El Niño cycle and FX returns

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Abstract

El Niño cycle is a slow-moving global climate shock that hits multiple countries over time in relatively predictable patterns, affecting productivity, trade and growth prospects. Examining over different El Niño cycles, we discover a strong pattern of predictability in foreign exchange market. Currencies that have performed well (poorly) under previous El Niño cycles continue to perform well (poorly) when new El Niño cycle hits. Such predictability is robust to carry, short term momentum, long term momentum, value factors and all other standard controls. The predictability primarily comes from the spot returns rather than forward premium. We find that countries with appreciated currencies face stronger subsequent output gaps.

JEL Classification: F31, G12, G15, Q54

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1 Introduction

El Niño-Southern Oscillation (ENSO) cycle is a natural climate pattern that involves the warming of the Central and Eastern Pacific Ocean. The warming of the overlying air leads to rising air that sets up atmospheric circulation, with warm moisture on one side of the ocean and cool dry air on another, leading to a cascade of global weather effects over time. ENSO cycle is associated with droughts and floods that impacted agriculture, fisheries, and tourism, and has been found to impact the wider economic growth and inflation in different countries.

Despite the widespread impact of ENSO cycle on countries' economic fundamentals, there is no research on ENSO cycle on foreign exchange returns. Our research aims to fill in this gap and empirically document the impact of ENSO cycle on foreign exchange returns. We adopt an empirical strategy where we classify countries into those with foreign currency appreciation vs. those with foreign currency depreciation in previous ENSO cycles.

Examining different ENSO cycles from 2000 to 2023, we discover a strong pattern of predictability in the foreign exchange market. We sort currencies into those that have performed in the top quintile versus those that have performed in the bottom quintile under previous El Niño cycles. We find that the top quintile currencies continue to perform well when new El Niño cycles hit, while the bottom quintile currencies perform poorly when new El Niño cycles hit. This result is robust to control variables including carry, short-term momentum, long-term momentum, and value. Our results are robust to using either continuous sea surface temperature (SST) anomalies or discrete ENSO indicators as alternative definitions of El Niño.

Next, we examine whether the predictability comes from forward discount or spot returns. Based on decomposition of the currency excess returns, we find that a large part of the abnormal returns come from the spot returns rather than forward premium. This suggests that the currency market did not fully price in the effect of previous El Niño cycles when a new cycle hit.

Climate scientists typically classify climate regimes into El Niño cycle (usually considered more unfavorable), La Niña cycle (usually considered more favorable), and neutral state. As placebo tests, we compare the foreign exchange predictability results under El Niño vs. results under La Niña cycle and neutral states. We find that predictability only happens during El Niño states.

We seek to assess further how the abnormal returns from the El Niño cycle differ from existing factors in the literature. To that end, we compare different existing FX risk factors as defined by Nucera, Sarno, and Zinna (2024) with the portfolio returns of a High minus low exposure to ENSO cycle. These FX risk factors include carry (e.g. Lustig et al. 2011; Menkhoff et al. 2012a), short-term and long-term momentum (e.g. Asness et al. 2013; Menkhoff et al. 2012b), currency value (e.g. Asness et al. 2013; Kroencke et al. 2014; Menkhoff et al. 2017), net foreign assets and liabilities in domestic currencies (Della Corte et al. 2016b), term spread (Bekaert et al. 2007; Lustig et al. 2019), long-term yields (Ang and Chen 2010), and output gap (Colacito et al. 2020). We refer to these strategies as Carry, ST and LT Mom, Value, NFA, LDC, Term, LYld, and GAP. We find that the ENSO portfolio shows a negative correlation with the value factor (-0.53), but it is not significantly correlated with other factors.

Also, we evaluate the average excess returns of the ENSO portfolio and these other factors under El Niño, La Niña and neutral regime. We find that several factor returns, including carry, momentum, LDC, Term and ENSO are stronger during El Niño cycles, compared to other time periods. We then evaluate the abnormal returns (alphas) and exposure to ENSO portfolio returns (betas) for each of the individual factor returns. We find that different factors have some exposure to ENSO portfolio return, but the alphas from ENSO portfolios persist.

Beyond explaining currency predictability, we explore the investment implications of our findings. We construct an optimal tangency portfolio incorporating ENSO-based FX strategies and analyze its risk-return characteristics. Our results indicate that including

ENSO-related information improves the Sharpe ratio of a currency portfolio, suggesting that investors could enhance portfolio efficiency by integrating ENSO-based signals into their trading strategies. This result suggests that investors underestimate the systematic effects of ENSO cycles on different economies, creating an exploitable investment strategy.

Additionally, we evaluate how ENSO fare in explaining FX factor returns. We examine the pricing errors from time series regressions of each of FX factor returns on dollar, carry, and ENSO. We find that including ENSO as explanatory variable helps to reduce pricing errors in almost all portfolios. We conduct a similar exercise with cross sectional regressions. We again find that including ENSO helps to reduce pricing errors. A test based on Kan, Robotti and Shanken (2013) further confirms that ENSO factor enhances the cross-sectional R^2.

To further test the robustness of our findings, we implement several additional checks. First, instead of currency returns, we examine ENSO effect on international stock returns using MSCI international stock market indices. Investigating theta-sorted portfolio of international stock returns, we find highly significant results for El Niño cycle, but only if we use "USD returns", suggesting a strong "currency-ENSO" effect. Second, we find that the El Niño effect is present in both pre-2000 and post-2000 periods, though stronger in recent years, likely due to improved ENSO forecasting models. Third, we repeat our analysis using GBP instead of USD as the base currency and find similar results, indicating that our findings are not driven by a specific currency benchmark. Fourth, we repeat our analysis based on developed market currencies only and find our results to be robust, alleviating concerns that small emerging market currencies drive our results. Fifth, we find that our results are not driven by a small set of currencies that are perpetually in the long or short portfolios. Instead, currencies appear in different portfolios over time. Sixth, we find that portfolio turnover of the ENSO strategy is lower than that of carry or momentum strategies, thus alleviating the concerns that transaction costs might erode its performance. Lastly, we use different currency data sample filters and find our results to be robust.

A natural question that arises from our findings is the underlying macroeconomic mechanism driving these results. Colacito, Riddiough, and Sarno (2020) show that macroeconomic conditions can be captured by output gap, which is defined as the difference between a country's actual and potential level of output, using industrial production data. Their study finds that currencies associated with high output gap—indicating stronger economies—tend to outperform those with low output gap, which correspond to weaker economies.

Building on their approach, we use output gap to assess economic conditions across our set of countries. Our analysis reveals that the long positions in ENSO portfolios tend to have higher output gaps in the future, while the short positions are associated with lower output gaps. This provides an intuitive economic mechanism for our finding. We take long positions in currencies that have performed well in previous El Niño cycles, and it turns out that these tend to come from countries with improving or stronger economic fundamentals. Conversely, we short currencies that have underperformed in previous El Niño cycles, which turn out to tend to come from countries with weaker economic prospects going forward. This suggests that our ENSO portfolios naturally align with differences in future macroeconomic strength, reinforcing the link between currency predictability and future economic conditions.

Overall, our findings contribute to the growing literature on climate finance and currency risk premia. To the best of our knowledge, this is the first study to establish a link between global climate cycles and foreign exchange returns. Given climate scientists' predictions that future El Niño cycles will become more frequent and severe, our research highlights the growing importance of climate-based financial risk management. Future research could explore whether ENSO cycles also affect other asset classes, such as global equity markets, fixed income securities, or even cryptocurrency markets.

Our study contributes to the growing literature on the economic impact of the ENSO cycle. Prior research has documented the macroeconomic effects of El Niño, particularly its influence on the GDP growth. As El Niño increases flood risks and affects public health (Ward et al (2014); Kovats et al (2003)), it generally reduces productivity and hampers economic growth. Smith et al (2017) quantifies these losses, attributing $4.1trillionand5.7$ trillion in global income reductions to the 1982–83 and 1997–98 El Niño events. Callahan et al (2023) further point out that the negative economic effect of ENSO shocks is nonlinear, and while La Niña can bring some beneficial effect, they are generally weaker and less significant than the negative impact of El Niño. The economic consequences of El Niño also vary by region. In larger, more diversified economies, the positive and negative effects tend to offset each other, whereas smaller and less diversified developing countries are more vulnerable (Laosuthi and Selover (2007); Cashin et al (2017)). However, despite the predominant negative impact, Cashin et al (2017) additionally note that some countries may experience a net positive effect on real GDP growth from El Niño cycle.

Another focus of the existing literature is how El Niño events affect commodity markets. Brunner (2002) finds that El Niño increases commodity price volatility, typically driving prices higher due to supply disruptions. Ubilava (2016) confirms the link between sea surface temperature anomalies caused by ENSO shocks and agricultural commodity prices. Furthermore, incorporating ENSO factors into predictive models can improve commodity return forecasts, as suggested by Kitsios et al (2022). Building on these insights into the economic and trade related consequences of El Niño, our study examines its impact on foreign exchange returns. This area remains unexplored, and our findings provide valuable insights for market participants in assessing climate-related risks in the currency market.

Our research adds to the vast literature on foreign exchange predictability. This literature emphasize the roles of carry (e.g. Lustig et al. 2011; Menkhoff et al. 2012a), short-term and long-term momentum (e.g. Asness et al. 2013; Menkhoff et al. 2012b), currency value (e.g. Asness et al. 2013; Kroencke et al. 2014; Menkhoff et al. 2017), net foreign assets and liabilities in domestic currencies (Della Corte et al. 2016b), term spread (Bekaert et al. 2007; Lustig et al. 2019), long-term yields (Ang and Chen 2010), and output gap (Colacito et al. 2020). Notably, the foreign exchange literature has not taken into account the pervasive impact of climate cycle. Our paper is the first to bring the most important global climate cycle into the foreign currency literature.

Previous research has shown that climate risks are priced into the equity markets. For instance, Engle et al. (2020) develop a climate risk hedge portfolio using climate change news, suggesting that climate risk can be an asset pricing factor. Similarly, rising temperature and increased drought risks have also reflected in the stock prices (Bansal et al (2019); Hong et al (2019)). More recently, Lemoine et al (2024) find that improved forecasting of El Niño reduces firms' exposure to the climate shock in the equity market. Given these findings, it is natural to see if climate risk factors would influence foreign exchange market as well, though this remains underexplored. We fill in this gap and provide the first evidence that climate cycle has important impact on foreign exchange markets.

2 Data and Methodology

2.1 Definition of Spot and Excess Return of Currency

Our data sample covers the period from January 2000 to December 2023, with currency data sourced from Datastream. We use both spot rates and 1-month forward rates to calculate excess currency returns. Additionally, we apply data filters from Nucera, Sarno, and Zinna (2023).

We obtain spot exchange rates and one-month forward rates relative to the U.S. dollar (USD) from Datastream. Adopting the perspective of a U.S. investor, we define exchange rates in terms of USD per unit of foreign currency (FCU), expressed as USD/FCU. Consequently, a rise in the exchange rate indicates an appreciation of the foreign currency. Our empirical study relies on monthly data, using end-of-month FX rates spanning from January 2000 to December 2023. The dataset includes 49 currencies,[1] with 15 classified as belonging

[1]The countries include Australia, Austria, Belgium, Brazil, Bulgaria, Canada, Croatia, Cyprus, Czech Republic, Denmark, Egypt, euro area, Finland, France, Germany, Greece, Hong Kong, Hungary, Iceland, India, Indonesia, Ireland, Israel, Italy, Japan, Kuwait, Malaysia, Mexico, Netherlands, New Zealand, Norway, Philippines, Poland, Portugal, Rus- sia, Saudi Arabia, Singapore, Slovakia, Slovenia, South Africa, South Korea, Spain, Sweden, Switzerland, Taiwan, Thailand, Ukraine, the United Kingdom, and Turkey.

to developed economies based on established definitions in previous research (e.g., Lustig et al., 2011; Menkhoff et al., 2012a). However, the sample is not constant over time, as data for certain currencies are unavailable from the start of the period, resulting in an unbalanced panel of currencies.

We use q and f to denote the log of the spot and forward nominal exchange rate measured in home currency (USD) per foreign currency, respectively. An increase in q_i means an appreciation of the foreign currency i. Following Lustig and Verdelhan (2007), we define the log excess return ($\Delta\pi_{i,t+1}$) of the currency i at time $t+1$ as $\Delta\pi_{i,t+1} = \Delta q_{i,t+1} + i_{i,t} - i_{us,t} \approx q_{i,t+1} - f_{i,t}$ where $i_{i,t}$ and $i_{us,t}$ denote the foreign and domestic nominal risk-free rates over a one-period horizon. This is the return on buying a foreign currency (f_i) in the forward market at time t and then selling it in the spot market at time $t+1$. Since the forward rate satisfies the covered interest parity under normal conditions (see, Akram, Rime, and Sarno (2008)), it can be denoted as $f_{i,t} = log(1 + i_{us,t}) - log(1 + i_{i,t}) + q_{i,t}$. Therefore, the forward discount is simply the interest rate differential ($q_{i,t} - f_{i,t} \approx i_{i,t} - i_{us,t}$) which enables us to compute currency excess returns using forward contracts. For the CIP deviations, we apply the same data filters as in Nucera, Sarno, and Zinna (2023).[2]

We report the summary statistics in Table 1.

[Insert Table 1 Here]

2.2 Definition of ENSO Cycle

We determine ENSO cycles using sea surface temperature (SST) anomalies. Traditionally, scientists have categorized the strength of El Niño by identifying SST anomalies that surpass a predetermined threshold in a specific part of the equatorial Pacific. The Niño 3.4 region is the most frequently analyzed area, with the standard threshold being an SST anomaly

[2] The filters include countries with the following periods: Egypt (01/01/2011 – 30/08/2013; 03/10/2016 - 28/02/2017; 1/1/2023 – 31/12/2023); Indonesia (01/12/1997 – 31/07/1998; 01/02/2001 – 31/05/2005); Malaysia (01/05/1998 – 30/06/2005); Russia (01/12/2008 – 30/01/2009; 03/11/2014 – 27/02/2015); South Africa (01/08/1985 – 30/08/1985; 01/01/2002 – 31/05/2005); Turkey (01/11/2000 – 30/11/2001); and Ukraine (03/11/2014 – 31/12/2023).

of +0.5°C or higher. Since this region includes the western portion of the equatorial cold tongue, it effectively captures significant SST variations and gradients that influence deep tropical convection and atmospheric circulation patterns. A commonly applied criterion for defining an El Niño event is that the 3-month running mean SST anomalies must exceed this threshold for at least five consecutive periods.

Following scientific literature, we determine the onset of El Niño cycles using Anomalous Sea Surface Temperature (SST). Specifically, we follow the official NOAA description, "Warm and cold phases are defined as a minimum of five consecutive 3-month running averages of SST anomalies (ERSST.v5) in the Niño 3.4 region surpassing a threshold of +/- 0.5°C." This standard of measure is known as the Oceanic Niño Index (ONI).[3] As the El Niño cycle is global in nature, rather than country-specific, we apply the onset of El Niño cycle to all countries concurrently.

The El Niño cycle occurs every 2 to 7 years on average, but not according to a regular schedule. An El Niño typically last 9 to 12 months, but can last up to years.

[Insert Figure 1 Here]

2.3 Empirical Methodology

Since the ENSO cycle can influence various countries' fundamentals differentially - such as productivity, terms of trade (via exports and imports), and growth prospects - it should be reflected in the valuation of their currencies. We examine whether currency returns are predictable based on its predicted behavior of the ENSO cycle. If the ENSO cycle is fully anticipated in advance, as many climate scientists suggest, and well-understood by market participants, currency excess returns should not exhibit predictability during ENSO cycles. However, we find that currency excess returns are, in fact, predictable using exogenous and foreseeable ENSO cycle information. To demonstrate this, we rank 49 currencies based on

[3]See, https://www.ncei.noaa.gov/access/monitoring/enso/sst

their return sensitivity to the ENSO cycle, estimating this sensitivity as follows:

$$RX_{ct} = \alpha_c + \theta_c^{ENSO} ENSO_t + e_{ct} \tag{2.1}$$

where $ENSO_t$ is an indicator variable derived from the three-month moving averages of sea surface temperature (SST) anomalies in the Niño 3.4 region, with a threshold of +/- 0.5°C. Specifically, We define $ENSO_t = 1$ when the three-month running SST anomalies exceeds + 0.5°C and $ENSO_t = -1$ when it falls below - 0.5°C; otherwise $ENSO_t = 0$. For each month τ and currency c, θ_c^{ENSO} is estimated using 10 years of rolling sample ($\tau - 120 \leq t < \tau$). Currencies are then sorted into 5 portfolios based on θ_c^{ENSO}, and we analyze the summary statistics of excess currency returns in the subsequent month.

Alternatively, we access sensitivity to the ENSO cycle using a continuous measure of anomalous SST, defined as three-month moving average of SST anomalies (SST_t), with the following regression model:

$$RX_{ct} = \alpha_c + \theta_c^{SST} SST_t + e_{ct} \tag{2.2}$$

Utilizing the ENSO cycle dummy allows us to focus on the effects of warm or cold periods that deviate from the designated SST threshold, thereby highlighting the impact of anomalous climate phenomena. We will use Equation 2.1 as our baseline approach, but all results are almost identical regardless of using 2.1 or 2.2. Further details on the definitions of SST and ENSO are provided in the appendix.

3 Results on ENSO Portfolio Performance

3.1 ENSO Portfolio Performance and Decomposition

Table 2 presents various estimates of theta using θ_c^{ENSO} as the ENSO sensitivity measure. In addition to the base specification 2.1 we explore different model variations 3.1 to 3.3 to assess the robustness of theta under alternative controls. The regression equations are:

$$RX_{ct} = \alpha_c + \beta_c^{Carry} Carry_t + \theta_c^{ENSO} ENSO_t + e_{ct} \tag{3.1}$$

$$RX_{ct} = \alpha_c + \beta_c^{Carry} Carry_t + \beta_c^{Mom} MOMST_t + \theta_c^{ENSO} ENSO_t + e_{ct} \tag{3.2}$$

$$RX_{ct} = \alpha_c + \beta_c^{Carry} Carry_t + \beta_c^{Mom} MOMLT_t + \theta_c^{ENSO} ENSO_t + e_{ct} \tag{3.3}$$

where RX_{ct} is the excess return of currency c at time t, $Carry_t$ is the currency carry factor, $ENSO_t$ is an indicator variable derived from anomalous sea surface temperature, and $MOMST_t$ and $MOMLT_t$ correspond to the short-term and the long-term currency momentum factors, respectively.

Table 2 presents the average excess return of portfolios with high θ_c^{SST} (Port5), low θ_c^{SST} (Port1), and high minus low θ_c^{SST}(Port99). The average excess return of HML portfolio under all types of climate states is about 4.78% per year. Upon examining the source of the abnormal performance, we found that the majority of abnormal return is accrued during El Niño phase, yielding a statistically significant 7.83% per year.

This indicates that currencies which performed well during previous El Niño cycles (i.e. portfolio 5) tend to continue performing well in future cycles while currencies which performed badly during previous El Niño cycles (i.e. portfolio 1) tend to continue performing badly in future cycles, despite the fact that El Niño is a predictable long-term climate pattern. During Na Lina and neutral states, currencies which performed well during previous El Niño cycles no longer outperform in future cycles. Furthermore, we find that including carry, short-term momentum, and long-term momentum as extra controls do not change the results too much.

[Insert Table 2 Here]

Thus far, we use discrete ENSO indicators derived from the three-month moving averages of sea surface temperature anomalies to proxy for the onset of an El Niño cycle. In Table 3, we evaluate the robustness of this result by checking an alternative definition of El Niño, where we instead use continuous measure of anomalous sea surface temperature (SST) as proxy for the El Niño cycle. The results remain highly similar. This confirms that our results are robust to different definitions of ENSO cycles. Figure 2 presents the cumulative returns of high $\theta^{ENSO/SST}$ minus low $\theta^{ENSO/SST}$ portfolio based on both $ENSO_t$ and SST_t. This figures illustrates that the cumulative returns of $\theta^{ENSO/SST}$-sorted HML portfolio returns are primarily accumulated during El Niño phases and remain stable over time.

$ENSO_t$ is an indicator variable derived from the three-month moving averages of sea surface temperature (SST) anomalies in the Niño 3.4 region, with a threshold of +/- 0.5°C. Specifically, We define $ENSO_t = 1$ when the three-month running SST anomalies exceeds + 0.5°C and $ENSO_t = -1$ when it falls below - 0.5°C; otherwise $ENSO_t = 0$. For each month τ and currency c, θ_c^{ENSO} is estimated using 10 years of rolling sample ($\tau - 120 \leq t < \tau$). Currencies are then sorted into 5 portfolios based on θ_c^{ENSO}, and we analyze the summary statistics of excess currency returns in the subsequent month. Alternatively, we access sensitivity to the ENSO cycle using a continuous measure of anomalous SST, defined as three-month moving average of SST anomalies (SST_t), with the following regression model:

[Insert Table 3 and Figure 2 Here]

Next, we analyze whether the predictability stems from the forward discount or spot returns. This distinction is important because it helps identify the underlying drivers of currency return predictability—whether it is primarily a compensation for bearing currency risk as anticipated in the forward discount or driven by surprises in the spot market. To do so, we decompose the currency excess return to (i) forward discount and (ii) spot return.

Table 4 presents the results on forward discounts (Panel A) and spot rates (Panel B). By decomposing currency excess returns, we observe that a significant portion of the abnormal returns originates from spot returns rather than the forward premium. This suggests that the currency market did not fully price in the effect of previous El Niño cycles when a new cycle emerged. Our findings suggest that a large share of the abnormal returns can be explained by movements in spot prices.

[Insert Table 4 Here]

Figure 3 display average cumulative returns for portfolios that are formed at the beginning of an El Niño or La Niña phase. The event time (time=0) corresponds to the beginning of a cycle. Specifically, if the ENSO index indicates the start of an El Niño or La Niña phase, we initiate the decomposition exercise by tracking cumulative excess returns, spot returns, and forward discounts from 12 months before to 12 months after the portfolio formation. Our sample period (2000–2023) includes approximately eight El Niño and nine La Niña instances. We present the results separately for (i) the El Niño period and (ii) the La Niña period. Figure 3 shows that during the El Niño cycle, significant abnormal returns primarily stem from cumulative spot returns, whereas no similar pattern is observed during the La Niña cycle.

[Insert Figure 3 Here]

To better understand the abnormal performance of the theta-sorted HML portfolio returns (henceforth ENSO portfolio), particularly during the El Niño cycle, we examine its relationship with established traded FX risk factors from Nucera, Sarno, and Zinna (2024). For this analysis, the sample data is available only through December 2017.

3.2 ENSO Portfolio and Risk Factor Correlations

The first thing we do is to examine the correlation between the theta-sorted HML portfolio returns (ENSO Portfolio) and the established traded FX risk factors including carry (Carry), short-term and long-term momentum (ST and LT Mom), currency value (Value), net foreign assets (NFA), liabilities in domestic currencies (LDC), term spread (Term), long-term yields (LYld), and output gap (GAP).[4]

[4]The choice of currency portfolios stems from nine popular investment strategies: carry (e.g., Lustig et al., 2011; Menkhoff et al., 2012a), short-term and long-term momentum (e.g., Asness et al., 2013; Menkhoff et al., 2012b), currency value (e.g., Asness et al., 2013; Kroencke et al., 2014; Menkhoff et al., 2017), net foreign assets and liabilities in domestic currencies (Della Corte et al., 2016b), term spread (Bekaert et al.,

Table 5 shows the correlation results. Some of the factors are highly correlated. For example, Carry and LYld have correlation of 0.77, and NFA have correlation of 0.63 with LDC. We find that ENSO is not significantly correlated with other factors. The only factor that has relatively high correlation with ENSO portfolio is Value. The correlation between ENSO portfolio and Value is -0.53.

[Insert Table 5 Here]

3.3 Risk Factor Pricing and ENSO Portfolio

We next investigate whether the factors unique to one model produce nonzero alphas with respect to another model. That is, we explore the extent to which one model can price the factors of the other.

We start with presenting the average excess returns of those factors (along with ENSO portfolio) in our sample period from 2002 to 2017. Panel A of Table 6 shows the results. Notably, the realization of certain factor returns, particularly Carry, Momentum, LDC, Term, and ENSO, is stronger during El Niño cycles compared to other periods.

[Insert Table 6 Here]

We then present the abnormal returns (alphas) and exposure to ENSO portfolio returns (betas) for FX risk factors. In particular, each risk factor is regressed on ENSO portfolio returns using the equation $F = \alpha + \beta \cdot ENSO$, and results are reported for each ENSO cycle.

Panel B of Table 6 shows the results for the alphas, while Panel C reports the results for betas. Panel B reveals that the returns of both short- and long-term momentum factors are subsumed by the ENSO portfolio returns, whereas the risk premia of other factors remain largely unaffected. Panel C reveals that several factors exhibit loadings on ENSO, with short- and long-term momentum factors in particular displaying a positive association with

2007; Lustig et al., 2019), long-term yields (Ang and Chen, 2010), and output gap (Colacito et al., 2020). In what follows, we refer to these strategies as Carry, ST and LT Mom, Value, NFA, LDC, Term, LYld, and GAP, respectively.

ENSO portfolio returns. These loadings increase significantly during the El Niño phase, rendering the alphas for both momentum factors insignificant. Overall, Panels B and C of Table 6 suggest that while existing factors are related to ENSO portfolios, on balance these factors are distinct from ENSO portfolios.

Next, we reverse the roles of the dependent and independent variables from the previous regression. In particular, ENSO portfolio returns are regressed upon each risk factor using the equation $ENSO = \alpha + \beta \cdot F$, and results are reported for each ENSO cycle.

Panel D and E of Table 6 presents these regression results, showing that ENSO portfolio returns are not explained by exposure to any risk factors over the full sample period. However, during El Niño phases, a significant portion of the ENSO factor's abnormal performance appears to be driven by its exposure to both short-term and long-term momentum. During these periods, the factor's sensitivity to momentum increases, while its negative exposure to the value risk factor becomes more pronounced.

3.4 Optimal Allocation of ENSO Portfolio in Tangency Portfolios

Beyond examining currency predictability, we investigate its investment implications by constructing an optimal tangency portfolio that integrates ENSO-based FX strategies and evaluating its risk-return characteristics. To that end, we construct an optimal tangency portfolio based on all the FX factors including ENSO, and examine the weight on ENSO. In this exercise, we include the dollar factor, which along with carry factor, were considered by Verdelhan (2018) as the most important and pervasive factors underlying foreign exchange returns.

Table 7 presents the tangency portfolio weights, returns, and the maximum ex post Sharpe ratios achievable by combining various factors to construct the tangency portfolio. Our analysis demonstrates that incorporating the ENSO HML portfolio information meaningfully improves the Sharpe ratio of a currency portfolio, ranging from 0.038 to 0.115. This suggests that it provides valuable signals for enhancing portfolio efficiency. We find that the optimal weight assigned to the ENSO factor is substantial. In a portfolio that includes all the FX factors, the optimal weight on ENSO portfolio is 20%.

These findings indicate that the ENSO HML portfolio captures a fundamental aspect of currency markets that is not fully reflected in conventional trading strategies. By incorporating this ENSO portfolio, investors can attain improved risk-adjusted performance. Furthermore, based on the optimal weights in Tangency portfolio, investors would consistently allocate positive weights to ENSO portfolio across different combinations of factor-based strategies, with varying degree of marginal increase in Sharpe ratio. Hence, the positive impact of ENSO portfolio on portfolio efficiency appears to be pervasive, reinforcing its relevance for currency investment decisions.

[Insert Table 7 Here]

3.5 Model Performance in Explaining FX Anomalies

Next, we assess the role of ENSO HML portfolio in explaining FX factor returns. Specifically, we analyze the pricing errors from time series regressions of various FX factor returns on different combinations of the dollar, carry, and ENSO factors. Our aim is to assess whether there is an improvement in model fit. Such an improvement would imply that ENSO captures a systematic component of currency returns that is not fully reflected in standard FX factors.

3.5.A Models' Ability to Explain FX Anomalies I (Time-series alphas)

Table 8 compares the models on several measures that summarize abilities to accommodate the set of anomaly long-short spreads: dispersion of alpha ($\alpha_{HL} = \max \alpha - \min \alpha$), average absolute alpha (α_{ABS}), the Gibbons, Ross, and Shanken (1989) GRS p-values, which test the null hypothesis that all alphas are jointly zero ($pGRS$), and the average time-series R-squared (R^2). For the test assets, we analyze a total of 51 currency portfolios, constructed based on widely studied investment strategies in the foreign exchange market. These include 5 Carry, 5 Short-Term and 5 Long-Term Momentum (ST Mom and LT Mom), 5 Currency

Value (Value), 5 Net Foreign Assets (NFA), 6 Liabilities in Domestic Currencies (LDC), 5 Term Spread (Term), 5 Long-Term Yields (LYld), 5 Output Gap (GAP) portfolios, and 5 ENSO portfolios.

[Insert Table 8 Here]

The results in Table 8 indicate that incorporating ENSO as an explanatory variable consistently reduces pricing errors across nearly all portfolios during the El Niño phase, suggesting that ENSO adds meaningful explanatory power beyond traditional risk factors. However, when considering the entire sample period, the inclusion of ENSO alongside the Dollar and Carry factors does not lead to a significant drop in average absolute alpha (α_{ABS}) or an economically meaningful increase in the average time-series R-squared (R^2). Instead, the most notable improvements occur specifically during the El Niño phase.

Examining the El Niño period separately, we observe a substantial decrease in average absolute alpha (α_{ABS}) and a marginal increase in the model's explanatory power, as reflected by a higher R-squared (R^2). The most pronounced reductions in pricing errors occur within the Short-Term and Long-Term Momentum (MomST and MomLT), Value, Term Spread, and ENSO portfolios. When tested across all 51 portfolios, the inclusion of ENSO leads to a 40% reduction in the average alpha level compared to the benchmark model that includes only the Dollar factor. Similarly, relative to the model incorporating both the Dollar and Carry factors, adding ENSO results in a 30% reduction in average alpha. In contrast, during the La Niña phase, the ENSO factor does not provide any economically meaningful reduction in mispricing. This asymmetry between the El Niño and La Niña periods highlights the unique role of ENSO in shaping currency market risk and return dynamics, particularly in the presence of El Niño-driven economic conditions.

Overall, Table 8 reports the pricing errors from time-series regressions of FX factor returns on different combinations of the Dollar, Carry, and ENSO factors. We find that the inclusion of ENSO as an explanatory variable helps reduce pricing errors in nearly all portfolios during the El Niño cycle. This reinforces the importance of ENSO in enhancing FX factor models.

In other words, by including ENSO, we obtain a more accurate representation of how FX factor returns evolve over time, leading to a better understanding of the risk-return trade-offs in currency markets.

3.5.B Models' Ability to Explain FX Anomalies II (Cross-sectional Regression)

gMany asset pricing studies have employed the sample cross-sectional regression (CRS) R^2 as a measure of model performance of pricing abilities. Kan, Robotti, and Shanken (2013) derive the asymptotic distribution of this statistic and develop associated model comparison tests, taking into account the impact of model misspecification on the variability of the CSR estimates.

$$E(RX_i) = \lambda \cdot COV(RX_i, F) \tag{3.4}$$

where RX_i = excess return, λ = Price of covariance risk, F = Factor. We report the details of the estimation methodology of these statistics in Section B of the Appendix.

The models considered in our analysis include (i) Dollar factor alone, (ii) Dollar and ENSO factors, (iii) Dollar and Carry factors, and (iv) Dollar, Carry, and ENSO factors. In total, we examine 51 FX portfolios, sorted based on currencies' exposure to Carry, MomST, MomLT, Value, NFA, LDC, Term, LYld, GAP, and ENSO factors. For the two-pass cross-sectional regression (CSR) tests, we employ the following key metrics: (i) $R2$: R^2 from the cross-sectional regression, (ii) $pval_1$: $H0: R^2 = 1$: p-value of testing $R^2 = 1$, and (iii) $pval_2$: $H0: R^2 = 0$: p-value of testing $R^2 = 0$, both of which serve as model specification tests.

[Insert Table 9 Here]

Table 9 presents the results on the cross-sectional regressions. We again find that including ENSO helps to reduce pricing errors,particularly during the El Niño phase. In the first panel, we conduct a joint cross-sectional test across all currency portfolios, while in the subsequent panels, we estimate the CSR model separately for each subgroup of currency portfolios.

When tested on all 51 currency portfolios, we find that the explanatory power of ENSO jointly with Dollar and Carry is substantial, with an at R^2 of 48% over the full sample period and 64% during the El Niño phase. These R^2s are statistically significant different from zero, as indicated by the $pval_2$ test statistics in Table 9. the p-values of the test confirms that the model has statistically significant explanatory power for the cross-section of expected returns in all portfolios under the null hypothesis of the misspecified model ($H0 : R^2 = 0$).

To assess the incremental contribution of ENSO, we compare the two-factor model (Dollar and Carry) and the extended three-factor model augmented with ENSO. By doing so, we explore that the explanatory power of two nested models are different from each other and ask what the relative importance of ENSO is. Table 9 shows that augmenting the model with ENSO HML portfolio returns significantly improves the joint cross-sectional fits across various currency portfolios. Differences in R^2 are 8.4% and 34.4% during full sample period and El Niño phases respectively.

More specifically, during the El Niño phase, the inclusion of ENSO leads to improvements in R^2s of 8.4%, 62.8%, 68.4%, 65.9%, 8.3%, 5.8%, 4.3%, 3.3%, 6.5%, and 23.5% for the Carry, MomST, MomLT, Value, NFA, LDC, Term, LYld, GAP, and ENSO portfolios, respectively. These results highlight that the ENSO factor plays a particularly important role in explaining momentum, value, and term spread portfolios during El Niño episodes.

For an additional statistical assessment of the ENSO factor's pricing ability, we test whether the covariance risk (λ) of the additional factor is statistically different from zero with misspecification robust errors. If the price of covariance risk is significantly different from zero, the R^2 values of the two nested models are also statistically distinct. The results of this test are reported in Appendix Table A6.[5]

3.6 Additional Results and Robustness Checks

To further test the robustness of our findings, we implement several additional checks.

[5] Although we only show the case for the price of covariance risk, similar results can be obtained from the tests of the price of beta risk.

3.6.A Using Only Developed Countries' sample

There could be a concern that our results are primarily from poor performance of small emerging market currencies. In order to address this potential concern, we rerun our main regression analysis using only developed countries. The results are shown in Appendix Table A1. We find similar results. E. Same currencies in the portfolio There could be another concern that our results are driven by the performance of a small set of currencies that are perpetually in the long and short portfolios. We examine this possibility by checking the currency appearance by portfolio ranks. Appendix Table A2 reports the number of appearances of individual currencies in each portfolio rank based on the theta values. We find that currencies often fall within different portfolios at different times. This alleviates the concerns.

3.6.B Using British Pound (GBP) instead of US Dollar (USD) as Base currency

We repeat our analysis using GBP instead of USD as the base currency. This alleviates the concern that comes from the fact that our methodology captures a dollar specific risk. These results are shown in the Appendix Table A3. We find similar results with GBP as we did for USD. This indicates that our findings are not driven by a specific currency benchmark.

3.6.C Portfolio Turnover

One might wonder if the El Niño HML portfolio strategy involves a substantial amount of turnover, in which case transaction costs could substantially reduce the profitability. In Appendix Table A4, we compare the turnover of the El Niño HML portfolio to turnover in other strategies like momentum and carry. We find that the El Niño HML portfolio has a lower turnover than both carry and momentum strategy.

3.6.D Introduce additional filters

We have conducted robustness checks with some additional currency sample filters as in Nucera, Sarno and Zinna (2024, Page 60). These filters are based on CIP deviations following Kroencke et al. (2014) and Della Corte et al. (2016b). When these filters are applied, all the results remain similar.

3.6.E International Stock Returns

First, instead of currency returns, we examine ENSO effect on international stock returns using MSCI international stock market indices. Investigating theta-sorted portfolio of international stock returns,[6] we find highly significant results for El Niño cycle, but only if we use "USD returns", underscoring a strong "currency-ENSO" effect. These results are shown in the Appendix Table A5. We also conduct our analysis using pre-2000 and post-2000 time periods and find that the El Niño effect is present in both pre-2000 and post-2000 periods.

4 Economic Channel

A key question that follows from our findings is the macroeconomic mechanism underlying these results. Colacito, Riddiough, and Sarno (2020) demonstrate that macroeconomic conditions can be effectively captured by output gap, which is defined as the difference between a country's actual and potential level of output, using industrial production data. Their study finds that currencies associated with high output gaps—representing stronger economies—tend to appreciate, while those with low output gaps —reflecting weaker economies—tend to depreciate. This suggests that macroeconomic strength as proxied by output gaps plays a fundamental role in driving currency returns. Building on their frame-

[6] We use the following specifications to measure the ENSO-sensitivity of those stock market indices: (i) $RX_{ct} = \alpha_c + \theta_c^{ENSO} ENSO_t + e_{ct}$, (ii) $RX_{ct} = \alpha_c + \beta_c^{MKT} MKT_t + \theta_c^{ENSO} ENSO_t + e_{ct}$, and (iii) $RX_{ct} = \alpha_c + \beta_c^{MKT} MKT_t + \beta_c^{Size} Size_t + \beta_c^{Value} Value_t + \theta_c^{ENSO} ENSO_t + e_{ct}$. where RX_{ct} is the excess return of stock market indices of country c at time t, $ENSO_t$ is the indicator variable for $ENSO$ ($ENSO_t = 1$ for El Niño, $ENSO_t = 0$ for neutral, and $ENSO_t = -1$ for La Niña), and MKT_t, $Size_t$, and $Value_t$ is the market, size and value factors, respectively.

work, we analyze the relationship between ENSO portfolios and future output gaps across our sample of countries.

The output gap is measured as the difference between the (log) industrial production and its (log) trend. To extract the trend component from monthly industrial production data, we employ two statistical techniques: (i) the Hodrick-Prescott (HP) filter, used in Panel A, and (ii) the Baxter-King (BK) filter, used in Panel B. The HP filter is widely applied in macroeconomic analysis to separate trends from cyclical fluctuations by penalizing excessive variations in the trend component. In contrast, the BK filter is a band-pass filter designed to eliminate both high- and low-frequency fluctuations, thereby capturing the business cycle more effectively.

Figure 4 illustrates the cumulative output gap before and after the onset of an El Niño event. To mitigate distortions caused by extreme outliers in output gaps, we exclude the El Niño cycle closest to the COVID-19 period (December 31, 2019 – February 29, 2020).[7] Portfolio 5 shows the cumulative returns of FX portfolio that have the highest quintile of performance during past El Niño cycles, while portfolio 1 shows the returns of FX portfolio that with the lowest quintile of performance during past El Niño cycles. The HML portfolio tracks the cumulative returns of a high-minus-low (HML) strategy, calculated as the difference between Portfolio 5 and Portfolio 1 returns.

[Insert Figure 4 Here]

As seen in Figure 4, we find a clear relationship between El Niño portfolio returns with output gaps. To formally access this relationship, Table 10 presents the cumulative output gap with various leads and lags (12-, 6-, 3- and 1-month) on ENSO HML portfolio returns and presents tstatistics associated with those means. Specifically, the long positions in El Niño portfolios tend to be associated with higher output gaps in these countries, while the

[7]The equivalent figure for the full sample period is provided in Appendix Figure A1. While the HP filter exhibits distortions in output gaps due to the COVID-19 period, the BK filter produces a more stable output gap estimate. This robustness arises from the BK filter's lower sensitivity to low-frequency trends that could otherwise distort the output gap measurement.

short positions are linked to lower output gaps. The association starts 12 months before the onset of El Niño cycles and continues over the next 12 months.

[Insert Table 10 Here]

To formally assess this relationship, Table 10 presents the averages and t-statistics of the differences in cumulative output gaps between high and low theta currencies across various time horizons (12-, 6-, 3-, and 1-month leads and lags). The reported lag values are calculated by subtracting the lagged value from the current value, where a positive lagged cumulative output gap indicates that high theta currencies experienced a higher output gap than low theta currencies during the previous lagged months. The forward values are calculated by subtracting the current value from the forward value, with a positive value indicating a higher output gap for high theta currencies than low theta currencies after portfolio formation in the forward months. The results indicate that long positions in El Niño portfolios are generally associated with higher output gaps, whereas short positions correspond to lower output gaps. This pattern emerges as early as 12 months before the onset of El Niño cycles and persists for up to 12 months afterward.

This result aligns with the idea that currencies that have performed well in previous El Niño tend to come from countries with improving or stronger economic fundamentals, while those that have underperformed in El Niño are often from countries with weaker economic outlooks. In other words, the return patterns captured by El Niño portfolios naturally reflect cross-country differences in macroeconomic strength. This finding reinforces the notion that economic fundamentals play a crucial role in shaping FX factor dynamics and highlights the importance of considering macroeconomic conditions when analyzing currency market strategies.

Importantly, as our previous results indicate, the El Niño portfolios are important in predicting future FX returns above and beyond using current economic conditions (output gaps). This suggests that El Niño portfolios are more predictive of subsequent foreign exchange returns and economic conditions above and beyond the current output gaps. Intuitively, we long currencies that have done well in previous El Niño cycles, and these countries tend to have stronger economies going forward. We short currencies that have done poorly in previous El Niño cycles, and these countries tend to have weaker economies going forward.

5 Conclusion

El Niño cycle is one of the most important global climate events that lead to dramatic changes in multiple countries. While previous researchers have focused on different economic and social impacts of El Niño, we present the first evidence of El Niño on currency market. We document a strong pattern of predictability on foreign exchange returns. Currencies that have done the best (worst) in the past El Niño cycles continue to outperform (underperform) in future cycles.

We find that such foreign exchange predictability is robust to carry, momentum, value factors, and all other standard controls. The predictability primarily comes from spot returns rather than interest rate differentials, suggesting that market participants have not incorporated this information in the pricing of the currencies. The predictability is robust to a variety of robustness checks. We further document that a sizable allocation should be allocated to the El Niño portfolio in an optimal currency portfolio.

We provide evidence that the channel operates through output gap, which serves as a strong indicator of overall economic performance. At the start of an El Niño cycle, currencies that previously did well tend to have higher economic performance going forward, as captured by output gap. This, in turn, leads to an increase in foreign exchange returns.

Under current emission scenarios, scientists predict that future El Niño cycles will become more intense, with greater amplitude and stronger climate impacts. Researchers have conjectured that subsequent impact on economic growth can be even bigger. (See for example Callahan et al. 2023) Future research can examine how foreign exchange returns would be impacted under different scenarios.

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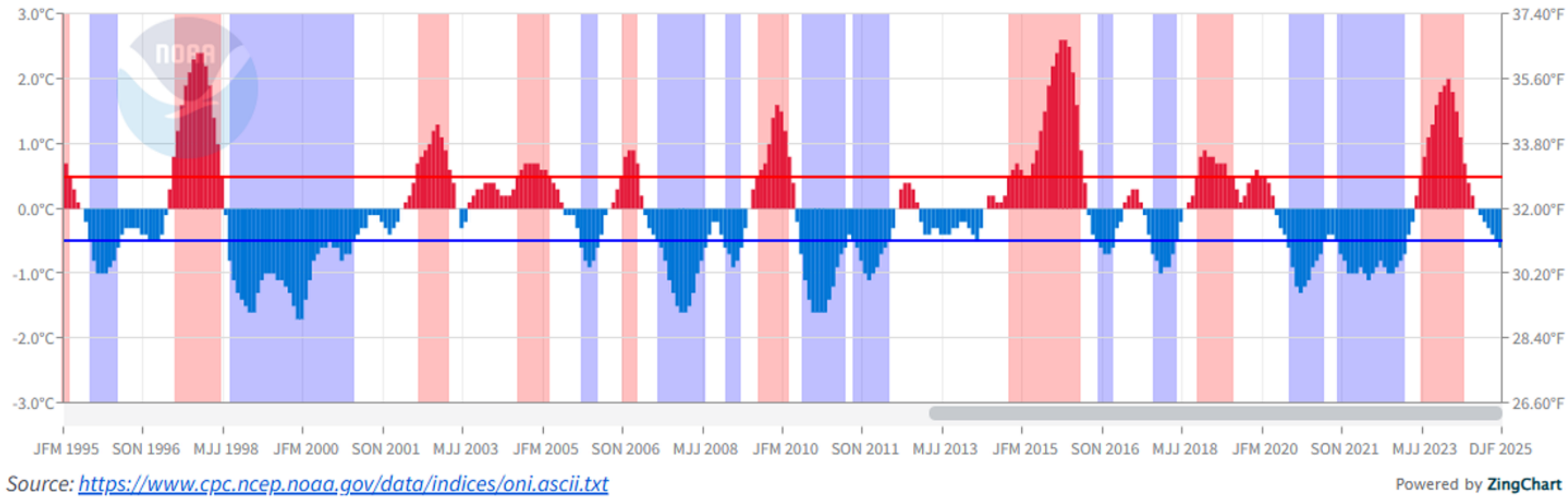


Fig. 1: Oceanic Niño Index (ONI) Over Time

This figure shows the Oceanic Niño Index (ONI) over time, representing the 3-month running mean of Niño 3.4 sea surface temperature (SST) anomalies. El Niño (La Niña) is a phenomenon in the equatorial Pacific Ocean characterized by a five consecutive 3-month running mean of sea surface temperature (SST) anomalies in the Niño 3.4 region that is above (below) the threshold of +0.5°C (-0.5°C). This standard of measure is known as the Oceanic Niño Index (ONI) and WARM and COLD phases are defined as a minimum of five consecutive 3-month running averages of SST anomalies (ERSST.v5) in the Niño 3.4 region surpassing a threshold of +/- 0.5°C.

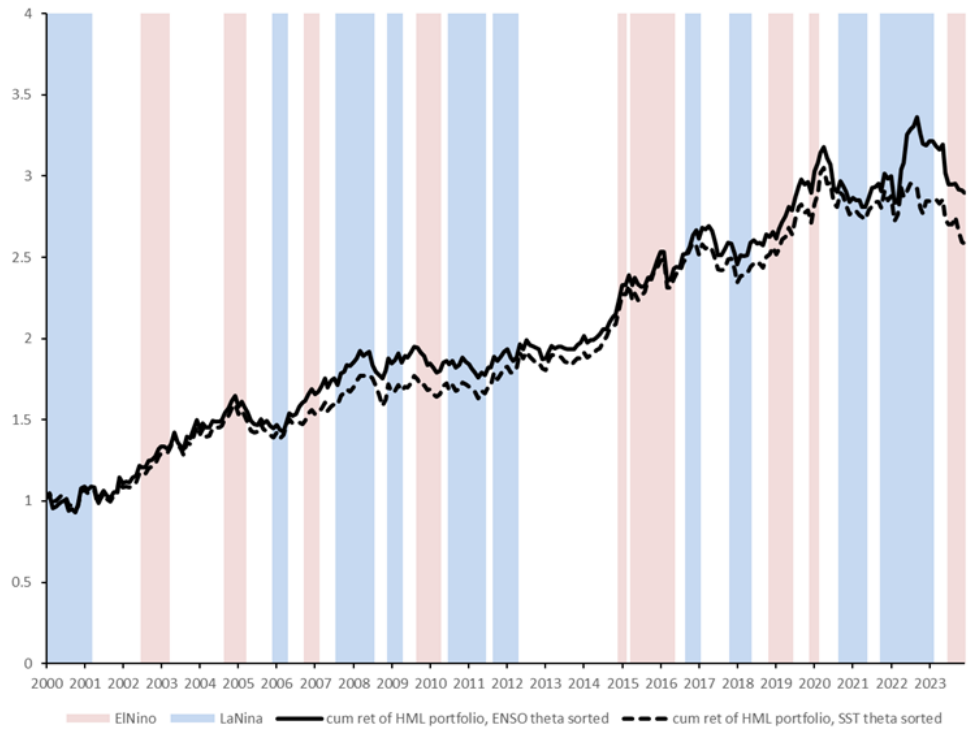
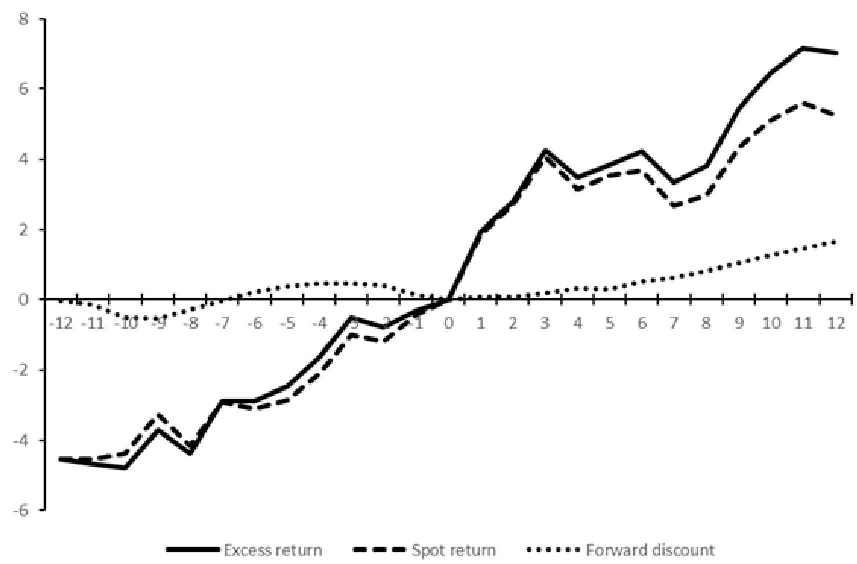


Fig. 2: Cumulative returns of ENSO and SST sorted HML portfolios

This figure illustrates the cumulative returns of a high θ minus low θ portfolio. The solid line represents the cumulative returns from HML portfolios sorted based on $\theta^{ENSO}_{c,\tau}$, while the dotted line corresponds to portfolios sorted on $\theta^{SST}_{c,\tau}$. For each currency c and month τ, $\theta^{ENSO}_{c,\tau}$ is estimated using a 10-year rolling window prior to month τ from the following regression: $RX_{ct} = \alpha_c + \beta^{Carry}_c Carry_t + \theta^{ENSO}_c ENSO_t + e_{ct}$. Here, $ENSO_t$ is a signed indicator variable representing the ENSO phase, where $ENSO_t = 1$ for El Niño, $ENSO_t = 0$ for neutral conditions, and $ENSO_t = -1$ for La Niña. $\theta^{SST}_{c,\tau}$ is estimated similarly. SST_t denotes the anomalous sea surface temperature.

Panel A. El Niño period



Panel B. La Niña period

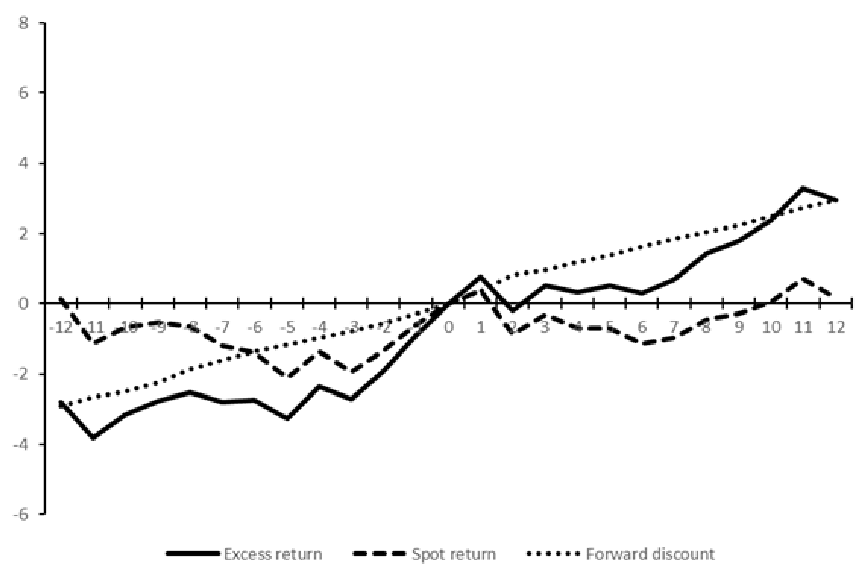


Fig. 3: Decomposition of Currency Excess Returns

This figure presents the average cumulative returns (in percentage) of portfolios formed at the beginning of an ENSO cycle (El Niño for Panel A and La Niña for Panel B), plotted over a 12-month event window.

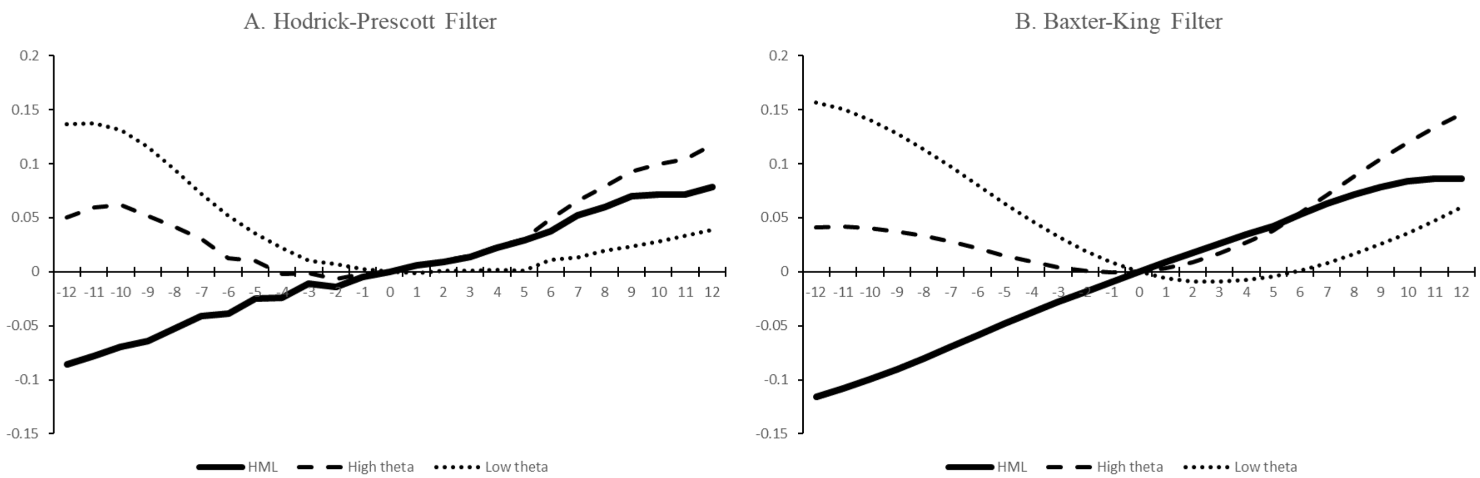


Fig. 4: Cumulative Output Gap Before and After El Niño

This figure illustrates the cumulative output gap 12 months before and after the onset of El Niño (t = 0). We estimate output gaps using two statistical techniques to extract a cyclical component from monthly industrial production data: (i) Hodrick-Prescott Filter for Panel A, (ii) Baxter-King Filter for Panel B. We excluded one El Niño cycle closest to COVID19, which is from 2019-12 to 2020-02 (31DEC2019 - 29FEB2020).

Table 1: Summary Statistics

The table presents summary statistics for currencies included in our sample after 2000, the year from which we construct currency portfolios. The variable RX represents the excess return in percentage terms and is calculated as $100 \times (f^k_{t-1} - s^k_t)$, where: s^k_t is the log spot rate (foreign currency units per USD) for currency k, and f^k_{t-1} is the log one-month forward rate (foreign currency units per USD). The variable FD represents the forward discount in percentage terms and is calculated as $100 \times (f^k_t - s^k_t)$, where f^k_t and s^k_t are defined as above. The forward discount is not annualized.

Description	ISO	start	end	rx_{mean}	rx_{std}	fd_{mean}	fd_{std}	fd_{min}	fd_{max}
Australia	AUD	1996-12	2023-12	0.07	3.50	0.12	0.16	-0.15	0.44
Brazil	BRL	2004-03	2023-12	0.44	4.45	0.65	0.32	0.00	1.46
Bulgaria	BGN	2004-03	2023-12	-0.08	2.68	-0.03	0.15	-0.27	0.44
Canada	CAD	1977-02	2023-12	0.00	2.02	0.05	0.13	-0.46	0.48
Croatia	HRK	2004-03	2022-12	-0.02	2.80	0.04	0.24	-0.40	1.31
Cyprus	CYP	2004-03	2007-12	0.40	2.02	0.01	0.17	-0.19	0.43
Czech Repulbic	CZK	1996-12	2023-12	0.12	3.41	0.06	0.31	-0.56	3.34
Denmark	DKK	1977-02	2023-12	0.04	3.04	0.06	0.29	-1.03	1.67
Egypt	EGP	2004-03	2022-12	0.86	2.50	1.21	1.80	-2.47	14.35
Euro erea	EUR	1996-12	2023-12	-0.14	2.71	-0.09	0.25	-1.64	1.46
Hong Kong	HKD	1996-12	2023-12	-0.02	0.17	-0.02	0.10	-0.18	1.17
Hungary	HUF	1997-10	2023-12	0.18	3.83	0.37	0.36	-0.32	1.38
Iceland	ISK	2004-03	2023-12	0.12	3.94	0.39	0.22	0.04	1.35
India	INR	1997-10	2023-12	0.11	1.97	0.37	0.21	-0.18	1.18
Indonesia	IDR	1996-12	2023-12	0.29	4.54	0.50	0.66	-0.01	5.01
Israel	ILS	2004-03	2023-12	0.08	2.40	-0.01	0.11	-0.27	0.27
Japan	JPY	1978-06	2023-12	-0.17	3.24	-0.24	0.22	-1.15	0.36
Kuwait	KWD	1996-12	2023-12	0.03	0.63	0.04	0.10	-0.25	0.73
Malaysia	MYR	1996-12	2023-12	-0.15	2.59	0.09	0.15	-0.32	0.76
Mexico	MXN	1996-12	2023-12	0.33	3.14	0.57	0.44	0.14	2.81
New Zealand	NZD	1996-12	2023-12	0.13	3.69	0.16	0.15	-0.18	0.55
Norway	NOK	1977-02	2023-12	0.02	3.20	0.13	0.28	-1.10	1.94
Philippines	PHP	1996-12	2023-12	0.05	2.23	0.28	0.29	-0.18	1.99
Poland	PLN	2002-02	2023-12	0.20	3.88	0.17	0.19	-0.12	0.80
Russia	RUB	2004-03	2023-12	0.43	5.33	0.67	0.94	-0.24	6.11
Saudi Arabia	SAR	1996-12	2023-12	0.01	0.10	0.01	0.05	-0.27	0.24
Singapore	SGD	1996-12	2023-12	-0.04	1.69	-0.05	0.11	-0.37	0.70
Slovakia	SKK	2002-02	2008-12	1.11	3.36	0.14	0.24	-0.19	0.60
Slovenia	SIT	2004-03	2006-12	0.22	2.17	0.02	0.15	-0.17	0.33
South Africa	ZAR	1996-12	2023-12	-0.17	4.37	0.51	0.21	0.18	1.54
South Korea	KRW	2002-02	2023-12	0.06	3.10	0.05	0.15	-0.89	0.31
Sweden	SEK	1977-02	2023-12	-0.06	3.14	0.09	0.32	-0.53	3.63
Switzerland	CHF	1977-02	2023-12	-0.03	3.36	-0.22	0.25	-1.28	0.48
Taiwan	TWD	1996-12	2023-12	-0.12	1.55	-0.09	0.24	-1.23	1.28
Thailand	THB	1996-12	2023-12	0.04	3.00	0.12	0.39	-0.36	4.51
Ukraine	UAH	2004-03	2014-01	0.31	3.30	0.71	0.70	-0.33	4.80
UK	GBP	1996-12	2023-12	-0.06	2.48	0.03	0.11	-0.27	0.29

Table 2: ENSO Sensitivity Based on the ENSO indicator

This table presents the average returns and t-statistics of theta-sorted portfolios, where theta is estimated using the ENSO indicator variable. We examine model variations with alternative controls to assess the robustness of the portfolio results. The regression equations are: (1) $RX_{ct} = \alpha_c + \theta_c^{ENSO} ENSO_t + e_{ct}$, (2) $RX_{ct} = \alpha_c + \beta_c^{Carry} Carry_t + \theta_c^{ENSO} ENSO_t + e_{ct}$, (3) $RX_{ct} = \alpha_c + \beta_c^{Carry} Carry_t + \beta_c^{Mom} MOMST_t + \theta_c^{ENSO} ENSO_t + e_{ct}$ and $RX_{ct} = \alpha_c + \beta_c^{Carry} Carry_t + \beta_c^{Mom} MOMLT_t + \theta_c^{ENSO} ENSO_t + e_{ct}$, where RX_{ct} is the excess return of currency c at time t, $Carry_t$ is the currency carry factor, $ENSO_t$ is the indicator variable for $ENSO$ ($ENSO_t = 1$ for El Niño, $ENSO_t = 0$ for neutral, and $ENSO_t = -1$ for La Niña), and $MOMST_t$ and $MOMLT_t$ are short-term and long-term currency momentum factors, respectively.

		Panel A. Without Controls				Panel B. With Carry			
PortName	Type	ElNiño	Neutral	LaNiña	All	ElNiño	Neutral	LaNiña	All
$Port_1$	mean	-3.64%	0.53%	1.96%	0.11%	-2.76%	0.33%	-1.38%	-0.90%
	tval	(-1.00)	(0.22)	(0.61)	(0.06)	(-0.76)	(0.12)	(-0.36)	(-0.47)
$Port_2$	mean	-1.74%	1.63%	-3.23%	-0.72%	-2.86%	2.22%	-1.07%	0.03%
	tval	(-0.59)	(0.80)	(-0.98)	(-0.46)	(-1.05)	(1.22)	(-0.38)	(0.02)
$Port_3$	mean	-1.21%	1.01%	-0.24%	0.11%	-0.33%	1.74%	0.35%	0.83%
	tval	(-0.45)	(0.50)	(-0.09)	(0.08)	(-0.12)	(0.89)	(0.12)	(0.58)
$Port_4$	mean	2.87%	1.53%	2.60%	2.18%	0.88%	0.73%	2.93%	1.50%
	tval	(0.98)	(0.74)	(0.87)	(1.45)	(0.30)	(0.39)	(1.05)	(1.06)
$Port_5$	mean	3.52%	4.36%	3.39%	3.86% **	5.06% *	3.73%	3.31%	3.88% **
	tval	(1.09)	(1.62)	(0.99)	(2.14)	(1.65)	(1.39)	(0.95)	(2.15)
$Port_{HML}$	mean	7.16% **	3.83% *	1.44%	3.75% **	7.83% **	3.40%	4.69%	4.78% ***
	tval	(2.23)	(1.75)	(0.52)	(2.48)	(2.48)	(1.37)	(1.46)	(2.84)

		Panel C. With Carry and ST Momentum				Panel D. With Carry and LT Momentum			
PortName	Type	ElNiño	Neutral	LaNiña	All	ElNiño	Neutral	LaNiña	All
$Port_1$	mean	-3.03%	0.33%	-0.57%	-0.69%	-3.17%	0.34%	-1.82%	-1.14%
	tval	(-0.82)	(0.12)	(-0.15)	(-0.35)	(-0.86)	(0.12)	(-0.47)	(-0.58)
$Port_2$	mean	-3.18%	2.42%	-1.42%	-0.07%	-3.06%	2.79%	-0.74%	0.35%
	tval	(-1.16)	(1.36)	(-0.51)	(-0.05)	(-1.09)	(1.58)	(-0.28)	(0.26)
$Port_3$	mean	-0.14%	0.95%	0.70%	0.63%	0.97%	0.84%	1.93%	1.23%
	tval	(-0.05)	(0.48)	(0.25)	(0.45)	(0.38)	(0.44)	(0.71)	(0.91)
$Port_4$	mean	1.89%	0.95%	1.93%	1.48%	1.38%	0.58%	0.64%	0.77%
	tval	(0.62)	(0.51)	(0.72)	(1.07)	(0.48)	(0.30)	(0.22)	(0.53)
$Port_5$	mean	4.33%	4.19%	3.56%	4.01% **	3.58%	4.35%	4.00%	4.07% **
	tval	(1.43)	(1.56)	(1.02)	(2.23)	(1.08)	(1.60)	(1.13)	(2.21)
$Port_{HML}$	mean	7.36% **	3.86%	4.14%	4.71% ***	6.76% **	4.01%	5.82% *	5.21% ***
	tval	(2.36)	(1.51)	(1.26)	(2.73)	(2.28)	(1.62)	(1.83)	(3.13)

Table 3: ENSO Sensitivity Based on Anomalous Sea Surface Temperature (SST)

This table presents the average returns and t-statistics of theta-sorted portfolios, where theta is estimated using SST (anomalous sea surface temperature). We examine model variations with alternative controls to assess the robustness of the portfolio results. The regression equations are: (1) $RX_{ct} = \alpha_c + \theta_c^{SST} SST_t + e_{ct}$, (2) $RX_{ct} = \alpha_c + \beta_c^{Carry} Carry_t + \theta_c^{SST} SST_t + e_{ct}$, (3) $RX_{ct} = \alpha_c + \beta_c^{Carry} Carry_t + \beta_c^{Mom} MOMST_t + \theta_c^{SST} SST_t + e_{ct}$ and $RX_{ct} = \alpha_c + \beta_c^{Carry} Carry_t + \beta_c^{Mom} MOMLT_t + \theta_c^{SST} SST_t + e_{ct}$, where RX_{ct} is the excess return of currency c at time t, $Carry_t$ is the currency carry factor, SST_t is the sea surface temperature anomalies, and $MOMST_t$ and $MOMLT_t$ are short-term and long-term currency momentum factors, respectively.

		Panel A. Without Controls				Panel B. With Carry			
PortName	Type	ElNiño	Neutral	LaNiña	All	ElNiño	Neutral	LaNiña	All
$Port_1$	mean	-2.92%	1.86%	0.30%	0.31%	-3.73%	1.22%	-1.37%	-0.71%
	tval	(-0.83)	(0.88)	(0.09)	(0.19)	(-1.01)	(0.49)	(-0.37)	(-0.38)
$Port_2$	mean	-1.79%	1.13%	-1.49%	-0.37%	-0.54%	2.10%	0.68%	1.06%
	tval	(-0.59)	(0.54)	(-0.51)	(-0.25)	(-0.19)	(1.05)	(0.23)	(0.73)
$Port_3$	mean	-1.35%	1.30%	0.41%	0.43%	-1.66%	1.47%	0.29%	0.40%
	tval	(-0.51)	(0.71)	(0.15)	(0.32)	(-0.63)	(0.83)	(0.11)	(0.30)
$Port_4$	mean	1.50%	0.50%	1.83%	1.16%	0.80%	0.36%	1.56%	0.86%
	tval	(0.47)	(0.22)	(0.60)	(0.73)	(0.25)	(0.17)	(0.53)	(0.55)
$Port_5$	mean	4.74%	4.49% *	3.47%	4.20% **	5.07% *	3.71%	2.47%	3.59% **
	tval	(1.55)	(1.67)	(0.98)	(2.32)	(1.70)	(1.43)	(0.72)	(2.06)
$Port_{HML}$	mean	7.66% **	2.62%	3.17%	3.89% **	8.79% ***	2.49%	3.84%	4.30% **
	tval	(2.30)	(1.14)	(1.19)	(2.52)	(2.60)	(0.97)	(1.32)	(2.56)

		Panel C. With Carry and ST Momentum				Panel D. With Carry and LT Momentum			
PortName	Type	ElNiño	Neutral	LaNiña	All	ElNiño	Neutral	LaNiña	All
$Port_1$	mean	-3.72%	1.68%	-0.42%	-0.19%	-3.62%	1.25%	-0.27%	-0.30%
	tval	(-1.00)	(0.67)	(-0.11)	(-0.10)	(-0.98)	(0.51)	(-0.07)	(-0.17)
$Port_2$	mean	-0.18%	2.17%	0.32%	1.04%	-0.44%	2.40%	-0.25%	0.90%
	tval	(-0.06)	(1.10)	(0.11)	(0.73)	(-0.15)	(1.15)	(-0.09)	(0.61)
$Port_3$	mean	-1.59%	0.92%	0.59%	0.27%	-1.34%	1.50%	1.66%	0.94%
	tval	(-0.66)	(0.54)	(0.21)	(0.21)	(-0.57)	(0.90)	(0.61)	(0.74)
$Port_4$	mean	1.32%	0.55%	1.08%	0.89%	0.64%	-0.35%	-0.29%	-0.12%
	tval	(0.43)	(0.26)	(0.38)	(0.60)	(0.21)	(-0.16)	(-0.10)	(-0.07)
$Port_5$	mean	3.96%	3.68%	2.24%	3.26% *	4.56%	4.12%	3.08%	3.87% **
	tval	(1.29)	(1.38)	(0.64)	(1.82)	(1.44)	(1.57)	(0.92)	(2.20)
$Port_{HML}$	mean	7.68% **	2.01%	2.66%	3.45% **	8.18% ***	2.86%	3.35%	4.17% **
	tval	(2.41)	(0.80)	(0.89)	(2.09)	(2.59)	(1.15)	(1.13)	(2.53)

Table 4: Decomposition of Currency Excess Returns

This table presents the decomposition of the excess currency returns of our portfolios, sorted by θ_{ENSO}, into forward discounts and spot returns. The regression equation used to estimate θ_{ENSO} is $RX_{ct} = \alpha_c + \beta_c^{Carry} Carry_t + \theta_c^{ENSO} ENSO_t + e_{ct}$.

		Panel A. Forward Discount				Panel B. Spot Return			
PortName	Type	ElNiño	Neutral	LaNiña	All	ElNiño	Neutral	LaNiña	All
$Port_1$	mean	1.56% ***	1.34% ***	2.64% ***	1.79% ***	-6.17%	-0.79%	0.46%	-1.67%
	tval	(4.67)	(3.40)	(6.12)	(7.47)	(-1.61)	(-0.30)	(0.11)	(-0.85)
$Port_2$	mean	1.09% ***	1.33% ***	0.86% ***	1.13% ***	-4.44%	1.86%	-1.74%	-0.71%
	tval	(5.05)	(9.12)	(4.61)	(11.10)	(-1.44)	(0.93)	(-0.53)	(-0.46)
$Port_3$	mean	0.69% ***	0.98% ***	0.89% ***	0.88% ***	-1.91%	-1.22%	1.95%	-0.42%
	tval	(3.93)	(8.60)	(5.93)	(10.95)	(-0.72)	(-0.60)	(0.66)	(-0.29)
$Port_4$	mean	1.55% ***	1.34% ***	1.39% ***	1.40% ***	-0.27%	-0.17%	1.22%	0.23%
	tval	(5.12)	(7.50)	(2.85)	(7.68)	(-0.09)	(-0.08)	(0.34)	(0.14)
$Port_5$	mean	3.55% ***	3.14% ***	3.37% ***	3.31% ***	2.32%	0.04%	1.97%	1.16%
	tval	(7.87)	(11.31)	(7.60)	(15.50)	(0.80)	(0.01)	(0.60)	(0.67)
$Port_{HML}$	mean	1.99% ***	1.80% ***	0.73%	1.52% ***	8.49% **	0.82%	1.51%	2.83% *
	tval	(3.68)	(3.81)	(1.36)	(5.06)	(2.40)	(0.35)	(0.48)	(1.69)

Table 5: Correlation Analysis of ENSO Portfolio and FX Risk Factors

This table examines the correlation between the theta-sorted HML portfolio returns (ENSO portfolio) and established traded FX risk factors as defined by Nucera, Sarno, and Zinna (2024). These FX risk factors include carry (Carry), short-term and long-term momentum (ST and LT Mom), currency value (Value), net foreign assets (NFA), liabilities in domestic currencies (LDC), term spread (Term), long-term yields (LYld), and output gap (GAP). The analysis focuses on the El Niño cycle and utilizes sample data available through December 2017.

	Carry	MomST	MomLT	Value	NFA	LDC	Term	LYld	GAP	ENSO
Carry										
MomST	-0.23									
MomLT	0.16	0.31								
Value	-0.12	-0.12	-0.45							
NFA	0.37	-0.22	-0.08	-0.16						
LDC	0.49	-0.33	-0.06	-0.17	0.63					
Term	0.49	-0.29	0.07	-0.27	0.32	0.41				
LYld	0.77	-0.28	-0.02	-0.02	0.38	0.38	0.43			
GAP	-0.17	0.17	-0.09	0.18	-0.18	-0.11	-0.18	-0.09		
ENSO	0.02	0.11	0.32	-0.53	-0.06	-0.01	0.28	-0.07	0.00	

Table 6: Spanning Tests

This table presents results from mean-variance spanning tests. Panel A reports the average excess returns (in percentage) of FX risk factors, including the ENSO portfolio, during the sample period from 2002 to 2017. Panel B and C report the abnormal returns (alphas) and exposure to ENSO portfolio returns (betas) for FX risk factors, respectively. Each risk factor is regressed on ENSO portfolio returns using the equation $F = \alpha + \beta \cdot ENSO_{HML}$, and results are reported for each ENSO cycle. Panel D and E report the abnormal returns (alphas) and exposure to FX risk factors (betas) for the ENSO portfolio, respectively. The ENSO portfolio returns are regressed on the other factor returns using the equation $ENSO_{HML} = \alpha + \beta \cdot F$, and the results are reported.

Period	Test Factor:	Carry	MomST	MomLT	Value	NFA	LDC	Term	LYld	GAP
					Panel A. Average Excess Returns					
All Times	Avg. Ret	8.45 ***	4.44 **	4.08 **	1.21	4.06 **	4.48 **	1.50	3.35	4.35 **
	t-stat	(4.10)	(2.31)	(1.97)	(0.69)	(2.08)	(2.14)	(0.68)	(1.57)	(2.50)
El Niño	Avg. Ret	13.55 ***	7.73 **	10.45 ***	-2.66	3.13	9.97 ***	8.51 ***	5.81 *	3.12
	t-stat	(4.01)	(2.06)	(2.78)	(-0.86)	(0.86)	(2.77)	(3.08)	(1.82)	(0.93)
Ni Nina	Avg. Ret	5.67	-1.26	-1.29	-0.39	3.23	2.94	-3.33	3.62	5.70
	t-stat	(1.46)	(-0.33)	(-0.31)	(-0.12)	(0.79)	(1.44)	(-0.67)	(0.76)	(1.18)
					Panel B. Alphas FX factors ($F = \alpha + \beta \cdot ENSO_{HML}$)					
All Times	mean	8.36 ***	3.87 *	2.23	3.71 **	4.38 **	4.54 **	0.08	3.75 *	4.34 **
	t-stat	(3.92)	(1.85)	(1.26)	(2.42)	(2.04)	(2.07)	(0.03)	(1.65)	(2.40)
El Niño	mean	14.51 ***	3.70	4.06	2.23	5.02 **	11.24 ***	7.39 **	9.23 ***	3.39
	t-stat	(3.82)	(1.25)	(1.40)	(0.86)	(2.09)	(3.80)	(2.44)	(3.04)	(0.98)
Ni Nina	mean	5.37	-1.01	-2.77	1.42	4.12	3.51 *	-4.36	3.31	5.57
	t-stat	(1.39)	(-0.26)	(-0.66)	(0.47)	(0.98)	(1.76)	(-0.88)	(0.70)	(1.17)
					Panel C. Betas FX factors ($F = \alpha + \beta \cdot ENSO_{HML}$)					
All Times	mean	0.02	0.10	0.33 ***	-0.45 ***	-0.06	-0.01	0.25 ***	-0.07	0.00
	t-stat	(0.24)	(1.03)	(2.77)	(-6.19)	(-0.45)	(-0.13)	(3.62)	(-0.74)	(0.02)
El Niño	mean	-0.10	0.42 ***	0.67 ***	-0.51 ***	-0.20	-0.13	0.12	-0.36 ***	-0.03
	t-stat	(-1.18)	(5.58)	(5.40)	(-5.98)	(-1.04)	(-0.85)	(1.23)	(-5.82)	(-0.19)
Ni Nina	mean	0.06	-0.05	0.31 *	-0.38 ***	-0.19	-0.12	0.21 *	0.07	0.03
	t-stat	(0.44)	(-0.40)	(1.88)	(-3.97)	(-1.03)	(-1.02)	(1.75)	(0.40)	(0.25)
					Panel D. Alphas ENSO factor ($ENSO_{HML} = \alpha + \beta \cdot F$)					
All Times	mean	5.43 ***	5.09 ***	4.35 **	6.36 ***	5.89 ***	5.66 ***	5.11 ***	5.84 ***	5.59 ***
	t-stat	(2.72)	(2.76)	(2.29)	(3.83)	(3.15)	(3.00)	(3.13)	(3.18)	(3.13)
El Niño	mean	11.41 ***	5.14	1.90	7.37 **	10.56 ***	11.53 ***	7.22 *	12.39 ***	9.67 ***
	t-stat	(2.67)	(1.37)	(0.59)	(2.55)	(3.05)	(2.58)	(1.93)	(3.33)	(2.58)
Ni Nina	mean	4.40	4.73	5.16	4.55	5.47	5.85	5.60	4.59	4.66
	t-stat	(1.07)	(1.17)	(1.31)	(1.22)	(1.34)	(1.49)	(1.44)	(1.15)	(1.20)
					E. Betas ENSO factor ($ENSO_{HML} = \alpha + \beta \cdot F$)					
All Times	mean	0.02	0.11	0.30 ***	-0.63 ***	-0.07	-0.02	0.32 ***	-0.07	0.00
	t-stat	(0.24)	(0.98)	(2.59)	(-6.91)	(-0.44)	(-0.12)	(5.63)	(-0.70)	(0.02)
El Niño	mean	-0.14	0.57 ***	0.73 ***	-0.82 ***	-0.32	-0.20	0.28	-0.49 **	-0.03
	t-stat	(-1.25)	(3.46)	(5.96)	(-5.49)	(-1.12)	(-1.01)	(1.32)	(-2.37)	(-0.19)
Ni Nina	mean	0.07	-0.06	0.28 *	-0.64 ***	-0.21	-0.35	0.24 **	0.06	0.03
	t-stat	(0.45)	(-0.41)	(1.79)	(-4.84)	(-0.96)	(-1.09)	(2.14)	(0.41)	(0.24)

Table 7: Optimal Weights in Tangency Portfolio

This table presents the optimal weights of the ENSO portfolio in the Tangency portfolio.

	Panel A. Optimal Weights in Tangency Portfolio											Panel B. Summary Statistics			
	Dollar	Carry	MomST	MomLT	Value	NFA	LDC	Term	LYld	GAP	ENSO	Mean	STDEV	SR	Diff in SR
Model 1	15%	85%										0.641	1.860	0.345	
	14%	54%									32%	0.571	1.425	0.400	0.056
Model 2	13%	66%			21%							0.521	1.451	0.359	
	11%	30%			29%						30%	0.410	0.865	0.474	0.115
Model 3	13%	40%	30%		17%							0.450	0.975	0.461	
	12%	25%	18%		24%						21%	0.399	0.721	0.554	0.093
Model 4	14%	50%	36%	0%								0.525	1.201	0.437	
	14%	42%	30%	-6%							20%	0.521	1.096	0.475	0.038
Model 5	34%					-13%	30%	-1%	12%	39%		0.335	1.115	0.300	
	28%					-10%	24%	-15%	15%	27%	31%	0.401	1.039	0.385	0.085
Model 6	12%	49%	18%	6%	15%	2%	7%	-2%	-23%	18%		0.506	0.918	0.551	
	10%	35%	13%	3%	22%	2%	7%	-8%	-14%	11%	20%	0.471	0.753	0.625	0.074

Table 8: Pricing Errors from Time-Series Regression

This table compares the models based on their ability to explain FX anomalies using time-series alphas. Measures include the dispersion of alpha ($alpha_{HL}$: $max–min\alpha$), average absolute alpha (α_{ABS}), the Gibbons, Ross, and Shanken (1989) *GRS* test for whether all alphas are zero (p_{GRS}), and the average time-series R^2. The analysis is conducted on all 51 FX portfolios (ALL) portfolio, and also on subsets of portfolios sorted on specific factors, including Carry, MomST, MomLT, Value, NFA, LDC, Term, LYld, GAP, and ENSO portfolios. The models evaluated include (i) Dollar factor alone, (ii) Dollar + ENSO factors, (iii) Dollar + Carry factors, and (iv) Dollar + Carry + ENSO factors. The analysis is performed separately for three distinct cycles: the full sample period (All Time), El Niño cycles, and La Niña cycles.

		All times				**El Niño**				**La Niña**			
Portfolio	Factor	α_{HL}	α_{ABS}	pGRS	R^2	α_{HL}	α_{ABS}	pGRS	R^2	α_{HL}	α_{ABS}	pGRS	R^2
ALL	Dollar	811	139	0.00	0.80	1516	266	0.00	0.77	935	168	0.00	0.82
	Dollar + ENSO	808	133	0.00	0.82	1663	221	0.00	0.80	853	156	0.00	0.83
	Dollar + Carry	695	114	0.00	0.82	1339	228	0.00	0.79	995	163	0.00	0.85
	Dollar + Carry + ENSO	698	114	0.00	0.84	1182	161	0.00	0.83	933	154	0.00	0.86
Carry	Dollar	750	187	0.00	0.82	1315	341	0.00	0.78	630	171	0.00	0.83
	Dollar + ENSO	727	187	0.00	0.82	1398	362	0.00	0.78	462	136	0.00	0.83
	Dollar + Carry	174	43	0.00	0.91	347	143	0.00	0.89	323	142	0.00	0.93
	Dollar + Carry + ENSO	188	47	0.00	0.91	372	163	0.00	0.89	276	118	0.00	0.93
MomST	Dollar	525	174	0.00	0.78	822	195	0.00	0.76	213	71	0.00	0.80
	Dollar + ENSO	476	159	0.00	0.78	406	125	0.00	0.77	207	67	0.00	0.80
	Dollar + Carry	669	220	0.00	0.79	1071	267	0.00	0.76	206	57	0.00	0.81
	Dollar + Carry + ENSO	618	206	0.00	0.79	618	189	0.00	0.78	185	54	0.00	0.81
MomLT	Dollar	468	126	0.00	0.78	1048	322	0.00	0.74	352	107	0.00	0.81
	Dollar + ENSO	392	111	0.00	0.79	685	183	0.00	0.82	451	104	0.00	0.81
	Dollar + Carry	268	103	0.00	0.79	1032	291	0.00	0.74	394	135	0.00	0.83
	Dollar + Carry + ENSO	302	87	0.00	0.80	518	158	0.00	0.82	450	128	0.00	0.83
Value	Dollar	356	111	0.00	0.81	654	232	0.00	0.78	726	234	0.00	0.84
	Dollar + ENSO	436	153	0.00	0.84	553	183	0.00	0.82	695	214	0.00	0.86
	Dollar + Carry	391	96	0.00	0.81	756	236	0.00	0.79	674	213	0.00	0.84
	Dollar + Carry + ENSO	483	141	0.00	0.84	435	179	0.00	0.83	659	200	0.00	0.86
NFA	Dollar	449	106	0.00	0.85	990	248	0.00	0.82	487	129	0.00	0.88
	Dollar + ENSO	406	94	0.00	0.85	920	219	0.00	0.83	492	143	0.00	0.88
	Dollar + Carry	158	49	0.00	0.88	478	145	0.00	0.85	396	124	0.00	0.91
	Dollar + Carry + ENSO	179	55	0.00	0.89	338	110	0.00	0.85	429	138	0.00	0.91
LDC	Dollar	372	118	0.00	0.79	914	318	0.00	0.77	368	137	0.00	0.85
	Dollar + ENSO	375	104	0.00	0.80	1022	292	0.00	0.77	367	119	0.00	0.85
	Dollar + Carry	114	39	0.00	0.82	611	224	0.00	0.78	394	108	0.00	0.87
	Dollar + Carry + ENSO	175	63	0.00	0.82	684	188	0.00	0.78	375	104	0.00	0.87
Term	Dollar	291	102	0.00	0.82	863	290	0.00	0.81	587	194	0.00	0.81
	Dollar + ENSO	248	111	0.00	0.83	747	251	0.00	0.82	742	232	0.00	0.82
	Dollar + Carry	274	96	0.00	0.84	539	157	0.00	0.83	685	206	0.00	0.83
	Dollar + Carry + ENSO	415	132	0.00	0.84	460	97	0.00	0.83	802	238	0.00	0.84
Lyld	Dollar	317	116	0.00	0.82	821	225	0.00	0.79	429	147	0.00	0.82
	Dollar + ENSO	334	135	0.00	0.82	1055	332	0.00	0.80	567	172	0.00	0.82
	Dollar + Carry	410	129	0.00	0.87	554	156	0.00	0.84	530	161	0.00	0.88
	Dollar + Carry + ENSO	388	123	0.00	0.87	443	144	0.00	0.85	630	184	0.00	0.88
GAP	Dollar	572	195	0.00	0.78	424	150	0.00	0.74	800	216	0.00	0.79
	Dollar + ENSO	550	196	0.00	0.78	591	196	0.00	0.74	853	229	0.00	0.78
	Dollar + Carry	618	227	0.00	0.78	765	238	0.00	0.74	915	236	0.00	0.79
	Dollar + Carry + ENSO	628	227	0.00	0.78	893	307	0.00	0.74	933	240	0.00	0.79
ENSO	Dollar	490	144	0.00	0.75	1059	331	0.00	0.74	657	144	0.00	0.77
	Dollar + ENSO	117	44	0.00	0.86	121	37	1.00	0.88	401	121	0.00	0.85
	Dollar + Carry	558	155	0.00	0.75	1212	421	0.00	0.72	823	264	0.00	0.78
	Dollar + Carry + ENSO	226	73	0.00	0.86	205	65	0.00	0.89	455	145	1.00	0.88

Table 9: R^2 from Cross-sectional Regression

This table reports the R^2 values from cross-sectional regressions (CSR) conducted on 51 FX portfolios, referred to as the “ALL” portfolio, and also on subsets of portfolios sorted on specific factors, including 5 Carry, 5 Short-Term and 5 Long-Term Momentum (ST Mom and LT Mom), 5 Currency Value (Value), 5 Net Foreign Assets (NFA), 6 Liabilities in Domestic Currencies (LDC), 5 Term Spread (Term), 5 Long-Term Yields (LYld), 5 Output Gap (GAP) portfolios, and 5 ENSO portfolios. The models evaluated include (i) Dollar factor alone, (ii) Dollar + ENSO factors, (iii) Dollar + Carry factors, and (iv) Dollar + Carry + ENSO factors.The analysis is performed separately for three distinct cycles: the full sample period (All Time), El Niño cycles, and La Niña cycles.

		All time			El Niño			La Niña		
Portfolio	Factor	CSR R^2	$pval_1$ $H0: R^2 = 1$	$pval_2$ $H0: R^2 = 0$	CSR R^2	$pval_1$ $H0: R^2 = 1$	$pval_2$ $H0: R^2 = 0$	CSR R^2	$pval_1$ $H0: R^2 = 1$	$pval_2$ [t] $H0: R^2 = 0$
ALL	Dollar	0.06	0.00	0.21	0.00	0.00	0.84	0.05	0.37	0.60
	Dollar + ENSO	0.19	0.00	0.06	0.27	0.00	0.06	0.19	0.41	0.56
	Dollar + Carry	0.39	0.00	0.01	0.30	0.02	0.11	0.11	0.27	0.75
	Dollar + Carry + ENSO	0.48	0.00	0.01	0.64	0.16	0.00	0.21	0.23	0.74
Carry	Dollar	0.41	0.00	0.00	0.08	0.00	0.47	0.08	0.17	0.59
	Dollar + ENSO	0.64	0.46	0.27	0.88	0.90	0.09	0.91	0.61	0.18
	Dollar + Carry	0.96	0.18	0.00	0.91	0.15	0.00	0.76	0.22	0.26
	Dollar + Carry + ENSO	1.00	0.76	0.00	1.00	0.84	0.00	0.99	0.86	0.19
MomST	Dollar	0.73	0.42	0.06	0.12	0.13	0.54	0.88	1.00	0.58
	Dollar + ENSO	0.91	0.71	0.05	0.93	0.83	0.06	0.90	0.99	0.81
	Dollar + Carry	0.75	0.42	0.15	0.32	0.19	0.60	0.93	0.99	0.84
	Dollar + Carry + ENSO	0.96	0.73	0.06	0.95	0.57	0.09	1.00	0.98	0.91
MomLT	Dollar	0.00	0.03	0.95	0.04	0.00	0.78	0.13	0.39	0.74
	Dollar + ENSO	0.44	0.01	0.26	0.80	0.08	0.01	0.44	0.52	0.76
	Dollar + Carry	0.91	0.71	0.01	0.28	0.16	0.70	0.24	0.14	0.86
	Dollar + Carry + ENSO	0.94	0.32	0.04	0.97	0.53	0.00	1.00	1.00	0.62
Value	Dollar	0.76	0.84	0.04	0.24	0.29	0.41	0.10	0.18	0.48
	Dollar + ENSO	0.80	0.65	0.13	0.70	0.23	0.17	0.22	0.07	0.61
	Dollar + Carry	0.78	0.69	0.11	0.33	0.26	0.57	0.94	0.90	0.02
	Dollar + Carry + ENSO	0.80	0.37	0.22	0.99	0.79	0.11	0.94	0.60	0.12
NFA	Dollar	0.46	0.00	0.02	0.08	0.00	0.37	0.35	0.30	0.46
	Dollar + ENSO	0.64	0.02	0.01	0.72	0.24	0.01	0.42	0.23	0.69
	Dollar + Carry	0.91	0.22	0.00	0.92	0.56	0.00	0.71	0.26	0.47
	Dollar + Carry + ENSO	0.93	0.12	0.00	1.00	0.87	0.00	0.87	0.39	0.50
LDC	Dollar	0.35	0.03	0.07	0.19	0.01	0.20	0.23	0.66	0.67
	Dollar + ENSO	0.36	0.02	0.17	0.24	0.01	0.39	0.58	0.74	0.70
	Dollar + Carry	0.95	0.81	0.01	0.81	0.51	0.01	0.79	0.85	0.60
	Dollar + Carry + ENSO	0.95	0.64	0.01	0.87	0.60	0.01	0.84	0.79	0.73
Term	Dollar	0.02	0.30	0.79	0.14	0.10	0.47	0.23	0.42	0.39
	Dollar + ENSO	0.87	0.75	0.26	0.59	0.10	0.10	0.55	0.41	0.46
	Dollar + Carry	0.75	0.59	0.31	0.83	0.55	0.03	0.36	0.27	0.64
	Dollar + Carry + ENSO	0.89	0.55	0.41	0.87	0.36	0.04	0.75	0.50	0.51
Lyld	Dollar	0.89	0.82	0.01	0.00	0.04	0.93	0.05	0.64	0.80
	Dollar + ENSO	0.96	0.87	0.01	0.75	0.35	0.10	0.06	0.45	0.98
	Dollar + Carry	0.91	0.60	0.04	0.96	0.89	0.05	0.23	0.33	0.89
	Dollar + Carry + ENSO	0.96	0.56	0.05	1.00	0.91	0.05	0.27	0.20	0.97
GAP	Dollar	0.62	0.30	0.04	0.22	0.62	0.58	0.05	0.17	0.72
	Dollar + ENSO	0.63	0.22	0.14	0.44	0.55	0.72	0.10	0.10	0.94
	Dollar + Carry	0.71	0.37	0.24	0.93	0.97	0.40	0.65	0.53	0.41
	Dollar + Carry + ENSO	0.79	0.50	0.40	0.99	0.93	0.57	0.65	0.25	0.63
ENSO	Dollar	0.01	0.01	0.79	0.42	0.17	0.10	0.01	0.10	0.89
	Dollar + ENSO	0.92	0.36	0.01	0.99	0.67	0.00	0.76	0.54	0.18
	Dollar + Carry	0.11	0.10	0.83	0.76	0.59	0.08	0.11	0.11	0.84
	Dollar + Carry + ENSO	0.87	0.13	0.04	0.99	0.60	0.02	0.72	0.05	0.25

Table 10: ENSO cycle and Output Gaps

This table presents the averages and t-statistics of the differences in cumulative output gaps between high and low theta currencies. The reported lag values are calculated by subtracting the lagged value from the current value, where a positive lagged cumulative output gap indicates that high theta currencies experienced a higher output gap than low theta currencies during the previous lagged months. The forward values are calculated by subtracting the current value from the forward value, with a positive value indicating a higher output gap for high theta currencies than low theta currencies after portfolio formation in the forward months. The output gap is estimated as (log) industrial production minus the (log) trend in industrial production. The trend is estimated using the Hodrick-Prescott filter and the Baxter-King filter in Panel A and B, respectively. The COVID-19 period was excluded due to its abnormally large output gaps.

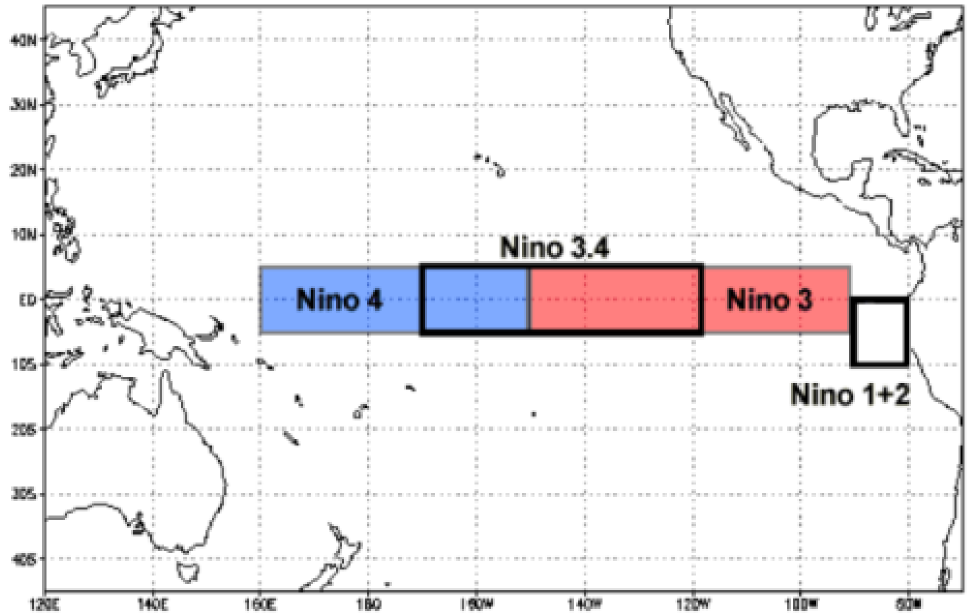
		Panel A. Hodrick-Prescott filter				Panel B. Baxter-King filter			
Horizon	Type	ElNiño	Neutral	LaNiña	All	ElNiño	Neutral	LaNiña	All
$\text{Lag}_{12m:0}$	mean	8.51% ***	-1.92%	-3.81% *	-0.33%	11.11% ***	0.03%	-3.22%	1.29%
	tval	(3.65)	(-1.33)	(-1.83)	(-0.30)	(4.80)	(0.02)	(-1.38)	(1.05)
$\text{Lag}_{6m:0}$	mean	4.45% ***	-1.84% *	-0.44%	-0.01%	5.40% ***	-0.12%	-1.12%	0.72%
	tval	(3.65)	(-1.74)	(-0.43)	(-0.02)	(3.89)	(-0.12)	(-0.95)	(1.05)
$\text{Lag}_{3m:0}$	mean	2.29% ***	-1.04%	-0.39%	-0.10%	2.64% ***	-0.08%	-0.36%	0.41%
	tval	(3.55)	(-1.63)	(-0.59)	(-0.26)	(3.69)	(-0.15)	(-0.61)	(1.16)
$\text{Lag}_{1m:0}$	mean	0.77% ***	-0.34%	-0.19%	-0.05%	0.86% ***	-0.02%	-0.08%	0.15%
	tval	(3.02)	(-1.50)	(-0.67)	(-0.34)	(3.62)	(-0.11)	(-0.39)	(1.26)
$\text{Forward}_{0:1m}$	mean	0.50% *	-0.28%	-0.16%	-0.07%	0.83% ***	0.00%	-0.05%	0.16%
	tval	(1.65)	(-1.31)	(-0.57)	(-0.49)	(3.65)	(0.00)	(-0.23)	(1.37)
$\text{Forward}_{0:3m}$	mean	1.60% **	-0.67%	-0.43%	-0.10%	2.34% ***	0.09%	-0.07%	0.52%
	tval	(2.11)	(-1.21)	(-0.57)	(-0.26)	(3.71)	(0.17)	(-0.11)	(1.47)
$\text{Forward}_{0:6m}$	mean	2.81% **	0.04%	-1.32%	0.17%	3.71% ***	0.65%	0.05%	1.10%
	tval	(2.50)	(0.04)	(-0.98)	(0.24)	(3.45)	(0.62)	(0.04)	(1.59)
$\text{Forward}_{0:12m}$	mean	1.67%	1.97%	-0.83%	0.94%	0.61%	2.99%	1.99%	2.16% *
	tval	(0.97)	(1.17)	(-0.37)	(0.82)	(0.32)	(1.60)	(0.79)	(1.70)

Appendix for
"El Niño cycle and FX returns"

Joon Woo Bae, Taehoon Lim, David Ng, and Lucio Sarno

A. SST and ENSO definition

Equatorial Pacific Sea Surface Temperatures (SST)

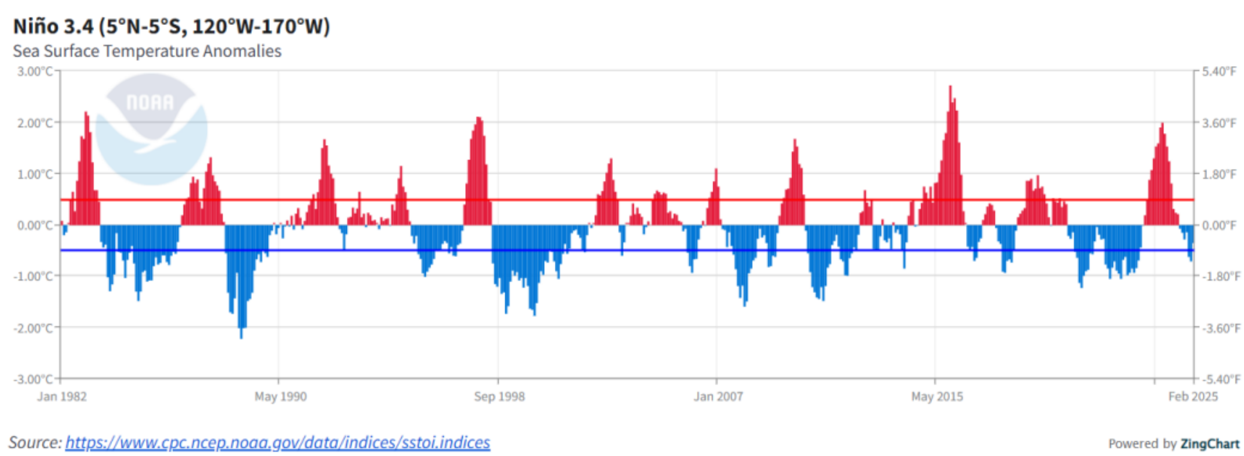


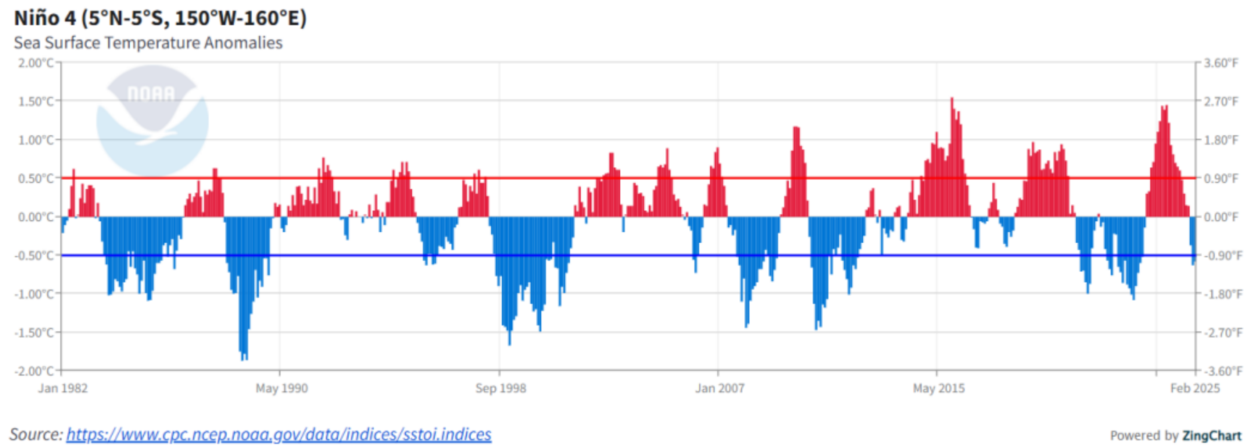
El Niño (La Niña) is a phenomenon in the equatorial Pacific Ocean characterized by a five consecutive 3-month running mean of sea surface temperature (SST) anomalies in the Niño 3.4 region that is above (below) the threshold of +0.5°C (-0.5°C). This standard of measure is known as the Oceanic Niño Index (ONI).

Historically, scientists have classified the intensity of El Niño based on SST anomalies exceeding a pre-selected threshold in a certain region of the equatorial Pacific. The most commonly used region is the Niño 3.4 region, and the most commonly used threshold is a positive SST departure from normal greater than or equal to +0.5°C. Since this region encompasses the western half of the equatorial cold tongue region, it provides a good measure of important changes in SST and SST gradients that result in changes in the pattern of deep tropical convection and atmospheric circulation. The criteria, that is often used to classify El Niño episodes, is that five consecutive 3-month running mean SST anomalies exceed the threshold.

Studies have shown that a necessary condition for the development and persistence of deep convection (enhanced cloudiness and precipitation) in the Tropics is that the local SST be 28°C or greater. Once the pattern of deep convection has been altered due to anomalous SSTs, the tropical and subtropical atmospheric circulation adjusts to the new pattern of tropical heating, resulting in anomalous patterns of precipitation and temperature that extend well beyond the region of the equatorial Pacific. An SST anomaly of +0.5°C in the Niño 3.4 region is sufficient to reach this threshold from late March to mid-June. During the remainder of the year a larger SST anomaly, up to +1.5°C in November-December-January, is required in order to reach the threshold to support persistent deep convection in that region. Warm and cold phases are defined as a minimum of five consecutive 3-month running averages of SST anomalies (ERSST.v5) in the Niño 3.4 region surpassing a threshold of +/- 0.5°C.

SST values in the Niño 3.4 region may not be the best choice for determining La Niña episodes but, for consistency, the index has been defined by negative anomalies in this area. A better choice might be the Niño 4 region, since that region normally has SSTs at or above the threshold for deep convection throughout the year. An SST anomaly of -0.5°C in that region would be sufficient to bring water temperatures below the 28°C threshold, which would result in a significant westward shift in the pattern of deep convection in the tropical Pacific.





Sea surface temperature anomalies were calculated using the Extended Reconstructed Sea Surface Temperature version 5 (ERSST.v5).

B. Cross-sectional asset pricing model

Let f be a K-vector of factors, R be a vector of returns on N test assets with mean μ_R and covariance matrix V_R, and β be the $N \times K$ matrix of multiple regression betas of the N assets with respect to the K factors. Let $Y_t = [f_t', R_t']'$ be an $N+K$ vector. Denote the mean and variance of Y_t as

$$\begin{aligned} \mu = E[Y_t] &= \begin{bmatrix} \mu_f \\ \mu_R \end{bmatrix} \\ V = Var[Y_t] &= \begin{bmatrix} V_f & V_{fR} \\ V_{Rf} & V_R \end{bmatrix} \end{aligned}$$

If the K factor asset pricing model holds, the expected returns of the N assets are given by $\mu_R = X\gamma$, where $X = [1_N, \beta]$ and $\gamma = [\gamma_0, \gamma_1']'$ is a vector consisting of the zero-beta rate and risk premia on the K factors. In a constant beta case, the two-pass cross-sectional regression (CSR) method first obtains estimates $\hat{\beta}$ by running the following multivariate regression:

$$\begin{aligned} R_t &= \alpha + \beta f_t + \epsilon_t, \quad t = 1, \cdots, T \\ \hat{\beta} &= \hat{V}_{Rf}\hat{V}_f^{-1} \\ \gamma_W &= argmin_\gamma (\mu_R - X\gamma)' W (\mu_R - X\gamma) = (X'WX)^{-1}X'W\mu_R \\ \hat{\gamma} &= (\hat{X}'W\hat{X})^{-1}\hat{X}'W\hat{\mu}_R \end{aligned}$$

where $W = I_N$ under OLS CSR and $W = \Sigma^{-1} = (V_R - V_{Rf}V_f^{-1}V_{fR})^{-1}$ under GLS CSR (or equivalently use $W = V_R^{-1}$).

A normalized goodness-of-fit measure of the model (cross-sectional R^2) can be defined as $\rho_W^2 = 1 - \frac{Q}{Q_0}$, where $Q = e'_W W e_W$, $Q_0 = e'_0 W e_0$, $e_W = [I_N - X(X'WX)^{-1}X'W]\mu_R$, and $e_0 = [I_N - 1_N(1_N'W1_N)^{-1}1_N'W]\mu_R$.

Shanken (1992) provides asymptotic distribution of γ adjusted for the errors-in-variables problem accounting for the estimation errors in β. For OLS CSR, and GLS CSR,

$$\sqrt{T}(\check{\gamma} - \gamma) \overset{A}{\sim} N(0_{K+1}, (1 + \gamma' V_f^{-1}\gamma)(X'X)^{-1}(X'\Sigma X)(X'X)^{-1} + \begin{bmatrix} 0 & 0_K' \\ 0_K & V_f \end{bmatrix}$$

$$\sqrt{T}(\check{\gamma}-\gamma) \overset{A}{\sim} N\left(0_{K+1}, (1+\gamma' V_f^{-1}\gamma)(X'\Sigma X)^{-1} + \begin{bmatrix} 0 & 0_K' \\ 0_K & V_f \end{bmatrix}\right.$$

Kan et al. (2013) further investigate the asymptotic distribution of $\hat{\gamma}$ under potentially misspecified models as well as under the case when the factors and returns are i.i.d. multivariate elliptical distribution. The distribution is given by

$$\begin{aligned}
\sqrt{T}(\check{\gamma}-\gamma) &\overset{A}{\sim} N(0_{K+1}, V(\hat{\gamma})) \\
V(\hat{\gamma}) &= \sum_{j=-\infty}^{\infty} E[h_t h_{t+j}'] \\
h_t &= (\gamma_t - \gamma) - (\theta_t - \theta)w_t + Hz_t
\end{aligned}$$

where $\theta_t = [\gamma_{0t}, (\gamma_{1t} - f_t)']'$, $\theta = [\gamma_0,\ (\gamma_1 - \mu_f)']'$, $u_t = e'W(R_t - \mu_R)$, $w_t = \gamma_1' V_f^{-1}(f_t - \mu_f)$, and $z_t = [0, u_t(f_t - \mu_f)' V_f^{-1}]'$. Note that the term h_t is now specified with three terms which are the asymptotic variance of γ when the true β is used, the errors-in-variables (EIV) adjustment term, and the misspecification adjustment term. Please see Kan et al. (2013) for details of the estimation.

An alternative specification is in terms of the $N \times K$ matrix V_{Rf} of covariances between returns and the factors.

$$\begin{aligned}
\mu_R &= X\gamma = C\lambda \\
\hat{\lambda} &= (\hat{C}'W\hat{C})^{-1}\hat{C}'W\hat{\mu}_R
\end{aligned}$$

where $C = [1_N, V_{RF}]$ and $\lambda_W = [\lambda_{W,0}, \lambda_{W,1}']'$.

Although the pricing errors from this alternative CSR are the same as those in the one using β above (thus the cross-sectional R^2 will also be the same), they emphasize the differences in the economic interpretation of the pricing coefficients. In fact, according to Kan et al. (2013), what matters is whether the price of covariance risk associated additional factors is nonzero if we want to answer whether the extra factors improve the cross-sectional R^2. Therefore, we apply tests based on λ in the empirical testing. The methodologies about how to use the asymptotic distribution of the sample R^2 ($\hat{\rho}$) in the second-pass CSR as the basis for a specification test are also presented.

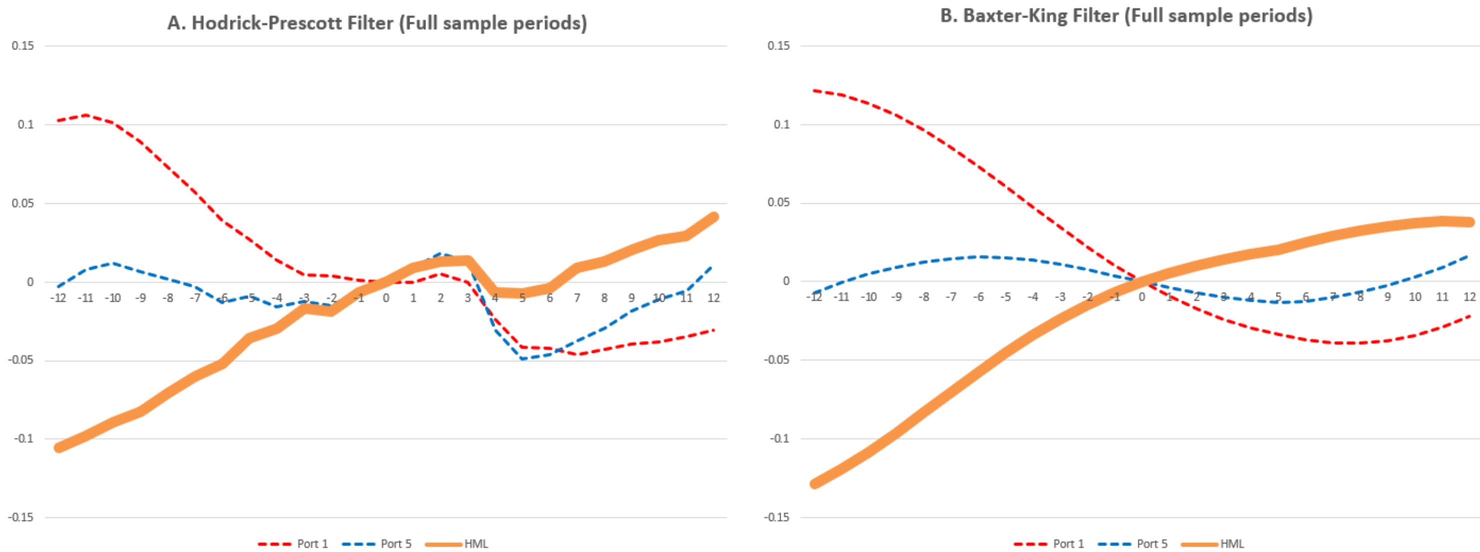


Fig. A1: Cumulative Output Gap Before and After El Niño (Full Sample)

This figure illustrates the cumulative output gap 12 months before and after the onset of El Niño ($t = 0$). We estimate output gaps using two statistical techniques to extract a cyclical component from monthly industrial production data: (i) Hodrick-Prescott Filter for Panel A, (ii) Baxter-King Filter for Panel B. We use full sample periods including the El Niño cycle closest to COVID19.

Table A1: Developed Market Currency Returns using ENSO and SST

This table presents various estimates of theta using the ENSO indicator variable (ONI_t) as the ENSO sensitivity measure. We explore different model variations to assess the robustness of theta under alternative controls. The regression equations are: (1) $RX_{ct} = \alpha_c + \beta_c^{Carry} Carry_t + \theta_c^{ENSO} ENSO_t + e_{ct}$, (2) $RX_{ct} = \alpha_c + \beta_c^{Carry} Carry_t + \theta_c^{SST} SST_t + e_{ct}$, where RX_{ct} is the excess return of currency c at time t, $Carry_t$ is the currency carry factor, $ENSO_t$ is the indicator variable for $ENSO$ ($ENSO_t = 1$ for El Niño, $ENSO_t = 0$ for neutral, and $ENSO_t = -1$ for La Niña), and SST_t is the anomalous sea surface temperature. Sample includes developed market currencies only, based on Menkhoff et al. (2012, JFE) and Menkhoff et al. (2012, JF). Countries include Australia, Belgium, Canada, Denmark, Euro area, France, Germany, Italy, Japan, Netherlands, New Zealand, Norway, Sweden, Switzerland, and the United Kingdom. Limitation is caused by the introduction of the euro in January 1999, the sample of developed countries covers only 10 currencies.

		Panel A. Using ENSO				Panel B. Using SST			
PortName	Type	ElNiño	Neutral	LaNiña	All	ElNiño	Neutral	LaNiña	All
$Port_1$	mean	-4.36%	2.38%	-1.69%	-0.43%	-3.41%	2.97%	-2.19%	-0.12%
	tval	(-1.06)	(0.86)	(-0.43)	(-0.21)	(-0.84)	(1.07)	(-0.57)	(-0.06)
$Port_2$	mean	-2.86%	1.18%	-0.07%	-0.11%	-1.69%	2.90%	0.82%	1.22%
	tval	(-0.76)	(0.46)	(-0.02)	(-0.06)	(-0.47)	(1.11)	(0.23)	(0.66)
$Port_3$	mean	0.60%	1.64%	0.56%	1.05%	-1.99%	-0.04%	1.22%	-0.04%
	tval	(0.17)	(0.62)	(0.15)	(0.57)	(-0.54)	(-0.01)	(0.34)	(-0.02)
$Port_4$	mean	-2.09%	3.27%	1.00%	1.36%	-1.48%	3.03%	0.67%	1.27%
	tval	(-0.52)	(1.20)	(0.28)	(0.71)	(-0.37)	(1.05)	(0.18)	(0.65)
$Port_5$	mean	2.13%	-0.28%	0.69%	0.56%	1.98%	-0.68%	-0.22%	0.05%
	tval	(0.64)	(-0.10)	(0.17)	(0.28)	(0.53)	(-0.25)	(-0.06)	(0.02)
$Port_{HML}$	mean	6.50% *	-2.66%	2.38%	0.99%	5.39% *	-3.65%	1.97%	0.17%
	tval	(1.85)	(-0.89)	(0.63)	(0.50)	(1.68)	(-1.39)	(0.56)	(0.09)

Table A2: Currency Appearance by Portfolio Rank

This table reports the number of appearances of individual currencies in each portfolio rank based on their theta values. Portfolio Rank 1 corresponds to currencies with the lowest theta values, while Portfolio Rank 5 corresponds to those with the highest theta values. The top seven currencies for each rank are highlighted. For Portfolio Rank 1 (Low Theta), the most frequently appearing currencies include PLN, MXN, ZAR, NOK, AUD, CZK, and JPY. In contrast, Portfolio Rank 5 (High Theta) is dominated by currencies such as INR, JPY, SEK, ISK, EGP, DKK, and IDR.

Currency	Country Name	Rank 1	Rank 2	Rank 3	Rank 4	Rank 5	Total Count
AUD	Australia	103	61	65	35	0	264
BGN	Bulgaria	67	68	33	9	0	177
BRL	Brazil	49	52	36	25	15	177
CAD	Canada	0	73	176	39	0	288
CHF	Switzerland	25	105	53	95	10	288
CZK	Czech Repulbic	103	23	41	21	76	264
DKK	Denmark	17	103	45	26	97	288
EGP	Egypt	0	2	16	10	101	129
EUR	Euro erea	24	107	44	67	22	264
GBP	United Kingdom	71	4	57	125	7	264
HKD	Hong Kong	0	43	61	131	29	264
HRK	Croatia	54	48	39	24	0	165
HUF	Hungary	63	51	29	17	94	254
IDR	Indonesia	34	12	19	43	96	204
ILS	Israel	3	39	87	37	11	177
INR	India	24	39	17	10	164	254
ISK	Iceland	13	17	28	9	110	177
JPY	Japan	100	9	8	47	124	288
KRW	South Korea	20	28	33	36	85	202
KWD	Kuwait	0	35	112	117	0	264
MXN	Mexico	113	104	47	0	0	264
MYR	Malaysia	0	18	21	103	20	162
NOK	Norway	105	40	43	98	2	288
NZD	New Zealand	8	44	43	62	63	264
PHP	Philippines	70	22	27	66	79	264
PLN	Poland	116	71	9	5	1	202
RUB	Russia	26	35	39	61	12	173
SAR	Saudi Arabia	0	64	40	65	95	264
SEK	Sweden	28	62	43	44	111	288
SGD	Singapore	0	19	182	63	0	264
SKK	Slovakia	0	0	9	1	12	22
THB	Thailand	8	67	40	114	35	264
TWD	Taiwan	88	73	99	4	0	264
UAH	Ukraine	11	7	4	36	0	58
ZAR	South Africa	106	100	17	0	0	223

Table A3: Portfolio Results with GBP as Base Currency

This table focuses on the estimation of theta after changing the base currency from USD to GBP, highlighting the comparison between results with different base currencies and specifications. The analysis includes:full sample (using ENSO and SST with Carry factor) and subset of 10 Developed Market (DM) Currencies (using ENSO and SST with Carry factor). The regression equations are: (1) $RX_{ct} = \alpha_c + \beta_c^{Carry} Carry_t + \theta_c^{ENSO} ENSO_t + e_{ct}$, (2) $RX_{ct} = \alpha_c + \beta_c^{Carry} Carry_t + \theta_c^{SST} SST_t + e_{ct}$, where RX_{ct} is the excess return of currency c at time t, $Carry_t$ is the currency carry factor, $ENSO_t$ is the indicator variable for $ENSO$ ($ENSO_t = 1$ for El Niño, $ENSO_t = 0$ for neutral, and $ENSO_t = -1$ for La Niña), and SST_t is the anomalous sea surface temperature.

		Panel A. Using ENSO (All currencies)				Panel B. Using SST (All currencies)			
PortName	Type	ElNiño	Neutral	LaNiña	All	ElNiño	Neutral	LaNiña	All
$Port_1$	mean	1.87%	-2.03%	-0.63%	-0.73%	1.12%	-1.44%	1.27%	0.01%
	tval	(0.50)	(-0.78)	(-0.20)	(-0.41)	(0.29)	(-0.58)	(0.40)	(0.01)
$Port_2$	mean	2.89%	0.64%	0.49%	1.08%	5.36%	1.02%	0.85%	1.90%
	tval	(0.86)	(0.27)	(0.19)	(0.69)	(1.46)	(0.42)	(0.33)	(1.19)
$Port_3$	mean	4.78%	0.47%	0.79%	1.51%	3.46%	0.03%	1.88%	1.38%
	tval	(1.25)	(0.22)	(0.34)	(1.01)	(0.96)	(0.01)	(0.81)	(0.96)
$Port_4$	mean	7.95% **	-0.94%	5.19% *	3.02% *	6.59% *	-1.50%	2.61%	1.61%
	tval	(2.28)	(-0.40)	(1.96)	(1.90)	(1.92)	(-0.67)	(0.97)	(1.04)
$Port_5$	mean	10.62% ***	1.48%	3.57%	4.14% **	11.51% ***	1.50%	3.41%	4.29% **
	tval	(2.77)	(0.57)	(1.07)	(2.27)	(2.92)	(0.56)	(1.04)	(2.33)
$Port_{HML}$	mean	8.75% ***	3.51%	4.20%	4.87% ***	10.39% ***	2.94%	2.13%	4.28% **
	tval	(2.79)	(1.38)	(1.28)	(2.82)	(3.12)	(1.15)	(0.70)	(2.51)

		Panel C. Using ENSO (DM currencies)				Panel D. Using SST (DM currencies)			
PortName	Type	ElNiño	Neutral	LaNiña	All	ElNiño	Neutral	LaNiña	All
$Port_1$	mean	0.09%	-1.58%	-0.84%	-0.97%	2.49%	0.79%	-1.08%	0.53%
	tval	(0.02)	(-0.53)	(-0.26)	(-0.51)	(0.61)	(0.26)	(-0.34)	(0.28)
$Port_2$	mean	2.34%	1.02%	1.02%	1.30%	2.68%	0.15%	1.30%	1.08%
	tval	(0.63)	(0.43)	(0.39)	(0.82)	(0.72)	(0.07)	(0.49)	(0.69)
$Port_3$	mean	4.73%	-0.02%	0.52%	1.18%	2.43%	0.06%	2.72%	1.46%
	tval	(1.33)	(-0.01)	(0.20)	(0.74)	(0.68)	(0.03)	(1.06)	(0.96)
$Port_4$	mean	5.47%	0.53%	2.99%	2.41%	5.07%	-0.48%	0.65%	1.09%
	tval	(1.32)	(0.21)	(1.05)	(1.40)	(1.18)	(-0.17)	(0.23)	(0.60)
$Port_5$	mean	10.56% **	-1.89%	1.41%	1.89%	10.51% **	-2.41%	1.80%	1.77%
	tval	(2.50)	(-0.72)	(0.41)	(1.00)	(2.45)	(-0.92)	(0.55)	(0.95)
$Port_{HML}$	mean	10.47% ***	-0.31%	2.25%	2.86%	8.02% **	-3.20%	2.87%	1.24%
	tval	(2.69)	(-0.09)	(0.56)	(1.28)	(2.23)	(-1.01)	(0.81)	(0.61)

Table A4: Turnover of Long-Short Portfolios Based on Theta ENSO or SST

This table presents the mean and standard deviation of monthly turnover for long-short portfolios constructed based on theta values estimated using either ENSO or SST without any control variables. The turnover is calculated as:

$$Tunover = 0.5 \cdot \sum_{c \text{ in portfolio 1}} |\Delta Weight_{fx}| + 0.5 \cdot \sum_{fx \text{ in portfolio 5}} |\Delta Weight_{fx}|$$

PortName	turnover mean	turnover std
Carry	0.1139	0.0947
Momentum (1m)	0.7690	0.1521
Momentum (12m)	0.2378	0.1248
$ENSO_{HML}$	0.0726	0.1191
$ENSO_{HML}$ (wCarry)	0.0734	0.1174
SST_{HML}	0.0713	0.1204
SST_{HML} (wCarry)	0.0667	0.1206

Table A5: Theta-Sorted Portfolio Returns using MSCI stock market indices

This table presents regression results for Theta-sorted portfolios using MSCI international stock market indices. USD-denominated stock market returns are used from Panel A to C and local currency-denominated stock market returns are used from Panel D to F. We use the following specifications to measure the ENSO-sensitivity of those stock market indices: (i) $RX_{ct} = \alpha_c + \theta_c^{ENSO} ENSO_t + e_{ct}$, (ii) $RX_{ct} = \alpha_c + \beta_c^{MKT} MKT_t + \theta_c^{ENSO} ENSO_t + e_{ct}$, and (iii) $RX_{ct} = \alpha_c + \beta_c^{MKT} MKT_t + \beta_c^{Size} Size_t + \beta_c^{Value} Value_t + \theta_c^{ENSO} ENSO_t + e_{ct}$. where RX_{ct} is the excess return of stock market indices of country c at time t, $ENSO_t$ is the indicator variable for $ENSO$ ($ENSO_t = 1$ for El Niño, $ENSO_t = 0$ for neutral, and $ENSO_t = -1$ for La Niña), and MKT_t, $Size_t$, and $Value_t$ is the market, size and value factors, respectively.

Panel A - C: Using USD-denominated returns

		Panel A. Wihtout Controls				Panel B. Market Factor				Panel C. FF3 Factors			
PortName	Type	ElNiño	Neutral	LaNiña	All	ElNiño	Neutral	LaNiña	All	ElNiño	Neutral	LaNiña	All
Port_1	mean	-7.52%	11.52% **	13.40% *	7.23% **	-7.58%	11.78% **	13.98% *	7.50% **	-7.60%	12.76% ***	11.20%	7.12% **
	tval	(-1.13)	(2.47)	(1.82)	(2.08)	(-1.14)	(2.51)	(1.91)	(2.16)	(-1.05)	(2.73)	(1.55)	(2.01)
Port_2	mean	1.84%	12.80% ***	11.50% *	9.63% ***	2.49%	12.70% ***	10.25% *	9.38% ***	2.40%	11.62% ***	10.22% *	8.86% ***
	tval	(0.29)	(2.97)	(1.86)	(3.10)	(0.40)	(2.91)	(1.70)	(3.03)	(0.42)	(2.66)	(1.66)	(2.90)
Port_3	mean	4.73%	8.81% **	8.14%	7.57% **	5.16%	9.03% **	8.28%	7.82% ***	4.76%	9.23% **	10.71% *	8.53% ***
	tval	(0.78)	(2.08)	(1.43)	(2.55)	(0.85)	(2.15)	(1.42)	(2.63)	(0.78)	(2.19)	(1.84)	(2.85)
Port_4	mean	8.08%	9.06% **	7.79%	8.44% ***	6.35%	8.08% *	8.60%	7.79% ***	6.50%	9.34% **	8.16%	8.27% ***
	tval	(1.37)	(2.15)	(1.41)	(2.90)	(1.06)	(1.93)	(1.56)	(2.67)	(1.09)	(2.25)	(1.44)	(2.83)
Port_5	mean	4.67%	10.72% **	8.54%	8.54% ***	5.59%	11.64% ***	8.46%	9.17% ***	6.03%	10.31% **	9.15%	8.88% ***
	tval	(0.69)	(2.46)	(1.44)	(2.72)	(0.84)	(2.66)	(1.44)	(2.95)	(0.90)	(2.35)	(1.57)	(2.85)
Port_{HML}	mean	12.19% **	-0.80%	-4.86%	1.31%	13.17% **	-0.13%	-5.52%	1.67%	13.63% ***	-2.45%	-2.05%	1.76%
	tval	(2.32)	(-0.26)	(-0.91)	(0.52)	(2.51)	(-0.04)	(-1.06)	(0.67)	(2.59)	(-0.82)	(-0.40)	(0.72)

Panel D - F: Using local currency-denominated returns

		Panel D. Wihtout Controls				Panel E. Market Factor				Panel F. FF3 Factors			
PortName	Type	ElNiño	Neutral	LaNiña	All	ElNiño	Neutral	LaNiña	All	ElNiño	Neutral	LaNiña	All
Port_1	mean	-1.76%	11.61% ***	9.33% *	7.54% ***	-1.77%	10.98% ***	9.09% *	7.18% **	-1.72%	12.35% ***	8.08%	7.52% ***
	tval	(-0.30)	(2.82)	(1.79)	(2.66)	(-0.30)	(2.69)	(1.73)	(2.54)	(-0.30)	(2.90)	(1.51)	(2.60)
Port_2	mean	1.04%	13.04% ***	12.93% **	9.96% ***	0.46%	13.23% ***	13.63% **	10.10% ***	1.91%	12.28% ***	11.16% **	9.31% ***
	tval	(0.19)	(3.50)	(2.47)	(3.69)	(0.08)	(3.55)	(2.57)	(3.68)	(0.33)	(3.36)	(2.21)	(3.49)
Port_3	mean	3.29%	7.37% **	9.52% **	6.96% ***	2.60%	7.58% **	8.74% **	6.66% ***	1.25%	7.94% **	10.27% **	6.92% ***
	tval	(0.57)	(2.05)	(2.23)	(2.77)	(0.45)	(2.02)	(2.08)	(2.61)	(0.22)	(2.14)	(2.35)	(2.71)
Port_4	mean	2.22%	7.04% **	8.19% *	6.15% **	4.60%	7.41% **	8.55% **	7.03% ***	5.12%	6.94% **	9.51% **	7.23% ***
	tval	(0.40)	(2.00)	(1.94)	(2.49)	(0.88)	(2.14)	(2.02)	(2.93)	(0.96)	(2.06)	(2.28)	(3.04)
Port_5	mean	4.30%	10.22% ***	8.41% *	8.18% ***	3.23%	9.77% **	8.42% *	7.71% ***	2.26%	9.73% **	9.49% **	7.76% ***
	tval	(0.71)	(2.61)	(1.86)	(3.04)	(0.51)	(2.52)	(1.89)	(2.84)	(0.36)	(2.43)	(2.11)	(2.82)
Port_{HML}	mean	6.06%	-1.39%	-0.91%	0.65%	5.00%	-1.21%	-0.67%	0.53%	3.98%	-2.62%	1.41%	0.24%
	tval	(1.56)	(-0.50)	(-0.25)	(0.34)	(1.27)	(-0.43)	(-0.18)	(0.27)	(1.02)	(-0.96)	(0.38)	(0.13)

Table A6: Price of Covariance Risk

This table evaluates the price of covariance risk (λ) for the two-factor model (Dollar and Carry) and the extended three-factor model that includes ENSO. Metrics include the price of covariance risk (λ), t-statistics of λ using Fama-MacBeth methodology ($tstat_{FM}$), and the Kan, Robotti, and Shanken (2013) misspecification-robust t-ratio ($tstat_{KRS}$).

	All Time				**El Niño**				**La Niña**			
Panel A. Using 5 θ_c^{ENSO} sorted portfolios for the two-factor model												
	Intercept	Dollar		ENSO	Intercept	Dollar		ENSO	Intercept	Dollar		ENSO
λ	0.00	10.25		8.20	0.00	8.36		18.05	-0.01	29.92		12.77
$tstat_{FM}$	-0.56	1.36		2.63	0.03	0.52		2.62	-1.46	1.85		1.80
$tstat_{KRS}$	-0.44	0.90		2.27	0.03	0.04		2.88	-1.02	1.28		0.71
Panel B. Using 5 θ_c^{ENSO} sorted portfolios for the three-factor model												
	Intercept	Dollar	Carry	ENSO	Intercept	Dollar	Carry	ENSO	Intercept	Dollar	Carry	ENSO
λ	0.00	-0.65	11.44	6.37	0.00	-0.58	27.53	17.20	0.00	4.23	2.86	5.94
$tstat_{FM}$	2.64	-0.15	2.93	1.88	1.52	-0.06	3.49	2.52	1.66	0.56	0.40	1.00
$tstat_{KRS}$	1.84	0.49	2.66	1.97	0.99	0.07	2.89	2.75	1.18	0.59	0.60	0.92
Panel C. Using all inclusive 51 FX portfolios for the two-factor model												
	Intercept	Dollar		ENSO	Intercept	Dollar		ENSO	Intercept	Dollar		ENSO
λ	0.00	4.72		7.45	0.00	5.75		16.22	0.00	6.36		7.32
$tstat_{FM}$	1.64	1.14		2.14	1.14	0.60		2.31	1.83	0.86		1.11
$tstat_{KRS}$	1.28	0.91		2.05	0.59	0.20		2.40	1.35	0.53		0.87
Panel D. Using all inclusive 51 FX portfolios for the three-factor model												
	Intercept	Dollar	Carry	ENSO	Intercept	Dollar	Carry	ENSO	Intercept	Dollar	Carry	ENSO
λ	0.00	-0.65	11.44	6.37	0.00	-0.58	27.53	17.20	0.00	4.23	2.86	5.94
$tstat_{FM}$	2.64	-0.15	2.93	1.88	1.52	-0.06	3.49	2.52	1.66	0.56	0.40	1.00
$tstat_{KRS}$	1.84	0.49	2.66	1.97	0.99	0.07	2.89	2.75	1.18	0.59	0.60	0.92