The Impact of El Niño-Southern Oscillation on Commodity Futures Indices

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Abstract

The influence of both phases of El Niño-Southern Oscillation (ENSO) on commodity futures index returns is evaluated for the period between 1970 and 2016. Additionally, the potential of ENSO related trading is examined. Associations of the Oceanic Niño Index (ONI) with commodity index returns are studied by Granger causality tests, ordinary least squared regressions and a mean return analysis approach. In general, the results of the effect measurements indicate the existence of larger and statistically more significant effects during La Niña phases for most of the commodities. Surprisingly, El Niño effects show relatively low statistical significance in measured effects. Historical performance tests of ONI triggered trading strategies with varying holding periods indicate potential to exploit ENSO related effects especially for short investments.

Keywords: ENSO events, commodity futures, effect measurement, trading strategies
JEL classifications: G11, G13, G14, Q02
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[1] We are grateful for the continuous support and valuable guidance throughout the course of writing this thesis.

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1. Introduction

The El Niño-Southern Oscillation (ENSO) is a medium-frequency weather pattern that can have substantial impacts on local economies. The pattern consists of two phases, a warm phase referred to as El Niño and a cold phase, the so-called La Niña. ENSO can be measured by sea surface temperature (SST) anomalies in the Pacific Ocean. Due to changes in the water temperatures and disturbances in atmospheric pressure, ENSO events can affect local weather conditions, entailing disruptions in agricultural and other commodity markets. The phenomenon has attracted attention by an increasing number of economists in recent years who studied, among others, the impact of ENSO events on crop yields, commodity prices and macro-economic conditions. Previous research often utilizes prices of physical commodities that have high historic availability, yet provide limited meaningfulness for actors in financial markets. Furthermore, the timing of effects is often neglected. This gap in research leads to the main questions of this thesis: To what extent are ENSO related effects in futures-based commodity index data measurable and financially exploitable? This question can be of interest to numerous stakeholders, e.g. investment managers, raw material producers as well as intermediaries who are exposed to price changes.

The empirical approach to measure price effects is threefold in order to investigate different aspects of the relationship between ENSO and commodity index returns: (1) Correlations and Granger causality tests are employed to analyse if ENSO related climatological data has predictive value for commodity index returns. (2) OLS time series regressions indicate effect direction and size. (3) Mean return plots in combination with dummy variable regressions provide information about the development of return effects over time and potential lags. Subsequently to measuring the effects, indicative trading strategies are defined and tested on historical performance to point out the potential of ENSO related commodity investments. Thereby, it is examined whether it is feasible to time trades based on the ENSO phenomenon.

In general, the results of the effect measurements indicate the existence of larger and statistically more significant effects during La Niña phases for most of the commodities. La Niña shows significant positive impact on a variety of commodities, namely soybeans and soybean related products, wheat, corn, sugar, cotton and nickel. Crude oil and heating oil instead are negatively impacted during La Niña phases. For El Niño, we find negative return effects on soybeans and soybean related commodities as well as for crude oil and heating oil.

In contrast, El Niño affects wheat and sugar returns positively. Overall, we only find meaningful qualitative explanations for a link between ENSO and agricultural as well as petroleum commodities. For such commodities, we find the clearest effects inherit in soybean oil, corn, sugar, cotton, crude oil and heating oil. The findings for the trading strategies overall suggest high monthly geometric excess returns in absolute means for most of the commodities during both ENSO events. Measured effects and qualitative explanations suggest that these returns are ENSO related. Furthermore, we find evidence that ENSO events are priced in quickly, thus, timing is indispensable.

The remainder of this paper is structured as follows: *Section 2* provides a literature overview related to the ENSO weather patterns and commodity investments. *Section 3* explains the empirical approach including data description and methodology. *Section 4* presents and analyses the results of the empirical approach. *Section 5* discusses limitations of the approach used. *Section 6* concludes.

2. Literature Review

2.1. The Weather Phenomenon El Niño-Southern Oscillation

The El Niño-Southern Oscillation (ENSO) is a medium frequency weather pattern that brings reoccurring changes to the global weather. The name El Niño dates to references by South American fisherman from the west coast who recognized unusually warm waters in the Pacific Ocean around year-ends. In Spanish, El Niño means Christ child and refers to the occurrence of the weather phenomenon around Christmas time. By now, the mentioning of El Niño usually refers to irregular strong warm water currents in the Pacific Ocean and the accompanied global weather effects. These warm water periods are followed by either neutral periods or directly by the opposing cooling phase of the tropical Pacific, the so-called La Niña (Spanish for ‘the girl’). This alternating cycle is often called El Niño-Southern Oscillation (ENSO) due to the collaborating effect of oceanic temperature changes and atmospheric pressure anomalies (Trenberth, 1997).

The development of the distinct ENSO phases is initiated by changes in the air pressure system above the Pacific coasts. Usually, atmospheric pressure is relatively low in the Western Pacific (i.e. Southeast Asia, Australia) and high in the Eastern Pacific. This air pressure differential causes trade winds to move from the high-pressure East to the low-pressure West, pushing surface water in the Pacific Ocean from the coast of South America westwards toward

Australia and Southeast Asia ("Walker Circulation"). Thereby, cold water from lower levels dwells up at the coast of South America, while the water piles up in the Western Pacific Ocean. In fact, this leads to a difference in sea level of about half a meter, allowing the sun to heat up the surface water.

Occasionally, the trade winds of the Walker Circulation relax and, thus, potentially trigger an El Niño event. Softer trade winds can cause warm water to swell back to the East. The water flowing back contains an immense amount of thermal energy which heats up the air above the surface of the Eastern Pacific coast, leading to an upward atmospheric pull which disrupts the Walker Circulation to an even greater extent. This in turn allows more warm water to swell back from west to east, resulting in a self-supporting cycle. Such an El Niño event can have effects on the global climate conditions and can sustain for a period of several months up to a few years (Becker, 2016).

Often, but not necessarily, El Niño periods are followed by La Niña phases which are triggered by stronger than normal westward trade winds. These winds increase the piling up of warm water in the Western Pacific Ocean and increase the upwelling of cold water in the Eastern Pacific Ocean.

2.1.1. ENSO Indicators

The two most prevalent indicators to measure ENSO activity are the Southern Oscillation Index (SOI) and Oceanic Niño Index (ONI). The SOI is calculated by differences in air pressure between Tahiti in the East Pacific and Darwin in the West Pacific. Whereas a negative SOI value indicates El Niño events, a positive index stands for La Niña events. ONI is calculated based on sea surface temperature anomalies by the U.S. National Oceanographic and Atmospheric Administration (NOAA). These anomalies are measured in the NIÑO3.4 region which lies in the Central Equatorial Pacific. The NOAA defines warm and cold phases as a minimum of five consecutive 3-month running average of SST (ONI) surpassing a threshold of +0.5℃ for El Niño or -0.5℃ for La Niña.

Figure 1 **Historical Development of Oceanic Niño Index (ONI)**

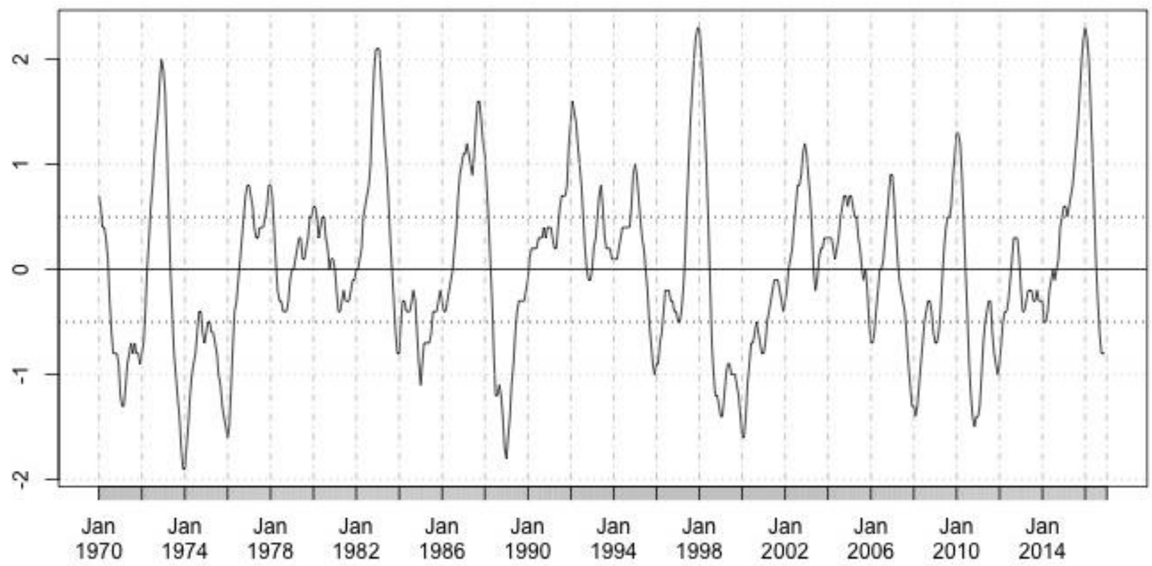


Figure 2 **Historical Development of Southern Oscillation Index (SOI)**

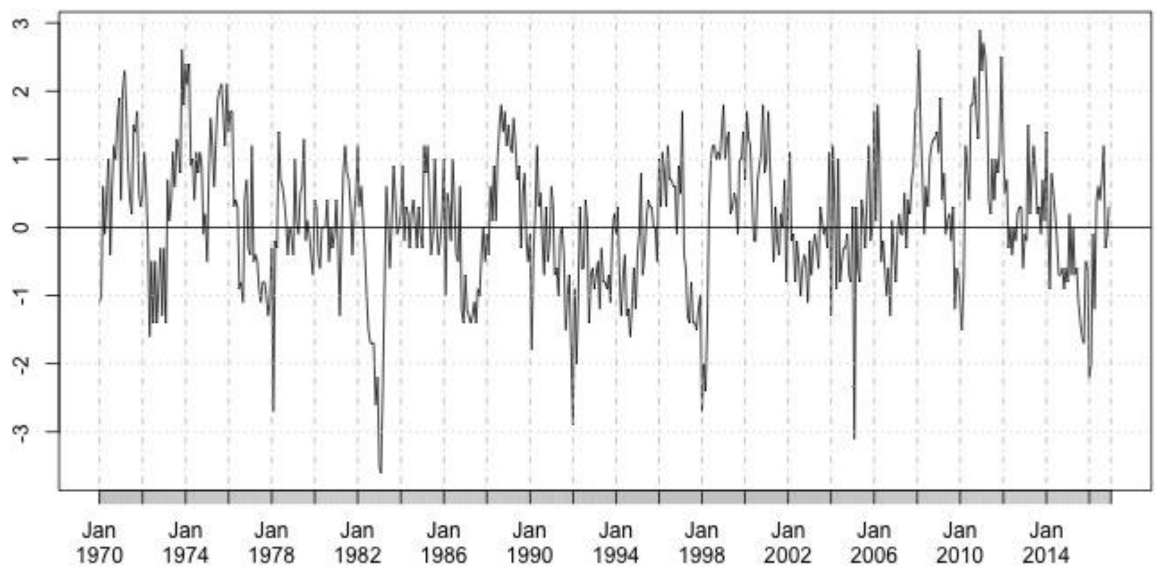


Figure 1 and 2 plot the historical development of the El Niño-Southern Oscillation (ENSO) measures Oceanic Niño index (ONI) and Southern Oscillation Index (SOI). The monthly data is collected from the United States National Oceanic Atmospheric Administration (NOAA) for the period from January 1970 to December 2016. The NOAA definition requires ONI to breach a threshold of 0.5 for El Niño or -0.5 for La Niña for a minimum of five consecutive months.

2.1.2. Consequences to Regional Weather and Economies

Both, warm and cold periods, can have considerable impact on regional weather and ecological conditions. Even though the regional magnitudes of ENSO impacts differ from case to case, experts agreed on generalized regions which are affected in most cases. These patterns occur in the form of geographical shifts in precipitation but also temperature variations.

El Niño periods can have severe consequences. The strong warming of the sea off the shore of Ecuador and northern Peru entails negative implications for the local fishing and guano industry. Fish populations are depleted due to their dependence on upwelling nutrient-rich waters, which in turn leads to starvation of seabirds. Furthermore, evaporation of warm sea waters has interfering effects on regional precipitation patterns (Caviedes, 2001). The southern United States, Peru, Ecuador, parts of Argentina, Central Asian countries and the east of Africa face excess precipitation. In the United States, more rainfall in the south benefits California lime, almond and avocado harvests. Parts of the US and Canada enjoy warmer weather and better fishing conditions. Cashin et al (2015) state that in South America, higher precipitation can benefit vegetation and certain crops in arid regions. However, according to Caviedes (2001) floods and landslides can entail damages and heavy rains might also entail soil erosion. At the same time, abnormal weather conditions such as the disruption of the Walker Circulation, occurrence of high pressure systems (referred to as 'blocking') or non-appearance of humid winds can lead to dry spells or outright droughts in several regions. Dryness is often experienced in certain regions in Africa, India, Southeast Asia, Australia, northern Brazil and Central America. (Caviedes, 2001). In southern Africa aridity has general negative effects on agricultural output, in Indonesia yields of coffee beans, cocoa, palm oil and other commodities are deteriorated. Cashin et al (2015) explain that India, a major producer of rice and sorghum, normally faces a weak monsoon and warmer conditions exacerbating to high aridity boreal summer. Parts of Central America show dry conditions and Mexico experiences benefitting conditions for oil production due to alternating geographical impacts of hurricanes. The International Research Institute for Climate and Society (IRI) provides *Figures 3 and 4* below, which are based on the works of Ropelewski and Halpert (1987) and Mason and Goddard (2001).

Figure 3 **El Niño Worldwide Precipitation Map**

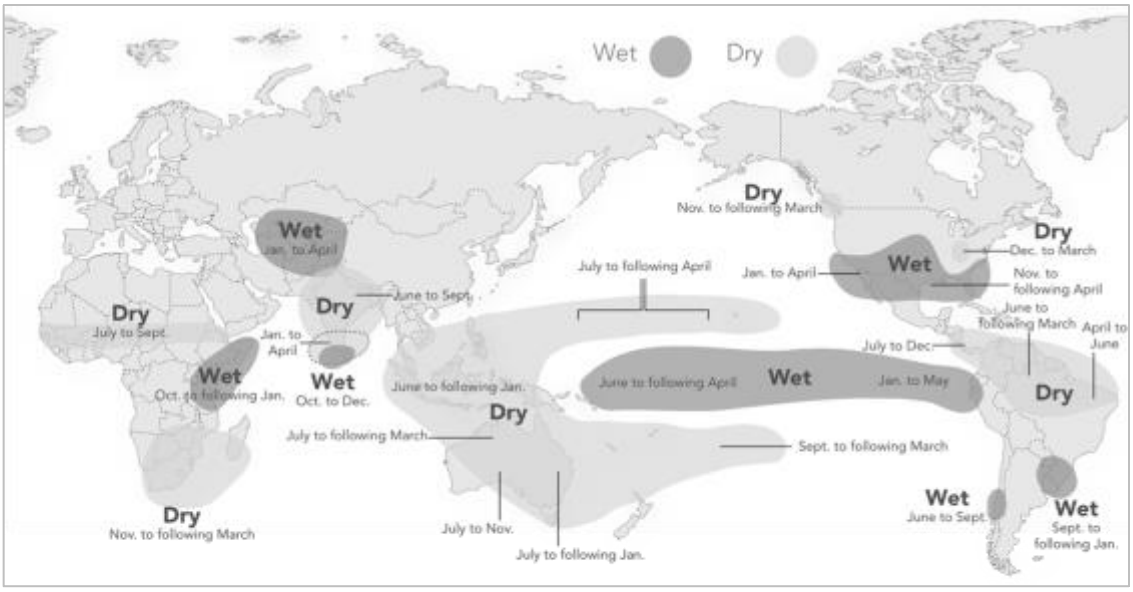


Figure 4 **La Niña Worldwide Precipitation Map**

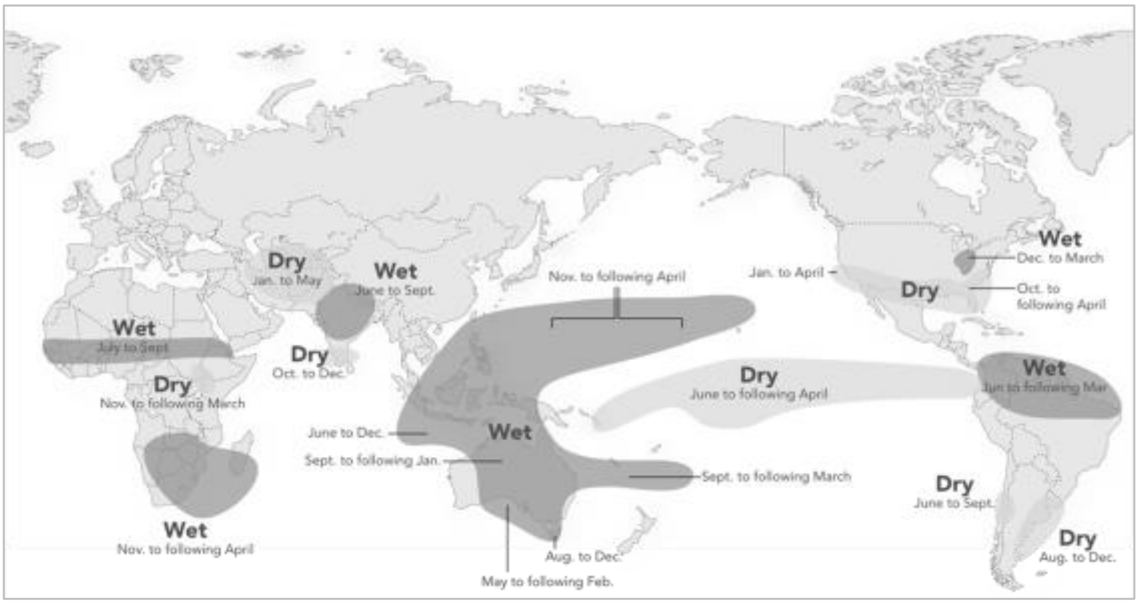


Figure 3 and 4 show world-wide precipitation shifts for El Niño and La Niña phases. Even though the impacts depend on specific ENSO events, strongest shifts remain similar. The maps are provided by the International Research Institute for Climate and Society and based on the works of Ropelewski and Halpert (1987) and Mason and Goddard (2001).

The impact of La Niña periods is in general relatively contrary to those of El Niño. Areas close to the Pacific Ocean which experience high precipitation during El Niño periods, are more likely to face droughts. Rainfall is generally enhanced over parts of Africa, India, Southeast Asia and Australia and parts of Brazil, Central America and the United States. On the other hand, parts of Central Asia and India, the west of South America and subtropical North America as well as southern Brazil and Argentina see drier than normal weather conditions during their respective winter seasons. Alaska, western Canada and the northwest of the United States get colder than normal air due to a lack of stimuli from the Pacific Ocean while the south-eastern United States become warmer and drier than in normal periods. In Caviedes (2001) it is stated that the Indian monsoon season tends to come along with enhanced rainfall during summer seasons.

2.2. Previously Measured Effects of ENSO Events

To analyse ENSO effects on commodity prices, the scope needs to be broadened to economic growth, general inflation and commodity price inflation. These three measures can regularly be found in ENSO related literature and several sources (e.g. Brunner, 2002; Laosuthi and Selover ,2007; Cashin et al, 2015) claim that there exists an interdependence between these measures. Thus, the analysis of causes for commodity price inflation becomes sounder if economic growth and inflation measures are incorporated in addition to ENSO measures.

2.2.1. ENSO Impact on GDP Growth

Cashin et al (2015) find statistically significant GDP growth effects following El Niño shocks on most analysed economies during the subsequent four quarters. These effects are measured by impulse response functions to a one standard deviation reduction in SOI anomalies. Statistically significant effects of El Niño shocks on GDP output are usually not evident over all quarters, as major El Niño impacts are experienced during specific seasons, depending on the geographic regions. Australia, New Zealand, India, Indonesia and South Africa experience a negative real GDP growth following an El Niño event. The authors explain these negative GDP growth effects by lower agricultural output due to droughts in Southern Australia, New Zealand, Indonesia and South Africa, floods in New Zealand and weak monsoons in India. Contrary, Argentina, Brazil, Canada, China, Chile, Europe, Japan, Mexico, Singapore, Thailand and the USA experience positive GDP growth due to beneficial temperatures, more rain and less frequent natural disasters. Overall, El Niño seems to stimulate global GDP growth as those economies affected positively account for a higher fraction of the global economic output than those negatively affected.

Laosuthi and Selover (2007) examine the effects of ENSO on economic growth in a different way than Cashin et al (2015). Contrary to the approach of Cashin et al, who analyse only El Niño shocks, Laosuthi and Selover estimate correlations between SOI (as ENSO measure) and GDP growth over the whole period from 1950 to 2000. The authors find statistically significant negative effects on growth in Mexico, South Africa, Australia, Canada and France. However, data for most countries shows weak and insignificant ENSO effects on the economic output.

2.2.2. ENSO Impact on Commodity Prices

Cashin et al (2015) analyse El Niño effects on real commodity prices. They argue that not only non-fuel commodities are affected, but also crude oil prices are inflated both due to higher demand caused by higher energy needs and lower supply from thermal power plants and hydroelectric dams. These findings are supported by GVAR models and statistical significance is tested with an impulse response analyses of oil prices and non-fuel commodity prices to a one standard deviation reduction in SOI anomalies. They show that both, non-fuel commodity prices and oil prices are increasing quarter on quarter for the analysed horizon of one year. The effect is significant for non-fuel prices from the second quarter onwards (95% confidence) as well as for oil prices from the first quarter (84% confidence) and from the second quarter onwards (95% confidence). Cashin et al (2015) suggest that the positive shock in non-fuel prices is triggered by lower supply from the Asia-Pacific region and then reinforced by higher global demand. The same goes for fuel prices which are driven by higher global demand due to El Niño caused growth effects on major economies.

Laosuthi and Selover (2007) use correlations and Granger tests with different annual, quarterly and monthly lags for the SOI to study the relationship between SOI and commodity price inflation. Their findings suggest that the relationship is weaker than the one found by Brunner (2002) and Cashin et al (2015). Correlations between SOI and commodity price inflation are modest, showing negative correlation for seven out of 15 commodities and positive correlation for the remaining eight. The analysed commodities are banana, cacao, coconut, coffee, cotton, maize, palm oil, pepper, rice, rubber, sorghum, soybeans, sugar, tea and wheat. For maize and sorghum these correlations are statistically significant and positive. Statistically significant Granger causality is found for maize and sorghum with one annual lag and for soybean, maize and sorghum with two annual lags. The same analysis with quarterly data shows significance for maize price inflation at two and four quarter lags, at four and six quarter lags for coconut oil, at six quarter lag for palm oil and two quarter lag for rice price. Laosuthi and Selover (2007) do not find statistical significance for monthly data and suggest that this could be due to seasonality or higher noise in the data.

Brunner (2002) constructs econometric models to research the impact of ENSO cycles on non-oil commodity prices and on price inflation and GDP growth in the G7 countries. He uses vector autoregressive (VAR) models and impulse response functions to estimate the effects of ENSO on commodity prices. The tests indicate a statistical relationship between commodity prices and ENSO and to a lesser extent also for inflation and GDP growth. Nevertheless, no economic significance is given. According to Brunner, ENSO affects variances in coconut oil prices most, followed by palm-, soybean-, and groundnut oil and other food items such as rice, wheat, soybeans and maize. Moreover, fish meal and rubber prices as well as iron ore and copper are influenced by ENSO shocks.

Ubilava (2012) studies the relationship between ENSO conditions and world coffee prices. The author finds that the price effect is varying, depending on the two coffee sorts Robusta and Arabica. El Niño events tend to affect Arabica prices negatively and Robusta prices only to a lesser extent. With a time-lag of a few months, this trend reverts and Robusta prices increase over the pre-El Niño levels. These effects are opposite in La Niña times. In general, Robusta coffee prices are well below Arabica coffee prices. Thus, in El Niño periods, the prices of lower quality Robusta and higher quality Arabica coffee converge while in La Niña periods the prices diverge.

Ubilava and Holt (2013) examine El Niño effects on world vegetable oils. The shocks observed had permanent effects on oil prices. Prices increase for positive ENSO events (El Niño) and decrease for negative ENSO events (La Niña). Coconut oil and palm kernel oil prices react the most to ENSO shocks, while the magnitude of effects for groundnut oil was the lowest using their statistical methods.

Ubilava (2014) finds that world wheat prices are negatively affected by positive ENSO shocks and adversely affected by negative shocks. La Niña effects tend to have a bigger amplitude than El Niño effects due to asymmetries and storage effects. In times of La Niña, wheat prices increase due to a lack of supply which can only be absorbed to a certain extent by storages. On the other hand, during El Niño times, wheat prices react less since an excess supply can be stored to avoid extreme decreases in prices.

Linking rice production to ENSO based climate variability is topic of the research of Naylor et al (2001). Their regression results show a strong connection between sea surface temperature anomalies and rice production in Indonesia. According to the authors, 40% of rice output variances can be explained by year-to-year fluctuations in SST anomalies measured with a lag of four and eight months.

Iizumi et al (2014) study the impact of El Niño-Southern Oscillation on global crop yields. Besides presenting a global map with visualised impacts, the authors show that during El Niño the global mean soybean yield improves between 2.9% to 3.5% and on the contrary, in La Niña years the global soybean yield is influenced negatively between -1.6% to -1.0%. Yields for maize, rice and wheat are affected mostly negatively in a range of -4.0% to -0.2% during both, El Niño and La Niña periods. Iizumi et al (2014) measure the geographical distributions of El Niño and La Niña impacts on crop yields as deviations from the running 5-year means. They find significant negative effects for El Niño periods in 22-24% of harvested areas worldwide and positive effects for 30-36% of harvested areas worldwide. For La Niña periods the observed effects differ and only 2-4% of worldwide harvested areas are positively affected and at the same time 9-13% show negative impacts. Overall La Niña effects on harvested areas and crop yields tend to be lower than those of El Niño. In all periods, there are offsetting effects where yields in some regions are positively affected and negatively impacted in other regions.

2.2.3. ENSO Impact on Inflation

In addition to economic stimulation and rising commodity prices, Cashin et al (2015) find statistically significant upward pressure for consumer price indices (CPI) around the globe. The authors suggest that this broad inflation occurs due to commodity price inflation, government policies and aggregate demand-side pressure from higher economic activity. The inflation measures increase most in economies in which food accounts for a high fraction in the CPI baskets as it is the case for many Asian countries such as Thailand, India and Indonesia. Support to this result is given by a positive correlation between the share of food in the CPI and the inflation responses to El Niño shocks.

2.3. Predictability of ENSO Events

Commonly, ENSO prediction models can be separated into three different categories, purely statistical models, physical ocean-statistical atmosphere hybrid models and fully physical ocean-atmosphere coupled models. Generally, an ensemble forecast seems more powerful than individual forecasts and the different groups of models have their advantages in predictions with different lead times (Chen and Cane, 2008).

Fedorov et al (2003) state that it is difficult to predict El Niño events and attempts to do so have not been very successful at this time. According to them, the main challenge in predicting an El Niño event and its amplitude is that it is caused by an interplay between the Southern Oscillation and atmospheric noise. The authors arrive at the conclusion that the influence of random atmospheric disturbances differs, depending on the phase of the oscillation and thus, the predictability of specific El Niño events is limited. In an analysis of twelve different statistical and dynamic models, the authors find that for the 1997/98 El Niño, as well as for the 2002 El Niño, the forecasts regarding the timing, duration and magnitude were differing substantially from each other. The existing models are capable of predicting the occurrence of at least some El Niño events. However, the magnitude of those events is more difficult to predict since it depends on random atmospheric disturbances.

Chen et al (2004) use a coupled-ocean atmosphere model to predict El Niño events in retrospective with a lead time of up to two years. The authors conduct retrospective forecasts of ENSO events for a 148-year period from 1857 to 2003. This period is studied since observations dating back further are lacking quality. They find that El Niño events are mostly dependent on initial oceanic conditions (sea surface temperatures) and to a lesser extent on random and unpredictable atmospheric noise, although westerly wind bursts do have effects on the duration and amplitude of ENSO events. During the 148-year period examined, 24 El Niño (anomaly of 1℃ warmer water) and 23 La Niña (anomaly of 1℃ colder water) events have occurred in the Niño3.4 region in the Central Equatorial Pacific. The simple model used could predict most events at a six-month lead time and even with a two-year lead time the model could successfully predict major ENSO events. Nevertheless, errors exist in the forecasted amplitude of these events and in the predicted start of El Niño and La Niña periods respectively. One of the biggest issues of this model is the inability to predict smaller ENSO events.

Nowadays, the probabilistic forecasts of ENSO events by the International Research Institute for Climate and Society seem to provide a promising data source and method. These probabilistic monthly forecasts are available from 2002 onwards and include human judgements as well as model output (IRI, 2017).

2.4. Commodity Investments

Investing in commodities entails various obstacles for investors such as the exposure to physical deliveries, regional price differences, various currencies and seasonality patterns. From a pure investment point of view, it generally is favourable if futures contracts imply cash settlement instead of physical delivery. Moreover, the commodity should be traded in the markets with sufficient liquidity to allow investments and divestments when necessary. Demidova-Menzel and Heidorn (2007) point out that despite high volatility, commodity investments can reduce overall volatility of a portfolio due to a low correlation with other asset classes such as stocks or bonds. Moreover, commodities are real assets and thus are strongly linked to inflation rates and can offer a natural hedge against value changes of money.

2.4.1. Types of Commodity Investments

Demidova-Menzel and Heidorn (2007) provide a distinct overview on commodity investments. Commodity related investments include direct investments in physical commodities, direct investments into commodity-exposed companies and investments into commodity products such as futures, options, ETF’s or other structured products. Investments into physical commodities, if available, require physical storage for the commodity and thus can be difficult. Direct investments into commodity-exposed companies do not require physical storage for an investor but inherit a different obstacle. An investment in commodity exposed companies is not a pure investment into a specific commodity as many companies are horizontally or vertically diversified. Moreover, an equity investment also depends on other factors that influence the earnings and value of the company, e.g. general stock market conditions. According to Demidova-Menzel and Heidorn (2007), studies show, that the correlation of returns on commodity related companies are closer correlated to overall equity markets than to their underlying commodities. Commodity futures offer tradability including the opportunity of taking both long and short positions in commodities. Additionally, they are often cash settled and are closely linked to the underlying commodity price. One major issue which commodity futures inherit lies in rather short-term contract lengths and thus a high exposure to seasonality and short-term volatility in the underlying price.

Demidova-Menzel and Heidorn (2007) take a detailed look on commodity futures indices. These allow investments in a basket of commodities, e.g. agricultural commodities or an aggregate investment into Arabica coffee. This is important as futures are usually specific on one commodity type and region and thus a broad variety of futures exists per commodity.

Moreover, commodity futures indices also provide the service of rolling over expiring futures into new futures according to a predetermined roll strategy.

Indices based on commodity futures provide three sources of returns - the spot price return of the underlying commodity, collateral return and roll return. The collateral return is the yield earned by an investment into the risk-free rate, assuming the full value of the underlying futures is invested. The roll return is generated from exchanging close-to-expiration futures contracts into longer-maturity contracts. Depending on the current slope of the term structure of futures prices and the rolling strategy, this return can be positive or negative.

2.4.2. Commodity Futures Investment Strategies

Lesmond et al (2001) show that the availability of short selling is a key characteristic of futures investment strategies. In contrast to equity markets, short selling in futures markets is relatively easy. Positive abnormal returns in equity momentum strategies rely heavily on short-sales, although in practice it can be difficult to take short positions in equities.

Narayan et al (2015) examine momentum-based trading strategies in commodity futures markets. They allow for long and short positions in the best and worst performing commodities and find that investors can earn statistically significant profits with momentum-based trades. They base their analysis on oil, gold, silver and platinum futures as these commodities account for more than two thirds of total trading volumes in commodity markets. Wang and Yu (2004) examine contrarian futures-based trading strategies. They find return reversals over a one-week time horizon in several futures markets, among them commodity futures markets, and suggest that it is possible to generate abnormal profits from contrarian commodity strategies even after transactions costs. Vrugt et al (2004) employ macroeconomic trading signals based on business cycles, monetary policies and market sentiment and find that these signals can generate profitable trades.

3. Empirical Approach

This part will be structured as follows. First, the data employed in this study is explained and critically discussed. Second, the methodology employed for measuring ENSO related price effects is described including (1) correlations and Granger causality tests, (2) time series regressions and (3) mean return analysis. Third, the methodology utilized for trading strategies and historical performance tests is explained.

3.1. Data

3.1.1. Data Description

This thesis is reliant on following data sources: the United States National Oceanic and Atmospheric Administration (NOAA, 2017) for ENSO related weather data, BLOOMBERG (2017) for commodity price indices and the iLibrary of the Organization for Economic Co-operation and Development (OECDiLibrary, 2017) for inflation data.

The NOAA publishes monthly data on the two ENSO measures Oceanic Niño Index (ONI) and Southern Oscillation Index (SOI), starting in 1950. Both measures indicate anomalies from long-term means. In the case of the ONI measure, a monthly calculated, three-month running mean of Sea Surface Temperatures (SST) is employed for comparison to a long-term average. Due to an overall warming trend of the sea temperatures, the 30-year average periods are adjusted by the NOAA to avoid incorporating global long-term weather trends in the forecasting of ENSO events. Specifically, the NOAA creates so-called centred 30-year base periods, which are updated every five years. For instance, during the period from 1961 - 1965, the SST anomalies are computed against the base period from 1946 - 1975. Since the encompassing 30-year period is not available in the present, the computations are compared to the last available base period, e.g. in 2017, the period from 1986 - 2015 is used. These base periods will be adjusted, as soon as data is available. The implication of this method is that SST anomalies from the most recent decade are subject to slight adjustments in the future, when new data points occur and the final 30-year averages can be employed. *Table 1* provides summary statistics for the ENSO indicators ONI and SOI between January 1970 and December 2016.

Table 1 **Summary Statistics for ENSO Indicators**

This table reports summary statistics for the monthly El Niño-Southern Oscillation (ENSO) measures Oceanic Niño Index (ONI) and Southern Oscillation Index (SOI). The monthly data is collected from the United States National Oceanic Atmospheric Administration (NOAA) for the period from January 1970 to December 2016. The NOAA definition requires ONI to breach a threshold of 0.5 for El Niño or -0.5 for La Niña for a minimum of five consecutive months.

Measure	Observations	Mean	SD	Min	Max
ONI	564	-0.004	0.825	-1.900	2.300
SOI	564	0.104	1.010	-3.600	2.900

The S&P GSCI Total Return commodity indices are chosen as a proxy for commodity prices throughout this paper. The dataset, withdrawn from BLOOMBERG, contains daily time series data for prices of 18 single commodity indices and one weighted commodity portfolio, the S&P GSCI TR index, an all commodities index[2]. The indices are based on commodity futures prices and employ a standard roll strategy. Indices using a standard roll strategy usually invest in a single futures contract, which is normally the first nearby, most liquid expiration month. Upon reaching expiration date, they roll-over in another single futures contract. Commodity indices are chosen for this thesis because they are reaching back as far as 1970 and are both directly investable and are based on an approach which is imitable for every investor. In order to match the ENSO measures retrieved from the NOAA, daily GSCI data is transformed to monthly data. In this procedure, the respective data point from the last trading day of each month is used. For the mean return analysis, the data is transformed to a three-month basis.

Additionally, OECD Inflation data is withdrawn from the OECD iLibrary. The collected time series reaches from February 1970 to December 2016 and provides monthly consumer price percentage changes for the entire basket. *Table 2* provides summary statistics for monthly returns of the collected commodity price index data and OECD inflation.

[2] The weights of the all commodities index are not reported. However, a high correlation between the all commodities index and crude oil returns (R = 0.91) indicates a high loading on petroleum commodities.

Table 2 **Summary Statistics for Monthly Commodity Return Data**

This table displays summary statistics for monthly S&P GSCI Total Return commodity indices returns and inflation for member countries of the Organization for Economic Co-operation and Development (OECD). The commodity index data is collected from BLOOMBERG and returns data reaches from February 1970 to January 2017. For some commodities data is not available for the entire time frame. OECD inflation data is collected from the OECD iLibrary data base and reaches from February 1970 to December 2016.

Commodity	Observations	Mean	STD	Min	Max
All Commodities	565	0.0073	0.0578	-0.2820	0.2577
Wheat	565	0.0027	0.0793	-0.2527	0.4239
Corn	565	0.0025	0.0765	-0.2280	0.4655
Soybean Meal	265	0.0148	0.0814	-0.2042	0.3015
Soybeans	565	0.0099	0.0814	-0.2198	0.5683
Soybean Oil	145	0.0026	0.0730	-0.2510	0.2668
Cocoa	397	0.0000	0.0815	-0.2494	0.3522
Coffee	433	0.0046	0.1074	-0.3089	0.5424
Cotton	481	0.0046	0.0701	-0.2258	0.2752
Sugar	529	0.0071	0.1157	-0.2969	0.6863
Aluminium	313	-0.0004	0.0549	-0.1676	0.1592
Zinc	313	0.0038	0.0720	-0.3417	0.2806
Lead	265	0.0087	0.0831	-0.2743	0.2703
Nickel	289	0.0082	0.0985	-0.2748	0.3516
Copper	481	0.0104	0.0769	-0.3555	0.3843
Gold	469	0.0055	0.0561	-0.2041	0.2823
Silver	529	0.0079	0.0957	-0.4687	0.5591
Crude Oil	361	0.0086	0.0961	-0.3243	0.4889
Heating Oil	409	0.0090	0.0920	-0.2886	0.3760
OECD inflation	563	0.0047	0.0035	-0.0094	0.0187

3.1.2. Critical Discussion of Data Sources

This part briefly discusses potential shortcomings and the reasoning for choosing the ENSO related weather data of the NOAA and the S&P GSCI Total Return commodity indices.

Both the measurement of effects as well as the trading strategies are based on ONI measures. Since these are publicly available, prices could already be affected before the official ENSO limits, set by the NOAA, are breached. Probabilistic predictions for ENSO events provided by the NOAA could mitigate this issue due to possible timing advantages. However, such predictions are also published and the historical availability is limited. Thus, it was decided to use the ENSO measures presented above for the purposes of this paper.

Employing GSCI Total return data as a proxy for commodity prices entails two issues. First, the process of rolling can significantly affect the performance of commodity investments and second, the data quality of GSCI indices prior to their launch is questionable. As Erb and

Harvey (2006) find, rolling yields can affect the performance both positively and negatively, depending on the respective term structure of futures prices. The standard case, in which a commodity has a lower spot price than forward price, is called contango. Opposite to that is a relationship known as backwardation, in which the spot price of a commodity is higher than the forward price. Erb and Harvey (2006) analyse the cross-section of commodity futures returns and find a negative roll return in two thirds of analysed commodities and a positive roll return in one third of the analysed commodities. S&P GSCI Total Return indices employ a standard roll strategy in which the about-to-expire futures contract is rolled over into the next nearby contract month, which can be expensive in a contango environment.

The second issue with index data is that the calculation of historical values prior to the launch of the GSCI indices in 1991 can reduce the quality of the data. According to S&P Dow Jones Indices (2017), back-testing procedures are subject to limitations due to an application of index methodology in hindsight. The reasoning for choosing index data regardless is that data provided by other sources such as the World Bank (2017) are often based on prices for physical goods and, thus, unsuitable for the purposes of this thesis.

Furthermore, historical performance tests with more frequent than monthly data points could have been beneficial to implement advanced trading conditions (e.g. stop loss conditions). However, as the ENSO measures, employed as buying signals for the trading strategies, are only available monthly, it was decided to transform the entire data set to a monthly basis.

3.2. Methodology for Measuring of Effects

The methodologies used to study economic effects of ENSO events in existing literature are mainly reliant on Granger causality tests (e.g. Brunner, 2002; Laosuthi, 2007), correlations (Laosuthi, 2007), vector autoregressive models (Brunner, 2002; Ubilava, 2012; Cashin et al, 2015) or smooth transition vector error correction (Ubilava and Holt, 2013). This thesis utilizes correlations, Granger causality, OLS time series regressions and a mean return analysis.

3.2.1. Granger Causality Tests and Correlations

Granger causality tests are employed to identify if precedent variation in the Oceanic Niño Index has explanatory power of variations in commodity prices. Before conducting Granger tests, the time series data is tested on stationarity. For these purposes, Augmented Dickey Fuller tests are applied. The time series data of the ONI measure and commodity indices are tested positively on stationarity. Therefore, the data does not have to be transformed. The following relationship is tested:

$$\mathrm{ONI}_{\mathrm{t-k}} \rightarrow R_{i,t}$$

where ONI refers to the ENSO measure Oceanic Niño Index at time t-k, R is the return of commodity i at time t, k is the lag in months. The tests are estimated for a lag of three and six months. In the results part correlations and Granger estimates are displayed (see *Section 4*).

3.2.2. Times Series Regression Model

Regressions are utilized in order to measure potential effect directions and sizes. In the time series regression model, an ordinary least squared (OLS) approach is followed and commodity returns are regressed on the ENSO measure while controlling for OECD Inflation. This control variable is selected to adjust for macroeconomic effects. Regressions are run of the following form:

$$R_{t,i} = \alpha_i + \beta_{0,i} * ONI_t + \beta_{1,i} * INF_t + \epsilon_{t,i}$$

where R is the total return of commodity index i at time t, ONI represents the ENSO measure at time t, INF is the OECD inflation rate at time t and ϵ is the model error term at time t for commodity i. As independent variables are chosen without lags, this model relies on the assumption that changes in ENSO data are priced in immediately. In addition to the whole dataset, the regression is estimated for two subsets. *Subset I* contains only periods in which ONI values are greater or equal to zero, *Subset II* contains the periods in which ONI values are negative. Therefore, *Subset I* captures mainly El Niño related effects and *Subset II* primarily La Niña related impacts. The aim of choosing these subsets is to investigate possible differing effects in the two ENSO phases.

3.2.1. Mean Return Analysis

For visualising the development of ENSO price effects and potential lags, mean returns of historical phases of La Niña and El Niño are plotted versus mean returns over neutral periods. ENSO events were selected based on the official NOAA definition that ONI values must remain at a level greater or equal to 0.5 for El Niño and smaller or equal to -0.5 for La Niña for at least five consecutive months. Furthermore, we define ENSO phases to always start in June and reach to May in the following year because ENSO events, both El Niño and La Niña, usually start in the second half of the year, reaching the peak in northern winter and decrease subsequently. Defining yearly phases starting in June ensures a long enough timeframe for comparison purposes, yet allows for clear distinction between separate phases. Out of the 46 year-long periods from June 1970 to May 2015, 16 El Niño phases and 14 La Niña phases were identified, the remaining 16 are neutral. If an ENSO event lasts longer than one year it is separated into more phases. The identified event phases are shown in *Table 3*.

For reduction of noise, monthly returns are cumulated to three-month returns for the entire dataset. The three-month periods are defined to include the months June-August, September-November, December-February and March-May. These periods are selected as they match into the previously defined year-long event phases. Finally, the mean returns for these three-month periods are computed and plotted for defined El Niño, La Niña and neutral phases.

Table 3 **Identified ENSO Event Phases**

This table displays identified El Niño-Southern Oscillation (ENSO) phases from 1970 to 2016. The phases are defined to start in June and end in May of the following year and selected to match the official definition by the United States National Oceanic Atmospheric Administration (NOAA). The NOAA definition requires ONI to breach a threshold of 0.5 for El Niño or -0.5 for La Niña for a minimum of five consecutive months. Of the 46 year-long periods form June 1970 to May 2016, 16 were identified as El Niño phases and 14 as La Niña phases. The column month of breach shown in the table below refers to the initial breach of the ONI threshold or states 'ongoing' if the previous ENSO event extends over a period longer than one year.

El Niño Phases (June to following May)

ENSO Periods	Month of breach	Months above threshold	Max ONI
72/73	Jun-72	10	1.9
76/77	Oct-76	6	0.8
77/78	Oct-77	5	0.8
79/80	Nov-79	6	0.6
82/83	May-82	12	2.1
86/87	Oct-86	9	1.2
87/88	ongoing	9	1.6
91/92	Jul-91	12	1.6
94/95	Nov-94	6	1
97/98	Jun-97	12	2.3
02/03	Jul-02	9	1.2
04/05	Aug-04	10	0.7
06/07	Oct-06	5	0.9
09/10	Aug-09	10	1.3
14/15	Dec-14	7	0.8
15/16	ongoing	12	2.3

La Niña Phases (June to following May)

ENSO Periods	Month of breach	Months above threshold	Min ONI
70/71	Aug-70	11	-1.3
71/72	ongoing	8	-0.9
73/74	Jul-73	12	-1.9
74/75	ongoing[1]	10	-0.8
75/76	ongoing	10	-1.6
84/85	Nov-84	8	-1.1
88/89	Jun-88	12	-1.8
95/96	Sep-95	8	-0.9
98/99	Aug-98	11	-1.4
99/00	ongoing	12	-1.6
00/01	ongoing	9	-0.8
07/08	Sep-07	10	-1.4
10/11	Aug-08	10	-1.5
11/12	Sep-11	7	-0.9

Note: (1) ONI values for September and October 1974 below threshold.

3.3. Methodology for Trading Strategies and Historical Performance Tests

Two types of ENSO timing strategies are generated at the per commodity level. The strategies are created identically in terms of entry dates, which are based on ENSO weather measures, but differ in terms of selling condition. In *Selling Strategy I*, a fixed holding period is set. Hence, varying exit months and holding periods for different ENSO events are implied. In *Selling Strategy II*, a fixed exit month is determined, implying identical exit dates for each commodity and each ENSO event. Subsequently, the strategies are tested on historical performance.

Analysis of sea surface temperatures shows that both El Niño and La Niña events tend to start during boreal spring without showing significant temperature increases and effects. The changes in ONI data and weather become stronger and more obvious during boreal summer and autumn and usually peak in the winter months. Thus, entry trades are generally defined to be only placed in months within the six-month period from June to November when ENSO weather effects reach traction and public awareness starts to be prevalent. Below, it will be referred to the period between June and November as *Entry Period*. The first half of the year is excluded for following reason. An entry into a trade could be too early in the first half since temperature anomalies early in the year can be misleading. Moreover, ENSO events usually peak during the boreal winter, so an early investment could expose an investor to unwanted noise or seasonality.

Two options were considered as underlying for the buying signal: the previously discussed ENSO weather data in form of ONI or SOI and more complex probabilistic forecasts. Due to a limited historical availability of the more accurate probabilistic ENSO event forecasts, the entry timing is based on ENSO measures. Reliable data for these measures (ONI, SOI) can be obtained from the NOAA from 1950 onwards. The two ENSO measures ONI and SOI show high negative correlation (R = -0.74). Given the correlation, we choose one of the measures as our trading signal, namely ONI. An investment into a commodity is only assumed if a signal is generated by ONI. The divestment follows according to the respective selling strategy.

Next, two options for defining an ONI based signal for an investment into commodities were considered. The first one is triggered by a single rise above the threshold of 0.5℃ anomaly from the long-run average (i.e. an ONI value of greater or equal to 0.5 for El Niño events and a value smaller or equal to -0.5 for La Niña events) during the *Entry Period*. In the second option considered, the rise above the threshold must remain for at least three consecutive months. This three-month approach inherits the advantage of eliminating misleading signals (false positive). Nevertheless, implementing this buying strategy has two highly limiting consequences. First, it indicates buy signals late and thus, the investor might miss early movements of commodity prices as reaction to a starting ENSO event. Second, if three consecutive months must be breached within the defined *Entry Period*, only signals which start before October will be captured. This limits possible investments and historical data from *Table 3* shows that some of the initial ENSO breaches occurred in October or even later. Since the single-month strategy only generated five misleading signals for El Niño (i.e. El Niño was indicated 21 times ex ante but only occurred 16 times) during the analysed period, emphasis is put on the first entrance strategy to incorporate early price reactions. In the case of La Niña, the single-month breach entry strategy generated 19 buy signals and 14 La Niña events occurred.

Following the entry into trades, the determination of the exit signal or holding period are essential. We considered two simple non-commodity specific exit options. For *Selling Strategy I* the holding period is fixed and results are derived for holding periods of one and six months. *Selling Strategy II* implies an investment until a specific month between December and May following the ONI breach, independent on the time of the entry into the trade. Thus, the length of the holding period can vary between one and eleven months. Subsequently, geometric monthly returns and excess returns over a buy-and-hold strategy are calculated for each commodity. Results for the exit strategies are derived for *Selling Strategy I* for one and six months and for *Selling Strategy II* for exit in March. Results for *Selling Strategy I* are explained in *Section 4.2.*, results for *Selling Strategy II* are stated in the *Appendix*.

For tests of historical performance of previously described strategies, again S&P GSCI indices are used because these are based on futures prices and follow a roll-over approach which would have been historically imitable by any investor. In *Section 3.1.*, the reasoning for the choice of S&P GSCI indices and the methodology behind these futures-based indices is explained in more detail. The tests for ENSO based strategies begin with the availability of investable commodity products in 1970. Due to varying time series length of the commodity indices, the historical test could not be conducted back to 1970 for all commodities. The tests for the trading strategies are started with only three commodity indices in 1970 (corn, wheat and soybeans) and the most recent one added is soybean oil in 2005. All in all, 18 different commodity indices are analysed over time from 1970 to the beginning of 2017.

The described trading strategies are based on characteristics and patterns of ENSO events and do not assert the claim of being the best possible trading strategy for past returns. There are ways to optimize these returns, especially by adjusting the trades on a per commodity basis since different commodities show varying responses to changes in weather patterns in terms of lags, lengths and magnitudes.

4. Results

This section will be structured as follows. First, the results for measured effects will be presented. This includes the following parts: (1) The results for the correlations and Granger tests. (2) The results for the time series regression. (3) The mean return analysis. This part provides an extensive interpretation. (4) A summary of measured effects. Afterwards, the results of the trading strategies are reported and explained.

4.1. Results for Measuring of Effects

4.1.1. Correlations and Granger Test

Table 4 reports the correlations and Granger causalities with lags of three and six months for all commodities on the ENSO measure ONI. Positive correlations indicate a positive return effect for El Niño and a negative effect for La Niña. Out of the total 19 commodity indices, 13 show a negative effect. This indicates that El Niño (La Niña) mostly has a negative (positive) effect on commodity returns. It must be pointed out, however, that possible non-linear effects cannot be identified by correlations.

In general, the correlations range from -0.1575 to 0.0492. The most negative being the petroleum commodities and the most positive being soybeans. The sizes of these correlations seem to be mainly in line with the correlations found by Laosuthi and Selover (2007). The authors find correlations for quarterly data between commodity returns and SOI (which has a high negative correlation with ONI, see *Section 3.3.*) within a range of -0.0778 to 0.0658 for those commodities which are part of our study. However, they find differing direction of correlations for coffee and cotton. The correlation coefficient for the all commodity index is -0.0776. The reason for the highly negative result for the all commodities index might be the overweighting of petroleum in this index. The index shows a Granger causality with a P-value of 0.0619 at a lag of six months which would be considered statistically significant with 90% confidence.

The correlations for agricultural commodity returns show mainly negative values apart from soybeans, cocoa and cotton. The largest negative coefficients are the ones of soybean meal and soybean oil with a value of -0.0647 and -0.0788 respectively. However, the correlation of soybeans shows a value of 0.0492. The difference in sign of these the correlations of these commodities is contrary to expectations as soybean meal and oil are related products to soybeans. Furthermore, for soybean oil and soybeans, the estimates suggest a Granger causality at the six-month lag level, for soybean oil also at the three-month level. Wheat has a correlation coefficient of -0.0364 and shows statistically significant Granger causalities both for the three and six month lags.

The results for metals show low correlation estimates in absolute terms compared to agriculture commodities. Nickel and copper show the lowest correlation coefficients with values of -0.0379 and -0.0263 respectively and gold and silver the highest with values of 0.0433 and 0.0370 respectively. Granger causality was found for copper at the six-month lag level with a statistical significance at the 10% level. The correlations of the energy commodities crude oil and heating oil include the highest negative values, which seems to suggest that El Niño (La Niña) has a negative (positive) effect on returns.

Further, the correlation for crude oil with ONI is -0.1575 and for heating oil the value is -0.1088. For crude oil the results suggest a Granger causality at the three- and six-month lag level but with higher statistical significance at the former. This suggests that a three-month lagged ONI time series is slightly more useful to predict crude oil returns. Heating oil shows statistically significant Granger causality for a lag of three months which indicates that the three-month lagged ONI value has predictive value for heating oil.

Table 4 **Correlations and Granger Causalities of Commodity Returns on ONI Measures**

This table presents the results for correlations of commodities returns and the Oceanic Niño Index (ONI) as well as Granger causalities of the form: $\mathrm{ONI}_{t-k} \rightarrow R_{i,t}$, where ONI refers to the employed ENSO measure at time t-k, R is the return of commodity i at time t, k is the lag in months. For the Granger tests, F-statistics and p-values for three and six month lags are reported. The estimates are calculated for the returns of 19 S&P GSCI commodity indices, collected from BLOOMBERG, over the period from February 1970 to January 2017. The ONI data is collected from the United States National Oceanic and Atmospheric Administration. (*** p<0.01, ** p<0.05, * p<0.1)

Commodities	Correlations with ONI	F-Statistic (3 lags)	P Value	F-Statistic (6 lags)	P Value
All commodities	-0.0776	0.8560	0.4638	2.0153	0.0619*
Wheat	-0.0364	3.3295	0.0194**	1.9377	0.0729*
Corn	-0.0346	1.4460	0.2284	1.2986	0.2558
Soybean meal	-0.0647	1.3501	0.2587	1.0073	0.4211
Soybeans	0.0492	1.6245	0.1826	2.2339	0.0387**
Soybean oil	-0.0788	4.3058	0.0062***	2.3670	0.0337**
Cocoa	0.0079	1.4848	0.2182	1.2156	0.2973
Coffee	-0.0372	0.3626	0.7801	0.3357	0.9180
Cotton	0.0183	0.4807	0.6958	1.4063	0.2104
Sugar	-0.0466	0.2363	0.8711	0.8407	0.5388
Aluminium	-0.0006	0.3562	0.7847	0.8494	0.5327
Zinc	-0.0127	0.5579	0.6432	1.0333	0.4037
Lead	0.0110	0.6643	0.5747	1.1204	0.3509
Nickel	-0.0379	0.2358	0.8714	0.8008	0.5700
Copper	-0.0263	0.2337	0.8729	1.9353	0.0737*
Gold	0.0433	0.3169	0.8132	0.7202	0.6335
Silver	0.0370	0.3909	0.7596	0.5133	0.7984
Crude oil	-0.1575	2.7748	0.0413**	2.0428	0.0595*
Heating oil	-0.1088	2.1564	0.0927*	1.5336	0.1658

4.1.2. Times Series Regression Model

Table 5 summarizes the multiple regression results of S&P GSCI commodity index returns on ONI and OECD inflation for the whole sample and the two subsets. Whereas *Subset I* only includes observations where ONI is greater or equal to zero (i.e. El Niño related observations), *Subset II* includes data points where ONI values are smaller than zero (i.e. La Niña related observations).

In general, inflation has a positive and statistically significant relationship with commodity returns in many cases, especially with energy commodities. The inflation coefficients for crude oil and heating oil are 9.699 and 6.3662 respectively. This suggests that a one percent rise in the consumer price index on average goes along with a 9.699% rise in crude oil return. The positive relationship of commodity returns and inflation compares well with previous literature (e.g. Furlong and Ingenito, 1996; Gorton G., & Rouwenhorst, K.G.,2006.).

For most commodities in the whole sample, the ONI coefficients show relatively low economic and statistical significance. For the whole data set the most significant and largest effects are measured for crude oil with -0.0192 and heating oil with a value of -0.0127 which provides evidence that El Niño (La Niña) has a negative (positive) effect on returns. The all commodities index coefficient for ONI with -0.0051 also shows a negative and statistically significant result. As there is evidence that the all commodities index is heavily weighted on petroleum, especially crude oil (the measured correlation coefficient of the all commodities index and crude oil returns is 0.9093), the similarity in effects was expected.

The two subsets differ both in terms of measured effect size and statistical significance. Subset I shows ONI coefficients with lower economic magnitude of ONI coefficients and fewer commodities with statistical significance. The subset suggests statistically significant (ten percent level) negative effects for lead (-0.0197), nickel (-0.0258) and crude oil (-0.0207) and, thus, provides evidence for negative return effects during El Niño events. *Subset II* reports in general results with higher economical and statistical relevance compared to *Subset I* and the whole sample. According to the estimates, La Niña affects returns positively for commodities with statistically significant results. This is the case for the all commodities index with an ONI coefficient of -0.0221, which is a gain comparable to the results of the commodities crude oil and heating oil which show statistically significant ONI coefficients of -0.0306 and -0.0401 respectively. The statistically significant results for agriculture commodities are corn (-0.0258), soybean oil (-0.0539), cotton (-0.0255) and sugar (-0.0397). For metals nickel copper and silver are statistically significant and show ONI coefficients of -0.0378, -0.0242 and -0.0308 respectively.

For the two subsets, it is interesting to note that the ONI estimates do not only differ in the effect magnitude but partly also in terms of direction. This is the case for the agriculture commodities corn, soybeans, soybean oil, cocoa, cotton, sugar and the metal commodities zinc, lead and silver. For the energy commodities, the price effects are consistent in terms of direction for both subsets. This result indicates that the above-mentioned commodities have a similar price effect for both ENSO periods. However, the measured effects are in general larger and more significant for La Niña.

In conclusion, the largest and statistically most significant effects are measured for La Niña periods and those happen to be always positive. Looking at commodities with a statistical significance level of at least five percent, corn, soybean oil, cotton, sugar, silver and heating oil show the largest positive return effects during La Niña. The less robust results for El Niño might indicate that El Niño has smaller non-significant effects on commodity returns. However, it could also be the case that El Niño effects are lagged in time (e.g. ONI showed a Granger causality for wheat and copper at the six-month lag level). Further, the ONI measures have non-linear effects on certain commodity prices and, thus, it is indicated that both La Niña and El Niño can affect these prices in the same direction.

Table 5 **Time Series Regression of Commodity Returns on ONI and Inflation**

This table reports results for the time series OLS regression of the form $R_{t,i} = \alpha_i + \beta_{0,i} * ONI_{t,} + \beta_{1,i} * INF_t + \epsilon_{t,i}$, where R refers to the total monthly return of commodity i at time t, ONI represents the ENSO measure Oceanic Niño Index at time t, INF is the OECD inflation rate at time t and ϵ is the model error term at time t for commodity i. The model is run for monthly S&P GSCI Commodity index returns collected from BLOOMBERG. Return data is available from February 1970 to January 2017, however not for all indices. The inflation data is collected from the OECD iLibrary. The model is estimated for the whole sample and two subsets. *Subset I* contains only data points for which ONI is greater or equal to zero (El Niño related). *Subset II* contains data for which ONI is smaller than zero (La Niña related). (*** p<0.01, ** p<0.05, * p<0.1)

	Whole sample				Subset I (ONI ≥ 0)				Subset II (ONI < 0)			
	Intercept	ONI Measure	Inflation	Obs.	Intercept	ONI Measure	Inflation	Obs.	Intercept	ONI Measure	Inflation	Obs.
All commodities	-0.0064	-0.0051*	2.936***	563	-0.0039	-0.0057	2.9808***	280	-0.0172**	-0.0221**	2.3232**	283
Wheat	-0.0024	-0.0034	1.0792	563	-0.0055	-0.0016	1.4094	280	-0.0012	-0.0047	0.6851	283
Corn	-0.0036	-0.0031	1.3023	563	-0.0080	0.0067	1.0511	280	-0.0181*	-0.0258**	1.0047	283
Soybean meal	0.0125*	-0.0060	0.7911	263	0.0133	-0.0084	1.4348	114	0.0140	-0.0046	0.4770	149
Soybeans	0.0055	0.0050	0.9334	563	0.0010	0.0073	1.6170	280	0.0047	-0.0026	-0.0617	283
Soybean oil	-0.0062	-0.0039	5.3359**	143	-0.0151	0.0147	3.7814	61	-0.0351**	-0.0539**	4.4483	82
Cocoa	0.0075	0.0008	-2.2830	395	0.0076	-0.0036	-1.4139	194	0.0136	0.0069	-3.0085	201
Coffee	-0.0058	-0.0055	2.8110	431	0.0061	-0.0122	1.3137	215	-0.0110	-0.0008	4.6628*	216
Cotton	-0.0038	0.0009	1.9453**	479	-0.0014	0.0016	1.9552*	255	-0.0207**	-0.0255**	1.4049	224
Sugar	-0.0010	-0.0064	1.7125	527	-0.0209	0.0147	2.8833	265	-0.0126	-0.0397**	-0.3808	262
Aluminium	-0.0052	0.0002	1.7846	311	0.0118	-0.0040	-2.3635	160	-0.0256***	-0.0145	4.9314***	151
Zinc	0.0057	-0.0012	-0.8480	311	0.0141	-0.0076	-1.8894	160	0.0034	0.0017	0.1854	151
Lead	0.0089	0.0010	-0.3625	263	0.0299**	-0.0197*	-1.4626	114	0.0101	0.0150	1.4344	149
Nickel	0.0048	-0.0042	1.4350	287	0.0324**	-0.0258*	0.0016	138	-0.0254*	-0.0378*	1.3307	149
Copper	0.0031	-0.0033	1.7284*	479	0.0098	-0.0042	0.9925	255	-0.0154	-0.0242*	2.5812	224
Gold	0.0007	0.0027	1.0986	467	-0.0003	0.0021	1.4782	243	0.0017	0.0007	0.3725	224
Silver	-0.0048	0.0047	2.6734**	527	-0.0093	0.0148	2.7535*	265	-0.0254**	-0.0308**	1.5884	262
Crude oil	-0.02***	-0.0192***	9.699***	359	-0.0137	-0.0207*	8.7029***	187	-0.0315**	-0.0306*	10.3747***	172
Heating oil	-0.0122*	-0.0127**	6.3662***	407	-0.0084	-0.0166	7.2224***	202	-0.0279**	-0.0401**	4.7216**	205

4.1.3. Mean Return Analysis

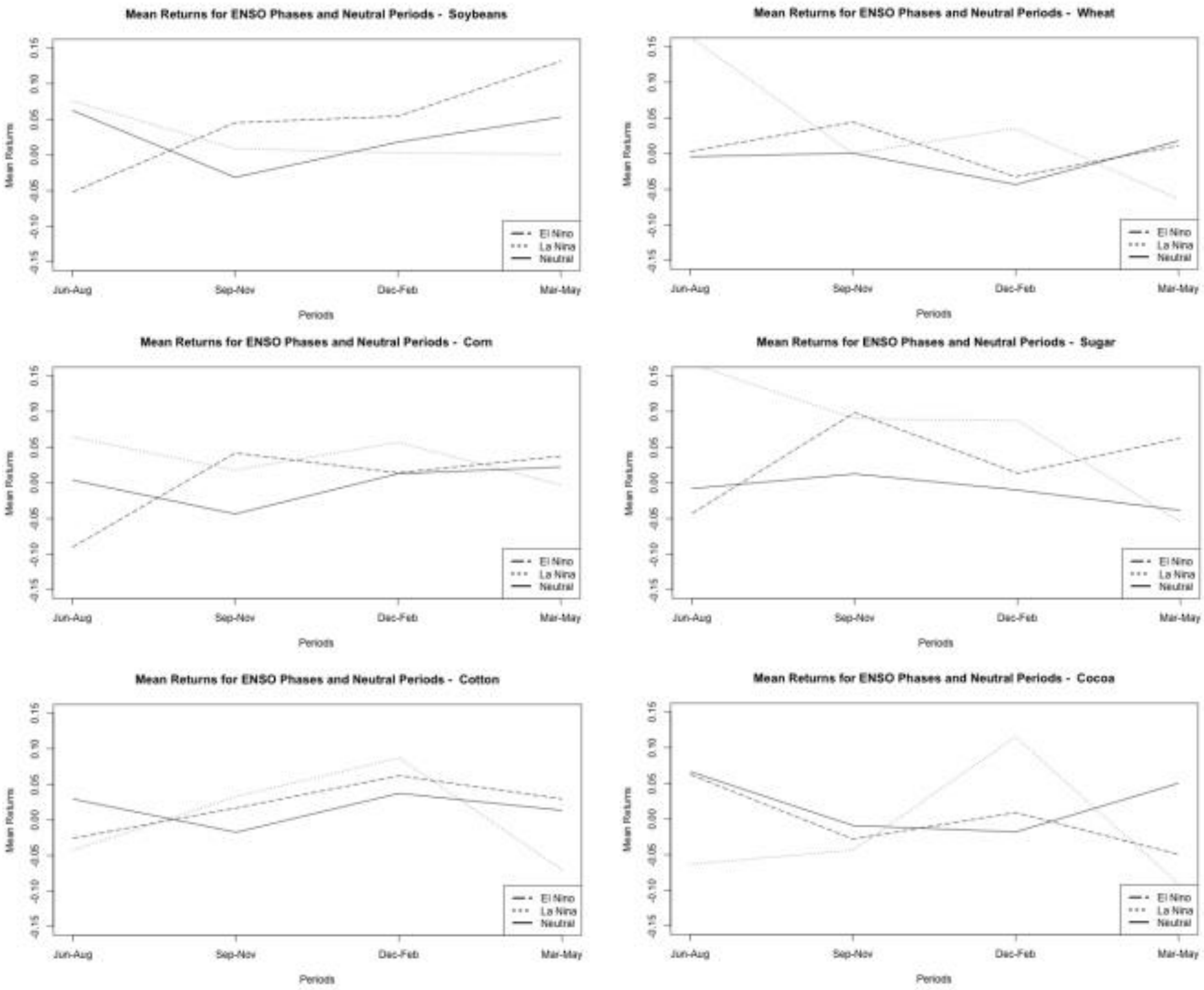
Figure 5, 6 & 7 show selected plots for the results of the mean return analysis. Mean returns are calculated for each commodity over four subsequent three-month periods, given El Niño, La Niña and neutral phases. Returns are cumulated to three-month periods to reduce noise in the plots. However, periods are differing from usual quarters to match the defined one-year long ENSO phases starting in June. Relative developments of returns during ENSO events and neutral periods suggest ENSO event return effects. We employ dummy variable regressions to test for statistical significance of these return differences[3]. If results of these tests show statistical significance, it will be highlighted in the description of results below. However, only a limited number of commodities show statistical significance. One reason for that could be the limited sample size. Graphs are displayed in this part for selected commodities for which the plots indicate relatively large effects. These commodities include the agriculture commodities soybeans, wheat, corn, sugar, cotton and cocoa; the metals nickel and zinc; as well as the energy commodities, crude oil and heating oil. It is noteworthy that the mean-return plots are fluctuating substantially for most commodities and thus indicate changing effects over time. In most cases, no consistent positive or negative excess return over the neutral periods becomes evident and the excess returns change from positive to negative or vice versa during the one-year period. Therefore, the interpretation of the mean-return plots does not claim absolute propriety and emphasis is laid on statistically significant results. When interpreting the effects per commodity, we draw links to previous literature and the precipitation maps (see *Figure 3 & 4*) as well as the findings from Granger tests and OLS regressions.

According to *Figure 5*, soybeans mean returns suggest a strong negative initial reaction during El Niño phases. In subsequent periods from September to May however, the El Niño mean returns remain higher compared to neutral means. Statistical significance is found for the negative impact in the first period. This result is in line with the argumentation in previous literature (e.g. Cashin et al, 2015), that El Niño can benefit soybean production due to wetter than normal climate in Southern America and the United States. According to the Food and Agriculture Organization of the United Nations (FAOSTAT, 2017), the countries with largest

[3] For this procedure commodity returns are regressed on dummy variables indicating specific periods. Two dummy variables are included for the La Niña and El Niño phases defined in Table 3 and three dummy variables for the three-month periods defined for the mean variance analysis (period 4 is excluded to avoid multi-collinearity). Additionally, interaction terms of the two ENSO event variables with the three period variables are added, which results in six additional terms. Finally, the OECD Inflation was added to control for macroeconomic effects. The coefficients of the interaction terms are studied to draw inferences about the incremental effects and statistical significance of having both an ENSO phase and one of the three periods in place.

soybean production are the United States, Brazil and Argentina. Iizumi et al (2014) find statistically significant results for global soybeans crop yields being positively affected during El Niño. These results are in accordance with Cashin et al (2015). Their results claim that the highest positive impacts are evident for North- and South America. The subsequent reversal in returns is counterintuitive to this explanation. However, one reason could be a mean-reverting tendency. For La Niña, the measured effects are mainly converse to El Niño. Following the logic from above, one interpretation could be that dryer conditions in South America and in the United States potentially harm crop production and might cause the prices of soybeans to increase. However, statistical significance is not found for these results. As can be seen in the result sections above, soybeans show a statistically significant Granger causality at the six-month lag, but do not show any significant results for coefficients in the time series regressions.

Figure 5 **Selected Mean Return Plots for Agriculture Commodities**



The figure shows plots of mean returns for six selected agriculture commodities over El Niño, La Niña and neutral phases. The phases are defined to start in June and end in the following May and are selected to match the official definition by the United States National Oceanic Atmospheric Administration (NOAA). For these purposes, 16 El Niño phases, 14 La Niña phases were identified. The year-long phase is divided into four periods for which mean returns are calculated (June-August, September-November, December-February and March-May). S&P GSCI commodity indices data is used as proxy for commodity prices. The price data starts in February 1970 and reaches to January 2017 but not all commodities indices are available for the whole timeframe.

Soybean meal and oil are derived products of soybeans which are created during soybean processing. Thus, it is expected that price effects show similar directions to soybeans in both ENSO phases. Correlations in returns with soybeans are 0.91 and 0.77 for soybean meal and soybean oil respectively. Confirming expectations, this relation becomes also apparent to a certain extent in the mean return plots, in which specific similarities in development can be seen (see *Appendix B: Figure I* for mean return plots of these commodities). Interestingly, La Niña mean returns show high magnitude positive return reactions for soybean oil for the first three periods. The OLS results from *Section 4.1.2.* also suggest a large statistically significant positive coefficient for soybean oil during La Niña. Soybean meal shows statistically significant effects in the second three-month period. For El Niño, the results suggest negative return reactions for the first three-month period for all soybean related commodities. However, the effects are reverting to a positive effect in the second three-month period (for soybean oil statistically significant). The mean-return analysis of soybean oil reveals relatively high variances in mean returns. One explanation for this volatility could be the short time-series of soybean oil which only starts in 2005 and thus is significantly shorter than for the other commodities analysed. Taken together, the results suggest negative effects for soybeans and soybean related commodities in the initial three-month period of El Niño phases, reverting to positive return effects in the second period. For La Niña, we measure a positive tendency especially in the second three-month period, which is generally in line with the findings of the OLS regression.

The results for wheat returns provide confirmatory evidence for large positive effects in La Niña phases, especially in period one and period three, in which also statistical significance for the incremental effects are found. For El Niño, the mean returns are consistently above the neutral periods means and the plot also suggests positive effects, especially for the second period. The results of the Granger tests in *Section 4.1.1.* suggest a statistically significant prediction power of the ENSO measure ONI on wheat at a lag level of three and six months. FAOSTAT (2017) reports China, India, the United States and Russia to be the countries with largest wheat production. According to the findings of Iizumi et al (2014), global crop yields for wheat fall during both ENSO phases, but in particular during La Niña events. The authors find negative yield impacts in parts of North America and Australia during El Niño phases. During La Niña phases, South America and Russia are countries which are negatively affected. The suggested effects in the plot are in line with findings of Iizumi et al (2014), as positive return differences from neutral periods are especially high during La Niña events but also existing during El Niño phases. Ubilava (2014) finds similar results for La Nina, but a small negative return impact for El Niño. In summary, wheat returns experience mainly positive effects from both ENSO phases.

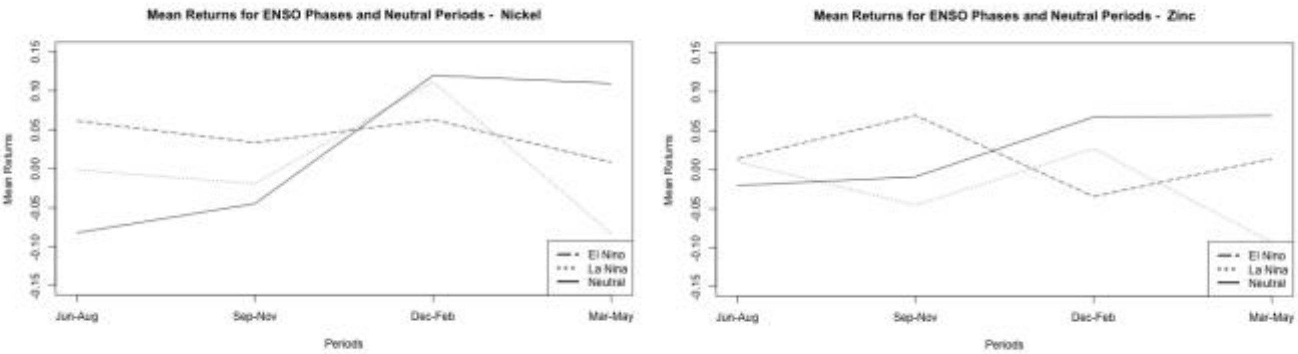
For corn, the graph suggests effect similarities in terms of direction with wheat for La Niña phases and to some extent also for El Niño events. Yet, the magnitude of the measured difference for La Niña phases is smaller. The evidence for positive La Niña effects is also supported by the findings from the regression analysis of *Subset II* in the previous part. The mean returns for El Niño suggest a negative effect in the first three-month period but revert to a positive effect especially during the consecutive months from September to November. According to FAOSTAT (2017), countries with the highest corn output are the United States, China and Brazil. Iizumi et al (2014) find statistically significant evidence for negative crop yield impacts on corn on a global scale during both phases. Since lower crop yields tend to push prices upwards, these findings are mainly in line with results in this thesis. Yet, the plots suggest a positive return impact in El Niño phases only after the first three-month period. The difference in findings could be explained by lagged price effects, different geographical focus of commodity price data or rolling cost distortions in the indices employed in this study. All in all, a clear effect for corn in El Niño phases cannot be derived due to a lack of statistical significance. In contrast, the effects for La Niña are generally positive and in line with OLS regression results.

Figure 5 shows that during the first three periods in La Niña phases, sugar returns are on average substantially positive compared to neutral phases. Apart from the very first three-month period, the plot suggests also a large positive effect for El Niño phases. These return patterns are in line with the OLS regression analysis, despite a lack of statistical significance for El Niño results. According to FAOSTAT (2017), Brazil and India are by far the largest producers of sugar canes. Like wheat and corn, sugar crops are sensitive to droughts and require sufficient rainfall to thrive (FAOSTAT, 2012). Therefore, a lack of rain in the major cultivation areas during El Niño periods can impact production yields negatively and, thus, returns positively. In La Niña periods, both dryness in southern India but also wet and warm conditions in northern Brazil are common. Taken together, sugar is affected positively by both ENSO phases.

The results for cocoa do not suggest a clear effect for El Niño, as the mean returns are fluctuating around the mean returns of neutral periods and are mainly low in magnitude. An exception is the last period, for which the plot suggests a large negative return impact. La Niña observations in general suggest larger effects, with a negative direction during summer and autumn but a substantially positive effect during winter (statistically significant). The countries with largest cocoa production are Ivory Coast, Ghana and Indonesia (FAOSTAT, 2017). From a weather point of view, El Niño is expected to cause dryness in Indonesia and parts of Ivory Coast and Ghana. Hence, it is expected that prices are pressured upward on average. However, the plot does only suggest a clear direction in the last period, in which the mean return difference is negative. In contrast, La Niña weather patterns should benefit crop yields due to opposing weather effects. The expected effects for La Niña are in line with the earlier described returns during summer and autumn, but surprisingly not with the subsequent statistically significant positive returns during winter. A comparison with the findings of the OLS regression in the previous part is not insightful as the measured coefficients showed minor economic and statistical significance. Further research is needed to develop a better understanding of the ENSO influence on cocoa crop yields and returns.

Regarding cotton, we find changing, but similar effect directions for both phases in the first three periods. The results suggest negative effects in the first period for both ENSO phases, but the effect reverts for the two subsequent periods. In the final period, El Niño mean returns remain higher than neutral mean returns, but La Niña mean returns fall to a negative level. For La Niña, we measure statistically significant positive return effects in the OLS regression and in the dummy regression for the third period. Interpreting these results from an agricultural point of view, FAOSTAT (2017) reports China, India, United States and Pakistan as the countries with the largest cotton production. Fraisse (n.d.) finds evidence that while La Niña impacts crop yields negatively on average, El Niño phases show geographically differing effects. Whereas areas in the southeast tend to have lower crop yields during El Niño phases, areas in the mid-south show higher yields on average. The southern states of the US often experience dryness during La Niña phases. These results are mainly in line with the findings in this paper as higher average returns compared to neutral periods are found both for El Niño and La Niña phases. Another reasoning for higher cotton returns during El Niño phases could be higher likelihood for dryness in India and parts of Pakistan due to disturbance of the monsoon. In summary, evidence for La Niña is strong and clear in favour of positive return effects, while interpretation for El Niño is ambiguous.

Figure 6 **Selected Mean Return Plots for Metals**



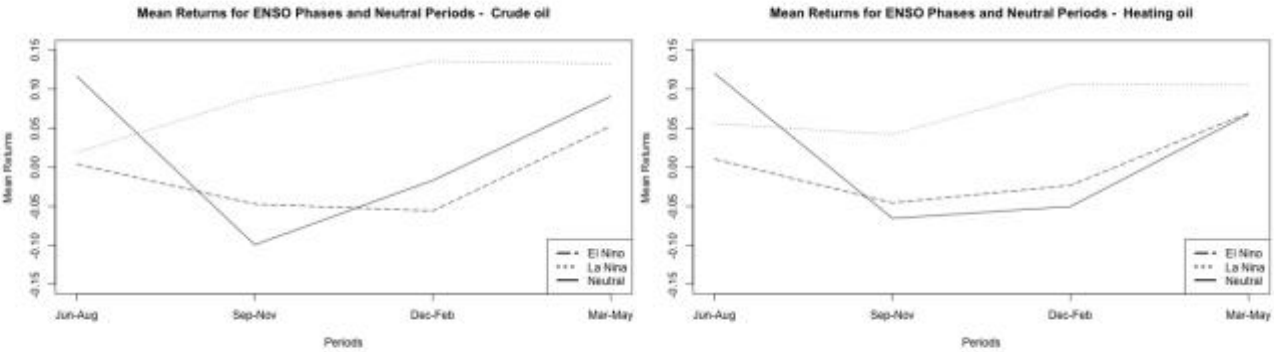
The figure shows plots of mean returns for two selected metal commodities over El Niño, La Niña and neutral phases. The phases are defined to start in June and end in the following May and are selected to match the official definition by the United States National Oceanic Atmospheric Administration (NOAA). For these purposes, 16 El Niño phases, 14 La Niña phases were identified. The year-long phase is divided into four periods for which mean returns are calculated (June-August, September-November, December-February and March-May). S&P GSCI commodity indices data is used as proxy for commodity prices. The price data starts in February 1970 and reaches to January 2017 but not all commodities indices are available for the whole timeframe.

This study includes the metals lead, nickel, zinc, aluminium, copper, silver and gold. Due to less apparent or fluctuating effects as well as a less clear intuitive link between ENSO events and metal returns, only the plots for nickel and zinc are shown and discussed in this section.

Figure 6 suggests that El Niño events impact nickel price returns positively during the first two periods but subsequently effects are reverting and returns show a negative difference from December to May. The OLS regressions show statistically significant negative impact in El Niño phases while the dummy regression indicates statistically significant return effects. For La Niña, the plots show a positive mean return difference in the first two three-month periods (statistically significant in the first period) and suggest a strong negative effect in the last period. The OLS regression supports these findings with statistically significant positive return effects (90% confidence). This is contrary to the argumentation of Cashin et al (2016) who argue that heavy rainfalls during La Niña periods in Indonesia – one of the largest producers of nickel – let prices decrease due to Indonesia's reliance on hydropower. With the same reasoning, they suggest rising prices due to disturbed monsoon and less rainfall during El Niño events. To sum up, we find evidence for positive return effects during La Niña. However, these findings are contrary to possible qualitative explanations. For El Niño, the evidence is unclear.

For zinc, the plot shows opposite and large mean return differences in the second period. In this period, the plot suggests that La Niña affects returns positively and El Niño negatively, relative to the neutral periods. Subsequently, according to the mean return plots, both El Niño and La Niña show meaningful negative effects compared to the neutral periods. According to our dummy regression, La Niña has a statistically significant positive impact on zinc returns in the first three-month period. However, the link between weather disturbances and returns is not clear for zinc. Nevertheless, one reasoning for the negative price impact during El Niño phases could be that floods in Peru hinder the production of zinc and thus prices show positive reactions. In general, results for zinc do not provide sufficient evidence to allow meaningful inferences.

Figure 7 **Mean Return Plots for Petroleum Commodities**



The figure shows plots of mean returns for the commodities crude oil and heating oil over El Niño, La Niña and neutral phases. The phases are defined to start in June and end in the following May and are selected to match the official definition by the United States National Oceanic Atmospheric Administration (NOAA). For these purposes, 16 El Niño phases, 14 La Niña phases were identified. The year-long phase is divided into four periods for which mean returns are calculated (June-August, September-November, December-February and March-May). S&P GSCI commodity indices data is used as proxy for commodity prices. The price data starts in February 1970 and reaches to January 2017 but not all commodities indices are available for the whole timeframe.

The similarities of the crude oil and heating oil plots suggest a close link between these two commodities which becomes also apparent in the correlation (R = 0.88). Both, crude oil and heating oil show negative effects for El Niño events in the first three-month period. Subsequently, both crude oil and heating oil returns show negative absolute returns in the two three-month periods from September to February. In general, the OLS regressions find a negative impact of EL Niño on returns (statistically significant for crude oil). La Niña plots offer evidence for a negative effect only in the first three-month period for both, crude oil and heating oil. Subsequently, La Niña effects revert and are positive. This is in line with the OLS regression findings. As El Niño regularly stimulates temperatures in North America, Canada and Japan, resulting in warmer winters and potential lower demand for oil, prices are expected to fall during this period. Mainly opposite weather effects are true for La Niña and thus, prices are assumed to rise. Another explanation might be a change from the supply side. Supply can be positively affected during El Niño periods due to beneficial weather in Mexico. La Niña events instead often cause disruptions through severe storms in the Gulf of Mexico and thereby narrow the supply of oil. Cashin et al (2015) find contrasting results to those stated in *Figure 7*. By employing impulse-response functions, the authors find positive oil price returns as reaction to El Niño caused oil price shocks. This is contrary to the findings derived from above plots and interpretation of ENSO weather impacts. In summary, petroleum commodity returns are mainly positively influenced by La Niña events and negatively by El Niño events.

4.1.4. Summary of Measured Effects

In summary, the results indicate the existence of larger and statistically more significant effects in La Niña phases for most of the commodities.

For El Niño, we find negative return effects on soybeans and soybean related commodities as well as for crude oil and heating oil. In contrast, El Niño affects wheat and sugar returns positively. The other commodities, namely cocoa, corn, cotton, nickel and zinc, do not reveal clear effects for El Niño phases.

La Niña shows significant positive return impact on several commodity. Soybeans and soybean related products, wheat, corn, sugar, cotton and nickel are positively affected during La Niña phases. Results for cocoa and zinc are ambiguous while crude oil and heating oil are negatively impacted during La Niña phases.

4.2. Trading Strategy Results

In contrast to the empirical analysis conducted in the prior parts of the paper, this section presents a more detailed perspective on potentially achievable trading results. The trading strategies employed serve the purpose of demonstrating the possibility of ENSO related investments, which are triggered by a breach of specific ONI thresholds as a buying signal. As described in *Section 3.2.*, historical performance is tested for different trading strategies in both El Niño and La Niña periods and compared to a buy-and-hold strategy over the whole sample period.

Table 6 and *Table 7* report the results for *Selling Strategy I* for El Niño and La Niña, including a fixed holding period of one and six months[4]. Fixed holding periods are chosen to visualise effects for equal investment lengths across commodities and for different ENSO events. The holding periods are chosen as one and six months to show the variation inherited in differing investment horizons. To put the trading strategy results in perspective, the buy-and-hold returns are added to the tables as comparison. Monthly geometric excess returns over the respective monthly geometric buy-and-hold returns are derived for each commodity and both holding periods. Trades are triggered by a breach of the ONI threshold of +/- 0.5℃ deviation from the long-term mean.

Table 6 shows the historical performance for *Selling Strategy I* during El Niño events. More specific, the results are shown for the 18 commodities analysed in this paper and the investment horizon lies between February 1970 and January 2017. Entry signals are generated by a breach of the +0.5℃ ONI threshold and the exit follows according to the fixed holding period of one or six months. The monthly geometric buy-and-hold return corresponds to the whole sample period. The commodities are ranked according to their one-month excess return over the buy-and-hold strategy, starting with the highest.

In general, the trading strategy causes both positive and negative excess returns in the two holding periods. Both, positive and negative returns can be beneficial to the investor, depending on the respective long or short positioning in the market. Since commodity index futures data is chosen to examine the returns, the availability of long and short positioning for the investor is given. Comparing the monthly excess returns of the one-month and six-month holding periods, significant differences between these two become evident. In general, the shorter holding period triggers bigger movements in excess returns, both positive and negative.

[4] Results for Selling Strategy II and exit month March can be found in the Appendix.

This holds true for all commodities but wheat, heating oil and crude oil. These commodities show relatively low absolute excess returns for the one-month period and slightly higher absolute excess returns for a six-month holding period. One possible explanation for this observation is that ENSO events cause initial prices spikes which tend to revert to some extent afterwards. The one-month holding period captures only the initial spikes but not the following reversal.

In addition, a few commodities show a change in direction of the excess returns when comparing one-month holding period to six-month holding period (aluminium, copper, zinc, soybean oil, soybeans and corn). For these commodities, the reverting effects seem to exceed the initial price spike. However, it is possible that the reversion is subject to a seasonal pattern or other effects, depending on the respective commodity. According to the results, coffee, nickel, silver and zinc with values of 4.18%, 3.87%, 3.81% and 3.28% respectively show the largest positive monthly geometric returns (higher than three percent) for the trading strategy with a one-month holding period. The returns for these commodities fall drastically when increasing the holding period to six months. The commodities with lowest returns for the one-month period are soybean meal with -5.73%, sugar with -2.42%, soybean oil with -2.32% and soybeans with -2.04%. Also in this case, six-month holding period returns are far smaller. Interestingly, for crude oil the results are in line with the statistically significant results from the OLS regression (see *Section 4.1.2.)*. For nickel and lead, the negative return effect suggested by the OLS regression cannot be recognized. The measured effects for the first three-month period in the mean variance analysis suggest similar effects to the performance of trading strategies with one-month holding period. For all commodities for which such measured effects are statistically significant (see *Footnote 3* for details on significance measurement), i.e. coffee, nickel and soybeans, the trading strategy returns have similar directions.

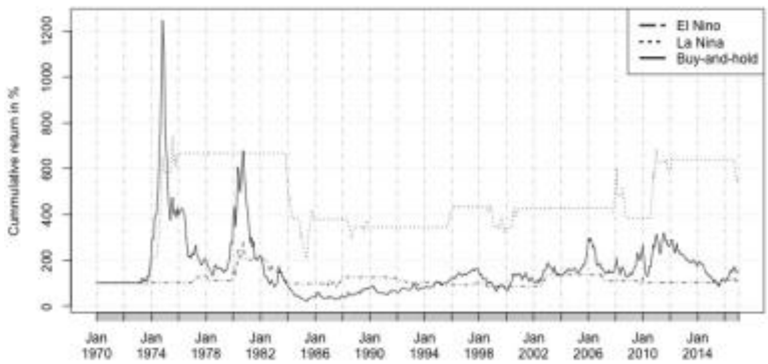
Table 6 **Historical Performance of Selling Strategy I for El Niño Phases**

The table reports a summary of the historical performance of Selling Strategy I during El Niño phases. The buying signal is a single ONI threshold breach of 0.5 within the period from June to November. The respective geometric monthly excess return over the buy-and-hold strategy is derived for the holding period of one and six months. Commodities are ranked by their one-month excess returns from highest to lowest. The investment horizon lies between February 1970 and January 2017, not all commodities are available for the entire period.

Commodity	1 Month Excess Return	6 Month Excess Return	Buy-and-hold Return	Number of Invested Months (1M Holding Period)
Coffee	0.0418	0.0108	-0.0008	16
Nickel	0.0387	0.0063	0.0033	10
Silver	0.0381	0.0021	0.0030	20
Zinc	0.0319	-0.0018	0.0011	12
Lead	0.0192	0.0023	0.0058	8
Gold	0.0186	0.0018	0.0038	18
Cotton	0.0181	0.0050	0.0021	19
Copper	0.0108	-0.0025	0.0074	19
Aluminium	0.0066	-0.0005	-0.0020	12
Cocoa	0.0063	0.0048	-0.0041	14
Heating Oil	-0.0007	-0.0136	0.0049	15
Wheat	-0.0048	0.0049	-0.0004	21
Crude Oil	-0.0082	-0.0146	0.0044	13
Corn	-0.0093	0.0011	-0.0003	21
Soybeans	-0.0204	0.0011	0.0067	21
Soybean Oil	-0.0232	0.0098	-0.0013	4
Sugar	-0.0242	-0.0003	0.0008	20
Soybean Meal	-0.0573	-0.0222	0.0116	8

Figure 8 exemplifies the historical performance of the trading strategies with a six-month holding period for the case of sugar. The graph shows the cumulative performance for the El Niño investment strategy, La Niña investment strategy and a buy-and-hold strategy over the whole sample period from 1970 to 2017. When a buying signal for El Niño or La Niña investments is generated, the sugar commodity index is purchased and held for six months.

Figure 8 **Historical Performance of Sugar ENSO Trading**



This Figure plots cumulative returns for sugar, employing an El Niño, La Niña and buy-and-hold strategy. The buying signal is a single ONI threshold breach of +/-0.5 within the period from June to November. The investments follow a fixed holding period of six months. The historical performance test uses S&P GSCI sugar index data which is available from 1973 and reaches to January 2017.

The simple buy-and-hold strategy resembles the performance of the sugar commodity index over the whole sample period. Two extreme spikes become obvious, one in 1974 and one in 1980/81. As one can see, the 1974 price spike was in alignment with a La Niña period and consequently the La Niña trading strategy was beneficially affected by the hike. The 1980/81 extreme occurred during an El Niño period and thus, the El Niño trading strategy could generate abnormal positive returns. Due to timing of entry and exits, the La Niña strategy performs better than the El Niño strategy and the buy-and-hold in this specific sample period. A large fraction of this superior return results from the early phase of the sample and the before-mentioned spikes. The number of invested months for the El Niño and La Niña strategies is significantly lower than for the buy-and-hold strategy.

Table 7 provides the historical performance for *Selling Strategy I* during La Niña phases. The reasoning and methodology is similar as explained above for El Niño phases apart from the fact that a breach of the ONI threshold is now recognised once the temperature deviates more than -0.5℃ from the long-term average.

Table 7 **Historical Performance of Selling Strategy I for La Niña Phases**

The table reports a summary of the historical performance of Selling Strategy I during La Niña phases. The buying signal is a single ONI threshold breach of 0.5 within the period from June to November. The respective geometric monthly excess return over the buy-and-hold strategy is derived for the holding period of one and six months. Commodities are ranked by their one-month excess returns from highest to lowest. The investment horizon lies between February 1970 and January 2017, not all commodities are available for the entire period.

Commodity	1 Month Excess Return	6 Month Excess Return	Buy-and-hold Return	Number of Invested Months (1M Holding Period)
Lead	0.0628	-0.0076	0.0058	9
Sugar	0.0412	0.0167	0.0008	17
Crude Oil	0.0319	0.0028	0.0044	11
Heating Oil	0.0296	0.0145	0.0049	14
Soybean Oil	0.0256	-0.0016	-0.0013	5
Nickel	0.0175	-0.0007	0.0033	9
Silver	0.0156	-0.0004	0.0030	17
Wheat	0.0153	0.0047	-0.0004	19
Zinc	0.0091	-0.0045	0.0011	9
Aluminium	0.0088	-0.0059	-0.0020	9
Cotton	0.0087	0.0003	0.0021	14
Copper	0.0038	-0.0019	0.0074	14
Soybeans	0.0024	-0.0078	0.0067	19
Gold	-0.0008	-0.0002	0.0038	14
Soybean Meal	-0.0098	0.0032	0.0116	9
Cocoa	-0.0112	-0.0080	-0.0041	13
Corn	-0.0115	0.0047	-0.0003	19
Coffee	-0.0425	0.0026	-0.0008	14

In general, comparing El Niño and La Niña trading on a one month basis, the results suggest a positive return effect for more commodities during La Niña, as only five commodities show a negative monthly geometric return. Yet, this does not hold in the longer term. For all commodities apart from soybeans, the absolute excess returns are higher in the case of a one month holding period. Thus, similar to before, the results indicate a relatively high initial La Niña response of commodity returns. Eleven commodities even change the direction of excess returns comparing one-month holding period with six and, thus, highlight the significance of timing for overall trading performance. Moreover, our findings suggest that it is necessary to further examine each individual commodity to find the optimal holding period in relation to ENSO based trading. The commodities with a positive excess return above three percent are lead with a value of 6.28%, sugar with a value of 4.12% and crude oil with a value of 3.19%. Again, the geometric excess returns decrease significantly with an increase in holding period, in the case of lead the excess returns even revert. Regarding the results with negative excess returns, coffee shows particularly large negative returns with a value of -4.25%. The La Niña trading strategy results for a one-month holding period are highly in line with the findings in the OLS regression (*Section 3.2.*), in which positive and statistically significant results are found for sugar, crude oil, heating oil, soybean oil, nickel, silver, copper, cotton and corn. Hence, corn is the only commodity for which differing evidence in the trading strategies is found. For La Niña, the measured effects for the first three-month period in the mean variance analysis suggest similar effects to the performance of trading strategies with one-month holding period. All commodities for which such measured effects are statistically significant (see *Footnote 3*), i.e. lead, nickel, wheat and zinc, the trading strategy returns have similar directions.

In the following, the trading strategy results for coffee, sugar, cocoa, nickel and crude oil are discussed in greater detail. It appears, that coffee delivers the most robust trading results. The effect is exactly opposite with high positive one-month excess returns during El Niño (4.18%) and strong negative one-month excess returns during La Niña (-4.25%). Interestingly, the findings of the effect measurement in *Section 4.1.* are less clear and suggest the following. In the mean return analysis, the El Niño effects measured are statistically significant positive (90% confidence), for La Niña effects are less clear. The OLS regression does not report statistically significant results. The performance of sugar is in line with the effects found in the OLS regression and mean-return analysis. La Niña weather drives sugar prices upward (4.12% one-month excess return) while El Niño weather conditions cause an initial drop in prices (--2.42% one-month excess return) and a reversion afterwards (-0.03% one-month excess return). Moreover, cocoa delivers constant positive excess returns in El Niño phases (0.63% one-month excess return and 0.48% six-month excess return) and constant negative excess returns in La Niña phases (-1.12% one-month excess return and -0.8% six-month excess return). These findings for cocoa are in line with the qualitative explanation given in the mean-return analysis, even though the mean-return plots do not clearly support this. As suggested by the plots from the mean-return analysis, nickel shows high initial positive price reactions to both El Niño and La Niña events (3.87% one-month excess return for El Niño and 1.75% one-month excess return for La Niña). Subsequently these positive excess returns diminish and eventually turn negative. The patterns found for crude oil in the employed OLS regression and mean-return analysis are mostly consistent with the performance of the conducted trading strategy. Crude oil prices react negative to beneficial weather conditions and increased supply during El Niño phases and negative due to non-beneficial weather conditions during La Niña phases. The one- and six-month holding period El Niño excess returns of -0.82% and -1.46% confirm these findings as well as the positive La Niña excess returns of 3.19% and 0.28% for one- and six-month holding period respectively.

Overall, the strategies suggest high monthly geometric excess returns in absolute means over the continuous buy-and-hold for most of the commodities during El Niño and La Niña events. Comparisons of results with both the measured effects in prior sections and qualitative explanations, provide strong indication that these are ENSO related and not pure chance. Furthermore, the measured returns for the one-month period suggest higher monthly geometric returns, providing evidence that price reactions are happening quickly, thus, timing is essential.

5. Limitations of Approach

This part discusses the limitations of the employed empirical approach. As the utilized data is already critically discussed in *Section 3.1.2.*, this part focuses on the methodology. First, the general assumption of the empirical model is discussed. Afterwards, we discuss the employed models specifically.

In the case of this thesis, historical data is utilized to estimate models which could allow predictions for future commodity price developments. Therefore, it is important to discuss factors which might alleviate the assumption of reoccurrence of historical patterns. Regarding the demand side of commodity markets, increased possibilities for substituting commodities might mitigate future ENSO effects on commodity prices. Substitution could happen in terms of geographical origin, e.g. due to ongoing globalisation and further reduction of transportation costs. Consequently, commodity buyers can relatively easy switch to suppliers from other countries if weather affects crop yields locally. On the other hand, commodity purchasers could substitute ENSO reliant commodities with alternative commodities which are less dependent on weather effects. One example for substituting effects is described by Caviedes (2001) where a decline in fish meal production due to weather changes was substituted in the 1970s by soybean meal as major source for animal forage. Another more general case is the substitution of fossil fuels by biofuels, studied by Ji and Fan (2012).

Another influencing factor of the world demand for commodities are so-called super cycles, as seen in the beginning of the new century with exceptional growth in developing countries, especially China. By today, China accounts for almost 50% of the world’s industrial metal consumption and is a major driver in world commodity prices. Moreover, sudden income growth in China, but also in India and other developing countries led to an increase in worldwide demand and agricultural commodity prices. As this growth cycle now normalises, the pressure on commodity prices releases and thus could significantly impact future price developments (World Bank, 2015).

From the supply side perspective, producers of agricultural commodities might be able to react quicker to approaching ENSO events in the future due to advancements in forecasting methods (*Section 2.3.*). Thereby, they can adapt fertilization and type of cultivated crop in order to mitigate the impact of ENSO related weather changes on their harvests. What is more, improvements in storage and preservability could potentially have mitigating effects on ENSO related negative crop yield impacts.

Granger causalities suggest that past values of one time series are useful for predicting another time series (Granger, 1969). However, statistically significant Granger causalities between two variables do not necessarily imply that a true cause and effect relationship exits. For example, when considering two variables, where one variable Granger causes the other, it could be the case that both are affected by an unknown exogenous variable with different lags. In this paper, such a case is considered unlikely due to the exogeneity of the ONI as weather related measure.

Next, the limitations of the OLS regression are discussed. As macro-economic effects could have confounding influence on the dependent variable, inflation was added as a control variable. Moreover, utilizing OLS regressions does not account for possible non-linarites or lagged effects. Through the separation of the dataset into two subsets with negative and non-negative ONI values, it is accounted for differing effect sizes and directions of the two ENSO phases. However, for studying lagged and non-linear effect sizes, the mean return analysis is employed.

One limitation of the employed mean return analysis is the limited number of historic ENSO phases that overlap with the time horizon of utilized time series data. This issue is especially problematic for commodities for which time series data is available only after 1970 as this limits the sample size. Due to this fact, it is not surprising that statistical significance was only found for a relatively small number of analysed commodities (see *Footnote 3*). The utilization of commodity data with longer historic availability could have alleviated this issue. However, such data is often not derived from the common financial markets such as stock exchanges, but rather determined in local auctions or other price finding mechanisms which do not necessarily resemble globally available investment possibilities. As the aim of this study was to demonstrate investment opportunities and thus the possibility of investing is key, futures-based index data was chosen. Another important characteristic of the mean-return analysis is the fact that due to a relatively small number of events which are incorporated, extreme events can influence the outcome significantly. Mean-returns in this paper are not adjusted for extreme events as the underlying reason for most of these extreme price changes is not determinable with certainty. Thus, it is frequently ambiguous whether these extremes are ENSO related. Furthermore, the selection of ENSO phases was conducted in accordance with the official definition of the NOAA, but defined by us as one-year long from June to the following May (see *Table 3*). A one-year period was chosen for comparability reasons. However, some of the ENSO events last longer than one year. Such ENSO events were split into more than one year-long periods. For example, the La Niña event lasting over three years from 1998 to 2001 was separated in to three single one-year La Niña phases. This approach was followed in order to increase the sample size of ENSO events. However, one could argue that ongoing ENSO phases can have differing effects on commodity prices from single-year ENSO events.

The trading strategies in this thesis are based on ENSO related weather data and performance is measured based on historical commodity index returns. Due to limited frequency of ENSO events and a relatively short timeframe, a separation into in-sample and out-of-sample period is not performed. Therefore, the trading strategies are not evaluated on their forecasting performance and rather serve as indication. Moreover, in the historical tests of the strategies trading costs are neglected.

6. Concluding Remarks

Existing research on economic ENSO effects mainly examines the influence of ENSO on economies and commodity prices. This paper contributes to existing research by studying price effects based on investable commodity index data and by pointing out ways how to exploit ENSO related return patterns. In order to shed light on different aspects of commodity return effects, the empirical approach in this paper is threefold. Granger causality tests are employed to analyse if ENSO related climatological data has predictive value for commodity index returns. OLS time series regressions indicate effect direction and size. Finally, mean return plots in combination with dummy variable regressions provide information about the development of effects over time and potential lags.

In summary, the results of the effect measurements indicate the existence of larger and statistically more significant effects during La Niña phases for most of the commodities. La Niña shows significant positive impact on soybeans and soybean related products, wheat, corn, sugar, cotton and nickel. Crude oil and heating oil instead are negatively impacted during La

Niña phases. For El Niño, we find negative return effects on soybeans and soybean related commodities as well as for crude oil and heating oil. In contrast, El Niño affects wheat and sugar returns positively. In general, we only find meaningful qualitative explanations for a link between ENSO and agricultural as well as petroleum commodities. For such commodities, we find the clearest effects inherit in soybean oil, corn, sugar, cotton, crude oil and heating oil.

The study of ENSO effects serves as first step towards enhancing our understanding of ENSO related investing. Subsequently, trading strategies for exploiting such effects are defined and tested on historical performance. ENSO related climatological data is the underlying measure for the buying signal. The overall findings for the trading strategies suggest high monthly geometric excess returns in absolute means for most of the commodities during both ENSO events. Measured effects and qualitative explanations suggest that these returns are ENSO related. Furthermore, we find evidence that ENSO events are priced in quickly, thus, timing is indispensable. Finally, due to several limitations in the empirical approach, caution must be exercised when interpreting results. The futures-based indices can be affected by rolling yields and the sample size is constrained due to a lack of historical availability. Changing trends in commodity markets reduce the meaningfulness of results for the future. The most important limitation inhibited in the model is the impact of extreme events, affecting especially the mean return analysis and historical performance tests.

We conclude that ENSO with its two distinct phases, El Niño and La Niña, has impact on returns in futures-based commodity index data. Furthermore, we find evidence that opportunities to exploit this relationship in commodity futures markets exist but depend on the respective commodity.

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Appendix

Appendix A: Tables

Appendix B: Figures

Table I **Historical Performance of Selling Strategy II El Niño**

The table shows a summary of the historical performance of Selling Strategy II during El Niño phases, employing March as exit month. The buying signal is a single ONI threshold (+0.5℃) breach within the period from June to November. The respective geometric monthly excess return over the buy-and-hold strategy is derived for the exit month March. Commodities are ranked by their one-month excess returns from highest to lowest. The investment horizon lies between February 1970 and January 2017, not all commodities are available for the entire period.

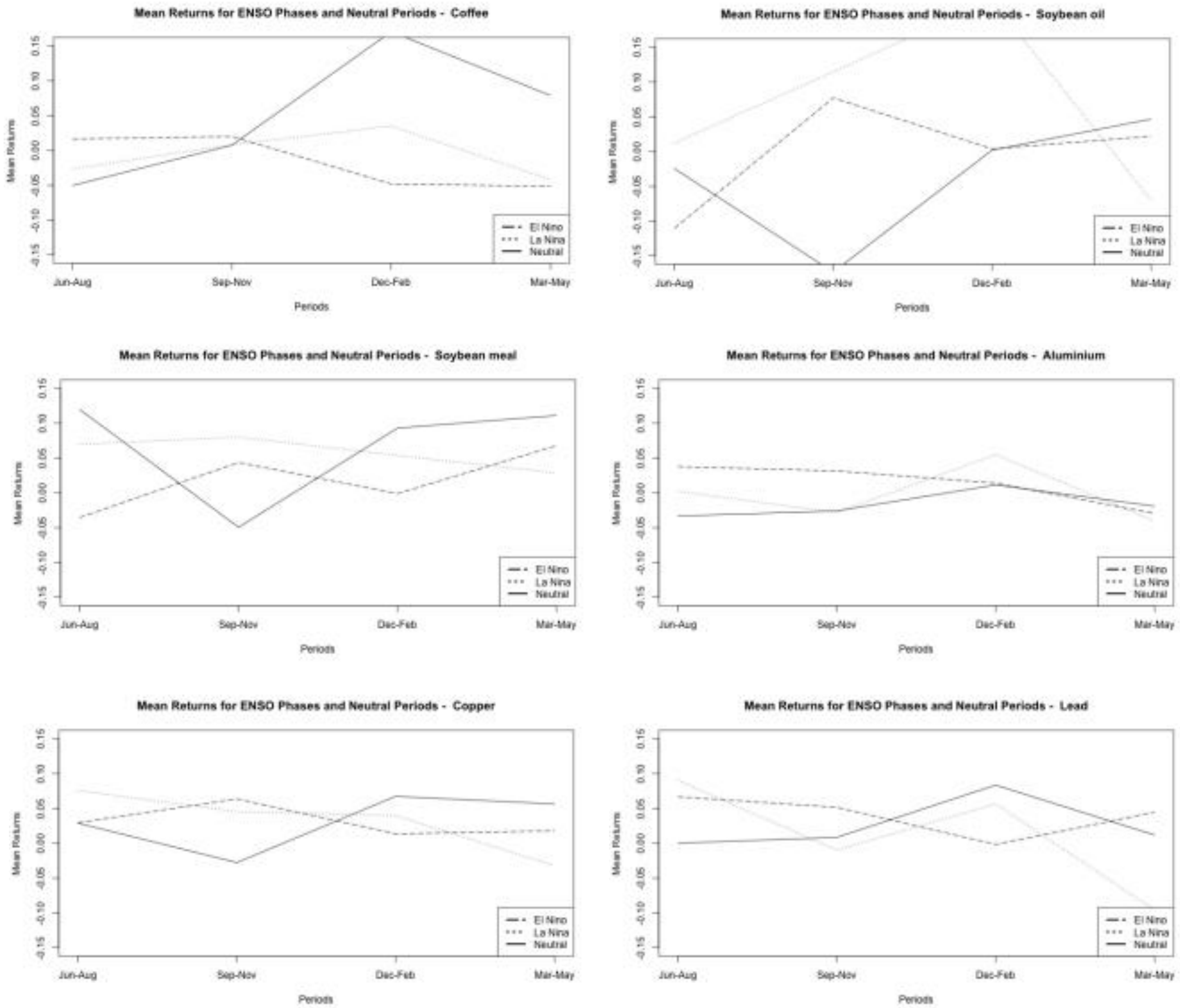
Commodity	March Excess Return	Buy-and-hold Return	Number of Invested Months
Soybean Oil	0.0084	-0.0013	30
Coffee	0.0067	-0.0008	125
Nickel	0.0060	0.0033	76
Cotton	0.0052	0.0021	143
Lead	0.0031	0.0058	63
Silver	0.0027	0.0030	148
Aluminium	0.0013	-0.0020	91
Corn	0.0010	-0.0003	155
Soybeans	0.0001	0.0067	155
Gold	-0.0013	0.0038	138
Wheat	-0.0014	-0.0004	155
Zinc	-0.0016	0.0011	91
Copper	-0.0027	0.0074	143
Cocoa	-0.0027	-0.0041	107
Heating Oil	-0.0073	0.0049	116
Sugar	-0.0100	0.0008	148
Crude Oil	-0.0101	0.0044	102
Soybean Meal	-0.0207	0.0116	63

Table II **Historical Performance of Selling Strategy II La Niña**

The table shows a summary of the historical performance of Selling Strategy II during La Niña phases, employing March as exit month. The buying signal is a single ONI threshold (-0.5℃) breach within the period from June to November. The respective geometric monthly excess return over the buy-and-hold strategy is derived for the exit month March. Commodities are ranked by their one-month excess returns from highest to lowest. The investment horizon lies between February 1970 and January 2017, not all commodities are available for the entire period.

Commodity	March Excess Return	Buy-and-hold Return	Number of Invested Months
Sugar	0.0177	0.0008	124
Crude Oil	0.0138	0.0044	81
Heating Oil	0.0126	0.0049	98
Copper	0.0094	0.0074	98
Corn	0.0012	-0.0003	140
Soybean Meal	0.0127	0.0116	63
Cotton	0.0021	0.0021	98
Silver	0.0029	0.0030	124
Coffee	-0.0013	-0.0008	98
Wheat	-0.0011	-0.0004	140
Soybean Oil	-0.0021	-0.0013	32
Gold	0.0016	0.0038	98
Lead	0.0013	0.0058	63
Nickel	-0.0016	0.0033	63
Cocoa	-0.0094	-0.0041	96
Zinc	-0.0061	0.0011	63
Aluminium	-0.0092	-0.0020	63
Soybeans	-0.0022	0.0067	140

Figure I **Remaining Mean Return Plots**



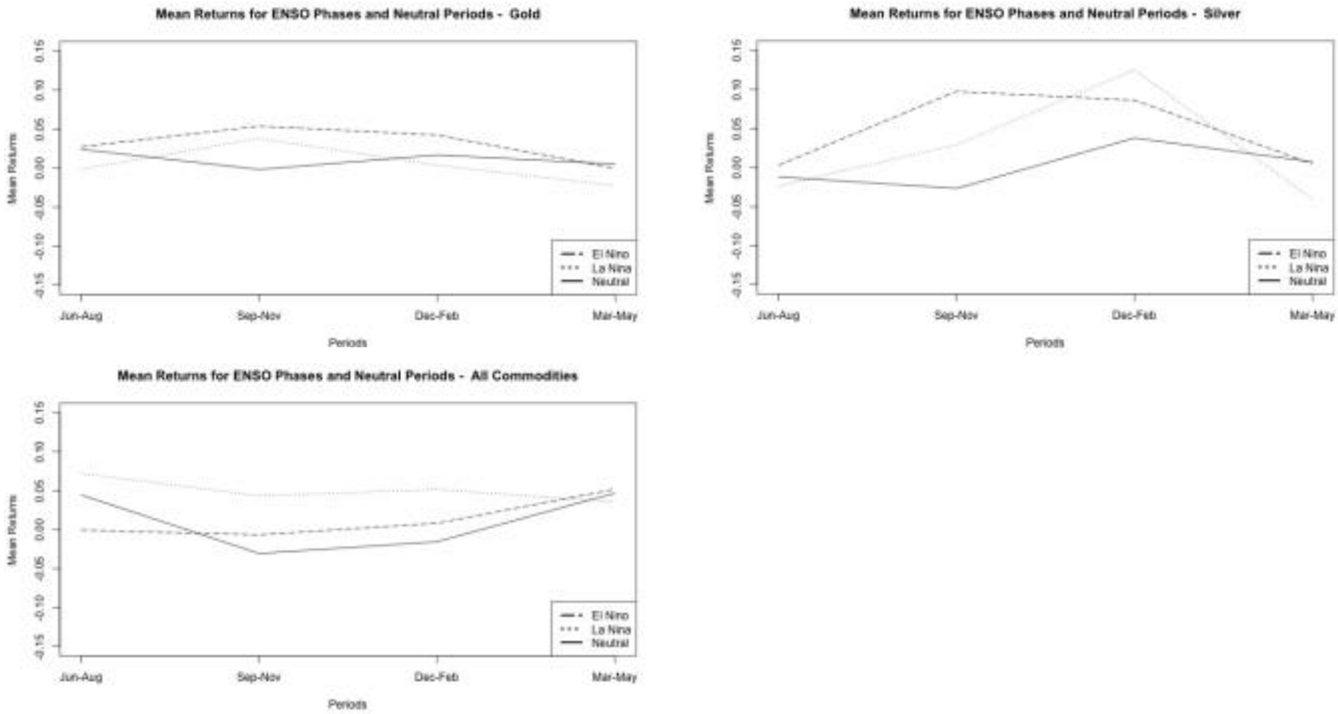
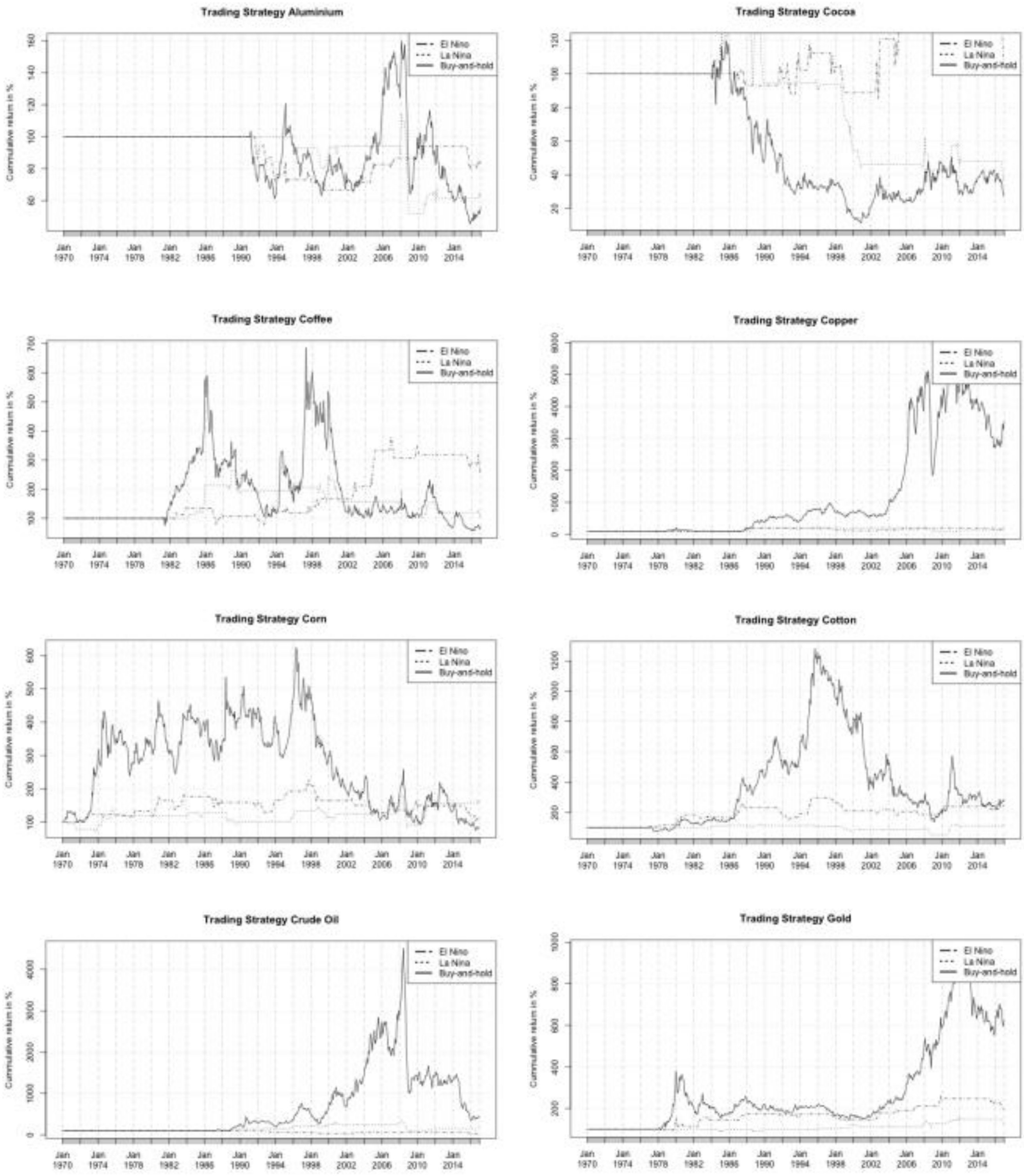


Figure I shows plots of mean returns for nine selected commodities over El Niño, La Niña and neutral phases. The phases are defined to start in June and end in the following May and are selected to match the official definition by the United States National Oceanic Atmospheric Administration (NOAA). For these purposes, 16 El Niño phases, 14 La Niña phases were identified. The year-long phase is divided into four periods for which mean returns are calculated (June-August, September-November, December-February and March-May). S&P GSCI commodity indices data is used as proxy for commodity prices. The price data starts in February 1970 and reaches to January 2017 but not all commodities indices are available for the whole timeframe. Statistical significance is found for effects of coffee (El Niño, period 1), lead (La Niña, period 1), soybean meal (La Niña, period 2).

Figure II **Remaining Trading Strategies**



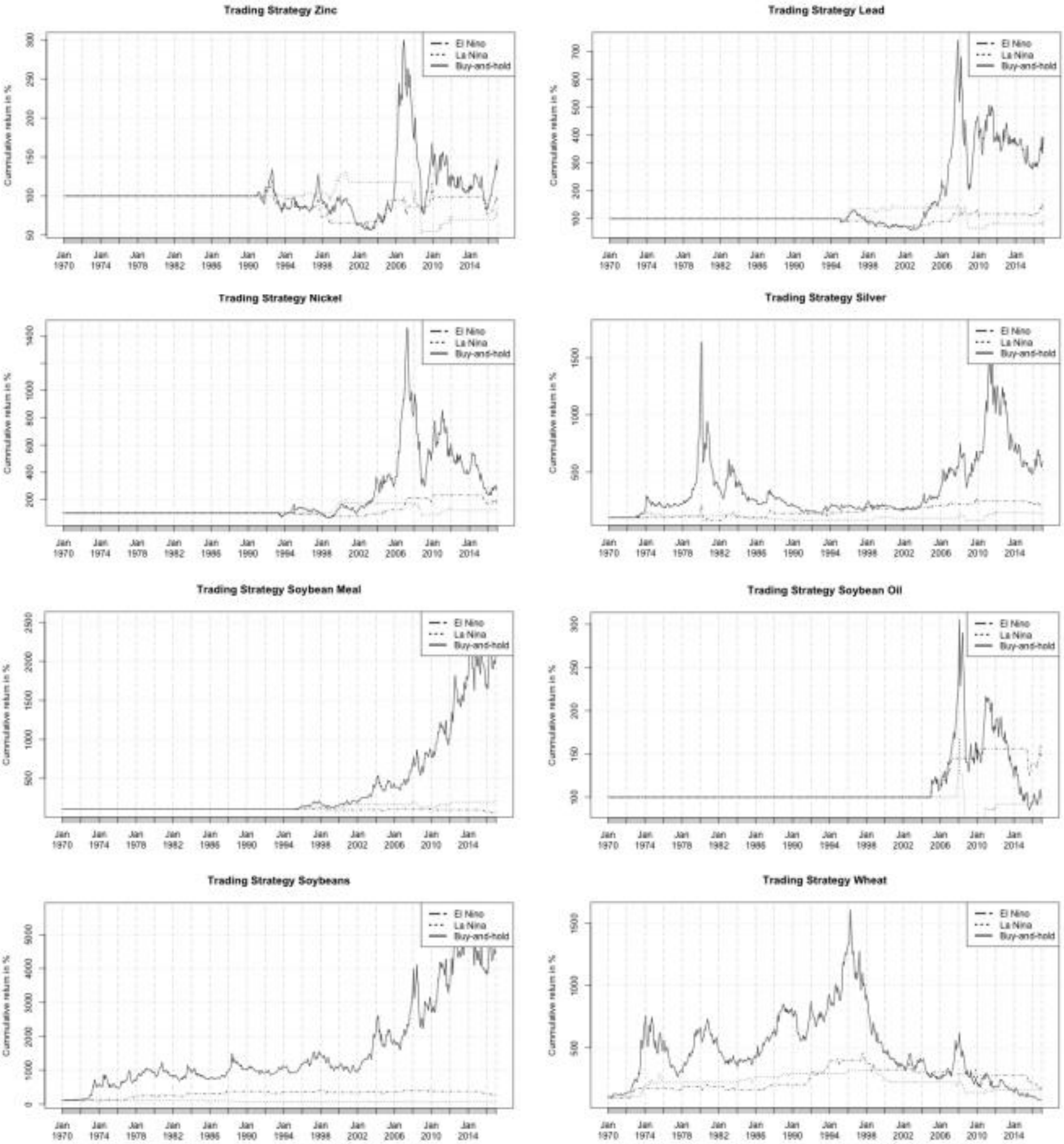


Figure II displays trading strategy plots which are showing cumulative returns per commodity, employing an El Niño, La Niña and buy-and-hold strategy. The buying signal is a single ONI threshold breach of +/-0.5 within the period from June to November. The investments follow a fixed holding period of six months. The historical performance test uses S&P GSCI sugar index data which is available from 1973 and reach to January 2017.