations and targets, we prefer basing the overall effect mainly on GDP-based influences (real output).

Table 1: Overview Indices

Country	Index	GDP	Inflation	Overal effect
Argentina	Merval	+	+	**+**
Australia	S&P/ASX 200	-	-	**-**
Brazil	Bovespa	-/+	-	**-/+**
Canada	S&P/TSX	+	-	**+**
Chile	IPSA	-/+		**-/+**
China	SSE Composite	+	+	**+**
Europe	MSCI Europe	+		**+**
India	NIFTY 50	-	+	**-**
Indonesia	Jakarata Composite	-	+	**-**
Japan	Nikkei 225	-/+	+	**-/+**
South Korea	KOSPI		+	
Malaysia	KLCI		+	
Mexico	IPC	+	+	**+**
New Zealand	S&P/ NZX 50 Gross	-	-	**-**
Peru	S&P Lima Select	-/+	-	**-/+**
Philippines	PSEi Composite		+	
South Africa	Dow Jones South Africa	-	+	**-**
Saudi Arabia	Tadawul All Share		+	
Singapore	STI Index	+	-	**+**
Thailand	SET		+	
United States	US SPX 500	+	+	**+**

Note: in the case of long-term spillover effects, as a result of international trade for example, reversing the initial shock, we marked it as '-/+'. If no significant influence was concluded, we left the spot empty.

Not all data stretches back in time to the same extent (Table 2). For that reason we divide the dataset into two separate parts. To incorporate as much El Niño events as possible, we first of all study the S&P500 starting in 1927. We take monthly closing prices to calculate the returns. The second part exists of all indices mentioned in table 1. All returns are calculated in the same fashion and in their respective currencies, as we want to exclude currency effects that could lead to spurious results. Finally, we subtract the risk-free rate supplied by the Fama and French website from all returns to solely investigate excess returns.

Table 2: Descriptive Statistics Stock Indices

Country	Start	Observations	Mean	Volatility	Skewness	Kurtosis
Argentina	30-9-2003	166	2.44	9.51	-0.13	4.02
Australia	31-5-2000	206	0.24	3.70	-0.65	3.37
Brazil	31-10-2012	57	0.28	6.09	0.32	2.90
Canada	29-7-1994	276	0.37	4.17	-1.02	6.41
Chile	28-4-2006	135	0.59	4.38	0.32	3.48
China	29-7-2005	144	1.34	9.28	-0.15	3.81
Europe	29-6-2001	193	-0.09	5.37	-0.47	3.9
India	28-2-2001	197	1.12	6.68	-0.17	4.87
Indonesia	29-8-2003	167	1.56	5.94	-1.01	8.41
Japan	31-7-2000	204	0.1	5.61	-0.51	3.77
South Korea	28-2-2002	185	0.69	5.53	-0.43	4.53
Malaysia	30-11-1999	212	0.36	4.25	-0.21	4.51
Mexico	28-9-2001	190	1.11	4.84	-0.53	4.14
New Zealand	31-12-1999	211	0.21	3.32	-0.63	3.81
Peru	29-2-2012	65	0.02	6.02	0.10	2.72
Philippines	29-2-2000	209	0.7	5.9	-0.39	4.36
South Africa	31-12-1999	211	0.91	4.84	-0.07	3.42
Saudi Arabia	31-8-2006	131	-0.10	7.18	-0.27	4.17
Singapore	31-3-2008	112	0.18	5.33	-0.35	8.10
Thailand	28-2-2001	197	0.87	6.06	-0.73	6.32
United States	28-2-1992	305	0.46	4.07	-0.68	4.46

Obviously, the datasets differ in size to a large extent. However, as the most recent El Niño phase of 2015-2016 was of above-average intensity, every dataset contains at least one sustained period of relevant observations. Not surprisingly, emerging markets like Argentina, Brazil, China and Saudi-Arabia behaved more volatile than most of the other countries. The means are calculated using monthly excess returns.

As the control variables we mention in section 3.2 started appearing later than the corresponding stock returns in some situations, we choose to only add an observation to the dataset if both are available.

3.1 ENSO data

As mentioned earlier in this study, several different ways of measuring the intensity and occurrence of El Niño events exist. We gather the datasets from the National Oceanic & Atmospheric Administration. Based on their applicability, relevance and size, we restrict our scope to the Southern Oscillation Index, Oceanic Niño Index, Outgoing Longwave Radiation Index and a Multivariate ENSO Index used by NOAA. As all methods have their respective strengths and weaknesses, we first explore to what extent they are correlated. We use a correlation matrix in this process.

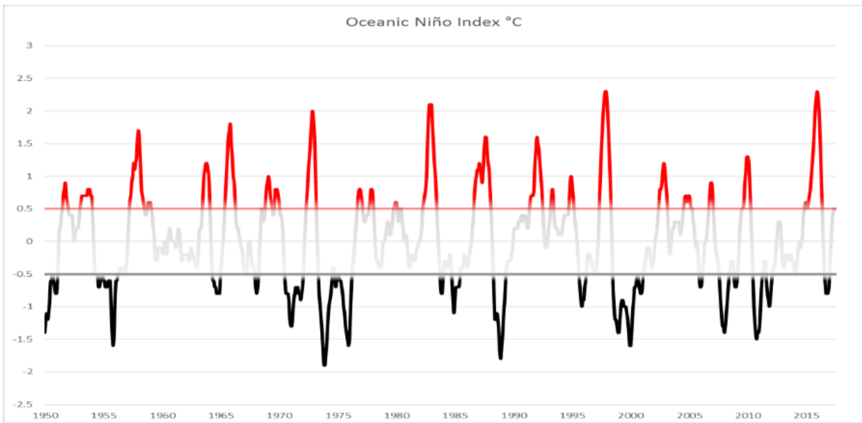
Table 3: Correlation Matrix ENSO

	SOI	*ONI*	*OLR*	*MEI*
Southern Oscillation Index				
Oceanic Niño Index	*-0.74713*			
Outgoing Longwave Radiation	*0.70363*	*-0.79444*		
Multivariate ENSO Index	*-0.77004*	*0.91772*	*-0.7689*	

We take absolute values of the correlations and sum these to be able to rank the data sources. One important aspect of the methodologies applied in the SOI and ONI, is that they require sustained negative and positive values respectively to indicate the occurrence of El Niño events. Hence, they are negatively correlated and stress the importance of using absolute values when adding up the scores.

Despite all four indices capture the movements of the remaining three rather well, the Oceanic Niño Index performs best. Surprisingly, the Multivariate ENSO Index, which by construction consists of all other three indices, comes second to the ONI. The OLR and SOI follow in third and fourth place respectively. As the difference between first and second place is rather small, we follow NOAA in that their primary indicator of ENSO climate patterns is the ONI. As figure 4 shows, temperature anomalies that sustainably cross the 0.5 threshold implicate the occurrence of an El Niño event (displayed red in Figure 4). Higher peaks implicate that the event was stronger. Values smaller than, but greater than 0.5 and -0.5 respectively have been blurred, as these observations neither indicate El Niño events, nor mirroring La Niña events.

Figure 4: ONI



3.2 Control variables

The Oceanic Niño Index observes sea surface temperature anomalies, which we assume are strictly caused by nature's forces and independent of any variables causing deviations in stock returns. We therefore treat the ONI variable as being exogenous. However, El Niño events are related to commodity markets world-wide. In their turn, commodity prices will impact company earnings and will thereby most likely affect stock prices as a consequence. For this reason, it is important to add commodity prices to our datasets. We do however not follow Cashin et al. (2014) in the same fashion, i.e., they divide the commodity price variable into two: a fuel commodity variable (as a proxy to crude oil prices) and a non-fuel commodity variable. As we are interested in how stock prices of companies are affected, we choose not to split it up in our research and stick with a single commodity variable supplied by the International Monetary Fund[3]: All Commodity Price Index. The indices used in our datasets consist of several thousand underlying companies, each one more or less connected to commodity prices of some sort. For this reason, we do not see any added value in splitting the variable up into sub-categories.

Stock indices react intensively to over- and undervaluation mostly observed during ending phases of economic cycles. To absorb some of the variability caused by periods of contraction and expansion, we include the valuation variable price-to-earnings ratio of the countries used in our dataset. Furthermore, to tell us something about the quality of these earnings, we add the average dividend payed over the past 12 months. Finally, we follow Cashin et al. (2014) in that sense, that we include interest rates. However, while they split short-term and long-term rates up into two variables, we subtract the former from the latter to create one variable that covers the total interest rate structure: Yield Spread. More specifically, we subtract the yield on government bonds with 2 years (we took 3 years as a substitute if 2 year bonds were missing) to maturity from that of bonds with 10 years to maturity. This number tells us something about the slope of the yield curve; it tells us something about economic conditions. Contracting yield curves usually indicate a worsening of economic conditions, while a widening indicates stable economic conditions.

[3] See http://www.imf.org/external/np/res/commod/index.aspx for more details on the composition of this index.

4. Methodology

To intensively study the effects of El Niño on stock markets world-wide, we split this section up into two parts. First of all, we look at the relationship throughout time by taking into regard the complete dataset and by breaking it up into separate windows of time. Thereafter, we deviate from the time dimension and study the effects in a cross-sectional dimension to establish an understanding of the relationship across countries.

4.1 Time-series

In an effort to capture the effect of El Niño on stock markets throughout time, we construct an Ordinary Least Squares (OLS) regression and start with the following model:

$$R_{i,t} - RF_t = \alpha_i + \beta_{0i}ONI_t + \beta_{1i}ONI_{t-1} + \gamma_i PE_t + \delta_i YS_t + \mu_i DIV_t + \pi_i COM_t + \epsilon_{i,t} \qquad (1)$$

where RF_t represents the risk-free rate, PE_t the Price-to-Earnings Ratio, YS_t the spread between yields on government bonds with a maturity of 10 years and with a maturity of 2 years, COM_t the price of the All Commodity Price Index and DIV_t the 12-month average dividend yield. All data is measured on a month-to-month basis.

Furthermore, possible correlation in the errors found in our model might lead to biased results. More specifically, the standard errors will not be valid and better estimators exists. We therefore test the model using a Breusch-Godfrey test.

$$\mu_t = \rho_1\mu_{t-1} + \rho_2\mu_{t-2} + .. + \rho_r\mu_{r-1} + \tau_t \qquad \text{and: } \tau_t \sim N(0,\sigma_\tau^2) \qquad (2)$$

where ρ_t indicates the relationship between residual μ_t and a previous value μ_{t-r}. We study monthly observations and therefore apply 12 lagged values. The null hypothesis states that there is no significant relationship between the errors; there is no sign of autocorrelation.

Second, we check the model for heteroscedasticity, i.e. non-constant variance of the residuals, by means of the White's test (White, 1980). Under the null-hypothesis the errors are homoscedastic.

Based on the combined results of the two tests named above, we adjusted the models if necessary. More specifically, if the model included heteroscedasticity and/or serial correlation, we adjusted the model using Newey-West Standard errors. If the model solely included heteroscedasticity, we applied White's robust standard errors.

Table 4: Breusch-Godfrey test (left) & Table 5: White's test (right)

	BG		White	
Country	χ^2	P-value	Test statistic	χ^2
Argentina	4.87	0.96	37.12	0.01
Australia	10.92	0.54	53.59	0.00
Brazil	9.76	0.64	22.49	0.71
Canada	3.78	0.99	50.47	0.00
Chile	10.41	0.58	57.86	0.00
China	18.18	0.11	48.96	0.01
Europe	12.27	0.42	78.62	0.00
India	11.18	0.51	63.59	0.00
Indonesia	10.50	0.57	88.58	0.00
Japan	6.91	0.86	48.77	0.01
South Korea	9.29	0.68	52.63	0.00
Malaysia	15.61	0.21	53.71	0.00
Mexico	16.74	0.16	50.23	0.00
New Zealand	14.96	0.24	30.41	0.30
Peru	8.39	0.75	30.58	0.29
Philippines	4.99	0.96	57.24	0.00
South Africa	8.04	0.78	44.51	0.02
Saudi Arabia	9.97	0.62	30.88	0.06
Singapore	12.82	0.38	54.71	0.00
Thailand	9.17	0.69	83.00	0.00
United States	14.13	0.29	75.55	0.00

Finally, as we are dealing with prices of stocks and commodities, which are commonly known to include trends over time, we check the datasets for non-stationarity. The problem of non-stationarity in stock prices is easily resolved by studying returns, rather than prices. However, the All Commodity Price Index is still vulnerable and therefore, we apply the Augmented Dickey-Fuller test. The null-hypothesis is that the process contains a unit root. The alternative hypothesis in this case, indicates stationarity. The more negative the results the test, the stronger the rejection of the null-hypothesis.

By visual inspection, the indexed data (2005 = 100) is likely to include a positive trend throughout time (Appendix 1). For that reason, we include a trend in the Augmented Dickey-Fuller test. The results supports the statement of non-stationarity, as the null-hypothesis of a unit root cannot be rejected (see Appendix 2). To solve this problem in the data, we create a substituting variable by taking the returns of the ACPI (see Appendix 3).

To investigate how the results differ throughout time, we apply the following time-varying model to the United States dataset because of the abundance of observations:

$$R_{i,t} - RF_t = \alpha_{i,t} + \beta_{i,t}ONI_t + \beta_{1i,t}ONI_{t-1} + \gamma_{i,t}PE_t + \delta_{i,t}YS_t + \mu_{i,t}DIV_t + \pi_{i,t}COM_t + \epsilon_{i,t} \quad (3)$$

We take rolling windows of 120 months to establish an understanding of how the relationship between the stock returns and EL Niño changes throughout time.

4.2 Cross-section

To study how the effects of El Niño differ across countries, we construct portfolios of El Niño 'winners' and 'losers'. More specifically, stock indices that are positively correlated to the strength of El Niño events leads to the classification of that country being a 'winner'. Reversely, a negative relationship leads to the classification of being a 'loser'. We go as far back as possible regarding the pricing data of the stock indices. To makes sure all countries are a possible investment object, we therefore start the portfolio data at June 2003 (start of the S&P/ NZX 50 Gross Index in USD). As the data required earlier in the time-series regression go less far back because of availability problems in the control variables, the exact dates are in small conflict. We do however make the assumption that the conclusions following the time-series regressions are representative as well to the cross-section datasets. A benefit of this approach is that the dataset will incorporate more El Niño/ La Niña observations.

We then contribute the weight equally across the countries. We go long El Niño winners and short El Niño losers during periods of El Niño activity. During the mirroring phase, La Niña, we reverse the weights: we go long El Niño losers and short El Niño winners. During periods that indicate neither the occurrence of El Niño, nor the occurrence of La Niña, we are not invested and assume no further growth of the portfolio.

5 Results

In this section we discuss the results in an effort to answer the main research questions and the two sub-questions. First of all, we look at the time-series results on a global scale. Second, we study the results for the time -varying dataset from the United States. Lastly, we look at the hypothetical portfolio created using an El- Niño strategy.

5.1 Time-Series

We ran the regressions mentioned in section 4.1 separately for all countries in our dataset. We then corrected, if needed, the standard errors to increase the validity of our results. We corrected all countries for heteroscedasticity, except Brazil, New-Zealand, Peru and Saudi-Arabia, by using White's robust standard errors.

We start with the regressions that solely link the ONI and it's lagged value to the excess returns (see Appendix 4). As these results might include some of the variability caused by other variables, we thereafter include the control variables (see Appendix 5). Only the control variables that show a significant relationship to the excess returns at a 90% confidence level, i.e. the p-value is smaller than 0.10, are kept. Finally, we add the relevant control variables to the first regression (see Table 6).

In general, we do not find any significant relationships between ENSO and the stock returns in our data. We do find a significant result for Peru, however, after adding the control variables the connection is no longer significant. This indicates that some of the variability seemingly caused by the ONI in the first regression, is partly caused by the control variables through the ONI. Moreover, we were not able to reject the null-hypothesis that the ONI and it's first-order lagged value have significant impact on the excess returns of the investigated stock indices.

If we match the results (Table 6) to table 1 and focus on the coefficients of the Oceanic Niño Index (not the lagged values) we do see comparisons with the results found by Cashin et al. (2014). All countries that were found to be positively impacted on a macroeconomic scale display positive coefficients: Argentina, Canada, China, Europe, Mexico, Singapore and the United States. Due to the lower temperatures and heavy rainfall these countries seem to be positively affected. More specifically, it might boost agricultural companies in Argentina and the United States. As a result of spillover effects, Mexican, Canadian and European companies may therefor trade more internationally and see their profits rise.

Coefficients of companies that were identified to have differing macroeconomic results throughout time are often multidirectional. Peru for example, shows a strong negative relationship for the ordinary ONI value. The lagged value however, is strongly positive. This difference may be caused by the effects El Niño has in this region, i.e. positive to agriculture as a result of rainfall, but negative to fishery as a result of the upwelling of warm nutrient-poor water. It is also the model with the highest R-squared: 0.30, indicating that 30% of the variability in the excess stock-returns is caused by the dependent variables. The relatively high R-squared values for Brazil and Saudi-Arabia may also be caused by a strong correlation between the fuel-commodity party of the All Commodity Price Index variable and the returns on companies in these oil-exporting countries. Note that the ACPI is also significant in both countries (see Appendix 5). Furthermore, when the adjusted R-squared is available, we see that in all four cases it is lower than the usual R-squared value. The reason behind this is that the usual R-squared by definition increases by adding variables. The adjusted R-squared however, penalizes adding extra variables. If we compare the R-squared values in Appendix 1 to Table 6, we see that most of the variability is actually caused by the control variables, rather than the ONI.

These results may be biased however, as the companies that are truly affected by El Niño possibly make up just a small part of the total index.

Table 6: Time-series results

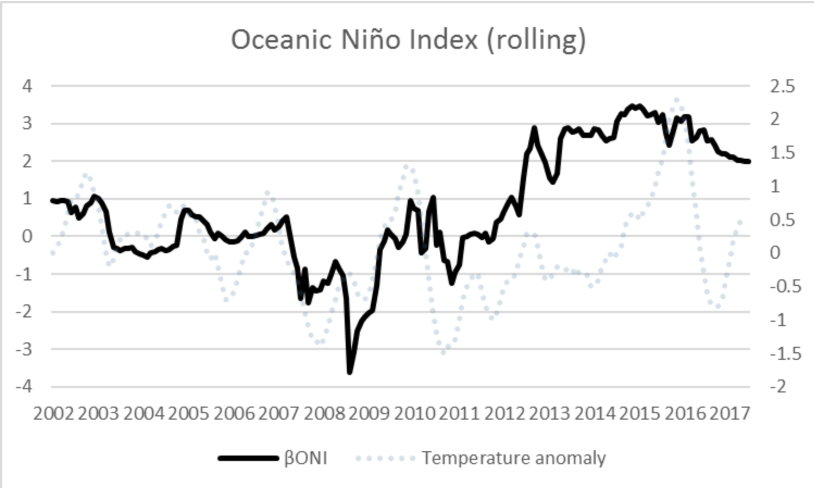
Country	ONI	ONI(t-1)	Price-to-Earnings	Dividend	ACPI	Yield Spread	R-Squared
Argentina	2.32	-2.39		-1.75	0.34		0.08
	(0.53)	(0.50)		(0.03)	(0.10)		
Australia	0.21	0.16		-0.80	0.13		0.07
	(0.88)	(0.91)		(0.06)	(0.05)		
Brazil	-1.63	2.09			0.64		0.23
	(0.67)	(0.59)			(0.00)		(0.18)
Canada	0.57	-0.52			0.25		0.08
	(0.66)	(0.67)			(0.00)		
Chile	0.82	-0.29			0.20	0.65	0.10
	(0.66)	(0.87)			(0.00)	(0.26)	
China	0.96	0.05	0.51	3.52			0.11
	(0.83)	(0.99)	(0.00)	(0.02)			
Europe	1.12	-1.63		-1.17		1.23	0.04
	(0.63)	(0.45)		(0.03)		(0.05)	
India	1.72	-1.48					0.00
	(0.51)	(0.57)					
Indonesia	0.46	0.24			0.34		0.09
	(0.84)	(0.91)			(0.03)		
Japan	3.14	-3.04			0.24	-1.78	0.06
	(0.16)	(0.16)			(0.03)	(0.10)	
South Korea	-0.32	0.33	0.04		0.22		0.07
	(0.88)	(0.87)	(0.00)		(0.05)		
Malaysia	1.87	-1.46	0.18		0.19	-1.62	0.11
	(0.18)	(0.28)	(0.01)		(0.01)	(0.03)	
Mexico	0.46	-0.32		-2.34			0.04
	(0.79)	(0.86)		(0.06)			
New Zealand	1.24	-0.88		-0.92			0.08
	(0.31)	(0.47)		(0.00)			(0.07)
Peru	-4.78	5.91	0.48		0.41		0.30
	(0.18)	(0.09)	(0.18)		(0.09)		(0.30)
Philippines	-0.73	1.40					0.01
	(0.70)	(0.46)					
South Africa	0.21	0.02		-1.58	0.15		0.07
	(0.90)	(0.99)		(0.04)	(0.03)		
Saudi Arabia	-2.98	1.74	0.67		0.40		0.19
	(0.32)	(0.56)	(0.01)		(0.00)		(0.17)
Singapore	1.76	-2.44	0.53		0.35	-2.02	0.26
	(0.45)	(0.26)	(0.04)		(0.01)	(0.03)	
Thailand	-0.99	0.53	0.36		0.24		0.11
	(0.61)	(0.77)	(0.00)		(0.07)		
United States	0.87	-0.80					0.00
	(0.52)	(0.53)					

Note: In case White standard errors were applied, the adjusted R-squared is omitted. If usual errors were applied, the adjusted R-squared is mentioned below the regular R-squared in parenthesis.

5.2 Time-Varying

As the dataset containing stock returns from the United States, or more specifically, the S&P500 Index contains the largest amount of observations, we use this index to investigate the relationship between El Niño and stock markets throughout time. By taking a window of 120 observations (10 years) and rolling this forward throughout time, we are able to study the coefficients in the presence and absence of an El Niño phase. The first observation contains information from March 1992 until February 2002. The second from April 1992 until March 2002 and so forth.

Figure 5: OCI beta



As figure 5 shows, the beta coefficient of both the ONI depends strongly on what point in time we observe. The dotted line expresses the temperature anomaly observed in the Oceanic Niño Index. As the intensity of the events grow, i.e. as the temperature anomaly is larger, the ONI seems to have a bigger coefficient. This makes sense, as stronger events have more severe impact on the affected regions. The US, according to Cashin et al. (2014), is positively affected by El Niño activity. A stronger event may enlarge the magnitude of these effects. Furthermore, as the effects grow stronger, and part of the positive US effect is caused by international trading with Canada and Mexico, it might even further be reinforced.

5.3 Cross-Section

To investigate how El Niño affects stock returns in the cross-section, we construct a hypothetical portfolio. As none of the countries in the time-series regression were significantly connected to ENSO, we deliberately let go of this fact and focus solely on the direction of the coefficients. The fact that most of the countries in our results followed the results of Cashin et al. (2014) in a sense of direction, supports this decision. Countries that scored well in the time-series regression in this paper, i.e. countries that have a positive coefficient, are invested in during periods of El Niño activity. Reversely, we short countries that performed less well in the time-series dimension. The ONI serves as a trigger: if the value crosses 0.5 the portfolio is constructed. If the value drops below 0.5 again, we liquidate the portfolio until the next trigger. Should the value drop below -0.5, then we reverse the weights; we short the winners and long the losers.

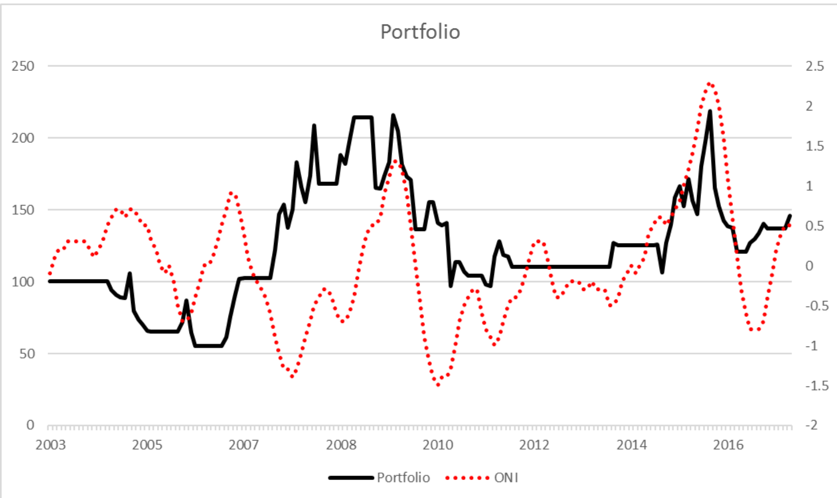
As opposed to the time-series section, we calculated all stock returns in one currency: United States Dollar. Previously, all currency influences had to be excluded to focus on the local impact of El Niño. Now, we deliberately include the currency effect to be able to express the total return on the portfolio throughout time. However, we assume interest rates to be negligible as we are not invested through periods where the ONI moves between -0.5 and 0.5.

In total we end up with 11 'winners' and 9 'losers'. The weights are equally distributed amongst the countries. The expected return on portfolio P is equal to:

$$E(R_P) = \Sigma_i x_i R_i \tag{4}$$

where 'x' resembles the weight of index 'i' and R resembles the return.

Figure 6: Portfolio development



As figure 6 shows, the portfolio starts out losing money. However, as soon as the events occur with greater intensity the portfolio starts growing. This is an expected result, as the affected regions and their respective countries are more severely impacted both in a positive or negative sense. A more severe El Niño may trigger an above-average amount of rainfall, even for this phase, and thereby boost sectors like agriculture even more. Based on the above, an El Niño strategy can be profitable. However, it is important to notice that this is a hypothetical portfolio, thereby disregarding transaction costs and other restrictions. To further investigate the excess returns, we statistically test the significance of the results and compare the performance to the Risk-free rate supplied by Fama and French.

Table 7: Portfolio statistics

Returns	
Mean	0.63%
Volatility	8.98%
Excess Returns	
Mean	0.54%
Volatility	8.96%
Observations	168
Sharpe Ratio*	0.21
T-statistic	0.78

*Annualized Sharpe Ratio

We find that although the average monthly return is positive, we do not have enough evidence to reject the null-hypothesis that the mean is actually equal to zero. The Sharpe Ratio, a number that tells us to what extent the excess return can be justified in a sense of risk, indicates that the strategy is indeed profitable. The combination of having both a low Sharpe Ratio and a low t-statistic indicates that the profit made following this strategy may be caused by luck, rather than skill.

6 Conclusion

In this paper we investigate how El Niño events are related to stock returns on a global scale. We review possible data sources of El Niño Southern Oscillation (ENSO) and conclude that the Oceanic Niño Index is best suitable. First of all, we study the effects on 21 countries in a time-series dimension. Second, we zoom-in unto the United States and take rolling-windows to study the relationship throughout time. Thereafter, we construct a portfolio of El Niño winners and losers; countries that are positively affected or negatively affected, respectively. We find no significant relationship for any of the countries in our dataset. We do however find coefficients that are mostly in line with previous research. They indicate that Argentina, Canada, Chile, China, Europe, India, Japan, Malaysia, Mexico, New-Zealand, Singapore and the United States are positively correlated, though not significantly, to ENSO. Australia, Brazil, Indonesia, South Korea, Peru, Philippines, South Africa, Saudi-Arabia and Thailand are negatively correlated, not significantly neither, to ENSO. The rolling U.S. data indicates that the strength of the sea-surface temperature anomaly caused by El Niño is to some extent related to the size of the impact on stock returns. Finally, we find that the El Niño trading strategy can be profitable, but suspect the outperformance to be associated with luck rather than skill.

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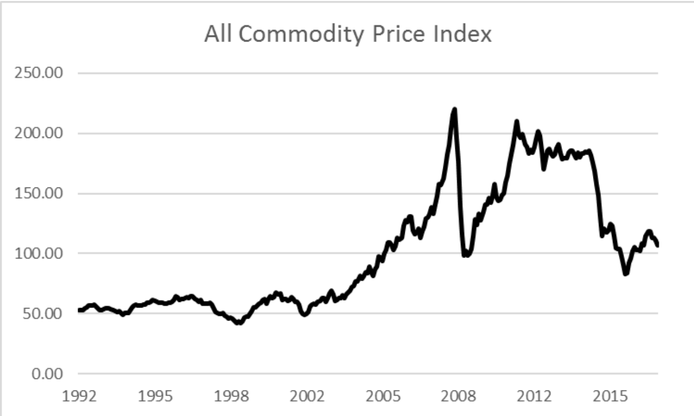
8 Appendix

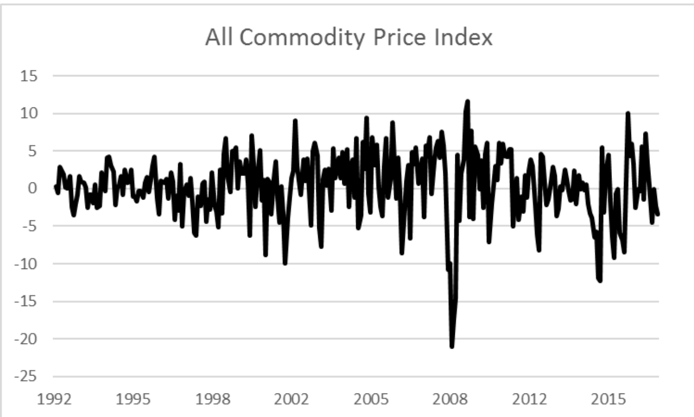
Appendix 1: ACPI



Appendix 2: Augmented Dickey-Fuller test on All Commodity Price Index

Variable:	ACPI			
Observations:	305			
	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-1.000	-3.988	-3.428	-3.130
P-value:	**0.9442**			

Appendix 3: Returns ACPI



Appendix 4: Results Oceanic Niño Index

Country	ONI	ONI(t-1)	R-Squared
Argentina	3.01	-2.44	0.01
	(0.44)	(0.50)	
Australia	0.22	0.03	0.00
	(0.88)	(0.98)	
Brazil	-7.09	6.73	0.06
	(0.07)	(0.09)	(0.02)
Canada	0.77	-0.91	0.00
	(0.58)	(0.49)	
Chile	1.23	-0.65	0.01
	(0.53)	(0.73)	
China	0.14	0.60	0.00
	(0.97)	(0.86)	
Europe	1.56	-1.67	0.00
	(0.49)	(0.44)	
India	1.72	-1.48	0.00
	(0.51)	(0.57)	
Indonesia	0.29	0.07	0.00
	(0.90)	(0.97)	
Japan	2.91	-2.87	0.01
	(0.20)	(0.20)	
South Korea	0.38	-0.57	0.00
	(0.86)	(0.78)	
Malaysia	0.83	-0.80	0.00
	(0.57)	(0.57)	
Mexico	0.85	-0.55	0.00
	(0.61)	(0.74)	
New Zealand	0.92	-0.16	0.03
	(0.46)	(0.90)	(0.02)
Peru	-9.13	9.43	0.10
	(0.02)	(0.01)	(0.07)
Philippines	-0.73	1.40	0.01
	(0.70)	(0.46)	
South Africa	0.02	-0.18	0.00
	(0.99)	(0.92)	
Saudi Arabia	-0.64	-0.71	0.02
	(0.84)	(0.82)	(0.01)
Singapore	3.42	-3.44	0.02
	(0.19)	(0.18)	
Thailand	0.80	-1.03	0.00
	(0.69)	(0.59)	
United States	0.87	-0.80	0.00
	(0.52)	(0.53)	

Appendix 5: Results Control variables

Country	Price-to-Earnings	Dividend	ACPI	Yield Spread	R-Squared
Argentina	0.00	-1.72	0.34		0.08
	(0.45)	(0.02)	(0.08)		
Australia	0.02	-1.03	0.13	0.86	0.08
	(0.67)	(0.03)	(0.05)	(0.19)	
Brazil	0.01	-2.34	0.52	0.75	0.27
	(0.50)	(0.12)	(0.10)	(0.30)	(0.21)
Canada	0.04	-0.38	0.24	0.58	0.09
	(0.52)	(0.25)	(0.00)	(0.19)	
Chile	0.09	-0.72	0.16	0.99	0.10
	(0.58)	(0.46)	(0.03)	(0.08)	
China	0.52	3.88	0.10	-0.50	0.11
	(0.00)	(0.01)	(0.65)	(0.77)	
Europe	-0.00	-1.03	0.07	1.19	0.04
	(0.77)	(0.06)	(0.46)	(0.07)	
India	0.39	1.39	0.16	1.06	0.05
	(0.16)	(0.66)	(0.21)	(0.24)	
Indonesia	0.19	0.03	0.29	0.72	0.11
	(0.12)	(0.98)	(0.03)	(0.28)	
Japan	-0.00	-0.97	0.24	-2.32	0.05
	(0.82)	(0.37)	(0.03)	(0.10)	
South Korea	0.03	-1.05	0.21	1.03	0.09
	(0.00)	(0.32)	(0.06)	(0.39)	
Malaysia	0.14	-0.58	0.17	-1.78	0.11
	(0.06)	(0.28)	(0.01)	(0.01)	
Mexico	-0.03	-2.27	0.11	0.53	0.07
	(0.47)	(0.06)	(0.24)	(0.21)	
New Zealand	0.05	-0.90	0.04	-0.02	0.08
	(0.14)	(0.00)	(0.41)	(0.93)	(0.07)
Peru	0.47	-0.04	0.44	-0.13	0.24
	(0.03)	(0.95)	(0.00)	(0.88)	(0.19)
Philippines	-0.01	-0.98	0.16	-0.09	0.05
	(0.26)	(0.10)	(0.14)	(0.72)	
South Africa	-0.03	-1.62	0.15	0.54	0.08
	(0.51)	(0.03)	(0.04)	(0.10)	
Saudi Arabia	0.90	2.42	0.44		0.19
	(0.01)	(0.12)	(0.00)		(0.17)
Singapore	0.42	-0.47	0.36	-1.83	0.25
	(0.06)	(0.57)	(0.01)	(0.07)	
Thailand	0.32	-0.46	0.23	0.02	0.11
	(0.00)	(0.50)	(0.05)	(0.98)	
United States	0.05	-0.31	0.12	0.07	0.02
	(0.31)	(0.58)	(0.11)	(0.80)	

Note: As yield spreads were not available for Argentina and Saudi-Arabia, they are omitted from the results.