Fall 2017

Essays on the El Niño Anomaly and Stock Return Predictability

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ESSAYS ON THE EL NIÑO ANOMALY AND STOCK RETURN PREDICTABILITY

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A Dissertation Submitted to the Faculty of

Old Dominion University in Partial Fulfillment of the

Requirements for the Degree of

DOCTOR OF PHILOSOPHY

FINANCE

OLD DOMINION UNIVERSITY

December 2017

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ABSTRACT

TWO ESSAYS ON THE EL NIÑO ANOMALY AND STOCK RETURN PREDICTABILITY

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This dissertation is to examine the impact of the El Niño phenomenon on the international stock market, both at the aggregate level and the portfolio level.

In first essay, I study the predictive relation between the El Niño phenomenon and international stock market aggregate returns. I find that the El Niño anomaly can predict all 14 countries' stock returns. Specifically, the El Niño unconditional effect can predict stock return negatively in Japan, Malaysia, and South Africa, while the El Niño conditional on winter season can predict positively stock returns in 13 countries' stock markets except for Japan. This conditional effect is stronger in January and February than in December. These results are robust after controlling for investor sentiment, weather, and seasonal affective disorder effects. The implication of this study suggests that current asset pricing models are incomplete and need to incorporate a prominent role for the El Niño phenomenon.

In second essay, I study the predictive effects of the El Niño anomaly on returns of forty-nine US industries and portfolios formed based on many common strategies. I also examine the predictive effects of the El Niño anomaly on portfolio returns in ten other countries besides the

US. For forty-nine US industries, the unconditional El Niño anomaly can predict eight industries' portfolio returns; conditional on winter month, the El Niño anomaly can predict twenty-two industries' portfolio returns. Overall, twenty-seven industries' returns can be affected by the El Niño anomaly. For ten countries' value premiums, the unconditional El Niño anomaly can predict three of them. Conditional on winter season (winter month), the El Niño anomaly can predict four (five) of them. Overall, seven countries' value premiums can be affected by the El Niño anomaly. For ten US portfolio returns, unconditionally the El Niño anomaly can negatively predict return of portfolio formed based on cash flow/price ratio. Conditional on winter month, the El Niño anomaly can predict four portfolios' returns. For six Japanese portfolios, conditional on winter month, the El Niño anomaly can predict five returns. Those findings remain robust using various different GARCH models.

Members of Dissertation Committee: Dr. Licheng Sun

Dr. Mohammad Najand

Dr. David Selover

ACKNOWLEDGMENTS

This dissertation cannot be completed without tremendous support from many people during my pursuant of the PhD degree at Old Dominion University.

First, I would like to extend my greatest appreciation to the chair of my dissertation committee, Dr. Licheng Sun. His broad research interests and solid research skills helped me navigate through the predictive relation between the El Niño anomaly and international stock returns, which is an under-studied hot topic. His diligent work ethic and willingness to mentor me have been invaluable to me when I was in difficult times.

Second, I would like to thank the members of my dissertation committee, Dr. Najand and Dr. Selover. They are always standing by and ready to provide support to me when I needed. Their willingness to help students and humble personalities also played an important role in shaping my teaching philosophy.

Third, I enjoyed the education provided by many influential ODU faculties, like Dr. John Doukas, Dr. Ken Yung, Dr. William Judge, and others. Their rigorous lectures and research demands helped me develop a solid scholarship.

Lastly, I would like to thank Ms. Katrina Davenport, Jackson Shen, Jian Yi, and Qiuye Cai, who are always helpful in my PhD study.

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INTRODUCTION

Traditional finance theory argues that in a perfectly competitive capital market, rational investors optimize their portfolio returns through diversification. In equilibrium, the stock prices equal the discounted value of expected cash flows. The cross-section of expected returns depends only on the systematic risks. Even if some investors are irrational, their demands will be offset by arbitrageurs and bear no impact on stock prices.

In a seminal paper, Baker and Wurgler (2006) study how investor sentiment can significantly influence the cross-section of stock returns. They argue that a broad-based wave of sentiment has cross-sectional effects and provide empirical evidence that when investor sentiment is high, the future returns would be low for small stocks, young stocks, high volatility stocks, unprofitable stocks, non-dividend-paying stocks, extreme growth stocks, and distressed stocks. Baker, Wurgler, and Yuan (2012) construct an investor sentiment index for both the local market and the global market and provide international evidence that investor sentiment is a negative predictor of the time-series of cross-sectional returns within markets. It is widely acknowledged by both academicians and practitioners that the stock market is heavily influenced not only by the fundamental economics but also by non-fundamental factors such as investor sentiment.

In a recent paper, Cashin, Mohaddes, and Raissi (2017) study the impact of the exogenous El Niño anomaly on different regions cross-sectionally and provide empirical evidences that the El Niño anomaly may have significant influence on real output growth, inflation, energy and non-fuel commodity prices. Given the important relations between stock market and macro economy, it is interesting to examine the impact of the El Niño phenomenon on stock markets. I argue that since the El Niño anomaly has widespread influential climate impacts through teleconnections, it should have widespread impact on international stock market.

The El Niño occurs when there is an abnormal warm temperature in the Pacific Ocean. The interaction between the atmosphere and the ocean prevents the cold nutrient-abundant water from reaching the surface of the ocean. The fishing industry along the South America will feel the pain first. However, through teleconnections, this regional weather phenomenon has broad global impact. Typical El Niño effect is likely to develop around Christmas. It has its largest impacts during the winter season in northern hemisphere (Rasmusson and Carpenter (1982), Tziperman et al., (1994), Trenberth (1997)). Since El Niño anomaly is time variant, its impact on international stock markets should peak in the winter season. Specifically, I look at the conditional impact of the El Niño anomaly on stock market (conditional either on winter season or winter month). I argue that if the El Niño anomaly have impact on international stock market, this impact would be more pronounced during winter season or winter month.

Essay one studies the potential impact of the El Niño anomaly on international stock market aggregate returns. I show that the El Niño phenomenon can predict all 14 countries' stock market returns. Unconditional El Niño effect can predict negatively stock return, while El Niño conditional on winter season can predict positively stock return. Especially, the unconditional El Niño anomaly can negatively predict a few countries' stock return, while the El Niño conditional on winter season can positively predict most countries' stock return even after controlling for several key economic variables (three-month Treasury bill rate, dividend yield, countries' own lagged returns, and lagged U.S. stock return, current and future economic activities) as well as investor sentiment effect, weather effect, and seasonal affective disorder effect.

I also find that sources of the documented predictability of the El Niño phenomenon could be from either economic fundamentals or investor sentiment or both. And there appear to be some heterogeneities across various countries.

Essay two studies the effect of the El Niño anomaly on stock returns at the portfolio level. Novy-Marx (2014) identifies the El Niño phenomenon significantly predicts the performance of accrual based strategy as well as beta arbitrage strategy using unilateral OLS regression and US data. Following Baker and Wurgler (2006), I distinguish novel predictability effects from well-known comovements using multivariate regression and study the predictive effects of the El Niño anomaly on returns of forty-nine US industries' and portfolios formed based on a variety of common strategies. I also examine the predictive effects of the El Niño anomaly on portfolio returns in ten other countries besides the US since the El Niño anomaly is an international phenomenon.

I find that the El Niño anomaly may have prevailing impact on the stock return at portfolio level. For 49 US industries, the unconditional El Niño anomaly can predict eight industries' portfolios return; conditional on winter month, the El Niño anomaly can predict twenty-two industries' portfolios return. Overall, twenty-seven industries' returns are affected by the El Niño anomaly. For ten countries' value premiums, the unconditional El Niño anomaly can predict three of them. Conditional on winter season (winter month), the El Niño anomaly can predict four (five) of them. Overall, seven countries' value premium can be affected by the El Niño anomaly. For ten US portfolio returns, unconditionally the El Niño anomaly can negatively predict return of portfolio formed based on Cash Flow/Price ratio (CF/P). Conditional on winter month, the El Niño anomaly can predict four portfolios' return. For six Japanese portfolios, conditional on winter month, the El Niño anomaly can predict five returns. Those findings remain robust using different GARCH models.

Novy-Marx (2014) shows the El Niño anomaly can predict returns of two portfolios (formed based on accruals and beta arbitrage) based on US data. I show that the El Niño anomaly can predict returns of portfolios formed based on many other common strategies and industries. I also provide international evidence on the effect of the El Niño anomaly on portfolios return. It is not surprising since the El Niño anomaly is an international phenomenon.

ESSAY ONE

INTERNATIONAL STOCK RETURN PREDICTABILITY: EVIDENCE FROM THE EL NIÑO PHENOMENON

Abstract

I study the predictive relation between the El Niño phenomenon and international stock returns. I find that the El Niño anomaly can predict all 14 countries' stock returns. Specifically, the El Niño unconditional effect can predict stock return negatively in Japan, Malaysia, and South Africa, while the El Niño conditional on winter season can predict positively stock return in 13 countries' stock return except for Japan. This conditional effect is stronger in January and February than in December. These results are robust after controlling for investor sentiment, weather, and seasonal affective disorder effects. The implication of this paper suggests that current asset pricing models are incomplete and need to incorporate a prominent role for the El Niño phenomenon.

JEL Classification: G12, G14, G15

Keywords: the El Niño Phenomenon, International Stock Return Predictability, Investor Sentiment, Weather Effect, Seasonal Affective Disorder (SAD)

I. Introduction

Literature has documented a large number of economic variables which have predictive power over aggregate stock market returns. Those predictors includes short-term interest rate (Fama and Schwert 1977; Breen, Glosten, and Jagannathan 1989; Ang and Bekaert 2007), dividend yield (Fama and French 1988; Ang and Bekaert 2007), inflation (Fama and Schwert 1977), term spreads (Campbell 1987; Fama and French 1988), earnings-price ratio (Campbell and Shiller 1988), book-to-market ratio (Kothari and Shanken 1997; Pontiff and Schall 1998), stock volatility (French, Schwert, and Stambaugh 1987; Guo 2006), consumption surplus ratio (Campbell and Cochrane 1999), equity share of new issuance (Baker and Wurgler 2000), consumption-wealth ratio (Lettau and Ludvigson 2001), aggregate short interest (Lamont and Stein 2004), output gap (Cooper and Priestley 2009).

In a seminal paper, Baker and Wurgler (2006) provide empirical evidence that investor sentiment, broadly defined as the propensity to speculate, has significant cross-sectional effects. Their sentiment index can negatively predict the return of stocks which are attractive to speculators and unattractive to arbitrageurs, namely younger stocks, small stocks, extreme growth stocks, and distressed stocks. Stambaugh, Yu, and Yuan (2012) find that investor sentiment has significant negative predictive power for the short legs of long-short investment strategies. Baker, Wurgler, and Yuan (2012) construct investor sentiment index for both local market and global market and provide international evidence that investor sentiment is a negative predictor of the time-series of cross-sectional returns within markets. Huang, Jiang, Tu, and Zhou (2015) construct a new investor sentiment index with the purpose of predicting the aggregate stock market and find that investor sentiment has much greater predictive power for the aggregate stock market. They also find that the return predictability of investor sentiment come from investor's biased belief about future cash flow rather than discount rates. Motivated by psychological evidence on limited investor attention and anchoring, Li and Yu (2012) propose two variables, namely the nearness to the Dow 52-week high and the nearness to the Dow historical high, and find both can predict significantly future aggregate stock market returns.

There are several papers looking at the economic impact of El Niño phenomenon. Brunner (2002) suggests that the Southern Oscillation (ENSO) cycle can explain about 10-20% of the variation in the GDP growth and inflation of G-7 economies and about 20% of real commodity price movements over the period of 1963-1997. Laosuthi and Selover (2007) find the El Niño has relatively little detectable effect on the business cycles of most of the countries in their sample. Cashin, Mohaddes, and Raissi (2017) study the macroeconomic effects of El Niño. They show that there are considerable heterogeneities in the responses of different countries to El Niño shocks in terms of real output growth, inflation, energy and non-fuel commodity prices. They conclude that the likelihood and effects of El Niño phenomenon should be part of macroeconomic policy formulation process. Given the important relations between stock market and macro economy, it is interesting to examine the impact of El Niño phenomenon on stock market. Novy-Marx (2014) finds the El Niño phenomenon significantly predicts the performance of accrual based strategy as well as beta arbitrage strategy and calls for further research. The current paper moves along this direction. I examine the potential predicting power of the El Niño phenomenon on international stock market returns. I find that the El Niño phenomenon can predict all 14 countries' stock market returns. Unconditional El Niño effect can predict negatively stock return, while El Niño conditional on winter season can predict positively stock return.

My analysis of the predictive relation between the El Niño phenomenon and international stock returns proceeds in three steps. First, I estimate a benchmark predictive regression model for 14 countries using monthly data from 1982:01 to 2014:12, where each predictive regression relates a countries' excess stock return to its lagged three-month Treasury bill rate, dividend yield, own return, and U.S. return. In line with Ang and Bekaert (2007), I find the lagged three-month Treasury bill rate significantly predicts negatively excess stock returns in Canada, Germany, Netherlands, South Africa, and United Kingdom, while dividend yield significantly predicts positively excess stock return in 10 countries except for Australia, Canada, Italy, and Switzerland. In line with Rapach, Strauss, & Zhou (2013), I find a strong predictive power of U.S. return in seven countries. The results, not only the positive sign but also the magnitude of the coefficients, are almost the same as in Rapach, Strauss, & Zhou (2013).

Second, I examine the relationships of the El Niño phenomenon and 14 countries' excess returns using augmented predictive regressions, where each predictive regression includes the El Niño anomaly and the interaction term of the El Niño anomaly with winter season dummy variable. The findings demonstrate the universal predictive power of the El Niño anomaly: the unconditional El Niño effect can negatively predict stock returns in Japan, Malaysia, and South Africa, and the El Niño conditional on winter season has significant predictive power for 13 countries' stock return except for Japan, with higher El Niño anomaly on winter season forecasting higher returns.

Third, to address concerns related to the predictive power of the El Niño phenomenon, I conduct several robustness tests. As existing literature shows the investor sentiment can predict stock market returns (see Baker, Wurgler, & Yuan, (2012), Huang, Jiang, Tu, & Zhou, (2015)), I include the consumer confidence index in each predictive regression. In doing so, I obtain results consistent with the investor sentiment literature. Additionally, I find that investor sentiment conditional on winter season has positive predictive power compared to negative predictive power of unconditional investor sentiment in Canada and South Africa.

An existing literature documents the impact of weather and seasonal affective disorder (SAD) on stock market returns (see Saunders (1993), Hirshleifer and Shumway (2003), Kamstra, Kramer, & Levi, (2003), Goetzmann and Shu (2005), Cao and Wei (2005), and Kiger, Raviv, Rosett, Bayer, & Page, (2015)). I show that my analysis is robust to controlling for both weather and SAD effects. I also address the concern regarding the relation between the El Niño phenomenon and current or future economic activities. I use the current Consumer Price Index and lead Consumer Price Index to proxy for current and future economic activities respectively. The results show that the prevailing predictive power of the El Niño effect doesn't change.

To explore the source of predictability of the exogenous El Niño phenomenon, I examine the relations between the El Niño anomaly and the expectation of future economic activities as well as investor sentiment. I find the El Niño impacts on different countries are mixed.

The El Niño phenomenon is one of the most influential climate phenomenon in the world. It was named by Peruvian fisherman in the 1600s. In Spanish, El Niño means "the Christ child" since it is often developed during the Christmas season. It has its largest impacts during the winter season in northern hemisphere (Rasmusson and Carpenter (1982), Tziperman et al., (1994), Trenberth (1997)). It is associated with warming of the ocean surface temperatures in the central and eastern tropical Pacific Ocean, which can significantly influence weather patterns, ocean conditions, and marine fisheries worldwide. (http://nws.noaa.gov) To my knowledge, there is no literature that directly examines the impact of the El Niño phenomenon on aggregate stock market returns. My study fills this gap. As a response to Novy-Marx's call for further research on this topic, I provide evidence that is consistent with Paul A. Samuelson's claims: "Modern markets show considerable micro efficiency, …, I [hypothesize] considerable macro inefficiency, in the sense of long waves in the time series of aggregate indexes of security prices below and above various definitions of fundamental values." (Robert Shiller, (2001, p.243)). In sum, this paper suggests that current asset pricing models need to incorporate a prominent role for non-fundamental variables: conditional and unconditional El Niño phenomenon.

The rest of the paper is organized as follows. Section II describes the data, hypotheses, and empirical method. Section III reports empirical results. Section IV explores the source of the El Niño predictability. Section V concludes.

II. Data, Hypotheses, and Empirical Method

A. Data

I study the predictive power of the El Niño phenomenon on international stock market returns. International stock market return data are from Global Financial Data. Stock returns are derived from the "Total Return Indices – Stocks" series, and excess returns are computed relative to each countries' three-month Treasury bill rate. I also require dividend yield data for each country. Following convention, a smoothed dividend series (an average of dividends from month t-11 through month t) is used to compute the dividend yield. Table 1 panel A reports summary statistics for monthly excess returns (in percent) for 14 countries which meet the data requirements. The average monthly excess returns range from 0.28 (Italy) to 0.83 (Sweden). The standard deviations are from 4.36 (the United States) to 7.58 (Malaysia). The minimum monthly return is observed in Australia (-43.08) and the maximum is observed in Malaysia (35.89). The autocorrelation ranges from 0.02 (Australia) to 0.18 (Switzerland). The United States has the highest Sharp ratio (0.16), while Italy has the lowest Sharp ratio (0.04). Malaysia has the lowest correlation with the United States (0.35) while Canada has the highest correlation with the United States (0.77).

[Insert Table 1 panel A here]

Following Novy-Marx (2014), I use the El Niño data from the Climate Prediction Center of National Oceanic and Atmospheric Administration (NOAA) which are available at http://www.cpc.ncep.noaa.gov/data/indices/sstoi.indices. The data begins 1982:01 and is reported in Table 1 panel B. Climate Prediction Center provides monthly sea surface temperature anomalies from the average measured over a 1981-2010 base period. It covers four different regions of the equatorial pacific. Following Novy-Marx (2014), the data covering region Niño 1+2 (0-10°South) (90°West-80°West) is used for the United States. I also use this regional data for Canada and European countries. Figure 1 plots this regional data.

[Insert Table 1 panel B here]

[Insert Figure 1 here]

Since the region Niño 3 (5°North-5°South) (150°West-90°West) data is used by Japan Meteorological Agency to monitor the El Niño phenomenon as well as to analysis the impact on Japan, this regional data is used for Japan. I also use this regional data for Malaysia. Figure 2 plots this regional data.

[Insert Figure 2 here]

Because region Niño 3.4 (5°North-5°South) (170-120°West) is used by Bureau of Meteorology of Australia and South Africa Weather Service to monitor El Niño development, I use this regional data for Australia and South Africa. Figure 3 plots this regional data.

[Insert Figure 3 here]

I control for investor sentiment effect, weather effect and seasonal affective disorder effect in this study. Based on Baker, Wurgler, Yuan (2012), I use monthly consumer confidence index to control for investor sentiment effect. The data are from Global Financial Data and reported in Table 1 panel C. Over sample periods, Italy has the highest monthly consumer confidence index of 100.90, while France has the lowest monthly consumer confidence index of 99.13. The standard deviation varies from 2.08 in UK to 4.14 in Japan. The minimum monthly consumer confidence index varies from 86.47 in Japan to 94.58 in France. The maximum monthly consumer confidence index varies from 104 in Australia to 109.30 in Sweden.

[Insert Table 1 panel C here]

Following Cao and Wei (2005), I use monthly mean temperature of the city corresponding to each country return index's stock exchange to control for weather effect. The data are from National Oceanic and Atmospheric Administration (NOAA) and are available at http://www.ncdc.noaa.gov/cdo-web/. Table 1 panel D reports the data. Over sample periods, Kuala Lumpur of Malaysia has the highest mean monthly mean temperature of 83.29°F, and Stockholm of Sweden has the lowest mean monthly mean temperature of 44.61°F. Kuala Lumpur also has the least standard deviation of 1.23, while Toronto of Canada has the highest standard deviation of 17.40. The minimum monthly mean temperature varies from 9°F in

Stockholm to 79°F in Kuala Lumpur. The maximum monthly mean temperature varies from 69.8°F in Amsterdam, Netherlands to 88.2°F in Milan, Italy. The autocorrelation varies from 0.69 in Kuala Lumpur to 0.84 in Toronto, Milan, Tokyo, and New York City.

[Insert Table 1 panel D here]

Based on Kamstra et al. (2003), I use monthly mean duration of daylight of the city corresponding to each country return index's stock exchange to control for seasonal affective disorder effect. The data are from US Navy and are available at http://aa.usno.navy.mil/data/docs/Dur_OneYear.php. Table 1 panel E reports the data. Johannesburg of South Africa has the lowest mean duration of daylight of 725.90 minutes per month while Stockholm has the highest mean duration of daylight of 740.90 minutes per month. Stockholm also has the highest standard deviation of 248.36 while Kuala Lumpur has the lowest standard deviation of 7.25. The minimum monthly mean duration of daylight varies from 374 minutes in Stockholm to 717 minutes in Kuala Lumpur. The maximum monthly mean duration of daylight varies from 737 minutes in Kuala Lumpur to 1108 minutes in Stockholm. Following Kamstra et al. (2007) and McTier, Tse, Wald (2013), I also use the SAD onset variable, which measures the clinical growth rate of SAD instrumented by the number of hours of night for the United States. The data are available at http://markkamstra.com/. Qualitatively similar results are obtained with different measures I explored.

[Insert Table 1 panel E here]

Dictated by data availability, the sample spans from 1982:01 to 2014:12 and covers 14 countries: Australia, Belgium, Canada, France, Germany, Italy, Japan, and Malaysia (Malaysia is the only country without consumer confidence index data), Netherlands, South Africa, Sweden, Switzerland, United Kingdom, and the United States.

B. Hypotheses

The definition of the El Niño anomaly is provided by Merriam-Webster.com as follows:

"An irregularly recurring flow of unusually warm surface waters from the Pacific Ocean toward and along the western coast of South America that prevents upwelling of nutrient-rich cold deep water and that disrupts typical regional and global weather patterns."

Climate Prediction Center provides monthly sea surface temperature anomalies from the average measured over a 1981-2010 base period. These sea surface temperature anomalies not only have local impacts but also have remote impacts through teleconnections. Teleconnections are defined by the American Meteorological Society as*: "A linkage between weather changes occurring in widely separated regions of the globe."* The acceptance of sea surface temperature anomalies as a surface climate force that affects the weather at large distances is an accepted teleconnection effect. Indeed, this teleconnection effect is why there are major global climate anomalies when an El Niño occurs. Some of the major global climate anomalies when an El Niño occurs are:

-Europe is less affected by El Niño, but weather patterns are abnormal

-The southwest and California are affected by storms, flooding and mudslides

-Northern States and the Pacific Northwest become warmer and drier than usual. Fisheries are disrupted.

-Gulf states became cool and wet. Flooding occurs.

-In the Pacific Ocean stronger hurricanes occur.

-In the Atlantic Ocean fewer hurricanes occur.

-South Africa is affected by drought.

-Indonesia and New Guinea are affected by drought and severe forest fires.

-Australia is affected by drought, forest fires and crop failures.

-Flooding in Ecuador and Northern Peru.

-In Chile, fisheries are disrupted.

-Southern Brazil, Argentina, and Paraguay experience heavy rains.

The presence of El Niño anomaly can significantly influence weather patterns, ocean conditions, and marine fisheries across the globe which eventually causes significant impact on real output growth, inflation, energy and non-fuel commodity prices. (Brunner (2002), Cashin, Mohaddes, and Raissi (2017)). Given the significant international macroeconomic impact of El Niño anomaly and the close relation between macro economy and stock market, my first hypothesis is:

H1: The El Niño anomaly should have impact on international stock markets.

Typical El Niño effect is likely to develop around Christmas. It has its largest impacts during the winter season in northern hemisphere (Rasmusson and Carpenter (1982), Tziperman et al., (1994), Trenberth (1997)). Since El Niño anomaly is time variant, its' impact on international stock markets should peak in the winter season. My second hypothesis is:

H2: Conditional on winter season, the El Niño anomaly should have impact on international stock markets.

C. Empirical Method

Following Ang and Bekaert (2007), Rapach, Strauss, and Zhou (2013), I use the benchmark predictive regression model:

$$r_{i,t+1} = \beta_{i,0} + \beta_{i,b} TB_{i,t} + \beta_{i,d} DY_{i,t} + \beta_{i,i} r_{i,t} + \beta_{i,USA} r_{USA,t} + \varepsilon_{i,t+1} \tag{1}$$

Where $r_{i,t+1}$ is the return on a broad stock market index in excess of the risk-free rate from the end of month t to the end of month t+1 for country i (i =1,…, N), $TB_{i,t}$ ($DY_{i,t}$) is the three month Treasury Bill rate (log dividend yield) at the end of month t, $\varepsilon_{i,t+1}$ is a zero-mean disturbance term, $r_{i,t}$ is the lagged return of country i at month t, $r_{USA,t}$ is the lagged return of the United States at month t.

Table 2 reports the ordinary least squares (OLS) estimates of the benchmark predictive regression, (1). The $\widehat{\beta_{i,b}}$ estimates are negative and statistically significant in Canada, Germany, Netherlands, South Africa, and United Kingdom. The $\widehat{\beta_{i,d}}$ estimates are positive and statistically significant in 10 countries except for Australia, Canada, Italy, and Switzerland. The $\widehat{\beta_{i,USA}}$ estimates are positive and statistically significant in Australia, Belgium, Germany, Japan, Netherlands, South Africa, and Sweden. Rapach, Strauss, and Zhou (2013) reports positive and statistically significant $\widehat{\beta_{i,USA}}$ in Australia, Germany, Netherlands, and Sweden. Their sample does not include Belgium and South Africa. Overall, the benchmark predictive regression estimates are in line with the extant literature. The adjusted R^2 ranges from 0.30% (Italy) to 4.50% (Sweden).

[Insert Table 2 here]

My primary regressions use sea surface temperature anomalies and a dummy variable for winter season derived from the benchmark predictive regression model.

$$r_{i,t+1} = \beta_{i,0} + \beta_{i,b}TB_{i,t} + \beta_{i,d}DY_{i,t} + \beta_{i,i}r_{i,t} + \beta_{i,USA}r_{USA,t} + \beta_{i,E}ELNINO_{i,t} + \beta_{i,W}WINTER_t + \beta_{i,EW}ELNINO_{i,t} * WINTER_t + \varepsilon_{i,t+1} \tag{2}$$

Where *ELNINO* is the sea surface temperature anomaly. *WINTER* is the dummy variable equals 1 if it is in December/January/February, 0 otherwise. (For Australia and South Africa, *WINTER* equals 1 if it is in June/July/August, 0 otherwise.)

In order to test the conditional and unconditional El Niño effects, I also run the following predictive regression models.

$$r_{i,t+1} = \beta_{i,0} + \beta_{i,b}TB_{i,t} + \beta_{i,d}DY_{i,t} + \beta_{i,i}r_{i,t} + \beta_{i,USA}r_{USA,t} + \beta_{i,E}ELNINO_{i,t} + \varepsilon_{i,t+1} \tag{3}$$

$$r_{i,t+1} = \beta_{i,0} + \beta_{i,b}TB_{i,t} + \beta_{i,d}DY_{i,t} + \beta_{i,i}r_{i,t} + \beta_{i,USA}r_{USA,t} + \beta_{i,W}WINTER_t + \varepsilon_{i,t+1} \tag{4}$$

I control for investor sentiment effect in our regressions based on Baker, Wurgler, Yuan (2012).

$$r_{i,t+1} = \beta_{i,0} + \beta_{i,b}TB_{i,t} + \beta_{i,d}DY_{i,t} + \beta_{i,i}r_{i,t} + \beta_{i,USA}r_{USA,t} + \beta_{i,E}ELNINO_t + \beta_{i,\mathrm{S}}SENT_t + \beta_{i,\mathrm{W}}WINTER_t + \beta_{i,EW}ELNINO_t * WINTER_t + \beta_{i,SW}SENT_t * WINTER_t + \varepsilon_{i,t+1} \tag{5}$$

I also control for weather effect and seasonal affective disorder (SAD) effect in regressions.

$$r_{i,t+1} = \beta_{i,0} + \beta_{i,b}TB_{i,t} + \beta_{i,d}DY_{i,t} + \beta_{i,i}r_{i,t} + \beta_{i,USA}r_{USA,t} + \beta_{i,E}ELNINO_t + \beta_{i,\mathrm{W}}WINTER_t + \beta_{i,EW}ELNINO_t * WINTER_t + \beta_{i,SAD}SAD_{i,t+1} + \beta_{i,TEMP}TEMP_{i,t+1} + \varepsilon_{i,t+1} \tag{6}$$

In order to see if El Niño has the same predictive pattern in each month of the winter season, I use winter month dummy to replace *WINTER* dummy based on equation (7).

$$r_{i,t+1} = \beta_{i,0} + \beta_{i,b}TB_{i,t} + \beta_{i,d}DY_{i,t} + \beta_{i,i}r_{i,t} + \beta_{i,USA}r_{USA,t} + \beta_{i,E}ELNINO_t + \beta_{i,M1}M1_t + \beta_{i,M2}M2_t + \beta_{i,M3}M3_t + \beta_{i,EM1}ELNINO_t * M1_t + \beta_{i,EM2}ELNINO_t * M2_t + \beta_{i,EM3}ELNINO_tM3_t + \varepsilon_{i,t+1} \tag{7}$$

In order to see if there is any relation between the El Niño effect and current or future economic activities, I use current or lead Consumer Price Index in regression based on equation (8) and (9).

$$r_{i,t+1} = \beta_{i,0} + \beta_{i,b}TB_{i,t} + \beta_{i,d}DY_{i,t} + \beta_{i,i}r_{i,t} + \beta_{i,USA}r_{USA,t} + \beta_{i,E}ELNINO_t + \beta_{i,EW}ELNINO_t * WINTER_t + \beta_{i,\mathrm{CPIC}}CPI_{i,t+1} + \varepsilon_{i,t+1} \tag{8}$$

$$r_{i,t+1} = \beta_{i,0} + \beta_{i,b}TB_{i,t} + \beta_{i,d}DY_{i,t} + \beta_{i,i}r_{i,t} + \beta_{i,USA}r_{USA,t} + \beta_{i,E}ELNINO_t + \beta_{i,EW}ELNINO_t * WINTER_t + \beta_{i,\mathrm{CPIF}}CPI_{i,t+2} + \varepsilon_{i,t+1} \tag{9}$$

III. Empirical Results

Table 3 reports the main findings based on equation (2). In column (6), I find the unconditional El Niño effect can predict negative stock returns in Japan, Malaysia, and South Africa. These provide support to hypothesis 1. In column (8), I find the striking results which show that El Niño conditional on winter season has significant predictive power for 13 countries' stock return except for Japan, with higher El Niño anomaly on winter season forecasting higher stock returns. These provide support to our hypothesis 2. The coefficient estimates in column (2), (3), and (5) are in line with extant literature. The adjusted R^2 ranges from 0.83% in Australia to 6.69% in Sweden.

It is interesting since during winter season, from December to February, the El Niño phenomenon may contribute to the most prominent temperature departures throughout the world which include warmer than normal conditions in Japan and cooler than normal conditions along the Gulf coast of the United States. Table 3 confirms the opposite predictive effect of the El Niño phenomenon in winter season in these two countries' stock return. The coefficient estimate of unconditional El Niño effect in Japan is -0.80, while the coefficient estimate of El Niño conditional on winter season in the U.S. is 0.89, both are statistically significant.

[Insert Table 3 here]

To verify the strong predictive power of El Niño conditional on winter effect, I run regressions based on equation (3) and (4). Table 4 shows that El Niño unconditional effect can negatively predict the stock return in Japan only which provides support to hypothesis 1. Table

5 shows the winter season can positively predict the stock return in France, Germany, and Sweden.

[Insert Table 4 here]

[Insert Table 5 here]

To further confirm the impact of the El Niño anomaly, an ANOVA partial F-test is conducted to compare the full model (equation 2) and reduced model (equation 1). Table 28 reports the results. It appears that the impact of the El Niño anomaly (either conditionally or unconditionally) can be found in eight countries: Belgium, France, Italy, Japan, Malaysia, Netherlands, South Africa, and Sweden.

[Insert Table 28 here]

Overall, the findings show that the El Niño phenomenon can predict all 14 countries' stock return. Unconditional El Niño anomaly can negatively predict a few countries' stock return, while El Niño conditional on winter season can positively predict most countries' stock return.

To examine the robustness of the results in Table 3, I test the predictive power of conditional and unconditional El Niño effect while controlling for investor sentiment based on equation (5) (I exclude Malaysia since Global Financial Data does not have the consumer confidence index data for Malaysia). Table 6 reports the results. Consistent with Baker, Wurgler, Yuan (2012), column (7) shows unconditional investor sentiment can negatively predict stock return in Belgium, Germany, Italy, and Sweden. Interestingly, I also find that investor sentiment conditional on winter season can positively predict stock return in Canada and South Africa (see column (10)). Column (6) shows unconditional El Niño effect can negatively predict stock return in Germany, Japan, and United Kingdom, while column (9) shows El Niño conditional on winter season can predict positive stock returns in 10 countries except for Japan, South Africa, and United Kingdom. Overall, Table 6 shows that El Niño effect can predict 12 countries' stock return except for South Africa with unconditional El Niño effect negatively predicting a few countries' stock return, while El Niño conditional on winter effect positively predicting most countries' stock return.

[Insert Table 6 here]

To examine the robustness of the results in Table 3, I also test the predictive power of conditional and unconditional El Niño effect when controlling for weather effect and seasonal affective disorder effect based on equation (6). Table 7 reports the result. Consistent with Cao and Wei (2005), column (10) shows statistically significant negative correlation between temperature and stock returns in ten countries except for Australia, Canada, Malaysia, and South Africa. Consistent with Kamstra et al. (2003), the coefficient of SAD variable is negative and statistically significant in United Kingdom. For the El Niño variable, column (6) shows the negative impact of unconditional El Niño in Japan, Malaysia, and South Africa and column (8) shows the positive impact of El Niño conditional on winter season in 13 countries except for Australia.

[Insert Table 7 here]

In order to see if El Niño has the same predictive pattern in each month of the winter season, I use winter month dummy to replace the WINTER dummy in regressions based on equation (7). Table 8 reports the results. In column (6), I find negative impact of unconditional El Niño in Japan, Malaysia, and South Africa. In column (10), I find positive impact of conditional on December in Belgium, Italy, Japan, and Sweden. In column (11), I find positive impact of conditional on January in 10 countries except for Australia, Belgium, Japan, and

Netherlands. In column (12), I find positive impact of conditional on February in 9 countries except for Australia, Japan, South Africa, Switzerland, and United Kingdom. So the El Niño conditional on January and February impacts are stronger than conditional on December impact.

[Insert Table 8 here]

In order to see if there is any relation between the El Niño and current or future economic activities, I include current or lead Consumer Price Index (CPI) in regressions based on equation (8) and (9). The CPI is the most widely used measure of inflation and it provides information about price changes in the nation's economy. The lead CPI reflects the expectation about future economic activities. Tables 9 and 10 show that the prevailing predictive power of the El Niño effect doesn't change. Additionally, it is interesting that both the current and lead Consumer Price Indexes are negative predictors to the excess stock return in Belgium, Canada, France, Japan, Netherlands, South Africa, and Sweden.

[Insert Table 9 here]

[Insert Table 10 here]

IV. Source of El Niño Predictability

In this section, I explore the source of predictability of the El Niño anomaly. Previous literature suggests that stock return can be predicted either by economic variables or investor sentiment. From this perspective, the ability of El Niño anomaly to forecast aggregate stock market returns may come from either economic variables or investor sentiment or both.

I use a univariate predictive regression

$$Inflation_{i,t+1} = a + bELNINO_{i,t} + \varepsilon_{i,t+1} \tag{10}$$

to investigate the relation between the El Niño anomaly and future economic activities. The left side dependent variable is the expectation of future inflation which is widely used by the society as a guide to making economic decisions. Table 11 reports the results. It displays distinct pattern for the El Niño anomaly predictability. Other than Japan, the El Niño anomaly can predict 13 countries' expectations of future inflation. Specifically, it positively predicts the expectation of future inflation in Australia and negatively predicts the expectation of future inflation in the rest of 12 countries. These results are consistent with the findings of Cashin, Mohaddes, and Raissi (2017).

[Insert Table 11 here]

I use the univariate predictive regressions

$$Investor\ Sentiment^{\perp}_{i,t+1} = c + dELNINO_{i,t} + \delta_{i,t+1} \tag{11}$$

to investigate the relation between the El Niño anomaly and investor sentiment. The left side dependent variable is the orthogonalized investor sentiment. It is the residual from the univariate regressions

$$Investor\ Sentiment_{i,t} = e + fInflation_{i,t} + \mu_{i,t} \tag{12}$$

Following Baker and Wurgler (2006), this orthogonalized investor sentiment will be cleaner proxy to capture the relation between the El Niño anomaly and investor sentiment. Table 12 reports the results. It shows that the El Niño anomaly can predict seven countries' investor sentiment. Specifically, it positively predicts investor sentiment in Australia and United Kingdom and negatively predicts investor sentiment in Belgium, Germany, Italy, Switzerland and Japan.

[Insert Table 12 here]

Taking together, I find that the El Niño anomaly has considerable heterogeneous impacts on 14 countries. It has a positive impact on both expectation of future economic activities and investor sentiment in Australia. It has negative impact on both expectation of future economic activities and investor sentiment in Belgium, Germany, Italy, Switzerland. It only has negative impact on expectation of future economic activities in Canada, France, Netherlands, South Africa, Sweden, and the United States. It only has negative impact on investor sentiment in Japan. It has positive impact on investor sentiment and negative impact on expectation of future economic activities in United Kingdom. Since I do not have investor sentiment data for Malaysia, I do not know if the El Niño anomaly would have impact on investor sentiment in that country but I do know the El Niño anomaly has a negative impact on the expectation of future economic activities in Malaysia.

V. Conclusion

I study the predictive relation between the El Niño phenomenon and fourteen countries' aggregate stock market returns, a previously untouched aspect of international return predictability. I find that the El Niño phenomenon has strong predictive power on all fourteen countries' stock returns. Especially, the unconditional El Niño anomaly can negatively predict a few countries' stock return, while the El Niño conditional on winter season can positively predict most countries' stock return even after controlling for several key economic variables (three-month Treasury bill rate, dividend yield, countries' own lagged returns, and lagged U.S. stock return, current and future economic activities) as well as investor sentiment effect, weather effect, and SAD effect.

I also find that source of the documented predictability of the El Niño phenomenon could be from either economic fundamentals or investor sentiment or both. And there appear to be some heterogeneities across various countries.

The results suggest an important implication which means current asset pricing models are incomplete and need to incorporate a prominent role of the El Niño phenomenon.

ESSAY TWO

THE EL NIÑO ANOMALY AND THE CROSS-SECTION OF STOCK RETURNS

1. Introduction

Traditional finance theory argues that in a perfect competitive capital market, rational investors optimize their portfolio returns through diversification. In equilibrium, the stock prices equal the discounted value of expected cash flows. The cross-section of expected returns depends only on the systematic risks. Even some investors are irrational. Their demands will be offset by arbitrageurs and bear no impact on stock prices.

In a seminal paper, Baker and Wurgler (2006) study how investor sentiment can significantly influence the cross-section of stock returns. They argue that a broad-based wave of sentiment has cross-sectional effects and provide empirical evidence that when investor sentiment is high, the future returns would be low for small stocks, young stocks, high volatility stocks, unprofitable stocks, non-dividend-paying stocks, extreme growth stocks, and distressed stocks. Baker, Wurgler, and Yuan (2012) construct an investor sentiment index for both local market and global market and provide international evidence that investor sentiment is a negative predictor of the time-series of cross-sectional returns within markets.

Cashin, Mohaddes, and Raissi (2017) study the impact of the exogenous El Niño anomaly on different regions cross-sectionally and provide empirical evidence that the El Niño anomaly may have significant influence on real output growth, inflation, energy and non-fuel commodity prices. Given the important relations between stock market and macro economy, it is interesting to examine the impact of El Niño phenomenon on stock market. Essay one has established that the El Niño anomaly, especially conditional on winter season, has prevailing impact on international stock aggrege market return. This paper studies the effect of the El Niño anomaly on stock returns by focusing on portfolio level. Novy-Marx (2014) finds that the El Niño phenomenon significantly predicts the performance of accrual based strategy as well as beta arbitrage strategy using unilateral OLS regression and US data. Following Baker and Wurgler (2006), I distinguish novel predictability effects from well-known comovement using multivariate regression and study the predictive effects of the El Niño anomaly on returns of 49 US industries as well as portfolios formed based on many common strategies. I also examine the predictive effects of the El Niño anomaly on portfolio returns in ten other countries besides the US since the El Niño anomaly is an international phenomenon.

The typical El Niño effect is likely to develop around Christmas. It has its largest impacts during the winter season in northern hemisphere (Rasmusson and Carpenter (1982), Tziperman et al., (1994), Trenberth (1997)). Since El Niño anomaly is time variant, its' impact on the international stock markets should peak in the winter season. Specifically, I look at the conditional impact of the El Niño anomaly on portfolios returns (conditional either on winter season or winter month). In most cases, I cannot find an unconditional impact; however, I do find a conditional impact.

2. Data and Empirical Results

I study the predictive effect of the El Niño anomaly on portfolio returns across the world.

2.1 The El Niño Anomaly and the US Industry Portfolio Returns

Data of 49 US industry portfolio returns are collected from Kenneth French's data library. Each NYSY, AMEX, and NASDAQ stock is assigned to an industry portfolio at the end of June of year t based on its four-digit SIC code at that time. Compustat SIC codes are used for the fiscal year ending in calendar year t-1. Whenever Compustat SIC codes are not available, CRSP SIC codes are used for June of year t. Returns are computed from July of t to June of t+1.

I do not report the impact of the El Niño anomaly on the following 22 industries since our data do not reveal significant results: Food Products, Tobacco Products, Printing and Publishing, Medical Equipment, Pharmaceutical Products, Chemicals, Rubber and Plastic Products, Construction, Steel works etc., Machinery, Electrical Equipment, Automobiles and Trucks, Shipping/Railroad Equipment, Defense, Precious Metals, Utilities, Personal Services, Measuring and Control Equipment, Business Supplies, Transportation, Real Estate, and Other.

Following Baker and Wurgler (2006), I begin with the predictive regression model:

$$r_{i,t+1} = \beta_{i,0} + \beta_{i,E}ELNINO_t + \beta_{i,EW}ELNINO_t * WINTER_t + \varepsilon_{i,t+1} \qquad (13)$$

Where the dependent variable $r_{i,t+1}$ is the portfolio return of industry *i* in excess of the risk-free rate from the end of month t to the end of month t+1. The independent variables include the lagged El Niño anomaly, the interaction term of the lagged El Niño anomaly and the winter dummy.

I progress with the multivariate predictive regression model:

$$r_{i,t+1} = \beta_{i,0} + \beta_{i,E}ELNINO_t + \beta_{i,EW}ELNINO_t * WINTER_t + \beta_{i,SENT}SENT_t + \beta_{i,RMKT}RMKT_{t+1} + \beta_{i,SMB}SMB_{t+1} + \beta_{i,HML}HML_{t+1} + \beta_{i,MOM}MOM_{t+1} + \varepsilon_{i,t+1} \quad (14)$$

$$r_{i,t+1} = \beta_{i,0} + \beta_{i,E}ELNINO_t + \beta_{i,EM1}ELNINO_t * M1_t + \beta_{i,EM2}ELNINO_t * M2_t + \beta_{i,EM3}ELNINO_t * M3_t + \beta_{i,SENT}SENT_t + \beta_{i,RMKT}RMKT_{t+1} + \beta_{i,SMB}SMB_{t+1} + \beta_{i,HML}HML_{t+1} + \beta_{i,MOM}MOM_{t+1} + \varepsilon_{i,t+1} \quad (15)$$

Where RMKT, SMB, HML, MOM, lagged SENT are control variables. The variable RMKT is the market risk premium which is the excess return of the value-weighted market over the risk-free rate. As described in Fama and French (1993), SMB is the return on portfolios of small and big stocks based on market equity (ME) in isolation of book-to-market ratio (BE/ME), HML is the return on portfolios of high and low stocks based on book-to-market ration (BE/ME) in isolation of market equity (ME). The details of how to construct these portfolios can be found on Kenneth French's website. MOM is the return on portfolios of high and low stocks based on prior 2-12 months return in isolation of market equity (ME). These data are from Kenneth French's data library. Based on Baker, Wurgler, Yuan (2012), I use monthly Consumer Confidence Index to measure investor sentiment variable SENT. This data is from Global Financial Data. WINTER is a dummy variable which equals 1 when it is in winter season (December-February), otherwise 0. M1/M2/M3 is winter month dummy variable which equals 1 when it is in each winter month, December/January/February respectively, otherwise 0.

Regression shows that the El Niño anomaly may have significant impact on 27 industry portfolio returns. Table 13 reports the results. Column (2) shows without control variables, unconditional El Niño anomaly may have negative impacts on four industry portfolio returns, namely Beer & Liquor, Aircraft, Coal, and Shipping Containers. Column (3) shows conditional on winter season, the El Niño anomaly may have positive impacts on twenty industry portfolio returns, namely Beer & Liquor, Entertainment, Consumer Goods, Apparel, Healthcare, Textiles, Construction Materials, Fabricated Products, aircraft, Mines, Communication, Business Services, Computer Hardware, Computer Software, Electronic Equipment, Shipping Containers, Wholesale, Retail, Restaurants & Hotels, Insurance. After controlling for RMKT, SMB, HML, MOM, and lagged SENT, column (4) shows unconditionally the El Niño anomaly may have negative impacts on seven industry portfolio returns (Apparel, Fabricated Products, Aircraft, Coal, Petroleum & Natural Gas, Shipping Containers, Insurance) and positive impacts on Computer Hardware industry portfolio return. Column (5) shows conditional on winter season, the El Niño anomaly may have positive impact on five industry portfolio returns (Consumer Goods, Aircraft, Business Services, Computer Software, Restaurants & Hotels) and negative impact on Agriculture and Finance Trading industries. When look at potential impact during each winter month, column (7) shows the El Niño anomaly in December has negative impact on Agriculture, Healthcare, Banking, and Finance Trading industry portfolios return in next January. While the impacts on Consumer Goods, Aircraft, Communication industries are positive. Column (8) shows the El Niño anomaly in January has positive impacts on nine industry portfolios return (Consumer Goods, Apparel, Healthcare, Construction Materials, Business Services, Shipping Containers, Wholesale, Retail, Restaurants & Hotels) and negative impacts on Candy & Soda, Communication industry portfolios return in February. Column (9) shows the El Niño anomaly in February has positive impacts on Beer & Liquor, Textile, Construction Materials, Mines, Computer Software industry portfolios return in March. While the impacts on Agriculture, Recreation, Entertainment, Electronic Equipment industry portfolios return are negative.

Interestingly, the El Niño anomaly may have negative impact on Agriculture industry and positive impact on Construction Materials industry. The increase of temperature in winter season may have detrimental damages on agricultural production. However, the relative warmer weather may increase the construction activities.

The increase of temperature may also lower the demand for winter heating energy consumption. This would lead to negative impact on Coal and Petroleum & Natural Gas industries. The reduced demand for energy consumption, especially in winter season, may give consumers more flexible expenditure power which could result in positive return in Beer & Liquor, Business Services, Computer Software, Consumer Goods, Wholesale, Retail, and Restaurant & Hotels industries.

The increase of temperature in winter season may help spread some types of disease. This will drive up medical expenditure which may explain the positive impact on Healthcare industry.

In terms of Insurance industry, the El Niño anomaly generally means unwelcome news. If individual medical expenditure goes up, the payout from insurance company will go up. If producers encounter production failure, it's very likely the payout from insurance company will go up too.

[Insert Table 13 here]

The effects of the El Niño anomaly on US industries are consistent with previous literature. For example, Fisher, Hanemann, Roberts, and Schlenker (2012) conclude that global warming will bring severe adverse potential impact to US agriculture. Zivin and Neidell (2014) find that temperature increase at the higher end of the distribution reduce labor productivity in sectors with high exposure to weather such as agriculture, transportation, utilities, and manufacturing. Balvers, Du, and Zhao (2017) use 25 size-value portfolios plus 30 US industry portfolios to study how US equity markets react to news contained in US temperature changes. They find that asset portfolios in more vulnerable industries have stronger negative loadings on a temperature shock factor. 18 out of 30 industry portfolios have statistically significant negative loadings, such as Transportation, Apparel, Textiles, Fabricated Products, Aircraft, Shipping Containers, Banking, Insurance, and Finance Trading.

My finding shows there is negative effect of the El Niño anomaly on US agricultural industry, Banking, and Finance Trading, conditional on either winter season or winter months. There are also negative effects of the El Niño anomaly, unconditionally, on Apparel, Fabricated Products, Aircraft, Shipping Containers, and Insurance. I contribute to literature by showing that the El Niño anomaly, as a special exogenous weather pattern, either unconditionally or conditional on winter season (months), may have significant impacts on many US industries.

2.2 The El Niño Anomaly and 10 Countries' Portfolio Returns

10 countries' portfolios are formed at the end of December each year by sorting on book-to-market ratio (BE/ME). The value-weighted returns for the following 12 months are computed. The value portfolios (High) contain firms in the top 30% and the growth portfolios (Low) contain firms in the bottom 30%. Data are from Kenneth French data library.

I run the following predictive regressions:

$$R_{X_{i,t+1}=High,t+1} - R_{X_{i,t}=Low,t+1} = \beta_{i.0} + \beta_{i,E}ELNINO_t + \beta_{i,EW}ELNINO_t * WINTER_t + \beta_{i,SENT}SENT_t + \beta_{i,RMKT}RMKT_{i,t+1} + \varepsilon_{i,t+1} \tag{16}$$

$$R_{X_{i,t+1}=High,t+1} - R_{X_{i,t}=Low,t+1} = \beta_{i.0} + \beta_{i,E}ELNINO_t + \beta_{i,EM1}ELNINO_t * M1_t + \beta_{i,EM2}ELNINO_t * M2_t + \beta_{i,EM3}ELNINO_t * M3_t + \beta_{i,SENT}SENT_t + \beta_{i,RMKT}RMKT_{i,t+1} + \varepsilon_{i,t+1} \tag{17}$$

The dependent variable is the value premium (long value portfolios and short growth portfolios). The independent variables include the lagged El Niño anomaly, the interaction term of the lagged El Niño anomaly and the winter dummy or the winter month dummy, lagged investor sentiment, and market risk premium. Table 14 reports the results. Column (2) shows unconditionally, the El Niño anomaly may have negative impact on Netherlands and positive impact on Australia and Switzerland. Column (3) shows conditional on winter season, the El Niño anomaly may have positive impact on Canada, Italy, Netherlands, and United Kingdom. Overall, among 10 countries' portfolio returns, 6 would be affected by the El Niño anomaly either unconditionally or conditional on winter season.

[Insert Table 14 here]

Table 15 reports the results when winter dummy is replaced by winter month dummy of each winter month. Column (2) shows the unconditional impact does not change, the El Niño anomaly may have negative impact on Netherlands and positive impact on Australia and Switzerland. Column (3) shows the El Niño anomaly in December would have positive impact on Canada, Italy, and negative impact on Switzerland value strategy return in January. Column

(4) shows the El Niño anomaly in January would have positive impact on Japan value strategy return in February. Column (5) shows the El Niño anomaly in February would have positive impact on Italy, Switzerland, and the United Kingdom value strategy return in March. Overall among 10 countries' portfolio returns, 7 would be affected by the El Niño anomaly either unconditionally or conditional on winter months.

[Insert Table 15 here]

Fama and French (1998) find that value stocks tend to have higher returns than growth stocks in twelve of thirteen major markets for the period 1975 through 1995. They show that an international CAPM model cannot explain the value premium. Instead, a two-factor model that includes a risk factor (the difference between global high and low book-to-market portfolios' returns) for relative distress can capture the value premium in international returns. My findings show that the El Niño anomaly, either unconditionally or conditional on winter season (months) may have predictive power on six countries value premium. My data are from 1982 to 2014. So I extend the literature by providing updated empirical evidence not related to contemporaneous response, but related to the forecasting response to the value premium.

2.3 The El Niño Anomaly and 10 US Portfolio Returns

10 US portfolios are formed by univariate sorting on size (ME), book-to-market ratio (BE/ME), operating profitability (OPP), earnings/price (E/P), cash flow/price (CF/P), dividend yield (D/P), variance (σ), accruals (ACC), market beta (β), net share issues (NSI). Data and the details for portfolios formed by each character can be found at Kenneth French data library.

I run the following predictive regressions:

$$R_{X_{i,t+1}=High,t+1} - R_{X_{i,t}=Low,t+1} = \beta_{i.0} + \beta_{i,E}ELNINO_t + \beta_{i,EW}ELNINO_t * WINTER_t + \beta_{i,SENT}SENT_t + \beta_{i,RMKT}RMKT_{i,t+1} + +\beta_{i,SMB}SMB_{t+1} + \beta_{i,HML}HML_{t+1} + \beta_{i,MOM}MOM_{t+1} + \varepsilon_{i,t+1} \quad (18)$$

$$R_{X_{i,t+1}=High,t+1} - R_{X_{i,t}=Low,t+1} = \beta_{i.0} + \beta_{i,E}ELNINO_t + \beta_{i,EM1}ELNINO_t * M1_t + \beta_{i,EM2}ELNINO_t * M2_t + \beta_{i,EM3}ELNINO_t * M3_t + \beta_{i,SENT}SENT_t + \beta_{i,RMKT}RMKT_{i,t+1} + +\beta_{i,SMB}SMB_{t+1} + \beta_{i,HML}HML_{t+1} + \beta_{i,MOM}MOM_{t+1} + \varepsilon_{i,t+1} \quad (19)$$

The dependent variable is the long-short portfolio return (long portfolios with high firm character and short portfolios with low firm character). The independent variables include the lagged El Niño anomaly, the interaction term of the lagged El Niño anomaly and the winter dummy or winter month dummy, lagged investor sentiment, the Fama-French factors (SMB and HML), momentum factor (MOM), and market risk premium (RMKT). I exclude SMB and HML from the control variables when I examine the returns of portfolios formed on size and book-to-market ratio. Table 16 reports the results. Column (2) shows unconditionally, the El Niño anomaly may have negative impact on Cash Flow/Price (CF/P) based portfolio return. Column (3) shows none of these 10 portfolios return would be affected by the El Niño anomaly conditional on the winter season. Column (4) shows investor sentiment can negatively predict return of portfolio formed on variance and positively predict return of portfolio formed on operating profitability. These are consistent with Baker and Wurgler (2006) findings which show that when investor sentiment is high, future returns are relatively low for firms with volatile stock returns and firms which are not profitable.

[Insert Table 16 here]

Table 17 reports the results when winter dummy is replaced with winter month dummy during the winter season. Again column (2) shows unconditionally, the El Niño anomaly may have negative impact on cash flow/price based portfolio return. Column (4) shows the El Niño anomaly in January may have negative impact on February return of portfolios formed on book-to-market ratio, cash flow/price, and dividend yield. Column (5) shows the El Niño anomaly in February may have positive impact on March return of portfolios formed on cash flow/price, dividend yield and negative impact on March return of beta strategy. The result on beta strategy is consistent with Novy-Marx (2014) finding.

[Insert Table 17 here]

As literature shows that there is strong value premium in average returns for US stocks (Fama and French (1992, 1996), Lakonishok, Shleifer, and Vishny (1994)). High BE/ME, CF/P, or D/P stocks have higher average returns than low BE/ME, CF/P, or D/P stocks. My findings on BE/ME, cash flow/price, dividend yield provide empirical evidence not related to contemporaneous response, but forecasting response of the El Niño to the value premium in the US.

It is interesting to find the opposite effects of the El Niño anomaly conditional on January on the US and Japan portfolio formed on book-to-market ratio. This conditional impact on the US portfolio is negative with coefficient of -0.67 while the impact on the Japanese portfolio is positive with coefficient of 2.55 (Table 14 column (4)), both are statistically significant. This is in consistent with the natural impact associated with the El Niño anomaly which causes warmer than normal conditions in Japan and cooler than normal conditions along the Gulf coast of the United States in winter season.

2.4 The El Niño Anomaly and Six Japanese Portfolio Returns

Six Japanese portfolios are formed on size (BE) and book-to-market (BE/ME). All stocks are sorted into two market capitalization and three book-to-market groups at the end of June of each year t. Big stocks are those in the top 90% of June market capitalization, and small stocks are those in the bottom 10%. The BE/ME breakpoints for big and small stocks are the 30% and 70% percentiles of the BE/ME. All returns are in US dollars, including dividends and capital gains, and are not continuously compounded. Data are from Kenneth French data library.

I run the following predictive regressions:

$$r_{i,t+1} = \beta_{i.0} + \beta_{i,E}ELNINO_t + \beta_{i,EW}ELNINO_t * WINTER_t + \beta_{i,SENT}SENT_t + \beta_{i,RMKT}RMKT_{i,t+1} + \beta_{i,MOM}MOM_{t+1} + \varepsilon_{i,t+1} \tag{20}$$

$$r_{i,t+1} = \beta_{i.0} + \beta_{i,E}ELNINO_t + \beta_{i,EM1}ELNINO_t * M1_t + \beta_{i,EM2}ELNINO_t * M2_t + \beta_{i,EM3}ELNINO_t * M3_t + \beta_{i,SENT}SENT_t + \beta_{i,RMKT}RMKT_{i,t+1} + \beta_{i,MOM}MOM_{t+1} + \varepsilon_{i,t+1} \tag{21}$$

The dependent variable is the portfolio excess return. The independent variables include the lagged El Nino anomaly, the interaction term of the lagged El Niño anomaly and the winter dummy or winter month dummy, the lagged investor sentiment, the market risk premium, and momentum factor.

Table 18 reports the result. Through column (2) and (3), I do not find any statistical significant impact of the El Niño anomaly, either unconditionally or conditional on winter season.

[Insert Table 18 here]

Table 19 reports the result when winter dummy is replaced with winter month dummy.

[Insert Table 19 here]

Again, through column (2), I do not find any unconditional impact of the El Niño anomaly. As to conditional impact, I find the El Niño anomaly may have significant influence on five portfolio returns. Column (3) shows conditional on December, the El Niño anomaly can positively predict the small growth stock portfolio return in January. Column (4) shows conditional on January, the El Niño anomaly can positively predict the small value stock portfolio and large growth stock portfolio returns in February. Also, conditional on January, the El Niño anomaly can negatively predict the return of portfolio formed by large stocks with middle book-to-market ratio. Column (5) shows conditional on February, the El Niño anomaly can negatively predict the return of portfolio formed by small growth stocks in March.

3. Robustness Test

3.1 **The El Niño anomaly and 10 US Portfolio Returns**

Glosten, Jagannathan, Runkle (1993) propose the following modified GARCH-in-Mean model:

$$r_{i,t+1} = a_0 + a_1\sigma^2_{i,t+1} + \epsilon_{i,t+1} \tag{22}$$

$$\sigma^2_{i,t+1} = b_0 + b_1\sigma^2_{i,t} + b_2\epsilon^2_{i,t} + b_3 I^-_{i,t}\epsilon^2_{i,t} + b_4 RF_t \tag{23}$$

Where equation (22) is the conditional mean equation and equation (23) is the conditional variance equation. $I^-_{i,t}$ is an indicator variable which equals 1 if the residual $\epsilon_{i,t}$ is negative, 0 otherwise. RF is the risk free interest rate. This model allows (1) seasonal patterns in volatility, (2) positive and negative innovations to returns having different impacts on conditional volatility, and (3) nominal interest rate to predict conditional variance. As Engle and Ng (1993) point out, GJR GARCH-in-Mean model is the best model in measuring and testing the impact of news on volatility and is widely adopted in literature.

I use the following modified GJR GARCH-in-Mean model to evaluate the predictive effect of the El Niño anomaly on the 10 US portfolios returns.

$$R_{X_{i,t+1=High,t+1}} - R_{X_{i,t+1}=Low,t+1}$$
$$= a_0 + a_1\sigma^2_{i,t+1} + a_2 ELNINO_t + a_3 ELNINO_t * WINTER_t + a_4 SENT_t$$
$$+ a_5 RMKT_{t+1} + a_6 MOM_{t+1} + a_7 SMB_{t+1} + a_8 HML_{t+1} + \epsilon_{i,t+1}$$

(24)

$$\sigma^2_{i,t+1} = b_0 + b_1\sigma^2_{i,t} + b_2\epsilon^2_{i,t} + b_3 I^-_{i,t}\epsilon^2_{i,t} + b_4 RF_t$$

(25)

Table 20 reports the results. The estimate coefficient of $a_1$is significant in two portfolios returns (positive in NSI and negative in E/P). The estimate coefficients of a_4 in two portfolios returns (-0.71 of variance and 0.31 of operating profitability) are consistent with Baker and Wurgler (2006) finding which shows investor sentiment can negatively predict returns of high volatility stocks and unprofitable stocks. However, none of the estimate coefficients of $a_2$and a_3 is statistically significant.

[Insert Table 20 here]

Then I replace the winter dummy with winter month dummy in order to take a further look at the conditional impact on each winter month. The model is as follows.

$$R_{X_{i,t+1=High,t+1}} - R_{X_{i,t+1}=Low,t+1}$$
$$= a_0 + a_1\sigma_{i,t+1}^2 + a_2ELNINO_t + a_3ELNINO_t * M1_t + a_4ELNINO_t * M2_t$$
$$+ a_5ELNINO_t * M3_t + a_6SENT_t + a_7RMKT_{t+1} + a_8MOM_{t+1} + a_9SMB_{t+1}$$
$$+ a_{10}HML_{t+1} + \epsilon_{i,t+1}$$

(26)

$$\sigma_{i,t+1}^2 = b_0 + b_1\sigma_{i,t}^2 + b_2\epsilon_{i,t}^2 + b_3I_{i,t}^-\epsilon_{i,t}^2 + b_4RF_t$$

(27)

Table 21 reports the results. None of the estimate coefficient of a_2 is significant. The estimate coefficients of a_3 is positive and significant in two portfolios returns (CF/P and D/P). The estimate coefficients of a_4 is negative and significant in three portfolios returns (BE/ME, CF/P, D/P). The estimate coefficient of a_5 is negative and significant in one portfolio return (NSI). Overall, Table 21 shows conditional on winter months, the El Niño anomaly may have predictive effect on four US portfolios returns.

[Insert Table 21 here]

Compared to Table 16 and Table 17, it seems previous results derived from OLS regression does not change. To further confirm this, I run a modified GARCH (1, 1) model with winter dummy as follows:

$$R_{X_{i,t+1=High,t+1}} - R_{X_{i,t+1}=Low,t+1}$$
$$= a_0 + a_1ELNINO_t + a_2ELNINO_t * WINTER_t + a_3SENT_t + a_4RMKT_{t+1}$$
$$+ a_5MOM_{t+1} + a_6SMB_{t+1} + a_7HML_{t+1} + \epsilon_{i,t+1}$$

(28)

$$\sigma_{i,t+1}^2 = b_0 + b_1\sigma_{i,t}^2 + b_2\epsilon_{i,t}^2 + b_3ELNINO_t$$

(29)

Table 22 shows none of the estimate coefficients of a_1 and a_2 is statistically significant. The estimate coefficient of b_3 is statistically significant only in the portfolio formed based on BE/ME. This shows that the El Niño anomaly has barely impact on the volatility of the portfolios returns.

[Insert Table 22 here]

I also run the following model with winter dummy being replaced by winter month dummy.

$$R_{X_{i,t+1=High,t+1}} - R_{X_{i,t+1=Low,t+1}} = a_0 + a_1 ELNINO_t + a_2 ELNINO_t * M1_t + a_3 ELNINO_t * M2_t + a_4 ELNINO_t * M3_t + a_5 SENT_t + a_6 RMKT_{t+1} + a_7 MOM_{t+1} + a_8 SMB_{t+1} + a_9 HML_{t+1} + \epsilon_{i,t+1}$$

(30)

$$\sigma^2_{i,t+1} = b_0 + b_1 \sigma^2_{i,t} + b_2 \epsilon^2_{i,t} + b_3 ELNINO_t$$

(31)

Table 23 shows none of the estimate coefficient of a_1 is statistically significant. The estimate coefficient of a_2 is positively significant in two portfolios (CF/P, D/P). The estimate coefficient of a_3 is negatively significant in two portfolios (BE/ME, D/P). None of the estimate coefficient of a_4 is statistically significant. The estimate coefficient of b_3 is positively significant in one portfolio (BE/ME). This again shows the El Niño anomaly has barely impact on the volatility of the portfolios returns. Using GARCH (1, 1) model does not change the results from OLS regression.

[Insert Table 23 here]

3.2 The El Niño anomaly and Six Japanese Portfolio Returns

First, I run the following modified GJR GARCH-in-Mean model on six Japanese portfolios excess returns.

$$r_{i,t+1} = a_0 + a_1\sigma_{i,t+1}^2 + a_2 ELNINO_t + a_3 ELNINO_t * WINTER_t + a_4 SENT_t + a_5 RMKT_{t+1} + a_6 MOM_{t+1} + \epsilon_{i,t+1} \quad (32)$$

$$\sigma_{i,t+1}^2 = b_0 + b_1\sigma_{i,t}^2 + b_2\epsilon_{i,t}^2 + b_3 I_{i,t}^{-}\epsilon_{i,t}^2 + b_4 RF_t \quad (33)$$

Table 24 shows none of the estimate coefficient of a_2 and a_3 is statistically significant. There is no El Niño impact on the excess return of these six Japanese portfolios, either unconditionally or conditional on winter season.

[Insert Table 24 here]

Then I replace the winter dummy in equation (32) with winter month dummy.

$$r_{i,t+1} = a_0 + a_1\sigma_{i,t+1}^2 + a_2 ELNINO_t + a_3 ELNINO_t * M1_t + a_4 ELNINO_t * M2_t + a_5 ELNINO_t * M3_t + a_6 SENT_t + a_7 RMKT_{t+1} + a_8 MOM_{t+1} + \epsilon_{i,t+1} \quad (34)$$

$$\sigma_{i,t+1}^2 = b_0 + b_1\sigma_{i,t}^2 + b_2\epsilon_{i,t}^2 + b_3 I_{i,t}^{-}\epsilon_{i,t}^2 + b_4 RF_t \quad (35)$$

Table 25 shows the estimate coefficient a_2 is negatively for small value stocks. The estimate coefficient a_3 is positive for small value stocks and negative for large with middle book-to-market ratio stocks. The estimate coefficient a_4 is positive for small value stocks, large value stocks, and negative for large with middle book-to-market ratio stocks. The estimate coefficient a_5 is positive for small growth stocks, large with middle book-to-market ratio stocks, negative for small with middle book-to-market ratio stocks, and large growth stocks. Overall, Table 25 shows unconditionally, the El Niño anomaly may negatively predict small growth stocks return only. Conditional on winter month, the El Niño anomaly may predict all six portfolios returns.

[Insert Table 25 here]

Next, I turn to GARCH (1, 1) model as follows:

$$r_{i,t+1} = a_0 + a_1 ELNINO_t + a_2 ELNINO_t * WINTER_t + a_3 SENT_t + a_4 RMKT_{t+1} + a_5 MOM_{t+1} + \epsilon_{i,t+1} \tag{36}$$

$$\sigma^2_{i,t+1} = b_0 + b_1 \sigma^2_{i,t} + b_2 \epsilon^2_{i,t} + b_3 ELNINO_t \tag{37}$$

Table 26 shows none of the estimate coefficient a_1, a_2, and b_3 is significant. The El Niño anomaly does not have impact on conditional variance and these six Japanese portfolios returns either unconditionally or conditional on winter season.

[Insert Table 26 here]

Then I replace the winter dummy in equation (36) with winter month dummy. The model becomes as follows.

$$r_{i,t+1} = a_0 + a_1 ELNINO_t + a_2 ELNINO_t * M1_t + a_3 ELNINO_t * M2_t + a_4 ELNINO_t * M3_t + a_5 SENT_t + a_6 RMKT_{t+1} + a_7 MOM_{t+1} + \epsilon_{i,t+1} \tag{38}$$

$$\sigma_{i,t+1}^2 = b_0 + b_1\sigma_{i,t}^2 + b_2\epsilon_{i,t}^2 + b_3 ELNINO_t \tag{39}$$

Table 27 shows none of the estimate coefficient of $b_3$is significant. The El Ni$\tilde{n}$o anomaly does not have impact on conditional variance. None of the estimate coefficient of a_1 is significant which means there is no unconditional El Ni$\tilde{n}$o impact. The estimate coefficient of a_2 is negatively significant for large with middle book-to-market ratio stocks. The estimate coefficient a_3 is positive for small value stocks and negative for large with middle book-to-market ratio stocks. The estimate coefficient of a_4 is negative for all small stocks and large growth stocks, it is positive for large with middle book-to-market ratio stocks. Overall, conditional on winter month, the El Ni$\tilde{n}$o anomaly does have impact on five Japanese portfolios returns.

[Insert Table 27 here]

4. Conclusion

This paper examines the predictability of the El Ni$\tilde{n}$o anomaly on stock returns at portfolio level. I find that the El Ni$\tilde{n}$o anomaly may have prevailing impact on the stock market. For 49 US industries, the unconditional El Ni$\tilde{n}$o anomaly can predict eight industries' portfolios return; conditional on winter month, the El Ni$\tilde{n}$o anomaly can predict twenty-two industries' portfolios return. Overall, 27 industries' return can be affected by the El Ni$\tilde{n}$o anomaly. For 10 countries' value premium, the unconditional El Ni$\tilde{n}$o anomaly can predict three of them. Conditional on winter season (winter month), the El Ni$\tilde{n}$o anomaly can predict four (five) of them. Overall, seven countries' value premium can be affected by the El Ni$\tilde{n}$o anomaly. For 10 US portfolios return, unconditionally the El Niño anomaly can negatively predict return of portfolio formed based on cash flow/price ratio. Conditional on winter month, the El Niño anomaly can predict four portfolios' return. For 6 Japanese portfolios, conditional on winter month, the El Niño anomaly can predict five returns. Those findings remain robust when I use different GARCH models.

Novy-Marx (2014) shows the El Niño anomaly can predict returns of two portfolios (formed based on accruals and beta arbitrage) based on US data. My findings show the El Niño anomaly can predict returns of portfolios formed based on many other common strategies and industries. I also provide international evidence on the effect of the El Niño anomaly on portfolios return. It is not surprising since the El Niño anomaly is an international phenomenon.

CONCLUSIONS

In this dissertation, I study the impact of the El Niño anomaly on the international stock returns which is an under-studied topic. I contribute to the finance literature by providing broad empirical evidence that the El Niño anomaly may have a widespread influence on international stock returns not only at the aggregate level, but also at industry or portfolio level. While the unconditional impact may not be so profound, the El Niño anomaly conditional on winter season or winter month does carry heavily influences.

Essay one shows that the El Niño phenomenon has a strong predictive power on all 14 countries' stock returns at aggregate level. Especially, the unconditional El Niño anomaly can negatively predict a few countries' stock return, while the El Niño conditional on winter season can positively predict most countries' stock return even after controlling for several key economic variables (three-month Treasury bill rate, dividend yield, countries' own lagged returns, and lagged U.S. stock return, current and future economic activities) as well as investor sentiment effect, weather effect, and SAD effect.

I also find that source of the documented predictability of the El Niño phenomenon could be from either economic fundamentals or investor sentiment or both. And there appears to be some heterogeneities across various countries.

Essay two examines the predictability of the El Niño anomaly on international stock returns at the portfolio level. I find that the El Niño anomaly may have a prevailing impact on the stock market. For forty-nine US industries, the unconditional El Niño anomaly can predict eight industries' portfolios return; conditional on winter month, the El Niño anomaly can predict twenty-two industries' portfolios return. Overall, twenty-seven industries' returns can be affected by the El Niño anomaly. For ten countries' value premium, the unconditional El Niño anomaly can predict three of them. Conditional on winter season (winter month), the El Niño anomaly can predict four (five) of them. Overall, seven countries' value premiums can be affected by the El Niño anomaly. For ten US portfolios returns, unconditionally the El Niño anomaly can negatively predict return of portfolio formed based on cash flow/price ratio. Conditional on winter month, the El Niño anomaly can predict four portfolios' return. For six Japanese portfolios, conditional on winter month, the El Niño anomaly can predict five returns. Those findings remain robust using different GARCH models.

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Table 1 Panel A
Summary Statistics, Monthly Country Excess Stock Returns,
1982:01 to 2014:12

Panel A reports summary statistics for monthly national currency excess returns (in percent) for 14 countries. The excess return is on a broad market index in excess of the three-month Treasury bill rate. Sharp ratio is the mean of the excess return divided by its standard deviation. Data are from Global Financial Data.

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Country	Mean	Standard Deviation	Minimum	Maximum	Autocorrelation	Sharpe Ratio	Correlation with U.S.
Australia	0.40	4.81	-43.08	15.20	0.02	0.08	0.58
Belgium	0.64	4.97	-31.77	23.55	0.15	0.13	0.61
Canada	0.38	4.40	-23.19	13.55	0.15	0.09	0.77
France	0.63	5.50	-22.52	21.64	0.12	0.11	0.67
Germany	0.61	5.70	-24.06	19.84	0.09	0.11	0.64
Italy	0.28	6.45	-16.14	24.51	0.07	0.04	0.49
Japan	0.33	5.46	-21.72	17.53	0.13	0.06	0.43
Malaysia	0.51	7.58	-35.00	35.89	0.12	0.07	0.35
Netherlands	0.76	5.26	-22.76	17.27	0.08	0.14	0.71
South Africa	0.56	6.09	-29.10	18.80	0.04	0.09	0.44
Sweden	0.83	6.23	-22.59	26.61	0.15	0.13	0.58
Switzerland	0.68	4.52	-24.94	12.23	0.18	0.15	0.69
U.K.	0.51	4.44	-27.25	12.93	0.03	0.12	0.76
United States	0.68	4.36	-21.97	13.00	0.05	0.16	

Table 1 Panel B

Summary Statistics and Correlations, Monthly El Niño Anomaly Measures,

Panel B reports summary statistics and correlations of monthly sea surface temperature anomalies from the average measured over a 1981-2010 base period in three regions. Data are from National Oceanic and Atmospheric Administration (NOAA).

(1)	(2)	(3)	(4)	(5)	(6)
Region	Mean	Standard Deviation	Minimum	Maximum	Autocorrelation
Region 1+2	0.03	1.18	-2.10	4.62	0.92
Region 3	-0.00	0.95	-2.07	3.62	0.94
Region 3.4	-0.01	0.93	-2.38	2.79	0.95

Correlations

	Region 1+2	Region 3	Region 3.4
Region 1+2	1.00		
Region 3	0.81	1.00	
Region 3.4	0.62	0.94	1.00

Table 1 Panel C
Summary Statistics, Monthly Consumer Confidence Index,

Panel C reports summary statistics for monthly consumer confidence index in 13 countries. Sample period is from 1982:01 to 2014:12 if not specified. Data are from Global Financial Data.

(1)	(2)	(3)	(4)	(5)	(6)	(7)
Country	Mean	Standard Deviation	Minimum	Maximum	Autocorrelation	Sample Period
Australia	99.90	2.31	92.97	104.00	0.98	
Belgium	100.10	2.94	94.28	107.40	0.99	
Canada	100.10	3.23	92.36	106.00	0.98	
France	99.13	2.09	94.58	104.40	0.97	
Germany	99.53	3.28	90.65	106.20	0.96	
Italy	100.90	3.22	91.87	108.50	0.97	
Japan	99.92	4.14	86.47	106.90	0.99	1982:06-2014:12
Malaysia	No Data Available					
Netherlands	100.30	2.38	94.38	105.40	0.98	
South Africa	99.89	3.08	92.36	106.50	0.98	1990:03-2014:12
Sweden	99.75	3.96	90.27	109.30	0.98	1995:10-2014:12
Switzerland	99.82	3.36	92.38	105.80	0.99	
United Kingdom	100.30	2.08	93.72	104.20	0.98	
United States	100.40	2.53	93.96	105.50	0.97	

Table 1 Panel D
Summary Statistics, Monthly Mean Temperature of the City of Country Return Index's Stock Exchange,
1982:01 to 2014:12

Panel D reports summary statistics for monthly mean temperature of the city corresponding to each country return index's stock exchange to control for weather effect. Data are from National Oceanic and Atmospheric Administration (NOAA).

(1) Country/City	(2) Mean	(3) Standard Deviation	(4) Minimum	(5) Maximum	(6) Autocorrelation
Australia/Sydney	65.17	6.82	51.80	77.20	0.82
Belgium/Brussels	51.35	10.35	26.80	73.90	0.79
Canada/Toronto	46.92	17.40	9.70	75.90	0.84
France/Paris	53.07	10.87	24.40	76.60	0.79
Germany/Frankfurt	51.14	12.17	24.80	75.40	0.81
Italy/Milan	58.26	13.95	30.90	88.20	0.84
Japan/Tokyo	61.76	13.67	37.80	86.40	0.84
Malaysia/Kuala Lumpur	83.29	1.23	79.00	86.90	0.69
Netherlands/Amsterdam	50.26	9.54	25.50	69.80	0.80
South Africa/Johannesburg	61.92	6.59	47.30	73.20	0.79
Sweden/Stockholm	44.61	13.59	9.00	70.00	0.82
Switzerland/Zurich	49.60	12.22	22.60	73.60	0.81
United Kingdom/London	51.72	9.10	30.70	74.20	0.80
United States/New York City	54.54	15.30	24.60	80.80	0.84

Table 1 Panel E
Summary Statistics, Monthly SAD measures,
1982:01 to 2014:12

Panel E reports summary statistics for monthly mean duration of daylight of the city corresponding to each country return index's stock exchange to control for SAD effect. Data are from US Navy.

(1)	(2)	(3)	(4)	(5)	(6)
Country/City	Mean	Standard Deviation	Minimum	Maximum	Autocorrelation
Australia/Sydney	726.00	92.03	596.00	861.00	0.86
Belgium/Brussels	735.00	173.40	481.00	986.00	0.86
Canada/Toronto	732.50	132.85	539.00	923.00	0.86
France/Paris	734.20	160.50	500.00	966.00	0.86
Germany/Frankfurt	734.60	168.40	488.00	978.00	0.86
Italy/Milan	732.70	141.39	527.00	936.00	0.86
Japan/Tokyo	730.30	98.57	587.00	871.00	0.86
Malaysia/Kuala Lumpur	726.50	7.25	717.00	737.00	0.86
Netherlands/Amsterdam	735.80	183.72	466.00	1002.00	0.86
South Africa/Johannesburg	725.90	67.17	631.00	825.00	0.86
Sweden/Stockholm	740.90	248.36	374.00	1108.00	0.86
Switzerland/Zurich	733.50	151.81	512.00	952.00	0.86
United Kingdom/London	735.30	177.82	475.00	993.00	0.86
United States/New York City	731.30	118.95	558.00	902.00	0.86

Table 2 Benchmark Predictive Regression Model Estimation Results, 1982:01 to 2014:12

The table reports OLS estimation of the predictive regression model

$$r_{i,t+1} = \beta_{i,0} + \beta_{i,b}TB_{i,t} + \beta_{i,d}DY_{i,t} + \beta_{i,i}r_{i,t} + \beta_{i,USA}r_{USA,t} + \varepsilon_{i,t+1} \qquad (1)$$

where $r_{i,t+1}$ is the monthly national currency excess return and $TB_{i,t}$ ($DY_{i,t}$) is the three-month Treasury bill rate (log dividend yield) for country i. $r_{i,t}$ is the lagged excess return. $r_{USA,t}$ is the lagged United States' excess return. Heteroskedasticity and autocorrelation consistent t-statistics, and adjusted R^2 are reported. *, **, *** denotes significance levels at 10%, 5%, and 1% respectively.

(1) Country i	(2) $\widehat{\beta_{i,b}}$	(3) $\widehat{\beta_{i,d}}$	(4) $\widehat{\beta_{i,i}}$	(5) $\widehat{\beta_{i,USA}}$	(6) adj. R^2
Australia	-0.48	1.50	-0.06	0.15**	0.77%
	(-0.53)	(0.98)	(-1.06)	(2.25)	
Belgium	-1.09	1.25**	0.05	0.17**	3.56%
	(-1.40)	(1.97)	(0.95)	(2.19)	
Canada	-1.41*	1.04	0.06	0.10	2.40%
	(-1.85)	(1.16)	(0.74)	(1.21)	
France	-0.97	2.18**	0.04	0.13	2.24%
	(-1.38)	(2.19)	(0.57)	(1.27)	
Germany	-2.87***	2.17**	-0.02	0.21**	2.67%
	(-2.92)	(2.22)	(-0.44)	(2.50)	
Italy	0.09	0.42	0.02	0.15	0.30%
	(0.10)	(0.39)	(0.31)	(1.30)	
Japan	0.99	1.13*	0.07	0.15**	2.59%
	(0.68)	(1.75)	(1.03)	(2.03)	
Malaysia	-0.31	3.16**	0.09	0.06	1.91%
	(-0.10)	(2.49)	(1.41)	(0.60)	
Netherlands	-3.33***	2.51***	-0.08	0.23**	3.62%
	(-4.04)	(3.13)	(-1.57)	(2.23)	
South Africa	-1.52**	3.00**	-0.02	0.12*	1.40%
	(-2.52)	(2.43)	(-0.37)	(1.85)	
Sweden	-0.50	2.00**	0.04	0.25**	4.50%
	(-0.59)	(2.03)	(0.70)	(2.31)	
Switzerland	-0.98	0.60	0.09	0.13	3.35%
	(-1.01)	(0.92)	(1.53)	(1.29)	
United Kingdom	-1.51***	3.77***	-0.09	0.13	2.45%
	(-2.62)	(4.77)	(-1.52)	(1.29)	
United States	-1.65	1.61**	0.04		0.90%
	(-1.62)	(2.51)	(0.50)		

Table 3 Predictive Power of the El Niño phenomenon on International Stock Returns, 1982:01 to 2014:12

The table reports OLS estimation of the predictive regression model

$$r_{i,t+1} = \beta_{i,0} + \beta_{i,b}TB_{i,t} + \beta_{i,d}DY_{i,t} + \beta_{i,i}r_{i,t} + \beta_{i,USA}r_{USA,t} + \beta_{i,E}ELNINO_t + \beta_{i,W}WINTER_t + \beta_{i,EW}ELNINO_t * WINTER_t + \varepsilon_{i,t+1} \quad (2)$$

where $r_{i,t+1}$ is the monthly national currency excess return and $TB_{i,t}$ ($DY_{i,t}$) is the three-month Treasury bill rate (log dividend yield) for country i. $r_{i,t}$ is the lagged excess return. $r_{USA,t}$ is the lagged United States' excess return. $ELNINO_t$ is the El Niño phenomenon measure. $WINTER_t$ is the dummy variable equals 1 if it is in December/January/February, 0 otherwise. (For Australia and South Africa, $WINTER_t$ equals 1 if it is in June/July/August, 0 otherwise). Heteroskedasticity and autocorrelation consistent t-statistics, and adjusted R^2 are reported. *, **, *** denotes significance levels at 10%, 5%, and 1% respectively.

(1) Country i	(2) $\widehat{\beta_{i,b}}$	(3) $\widehat{\beta_{i,d}}$	(4) $\widehat{\beta_{i,i}}$	(5) $\widehat{\beta_{i,USA}}$	(6) $\widehat{\beta_{i,E}}$	(7) $\widehat{\beta_{i,W}}$	(8) $\widehat{\beta_{i,EW}}$	(9) adj. R^2
Australia	-0.46	1.45	-0.07	0.16***	-0.10	0.66	0.94*	0.83%
	(-0.52)	(1.49)	(-1.45)	(2.68)	(-0.43)	(1.07)	(1.70)	
Belgium	-1.21	1.19*	0.05	0.17**	0.02	0.4	1.11***	4.16%
	(-1.56)	(1.96)	(0.84)	(2.14)	(0.10)	(0.74)	(2.74)	
Canada	-1.48*	1.06	0.05	0.10	-0.14	0.25	0.83***	2.44%
	(-1.96)	(1.24)	(0.65)	(1.22)	(-0.67)	(0.69)	(2.62)	
France	-1.06	2.20**	0.03	0.12	-0.28	1.00*	1.53***	3.69%
	(-1.50)	(2.17)	(0.49)	(1.25)	(-1.16)	(1.90)	(3.51)	
Germany	-2.90***	2.23**	-0.02	0.20**	-0.32	0.09	1.07**	2.71%
	(-3.01)	(2.23)	(-0.43)	(2.47)	(-1.25)	(0.15)	(2.30)	
Italy	-0.00	0.50	-0.00	0.15	-0.31	1.69***	2.03***	2.80%
	(0.00)	(0.46)	(-0.01)	(1.31)	(-0.86)	(2.73)	(3.55)	
Japan	1.51	1.36**	0.06	0.16**	-0.80***	0.99	0.81	3.71%
	(1.13)	(2.05)	(0.80)	(2.17)	(-2.87)	(1.51)	(1.62)	
Malaysia	0.04	3.14***	0.06	0.07	-1.42**	0.46	2.70***	4.15%
	(0.01)	(2.64)	(0.80)	(0.75)	(-2.52)	(0.56)	(3.21)	
Netherlands	-3.34***	2.39***	-0.09	0.23**	0.01	0.64	1.20***	4.43%
	(-4.15)	(3.40)	(-1.58)	(2.17)	(0.07)	(1.29)	(3.16)	
South Africa	-1.53***	3.06***	-0.03	0.12*	-0.57*	-0.16	1.82*	1.87%
	(-2.64)	(2.61)	(-0.65)	(1.76)	(-1.68)	(-0.20)	(1.88)	
Sweden	-0.62	2.01**	0.03	0.25**	-0.21	1.18**	2.06***	6.69%
	(-0.79)	(2.22)	(0.45)	(2.44)	(-0.78)	(2.40)	(3.85)	
Switzerland	-0.97	0.65	0.08	0.13	-0.02	-0.04	0.82*	3.35%
	(-0.99)	(1.06)	(1.33)	(1.29)	(-0.11)	(-0.10)	(1.90)	
United Kingdom	-1.59***	3.88***	-0.11	0.13	-0.20	0.46	0.79**	2.57%
	(-2.80)	(4.68)	(-1.62)	(1.29)	(-1.32)	(0.99)	(2.06)	
United States	-1.71*	1.60**	0.03		-0.14	0.05	0.89***	0.97%
	(-1.70)	(2.53)	(0.46)		(-0.82)	(0.12)	(2.80)	

Table 4 Predictive Regression Model Estimation Results, 1982:01 to 2014:12

The table reports OLS estimation of the predictive regression model

$$r_{i,t+1} = \beta_{i,0} + \beta_{i,b} TB_{i,t} + \beta_{i,d} DY_{i,t} + \beta_{i,i} r_{i,t} + \beta_{i,USA} r_{USA,t} + \beta_{i,E} ELNINO_t + \varepsilon_{i,t+1}$$

where $r_{i,t+1}$ is the monthly national currency excess return and $TB_{i,t}$ ($DY_{i,t}$) is the three-month Treasury bill rate (log dividend yield) for country i. $r_{i,t}$ is the lagged excess return. $r_{USA,t}$ is the lagged United States' excess return. $ELNINO_t$ is the El Niño anomaly measure. Heteroskedasticity and autocorrelation consistent t-statistics, and adjusted R^2 are reported. *, **, *** denotes significance levels at 10%, 5%, and 1% respectively.

(1) Country i	(2) $\widehat{\beta_{i,b}}$	(3) $\widehat{\beta_{i,d}}$	(4) $\widehat{\beta_{i,i}}$	(5) $\widehat{\beta_{i,USA}}$	(6) $\widehat{\beta_{i,E}}$	(7) adj. R^2
Australia	-0.47	1.48	-0.06	0.15**	0.06	0.53%
	(-0.51)	(0.87)	(-1.07)	(2.25)	(0.22)	
Belgium	-1.14	1.19*	0.05	0.17**	0.20	3.53%
	(-1.47)	(1.93)	(0.93)	(2.15)	(1.14)	
Canada	-1.41*	1.04	0.06	0.10	0.00	2.15%
	(-1.85)	(1.19)	(0.74)	(1.21)	(0.02)	
France	-0.96	2.19**	0.04	0.13	-0.03	1.99%
	(-1.34)	(2.16)	(0.57)	(1.26)	(-0.12)	
Germany	-2.82***	2.21**	-0.02	0.21**	-0.14	2.51%
	(-2.84)	(2.09)	(-0.47)	(2.53)	(-0.51)	
Italy	0.09	0.43	0.02	0.15	0.02	0.04%
	(0.08)	(0.40)	(0.32)	(1.31)	(0.04)	
Japan	1.48	1.31*	0.06	0.16**	-0.52**	3.15%
	(1.09)	(1.96)	(0.92)	(2.18)	(-2.16)	
Malaysia	0.13	3.15**	0.09	0.06	-0.45	1.97%
	(0.04)	(2.54)	(1.34)	(0.65)	(-1.05)	
Netherlands	-3.37***	2.46***	-0.09	0.23**	0.21	3.59%
	(-4.20)	(3.38)	(-1.62)	(2.24)	(1.19)	
South Africa	-1.59***	3.05**	-0.02	0.13*	-0.29	1.35%
	(-2.60)	(2.46)	(-0.40)	(1.86)	(-0.86)	
Sweden	-0.47	1.93**	0.04	0.25**	0.13	4.27%
	(-0.57)	(2.04)	(0.67)	(2.32)	(0.45)	
Switzerland	-0.98	0.58	0.09	0.13	0.12	3.20%
	(-1.01)	(0.94)	(1.51)	(1.29)	(0.65)	
United Kingdom	-1.49**	3.82***	-0.09	0.13	-0.07	2.19%
	(-2.51)	(4.54)	(-1.51)	(1.36)	(-0.42)	
United States	-1.65	1.61**	0.04		0.01	0.64%
	(-1.62)	(2.48)	(0.50)		(0.07)	

Table 5 Predictive Regression Model Estimation Results, 1982:01 to 2014:12

The table reports OLS estimation of the predictive regression model

$$r_{i,t+1} = \beta_{i,0} + \beta_{i,b}TB_{i,t} + \beta_{i,d}DY_{i,t} + \beta_{i,i}r_{i,t} + \beta_{i,USA}r_{USA,t} + \beta_{i,W}WINTER_t + \varepsilon_{i,t+1}$$

where $r_{i,t+1}$ is the monthly national currency excess return and $TB_{i,t}$ ($DY_{i,t}$) is the three-month Treasury bill rate (log dividend yield) for country i. $r_{i,t}$ is the lagged excess return. $r_{USA,t}$ is the lagged United States' excess return. $WINTER_t$ is the dummy variable equals 1 if it is in December/January/February, 0 otherwise. (For Australia and South Africa, $WINTER_t$ equals 1 if it is in June/July/August, 0 otherwise). Heteroskedasticity and autocorrelation consistent t-statistics, and adjusted R^2 are reported. *, **, *** denotes significance levels at 10%, 5%, and 1% respectively.

(1) Country i	(2) $\widehat{\beta_{i,b}}$	(3) $\widehat{\beta_{i,d}}$	(4) $\widehat{\beta_{i,i}}$	(5) $\widehat{\beta_{i,USA}}$	(6) $\widehat{\beta_{i,W}}$	(7) adj. R^2
Australia	-0.48	1.48	-0.07	0.16**	0.68	0.89%
	(-0.52)	(0.96)	(-1.13)	(2.28)	(1.18)	
Belgium	-1.10	1.25*	0.05	0.17**	0.40	3.42%
	(-1.41)	(1.96)	(0.87)	(2.18)	(0.72)	
Canada	-1.42*	1.05	0.06	0.10	0.27	2.22%
	(-1.85)	(1.16)	(0.70)	(1.24)	(0.71)	
France	-1.00	2.18**	0.03	0.13	1.02*	2.64%
	(-1.41)	(2.20)	(0.43)	(1.33)	(1.79)	
Germany	-2.87***	2.17**	-0.02	0.21**	0.10	2.43%
	(-2.92)	(2.22)	(-0.45)	(2.50)	(0.17)	
Italy	0.06	0.41	0.00	0.16	1.71**	1.34%
	(0.07)	(0.37)	(0.06)	(1.35)	(2.38)	
Japan	0.98	1.14*	0.07	0.15**	0.99	2.96%
	(0.68)	(1.75)	(0.92)	(2.03)	(1.51)	
Malaysia	-0.30	3.17**	0.09	0.06	0.35	1.70%
	(-0.10)	(2.50)	(1.35)	(0.60)	(0.41)	
Netherlands	-3.33***	2.51***	-0.09*	0.23**	0.65	3.65%
	(-4.03)	(3.13)	(-1.63)	(2.21)	(1.23)	
South Africa	-1.52**	3.00*	-0.02	0.12*	-0.15	1.16%
	(-2.53)	(1.86)	(-0.37)	(1.86)	(-0.17)	
Sweden	-0.46	1.98**	0.03	0.25**	1.14**	4.83%
	(-0.53)	(1.99)	(0.54)	(2.41)	(2.14)	
Switzerland	-0.98	0.60	0.09	0.13	-0.04	3.10%
	(-1.01)	(0.92)	(1.52)	(1.30)	(-0.09)	
United Kingdom	-1.50**	3.76***	-0.10	0.13	0.45	2.36%
	(-2.56)	(4.69)	(-1.54)	(1.38)	(0.94)	
United States	-1.65	1.61**	0.04		0.06	0.65%
	(-1.61)	(2.50)	(0.50)		(0.14)	

Table 6 Predictive Power of El Niño on International Stock Returns, 1982:01 to 2014:12

The table reports OLS estimation of the predictive regression model

$$r_{i,t+1} = \beta_{i,0} + \beta_{i,b}TB_{i,t} + \beta_{i,d}DY_{i,t} + \beta_{i,i}r_{i,t} + \beta_{i,USA}r_{USA,t} + \beta_{i,E}ELNINO_t + \beta_{i,W}WINTER_t + \beta_{i,S}SENT_{i,t} + \beta_{i,EW}ELNINO_t * WINTER_t + \beta_{i,SW}SENT_{i,t} * WINTER_t + \varepsilon_{i,t+1}$$

where $r_{i,t+1}$ is the monthly national currency excess return and $TB_{i,t}$ ($DY_{i,t}$) is the three-month Treasury bill rate (log dividend yield) for country i. $r_{i,t}$ is the lagged excess return. $r_{USA,t}$ is the lagged United States' excess return. $ELNINO_t$ is the El Niño anomaly measure. $WINTER_t$ is the dummy variable equals 1 if it is in December, or January, or February, 0 otherwise. (For Australia and South Africa, $WINTER_t$ equals 1 if it is in June/July/August, 0 otherwise). $SENT_{i,t}$ is country i's investor sentiment measure at month t. Heteroskedasticity and autocorrelation consistent t-statistics, and adjusted R^2 are reported. *, **, *** denotes significance levels at 10%, 5%, and 1% respectively.

(1) Country i	(2) $\widehat{\beta_{i,b}}$	(3) $\widehat{\beta_{i,d}}$	(4) $\widehat{\beta_{i,i}}$	(5) $\widehat{\beta_{i,USA}}$	(6) $\widehat{\beta_{i,E}}$	(7) $\widehat{\beta_{i,S}}$	(8) $\widehat{\beta_{i,W}}$	(9) $\widehat{\beta_{i,EW}}$	(10) $\widehat{\beta_{i,SW}}$	(11) adj. R^2
Australia	-0.13	2.17*	-0.07	0.15***	-0.06	0.12	-19.04	1.08*	0.20	0.94%
	(-0.15)	(1.85)	(-1.61)	(2.59)	(-0.27)	(0.95)	(-0.88)	(1.73)	(0.91)	
Belgium	-1.26*	-0.03	0.04	0.17**	-0.01	-0.21**	8.69	1.14***	-0.08	4.55%
	(-1.80)	(-0.04)	(0.70)	(2.16)	(-0.07)	(-2.18)	(0.56)	(2.74)	(-0.54)	
Canada	-1.56**	1.21	0.04	0.10	-0.14	-0.01	-10.83*	0.80***	0.20*	2.46%
	(-2.09)	(1.43)	(0.54)	(1.22)	(-0.69)	(-0.14)	(-1.63)	(2.65)	(1.66)	
France	-1.09	2.04**	0.04	0.12	-0.28	-0.03	24.30	1.60***	-0.24	3.48%
	(-1.52)	(2.03)	(0.57)	(1.12)	(-1.15)	(-0.21)	(0.93)	(4.11)	(-0.90)	
Germany	-2.54***	1.27	-0.03	0.20**	-0.43*	-0.24**	-18.64	1.16**	0.19	3.40%
	(-2.64)	(1.13)	(-0.56)	(2.51)	(-1.69)	(-2.44)	(-0.80)	(2.29)	(0.80)	
Italy	-0.35	-0.79	-0.01	0.15	-0.42	-0.24*	-10.83	2.09***	0.12	2.96%
	(-0.32)	(-0.59)	(-0.08)	(1.34)	(-1.11)	(-1.81)	(-0.59)	(3.81)	(0.68)	
Japan	1.43	1.72**	0.05	0.15**	-0.77***	0.06	0.05	0.83	0.01	3.54%
	(0.83)	(2.45)	(0.77)	(2.05)	(-2.70)	(0.55)	(0.00)	(1.56)	(0.07)	
Malaysia	NO SENTIMENT DATA									
Netherlands	-3.82***	3.13***	-0.09	0.22**	0.02	0.11	-3.25	1.18***	0.04	4.07%
	(-3.62)	(3.08)	(-1.62)	(2.15)	(0.13)	(0.70)	(-0.15)	(3.07)	(0.19)	
South Africa	-2.55***	1.29	-0.15**	0.15*	-0.39	-0.15	-69.92***	0.74	0.69***	4.98%
	(-2.99)	(0.94)	(-2.33)	(1.86)	(-1.08)	(-1.11)	(-2.81)	(0.77)	(2.77)	
Sweden	-10.09*	-1.86	0.02	0.13	-0.42	-0.26**	-11.18	1.71***	0.12	3.70%
	(-1.82)	(-0.72)	(0.21)	(0.87)	(-1.38)	(-2.49)	(-0.59)	(3.73)	(0.63)	
Switzerland	-1.12	0.28	0.07	0.14	-0.08	-0.11	11.15	0.75*	-0.11	4.00%
	(-1.06)	(0.43)	(1.06)	(1.37)	(-0.43)	(-1.57)	(0.85)	(1.67)	(-0.86)	
United Kingdom	-1.92***	5.02***	-0.11*	0.13	-0.31*	0.17	-16.63	0.66	0.17	2.84%
	(-3.24)	(4.66)	(-1.70)	(1.38)	(-1.81)	(1.15)	(-0.69)	(1.62)	(0.71)	
United States	-3.51***	2.71***	0.02		-0.17	0.19	-18.64	0.19***	0.19	1.75%
	(-3.58)	(3.71)	(0.23)		(-1.02)	(1.27)	(-1.03)	(3.14)	(1.04)	

Table 7 Predictive Power of El Niño on International Stock Returns, 1982:01 to 2014:12

The table reports OLS estimation of the predictive regression model

$$r_{i,t+1} = \beta_{i,0} + \beta_{i,b}TB_{i,t} + \beta_{i,d}DY_{i,t} + \beta_{i,i}r_{i,t} + \beta_{i,USA}r_{USA,t} + \beta_{i,E}EININO_t + \beta_{i,W}WINTER_t + \beta_{i,EW}ELNINO_t * WINTER_t + \beta_{i,SAD}SAD_{i,t+1} + \beta_{i,TEMP}TEMP_{i,t+1} + \varepsilon_{i,t+1}$$

where r is the monthly national currency excess return and TB (DY) is the three-month Treasury bill rate (log dividend yield) for country i . SAD is monthly mean daylight time of the city of national stock exchange (ONSET for the US). TEMP is monthly mean temperature of the city of national stock exchange. Heteroskedasticity and autocorrelation consistent t-statistics, and adjusted R square values are reported. *, **, *** denotes significance levels at 10%, 5%, and 1% respectively.

(1) Country i	(2) $\hat{\beta}_{i,b}$	(3) $\hat{\beta}_{i,d}$	(4) $\hat{\beta}_{i,i}$	(5) $\hat{\beta}_{i,USA}$	(6) $\hat{\beta}_{i,E}$	(7) $\tilde{\beta}_{i,W}$	(8) $\tilde{\beta}_{i,EW}$	(9) $\tilde{\beta}_{i,SAD}$	(10) $\tilde{\beta}_{i,TEMP}$	(11) adj. R^2
Australia	-0.22	1.26	-0.07	0.16**	-0.10	1.38*	0.99	-0.01	0.15	1.17%
	(-0.24)	(0.77)	(-1.12)	(2.23)	(-0.31)	(1.66)	(1.28)	(-1.25)	(1.56)	
Belgium	-1.40*	1.05*	0.05	0.16*	0.06	-0.65	1.12***	0.00**	-0.12***	5.29%
	(-1.79)	(1.70)	(0.81)	(1.93)	(0.38)	(-1.06)	(2.77)	(2.00)	(-2.85)	
Canada	-1.53**	0.99	0.06	0.09	-0.12	-0.75	0.84***	0.00	-0.04	2.87%
	(-2.00)	(1.15)	(0.72)	(1.08)	(-0.61)	(-1.32)	(2.61)	(0.37)	(-1.48)	
France	-1.18*	2.13**	0.02	0.12	-0.24	-0.19	1.49***	0.00	-0.11**	4.83%
	(-1.63)	(2.09)	(0.24)	(1.18)	(-0.93)	(-0.36)	(3.43)	(1.16)	(-2.56)	
Germany	-3.00***	2.10**	-0.02	0.20**	-0.28	-1.00*	1.08**	0.00	-0.09*	3.23%
	(-3.08)	(2.09)	(-0.47)	(2.28)	(-1.06)	(-1.64)	(2.30)	(0.94)	(-1.90)	
Italy	-0.12	0.44	-0.00	0.13	-0.30	0.61	2.07***	0.00	-0.09*	3.30%
	(-0.12)	(0.40)	(-0.02)	(1.16)	(-0.81)	(0.86)	(3.58)	(0.97)	(-1.96)	
Japan	1.20	1.34**	0.05	0.15**	-0.78***	-0.52	0.81*	0.01	-0.10**	4.66%
	(0.91)	(2.04)	(0.63)	(2.07)	(-2.72)	(-0.64)	(1.65)	(1.29)	(-2.25)	
Malaysia	-1.11	3.37**	-0.01	0.15	-2.14***	0.09	3.38**	-0.09	-0.50	6.79%
	(-0.21)	(2.49)	(-0.13)	(1.57)	(-4.48)	(0.08)	(2.55)	(-1.52)	(-0.90)	
Netherlands	-3.20***	2.15***	-0.09*	0.22**	0.05	-0.56	1.22***	0.00	-0.12***	5.30%
	(-4.04)	(2.84)	(-1.67)	(2.05)	(0.27)	(-0.96)	(3.29)	(1.44)	(-2.61)	
South Africa	-1.45**	2.87**	-0.04	0.12*	-0.63*	0.57	1.92*	-0.00	0.12	2.30%
	(-2.48)	(2.31)	(-0.73)	(1.72)	(-1.75)	(0.64)	(1.87)	(-0.25)	(1.19)	
Sweden	-0.72	1.99**	0.02	0.23**	-0.17	-0.36	2.06***	0.00	-0.09**	7.51%
	(-0.91)	(2.18)	(0.37)	(2.19)	(-0.62)	(-0.50)	(3.93)	(0.68)	(-2.25)	
Switzerland	-1.14	0.68	0.08	0.12	0.01	-0.83*	0.82*	0.00	-0.07**	3.96%
	(-1.18)	(1.14)	(1.20)	(1.22)	(0.06)	(-1.65)	(1.86)	(0.95)	(-2.16)	
United Kingdom	-1.55***	3.88***	-0.10*	0.13	-0.19	0.01	0.78**	-0.00**	-0.00***	2.90%
	(-2.65)	(4.62)	(-1.67)	(1.39)	(-1.26)	(0.03)	(2.02)	(-2.13)	(-5.79)	
United States	-1.78*	1.61**	0.02		-0.12	-1.37**	0.90***	-1.74	-0.04**	2.17%
	(-1.72)	(2.50)	(0.29)		(-0.70)	(-2.07)	(2.79)	(-1.18)	(-1.99)	

Table 8 Predictive Power of the El Niño phenomenon on International Stock Returns, 1982:01 to 2014:12

The table reports OLS estimation of the predictive regression model

$$r_{i,t+1} = \beta_{i,0} + \beta_{i,b} TB_{i,t} + \beta_{i,d} DY_{i,t} + \beta_{i,i} r_{i,t} + \beta_{i,USA} r_{USA,t} + \beta_{i,E} ELNINO_t + \beta_{i,M1} M1_t + \beta_{i,M2} M2_t + \beta_{i,M3} M3_t + \beta_{i,EM1} ELNINO_t * M1_t + \beta_{i,EM2} ELNINO_t * M2_t + \beta_{i,EM3} ELNINO_t * M3_t + \varepsilon_{i,t+1}$$

where r is the monthly national currency excess return and TB (DY) is the three-month Treasury bill rate (log dividend yield) for country i . M1/M2/M3 is dummy variable equals 1 if it is the first/second/third month of winter season, 0 otherwise. Heteroskedasticity and autocorrelation consistent t-statistics, and adjusted R square values are reported. *, **, *** denotes significance levels at 10%, 5%, and 1% respectively.

(1) Country i	(2) $\hat{\beta}_{i,b}$	(3) $\hat{\beta}_{i,d}$	(4) $\hat{\beta}_{i,i}$	(5) $\hat{\beta}_{i,USA}$	(6) $\hat{\beta}_{i,E}$	(7) $\widehat{\beta_{i,M1}}$	(8) $\widehat{\beta_{i,M2}}$	(9) $\widehat{\beta_{i,M3}}$	(10) $\widehat{\beta_{i,EM1}}$	(11) $\widehat{\beta_{i,EM2}}$	(12) $\widehat{\beta_{i,EM3}}$	(13) adj. R^2
Australia	-0.44	1.44	-0.06	0.15**	-0.10	1.53*	0.74	-0.30	0.96	1.16	0.75	0.44%
	(-0.47)	(0.85)	(-0.96)	(2.14)	(-0.29)	(1.81)	(0.96)	(-0.40)	(0.67)	(0.88)	(0.71)	
Belgium	-1.23	1.20**	0.05	0.16*	0.01	-0.53	1.07	0.59	1.09*	0.50	2.04***	3.91%
	(-1.59)	(2.00)	(0.96)	(1.94)	(0.09)	(-0.61)	(0.95)	(0.95)	(1.70)	(1.01)	(4.25)	
Canada	-1.46*	1.07	0.06	0.09	-0.14	0.25	-0.01	0.43	-0.02	1.47***	1.74***	2.29%
	(-1.95)	(1.25)	(0.70)	(1.11)	(-0.67)	(0.38)	(-0.01)	(0.70)	(-0.06)	(2.67)	(3.45)	
France	-1.09	2.28**	0.03	0.12	-0.28	0.53	1.28	1.14	0.96	1.28*	3.19***	3.36%
	(-1.52)	(2.25)	(0.46)	(1.16)	(-1.16)	(0.55)	(1.15)	(1.56)	(1.34)	(1.92)	(5.47)	
Germany	-2.90***	2.25**	-0.02	0.20**	-0.32	-0.75	0.27	0.64	0.32	1.34**	2.26***	2.40%
	(-3.01)	(2.26)	(-0.37)	(2.30)	(-1.25)	(-0.77)	(0.26)	(0.86)	(0.39)	(2.53)	(3.70)	
Italy	0.02	0.53	0.01	0.13	-0.31	2.80**	0.93	1.33	1.89**	1.28*	3.65**	2.60%
	(0.02)	(0.49)	(0.11)	(1.19)	(-0.86)	(2.50)	(0.77)	(1.26)	(2.44)	(1.66)	(2.22)	
Japan	1.56	1.35**	0.06	0.16**	-0.80***	0.46	0.50	1.94*	1.42*	0.25	0.44	3.45%
	(1.16)	(2.04)	(0.81)	(2.22)	(-2.88)	(0.47)	(0.61)	(1.87)	(1.78)	(0.53)	(0.46)	
Malaysia	0.14	3.11***	0.08	0.05	-1.39***	0.41	2.60**	-1.63	0.94	5.45***	1.56*	6.81%
	(0.04)	(2.68)	(1.24)	(0.55)	(-2.59)	(0.35)	(2.07)	(-1.62)	(1.31)	(3.00)	(1.78)	
Netherlands	-3.38***	2.43***	-0.09*	0.23**	0.01	0.27	-0.37	1.99**	0.86	0.87	2.45**	4.75%
	(-4.20)	(3.38)	(-1.65)	(2.16)	(0.07)	(0.30)	(-0.44)	(2.45)	(1.25)	(0.94)	(2.10)	
South Africa	-1.51***	3.01**	-0.02	0.13*	-0.57*	-0.32	0.55	-0.72	2.88	4.00*	-0.66	2.66%
	(-2.66)	(2.48)	(-0.49)	(1.92)	(-1.64)	(-0.28)	(0.41)	(-0.73)	(1.58)	(1.75)	(-0.70)	
Sweden	-0.57	1.96**	0.03	0.24**	-0.21	1.34	1.76*	0.28	2.10**	2.46***	1.34*	5.97%
	(-0.73)	(2.18)	(0.56)	(2.36)	(-0.78)	(1.27)	(1.95)	(0.33)	(2.40)	(2.92)	(1.66)	
Switzerland	-0.97	0.63	0.08	0.14	-0.02	-0.70	-0.11	0.68	0.77	1.07*	0.46	2.79%
	(-1.00)	(1.04)	(1.32)	(1.32)	(-0.11)	(-1.00)	(-0.14)	(1.12)	(1.43)	(1.80)	(0.81)	
United Kingdom	-1.57***	3.84***	-0.11	0.13	-0.20	0.14	0.47	0.73	0.68	0.97*	0.68	1.58%
	(-2.74)	(4.60)	(-1.59)	(1.40)	(-1.30)	(0.16)	(0.72)	(1.16)	(1.18)	(1.82)	(1.51)	
United States	-1.70*	1.60**	0.03		-0.14	0.16	-0.59	0.54	0.29	1.60***	1.14***	0.67%
	(-1.74)	(2.58)	(0.44)		(-0.82)	(0.20)	(-0.88)	(0.84)	(0.62)	(3.04)	(3.00)	

Table 9 Predictive Power of El Niño on International Stock Returns, 1982:01 to 2014:12

The table reports OLS estimation of the predictive regression model

$$r_{i,t+1} = \beta_{i,0} + \beta_{i,b}TB_{i,t} + \beta_{i,d}DY_{i,t} + \beta_{i,i}r_{i,t} + \beta_{i,USA}r_{USA,t} + \beta_{i,E}ELNINO_{i,t} + \beta_{i,W}WINTER_t + \beta_{i,EW}ELNINO_{i,t} * WINTER_t + \beta_{i,CPIC}CPI_{i,t+1} + \varepsilon_{i,t+1}$$

where r is the monthly national currency excess return and TB (DY) is the three-month Treasury bill rate (log dividend yield) for country i . Heteroskedasticity and autocorrelation consistent t-statistics, and adjusted R square values are reported. *, **, *** denotes significance levels at 10%, 5%, and 1% respectively.

(1) Country i	(2) $\hat{\beta}_{i,b}$	(3) $\hat{\beta}_{i,d}$	(4) $\hat{\beta}_{i,i}$	(5) $\hat{\beta}_{i,USA}$	(6) $\hat{\beta}_{i,E}$	(7) $\hat{\beta}_{i,W}$	(8) $\hat{\beta}_{i,EW}$	(9) $\widehat{\beta_{i,CPIC}}$	(10) adj. R^2
Australia	-0.80	2.25	-0.07	0.14**	0.05	-0.05	0.60	-0.02	0.17%
	(-0.29)	(0.98)	(-0.86)	(2.05)	(0.19)	(-0.10)	(0.88)	(-0.93)	
Belgium	-5.91***	1.41**	0.03	0.17**	0.01	0.43	1.02***	-0.10**	5.54%
	(-3.13)	(2.53)	(0.50)	(2.14)	(0.04)	(0.79)	(2.61)	(-2.15)	
Canada	-4.42***	1.24	0.03	0.11	-0.25	0.22	0.82**	-0.05***	3.18%
	(-3.66)	(1.48)	(0.36)	(1.36)	(-1.20)	(0.60)	(2.48)	(-2.75)	
France	-7.31***	2.54***	0.00	0.13	-0.33	1.02*	1.43***	-0.16***	5.77%
	(-3.37)	(2.63)	(0.00)	(1.37)	(-1.54)	(1.88)	(3.40)	(-2.94)	
Germany	-5.42**	1.71*	-0.03	0.20**	-0.34	0.08	1.02**	-0.05	3.04%
	(-2.05)	(1.68)	(-0.48)	(2.42)	(-1.37)	(0.13)	(2.22)	(-1.09)	
Italy	-2.57	1.01	-0.01	0.16	-0.29	1.70***	2.02***	-0.07	2.95%
	(-1.16)	(0.99)	(-0.12)	(1.34)	(-0.81)	(2.70)	(3.50)	(-1.21)	
Japan	-3.58	0.68	0.04	0.17**	-0.74***	0.91	0.75	-0.18***	4.82%
	(-1.56)	(1.04)	(0.51)	(2.28)	(-2.84)	(1.37)	(1.47)	(-2.69)	
Malaysia	-2.73	4.52***	0.05	0.08	-1.42***	0.46	2.64***	-0.05	4.73%
	(-0.66)	(2.81)	(0.69)	(0.79)	(-2.65)	(0.55)	(3.13)	(-1.40)	
Netherlands	-8.21***	1.70**	-0.11*	0.23**	-0.03	0.62	1.08***	-0.10**	6.25%
	(-3.39)	(2.40)	(-1.90)	(2.26)	(-0.19)	(1.23)	(2.88)	(-2.30)	
South Africa	-3.76***	3.36***	-0.05	0.13*	-0.76**	-0.12	1.83*	-0.03*	2.69%
	(-2.72)	(2.72)	(-0.88)	(1.94)	(-2.20)	(-0.15)	(1.93)	(-1.91)	
Sweden	-4.04**	1.89**	-0.00	0.27***	-0.31	1.11	2.03***	-0.03**	7.66%
	(-2.29)	(2.10)	(-0.01)	(2.66)	(-1.20)	(2.23)	(4.11)	(-2.20)	
Switzerland	-1.80	0.47	0.08	0.13	-0.04	-0.05	0.78*	-0.02	3.32%
	(-1.58)	(0.72)	(1.32)	(1.29)	(-0.23)	(-0.11)	(1.78)	(-1.01)	
United Kingdom	-2.86**	3.48***	-0.11*	0.14	-0.21	0.45	0.78**	-0.03	2.53%
	(-2.48)	(3.68)	(-1.76)	(1.47)	(-1.31)	(0.94)	(1.98)	(-1.26)	
United States	-1.82	1.56*	0.03		-0.14	0.05	0.89***	-0.00	0.72%
	(-1.54)	(1.96)	(0.46)		(-0.82)	(0.12)	(2.81)	(-0.10)	

Table 10 Predictive Power of El Niño on International Stock Returns, 1982:01 to 2014:12

The table reports OLS estimation of the predictive regression model

$$r_{i,t+1} = \beta_{i,0} + \beta_{i,b}TB_{i,t} + \beta_{i,d}DY_{i,t} + \beta_{i,i}r_{i,t} + \beta_{i,USA}r_{USA,t} + \beta_{i,E}ELNINO_{i,t} + \beta_{i,W}WINTER_t + \beta_{i,EW}ELNINO_{i,t} * WINTER_t + \beta_{i,CPIF}CPI_{i,t+2} + \varepsilon_{i,t+1}$$

where r is the monthly national currency excess return and TB (DY) is the three-month Treasury bill rate (log dividend yield) for country i . Heteroskedasticity and autocorrelation consistent t-statistics, and adjusted R square values are reported. *, **, *** denotes significance levels at 10%, 5%, and 1% respectively.

(1) Country i	(2) $\hat{\beta}_{i,b}$	(3) $\hat{\beta}_{i,d}$	(4) $\hat{\beta}_{i,i}$	(5) $\hat{\beta}_{i,USA}$	(6) $\hat{\beta}_{i,E}$	(7) $\hat{\beta}_{i,W}$	(8) $\hat{\beta}_{i,EW}$	(9) $\widehat{\beta_{i,CPIF}}$	(10) adj. R^2
Australia	-2.13	2.01	-0.08	0.13**	-0.00	-0.05	0.45	0.03	0.45%
	(-0.66)	(0.84)	(-1.04)	(2.16)	(-0.01)	(-0.09)	(0.69)	(0.90)	
Belgium	-5.80***	1.41**	0.03	0.17**	0.01	0.44	1.02***	-0.10**	5.47%
	(-3.14)	(2.52)	(0.51)	(2.14)	(0.04)	(0.80)	(2.61)	(-2.14)	
Canada	-4.28***	1.24	0.03	0.11	-0.24	0.23	0.82**	-0.05***	3.10%
	(-3.59)	(1.47)	(0.37)	(1.35)	(-1.18)	(0.63)	(2.49)	(-2.72)	
France	-7.27***	2.55***	0.00	0.13	-0.33	1.05*	1.43***	-0.16***	5.75%
	(-3.40)	(2.64)	(0.00)	(1.37)	(-1.54)	(1.94)	(3.39)	(-2.96)	
Germany	-5.33**	1.73*	-0.03	0.20**	-0.34	0.08	1.02**	-0.05	3.00%
	(-2.04)	(1.70)	(-0.48)	(2.42)	(-1.36)	(0.14)	(2.22)	(-1.07)	
Italy	-2.56	1.01	-0.01	0.16	-0.29	1.70***	2.02***	-0.07	2.95%
	(-1.17)	(0.99)	(-0.12)	(1.34)	(-0.82)	(2.71)	(3.50)	(-1.22)	
Japan	-3.30	0.70	0.04	0.17**	-0.75***	0.95	0.75	-0.17**	4.71%
	(-1.44)	(1.10)	(0.51)	(2.26)	(-2.87)	(1.43)	(1.48)	(-2.59)	
Malaysia	-2.69	4.50***	0.05	0.08	-1.42***	0.46	2.65***	-0.05	4.71%
	(-0.65)	(2.81)	(0.69)	(0.79)	(-2.65)	(0.55)	(3.13)	(-1.39)	
Netherlands	-8.21***	1.69**	-0.11*	0.23**	-0.03	0.66	1.08***	-0.10**	6.26%
	(-3.42)	(2.39)	(-1.90)	(2.25)	(-0.19)	(1.31)	(2.86)	(-2.32)	
South Africa	-3.78***	3.36***	-0.05	0.13*	-0.76**	-0.12	1.84*	-0.03*	2.71%
	(-2.73)	(2.72)	(-0.88)	(1.94)	(-2.21)	(-0.15)	(1.93)	(-1.93)	
Sweden	-4.05**	1.89**	-0.00	0.27***	-0.31	1.13**	2.02***	-0.03**	7.69%
	(-2.31)	(2.09)	(-0.01)	(2.66)	(-1.21)	(2.27)	(4.11)	(-2.23)	
Switzerland	-1.75	0.48	0.08	0.13	-0.04	-0.04	0.79*	-0.02	3.30%
	(-1.54)	(0.73)	(1.32)	(1.29)	(-0.23)	(-0.10)	(1.79)	(-0.97)	
United Kingdom	-2.84**	3.49***	-0.11*	0.14	-0.21	0.45	0.78**	-0.03	2.52%
	(-2.47)	(3.70)	(-1.75)	(1.47)	(-1.31)	(0.96)	(1.97)	(-1.25)	
United States	-1.72	1.59**	0.03		-0.14	0.05	0.89***	-0.00	0.72%
	(-1.46)	(2.02)	(0.46)		(-0.82)	(0.12)	(2.81)	(-0.01)	

Table 11 Forecasting inflation with El Niño anomaly

This table reports OLS estimation results for the univariate predictive regressions

$$Inflation_{i,t+1} = a + bELNINO_{i,t} + \varepsilon_{i,t+1}$$

We report the regression slopes, Newey-West t-statistics, as well as R squares. *,**,*** indicate significance at the 10%,5%, and 1% levels, respectively. The sample period is from 1982:01 to 2014:12.

(1) Country *i*	(2) $\hat{b}$	(3) Adj. R^2
Australia	1.09*	1.13%
	(1.93)	
Belgium	-1.70***	1.49%
	(-2.64)	
Canada	-2.28***	1.54%
	(-2.68)	
France	-1.77***	1.82%
	(-2.89)	
Germany	-1.37**	1.02%
	(-2.25)	
Italy	-2.37***	1.53%
	(-2.67)	
Japan	-0.41	0.19%
	(-1.32)	
Malaysia	-2.11**	0.80%
	(-2.05)	
Netherlands	-1.55**	1.32%
	(-2.50)	
South Africa	-3.42**	0.87%
	(-2.11)	
Sweden	-6.36***	1.49%
	(-2.64)	
Switzerland	-1.35**	1.29%
	(-2.48)	
United Kingdom	-1.67**	1.05%
	(-2.28)	
United States	-4.55**	1.32%
	(-2.51)	

Table 12 Forecasting investor sentiment with El Niño anomaly

This table reports OLS estimation results for the univariate predictive regressions

$$Investor\ Sentiment_{i,t+1}^{\perp} = c + dELNINO_{i,t} + \delta_{i,t+1}$$

Where left side dependent variable is the residual from the univariate regressions

$$Investor\ Sentiment_{i,t} = e + fInflation_{i,t} + \mu_{i,t}$$

We report the regression slopes, Newey-West t-statistics, as well as R squares. *,**,*** indicate significance at the 10%,5%, and 1% levels, respectively. The sample period is from 1982:01 to

(1) Country *i*	(2) $\hat{d}$	(3) R^2
Australia	0.22**	1.65%
	(1.99)	
Belgium	-0.27**	1.31%
	(-2.29)	
Canada	0.02	0.00%
	(0.14)	
France	-0.02	0.01%
	(-0.21)	
Germany	-0.48***	2.96%
	(-3.46)	
Italy	-0.34**	1.59%
	(-2.52)	
Japan	-0.68***	3.50%
	(-3.75)	
Malaysia	No data	
Netherlands	-0.16	0.67%
	(-1.62)	
South Africa	-0.09	0.06%
	(-0.43)	
Sweden	0.13	0.16%
	(0.61)	
Switzerland	-0.56***	3.95%
	(-4.02)	
United Kingdom	0.42***	5.80%
	(4.92)	
United States	0.00	0.00%
	(0.03)	

Table 13 Time Series Regressions of 27 US Industry Portfolio Returns, 1982:01 to 2014:12

Regressions of 27 US industry portfolio excess returns on lagged *El Nino* (conditional and unconditional on winter months), the market risk premium (*RMKT*), the Fama/French factors (*SMB* and *HML*), a momentumm factor (*MOM*), and lagged sentiment (*SENT*)

$$r_{i,t} = \beta_{i,0} + \beta_{i,E} ELNINO_{t-1} + \beta_{i,EW} ELNINO_{t-1} * WINTER_{t-1} + \beta_{i,S} SENT_{t-1} + \beta_{i,RMKT} RMKT_t + \beta_{i,SMB} SMB_t + \beta_{i,HML} HML_t + \beta_{i,MOM} MOM_t + \varepsilon_{i,t}$$

The columns from (2) to (3) report the estimated coefficients without controls. The columns from (4) to (5) report the estimated coefficients with *RMKT, SMB, HML, MOM*, and lagged *SENT* included as control variables. The columns from (6) to (9) reports the estimated coefficients using the same control variables with replacement the WINTER dummy by MONTH dummy variables. M1/M2/M3 denote December/January/Februry. Heteroskedasticity and autocorrelation consistent t-statistics are reported. *, **, *** denote significance levels at 10%, 5%, and 1% respectively. Data are from K. French data library.

				Controlling for RMKT, SMB, HML, MOM, and lagged SENT		Controlling for RMKT, SMB, HML, MOM, and lagged SENT			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Industry	$\widehat{\beta_{i,E}}$	$\widehat{\beta_{i,EW}}$	$\widehat{\beta_{i,E}}$	$\widehat{\beta_{i,EW}}$	$\widehat{\beta_{i,E}}$	$\widehat{\beta_{i,EM1}}$	$\widehat{\beta_{i,EM2}}$	$\widehat{\beta_{i,EM3}}$
1	Agriculture	-0.12	0.21	-0.03	-0.58*	-0.03	-1.34***	1.13	-1.57*
		(-0.34)	(0.50)	(-0.12)	(-1.91)	(-0.12)	(-2.70)	(1.55)	(-1.90)
2	Candy & Soda	0.03	-0.10	0.02	-0.77	0.02	-1.21	-1.09**	0.60
		(0.08)	(-0.14)	(0.06)	(-1.42)	(0.06)	(-1.22)	(-2.50)	(0.69)
3	Beer & Liquor	-0.25*	1.21***	-0.17	0.58	-0.17	0.12	0.12	2.23***
		(-1.84)	(2.84)	(-1.29)	(1.59)	(-1.31)	(0.32)	(0.26)	(3.06)
4	Recreation	0.23	0.62	0.30	-0.35	0.30	0.45	0.07	-2.93***
		(0.75)	(1.31)	(1.51)	(-0.87)	(1.51)	(0.71)	(0.08)	(-2.69)
5	Entertainment	-0.51	1.02**	-0.44	-0.12	-0.44	0.39	-0.16	-1.14*
		(-1.57)	(2.17)	(-1.62)	(-0.34)	(-1.62)	(0.53)	(-0.20)	(-1.67)
6	Consumer Goods	-0.18	1.32***	-0.11	0.60**	-0.11	0.66**	0.66**	0.38
		(-1.23)	(3.39)	(-1.09)	(2.22)	(-1.09)	(2.05)	(2.02)	(0.60)
7	Apparel	-0.47	1.43***	-0.42**	0.48	-0.42**	-0.12	1.34***	0.29
		(-1.55)	(3.13)	(-2.02)	(1.23)	(-2.02)	(-0.16)	(2.66)	(0.33)
8	Healthcare	-0.46	1.21*	-0.42	0.36	-0.42	-0.91*	1.70**	1.09
		(-1.37)	(1.91)	(-1.59)	(0.76)	(-1.59)	(-1.78)	(2.43)	(1.11)
9	Textiles	-0.20	1.20**	-0.27	0.34	-0.27	0.27	-0.25	1.25**
		(-0.63)	(2.34)	(-1.49)	(0.98)	(-1.51)	(0.40)	(-0.45)	(2.26)
10	Construction Materials	-0.23	1.34***	-0.21	0.32	-0.21	-0.22	0.65**	1.01**
		(-0.81)	(2.87)	(-1.46)	(1.15)	(-1.47)	(-0.57)	(2.02)	(1.99)
11	Fabricated Products	-0.48	1.19**	-0.43**	0.32	-0.43**	0.27	0.04	0.80
		(-1.46)	(2.11)	(-2.39)	(0.83)	(-2.39)	(0.62)	(0.05)	(1.09)

Table 13 Continued

				Controlling for RMKT, SMB, HML, MOM, and lagged SENT		Controlling for RMKT, SMB, HML, MOM, and lagged SENT			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Industry	$\widehat{\beta_{i,E}}$	$\widehat{\beta_{i,EW}}$	$\widehat{\beta_{i,E}}$	$\widehat{\beta_{i,EW}}$	$\widehat{\beta_{i,E}}$	$\widehat{\beta_{i,EM1}}$	$\widehat{\beta_{i,EM2}}$	$\widehat{\beta_{i,EM3}}$
12	Aircraft	-0.56**	1.91***	-0.54***	1.05***	-0.54***	1.48***	0.90	0.35
		(-2.20)	(4.95)	(-3.23)	(3.18)	(-3.24)	(3.15)	(1.15)	(0.31)
13	Mines	-0.39	1.40**	-0.35	0.48	-0.35	0.95	-1.28	2.14*
		(-1.06)	(2.21)	(-1.23)	(0.91)	(-1.24)	(1.34)	(-1.33)	(1.81)
14	Coal	-1.07**	-0.00	-0.99**	-1.10	-0.99**	-1.66	-0.92	-0.10
		(-2.25)	(-0.01)	(-2.18)	(-1.26)	(-2.19)	(-1.15)	(-0.56)	(-0.09)
15	Petroleum & Natural Gas	-0.28	0.59	-0.29*	-0.01	-0.29*	-0.16	-0.33	0.79
		(-1.19)	(1.39)	(-1.71)	(-0.03)	(-1.71)	(-0.32)	(-0.53)	(1.07)
16	Communication	0.06	1.21***	0.16	0.34	0.16	1.31**	-1.13***	0.49
		(0.24)	(2.99)	(0.89)	(1.10)	(0.90)	(2.29)	(-3.68)	(0.73)
17	Business Services	-0.19	1.51***	-0.03	0.41*	-0.03	0.37	0.65*	0.03
		(-0.77)	(3.63)	(-0.38)	(1.69)	(-0.37)	(1.04)	(1.74)	(0.09)
18	Computer Hardware	0.1	1.09*	0.39**	-0.33	0.39**	-0.18	0.18	-1.38
		(0.35)	(1.92)	(2.47)	(-0.82)	(2.51)	(-0.32)	(0.30)	(-1.60)
19	Computer Software	-0.15	2.34***	0.23	0.71*	0.23	1.2	-0.22	1.20***
		(-0.49)	(4.51)	(1.29)	(1.70)	(1.29)	(1.25)	(-0.38)	(2.82)
20	Electronic Equipment	-0.38	1.51***	-0.08	-0.01	-0.08	0.27	0.73	-1.78***
		(-1.27)	(3.15)	(-0.50)	(-0.04)	(-0.51)	(0.48)	(1.24)	(-4.04)
21	Shipping Containers	-0.57*	0.98**	-0.52**	0.1	-0.52**	-0.74	1.18**	0.09
		(-1.87)	(2.01)	(-2.12)	(0.22)	(-2.15)	(-1.30)	(2.41)	(0.16)
22	Wholesale	-0.10	0.96***	-0.01	0.03	-0.01	-0.52	0.95**	-0.18
		(-0.42)	(2.81)	(-0.12)	(0.13)	(-0.12)	(-1.26)	(2.41)	(-0.63)
23	Retail	-0.02	1.22***	0.09	0.23	0.09	-0.23	0.70*	0.38
		(-0.10)	(2.93)	(0.78)	(0.80)	(0.76)	(-0.41)	(1.91)	(0.61)
24	Restaurants & Hotels	-0.13	1.24***	-0.07	0.47*	-0.07	0.25	1.19**	-0.32
		(-0.64)	(3.19)	(-0.59)	(1.65)	(-0.59)	(0.57)	(2.40)	(-0.77)
25	Banking	0.02	0.73	-0.02	-0.13	-0.02	-0.73*	0.41	0.39
		(0.07)	(1.51)	(-0.17)	(-0.43)	(-0.18)	(-1.78)	(1.08)	(0.71)
26	Insurance	-0.19	1.03**	-0.21*	0.25	-0.21*	0.12	0.73	-0.26
		(-0.89)	(2.52)	(-1.94)	(1.19)	(-1.92)	(0.34)	(1.41)	(-0.39)
27	Finance Trading	-0.02	0.55	0.09	-0.67**	0.09	-1.11***	-0.30	-0.26
		(-0.08)	(1.02)	(0.58)	(-2.84)	(0.58)	(-3.31)	(-0.81)	(-0.65)

Table 14

Regressions of 10 countries' portfolio returns with winter dummy

The long-short portfolios are formed based on firm book-to-market ratio (BM/ME). Regressions of long-short portfolio returns on lagged ELNINO, WINTER dummy variable, SENTIMENT, and the market risk premium (RMKT).

$$R_{X_{i,t+1}=High,t+1} - R_{X_{i,t}=Low,t+1} = \beta_{i.0} + \beta_{i,E} ELNINO_t + \beta_{i,EW} ELNINO_t * WINTER_t + \beta_{i,SENT} SENT_t + \beta_{i,RMKT} RMKT_{i,t+1} + \varepsilon_{i,t+1} \qquad (16)$$

Where dependent variable is the monthly county i's value stategy return (long high BE/ME stocks and short low BE/ME stocks), ELNINO is the El Nino anomaly measure. WINTER is the dummy variable equals 1 if it is in December/January/February (June/July/August in Australia), 0 otherwise. Heteroskedasticity and autocorrelation consistent t-statistics are reported in parentheses. *, **, *** denote significance level at 10%, 5%, and 1% respectively. Data are from Ken French data library.

(1) Country *i*	(2) $\widehat{\beta_{i,E}}$	(3) $\widehat{\beta_{i,EW}}$	(4) $\widehat{\beta_{i,SENT}}$	(5) $\widehat{\beta_{i,RMKT}}$
Australia	0.61***	-0.35	0.03	-0.09**
	(2.82)	(-0.66)	(0.26)	(-2.37)
Belgium	-0.04	-0.41	0.02	0.14*
	(-0.25)	(-0.86)	(0.33)	(1.87)
Canada	-0.12	1.03*	-0.07	-0.11
	(-0.65)	(1.96)	(-1.27)	(-1.30)
France	0.31	-0.09	-0.08	0.19***
	(1.42)	(-0.18)	(-0.51)	(3.13)
Germany	0.07	-0.30	-0.04	-0.00
	(0.49)	(-0.65)	(-0.61)	(-0.05)
Italy	0.24	1.50**	-0.03	0.13*
	(1.21)	(2.21)	(-0.37)	(1.81)
Japan	-0.6	1.52	-0.10	-0.1
	(-1.56)	(1.43)	(-1.60)	(-1.27)
Netherlands	-0.48**	0.78**	-0.09	0.35***
	(-2.26)	(2.03)	(-0.68)	(3.75)
Switzerland	0.30*	-0.13	-0.03	0.20**
	(1.77)	(-0.41)	(-0.47)	(2.47)
United Kingdom	0.00	0.75*	-0.04	0.11**
	(0.03)	(1.70)	(-0.39)	(2.03)

Table 15
Regressions of 10 countries' portfolio returns with winter month dummy

The long-short portfolios are formed based on firm book-to-market ratio (BM/ME). Regressions of long-short portfolio returns on lagged ELNINO, WINTER dummy variable, SENTIMENT, and the market risk premium (RMKT).

$$R_{X_{i,t+1}=High,t+1} - R_{X_{i,t}=Low,t+1} = \beta_{i.0} + \beta_{i,E}ELNINO_t + \beta_{i,EM1}ELNINO_t * M1_t + \beta_{i,EM2}ELNINO_t * M2_t + \beta_{i,EM3}ELNINO_t * M3_t + \beta_{i,SENT}SENT_t + \beta_{i,RMKT}RMKT_{i,t+1} + \varepsilon_{i,t+1} \quad (17)$$

Where dependent variable is the monthly county *i*'s value stategy return (long high BE/ME stocks and short low BE/ME stocks), ELNINO is the El Nino anomaly measure. M1/M2/M3 is the dummy variable equals 1 if it is in December/January/February (June/July/August in Australia) respectively, 0 otherwise. Heteroskedasticity and autocorrelation consistent t-statistics are reported in parentheses. *, **, *** denote significance level at 10%, 5%, and 1% respectively. Data are from K. French data library. The sample period is from 1982:01 to 2014:12.

(1) Country *i*	(2) $\widehat{\beta_{i,E}}$	(3) $\widehat{\beta_{i,EM1}}$	(4) $\widehat{\beta_{i,EM2}}$	(5) $\widehat{\beta_{i,EM3}}$	(6) $\widehat{\beta_{i,SENT}}$	(7) $\widehat{\beta_{i,RMKT}}$
Australia	0.61***	0.45	-0.65	-0.67	0.03	-0.09**
	(2.83)	(0.47)	(-1.06)	(-0.94)	(0.26)	(-2.36)
Belgium	-0.04	-0.63	-0.16	-0.26	0.02	0.15*
	(-0.25)	(-0.88)	(-0.27)	(-0.39)	(0.32)	(1.88)
Canada	-0.11	1.54***	0.92	0.13	-0.07	-0.11
	(-0.65)	(3.14)	(0.70)	(0.17)	(-1.22)	(-1.23)
France	0.31	-0.05	-0.54	0.72	-0.07	0.20***
	(1.44)	(-0.05)	(-0.69)	(0.90)	(-0.43)	(3.28)
Germany	0.06	-1.57	0.83	0.75	-0.05	-0.02
	(0.42)	(-1.44)	(1.46)	(0.91)	(-0.71)	(-0.30)
Italy	0.24	2.20**	0.39	1.84**	-0.03	0.12*
	(1.20)	(2.18)	(0.51)	(2.04)	(-0.37)	(1.81)
Japan	-0.61	1.83	2.55***	-1.00	-0.10*	-0.10
	(-1.53)	(0.95)	(3.04)	(-1.04)	(-1.63)	(-1.33)
Netherlands	-0.48**	0.32	1.73	0.49	-0.09	0.36***
	(-2.22)	(0.48)	(1.47)	(0.44)	(-0.70)	(3.90)
Switzerland	0.29*	-0.78*	-0.24	1.61***	-0.04	0.21***
	(1.76)	(-1.63)	(-0.45)	(3.68)	(-0.48)	(2.61)
United Kingdom	0.00	0.73	0.31	1.59*	-0..04	0.12**
	(0.04)	(0.97)	(0.51)	(1.82)	(-0.40)	(2.12)

Table 16
Regressions of 10 US portfolio returns with winter dummy

The table reports OLS estimation of the predictive model

$R_{X_{i,t+1}=High,t+1} - R_{X_{i,t}=Low,t+1} = \beta_{i.0} + \beta_{i,E}ELNINO_t + \beta_{i,EW}ELNINO_t * WINTER_t + \beta_{i,SENT}SENT_t + \beta_{i,RMKT}RMKT_{i,t+1} + +\beta_{i,SMB}SMB_{t+1} + \beta_{i,HML}HML_{t+1} + \beta_{i,MOM}MOM_{t+1} + \varepsilon_{i,t+1}$ (18)

The long-short portfolios are formed based on firm characteristics (X). Regressions of long-short portfolio returns on lagged ELNINO, WINTER dummy variable, SENTIMENT, and the market risk premium (RMRF), the Fama-French factors (SMB and HML), and a momentum factor (MOM). SMB (HML) is not included as a control variable when long-short portfolios are formed based on ME (BE/ME). $ELNINO_t$ is the El Nino anomaly measure. $WINTER_t$ *is* a dummy variable equals 1 if it is in December/January/February, 0 otherwise. Heteroskedasticity and autocorrelation consistent t-statistics are reported in parentheses. *, **, *** denote significance level at 10%, 5%, and 1% respectively. Data are from K. French data library. The sample period is from 1982:01 to 2014:12.

(1) Portfolio X	(2) $\widehat{\beta_{i,E}}$	(3) $\widehat{\beta_{i,EW}}$	(4) $\widehat{\beta_{i,SENT}}$	(5) $\widehat{\beta_{i,RMKT}}$	(6) $\widehat{\beta_{i,MOM}}$	(7) $\widehat{\beta_{i,SMB}}$	(8) $\widehat{\beta_{i,HML}}$
ME	0.02	-0.04	0.04	-0.15***	-0.04		
	(0.13)	(-0.10)	(0.11)	(-3.04)	(-0.34)		
BE/ME	0.1	-0.18	0.54**	-0.14*	-0.16**		
	(1.02)	(-0.77)	(2.15)	(-1.87)	(-2.09)		
σ	0.01	-0.26	-0.59**	0.60***	-0.37***	0.99***	-0.59***
	(0.03)	(-0.85)	(-2.47)	(7.18)	(-4.24)	(9.67)	(-3.32)
OPP	-0.08	0.09	0.46***	-0,12***	0.07*	-0.43***	-0.09
	(-1.08)	(0.58)	(3.09)	(-2.86)	(1.77)	(-8.10)	(-1.33)
ACC	0.01	0.12	-0.19	0.02	-0.01	0.17***	0.15
	(0.13)	(0.58)	(-1.00)	(0.37)	(-0.11)	(3.06)	(1.48)
β	-0.02	-0.36	-0.56**	0.60***	-0.22***	0.65***	-0.51***
	(-0.15)	(-1.18)	(-2.49)	(10.56)	(-4.13)	(7.99)	(-4.52)
NSI	0.11	0.01	-0.31	0.19***	-0.11***	0.31***	-0.19*
	(0.89)	(0.03)	(-1.24)	(6.21)	(-3.57)	(8.35)	(-1.79)
E/P	-0.08	-0.1	0.21	-0.00	-0.01	0.07	0.74***
	(-0.89)	(-0.61)	(1.49)	(-0.13)	(-0.30)	(1.41)	(16.42)
CF/P	-0.11*	0.14	0.06	-0.07***	0.02	0.06	0.73***
	(-1.72)	(1.03)	(0.47)	(-3.06)	(0.82)	(1.28)	(13.84)
D/P	0.07	0.18	0.13	-0.24***	-0.06	-0.09	0.57***
	(0.74)	(0.87)	(0.87)	(-6.05)	(-1.47)	(-1.11)	(7.54)

Table 17
Regressions of 10 US portfolio returns with winter month dummy

The table reports OLS estimation of the predictive model

$$R_{X_{i,t+1}=High,t+1} - R_{X_{i,t}=Low,t+1} = \beta_{i.0} + \beta_{i,E}ELNINO_t + \beta_{i,EM1}ELNINO_t * M1_t + \beta_{i,EM2}ELNINO_t * M2_t + \beta_{i,EM3}ELNINO_t * M3_t + \beta_{i,SENT}SENT_t + \beta_{i,RMKT}RMKT_{i,t+1} + +\beta_{i,SMB}SMB_{t+1} + \beta_{i,HML}HML_{t+1} + \beta_{i,MOM}MOM_{t+1} + \varepsilon_{i,t+1} \quad (19)$$

The long-short portfolios are formed based on firm characteristics (X). Regressions of long-short portfolio returns on lagged ELNINO, winter month dummy, SENT, and the market risk premium (RMRF), the Fama-French factors (SMB and HML), and a momentum factor (MOM). SMB (HML) is not included as a control variable when long-short portfolios are formed based on ME (BE/ME). $ELNINO_t$ is the El Nino anomaly measure. M1/M2/M3 is a dummy variable equals 1 if it is in December/January/February respectively, 0 otherwise. Heteroskedasticity and autocorrelation consistent t-statistics are reported in parentheses. *, **, *** denote significance level at 10%, 5%, and 1% respectively. Data are from K. French data library. The sample period is from 1982:01 to 2014:12.

(1) Portfolio X	(2) $\widehat{\beta_{i,E}}$	(3) $\widehat{\beta_{i,EM1}}$	(4) $\widehat{\beta_{i,EM2}}$	(5) $\widehat{\beta_{i,EM3}}$	(6) $\widehat{\beta_{i,SENT}}$	(7) $\widehat{\beta_{i,RMKT}}$	(8) $\widehat{\beta_{i,MOM}}$	(9) $\widehat{\beta_{i,SMB}}$	(10) $\widehat{\beta_{i,HML}}$
ME	0.02	-0.14	0.33	-0.49	0.03	-0.15***	-0.05		
	(0.12)	(-0.25)	(0.58)	(-0.99)	(0.08)	(-2.96)	(-0.38)		
BE/ME	0.1	0.06	-0.67**	0.02	0.54**	-0.14*	-0.17**		
	(1.01)	(0.11)	(-1.98)	(0.06)	(2.16)	(-1.90)	(-2.30)		
σ	0.01	0.00	-0.30	-0.69	-0.60**	0.60***	-0.35***	0.99***	-0.57***
	(0.04)	(0.01)	(-0.79)	(-1.33)	(-2.50)	(7.10)	(-3.97)	(9.77)	(-3.27)
OPP	-0.08	0.08	0.03	0.2	0.46***	-0.12***	0.07	-0.43***	-0.10
	(-1.09)	(0.39)	(0.15)	(0.48)	(3.12)	(-2.85)	(1.61)	(-8.17)	(-1.36)
ACC	0.01	-0.11	0.19	0.45	-0.18	0.02	-0.01	0.16***	0.15
	(0.12)	(-0.27)	(0.54)	(1.40)	(-0.96)	(0.35)	(-0.22)	(3.12)	(1.48)
β	-0.02	-0.08	-0.38	-0.85**	-0.57**	0.61***	-0.21***	0.65***	-0.50***
	(-0.16)	(-0.26)	(-0.86)	(-2.01)	(-2.54)	(10.50)	(-3.85)	(8.12)	(-4.42)
NSI	0.11	-0.12	0.38	-0.23	-0.31	0.19***	-0.10***	0.31***	-0.18*
	(0.89)	(-0.37)	(1.53)	(-0.51)	(-1.25)	(6.13)	(-3.29)	(8.44)	(-1.71)
E/P	-0.08	-0.08	-0.16	-0.07	0.21	-0.00	-0.01	0.07	0.74***
	(-0.89)	(-0.26)	(-0.74)	(-0.26)	(1.49)	(-0.10)	(-0.31)	(1.39)	(16.20)
CF/P	-0.11*	0.43	-0.53***	0.57*	0.07	-0.06***	0.02	0.06	0.73***
	(-1.78)	(1.39)	(-2.98)	(1.77)	(0.50)	(-2.97)	(0.73)	(1.28)	(13.78)
D/P	0.07	0.48	-0.64**	0.77**	0.14	-0.24***	-0.06*	-0.09	0.56***
	(0.75)	(1.12)	(-2.03)	(2.30)	(0.92)	(-6.04)	(-1.63)	(-1.10)	(7.63)

Table 18
Regressions of 6 Japanese portfolio excess returns with winter dummy

The table reports OLS estimation of the predictive model

$$r_{i,t+1} = \beta_{i.0} + \beta_{i,E} ELNINO_t + \beta_{i,EW} ELNINO_t * WINTER_t + \beta_{i,SENT} SENT_t + \beta_{i,RMKT} RMKT_{i,t+1} + \beta_{i,MOM} MOM_{t+1} + \varepsilon_{i,t+1} \quad (20)$$

The portfolios are formed based on size (BE) and book-to-market ratio (BE/ME). Big stocks are in the top 90% of June market capitalization, small stocks are those in the bottom 10%. The BE/ME breakpoints for big and small stocks are the 30% and 70% percentiles of the BE/ME. Regressions of portfolio excess returns on lagged ELNINO, WINTER dummy variable, SENT, and the market risk premium (RMKT), and a momentum factor (MOM). ELNINO is the El Niño anomaly measure. WINTER is the dummy variable equals 1 if it is in Decemer/Janary/February, 0 otherwise. Heteroskedasticity and autocorrelation consistent t-statistics are reported in parentheses. *, **, *** denote significance level at 10%, 5%, and 1% respectively. Data are from K. French data library. The sample period is from 1990:11 to 2014:12.

(1) Portfolio *i*	(2) $\widehat{\beta_{i,E}}$	(3) $\widehat{\beta_{i,EW}}$	(4) $\widehat{\beta_{i,SENT}}$	(5) $\widehat{\beta_{i,RMKT}}$	(6) $\widehat{\beta_{i,MOM}}$
Small Size	-0.27	0.71	-0.11**	1.13***	-0.02
Low BM	(-0.94)	(1.09)	(-2.54)	(32.46)	(-0.19)
Small Size	-0.13	0.75	-0.05	0.98***	-0.12
Middle BM	(-0.34)	(1.24)	(-1.54)	(31.69)	(-1.21)
Small Size	-0.16	0.74	-0.08*	0.98***	-0.13
High BM	(-0.33)	(1.07)	(-1.66)	(24.07)	(-1.05)
Large Size	0.10	-0.19	0.01	1.04***	0.06
Low BM	(0.47)	(-0.66)	(0.27)	(33.01)	(1.06)
Large Size	-0.02	-0.14	0.03**	0.94***	-0.07**
Middle BM	(-0.17)	(-1.16)	(2.46)	(46.46)	(-2.59)
Large Size	-0.03	0.27	-0.02	0.98***	-0.10
High BM	(-0.10)	(0.63)	(-0.81)	(23.38)	(-0.63)

Table 19

Regressions of 6 Japanese portfolio excess returns with winter month dummy

The table reports OLS estimation of the predictive model

$$r_{i,t+1} = \beta_{i.0} + \beta_{i,E}ELNINO_t + \beta_{i,EM1}ELNINO_t * M1_t + \beta_{i,EM2}ELNINO_t * M2_t + \beta_{i,EM3}ELNINO_t * M3_t + \beta_{i,SENT}SENT_t + \beta_{i,RMKT}RMKT_{i,t+1} + \beta_{i,MOM}MOM_{t+1} + \varepsilon_{i,t+1} \quad (21)$$

The portfolios are formed based on size (BE) and book-to-market ratio (BE/ME). Big stocks are in the top 90% of June market capitalization, small stocks are those in the bottom 10%. The BE/ME breakpoints for big and small stocks are the 30% and 70% percentiles of the BE/ME. Regressions of portfolio excess returns on lagged ELNINO, WINTER dummy variable, SENT, and the market risk premium (RMKT), and a momentum factor (MOM). ELNINO is the El Niño anomaly measure. M1/M2/M3 is the dummy variable equals 1 if it is in Decemer/Janary/February respectively, 0 otherwise. Heteroskedasticity and autocorrelation consistent t-statistics are reported in parentheses. *, **, *** denote significance level at 10%, 5%, and 1% respectively. Data are from K. French data library. The sample period is from 1990:11 to 2014:12.

(1) Portfolio *i*	(2) $\widehat{\beta_{i,E}}$	(3) $\widehat{\beta_{i,EM1}}$	(4) $\widehat{\beta_{i,EM2}}$	(5) $\widehat{\beta_{i,EM3}}$	(6) $\widehat{\beta_{i,SENT}}$	(7) $\widehat{\beta_{i,RMKT}}$	(8) $\widehat{\beta_{i,MOM}}$
Small Size	-0.30	1.62*	0.63	-1.08*	-0.11**	1.13***	0.00
Low BM	(-0.96)	(1.92)	(0.76)	(-1.79)	(-2.54)	(32.98)	(0.05)
Small Size	-0.16	1.29	0.93**	-0.66	-0.05	0.98***	-0.10
Middle BM	(-0.37)	(1.33)	(2.19)	(-1.08)	(-1.62)	(31.67)	(-1.09)
Small Size	-0.18	1.10	1.12*	-0.63	-0.08*	0.98***	-0.11
High BM	(-0.36)	(1.10)	(1.83)	(-1.08)	(-1.73)	(23.77)	(-0.95)
Large Size	0.09	-0.09	-0.12	-0.49	0.00	1.04***	0.07
Low BM	(0.45)	(-0.21)	(-0.49)	(-1.39)	(0.26)	(32.58)	(1.11)
Large Size	-0.01	-0.19	-0.33***	0.25	0.03**	0.94***	-0.08***
Middle BM	(-0.11)	(-0.97)	(-2.61)	(1.00)	(2.50)	(44.88)	(-2.65)
Large Size	-0.03	-0.08	0.59**	0.47	-0.02	0.98***	-0.11
High BM	(-0.09)	(-0.12)	(2.23)	(0.89)	(-0.80)	(23.69)	(-1.10)

Table 20

Regressions of 10 US portfolio return: GJR GARCH-in-Mean model with winter dummy

This table reports the results from the GJR GARCH-in-Mean model using 10 US long-short portfolio returns.

$$R_{X_{i,t+1=High,t+1}} - R_{X_{i,t+1=Low,t+1}} = a_0 + a_1\sigma^2_{i,t+1} + a_2 ELNINO_t + a_3 ELNINO_t * WINTER_t + a_4 SENT_t + a_5 RMKT_{t+1} + a_6 MOM_{t+1} + a_7 SMB_{t+1} + a_8 HML_{t+1} + \epsilon_{i,t+1} \quad (24)$$

$$\sigma^2_{i,t+1} = b_0 + b_1\sigma^2_{i,t} + b_2\epsilon^2_{i,t} + b_3 I^-_{i,t}\epsilon^2_{i,t} + b_4 RF_t \quad (25)$$

The long-short portfolios are formed based on firm characteristics (X): firm size (ME), book-to-market ratio (BE/ME), total risk (σ), operating profitability (OPP), Accruals (ACC), market beta (β), net share issues (NSI), earnings/price (E/P), cash flow/price (CF/P), dividend yield (D/P). High is defined as a firm in the top 30 percentile, low is defined as a firm in the bottom 30 percentile. ELNINO is the El Niño anomaly measure. WINTER is the dummy variable equals 1 if it is in Decemer/Janary/February, 0 otherwise. The Bollerslev and Wooldridge robust t-statistics are reported in parenthesis. The sample period is from 1982:01 to 2014:12.

Portfolio X	a_0	a_1	a_2	a_3	a_4	a_5	a_6	a_7	a_8	b_0	b_1	b_2	b_3	b_4
ME	0.32	-0.02	-0.02	-0.04	0.38	-0.16***	0.06			0.56*	0.79***	0.17*	-0.01	0.51
	(1.18)	(-0.81)	(-0.14)	(-0.09)	(1.37)	(-3.71)	(1.34)			(1.77)	(8.98)	(1.82)	(-0.14)	(0.75)
BE/ME	-0.17	0.06	0.09	-0.14	0.24	-0.12***	-0.17***			0.91	0.71***	0.23***	-0.09	-0.31
	(-0.62)	(1.50)	(0.78)	(-0.59)	(0.86)	(-3.71)	(-5.20)			(1.61)	(6.98)	(2.72)	(-1.17)	(-0.45)
σ	-0.44**	0.01	-0.02	-0.13	-0.71***	0.43***	-0.27***	1.12***	-0.42***	1.09**	0.68***	0.28***	-0.04	-0.82
	(-2.19)	(0.35)	(-0.14)	(-0.48)	(-3.89)	(12.05)	(-7.58)	(18.40)	(-7.50)	(2.05)	(11.91)	(3.46)	(-0.36)	(-1.43)
OPP	0.08	0.07	-0.00	-0.05	0.31**	-0.08***	0.09***	-0.42***	-0.22***	0.22	0.75***	0.15**	0.06	-0.03
	(0.66)	(1.60)	(--0.03)	(-0.33)	(2.31)	(-3.92)	(4.29)	(-12.85)	(-6.95)	(1.56)	(9.48)	(2.35)	(0.71)	(-0.17)
ACC	-0.32	0.01	0.02	0.04	0.09	0.04	-0.02	0.18***	-0.04	0.53	0.76***	0.16**	-0.00	-0.39
	(-1.57)	(0.19)	(0.26)	(0.22)	(0.78)	(1.44)	(-0.52)	(4.19)	(-1.05)	(1.61)	(9.45)	(2.46)	(-0.01)	(-1.22)
β	0.00	0.00	-0.07	-0.05	-0.64***	0.51***	-0.28***	0.74***	-0.48***	1.31*	0.74***	0.22***	-0.10	-1.11
	(0.02)	(0.12)	(-0.61)	(-0.18)	(-3.07)	(15.79)	(-7.78)	(12.01)	(-8.43)	(1.76)	(9.50)	(2.82)	(-1.12)	(-1.37)
NSI	0.61***	-0.24***	-0.08	0.03	0.12	0.14***	-0.11***	0.38***	-0.02	0.06	0.96***	0.09***	-0.14***	0.03
	(3.07)	(-5.65)	(-1.37)	(0.09)	(1.02)	(6.07)	(-4.35)	(9.48)	(-0.61)	(0.96)	(68.25)	(25.60)	(-23.01)	(0.43)
E/P	-0.55***	0.18***	-0.03	-0.20	0.17	0.01	0.01	-0.01	0.79***	0.15	0.87***	0.01	0.14***	-0.04
	(-3.14)	(2.75)	(-0.45)	(-1.21)	(1.55)	(0.61)	(0.62)	(-0.44)	(21.12)	(1.55)	(18.79)	(0.42)	(2.93)	(-0.39)
CF/P	0.03	-0.01	-0.11	0.17	-0.01	-0.05***	-0.01	0.03	0.80***	0.03	0.90***	0.13**	-0.11	0.15*
	(0.18)	(-0.09)	(-1.32)	(0.77)	(-0.05)	(-2.63)	(-0.28)	(1.04)	(22.33)	(0.46)	(22.08)	(2.53)	(-1.58)	(1.78)
D/P	0.15	-0.01	0.03	0.28	0.09	-0.17***	-0.08***	-0.23***	0.66***	0.35	0.80***	0.19***	-0.07	-0.28
	(1.03)	(-0.24)	(0.32)	(0.98)	(0.70)	(-6.41)	(-3.15)	(-6.01)	(15.39)	(1.29)	(11.56)	(3.21)	(-0.72)	(-0.99)

Table 21

Regressions of 10 US portfolio return: GJR GARCH-in-Mean model with winter month dummy

This table reports the results from the GJR GARCH-in-Mean model using 10 US long-short portfolio returns.

$$R_{X_{i,t+1=High,t+1}} - R_{X_{i,t+1=Low,t+1}} = a_0 + a_1\sigma^2_{i,t+1} + a_2 ELNINO_t + a_3 ELNINO_t * M1_t + a_4 ELNINO_t * M2_t + a_5 ELNINO_t * M3_t + a_6 SENT_t + a_7 RMKT_{t+1} + a_8 MOM_{t+1} + a_9 SMB_{t+1} + a_{10} HML_{t+1} + \epsilon_{i,t+1} \quad (26)$$

$$\sigma^2_{i,t+1} = b_0 + b_1\sigma^2_{i,t} + b_2\epsilon^2_{i,t} + b_3 I^-_{i,t}\epsilon^2_{i,t} + b_4 RF_t \quad (27)$$

The long-short portfolios are formed based on firm characteristics (X): firm size (ME), book-to-market ratio (BE/ME), total risk (σ), operating profitability (OPP), Accruals (ACC), market beta (β), net share issues (NSI), earnings/price (E/P), cash flow/price (CF/P), dividend yield (D/P). High is defined as a firm in the top 30 percentile, low is defined as a firm in the bottom 30 percentile. ELNINO is the El Niño anomaly measure. M1/M2/M3 are the dummy variables equals1 1 if it is in Decemer/Janary/February respectively, 0 otherwise. The Bollerslev and Wooldridge robust t-statistics are reported in parenthesis. The sample period is from 1982:01 to 2014:12.

Portfolio X	a_0	a_1	a_2	a_3	a_4	a_5	a_6	a_7	a_8	a_9	a_{10}	b_0	b_1	b_2	b_3	b_4
ME	0.32	-0.02	-0.02	-0.22	0.25	-0.02	0.38	-0.16***	0.06			0.59*	0.78***	0.17*	-0.01	0.50
	(1.16)	(-0.82)	(-0.14)	(-0.37)	(0.39)	(-0.04)	(1.37)	(-3.69)	(1.39)			(1.81)	(8.86)	(1.82)	(-0.11)	(0.73)
BE/ME	-0.18	0.07	0.08	0.14	-0.61*	-0.16	0.24	-0.12***	-0.17***			0.91	0.71***	0.25***	-0.11	-0.34
	(-0.69)	(1.59)	(0.64)	(0.34)	(-1.76)	(-0.33)	(0.88)	(3.78)	(-5.36)			(1.60)	(7.02)	(2.82)	(-1.37)	(-0.49)
σ	-0.45**	0.01	-0.03	0.18	-0.41	-0.46	-0.73***	0.43***	-0.27***	1.12***	-0.41***	1.20**	0.66***	0.32***	-0.07	-0.95
	(-2.25)	(0.40)	(-0.26)	(0.53)	(-1.17)	(-1.11)	(-4.07)	(12.20)	(-7.78)	(18.83)	(-7.47)	(2.13)	(11.07)	(3.60)	(-0.71)	(-1.58)
OPP	0.09	0.07	-0.00	-0.03	-0.13	0.01	0.31**	-0.08***	0.09***	-0.42***	-0.22***	0.22	0.75***	0.15**	0.06	-0.04
	(0.69)	(1.59)	(-0.01)	(-0.15)	(-0.99)	(0.02)	(2.34)	(-3.90)	(4.26)	(-12.81)	(-6.98)	(1.56)	(9.52)	(2.35)	(0.71)	(-0.18)
ACC	-0.31	0.01	0.02	-0.10	0.20	0.20	0.10	0.04	-0.02	0.17***	-0.04	0.53	0.76***	0.16**	0.00	-0.38
	(-1.53)	(0.13)	(0.22)	(-0.28)	(0.69)	(0.69)	(0.86)	(1.42)	(-0.49)	(4.18)	(-1.01)	(1.60)	(9.53)	(2.43)	(0.04)	(-1.20)
β	0.01	0.00	-0.07	0.12	-0.18	-0.28	-0.65***	0.51***	-0.28***	0.73***	-0.49***	1.33*	0.74***	0.22***	-0.10	-1.14
	(0.05)	(0.11)	(-0.55)	(0.37)	(-0.49)	(-0.71)	(-3.10)	(15.78)	(-7.75)	(12.04)	(-8.43)	(1.77)	(9.39)	(2.79)	(-1.14)	(-1.38)
NSI	0.62***	-0.25***	-0.05	0.07	0.45	-0.77*	0.03	0.16***	-0.10***	0.38***	0.00	0.11*	0.95***	0.10***	-0.16***	0.00
	(4.35)	(-13.63)	(-0.78)	(0.16)	(0.65)	(-1.96)	(0.26)	(6.83)	(-3.82)	(9.50)	(0.07)	(1.82)	(65.05)	(29.57)	(-7.16)	(0.03)
E/P	-0.55***	0.18***	-0.03	-0.19	-0.25	-0.14	0.18	0.01	0.01	-0.01	0.79***	0.16	0.87***	0.01	0.14***	-0.04
	(-3.12)	(2.72)	(-0.46)	(-0.76)	(-0.78)	(-0.56)	(1.57)	(0.59)	(0.61)	(-0.44)	(21.09)	(1.55)	(18.67)	(0.46)	(2.89)	(-0.40)
CF/P	-0.00	0.01	-0.11	0.62*	-0.52**	0.15	-0.01	-0.05**	-0.01	0.02	0.80***	0.02	0.90***	0.13**	-0.10	0.13
	(-0.01)	(0.10)	(-1.28)	(1.94)	(-1.96)	(0.39)	(-0.04)	(-2.43)	(-0.36)	(0.79)	(23.27)	(0.36)	(24.04)	(2.45)	(-1.46)	(1.55)
D/P	0.13	-0.00	-0.01	0.90***	-1.00***	0.62	0.07	-0.15***	-0.09***	-0.26***	0.69***	0.30	0.81***	0.22***	-0.12	-0.26
	(.094)	(-0.09)	(-0.11)	(2.89)	(-2.78)	(1.34)	(0.62)	(-6.03)	(-3.60)	(-7.29)	(17.22)	(1.26)	(13.57)	(3.56)	(-1.28)	(-0.98)

Table 22
Regressions of 10 US portfolio returns: GARCH (1, 1) model with winter dummy

This table reports the results from the GARCH (1, 1) model using 10 US long-short portfolio returns.

$$R_{X_{i,t+1=High,t+1}} - R_{X_{i,t+1=Low,t+1}} = a_0 + a_1 ELNINO_t + a_2 ELNINO_t * WINTER_t + a_3 SENT_t + a_4 RMKT_{t+1} + a_5 MOM_{t+1} + a_6 SMB_{t+1} + a_7 HML_{t+1} + \epsilon_{i,t+1} \quad (28)$$

$$\sigma^2_{i,t+1} = b_0 + b_1 \sigma^2_{i,t} + b_2 \epsilon^2_{i,t} + b_3 ELNINO_t \quad (29)$$

The long-short portfolios are formed based on firm characteristics (X): firm size (ME), book-to-market ratio (BE/ME), total risk (σ), operating profitability (OPP), Accruals (ACC), market beta (β), net share issues (NSI), earnings/price (E/P), cash flow/price (CF/P), dividend yield (D/P). High is defined as a firm in the top 30 percentile, low is defined as a firm in the bottom 30 percentile. ELNINO is the El Niño anomaly measure. WINTER is the dummy variable equals 1 if it is in Decemer/Janary/February, 0 otherwise. The Bollerslev and Wooldridge robust t-statistics are reported in parenthesis. The sample period is from 1982:01 to 2014:12.

Portfolio X	a_1	a_2	b_3
ME	-0.06	-0.04	0.08
	(-0.35)	(-0.09)	(0.34)
BE/ME	0.12	-0.25	0.30**
	(1.07)	(-1.00)	(2.20)
σ	0.02	-0.16	0.18
	(0.12)	(-0.59)	(1.08)
OPP	0	-0.04	-0.01
	(0.02)	(-0.28)	(-0.24)
ACC	0.03	0.04	-0.02
	(0.35)	(0.17)	(-0.33)
β	-0.03	-0.11	0.21
	(-0.23)	(-0.44)	(1.66)
NSI	0.02	0.01	0.08
	(0.19)	(0.06)	(1.27)
E/P	-0.05	-0.14	0.05
	(-0.71)	(-0.77)	(0.94)
CF/P	-0.08	0.17	0.07
	(-0.94)	(0.78)	(1.14)
D/P	0.04	0.24	0.03
	(0.40)	(0.89)	(0.48)

Table 23
Regressions of 10 US portfolio returns: GARCH (1, 1) model with winter month dummy

This table reports the results from the GARCH (1, 1) model using 10 US long-short portfolio returns.

$$R_{X_{i,t+1=High,t+1}} - R_{X_{i,t+1}=Low,t+1} = a_0 + a_1 ELNINO_t + a_2 ELNINO_t * M1_t + a_3 ELNINO_t * M2_t + a_4 ELNINO_t * M3_t + a_5 SENT_t + a_6 RMKT_{t+1} + a_7 MOM_{t+1} + a_8 SMB_{t+1} + a_9 HML_{t+1} + \epsilon_{i,t+1} \quad (30)$$

$$\sigma^2_{i,t+1} = b_0 + b_1\sigma^2_{i,t} + b_2\epsilon^2_{i,t} + b_3 ELNINO_t \quad (31)$$

The long-short portfolios are formed based on firm characteristics (X): firm size (ME), book-to-market ratio (BE/ME), total risk (σ), operating profitability (OPP), Accruals (ACC), market beta (β), net share issues (NSI), earnings/price (E/P), cash flow/price (CF/P), dividend yield (D/P). High is defined as a firm in the top 30 percentile, low is defined as a firm in the bottom 30 percentile. ELNINO is the El Niño anomaly measure. M1/M2/M3 are the dummy variables equals1 1 if it is in Decemer/Janary/February respectively, 0 otherwise. The Bollerslev and Wooldridge robust t-statistics are reported in parenthesis. The sample period is from 1982:01 to 2014:12.

Portfolio X	a_1	a_2	a_3	a_4	b_3
ME	-0.06	-0.23	0.28	-0.05	0.09
	(-0.34)	(-0.39)	(0.44)	(-0.10)	(0.36)
BE/ME	0.11	0.08	-0.74*	-0.50	0.31**
	(1.01)	(0.21)	(-1.72)	(-0.73)	(2.28)
σ	0.01	0.02	-0.30	-0.35	0.16
	(0.05)	(0.06)	(-0.78)	(-0.80)	(0.95)
OPP	0.00	-0.02	-0.16	0.03	-0.01
	(0.04)	(-0.10)	(-1.20)	(0.07)	(-0.20)
ACC	0.03	-0.12	0.21	0.22	-0.02
	(0.32)	(-0.34)	(0.70)	(0.76)	(-0.38)
β	-0.03	-0.03	-0.18	-0.20	0.20
	(-0.22)	(-0.08)	(-0.43)	(-0.49)	(1.62)
NSI	0.02	-0.05	0.39	-0.36	0.07
	(0.20)	(-0.20)	(1.56)	(-0.75)	(1.22)
E/P	-0.05	-0.06	-0.29	-0.07	0.05
	(-0.73)	(-0.22)	(-0.95)	(-0.27)	(0.96)
CF/P	-0.08	0.60**	-0.54	0.35	0.06
	(-1.05)	(2.41)	(-1.61)	(0.59)	(1.63)
D/P	0.01	0.84**	-0.93***	0.60	0.02
	(0.09)	(2.38)	(-2.71)	(1.34)	(0.30)

Table 24

Regressions of 6 Japanese portfolio excess return: GJR GARCH-in-Mean model with winter dummy

This table reports the results from the GJR GARCH-in-Mean model using 6 Japanese portfolio excess returns.

$$r_{i,t+1} = a_0 + a_1\sigma^2_{i,t+1} + a_2ELNINO_t + a_3ELNINO_t * WINTER_t + a_4SENT_t + a_5RMKT_{t+1} + a_6MOM_{t+1} + \epsilon_{i,t+1} \quad (32)$$

$$\sigma^2_{i,t+1} = b_0 + b_1\sigma^2_{i,t} + b_2\epsilon^2_{i,t} + b_3I^-_{i,t}\epsilon^2_{i,t} + b_4RF_t \quad (33)$$

The portfolios are formed based on size (BE) and book-to-market ratio (BE/ME). Big stocks are in the top 90% of June market capitalization, small stocks are those in the bottom 10%. The BE/ME breakpoints for big and small stocks are the 30% and 70% percentiles of the BE/ME. ELNINO is the El Niño anomaly measure. WINTER is the dummy variable equals 1 if it is in Decemer/Janary/February, 0 otherwise. $I^-_{i,t}$ is an indicator variable which equals 1 if the residual $\epsilon_{i,t}$ is negative, 0 otherwise. RF is the risk free interest rate. The Bollerslev and Wooldridge robust t-statistics are reported in parenthesis. The sample period is from 1990:11 to 2014:12.

Portfolio *i*	a_0	a_1	a_2	a_3	a_4	a_5	a_6	b_0	b_1	b_2	b_3	b_4
Small Size	10.89**	-0.02	0.03	0.16	-0.11**	1.11***	0.08	3.47*	0.36	0.12	0.2	10.31*
Low BM	(2.23)	(-0.49)	(0.10)	(0.32)	(-2.19)	(25.12)	(1.29)	(1.85)	(1.44)	(1.01)	(1.08)	(1.69)
Small Size	6.00*	-0.02	0.22	-0.19	-0.06*	0.97***	0.07*	1.31**	0.59***	-0.01	0.32**	3.61**
Middle BM	(1.77)	(-0.36)	(0.87)	(-0.50)	(-1.73)	(31.44)	(1.64)	(2.41)	(4.03)	(-0.25)	(2.25)	(1.98)
Small Size	11.56***	-0.01	-0.19	0.4	-0.11***	1.00***	0.08*	0.68**	0.83***	-0.01	0.19**	0.51
High BM	(3.10)	(-0.34)	(-0.75)	(0.98)	(-3.09)	(27.77)	(1.67)	(2.47)	(13.85)	(-0.35)	(2.35)	(0.78)
Large Size	-0.93	0.00	0.04	-0.16	0.01	1.00***	0.03*	0.26**	0.64***	0.31	-0.03	-0.10
Low BM	(-0.39)	(0.08)	(0.42)	(-0.91)	(0.35)	(66.88)	(1.72)	(2.10)	(4.89)	(1.45)	(-0.17)	(-0.36)
Large Size	-2.53*	0.13	0.04	-0.16	0.02	0.97***	-0.04**	0.04	0.83***	0.05	0.13	0.09
Middle BM	(-1.62)	(1.36)	(0.57)	(-1.33)	(1.58)	(85.26)	(-2.47)	(1.09)	(13.07)	(1.06)	(1.49)	(1.46)
Large Size	0.95	0.01	-0.06	0.2	-0.01	1.02***	-0.04	0.18	0.71***	0.35***	-0.17	0.34
High BM	(0.37)	(0.41)	(-0.25)	(0.59)	(-0.30)	(49.50)	(-0.89)	(1.12)	(8.55)	(2.96)	(-1.09)	(0.89)

Table 25

Regressions of 6 Japanese portfolio excess return: GJR GARCH-in-Mean model with winter month dummy

This table reports the results from the GJR GARCH-in-Mean model using 6 Japanese portfolio excess returns.

$$r_{i,t+1} = a_0 + a_1\sigma_{i,t+1}^2 + a_2 ELNINO_t + a_3 ELNINO_t * M1_t + a_4 ELNINO_t * M2_t + a_5 ELNINO_t * M3_t + a_6 SENT_t + a_7 RMKT_{t+1} + a_8 MOM_{t+1} + \epsilon_{i,t+1} \quad (34)$$

$$\sigma_{i,t+1}^2 = b_0 + b_1\sigma_{i,t}^2 + b_2\epsilon_{i,t}^2 + b_3 I_{i,t}^- \epsilon_{i,t}^2 + b_4 RF_t \quad (35)$$

The portfolios are formed based on size (BE) and book-to-market ratio (BE/ME). Big stocks are in the top 90% of June market capitalization, small stocks are those in the bottom 10%. The BE/ME breakpoints for big and small stocks are the 30% and 70% percentiles of the BE/ME. ELNINO is the El Niño anomaly measure. M1/M2/M3 are the dummy variables equals1 1 if it is in Decemer/Janary/February respectively, 0 otherwise. $I_{i,t}^-$ is an indicator variable which equals 1 if the residual $\epsilon_{i,t}$ is negative, 0 otherwise. RF is the risk free interest rate. The Bollerslev and Wooldridge robust t-statistics are reported in parenthesis. The sample period is from 1990:11 to 2014:12.

Portfolio *i*	a_0	a_1	a_2	a_3	a_4	a_5	a_6	a_7	a_8	b_0	b_1	b_2	b_3	b_4
Small Size	11.73**	-0.03	-0.02	0.83	0.8	-1.99***	-0.12**	1.10***	0.09	3.56**	0.3	0.12	0.24	11.89*
Low BM	(2.50)	(-0.72)	(-0.05)	(1.18)	(1.00)	(-3.04)	(-2.44)	(25.64)	(1.56)	(2.01)	(1.25)	(1.01)	(1.29)	(1.85)
Small Size	6.04*	-0.02	0.21	0.14	0.64	-1.76***	-0.06*	0.97***	0.07*	1.26**	0.57***	-0.01	0.33**	4.42**
Middle BM	(1.80)	(-0.49)	(0.84)	(0.26)	(1.46)	(-3.02)	(-1.74)	(31.74)	(1.70)	(2.27)	(3.74)	(-0.27)	(2.29)	(2.02)
Small Size	12.73***	0.01	-0.38*	1.27**	1.72*	-1.42	-0.13***	0.97***	0.06*	0.14*	1.01***	-0.12***	0.17***	-0.05
High BM	(6.17)	(0.56)	(-1.76)	(2.24)	(1.78)	(-1.08)	(-6.31)	(28.13)	(1.90)	(1.82)	(34.38)	(-5.38)	(7.01)	(-0.25)
Large Size	-0.51	-0.00	0.00	0.22	-0.14	-0.64**	0.00	1.00***	0.04**	0.22**	0.62***	0.34	0.00	-0.10
Low BM	(-0.23)	(-0.03)	(0.05)	(0.92)	(-0.58)	(-1.97)	(0.18)	(72.33)	(2.40)	(2.18)	(5.15)	(1.60)	(0.02)	(-0.45)
Large Size	-2.49	0.13	0.06	-0.35**	-0.40***	0.49**	0.02	0.97***	-0.05***	0.03	0.83***	0.05	0.13	0.11**
Middle BM	(-1.58)	(1.47)	(0.85)	(-2.24)	(-2.85)	(2.03)	(1.54)	(85.90)	(-2.93)	(1.12)	(14.20)	(1.00)	(1.49)	(2.00)
Large Size	0.90	0.01	-0.06	-0.10	0.60*	0.50	-0.01	1.02***	-0.04	0.17	0.71***	0.35***	-0.16	0.27
High BM	(0.35)	(0.40)	(-0.28)	(-0.23)	(1.78)	(1.10)	(-0.27)	(49.89)	(-0.99)	(1.10)	(9.12)	(2.96)	(-1.08)	(0.78)

Table 26

Regressions of 6 Japanese portfolio excess Return: GARCH (1, 1) model with winter dummy

This table reports the results from the GARCH (1, 1) model using 6 Japanese portfolio excess returns.

$$r_{i,t+1} = a_0 + a_1 ELNINO_t + a_2 ELNINO_t * WINTER_t + a_3 SENT_t + a_4 RMKT_{t+1} + a_5 MOM_{t+1} + \epsilon_{i,t+1} \tag{36}$$

$$\sigma_{i,t+1}^2 = b_0 + b_1 \sigma_{i,t}^2 + b_2 \epsilon_{i,t}^2 + b_3 ELNINO_t \tag{37}$$

The portfolios are formed based on size (BE) and book-to-market ratio (BE/ME). Big stocks are in the top 90% of June market capitalization, small stocks are those in the bottom 10%. The BE/ME breakpoints for big and small stocks are the 30% and 70% percentiles of the BE/ME. ELNINO is the El Niño anomaly measure. WINTER is the dummy variable equals 1 if it is in Decemer/Janary/February, 0 otherwise. The Bollerslev and Wooldridge robust t-statistics are reported in parenthesis. The sample period is from 1990:11 to 2014:12.

Portfolio X	a_1	a_2	b_3
Small Size	-0.10	0.29	0.30
Low BM	(-0.27)	(0.49)	(0.33)
Small Size	0.14	0.05	0.07
Middle BM	(0.50)	(0.12)	(0.29)
Small Size	-0.16	0.57	-0.12
High BM	(-0.59)	(1.34)	(-0.30)
Large Size	0.03	-0.15	0.05
Low BM	(0.32)	(-0.76)	(0.62)
Large Size	0.03	-0.18	0.01
Middle BM	(0.52)	(-1.40)	(0.56)
Large Size	-0.04	0.20	0.14
High BM	(-0.18)	(0.65)	(0.80)

Table 27
Regressions of 6 Japanese portfolio excess return: GARCH (1, 1) model with winter month dummy

This table reports the results from the GARCH (1, 1) model using 6 Japanese portfolio excess returns.

$$r_{i,t+1} = a_0 + a_1 ELNINO_t + a_2 ELNINO_t * M1_t + a_3 ELNINO_t * M2_t + a_4 ELNINO_t * M3_t + a_5 SENT_t + a_6 RMKT_{t+1} + a_7 MOM_{t+1} + \epsilon_{i,t+1} \quad (38)$$

$$\sigma^2_{i,t+1} = b_0 + b_1 \sigma^2_{i,t} + b_2 \epsilon^2_{i,t} + b_3 ELNINO_t \quad (39)$$

The portfolios are formed based on size (BE) and book-to-market ratio (BE/ME). Big stocks are in the top 90% of June market capitalization, small stocks are those in the bottom 10%. The BE/ME breakpoints for big and small stocks are the 30% and 70% percentiles of the BE/ME. ELNINO is the El Niño anomaly measure. M1/M2/M3 are the dummy variables equals1 1 if it is in Decemer/Janary/February respectively, 0 otherwise. The Bollerslev and Wooldridge robust t-statistics are reported in parenthesis. The sample period is from 1990:11 to 2014:12.

Portfolio X	a_1	a_2	a_3	a_4	b_3
Small Size	-0.15	1.14	0.62	-1.65***	0.02
Low BM	(-0.40)	(1.53)	(0.62)	(-2.64)	(0.02)
Small Size	0.11	0.46	0.63	-1.90***	0.01
Middle BM	(0.36)	(0.78)	(1.35)	(-3.12)	(0.03)
Small Size	-0.19	0.83	1.30**	-1.09*	-0.17
High BM	(-0.69)	(1.43)	(2.45)	(-1.78)	(-0.44)
Large Size	-0.00	0.26	-0.10	-0.67*	0.10
Low BM	(-0.05)	(1.09)	(-0.38)	(-1.88)	(1.43)
Large Size	0.04	-0.31**	-0.43***	0.50**	0.03
Middle BM	(0.53)	(-2.07)	(-2.89)	(2.13)	(1.45)
Large Size	-0.04	-0.16	0.56	0.60	0.15
High BM	(-0.16)	(-0.37)	(1.53)	(1.40)	(0.97)

Table 28 ANOVA Partial F-test: 1982:01 to 2014:12

The table reports ANOVA partial F-test results based on full model and reduced model:

Full model: $r_{i,t+1} = \beta_{i,0} + \beta_{i,b}TB_{i,t} + \beta_{i,d}DY_{i,t} + \beta_{i,i}r_{i,t} + \beta_{i,USA}r_{USA,t} + \beta_{i,E}ELNINO_t + \beta_{i,EW}ELNINO_t * WINTER_t + \varepsilon_{i,t+1}$
Reduced model: $r_{i,t+1} = \beta_{i,0} + \beta_{i,b}TB_{i,t} + \beta_{i,d}DY_{i,t} + \beta_{i,i}r_{i,t} + \beta_{i,USA}r_{USA,t} + \varepsilon_{i,t+1}$

Country	F-Value	P-Value
Australia	0.91	0.40
Belgium	2.50	0.08*
Canada	1.44	0.24
France	3.16	0.04**
Germany	1.58	0.21
Italy	3.92	0.02**
Japan	2.51	0.08*
Malaysia	5.93	0.00***
Netherlands	2.58	0.08*
South Africa	2.40	0.09*
Sweden	4.64	0.01***
Switzerland	1.51	0.22
United Kingdom	1.31	0.27
United States	1.65	0.19

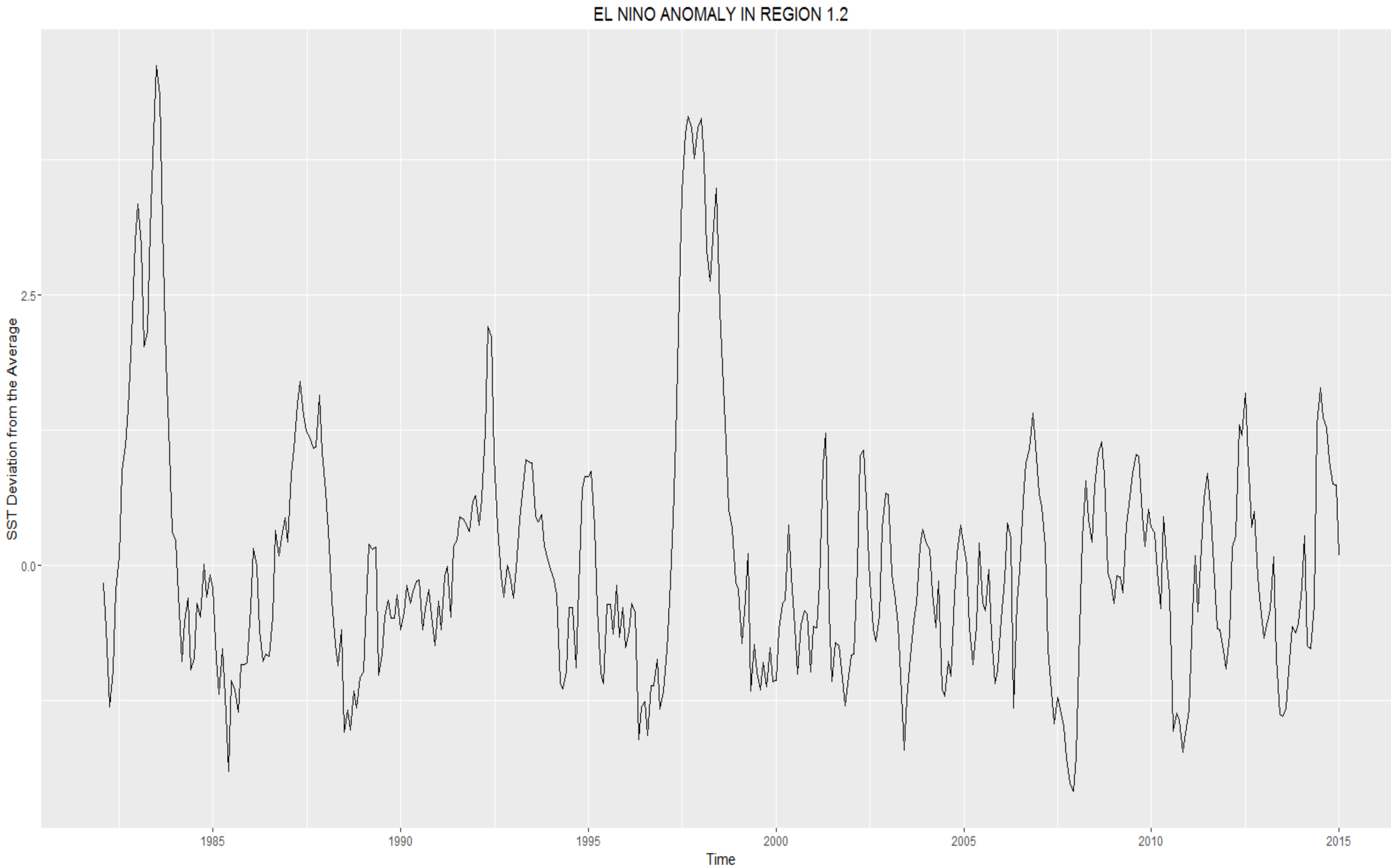

Figure 1 Monthly sea surface temperature anomaly from the average measured over a 1981-2010 base period in region 1+2

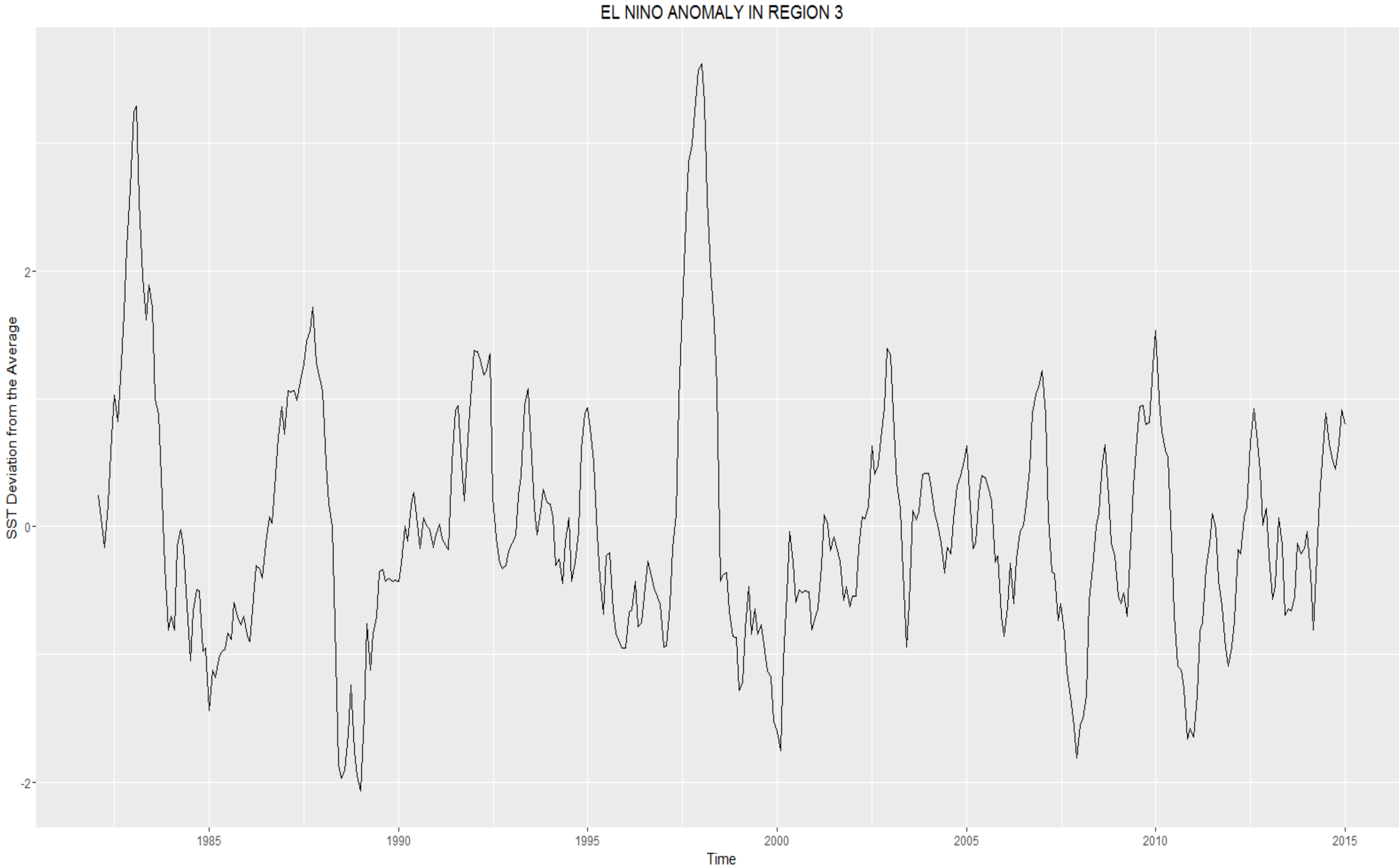

Figure 2 Monthly sea surface temperature anomaly from the average measured over a 1981-2010 base period in region 3

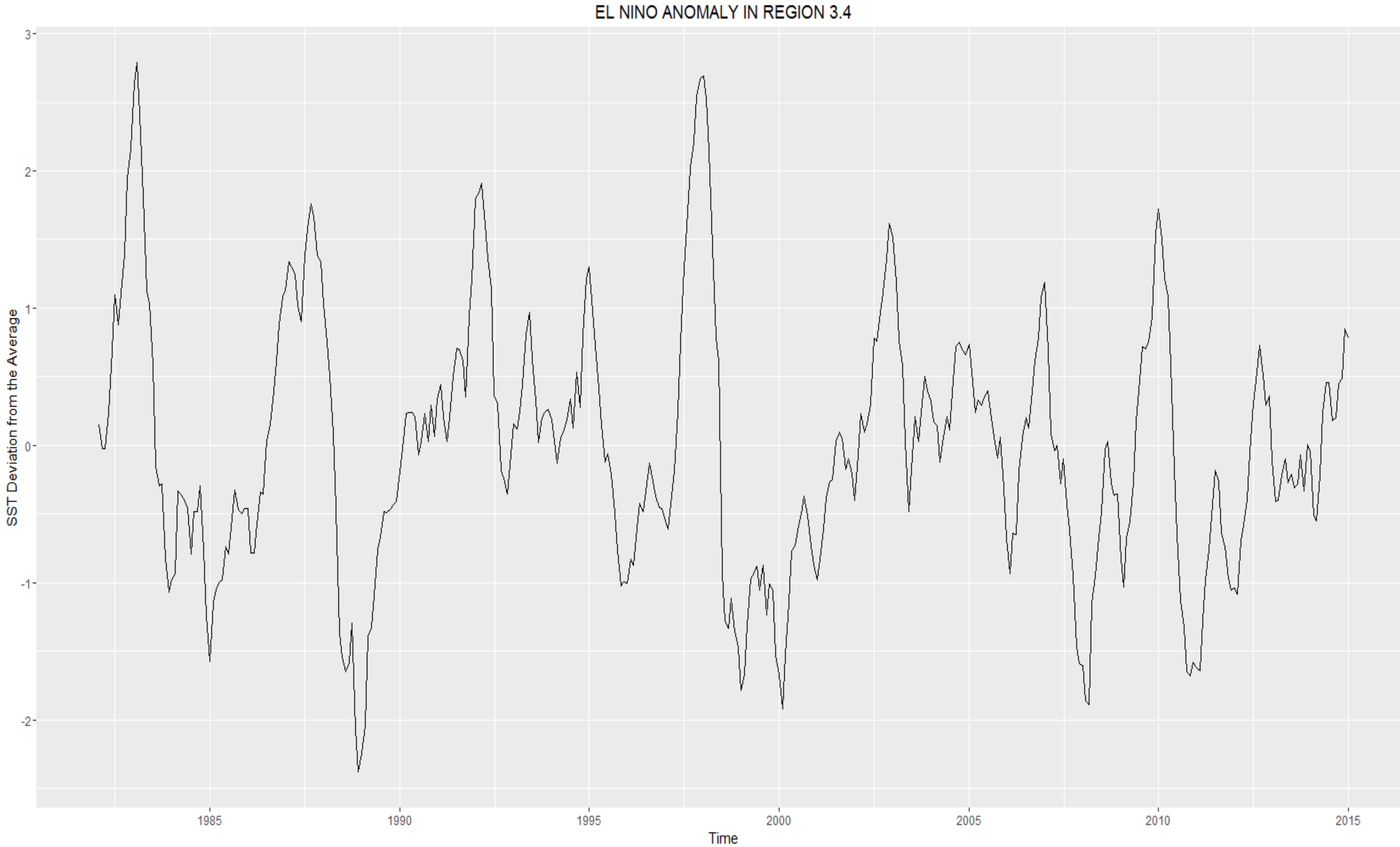

Figure 3 Monthly sea surface temperature anomaly from the average measured over a 1981-2010 base period in region 3.4

VITA

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Areas of Interests

- Research: Asset Pricing, Corporate Governance, Behavioral Finance
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Education

- Ph.D. in Finance, Old Dominion University, 2017
- M.S. in Agricultural Economics, Mississippi State University, 2006
- M.B.A. in Finance, University of Science and Technology of China, 2003

Publications

- Using Experimental Economics to Evaluate Alternative Subjective Elicitation Procedures, with Keith Coble and Darren Hudson, *Applied Economics*, 2011, 43(14):1729-1736.
- The Role of Individual Personality Type in Subjective Risk Elicitation Outcomes, with Keith Coble and Darren Hudson, *Journal of Risk Research*, 2009, 12(2):209-222.
- Preserving Low Cost Electricity While Improving the Riverine Environment: A Case Study of Ghana's Akosombo Dam Complex, with Paul Preckel, etc., *Power and Energy Society General Meeting, 2008 IEEE*, pp. 1-6.

Teaching Experience

- Adjunct Instructor: Old Dominion University, 2013 - present
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- **Consultant** Institutional and Managerial Strengthening, Huai River Water Pollution Control Project-Anhui Portion, World Bank. (2002-2004)
    - Advised on wastewater company corporatization through execution of business and Asset-handover legal agreements.
    - Developed wastewater company expertise in business planning, financial management, asset management, human resources management, and customer relations.
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