Climate and Commodity Prices: An Analysis of the Role of ENSO Forecasts in Agricultural Commodity Markets

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Table of Contents

Abstract
ENSO or El Niño Southern Oscillation represents the variation in sea surface temperatures across the equatorial Pacific Ocean. El Niño and La Niña are opposite extremes of the ENSO cycle, each bringing their own set of extreme weather conditions to locations around the world. Much research has been done on the impact of ENSO on agricultural commodity markets. Most of the academic research has concluded that the ENSO cycle explains a significant percentage of the variation in agricultural commodity output and prices.

This paper seeks to identify whether newly issued ENSO forecasts have a material impact on agricultural commodity prices. According to the semi-strong efficient markets hypothesis, securities prices should reflect all readily available public information. Therefore, if ENSO in fact drives commodity prices, then, accurate ENSO forecasts should be of significance to market participants. If markets are efficient, market participants should immediately adjust their commodity exposure to reflect the most up to date ENSO expectations. However, if markets are inefficient, agents will only slowly adjust their commodity exposure to reflect the latest ENSO expectations. Accurate ENSO forecasts should then be able to predict future commodity returns.

This paper finds that ENSO forecasts do in fact possess predictive power for future returns. The predictive power is most pronounced for sugar, palm oil, rubber and soybean oil markets. Agents do not seem to immediately adjust to new ENSO forecasts, be it from the International Research Institute for Climate and Society or from individual ENSO forecast models. This paper therefore concludes that agricultural markets may in fact violate semi-strong market efficiency. Moreover, the study serves as further proof that ENSO variation has a direct impact on commodity prices and that the nature of the relationship is likely non-linear.

However, there is one major qualification to these results. The dataset contains only ten years of forecast data. This constitutes only two to three full ENSO cycles. As such, the study demands further analysis, especially when a more comprehensive dataset can be gathered.

Acknowledgements
I would like to thank Professor Whitelaw for his dedication and guidance throughout the entire process. I am also indebted to Professor Ubilava at the Department of Agricultural and Resource Economics at the University of Sydney for providing his invaluable wisdom about ENSO and agricultural economics. I would also like to thank Professor Subrahmanyam and Jessica Rosenzweig for organizing a fantastic program, one dedicated to learning for its inherent sake. And finally, I would like to thank my family and close friends for providing me with an amazing support base to lean on during my four years of college.

I. Introduction of ENSO

A. ENSO Background

ENSO or El Niño Southern Oscillation measures the fluctuations in sea surface temperatures in the equatorial east Pacific. The ENSO phenomenon is considered by many climatologists to be one of the main sources of annual variation of weather conditions across the globe. In fact, many believe that ENSO is the second most important source of weather variation, only behind the seasonal cycle.[1] Research has shown that in some areas, ENSO variation explains nearly fifty-percent of the total variation in local weather conditions.[2]

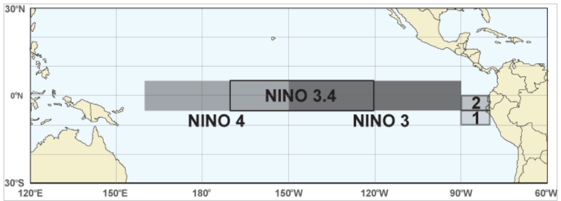
El Niño and La Niña represent mirror extremes of the ENSO phenomenon. Each brings about a different set of extreme weather conditions to regions around the world. An official El Niño, as defined by the National Oceanic Administration (NOAA) occurs when average sea surface temperatures in the ENSO 3.4 region of the Pacific Ocean deviate 0.5 degrees Celsius above normal, over a three month period. On the other hand, an official La Niña occurs when average sea surface temperatures in the ENSO 3.4 region of the Pacific Ocean deviate 0.5 degrees Celsius below normal, over the course of a three month period. Any temperature reading between +0.5 and -0.5 Celsius is officially categorized as a neutral or normal reading.[3] The ENSO 3.4 region refers to a distinct region in the equatorial Pacific Ocean at 120Wº-170ºW and 5ºN-5ºS (as shown in the chart below). Climatologists believe that out of the five distinct regions used to identify

[1] Why do we care about ENSO impacts? (n.d.). *What Are ENSO Impacts?* Retrieved from http://iri.columbia.edu/climate/ENSO/societal/impact/care.html

[2] Why do we care about ENSO impacts? (n.d.). *What Are ENSO Impacts?* Retrieved from http://iri.columbia.edu/climate/ENSO/societal/impact/care.html

[3] El Nino Definition. (n.d.). *El Nino Definition*. Retrieved from http://www.nws.noaa.gov/ost/climate/STIP/ElNinoDef.htm

ENSO variation, the ENSO 3.4 region and its temperature fluctuations contain the most information about ENSO's effect on global weather conditions.[4]



Source: Australian Bureau of Meteorology

According to studies conducted by the NOAA, El Niño and La Niña each tends to recur every three to five years. El Niño generally lasts nine to twelve months, while La Niña typically lasts one to three years. On average, each phenomenon develops from April until June, peaks from December through the following April, and then fades from May through July.[5]

Since the ENSO phenomenon occurs in the equatorial east Pacific, locations near the equator are most likely to be significantly impacted by ENSO's fluctuations.[6] Those areas include Southeast Asia, South and Central America and Australia. For example, during an El Niño, central and southern South America is more likely to receive flooding rains, while Australia and other Southeast Asian locations are more likely to experience extended periods of drought. On the other hand, during a La Niña, extreme rains are more likely in Southeast Asia while persistent drought is more likely in certain areas of South America. A visualization of the El Niño and La Niña phenomenon and their direct impacts can be found in Image 1 in Appendix B.

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[4] Monitoring ENSO. (n.d.). *Overview of the ENSO System: Monitoring*. Retrieved from http://iri.columbia.edu/climate/ENSO/background/monitoring.html

[5] Climate Prediction Center - ENSO FAQ. (n.d.). *Climate Prediction Center - ENSO FAQ*. Retrieved from http://www.cpc.ncep.noaa.gov/products/analysis_monitoring/ensostuff/ensofaq.shtml

[6] Effects of El Nino on Word Weather. (n.d.). *Effects of El Nino on the World Weather*. Retrieved from http://www.knmi.nl/research/global_climate/enso/effects/

However, ENSO's impacts are not strictly local to the equator. Recent climate research has connected ENSO to weather conditions across the globe, including North America, Africa and India.[7] For example, during an El Niño, the Southeast United States usually experiences a much warmer and stormier winter.[8] ENSO has even been connected to a large percentage of the variation in global cyclonic activity during the Atlantic hurricane season.[9]

Yet, it is important to note that a specific set of ENSO conditions does not guarantee a particular meteorological outcome. Rather, an ENSO regime, be it a La Niña or an El Niño, only increases the *probability* that a region will experience particular weather conditions. For areas most proximate to the equatorial Pacific, the ENSO-weather relationship will be quite strong. For areas further away from the equatorial Pacific, the connection between ENSO and local weather will be a bit weaker. [10]

B. ENSO Forecasts

Given ENSO's sweeping impacts on global weather conditions, much research has been undertaken to forecast the ENSO phenomenon accurately. Dozens of meteorological agencies around the world have developed complex models to forecast the ENSO 3.4 anomaly. Each of the major models varies in forecast output, reflecting different model methodologies and general uncertainty about the future of ENSO. Some

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[7] Effects of El Nino on Word Weather. (n.d.). *Effects of El Nino on the World Weather*. Retrieved from http://www.knmi.nl/research/global_climate/enso/effects/

[8] Climate Prediction Center - North American Winter Features. (n.d.). *Climate Prediction Center - North American Winter Features*. Retrieved from http://www.cpc.ncep.noaa.gov/products/analysis_monitoring/ensocycle/nawinter.shtml

[9] Effects of El Nino on Word Weather. (n.d.). *Effects of El Nino on the World Weather*. Retrieved from http://www.knmi.nl/research/global_climate/enso/effects/

[10] Effects of El Nino on Word Weather. (n.d.). *Effects of El Nino on the World Weather*. Retrieved from http://www.knmi.nl/research/global_climate/enso/effects/

models employ a statistical approach, using historical ENSO data to predict future ENSO 3.4 anomalies. Other models employ a more dynamic approach, incorporating physical information about the Pacific Ocean's thermal profiles to forecast ENSO. Image 2 in Appendix B contains a summary plot of all the major individual model projections for ENSO 3.4, as of mid-September 2012.

Given the idiosyncrasies across the twenty-five major models, the International Research Institute for Climate and Society (IRI) at Columbia University aggregates all individual model forecasts into a simple multi-model consensus mean. By aggregating all the models into one consensus number, the IRI mitigates idiosyncratic model biases and sample errors, analogous to the model averaging approach for forecasting stock returns.[11] Research has shown that multi-model mean forecasts, such as the IRI's multi-model consensus forecast, possess more skill than that of individual component models.[12] [13] [14] As such, the IRI's multi-model forecast is considered the go to source for ENSO forecasts by the NOAA and other worldwide meteorological agencies.

The IRI multi-model mean provides a nine-month forecast for the ENSO 3.4 anomaly. More specifically, each newly issued forecast projects ENSO anomalies for nine distinct three-month periods. For example, a forecast issued in mid-September 2012 provides forecasts for SON, OND, NDJ, DJF, JFM, FMA, MAM, AMJ and MJJ. The SON period, or September, October and November is the projected average three-month

[11] Rapach, D.E., J.K. Strauss, G. Zhou, 2010: Out-of-sample equity premium prediction: Combination forecasts and links to the real economy. *Review of Financial Studies*, **23**, 821-862.

[12] Yun, W. T., L. Stefanova, and T. N. Krishnamurti, 2003: Improvement of the multimodel superensemble technique for seasonal forecasts. *J. Climate*, **16,** 3834–3840.

[13] Kharin, V. V., and F. W. Zwiers, 2002: Climate predictions with multimodel ensembles. *J. Climate*, **15**, 793–799.

[14] Palmer, T., and Coauthors, 2004: Development of a European Multimodel Ensemble System for Seasonal to Interannual Prediction (DEMETER). *Bull. Amer. Meteor. Soc*., **85**, 853–872.

ENSO anomaly from September to November. OND presents the forecast for the average anomaly from October through December, and so forth. Per the table below, the IRI's multi-model mean forecast issued in September 2012 projected that a near term El Niño would moderate over the following nine months, turning into a neutral ENSO by the beginning of 2013.

Mid-September 2012	**SON**	**OND**	**NDJ**	**DJF**	**JFM**	**FMA**	**MAM**	**AMJ**	**MJJ**
Average	0.7	0.8	0.8	0.7	0.6	0.4	0.3	0.2	0.1

Source: IRI Website

There are numerous advantages to the IRI's ENSO forecast structure. First, given the significant month-to-month volatility in ENSO, the three month forecast period offers a forecast data set which is less noisy. Second, the IRI's three-month forecast period is compatible with the NOAA's official criteria of El Niño and La Niña. As mentioned above, for there to be an official El Niño or La Niña, there must be a three-month anomaly above or below a certain threshold. The three-month forecast period thereby enables forecasters to easily categorize an approaching El Niño or La Niña.

Given the potential value of the ENSO models, much research has been done to assess their overall accuracy. Research has conclusively found that that the average ENSO forecast model possesses a significant degree of skill. One study found that thirty-year hindcasts "yielded average correlation skills of 0.65, at six month lead times."[15] Although the same study found that real-time six-month forecasts from 2002-2011 produced a much lower skill of 0.42, climatologists have attributed the relatively poor

[15] Barnston, Anthony G., Michael K. Tippett, Michelle L. L'Heureux, Shuhua Li, David G. DeWitt, 2012: Skill of real-time seasonal ENSO model predictions during 2002–11: is our capability increasing?. *Bull. Amer. Meteor. Soc.*, **93**, 631–651.

result to lower overall variance in ENSO over the period- not model failure.[16] However, research has found that the accuracy of the ENSO forecast models deteriorates at distinct time periods. In particular, forecast accuracy deteriorates rather significantly during the northern hemisphere spring, a phenomenon known as the “spring predictability barrier.”[17] This makes forecasting ENSO quite challenging during the months of April, May and June.

II. ENSO and Commodities

A. ENSO and Agricultural Commodity Production

As mentioned in Section I, the peak in El Niño or La Niña conditions generally occurs between December and April. This time frame coincides with the rainy season in South America and the monsoon in East Asia, two events that are absolutely essential for successful crop cycles in each region. As such, El Niño and La Niña, and the extreme weather conditions they bring, can have a significant adverse impact on agriculture output around the equator.

However, these impacts are not strictly local in scope. In fact, many of the world’s bellwether commodities source a significant amount of production from equatorial regions. For example, Brazil and Argentina are the second and third largest producers of soybeans in the world. Similarly, Indonesia and Malaysia are the first and second largest palm oil producers in the world.[18]

[16] Barnston, Anthony G., Michael K. Tippett, Michelle L. L'Heureux, Shuhua Li, David G. DeWitt, 2012: Skill of real-time seasonal ENSO model predictions during 2002–11: is our capability increasing?. *Bull. Amer. Meteor. Soc.*, **93**, 631–651.

[17] Samelson, R. M., & Tziperman, E., 2001: Instability of the chaotic ENSO: The growth-phase predictability barrier. *Journal of the atmospheric sciences**, 58(23)***, 3613-3625.

[18] FAOSTAT. (n.d.). *United Nations FAOSTAT*. Retrieved from http://faostat.fao.org/default.aspx?lang=en

The connection between ENSO fluctuations and agricultural yields has been well documented in the academic literature. Researchers have found a significant relationship between ENSO and soybean yields in Argentina and Brazil.[19] Similarly, the literature has found a connection between ENSO and corn yields in the Corn Belt in the United States.[20] Other research has connected ENSO variation to peanut yields in Florida[21], corn yields in Zimbabwe[22], wheat yields in Mexico[23] and rice production in Sri Lanka[24] and the Philippines.[25]

Moreover, the discussion of ENSO and its effects on agricultural production has not been strictly academic in nature. In fact, practitioners, including journalists, analysts and traders have identified a connection between ENSO and agricultural yields. For example, in a Financial Times article titled "Lower El Niño prospects to hit crop yield," the author quotes a number of commodity analysts and traders who argue that the soybean, wheat and corn crops in Argentina and Brazil are materially influenced by

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[19] Podestá, G.P., C. D. Messina, M.O. Grondona and G.O. Magrin, 1998: Associations between grain crop yields in central-eastern Argentina and El Niño-Southern Oscillation. *Journal of Applied Meteorology,* **38**, 1488-1498.

[20] Phillips, J. G., C. Rosenzweig, and M. Cane, 1996: Exploring the potential for using ENSO forecasts in the U.S. corn belt. *Drought Network News*, **8**, 6–10.

[21] Mavromatis, T., Ss Jagtap, and Jw Jones, 2002: El Niño-Southern Oscillation Effects on Peanut Yield and Nitrogen Leaching. *Climate Research,* **22**, 129-40.

[22] Cane, Mark A., Gidon Eshel, and R. W. Buckland, 1994: Forecasting Zimbabwean Maize Yield Using Eastern Equatorial Pacific Sea Surface Temperature. *Nature,* **370.6486**, 204-05.

[23] Salinas–Zavala, C. A. y D. B. Lluch–Cota, 2003: Relationship between ENSO and Winter–wheat Yields in Sonora, Mexico. *Geofísica Internacional.* **42**, 341–350.

[24] Zubair L, 2002: El Nino–southern oscillation influences on rice production in Sri Lanka. *International Journal of Climatology,* **22**, 242–250.

[25] Roberts, Martha G., David Dawe, Walter P. Falcon, Rosamond L. Naylor, 2009: El niño–southern oscillation impacts on rice production in Luzon, the Philippines. *J. Appl. Meteor. Climatology*, **48**, 1718–1724.

ENSO.[26] Similarly, a Reuters report highlights the impact of ENSO on the production of a number of different commodities, including wheat, soybeans, sugar, palm oil and natural rubber.[27]

B. ENSO and Commodity Prices

Given the connection between ENSO and commodity supply, by extension, ENSO variation should also have a material impact on commodity prices. Holding all else equal, ENSO-driven negative supply shocks should prompt market participants to bid up the price of the affected commodities. Academic research has indeed found that ENSO significantly impacts global commodity prices. For example, Alan Brunner of the IMF found that a one-standard-deviation positive shock in ENSO increases overall commodity prices by 3.5-4 percent.[28] According to Brunner's findings, ENSO variation has the largest impact on the prices of coconut oil, palm oil, soybean oil, groundnut oil, rice, wheat, soybeans, corn, rubber, iron ore and copper. This conclusion is intuitive, as almost all of the aforementioned commodities are significantly sourced from tropical regions, where ENSO's impact is most direct.

A number of more specific studies have confirmed the relationship between ENSO and particular commodity prices. These studies have focused specifically on coffee, soybeans and the major vegetable oils.[29] [30] [31] Moreover, the studies have

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[26] Terazono, E. (2012, October 9). Lower El Niño prospects to hit crop yield. *Financial Times*. Retrieved from http://www.ft.com/intl/cms/s/0/70c2fb9c-1225-11e2-b9fd-00144feabdc0.html

[27] Fogarty, D. (2012, May 10). Why do El Nino and La Nina trigger weather chaos? *Reuters*. Retrieved from http://www.reuters.com/article/2012/05/10/us-climate-elnino-idUSBRE8490GU20120510

[28] Brunner, A, 2002: El Niño and World Primary Commodity Prices: Warm Water or Hot Air?. *The Review of Economics and Statistics*, **84**, 176-183.

[29] Keppenne, C. L., 1995: An ENSO signal in soybean futures prices. *J. Climate*, **8**, 1685–1689.

[30] Ubilava, D., 2012, El Niño, La Niña, and world coffee price dynamics. Agricultural Economics, **48**, 17–26.

identified the precise nature of the relationship between ENSO and prices. For example, Ubilava and Holt argue that vegetable oil prices rise during an El Niño and decline during La Niña. Furthermore, they argue that vegetable oil prices are more responsive to positive ENSO shocks during an El Niño, than during a neutral or La Niña regime. Conversely, vegetable oil prices are more sensitive to negative ENSO during a La Niña, than during neutral or El Niño regime.[32] Put differently, a move towards greater climate extremes has a greater impact on prices.

Practitioners have also begun to focus on the ENSO-commodity price relationship with respect to a number of major commodities, including soybeans, sugar, coffee, rice, rubber and palm oil. [33] [34] For example, in a recent article, a major commodities analyst writes, "Early talk of El Niño weather could spook the sugar market and trigger panic demand should this weather risk crystallize."[35] Similarly, a recent Credit Suisse report highlights the relationship between El Niño events and palm oil prices. As seen from Image 3 in Appendix B, many price spikes in palm oil have occurred concurrently with an El Niño.[36]

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[31] Ubilava, D., Holt, M., 2009. Nonlinearities in the world vegetable oil price system: El Nino effects. 2009 Annual Meeting, July 26–28, 2009, Agricultural and Applied Economics Association, Milwaukee, WI.

[32] Ubilava, D., Holt, M., 2009. Nonlinearities in the world vegetable oil price system: El Nino effects. 2009 Annual Meeting, July 26–28, 2009, Agricultural and Applied Economics Association, Milwaukee, WI.

[33] Shifts in commodity prices as El Nino fades. (n.d.). *Financial Times*. Retrieved from http://www.ft.com/intl/cms/s/0/47c3b7a2-14e6-11df-8f1d-00144feab49a.html

[34] La Nina Weather Pattern 'Is Dead,' World's Forecasters Say. (n.d.). *Bloomberg*. Retrieved from http://www.bloomberg.com/news/2012-03-27/la-nina-weather-pattern-is-dead-world-s-forecasters-say-2-.html

[35] Thukral, N., & Pardomuan, L. (2012, May 10). Asia faces threat to crops if El Nino unleashed again. *Reuters*. Retrieved from http://www.reuters.com/article/2012/05/10/us-commodities-elnino-idUSBRE8490HC20120510

[36] Min, T. T., Sandianto, A., & Oetomo, T. (n.d.). Money in your "palms" *Credit Suisse*.

III. Rationale and Research Questions

The Efficient Markets Hypothesis (EMH) is one of the hallmark hypotheses in academic finance. Eugene Fama, the father of the hypothesis, posits that security prices should be equivalent to the best estimate of fundamental value that can be made, given an "information set." Put differently, an efficient market is one in which security prices reflect all available information.[37]

There are three broad forms of the efficient market hypothesis: the weak, semi-strong and strong versions. Each version of the EMH reflects different conceptions about what constitutes the relevant information to market participants. The weak form of EMH claims that security prices reflect all information included in past prices. Therefore, market participants should not be able to generate abnormal returns from trading rules based on past prices (e.g., buy the biggest winners over the last year and short sell the biggest losers), commonly known as technical trading. The semi-strong version takes it one step further, arguing that security prices reflect all available public information. As such, traders should not be able to generate abnormal returns from the use of public information such as accounting metrics or brokerage analysts' reports. And finally, the strong version asserts that security prices reflect all information, even information held by corporate insiders and other private parties.

***In this study, I seek to investigate whether the semi-strong EMH holds in agricultural commodity markets*.** Since ENSO variation is documented to be a significant driver of agricultural commodity prices, by the semi-strong EMH, newly issued ENSO forecasts with predictive power for future weather patterns and prices

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[37] Fama, E. F., 2012: Efficient capital markets: II. *The journal of finance*, ***46*(5)**, 1575-1617.

should *also* impact current commodity prices, assuming a link between current and future prices. That is, ENSO will likely impact the future supply of the relevant commodity. Therefore, in anticipation of the likely shock to future supply, market participants should adjust the price they are willing to pay for the commodity today. Put differently, the new information should immediately become incorporated in the commodity's price. Since newly issued ENSO forecasts from the IRI are publicly released on the IRI's website and thus readily available, market participants should be able to seamlessly adjust their commodity exposure to reflect the new changes in ENSO expectations.

The academic inspiration for this study largely comes from a recent paper written by Boudoukh, Richardson, Shen and Whitelaw titled, "Do Asset Prices Reflect Fundamentals: Freshly Squeezed Evidence from the FCOJ Market."[38] The paper seeks to reject an observation from Roll's famous study from the 1980s, titled "Orange Juice and Weather", that the Frozen Concentrate Orange Juice market was excessively volatile relative to its principal underlying fundamental, the weather.[39] The recent paper counters that when incorporating weather *forecasts*, fundamentals actually explain a much larger percentage of the total variation in the FCOJ market. This notion may similarly hold true with respect to ENSO forecasts. If the ENSO climate phenomenon is a significant driver of commodity prices, then it should follow that the release of skillful ENSO forecasts should generate variation in commodity prices.

However, there are potentially important differences between the weather and FCOJ prices on the one hand, and ENSO forecast and commodity process on the other.

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[38] Boudoukh, J., Richardson, M., Shen, Y., Whitelaw, R., 2007: Do asset prices reflect fundamentals? Freshly squeezed evidence from the FOJC market. *Journal of Financial Economics* **83 (2)**, 397-412.

[39] Roll, R. 1984, Orange juice and weather, *American Economic Review*, **74**, 861-880.

Specifically, the production of oranges in concentrated in Florida, where the key weather phenomenon is the occurrence of freezing temperatures. The link between temperature and orange production is well known and freezes are only forecastable a few days in advance. In contrast, since ENSO forecasts operate on much longer horizons the link between ENSO and the weather is complex, and thus the effects on production and prices are potentially more difficult for the market to process.

In order to thoroughly answer the question as to whether the semi-strong EMH holds with respect to ENSO forecasts and agricultural commodity markets, I explore three specific questions:

1. Do newly issued IRI ENSO forecasts immediately impact agriculture commodity prices?
2. Even if the answer to question one is a distinct no, market participants may still be incorporating ENSO forecast information in their decision making. Market participants may factor in forecast information from individual ENSO models, prior to the IRI's "official" forecast release. If so, prices may in fact lead changes in the IRI's ENSO forecast, reflecting the most up to date ENSO expectations among market participants. Does the data support this story?
3. If newly issued IRI ENSO forecasts do not immediately impact commodity prices and prices do not lead changes in IRI ENSO forecasts, then market participants may not be incorporating ENSO forecast information in a timely fashion. If commodity prices do not incorporate ENSO forecast information, can ENSO forecasts predict future returns? This result might suggest the existence of profitable trading strategies using the most up to date ENSO expectations. For example, if a newly issued IRI forecast

predicts a strengthening La Niña in two months; can an individual generate abnormal returns by investing in a specific commodity, which will be impacted by the likely La Niña?

IV. Data Overview

In order to do conduct this research, a full set of monthly ENSO forecast data was gathered from Columbia University's International Research Institute for Climate and Society (IRI). The data is readily available on the IRI's public website. However, in order to eliminate some of the rounding error in the publicly released data, a more precise data set was retrieved directly from the chief climatologist at the IRI, Anthony Barnston. In addition, the precise dates of forecast issuance were gathered. Conveniently, the forecasts are always issued on the third Thursday of every month.[40] [41] The forecast dataset begins in March 2002 and ends in September 2012, when this study was conducted. For more details on the nature of this dataset, please see the aforementioned section, titled: "ENSO Forecasts."

In addition, futures prices were collected from the Thomson Reuters DataStream database for the following agricultural commodities: *natural rubber, palm oil, soybeans, Arabica coffee, soybean oil, sugar, rice and corn.* In addition, spot prices were gathered for *natural rubber, palm oil, soybeans and Arabica coffee*. Spot prices weren't gathered for soybean oil, sugar, rice and corn due to time constraints. These eight commodities will be the commodities of focus for this study.

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[40] Physical Sciences Division. (2012, February 12). *ESRL News*. Retrieved from http://www.esrl.noaa.gov/psd/people/klaus.wolter/SWcasts/

[41] Barnston, A. (2013, January 24). ENSO Plume Data [E-mail to the author].

The aforementioned commodities were chosen for numerous reasons. First, both academics and major brokerage houses have referred to these commodities as being most sensitive to ENSO variation. Second, all of these commodities are either primarily grown or have significant exposure to tropical climates, where ENSO is known to have the greatest impact on weather conditions. For example, the three largest sugar producers are Brazil, India and China. Similarly, palm oil and natural rubber production is concentrated in Indonesia, Malaysia and Thailand. Coffee, soybeans, rice and corn are also sourced from tropical regions.[42] And finally, these commodities are actively traded in highly liquid capital markets. Their prices are therefore more likely to reflect underlying fundamentals.

It is important to note that different splicing methodologies were used to construct the various futures price time series that appear in this study. For soybeans, soybean oil, Arabica coffee, sugar, rice and corn, the nearest term futures contract was rolled over at the beginning of every month. This methodology was deemed most appropriate, as the nearest term contract for the referenced commodities is the most actively traded. However, natural rubber and palm oil work a bit differently, as the most liquid contracts are much further out along the futures curve. For palm oil, the most liquid contract is the benchmark three-month contract. As such, the palm oil time series was constructed by rolling over the three-month futures contract after every month. Given the paucity of natural rubber data, the rubber price series was constructed by averaging the prices of all outstanding rubber contracts along the futures curve.

[42] FAOSTAT. (n.d.). *United Nations FAOSTAT*. Retrieved from http://faostat.fao.org/default.aspx?lang=en

For the reader's reference, the DataStream ids for the commodity series used in this study were: SOYBEAN, CS.CS00, PALOLCD, KPOC.03, RUBBSMR, JRUCS05, COFCLAR, NKCCS00, SOYAOIL, NSBCS00, CRRCS00 and CORNUS200.

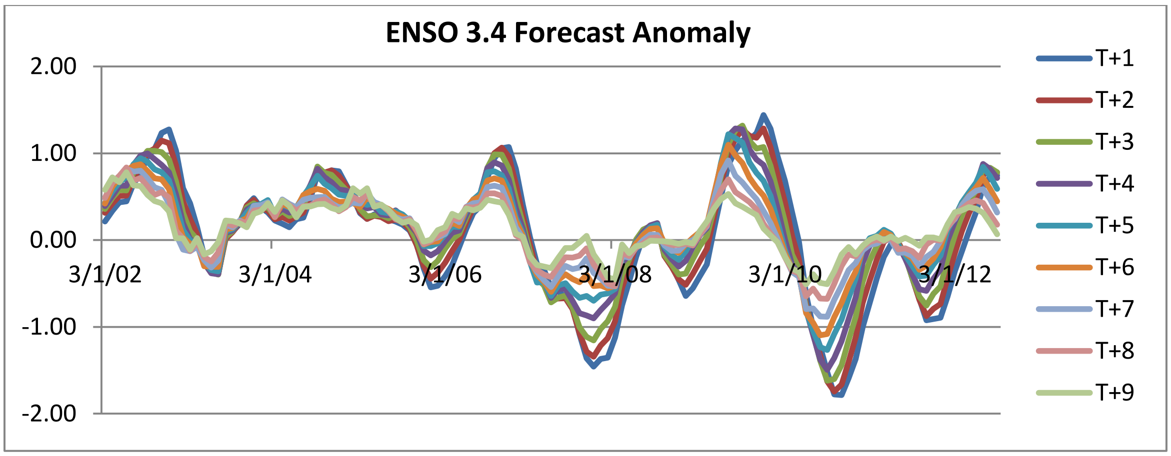
A. Methodology: Forecast Data

In order to draw any significant conclusions about the relationship between newly issued forecasts and commodity returns, there must first be a meaningful framework to analyze the set of forecast data for ENSO 3.4 temperature anomalies. As mentioned above in "ENSO Forecasts", each newly issued IRI forecast comes with nine separate data points. These data points represent monthly forecasts for nine distinct three-month periods. In essence, the forecast data set can be considered as nine distinct time-series. The table below shows descriptive statistics for these forecasts.

Descriptive Statistics	***T+1***	***T+2***	***T+3***	***T+4***	***T+5***	***T+6***	***T+7***	***T+8***	***T+9***
Mean	0.02	0.05	0.08	0.12	0.14	0.13	0.12	0.12	0.14
STDEV	0.73	0.70	0.65	0.59	0.52	0.46	0.40	0.34	0.29

Correlation Matrix	***T+1***	***T+2***	***T+3***	***T+4***	***T+5***	***T+6***	***T+7***	***T+8***	***T+9***
T+1	1.00								
T+2	0.99	1.00							
T+3	0.96	0.99	1.00						
T+4	0.91	0.96	0.99	1.00					
T+5	0.87	0.93	0.97	0.99	1.00				
T+6	0.83	0.90	0.94	0.98	0.99	1.00			
T+7	0.77	0.84	0.90	0.94	0.97	0.99	1.00		
T+8	0.73	0.79	0.85	0.89	0.93	0.96	0.99	1.00	
T+9	0.65	0.72	0.78	0.83	0.87	0.91	0.95	0.98	1.00

These forecast series are also plotted in the chart below. The data possesses a number of interesting features. First, the forecast series are highly correlated with one another. For example, a change in the one month forecast generally coincides with a similar change in the two-month forecast. In addition, the standard deviation for shorter lead time forecasts is significantly higher than that of longer lead time forecasts. This is largely due to the structure of the ENSO models. Shorter term forecasts are more sensitive to the underlying ENSO phenomenon, which is rather volatile. On the other hand, for longer term forecasts, the ENSO models generally extrapolate forecasts from shorter term forecast information. In essence, longer term forecasts generally flat line, thereby reducing the standard deviation of the respective series.



The first question is whether these IRI consensus forecasts contain meaningful information about the future evolution of the ENSO phenomenon. In order to test the significance of each of the forecast series, a simple regression was run. The regression relates each incremental piece of forecast information to the ultimate ENSO outcome. Since there are nine forecast points, there are nine distinct coefficients.

Where:

The results of the regression appear in Table 1 in Appendix A. Clearly, all the forecasts have incremental predictive power for future ENSO conditions relative to the forecasts for the same period issued one month previously. Put differently, each forecast point adds incremental information about the future of ENSO. The key question is how to use this information efficiently. The high correlation between the nine series evident in both the table and chart suggest that there might be a smaller number of factors driving all the forecasts. In other words, the forecast updates for the different horizons on any given date may contain similar information.

B. Principal Component Analysis

The mechanism that will be used to examine the dimensionality of the forecast data for this study is Principal Component Analysis (PCA). PCA finds the linear combination of the series in question, in this case the nine forecast series, that explains the largest fraction of the total variation across all the series. This linear combination is called the first principal component. The second principal component is the linear combination that explains the largest fraction of the remaining variation and that is orthogonal to (uncorrelated with) the first principal component. Principal components three through nine are defined analogously.

In order to conduct a PCA, the first step is to organize the entire data set into nine distinct column vectors, i.e., the nine forecast series.

Then, the covariance matrix of these column vectors is calculated:

Finally, the nine eigenvalues and eigenvectors are computed for this covariance matrix .

The eigenvector that corresponds to the largest eigenvalue is the first principal component of the data, i.e., the elements of this eigenvector defines the weights on the individual series in the first principal component. This component contains the most information about the total variability of the data. The fraction of variance explained by each successive principal component is given by the ratio of the corresponding eigenvalue to the sum of the eigenvalues. As seen from the set of eigenvalues below, out of the nine principal components, the first principal component explains almost all of the variance- 93% to be precise.

As such, *for the purpose of this study, only the first principal component will be used*. However, before the nine series can be reduced into one intelligible capture all number, each of the forecast series (must first be matched with the corresponding eigenvector.

Once the eigenvectors are matched with their respective forecast periods, the final numerical calculation can be completed:

Where:

Note that throughout the paper Forecast Information or “ ” refers to the above definition. Put concisely, the forecast information included in each monthly release is equal to the summation of the products of the nine forecasts points and their respective elements of the eigenvector corresponding to the first principal component. Note that the elements of this eigenvector are all positive and decreasing as the forecast horizon increases. In other words, the summary forecast information at any point in time puts positive weight on all the forecasts but is weighted more heavily towards the near-term forecasts.

V. Commodity Categorization

Before the study can adequately address if and how newly issued forecasts impact commodity prices, each commodity must first be categorized by its response to ENSO fluctuations. *The nature of each commodity’s ENSO-price relationship will dictate how prices react to new forecast information*. In a semi-strong efficient market, if a commodity’s price increases during an El Niño and decreases during a La Niña, forecast changes that indicate an impending El Niño should increase prices while forecast changes that indicate an impending La Niña should reduce prices. The opposite would be true when prices increase during a La Niña and decrease during an El Niño. Therefore, in order to properly model how forecast changes impact prices, each commodity in this study must first be categorized by its ENSO-price relationship.

The question then arises, what is the nature of the ENSO-price relationship for each of the eight commodities used in this study? The answer is unclear, as academic and practitioner research on specific commodities and their respective categorization has been relatively sparse and inconsistent. Academics have researched only three specific commodities or categories of commodities, namely soybeans, coffee and vegetable oils. In total, there have been only four papers written on specific commodities: two on soybeans,[43] [44] one on coffee,[45] and one on vegetable oils. [46] Moreover, some of the conclusions made by academic researchers differ from the views of practitioners. For example, Ubilava's paper concludes that El Niño shocks lead to price increases in palm oil, soy oil and other vegetable oils, while La Niña shocks generally lead to price declines. This seems to contradict some of the views held by practitioners, particularly with respect to palm oil.[47] [48]

Given the ambiguity of the existing research, this study will assume that for all of the eight commodities, excluding soybeans, prices generally increase during both climate extremes. This assumption is by no means outlandish, as El Niño and La Niña usually bring about an opposite set of extreme weather conditions to effected regions. If an El Niño increases the probability of flooding rains in a certain region, a La Niña is likely to

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[43] Keppenne, C. L., 1995: An ENSO signal in soybean future prices. *J. Climate,* **8,** 1685–1689.

[44] Letson, David & McCullough, B.D., 2001: Enso And Soybean Prices: Correlation Without Causality. Journal of Agricultural and Applied Economics, **33(03)**.

[45] Ubilava, D., 2012, El Niño, La Niña, and world coffee price dynamics. Agricultural Economics, **48**, 17–26.

[46] Ubilava, D., Holt, M., 2009. Nonlinearities in the world vegetable oil price system: El Nino effects. 2009 Annual Meeting, July 26–28, 2009, Agricultural and Applied Economics Association, Milwaukee, WI.

[47] La Nina Floods May Disrupt Malaysia Palm Oil Output, State Forecaster Says. (n.d.). *Bloomberg*. Retrieved from http://www.bloomberg.com/news/2010-08-06/la-nina-weather-may-flood-malaysia-s-palm-oil-areas-state-forecaster-says.html

[48] La Nina Returns, Bringing 'Severe' Rainfall To Malaysia; May Slow Palm Harvest. (n.d.). *Palm Oil HQ* Retrieved from http://www.palmoilhq.com/PalmOilNews/la-nina-returns-bringing-severe-rainfall-to-malaysia-may-slow-palm-harvest/

increase the likelihood of a crippling drought.[49] For instance, El Niño causes extensive drought in Malaysia and Indonesia, the two largest producers of palm oil, while a La Niña brings flooding rains. The same is true for natural rubber, which is sourced from the same regions in Southeast Asia, namely Thailand, Indonesia and Malaysia. Since El Niño and La Niña generally bring forth opposite weather extremes, the study assumes that for all commodities in this study, excluding soybeans, both climate extremes will generally lead to higher prices.

Why are soybeans excluded from this category? Academic and practitioner views seem to be in line with respect to the price-ENSO relationship for this commodity. Keppenne argues soybean prices are much more responsive to a La Niña than to an El Niño.[50] Most practitioners seem to share a similar view, postulating that relative to an El Niño, La Niña is actually quite bullish for soybean prices.[51] [52] As such, the commodity will be hypothesized to be in category two, namely a commodity where prices decrease during an El Niño and increase during a La Niña.

VI. Question 1: Do Newly Issued Forecasts Immediately Impact Prices?

A. Identifying the Relationship between Forecast Data and Prices

Since we now have 1) a framework with which to analyze the nine forecast series and 2) a categorization of how each commodity's price should react to ENSO, the study

[49] "Effects of El Niño on the World Weather." *Effects of El Niño on the World Weather*. N.p., n.d. Web. 16 Apr. 2013.

[50] Keppenne, C. L., 1995: An ENSO signal in soybean futures prices. *J. Climate*, **8**, 1685–1689.

[51] Bronstein, H. (2012, January 05). Analysis: Clock ticking for rains to save Argentine soy crop. *Reuters*. Retrieved April 11, 2013, from http://www.reuters.com/article/2012/01/05/us-argentina-grains-drought-idUSTRE8040OA20120105

[52] Lower El Niño prospects to hit crop yield. (n.d.). *Financial Times*. Retrieved from http://www.ft.com/cms/s/0/70c2fb9c-1225-11e2-b9fd-00144feabdc0.html

can proceed to analyze how prices for each commodity react to new forecast information. In order to empirically test the impact of newly issued forecasts on commodity prices, a linear regression model could be used. A natural choice is a regression that relates cumulative returns around the date of IRI forecast issuance to changes in forecast information, i.e.,

Where:

Note that throughout the paper refers to cumulative returns from n days before forecast issuance at time t to n days after forecast issuance at time t, FI_t refers to the forecast information released at date t, and FI_{t-1} refers to the forecast information released one *month* earlier at date t-1.

For this simple model, the sign of will vary based on the ENSO-price relationship for each commodity. Assuming semi-strong market efficiency, if negative ENSO anomalies cause the commodity's price to rise and positive ENSO anomalies cause price declines, then should be strictly negative. Positive forecast changes should lead market participants to bid down prices while negative forecast changes should lead agents to bid up prices. On the other hand, if prices increase during positive temperature anomalies and decrease during negative temperature anomalies, then should be strictly positive. Positive forecast changes should lead market participants to bid up prices while negative forecast changes should lead agents to bid down prices.

However, there are a number of issues with this simple formulation. First, per the original assumption, for most commodities, both extreme positive *and* extreme negative

ENSO anomalies lead to an increase in commodity prices. The above model assumes that for a particular commodity, one ENSO regime increases prices while the other regime decreases prices.

Moreover, the simple model does not incorporate the fundamental characteristic of the ENSO-price relationship that Ubilava and Holt identified with respect to vegetable oils. As explained in the section titled “ENSO and Commodity Prices”, Ubilava and Holts’ paper (ibid) suggests that vegetable oil prices do not react linearly to changes in ENSO. Put differently, during extreme ENSO conditions (either a strong El Niño or strong La Niña); movements towards even greater climate extremes may have a greater impact on prices than identical movements towards the mean.

Even though this conclusion was made strictly with respect to vegetable oil prices, the logic is likely applicable to all the commodities in this study. Changes around a neutral ENSO state are unlikely to have a huge impact on prices, as a neutral ENSO state enhances the likelihood of normal weather conditions. Anomalous weather conditions are much more likely to occur at either an extreme positive ENSO or extreme negative ENSO. As such, for all commodities, movements towards ENSO extremes should impact prices more significantly than equivalent movements to the mean/neutral climate.

The same underlying logic should apply to forecasts as well. A large change in forecast information should not necessarily be accompanied by a large change in prices. If the new forecast information predicts an even more extreme ENSO state relative to what was predicted last period, then prices should move, perhaps even dramatically.

However, if the new forecast information predicts a shift towards an average ENSO state, there may not be as significant of a price impact.

The regression should therefore be altered to reflect this fundamental characteristic. Cumulative returns around the forecast issuance date should not just depend on forecast changes and prices, but should also capture the fact that this relationship depends on the prior period's ENSO forecast.

B. Mathematical Framework

A specification that captures this intuition is

Where:

This new, more flexible mathematical framework, addresses the above qualifications. The model now incorporates seven out of the eight commodities in the study, namely those commodities where prices rise during both climate extremes. Put concisely, the new framework posits that forecast movements towards extremes should increase prices, holding all else equal. Moreover, for these seven commodities, the model now adjusts for the non-linear relationship between ENSO and prices. The model captures these characteristics via the term. To highlight the underlying intuition of the interaction term for the seven commodities, the term's four distinct possibilities are described below:

1. : A positive ENSO anomaly forecasted last period is projected to strengthen. Holding all else equal, prices should increase, implying is positive.

2. : A positive ENSO anomaly forecasted last period is projected to weaken. Holding all else equal, prices should decrease, implying is positive.

3. : A negative ENSO anomaly forecasted last period is projected to moderate. Holding all else equal, prices should decrease, implying is positive.

4. : A negative ENSO anomaly forecasted last period is projected to strengthen. Holding all else equal, prices should increase, implying is positive.

The model therefore posits that for a commodity adversely impacted by both temperature extremes, should be strictly positive. However, the above intuition does not suggest that for the seven commodities. If were set equal to zero, the model would perhaps erroneously assume complete symmetry. The model would assume that a move from an anomaly of 0.5° C to 1° C has the same impact on prices as a move from -0.5° C to -1° C. In other words, El Niño and La Niña would be modeled to have the same effect on commodity prices.

However, even if the commodity's prices may increase in both climate regimes, the degree of the impact may vary. For example, a recent report from the Malaysian Palm Oil Council finds that El Niño can reduce palm oil yields up to 30% while La Niña reduces yields only up to 15%.[53] As such, palm oil prices may react quite differently to positive forecast changes than to negative forecast changes. Moreover, even if the supply shocks are identical in both climate regimes, a change in commodity supply during an El

[53] http://www.mpoc.org.my/upload/P5_LingAhHong_POTSKL2012.pdf

Niño may not have the same price impact as an identical change in supply during a La Niña. The price shocks may be asymmetrical, as the interactions between supply and demand may differ based on the underlying climate regime.

A non-zero will be able to pick up the various asymmetries described above. If El Niño has a larger impact on prices, should be positive, as a positive directional changes in forecast information should cause prices to rise. However, if La Niña has a larger impact on prices, should be negative, as negative changes in forecast information should lead prices to increase more.

On an important side note, the nonlinear framework is also compatible with the one exception to the eight commodities, soybeans. For soybeans, where prices decrease during an El Niño, yet increase during a La Niña, the model hypothesizes that should be strictly negative, i.e.,

1. : Holding all else equal, prices should decrease, implying is negative
2. : Holding all else equal, prices should rise, implying is negative

Moreover, could also be non-zero, as the coefficient should capture any nonlinearity in the relationship between ENSO and soybean prices.

C. Hypothesis

The above regression was run for two distinct time periods of cumulative returns. The first time period used was the cumulative return from five days prior to the forecast release until five days after the forecast release. The second time period used was the cumulative return from one day prior to the forecast release until one day after the forecast release

The null hypothesis for all commodities including soybeans, is that . Put concisely, the null hypothesis asserts that there is absolutely no relationship between forecast changes and price movements. In other words, absolute forecast changes (and forecast changes relative to prior period forecasts should have no effect on prices. Assuming a significance level of 5%, the null hypothesis will be rejected for commodities excluding soybeans if and only if 1) *and* 2) the -statistic for is greater than 1.64.[54] For soybeans, the null hypothesis will be rejected if and only if 1) *and* 2) the -statistic for is less than -1.64.

D. Results

Table 2 in Appendix A reports the t-statistics from running the regression specified above for 8 futures contracts and 4 spot price series over the two different return windows. The t-statistics indicate that there is insufficient evidence to reject the null hypothesis. Nearly all of the t-statistics are small in magnitude. Moreover for the seven of eight commodities, many of the coefficients are negative, a counterintuitive result. As discussed above, holding all else equal prices should increase when forecasts move towards extremes- certainly not decrease. Moreover, for soybeans, is not always negative. The sign of the coefficient varies, depending on the futures and spot series. Similarly, is not statistically significant.

In order to determine if these results are robust, the regression was rerun with specific subsamples of the overall dataset, which, under the mathematical framework described above, would be most likely to generate a significant signal. Those categories include:

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[54] Note that this is a one-sided test since the alternative hypothesis is not that the coefficient is non-zero, but that it is positive.

1. : All else remaining equal, large forecast changes may have a large impact on prices.
2. : All else remaining equal, changes in forecast information may be more meaningful to market participants when prior forecasts projected extreme climate regimes.
3. : Perhaps market participants pay closer attention to forecast changes when forecasted ENSO anomalies are on the high side.
4. : Perhaps market participants pay closer attention to forecast changes when ENSO anomalies are lower
5. : As mentioned in the section titled "ENSO Forecast", ENSO forecasts issued in in April, May and June are significantly less accurate. As such, forecasts issued on those dates may be less meaningful to market participants. The model's signal may be clearer when those forecasts are excluded from the dataset.

After running the identical regression for each specific subsample of data, the same results were found. Very little statistical significance could be identified for either or . (Table 3 in Appendix A lists all of the relevant t-statistics for each subsample.) As such, the null hypothesis that commodity markets do not immediately react to IRI ENSO forecasts cannot be rejected.

VII. Question 2: Do prices predict future IRI ENSO forecasts?

One may erroneously conclude from the lack of significant results in question one that ENSO forecasts are categorically immaterial to market participants. This conclusion could be faulty simply because the analysis in question incorrectly assumes that the IRI's

ENSO forecast is the only source of ENSO forecast information available. In other words, every third Thursday of the month, a new IRI forecast is issued, which provides the only form of updated information about ENSO expectations to market participants. As such, the framework was structured such that prices would move around the date of the IRI's forecast issuance, when the new information would be received by market participants.

However, this assumption is not entirely accurate. Although the IRI's ENSO forecast is one of the most frequently used forecasts, it is not the sole available forecast. As mentioned in the "ENSO Forecasts" section, the IRI's forecast is simply an aggregation of twenty-one independent ENSO model forecasts. Each of the independent component models of the IRI consensus is released at a different date, reflecting the fact that many of the models are controlled by various different agencies. For example, the JMA model is issued by the Japanese Meteorological Authority while the POAMA model is issued by the Australian Bureau of Meteorology. Given the multitude of ENSO models, market participants may already be attuned to changing ENSO forecasts prior to the IRI's forecast release. Prices may therefore reflect changing ENSO expectations long before the IRI's forecasts are released. As such, prices wouldn't necessarily change within the immediate vicinity of the IRI's forecast; they would change before, when the individual model forecasts are released. Thus, the framework in question one, which solely employs IRI forecasts within the methodology, may be theoretically incorrect.

If so, what would be the proper framework to analyze the relationship between forecast changes and prices? In theory, if each individual model's forecast information and its respective issuance dates could be collected, a more accurate formulation could be developed. The framework would be identical to the one that appears in question one with one key difference- the forecast information would focus on each individual model. However, gathering the relevant information would simply be too tedious, as each forecast model is released at different increments and at different times.

A. Mathematical Framework

Due to these constraints the following framework will be used:

This regression is essentially an inverted version of the regression that appears in Question 1. This formulation posits that monthly IRI forecast changes should be related to cumulative returns prior to the forecast date. If market participants do indeed possess forecast information before the IRI's release, then prices prior to the IRI's release should change to reflect those up-to-date expectations. As such, changes in prices prior to the IRI's release may be able to predict changes to the IRI's forecast, which is simply an aggregate of the individual model forecasts.

As mentioned extensively in the "Commodity Categorization" section, for all of the commodities excluding soybeans, the study assumes that prices should increase under both climate extremes. The above formulation captures this relationship via the term. If the prior period IRI forecast (projected a positive or negative temperature anomaly and prices (moved higher prior to the IRI release, then holding all else equal, the upcoming IRI forecast is likely to project a more significant climate extreme. On the other hand, if the prior period predicted a positive or negative anomaly and prices moved lower, then holding all else equal, it is likely that the upcoming forecasts will predict a reversion towards neutral ENSO conditions. Put differently,

1. If then holding all else equal
2. If then holding all else equal
3. If then holding all else equal
4. If then holding all else equal

As such, for all of the commodities excluding soybeans, should be strictly positive, as any product of and will yield the same sign as .

Just like the formulation in question one, in this framework may be non-zero. The coefficient will reflect any asymmetries in the ENSO-price relationship. Even if both climate extremes lead to an increase in prices, one climate extreme may increase prices more than the other. If El Niño has a larger impact on a commodity's price relative to a La Niña, should be positive. For such a commodity, positive price changes prior to the IRI release are more likely to lead to significant positive changes in than negative changes. If La Niña has a larger impact on a commodity's price relative to El Niño, should be negative. For such commodities, positive price changes prior to the IRI's forecast release are more likely to lead to significant negative changes in than to positive changes in .

For soybeans, where prices decrease during an El Niño, yet increase during a La Niña, the model hypothesizes that should be strictly negative. If market participants bid up prices prior to the IRI forecast release, then should be negative. On the other hand, if market participants bid down prices prior to the IRI forecast release, then should be positive. may still be non-zero, as the coefficient should capture any nonlinearity in the relationship between ENSO and soybean prices.

B. Hypothesis

The above regression was run for multiple return periods. The first period used was the cumulative return from ten days prior to the release of the IRI's forecast to the day immediately preceding the date of forecast issuance. The second period used was the cumulative return from twenty days prior to the release of the IRI's forecast to the day immediately preceding the date of forecast issuance.

The null hypothesis for all commodities including soybeans, is that . Put concisely, the null hypothesis asserts that there is no relationship between price movements and changes in IRI forecast information. In other words, absolute price changes (and price changes relative to prior period forecasts should not lead forecast changes. Assuming a significance level of 5%, the null hypothesis will be rejected for commodities excluding soybeans if and only if 1) *and* 2) the -statistic for is greater than 1.64. For soybeans, the null hypothesis will be rejected if and only if 1) *and* 2) the -statistic for is less than -1.64.

C. Results

Table 4 in Appendix A reports the t-statistics from running the regression specified above for 8 futures contracts and 4 spot price series over two the different return windows. As seen from the t-statistics, there is insufficient evidence to reject the null hypothesis. Excluding rubber futures, there is little evidence that prices actually predict changes in the IRI's forecasts. Moreover for the category of commodities excluding soybeans, many of the coefficients for are negative, a counterintuitive result. As mentioned above, for all combinations of , should be strictly positive. Similarly, for soybean spot and futures, is positive and statistically insignificant, contrary to the initial intuition.

In order to determine if these results are robust, the regression was rerun with specific subsamples of the overall dataset, which, under the mathematical framework described above, would be most likely to generate a significant signal. These specific subsamples were also isolated during the analysis of question one.

1.

2.

3.

4.

5.

After running the regression for each subsample, the same results were found. Excluding rubber futures, very little statistical significance could be identified for either or . (See Table 5 in Appendix A for all of the relevant t-statistics for each category of data.) As such, the null hypothesis could not be rejected. Therefore, the results suggest that agricultural commodity prices do not lead changes in the IRI's forecasts. Put differently, the results suggest that market participants do not incorporate information from individual ENSO forecast models.

VIII. Question 3: Do Newly Issued Forecasts Predict Future Prices?

From the collective analysis in questions one and two, it appears that there is little or no evidence that agricultural commodity markets incorporate ENSO forecast information, be it from the IRI's consensus model or from individual forecast models. There are two possible explanations for these results. First, it may be that ENSO forecasts do not contain any valuable information about prices. As discussed extensively in the "ENSO Forecasts" section, ENSO forecasts are far from one-hundred percent accurate.

Moreover, even if the ENSO forecasts were completely accurate, ENSO conditions do not guarantee a specific set of weather outcomes. Thus, the connection from ENSO forecasts to ENSO conditions to commodity supply and finally to prices may be so weak that ENSO forecasts do not contain much price-relevant information. If ENSO forecasts do not contain any relevant information, then by the semi-strong efficient markets hypothesis, market participants should simply ignore them, which they seemingly do, per the above evidence.

Alternatively, it may be that despite the above results, ENSO forecasts actually contain significant information. The absence of an immediate adjustment in prices to new forecast information may indicate that market participants do not immediately adjust their expectations to reflect the latest information. Market participants may only slowly incorporate the new ENSO information into commodity prices. Put concisely, the agricultural commodity markets in the study may violate semi-strong market efficiency.

Such a conclusion would not be outlandish as violations of semi-strong efficiency have been documented in various markets. In the stock market, one famous example is Post Earnings Announcement Drift. Specifically, equities with positive earnings surprises generated significant abnormal returns nearly sixty days after the earnings announcement.[55] Thus, there is sufficient precedent to conjecture that market participants may underreact to material information in the sphere of agricultural commodities.

There is a rather simple way to test whether agricultural markets are inefficient. If the agricultural markets are inefficient, then ENSO forecasts should be able to predict future returns. Put differently, there may be an opportunity to generate some sort of

[55] Bernard, Victor L., and Jacob K. Thomas, 1990: Evidence that stock prices do not fully reflect the implications of current earnings for future earnings. *Journal of Accounting and Economic,* **13**, 305–340.

abnormal return from entering a trade, which captures the most up to date expectations. Such an idea is referred to in Keppenne's research on soybeans (ibid). Keppenne argues that given the strong ENSO-soybean price relationship, ENSO forecasts should theoretically be able to "predict the ENSO-related variability of the nearest-month futures [soybean] price."

A. Mathematical Framework

The mathematical framework applied to answer this question is extremely similar to that which appears in question one:

Like question one, the formulation relates commodity prices to changes in IRI forecast information. However, for this analysis, the framework relates changes in IRI forecasts to future commodity returns. and will bear similar meanings to the coefficients that appear in question one. For all commodities excluding soybeans, the model posits that should be strictly positive. Since either climate extreme should lead to higher prices for these commodities, forecast changes that project more significant climate extremes (holding all else equal should lead to higher prices in the future. Any forecast change that projects a reversion toward the mean (should lead to lower prices in the future.

Like question one, will reflect any asymmetries between El Niño and La Niña. If El Niño has a larger impact on prices, should be positive, as a positive directional changes in forecast information should lead prices to rise more in the future. However, if La Niña has a larger impact on prices, should be negative, as negative changes in forecast information should lead future prices to increase more. For soybeans, where prices decrease during an El Niño, yet increase during a La Niña, the model hypothesizes that should be strictly negative, as positive forecast changes should lead to lower prices in the future. could still be non-zero, as the coefficient should capture any nonlinearity in the relationship between ENSO and soybean prices.

B. Hypothesis

The above regression was run for four distinct time periods of cumulative returns:

1. [1,30] days after IRI forecast release
2. [31,60] days after IRI forecast release
3. [61,90] days after IRI forecast release
4. [91,120] days after IRI forecast release

The null hypothesis for all commodities including soybeans, is that . Put concisely, the null hypothesis asserts that there is no relationship between forecast changes and future commodity returns. In other words, forecast changes (and forecast changes relative to prior period forecasts should not be able to predict future prices. Assuming a significance level of 5%, the null hypothesis will be rejected for commodities excluding soybeans if and only if 1) *and* 2) the -statistic for is greater than 1.64. For soybeans, the null hypothesis will be rejected if and only if 1) *and* 2) the -statistic for is less than -1.64.

C. Results

Table 6 in Appendix A reports the t-statistics and coefficient estimates for 4 return windows and the 12 price series. As the t-statistics indicate, there is a large amount of statistical significance for both and , especially for the periods [61,90] and [91,120]. The significance is most pronounced for sugar, palm oil, rubber and soybean oil. Moreover, the sign of for all the statistically significant results is strictly positive. For all commodities excluding soybeans, this result affirms the notion that forecast movements towards climate extremes place positive pressure on prices. The null hypothesis for this category of commodities is therefore rejected. IRI ENSO forecasts do seem to predict future commodity returns. Moreover, most of the signs for are negative, suggesting that La Niña has a more significant impact on prices than an El Niño. For soybeans, the results also provide sufficient evidence to reject the null hypothesis. The statistically significant negative coefficient for verifies the notion that soybean prices are much more responsive to a La Niña than to an El Niño.

In addition, it appears that the results are not just statistically significant, but also economically significant. A one standard deviation negative forecast information shock ( ) during a negative temperature anomaly regime (results in an average cumulative return across the eight commodities of 4.2% and 3.5% for the [61, 90] and [91,120] periods respectively. Table 7 in Appendix A presents a detailed list of cumulative returns when there is a one standard deviation negative shock in forecast information during a La Niña. A parallel two standard deviation negative shock during a La Nina results in average cumulative returns of 8% and 7% for the [61, 90] and [91,120] periods respectively. The economic effect seems to be most acute for palm oil, rubber, sugar and soybean oil.

What would cause this violation of semi-strong efficiency? There are two possible causes. First, market participants may simply be unaware of the value of the forecasts. Knowledge of ENSO and all its effects requires a technical understanding of climate dynamics, knowledge which traders and investors are unlikely to possess. Alternatively, market participants may indeed be aware of the value of the forecasts. However, since the forecasts themselves are imperfect, agents may be unwilling to materially adjust their portfolio until they begin to see actual fluctuations in the ENSO phenomenon itself. The lag between the date of the forecast and the subsequent ENSO movement may be 60-120 days long. Agents may therefore underreact to new forecast information.

IX. Conclusions

Whatever the underlying reason for the inefficiency, the results of this study seem to support a number of important conclusions regarding both the nature of the ENSO-commodity price relationship as well as the nature of agricultural commodity markets. First and foremost, from the results it appears that ENSO variation seems to have a significant impact on agricultural commodity markets. If ENSO forecasts can predict future commodity returns, then by extension, the underlying ENSO cycle must have a significant relationship with commodity markets. These results serve as further support to the prevailing academic literature on the subject, which posits that there is indeed a relationship between ENSO and commodity prices. In particular, the study suggests that the ENSO-price relationship is particularly strong with respect to sugar, rubber, palm oil and soybean oil markets.

Second, the results serve as further evidence in support of Ubilava's assertion with respect to vegetable oils, namely that the ENSO-price relationship is non-linear. As seen from the analysis in question three, IRI ENSO forecasts contain even more predictive power for future returns when climate forecasts project a movement towards an even greater ENSO extreme. Put differently, the coefficient is positive and statistically significant. This result suggests that the ENSO-price relationship is strongest when ENSO is at an extreme phase, in agreement with Ubilava's conclusion.

Third, the results suggest that commodity prices rise more significantly during a La Nina than an El Nino. The negative result for in question three indicates that a forecast projecting a strengthening La Nina has more predictive power for future prices than that of a forecast projecting a strengthening El Nino. This seems to contradict Brunner's and Ubilava's research, which suggest that prices actually are more responsive to an El Nino.

And finally, the results provide significant evidence that agricultural commodity markets violate semi-strong market efficiency. Commodity markets seem to only gradually incorporate material ENSO forecast information. Agents clearly underreact to new IRI ENSO forecasts. Moreover, the effect is both statistically and economically significant. A one standard deviation negative shock during a La Nina can cause a 4-6% increase in commodity prices in a 30-day period.

However, there is one major qualification to these conclusions, especially with respect to the third conclusion. The dataset contains only ten years of forecast data. This constitutes only two to three full ENSO cycles. It is difficult to capture all of the intricacies of the ENSO-price relationship simply by analyzing only a ten year sample size. As such, this study warrants further analysis, particularly when a more comprehensive forecast dataset can be gathered.

Appendix A- Tables

Table 1

Regression Results	Coefficients	t-Stat
Intercept	0.10	4.06
F(T-1)-F(T-2)	1.72	9.41
F(T-2)-F(T-3)	1.03	5.12
F(T-3)-F(T-4)	0.95	4.77
F(T-4)-F(T-5)	0.51	2.65
F(T-5)-F(T-6)	0.75	3.82
F(T-6)-F(T-7)	0.81	4.31
F(T-7)-F(T-8)	1.07	6.01
F(T-8)-F(T-9)	1.45	7.50
F(T-9)	0.90	12.16

Table 2

T-Statistics for	[+1,-1]	[+5,-5]
Corn Futures	(0.23)	(0.55)
Coffee Spot	0.04	(0.66)
Coffee Futures	0.23	(0.46)
Palm Oil Spot	0.20	(0.60)
Palm Oil Futures	(0.12)	(0.83)
Rice Futures	1.12	0.81
Rubber Spot	1.12	0.63
Rubber Futures	0.98	(1.37)
Soybean Spot	0.04	(0.68)
Soybean Futures	0.23	(0.22)
Soybean Oil Futures	0.09	0.24
Sugar Futures	(0.10)	(1.05)

T-Statistics for	[+1,-1]	[+5,-5]
Corn Futures	0.26	0.05
Coffee Spot	(0.35)	(0.19)
Coffee Futures	(0.12)	0.25
Palm Oil Spot	1.62	1.03
Palm Oil Futures	1.65	1.10
Rice Futures	(0.65)	0.88
Rubber Spot	(1.45)	(1.48)
Rubber Futures	(1.22)	(2.19)
Soybean Spot	(0.35)	(0.65)
Soybean Futures	(0.12)	(0.28)
Soybean Oil Futures	0.09	0.35
Sugar Futures	(1.61)	1.31

Table 3

T- Statistics for	Excluding Spring Forecasts	abs( )> 0.45	abs( )>1	0	<0
Rubber Spot +1,-1	1.54	0.95	0.53	0.78	1.12
Rubber Spot +5,-5	1.29	0.80	0.08	0.88	0.65
Rubber Fut. +1,-1	1.57	0.70	0.69	0.28	0.69
Rubber Fut. +5,-5	(0.23)	(0.47)	(0.90)	(0.84)	0.13
Palm Spot +1,-1	1.35	0.25	(0.71)	0.33	0.56
Palm Spot +5,-5	0.35	(0.37)	(0.94)	(0.08)	(0.52)
Palm Fut. +1,-1	0.89	(0.24)	(1.48)	0.29	0.31
Palm Fut. +5, -5	(0.43)	(0.87)	(0.95)	(0.11)	(0.96)
Soybean Spot +1,-1	0.11	0.79	(0.39)	0.20	1.34
Soybean Spot +5,-5	(0.48)	(0.09)	(1.07)	(0.41)	0.86
Soybean Fut. +1,-1	0.46	0.85	(0.34)	(0.01)	1.46
Soybean Fut. +5,-5	(0.03)	0.53	(0.92)	(0.25)	1.33
Coffee Spot +1,-1	0.11	0.79	(0.39)	0.20	1.34
Coffee Spot +5, -5	(1.11)	0.08	(1.33)	(0.18)	0.85
Coffee Fut. +1,-1	0.46	0.85	(0.34)	(0.01)	1.46
Coffee Fut. +5,-5	(0.84)	0.35	(1.40)	(0.13)	1.10
Soybean Oil +1,-1	0.72	0.12	(0.56)	0.26	1.25
Soybean Oil +5,-5	(0.03)	0.44	(0.72)	0.45	1.13
Sugar Futures +1,-1	(0.53)	0.55	(0.68)	(0.41)	0.85
Sugar Futures +5,-5	(0.85)	0.16	(0.49)	(0.94)	(0.10)
Rice Futures +1,-1	1.14	0.96	0.15	0.98	0.42
Rice Futures +5,-5	(0.60)	0.97	(0.16)	1.80	0.65
Corn Futures +1,-1	0.21	0.40	(0.64)	0.48	0.67
Corn Futures +5,-5	(0.32)	0.17	(0.87)	(0.43)	0.51
T- Statistics for	**Excluding Spring Forecasts**	**abs( )> 0.45**	**abs( )>1**	**>0**	**<0**
Rubber Spot +1,-1	(1.30)	(1.06)	(1.29)	(1.10)	0.35
Rubber Spot +5,-5	(1.57)	(0.94)	(1.56)	(1.29)	(0.01)
Rubber Fut. +1,-1	(0.83)	(0.98)	(1.30)	(0.44)	(0.03)
Rubber Fut. +5,-5	(1.92)	(1.57)	(2.19)	(0.78)	(0.21)
Palm Spot +1,-1	1.98	1.21	1.76	0.24	1.27
Palm Spot +5,-5	1.59	0.56	1.46	0.18	0.40
Palm Fut. +1,-1	1.82	1.30	1.89	0.20	1.14
Palm Fut. +5, -5	1.51	0.60	1.40	0.24	(0.08)
Soybean Spot +1,-1	(0.55)	(0.87)	0.26	(0.54)	1.23
Soybean Spot +5,-5	(0.50)	(1.29)	0.13	(0.27)	0.89
Soybean Fut. +1,-1	(0.30)	(0.85)	0.45	(0.23)	1.32
Soybean Fut. +5,-5	0.04	(0.73)	0.66	(0.17)	1.32
Coffee Spot +1,-1	(0.55)	(0.87)	0.26	(0.54)	1.23
Coffee Spot +5, -5	0.15	(0.70)	0.61	(0.31)	1.06
Coffee Fut. +1,-1	(0.30)	(0.85)	0.45	(0.23)	1.32
Coffee Fut. +5,-5	0.57	(0.30)	1.24	(0.15)	1.38
Soybean Oil +1,-1	(0.34)	(0.72)	0.19	(0.37)	1.22
Soybean Oil +5,-5	0.70	(0.66)	0.92	(0.41)	1.26
Sugar Fut. +1,-1	(1.68)	(1.58)	(1.18)	(0.49)	0.31
Sugar Fut.+5,-5	0.62	0.97	1.97	0.92	0.89
Rice Fut.+1,-1	(0.21)	(1.06)	(0.52)	(0.79)	(0.05)
Rice Fut.+5,-5	1.95	0.57	0.82	(1.21)	0.94
Corn Fut.+1,-1	0.17	(0.13)	0.36	(0.71)	0.95
Corn Fut.+5,-5	0.49	(0.77)	0.81	0.10	0.68

Table 4

T-Statistics for	**[-10,-1]**	**[-20,1]**
Corn Futures	(0.24)	1.49
Coffee Spot	0.54	1.04
Coffee Futures	0.27	0.87
Palm Oil Spot	0.50	(0.12)
Palm Oil Futures	0.67	0.56
Rice Futures	(0.65)	(0.10)
Rubber Spot	0.43	0.26
Rubber Futures	(0.01)	0.72
Soybean Spot	0.54	0.78
Soybean Futures	0.27	0.52
Soybean Oil Futures	0.44	0.74
Sugar Futures	(0.96)	0.14

T-Statistics for	**[-10,-1]**	**[-20,1]**
Corn Futures	0.75	(0.12)
Coffee Spot	(0.55)	(0.76)
Coffee Futures	(0.17)	(0.94)
Palm Oil Spot	(0.70)	(1.37)
Palm Oil Futures	(0.72)	(0.83)
Rice Futures	0.39	(0.97)
Rubber Spot	(1.76)	(1.73)
Rubber Futures	(2.22)	(3.08)
Soybean Spot	(0.55)	(0.50)
Soybean Futures	(0.17)	(0.47)
Soybean Oil Futures	0.23	(0.55)
Sugar Futures	1.51	1.15

Table 5

T- Statistics for	Excluding Spring Forecasts	abs( )> 0.45	abs( )>1	0	<0
Rubber Spot -10,-1	(0.66)	0.05	(1.23)	1.21	0.24
Rubber Spot -20,-1	(0.55)	0.02	(1.56)	1.53	0.41
Rubber Fut. -10,-1	(0.60)	(0.35)	(1.16)	0.52	(0.00)
Rubber Fut. -20,-1	(0.46)	0.35	(0.96)	1.21	0.32
Palm Oil Spot -10,-1	(0.54)	0.27	(0.17)	0.21	0.31
Palm Oil Spot -20,-1	(0.71)	(0.90)	(1.40)	1.05	(0.60)
Palm Oil Fut. -10,-1	(0.49)	0.47	(0.17)	(0.08)	0.98
Palm Oil Fut. +5, -5	(0.71)	(0.28)	(0.84)	0.72	(0.10)
Soybean Spot -10,-1	(0.54)	1.19	(0.77)	0.88	1.12
Soybean Fut. -20,-1	(0.61)	1.77	(0.72)	1.32	1.02
Soybean Fut. -10,-1	(0.51)	1.04	(1.30)	0.72	1.55
Soybean Fut. -20,-1	(0.52)	1.35	(1.27)	1.14	1.29
Coffee Spot -10,-1	(0.54)	1.19	(0.77)	0.88	1.12
Coffee Spot +5, -5	(0.61)	1.77	(0.72)	1.32	1.02
Coffee Fut. -10,-1	(0.51)	1.04	(1.30)	0.72	1.55
Coffee Fut. -20,-1	(0.62)	1.73	(0.92)	1.29	1.20
Soybean Oil -10,-1	(0.52)	0.40	(0.24)	0.14	0.82
Soybean Oil -20,-1	(0.58)	0.63	(0.40)	0.78	0.42
Sugar Fut. -10,-1	(0.52)	0.26	(0.32)	(0.72)	(1.55)
Sugar Fut. -20,-1	(0.50)	0.72	0.12	0.05	(0.13)
Rice Fut. -10,-1	(0.55)	0.24	(0.13)	(0.39)	(0.05)
Rice Fut. -20,-1	(0.48)	1.00	0.26	(0.51)	0.10
Corn Fut. -10,-1	(0.50)	0.39	(1.20)	0.39	(0.03)
Corn Fut. -20,-1	(0.58)	1.78	(0.14)	1.23	1.54
T- Statistics for	**Excluding Spring Forecasts**	**abs( )> 0.45**	**abs( )>1**	**0**	**<0**
Rubber Spot -10,-1	0.18	(1.34)	(1.83)	(1.75)	(0.27)
Rubber Spot -20,-1	(0.01)	(1.53)	(1.70)	(2.17)	0.00
Rubber Fut. -10,-1	0.02	(1.85)	(2.34)	(1.51)	(0.56)
Rubber Fut. -20,-1	0.54	(2.30)	(2.87)	(2.26)	(0.74)
Palm Oil Spot -10,-1	0.67	(1.27)	(0.71)	(0.32)	(0.01)
Palm Oil Spot -20,-1	0.05	(1.78)	(1.67)	(1.64)	(0.61)
Palm Oil Fut. -10,-1	0.16	(1.48)	(0.71)	(0.17)	0.49
Palm Oil Fut. +5, -5	0.26	(2.12)	(1.34)	(1.04)	(0.49)
Soybean Spot -10,-1	(0.24)	(1.46)	(0.24)	(1.02)	0.96
Soybean Spot -20,-1	0.24	(1.92)	(0.54)	(1.26)	0.73
Soybean Fut. -10,-1	(0.59)	(1.16)	0.11	(0.92)	1.57
Soybean Fut. -20,-1	(0.29)	(1.45)	(0.08)	(1.27)	1.27
Coffee Spot -10,-1	(0.24)	(1.46)	(0.24)	(1.02)	0.96
Coffee Spot +5, -5	0.24	(1.92)	(0.54)	(1.26)	0.73
Coffee Fut. -10,-1	(0.59)	(1.16)	0.11	(0.92)	1.57
Coffee Fut. -20,-1	0.04	(1.97)	(0.57)	(1.41)	0.89
Soybean Oil -10,-1	1.14	(0.90)	0.13	0.05	0.82
Soybean Oil -20,-1	(0.13)	(1.44)	(0.65)	(0.67)	0.21
Sugar Fut. -10,-1	1.71	1.25	1.08	0.96	(0.72)
Sugar Fut. -20,-1	1.42	0.61	1.12	0.51	0.37
Rice Fut. -10,-1	1.25	0.13	0.42	0.19	0.33
Rice Fut. -20,-1	(0.09)	(0.72)	(0.75)	0.18	(0.20)
Corn Fut. -10,-1	0.84	(0.25)	0.82	(0.17)	0.64
Corn Fut. -20,-1	0.34	(1.64)	0.09	(0.78)	1.25

Table 6

T-Statistics for	[1,30]	[31,60]	[61,90]	[91,120]
Corn Futures	(0.30)	0.14	0.12	(1.62)
Coffee Spot	(0.02)	(0.61)	(1.70)	(2.54)
Coffee Futures	0.18	(1.11)	(1.60)	(2.41)
Palm Oil Spot	(1.11)	(2.37)	(4.26)	(3.09)
Palm Oil Futures	(0.63)	(2.22)	(3.38)	(2.94)
Rice Futures	(0.47)	(0.50)	(0.39)	(1.21)
Rubber Spot	1.05	(0.59)	(2.30)	(2.50)
Rubber Futures	0.34	(0.70)	(2.33)	(2.14)
Soybean Spot	(0.02)	(0.61)	(1.70)	(2.54)
Soybean Futures	0.18	(1.11)	(1.60)	(2.41)
Soybean Oil Futures	0.15	(1.69)	(1.82)	(2.99)
Sugar Futures	(0.01)	0.51	(2.41)	0.99

T-Statistics for	[1,30]	[31,60]	[61,90]	[91,120]
Corn Futures	0.82	0.87	3.06	1.38
Coffee Spot	(0.53)	(0.24)	1.97	1.34
Coffee Futures	(0.22)	(0.22)	2.49	1.58
Palm Oil Spot	0.73	1.69	3.05	2.71
Palm Oil Futures	1.16	1.73	3.64	2.57
Rice Futures	1.20	0.80	1.92	0.19
Rubber Spot	(0.84)	2.24	3.18	2.72
Rubber Futures	(1.10)	0.77	2.97	3.84
Soybean Spot	(0.53)	(0.24)	1.97	1.34
Soybean Futures	(0.22)	(0.22)	2.49	1.58
Soybean Oil Futures	(0.25)	0.80	2.73	1.69
Sugar Futures	3.68	3.30	1.92	0.13

Coefficient for	[1,30]	[31,60]	[61,90]	[91,120]
Corn Futures	(0.01)	0.00	0.00	(0.04)
Coffee Spot	(0.00)	(0.01)	(0.04)	(0.05)
Coffee Futures	0.00	(0.02)	(0.03)	(0.05)
Palm Oil Spot	(0.02)	(0.04)	(0.08)	(0.06)
Palm Oil Futures	(0.01)	(0.04)	(0.06)	(0.05)
Rice Futures	(0.01)	(0.01)	(0.01)	(0.02)
Rubber Spot	0.02	(0.01)	(0.05)	(0.05)
Rubber Futures	0.01	(0.02)	(0.05)	(0.05)
Soybean Spot	(0.00)	(0.01)	(0.04)	(0.05)
Soybean Futures	0.00	(0.02)	(0.03)	(0.05)
Soybean Oil Futures	0.00	(0.03)	(0.03)	(0.05)
Sugar Futures	(0.00)	0.01	(0.06)	0.03

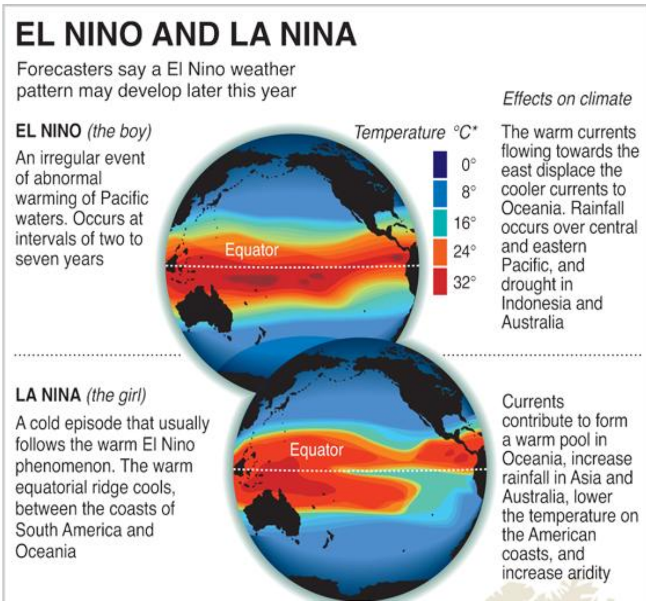
Coefficient for	[1,30]	[31,60]	[61,90]	[91,120]
Corn Futures	0.01	0.01	0.05	0.02
Coffee Spot	(0.01)	(0.00)	0.03	0.02
Coffee Futures	(0.00)	(0.00)	0.03	0.02
Palm Oil Spot	0.01	0.02	0.04	0.03
Palm Oil Futures	0.02	0.02	0.05	0.03
Rice Futures	0.02	0.01	0.03	0.00
Rubber Spot	(0.01)	0.03	0.04	0.04
Rubber Futures	(0.02)	0.01	0.05	0.06
Soybean Spot	(0.01)	(0.00)	0.03	0.02
Soybean Futures	(0.00)	(0.00)	0.03	0.02
Soybean Oil Futures	(0.00)	0.01	0.03	0.02
Sugar Futures	0.07	0.06	0.03	0.00

Table 7

Cumulative Returns	[1,30]	[31,60]	[61,90]	[91,120]
Palm Oil Spot	1.6%	3.5%	6.0%	4.8%
Palm Oil Futures	1.6%	3.4%	5.9%	4.7%
Sugar Futures	4.5%	3.5%	5.0%	-1.2%
Rubber Spot	-1.7%	2.7%	4.9%	4.5%
Rubber Futures	-1.5%	1.7%	5.7%	6.2%
Rice Futures	1.5%	1.2%	2.1%	1.2%
Soybean Oil Futures	-0.3%	2.2%	3.9%	3.8%
Soybean Spot	-0.5%	0.4%	3.4%	3.6%
Soybean Futures	-0.3%	0.8%	3.6%	3.6%
Corn Futures	1.1%	0.7%	2.9%	3.2%
Coffee Spot	-0.5%	0.4%	3.4%	3.6%
Coffee Futures	-0.3%	0.8%	3.6%	3.6%
Average	0.4%	1.8%	4.2%	3.5%

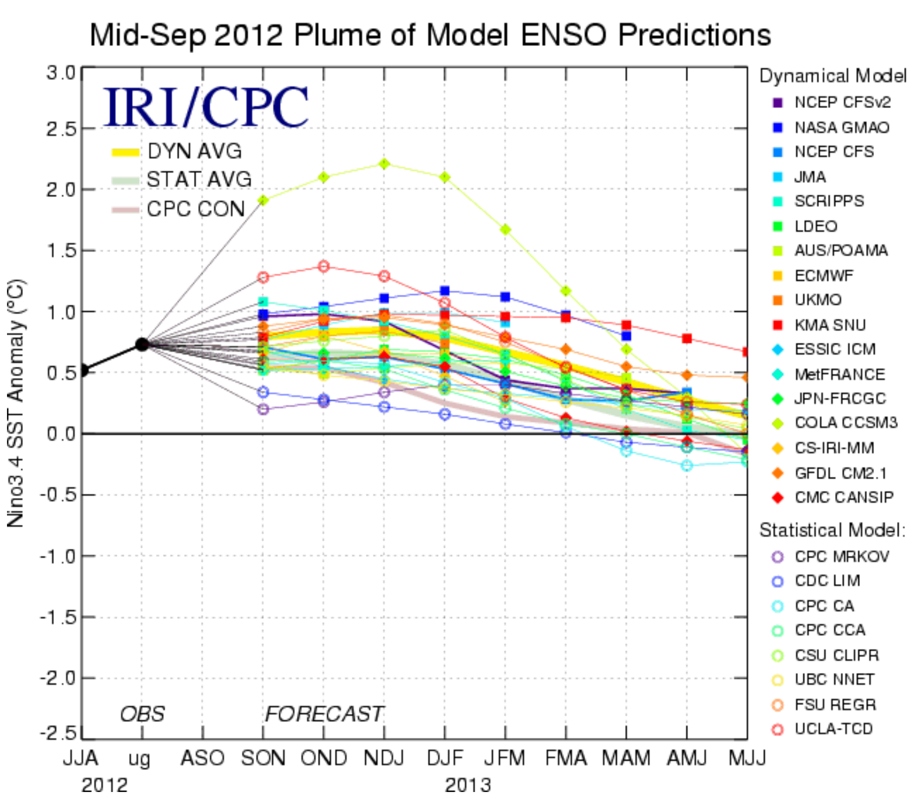
Appendix B- Images

Image 1:



Source: Reuters

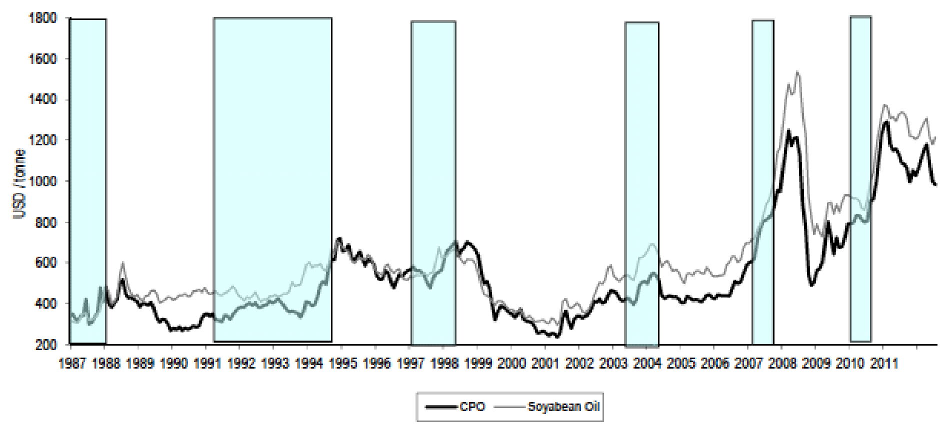
Image 2:



Source: IRI

Image 3:

Figure 18: **Palm oil prices (line chart) usually spike during El Nino episodes (marked in blue)**



Source: Oil World, National Oceonic and Atmospheric Administration (NOAA), Credit Suisse estimates

Source: Credit Suisse