El Niño and Currency 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 economic growth and international trade patterns across countries. Examining over different El Niño cycles, we discover a striking pattern of cross-sectional predictability in foreign exchange spot and excess returns. Currencies that appreciated (depreciated) under previous El Niño cycles tend to appreciate (depreciate) when a new El Niño cycle hits. This cross-sectional predictive information arises from the heterogeneous effects of El Niño on countries' business cycle conditions, resulting in heterogeneous exposures of currencies to El Niño cycles.

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1 Introduction

The El Niño-Southern Oscillation (ENSO) cycle is a major climate phenomenon that has widespread effect on global weather patterns, ecosystems, agriculture and economies. It 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. The ENSO cycle is associated with droughts and floods that impact agriculture, fisheries, and tourism, and has been found to impact economic growth and inflation heterogeneously in different countries (e.g. Cashin et al., 2017).

Given the widespread impact of the ENSO cycle on countries' future economic fundamentals, and given that theories of exchange rate determination postulate a link between exchange rates and economic fundamentals, it is surprising that there is no research on the predictive link between the ENSO cycle and foreign exchange returns. This paper fills this gap. Examining different ENSO cycles in an out-of-sample setting from 2000 to 2023, we discover a strong pattern of predictability in the foreign exchange market. We sort currencies into those that have performed best (in the top quintile) versus those that have performed worst (in the bottom quintile) under previous El Niño cycles. We find that the top quintile currencies tend to appreciate when new El Niño cycles hit and generate high average excess returns, while the bottom quintile currencies tend to depreciate when new El Niño cycles hit and generate low average excess returns. These results are robust to using either continuous sea surface temperature (SST) anomalies or discrete ENSO indicators as alternative definitions of El Niño. Moreover, by decomposing currency excess returns into spot returns and forward premia (or interest rate differentials), we find that a large part of the currency excess returns stem from spot returns rather than forward premia, implying that El Niño cycles predicts the cross-sectional variation in spot currency returns.

We further assess 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 et al. (2024) with the currency excess returns of an ENSO strategy that buys the currencies with high exposure and sells the currencies with low exposure to ENSO cycles. 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. Kroencke et al., 2014; Menkhoff et al., 2017), net foreign assets and liabilities in domestic currencies (Della Corte et al., 2016), 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 any of the other factors.

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 as well as neutral states. We find that predictability only occurs during El Niño states. Also, we evaluate the average excess returns of other currency 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 further explore the investment implications of our findings from the perspective of a currency investor that employs a broad set of trading strategies. Thus, we construct the 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 investment performance by integrating ENSO-based signals into their trading strategies. This result suggests that the systematic effects of ENSO cycles on different economies create an exploitable investment strategy whose returns are largely uncorrelated with canonical investment strategies in foreign exchange.

Additionally, we evaluate how an ENSO factor – constructed as the excess return from the proposed ENSO strategy – fares in explaining FX factor returns. We examine the pricing errors from time series regressions of each of the FX factor returns on dollar, carry, and ENSO. We find that including ENSO a factor 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 et al. (2013) further confirms that the ENSO factor enhances the cross-sectional R^2.

To further test the robustness of these findings, we implement several additional checks. First, instead of currency returns, we examine the ENSO effect on international stock returns using MSCI international stock market indices. Investigating a 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- and post-2000 periods, though stronger in recent years. Third, we repeat the 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 base. Fourth, we repeat the analysis based on developed market currencies only, and find the results to be robust, alleviating concerns that small emerging market currencies drive our results. Fifth, we find that the 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 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 the findings is the underlying macroeconomic mechanism driving these results. Colacito et al. (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 the 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 be countries with weaker economic prospects going forward. This suggests that the ENSO portfolios naturally align with differences in future macroeconomic strength in the cross section of countries, establishing a link between currency predictability and *future* economic conditions.

Related literature. Overall, our findings contribute to the growing literature on climate finance and asset returns. To the best of this 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 output 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 and Ubilava (2017) quantifies these losses, attributing \$4.1 trillion and \$5.7 trillion in global income reductions to the 1982–83 and 1997–98 El Niño events, respectively. Callahan and Mankin (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) note that some countries may experience a net positive effect on real output 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 (2018) 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, Zhang (2022)), 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., 2016), term spread (Bekaert et al., 2007; Lustig et al., 2019), long-term yields (Ang and Chen, 2010), and output gap (Colacito et al., 2020).[1] 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

[1] Our paper also complements recent evidence that real-side quantities forecast currency risk premia. Ma and Zhang (2023), for example, show that the U.S. residential-to-nonresidential investment share predicts dollar (and bilateral) excess returns via a nontradables-price channel. We instead exploit an exogenous, forecastable climate cycle (El Niño) to form country-specific exposures that sort currencies by expected spot appreciation in El Niño states.

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 (Ravi Bansal and Ochoa, 2019; Hong et al., 2019). More recently, Lemoine and Kapnick (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.

The remainder of the paper is as follows. Section 2 describes the data, the construction of currency excess returns, and the empirical methodology for identifying ENSO cycles and estimating their effects. Section 3 presents the main results on ENSO portfolio performance, decomposition of returns, and robustness to various risk factors. Section 4 explores the economic mechanism linking ENSO exposure to future macroeconomic fundamentals. Section 5 concludes.

2 Data and Methodology

2.1 Currency Excess Returns

Our data sample covers the period from January 1990 to December 2023. We obtain both spot rates and 1-month forward rates relative to the U.S. dollar (USD) from Datastream. We use data from the first 10 years (1990 to 1999) for in-sample analysis and the initial estimation of currency exposures to El Niño cycles. We then use data from 2000 to 2023 for out-of-sample analysis.

Adopting the perspective of a U.S. investor, the exchange rate is defined as the number 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. We rely on monthly data, using end-of-month FX rates spanning from January 1990 to December 2023. The dataset includes 49 currencies,[2] with 15 classified as belonging to developed economies based on established definitions in previous research (e.g., Lustig et al., 2011; Menkhoff et al., 2012a). The remaining currencies are classified as belonging to emerging markets. However, the currency universe is not constant over time, as data for some currencies are unavailable from the start of the sample and some currencies exit the sample in 1999 after the launch of the euro, resulting in an unbalanced panel of currencies.

We use s and f to denote the log of the spot and forward nominal exchange rate. Following Lustig and Verdelhan (2007), we define the log excess return of currency c at time $t+1$ as $RX_{c,t+1} = \Delta s_{c,t+1} + i_{c,t} - i_{us,t} \approx s_{c,t+1} - f_{c,t}$ where $i_{c,t}$ and $i_{us,t}$ denote the foreign and domestic nominal interest rates over a one-period horizon. This is the return for buying foreign currency (f_c) in the forward market at time t and then selling it in the spot market at time $t+1$. Under the covered interest parity (CIP) condition, $f_{c,t} = log(1+i_{us,t}) - log(1+i_{c,t}) + s_{c,t}$, implying that the forward discount is equal to the interest rate differential ($s_{c,t} - f_{c,t} \approx i_{c,t} - i_{us,t}$). We compute FX excess returns using forward rates rather than interest rate differentials for two main reasons. First, marginal investors (such as, e.g., hedge funds and large banks) that are responsible for the determination of exchange rates trade mostly using forward contracts (e.g., Koijen et al. 2018). Second, for many countries, forward rates are available for much longer time periods than short-term interest rates. It is reasonable, however, to exclude data points when CIP is strongly violated, and we do so.[3] We report the summary statistics in Table A1 in the Internet Appendix.

[2]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, Russia, Saudi Arabia, Singapore, Slovakia, Slovenia, South Africa, South Korea, Spain, Sweden, Switzerland, Taiwan, Thailand, Ukraine, the United Kingdom, and Turkey.

[3]Specifically, we apply the same data filters as in Nucera et al. (2024). 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).

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 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 average SST anomalies, also known as the Oceanic Niño Index (ONI), must exceed this threshold level.[4]

Therefore, we identify the onset of El Niño cycles based on SST anomalies, defined as the difference between observed SST and the long-term average SST for the same month over the past 30 years. According to 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." However, we relax the requirement of five consecutive observations to allow for more timely detection of ENSO phases. Since the El Niño cycle is global in nature, rather than country-specific, we apply its onset uniformly across all countries.

[Insert Figure 1 Here]

This figure shows the ONI over time, tracking the average SST anomalies in the Niño 3.4 region over three months. While El Niño occurs when the SST anomalies are consistently above +0.5°C for consecutive 3-month periods, La Niña happens when the SST anomalies are consistently below -0.5°C for the same duration. The ONI helps identify these warm (El

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

Niño) and cold (La Niña) phases based on these temperature thresholds. As we can see from the figure, the El Niño cycle occurs every 2 to 7 years on average, but not according to a regular schedule. An El Niño cycle typically lasts 9 to 12 months, but can last up to several years.

2.3 Empirical Methodology

The ENSO cycle exerts heterogeneous macroeconomic effects across countries, influencing productivity, terms of trade (via exports and imports), and overall growth prospects. These asymmetries, in principle, should be reflected in the valuation of currencies.[5] This paper examines whether predictable fluctuations in the ENSO cycle translate into systematic patterns in currency excess returns. If markets fully internalized the implications of the ENSO cycle—whose dynamics are well-studied and forecastable by climate scientists—then exchange rate movements should already reflect this information, and no excess return predictability would arise. However, our results suggest otherwise: currency returns display cross-sectional predictability based on prior exposures to ENSO, indicating that markets may not fully incorporate climate-related information into currency pricing.

To demonstrate this, we rank 49 currencies based on 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 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

[5] See, e.g., Colacito et al. (2020), Della Corte et al. (2016), Lustig et al. (2019), and Menkhoff et al. (2017).

sorted into 5 portfolios based on θ_c^{ENSO}, and we compute the summary statistics of currency excess returns in the subsequent month.

In addition to the baseline specification (2.1) we explore different model variations as in (2.2) to (2.4) to assess the robustness of theta estimates under alternative controls. The regressions are:

$$RX_{ct} = \alpha_c + \beta_c^{Carry} Carry_t + \theta_c^{ENSO} ENSO_t + e_{ct} \tag{2.2}$$

$$RX_{ct} = \alpha_c + \beta_c^{Carry} Carry_t + \beta_c^{MomST} MOMST_t + \theta_c^{ENSO} ENSO_t + e_{ct} \tag{2.3}$$

$$RX_{ct} = \alpha_c + \beta_c^{Carry} Carry_t + \beta_c^{MomLT} MOMLT_t + \theta_c^{ENSO} ENSO_t + e_{ct} \tag{2.4}$$

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.

3 Results on ENSO Portfolio Performance

Having established our empirical framework for estimating currencies' exposures to the ENSO cycle, we now examine how these exposures relate to future currency performance. Specifically, we form portfolios based on currencies' estimated sensitivities to ENSO and analyze their subsequent excess returns. This section presents the main empirical findings on portfolio performance, investigates the sources of return predictability, and evaluates the robustness of the ENSO effect across different climate regimes and control variables.

3.1 ENSO Portfolio Performance

We begin our analysis by examining the returns of portfolios formed on currencies' estimated sensitivities to the ENSO cycle. Panel A of Table 2 reports results relying on the baseline specification (2.1), which includes only the ENSO indicator as a predictor of currency excess returns. We report results considering El Niño, La Niña and Neutral states, separately and jointly (the "All" column). The high-minus-low (HML) portfolio—constructed as the return spread between currencies in the top and bottom quintiles of ENSO exposure (θ_c^{ENSO}) —earns an average excess return of approximately 3.75% per year across all three climate regimes. However, the bulk of this return is concentrated during El Niño episodes, where the average excess return rises to 7.16% per year, and is statistically significant. In contrast, returns during La Niña and neutral periods are markedly lower and not statistically distinguishable from zero at the 5% significance level. This pattern indicates that currencies that have historically performed well during prior El Niño cycles tend to do so again when a new El Niño cycle occurs, even though these climate events are to some extent forecastable.

Next, Panels B through D of Table 2 examine whether the ENSO return predictability persists after controlling for other well-known currency factors. Specifically, Panel B incorporates the currency carry factor (specification 2.2), and Panels C and D further adds short-term momentum and long-term momentum, respectively (specification 2.3 and 2.4). Across all three panels, we find that the ENSO-based HML portfolio continues to generate economically meaningful and statistically significant excess returns during El Niño phases. Adding these additional controls does not change the results qualitatively, reinforcing the view that the ENSO cycle contains predictive information for the cross-section of currency excess returns that is not fully captured by conventional risk factors such as carry and momentum.

[Insert Table 1 Here]

Thus far, in Table 1, we present various estimates of ENSO sensitivity using θ_c^{ENSO}, which is derived from regressions based on the discrete ENSO indicator. This specification relies on a threshold-based definition of the El Niño cycle, where $ENSO_t$ is constructed from the three-month moving average of sea surface temperature (SST) anomalies in the

Niño 3.4 region.[6] To examine the robustness of our results to alternative ENSO definitions, we consider a continuous measure of anomalous SST and re-estimate currency sensitivities using the following regression specification:

$$RX_{ct} = \alpha_c + \theta_c^{SST} SST_t + e_{ct} \tag{3.1}$$

Table 2 shows that the results are highly consistent with those in Table 1, confirming that our main findings are robust to the use of a continuous SST-based ENSO measure. Figure 2 further illustrates this by plotting the cumulative returns of high-minus-low $\theta^{ENSO/SST}$ portfolios constructed from both $ENSO_t$ and SST_t exposures. The figure shows that the majority of cumulative returns for both θ^{ENSO}- and θ^{SST}-sorted portfolios are realized during El Niño phases, and the return patterns remain stable over time. This supports the conclusion that the observed return predictability is closely tied to ENSO-related climate variation, regardless of whether ENSO is defined using discrete thresholds or continuous SST anomalies.

[Insert Table 2 and Figure 2 Here]

Next, we analyze the sources of currency return predictability by examining whether it arises from the forward discount or spot returns. This distinction is important as it helps us pinpoint the fundamental drivers behind currency return predictability. Specifically, it allows us to determine whether the predictability is primarily driven by interest rate differentials or by predictable shifts in spot exchange rates.

Table 3 presents the decomposition of currency excess returns into their two components—forward discounts (Panel A) and spot returns (Panel B)—based on the same θ^{ENSO} sorting used in our baseline portfolio construction. Focusing on the El Niño phase, we find that the high-minus-low (HML) average spread in forward discounts accounts for only 1.99% per annum, whereas the HML average spread in spot returns is much larger, at 8.49% per

[6] Further details on the definitions of SST and ENSO are provided in the Internet Appendix.

annum. These results indicate that the majority of the observed return differentials during El Niño periods stem from movements in spot exchange rates rather than from interest rate differentials, highlighting how ENSO-related patterns are predictive of the cross-section of spot exchange rate returns.

[Insert Table 3 Here]

To further illustrate the dynamics over time, Figure 3 plots the average cumulative returns of ENSO-sorted portfolios around the onset of ENSO phases, focusing on a 24-month event window from 12 months before to 12 months after the start of a cycle (event time = 0). The decomposition is shown separately for (i) El Niño and (ii) La Niña periods, and includes cumulative excess returns, forward discounts, and spot returns. During El Niño episodes, the cumulative return pattern is clearly driven by spot exchange rate movements, while forward discounts contribute only marginally. In contrast, no comparable return patterns are observed during La Niña periods. In essence, these results reinforce the conclusion that ENSO-related currency return predictability is closely tied to spot market movements, especially during El Niño phases.

[Insert Figure 3 Here]

3.2 ENSO Portfolio and Risk Factor Correlations

The strong performance of the ENSO-based HML portfolio documented in Section 3.1 raises the question of whether this return pattern reflects a novel risk exposure or is simply a manifestation of known currency return premia. To address this question, we assess the relationship between the ENSO portfolio and a comprehensive set of established FX risk factors drawn from the literature. These currency risk factors are derived from nine widely studied 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., 2016); Term spread (Bekaert et al., 2007; Lustig et al., 2019); Long-term yields (Ang and Chen, 2010); Output gap (Colacito et al., 2020). We refer to these strategies as Carry, ST and LT Mom, Value, NFA, LDC, Term, LYld, and GAP, respectively. These FX risk factors are also utilized in Nucera et al. (2024).[7]

As a first step, we examine the correlations between the θ^{ENSO}-sorted HML portfolio returns (ENSO portfolio) and the nine established FX risk factors described above. This analysis provides a preliminary assessment of whether the ENSO portfolio loads on known sources of currency return premia or captures a distinct return dimension. Table 4 reports the pairwise correlations. While some of the traditional factors are themselves highly correlated, we find that the ENSO portfolio exhibits low and statistically insignificant correlations with most of them. The only notable exception is the Value factor, with which the ENSO portfolio shows a negative correlation of -0.53. This suggests that the ENSO portfolio is not simply a proxy for existing FX risk factors, but may reflect a new source of return variation.

[Insert Table 4 Here]

3.3 Risk Factor Pricing and ENSO Portfolio

While Section 3.2 documents low correlations between the ENSO portfolio and most existing strategies, correlation alone does not reveal whether the return patterns attributed to ENSO can be spanned by known factors. Thus, we conduct a series of spanning regressions, in the spirit of Barillas and Shanken (2017), where the alpha from regressing one tradable factor on another serves as a measure of independent pricing information. This analysis helps determine whether ENSO exposures offer explanatory power beyond traditional sources of currency risk premia.

We begin by reporting the average excess returns of each factor, including the ENSO portfolio, in Panel A of Table 5. Consistent with earlier results, several factors — including

[7] For this analysis, the sample data is available only through December 2017.

Carry, short- and long-term Momentum, LDC, and ENSO — exhibit stronger performance during El Niño phases compared to other periods, suggesting that climate-driven dynamics may interact with multiple return drivers.

[Insert Table 5 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 static regression $F_t = \alpha + \beta \cdot ENSO_t + \epsilon_t$, for every factor F_t considered.

Panel B of Table 5 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 significant loadings on ENSO, with short- and long-term momentum factors in particular displaying a positive association with 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 5 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. Thus, ENSO portfolio excess returns are regressed upon each risk factor using the equation $ENSO_t = \alpha + \beta \cdot F_t + \epsilon_t$. Panels D and E of Table 5 present these regression results, showing that ENSO portfolio returns are not subsumed by 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- 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. Overall, none of the currency risk factors considered subsumes the information in the ENSO portfolio excess returns.

3.4 Optimal Allocation of ENSO Portfolio in Tangency Portfolios

The economic relevance of the ENSO portfolio extends beyond return predictability and raises important questions about its role in optimal currency portfolio construction. If the ENSO strategy reflects a distinct and robust source of return variation, then incorporating it into investment decisions should improve the overall risk-return tradeoff faced by currency investors. Therefore, we construct optimal tangency portfolios that include the ENSO portfolio alongside a broad set of standard FX factors. This exercise allows us to quantify the marginal contribution of ENSO exposures to portfolio efficiency and assess whether investors benefit from allocating capital to climate-sensitive currency strategies, as motivated by the broader implications discussed in the introduction.

Table 6 presents the tangency portfolio weights, returns, and the maximum ex post Sharpe ratios achievable by combining various factors to construct the tangency portfolio. This analysis demonstrates that incorporating the ENSO long-short portfolio information meaningfully improves the Sharpe ratio of a currency portfolio allocation, with the marginal increase in Sharpe ratio ranging from 0.038 to 0.115. We find that the optimal weight assigned to the ENSO factor is substantial. For example, in a portfolio that includes all the FX factors, the optimal weight on the ENSO portfolio is 20%, well above the average weight across strategies and smaller only than the Carry weight.

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 the ENSO portfolio, investors can attain a superior risk-return tradeoff. Furthermore, based on the optimal weights of the tangency portfolio, investors would consistently allocate positive weights to the ENSO strategy across different combinations of factor-based strategies, with varying degrees of marginal increase in Sharpe ratio. Hence, the positive impact of the ENSO portfolio on performance appears to be pervasive, reinforcing its relevance for currency investment decisions.

[Insert Table 6 Here]

3.5 Model Performance in Explaining FX Portfolio Excess Returns

Having established that the ENSO portfolio delivers strong returns and exhibits low correlation with traditional FX factors, a natural question is whether the inclusion of a ENSO factor enhances the performance of standard asset pricing models. To address this, we examine whether incorporating the ENSO factor helps reduce pricing errors in models of FX portfolio excess returns. Specifically, we evaluate whether models that include ENSO alongside conventional FX factors such as the Dollar and Carry generate lower average alphas, improved explanatory power, and better overall model fit. This analysis directly addresses whether climate-linked exposures, such as those arising from the ENSO cycle, contain systematic information relevant for explaining the cross-section and time-series variation in currency returns.

3.5.A Time-series alphas

To operationalize this test, we estimate time-series regressions of strategy-level excess returns on various combinations of risk factors and assess the resulting pricing errors. In particular, we compare models that include only the Dollar factor, the combination of Dollar and Carry, and an extended specification that incorporates the ENSO portfolio. If the ENSO factor captures a distinct source of return variation, its inclusion should systematically reduce pricing errors, especially during El Niño periods.

Table 7 compares the models on several measures: dispersion of alpha (α_{HL} = max α – min α), 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, 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 7 Here]

The results in Table 7 indicate that incorporating ENSO in the model 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). In essence, 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 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.[8]

3.5.B Cross-sectional alphas

While the time-series analysis in Section 3.5.A evaluates whether the ENSO factor improves the model's fit over time, a complementary test involves examining how well the factor explains average returns across portfolios. Cross-sectional asset pricing tests provide a natural framework for this evaluation. In this section, we examine the marginal contribution of the

[8]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.

ENSO factor to explaining the cross-section of FX portfolio excess returns, using standard two-pass cross-sectional regressions. This framework enables us to assess whether currencies with higher ENSO exposure earn systematically different returns, and whether such variation can be priced by models that include ENSO alongside traditional FX factors.

Many asset pricing studies have employed the sample cross-sectional regression (CSR) R^2 as a measure of model performance. Kan et al. (2013) derive the asymptotic distribution of this statistic and propose model comparison tests that account for sampling variation and potential misspecification. Following their framework, we use CSR-based R^2 statistics and hypothesis tests to evaluate the explanatory power of models with and without the ENSO factor. The formal specification is as follows:

$$E(RX_c) = \lambda \cdot COV(RX_c, F) \tag{3.2}$$

where RX_c = 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 8 Here]

Table 8 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 8. 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 whether the explanatory power of two nested models are different from each other and ask what the relative importance of ENSO is. Table 8 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 Table A9 in the Internet Appendix.[9]

[9]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 Additional Results and Robustness Checks

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

3.6.A Using Only Developed Countries' sample

There might be a concern that our results are largely driven by emerging market currencies. This could potentially skew our findings and raise questions about their generality. To address this issue, we conduct our main regression analysis again, but this time using data exclusively from developed countries.

The results of this analysis are presented in Internet Appendix Table A2, and they show similar outcomes to our original findings. This consistency suggests that the observed effects are not solely driven by the performance of emerging market currencies. Instead, it indicates that the patterns we identify are robust and applicable across different sets of countries.

3.6.B Currency composition

Another potential concern is that our results might be driven by the performance of a small set of currencies that consistently appear in the long and short portfolios. To investigate this possibility, we examined the frequency of currency appearances across different portfolio ranks. Table A3 in the Internet Appendix reports the number of times individual currencies appear in each portfolio rank based on their theta values. The analysis reveals that currencies frequently shift between different portfolios over time, rather than remaining fixed in the same portfolio.

This dynamic movement of currencies across portfolios alleviates concerns that our results are driven by a static set of currencies.

3.6.C A different base currency

We repeat the analysis using GBP instead of USD as the base currency. These results are shown in the Appendix Table A4. We find similar results as in our core results, indicating that our findings are not driven by using the USD as the currency base.

3.6.D Using ENSO based on Bayesian Hidden Markov Model

We repeat the analysis using ENSO phases classified by a Bayesian Hidden Markov Model (ENSO^{HMM}), rather than the threshold-based definition (±0.5°C SST anomalies) used in the main analysis. The HMM provides a probabilistic, data-driven alternative that accounts for regime persistence and parameter uncertainty. Despite methodological differences, ENSO^{HMM} and the threshold-based classification agree in 94% of monthly observations. As shown in Table A5 in the Internet Appendix, the empirical results using ENSO^{HMM} remain statistically and economically consistent with our baseline findings. This confirms that the results are robust to the method of ENSO classification and are not driven by arbitrary cutoff rules.

3.6.E Fama-MacBeth Regression

To further assess the robustness of our main findings, we conduct a Fama-MacBeth cross-sectional regression using θ^{ENSO}, the estimated return sensitivity to the ENSO cycle, as a predictor of next-month currency excess returns. In each month, we regress returns on θ^{ENSO} along with a set of control variables capturing individual country characteristics, including interest rate differentials, short- and long-term momentums, currency values, net foreign assets, liabilities in domestic currencies, term spreads, short- and long-term yields, and output gaps. Table A6 reports the results for the full sample (Panel A), as well as separately for El Niño (Panel B), La Niña (Panel C), and Neutral periods (Panel D). We find that θ^{ENSO} remains a statistically and economically significant predictor of cross-sectional currency excess returns during El Niño periods. These findings suggest that the predictive power of ENSO exposure holds even after accounting for a broad set of macro-financial characteristics across countries.

3.6.F 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 Table A7 in the Internet Appendix, 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, implying that transaction costs are unlikely to erode much of the excess returns of the ENSO strategy.

3.6.G International Stock Returns

Instead of currency returns, we examine the role of the ENSO effect on international stock returns using MSCI international stock market indices. Investigating a theta-sorted portfolio of international stock returns,[10] 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 Table A8 in the Internet Appendix. We also conduct the analysis using pre- and post-2000 time periods and find that the El Niño effect is present in both samples.

4 Economic Mechanism

A key question that follows from our findings is the macroeconomic mechanism underlying these results. Colacito et al. (2020) provide theory and empirical evidence on the link between currency excess returns and macroeconomic conditions, captured by the output gap. The output gap 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

[10] 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.

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 framework, 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 (also used by Colacito et al. (2020), among other methods): (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).[11] 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 since the onset of each El Niño cycle, calculated as the difference between Portfolio 5 and Portfolio 1 returns.

[Insert Figure 4 Here]

To formally assess this relationship, Table 9 presents the averages and t-statistics of the differences in average cumulative output gaps between high- and low-theta currencies across various horizons (12-, 6-, 3-, and 1-month leads and lags). For each month and theta group,

[11] 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.

we compute the average cumulative output gap over the specified horizons for the currencies belonging to that group. A positive difference between the averages of high- and low-theta currencies indicates that cumulative output gaps over the horizon were larger for high-theta currencies than for low-theta currencies. 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.

[Insert Table 9 Here]

This result aligns with the idea that currencies that have performed well in previous El Niño cycles tend to come from countries with improving or stronger economic fundamentals, while those that have underperformed in previous El Niño cycles tend to be 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. In a nutshell, because El Niño cycles predict output gaps across countries, the heterogeneous exposures of currency returns to El Niño cycles capture forward-looking information about differentials in output gaps across countries which, in turn, are related to the cross-section of currency excess returns.

5 Conclusion

El Niño cycle is one of the most important global climate events, exerting a variety of strong economic effects across the globe. While previous research has focused on differential economic and social impacts of El Niño, we present the first evidence of El Niño on global currency market. We document a strong pattern of predictability in foreign exchange returns. Currencies that have done the best (worst) in 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 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 currencies. The predictability is robust to a variety of robustness checks. We further document that a sizable weight is assigned to the El Niño portfolio in an optimal currency investment strategy.

We provide evidence that the source of predictability operates through the 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 (poorly) tend to have stronger (weaker) economic performance going forward, as captured by the output gap, in turn leading to currency appreciation (depreciation). In essence, El Niño embeds predictive information for the cross-section of currency (excess) returns by virtue of the fact that it acts as a leading indicator of the output gap.

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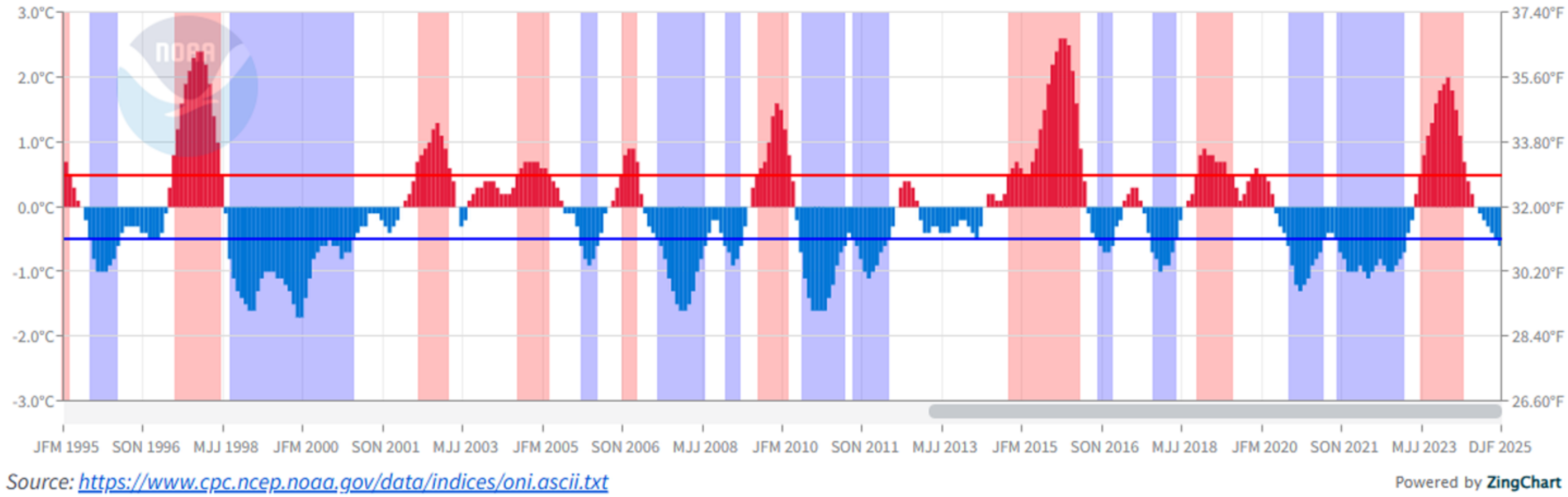


Fig. 1: Oceanic Niño Index (ONI) Over Time

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 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 3-month running averages of SST anomalies (ERSST.v5) in the Niño 3.4 region surpassing a threshold of +/- 0.5°C.

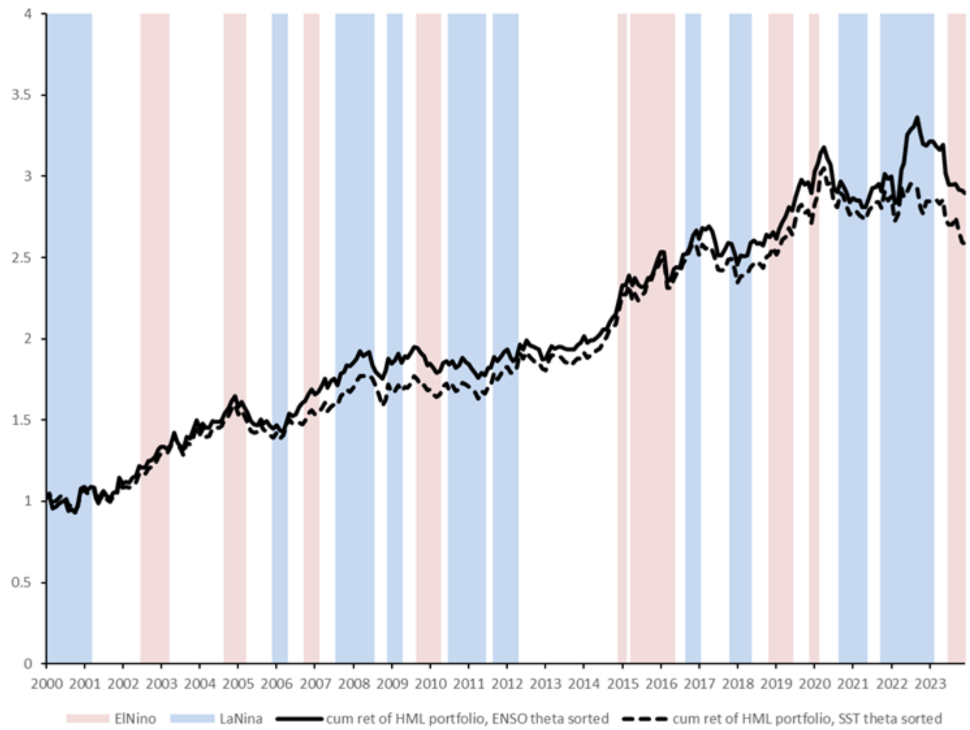
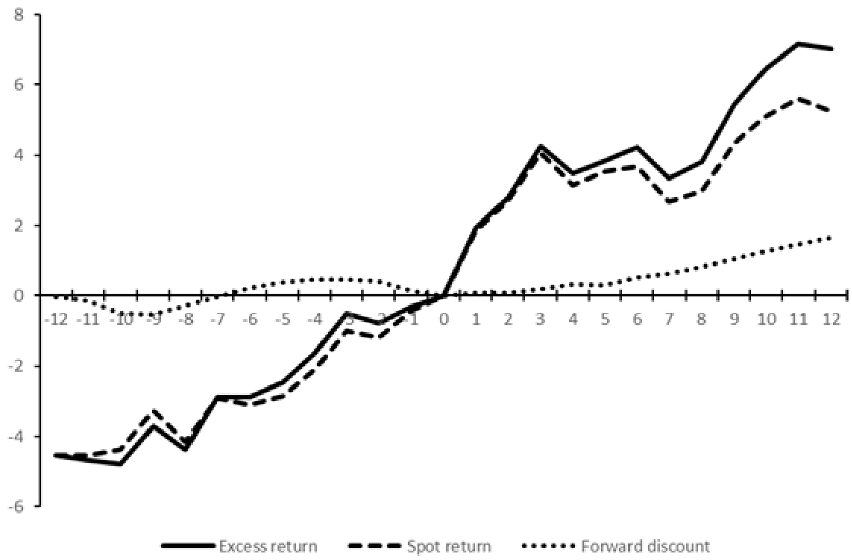


Fig. 2: Cumulative returns of ENSO and SST sorted HML portfolios

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

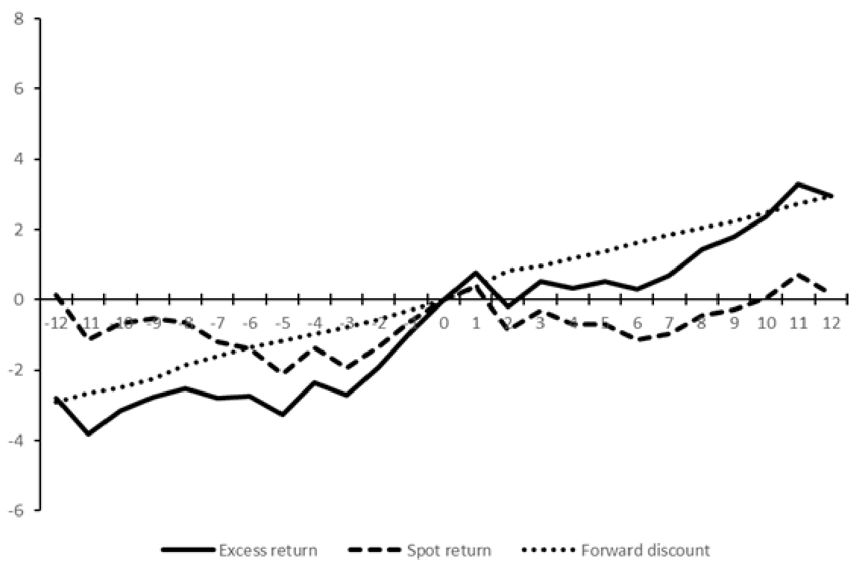


Fig. 3: Decomposition of Currency Excess Returns

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.

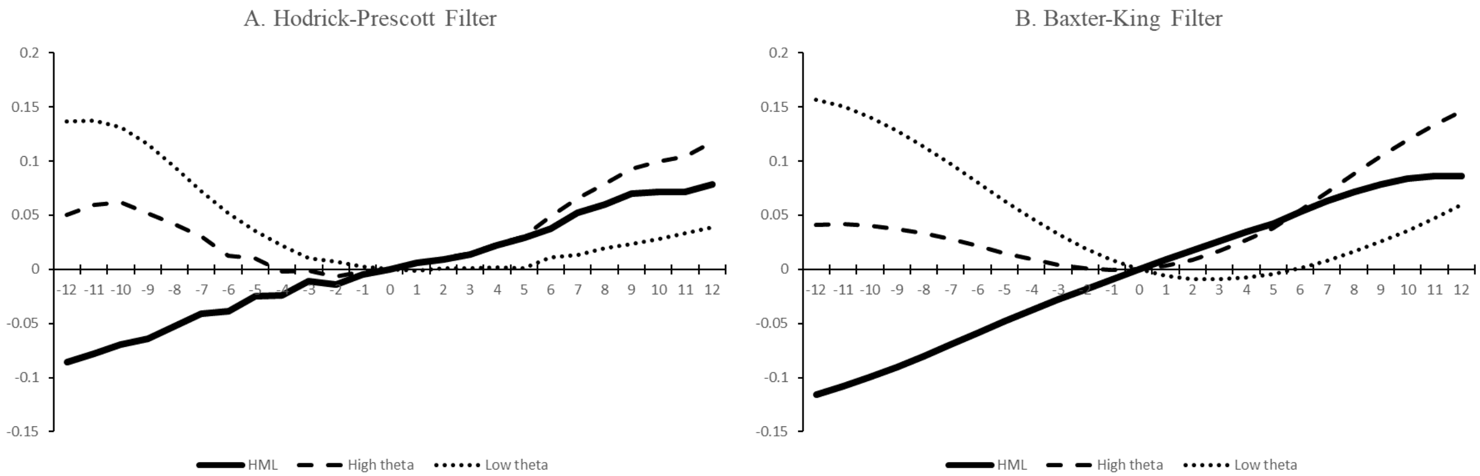


Fig. 4: Cumulative Output Gap Before and After El Niño

This figure illustrates the cumulative output gap 12 months before and after the onset of El Niño (t = 0). For each onset of an El Niño cycle, output gaps are averaged within the low- and high-theta groups over a 24-month window. These gaps are then cumulated across the window, normalized to zero at the onset, and subsequently averaged across all El Niño cycles. 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: 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 2: 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 3: 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 4: 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 5: 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 6: 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 7: 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 8: 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 9: ENSO cycle and Output Gaps

This table presents the time-series averages and associated t-statistics of the differences in average cumulative output gaps between high- and low-theta currencies across various horizons. For each month and theta group, we compute the average cumulative output gap over the specified horizons for the currencies belonging to that group. A positive difference between the averages of high- and low-theta currencies indicates that cumulative output gaps over the horizon were larger for high-theta currencies than for low-theta currencies. 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
-12 to 0 month	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)
-6 to 0 month	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)
-3 to 0 month	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)
-1 to 0 month	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)
0 to +1 month	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)
0 to +3 month	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)
0 to +6 month	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)
0 to +12 month	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)

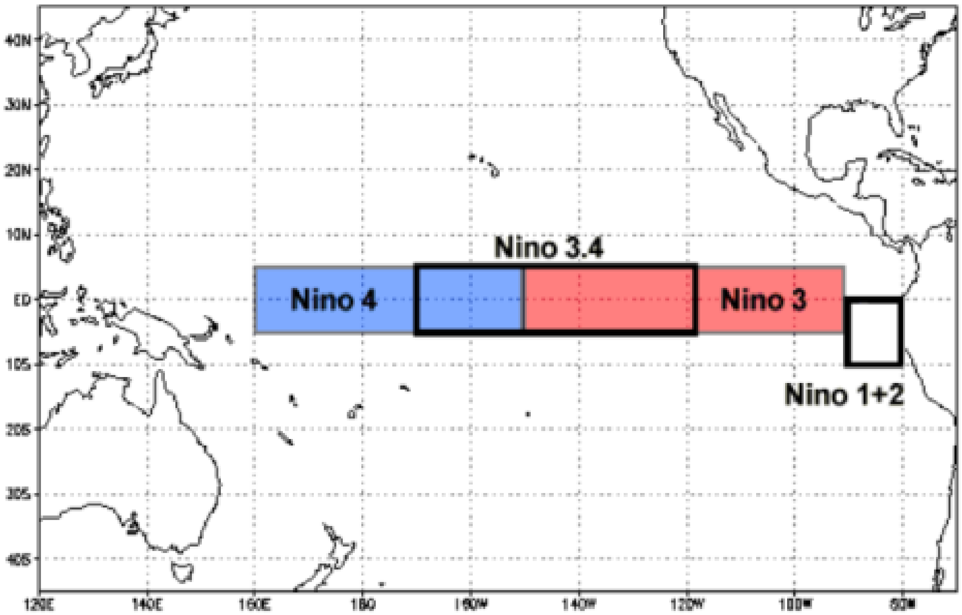
Internet Appendix for

"El Niño Cycle and Currency Returns"

(not for publication)

A. SST and ENSO definition

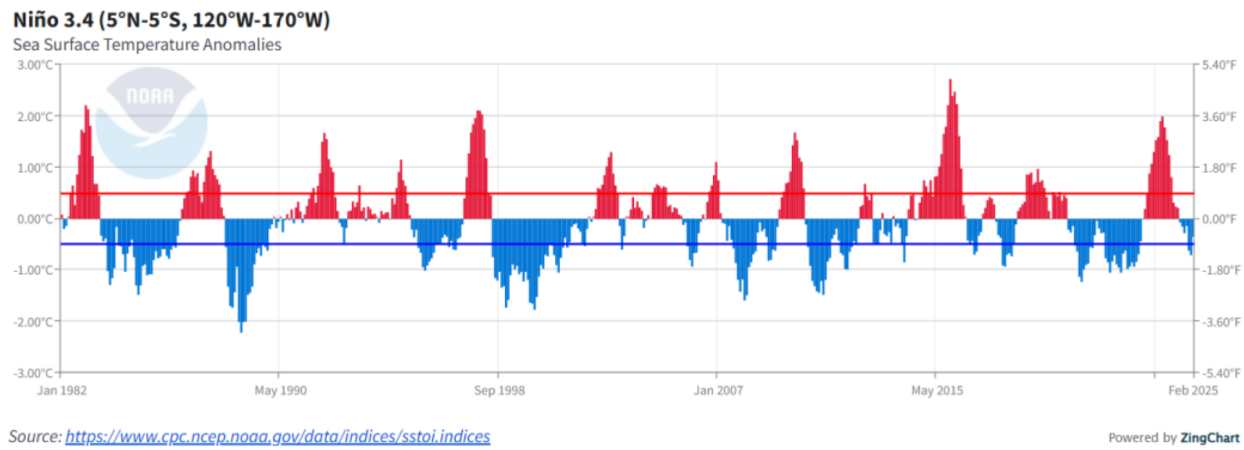
Equatorial Pacific Sea Surface Temperatures (SST)

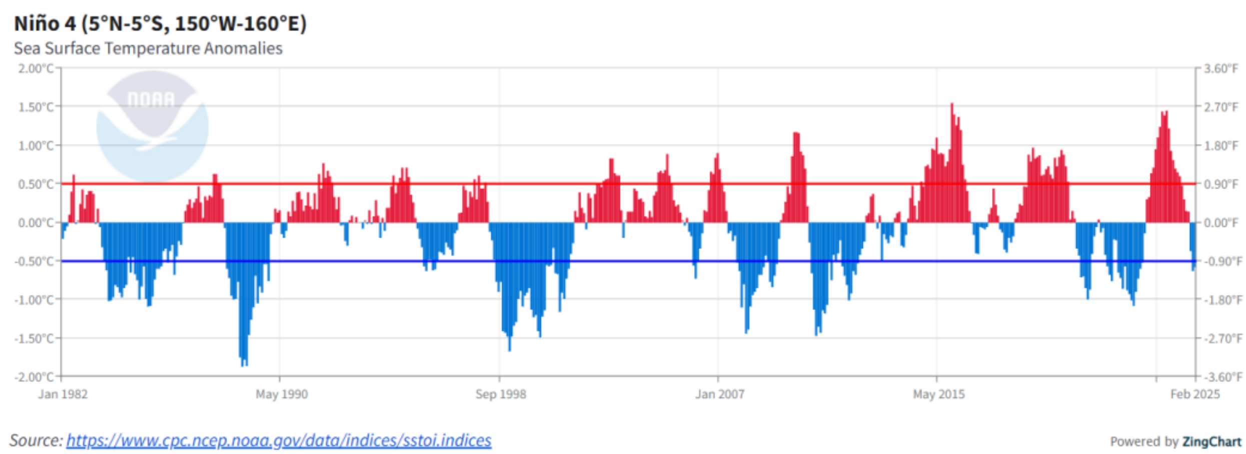


El Niño (La Niña) is a phenomenon in the equatorial Pacific Ocean characterized by a five consecutive 3-month running mean of sea surface temperature (SST) anomalies in the Niño 3.4 region that is above (below) the threshold of +0.5°C (-0.5°C). This standard of measure is known as the Oceanic Niño Index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

SST values in the Niño 3.4 region may not be the only, or even necessarily the best, choice for determining La Niña episodes but, for consistency, the index has been defined by negative anomalies in this area. Another 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. ENSO based on Bayesian Hidden Markov Model (HMM) Estimation

In the main analysis, ENSO phases are classified using a discrete indicator variable (ENSO) based on SST anomalies exceeding the threshold of $\pm 0.5\,^{\circ}\mathrm{C}$ in the Niño 3.4 region, following Oceanic Niño Index (ONI) employed by NOAA. This threshold-based approach is well-established in the climate science literature and provides a transparent and interpretable benchmark for identifying El Niño and La Niña episodes. Nevertheless, to test the robustness of our findings and to explore whether a more data-driven approach might yield similar insights, we also estimate ENSO regimes using a Bayesian Hidden Markov Model (HMM). The resulting classification, denoted as ENSO^{HMM}, offers a probabilistic alternative that does not rely on fixed thresholds.

The primary motivation for this exercise is to evaluate whether our empirical results are sensitive to the way ENSO states are defined. While the ±0.5°C cutoff is consistent with NOAA's operational definition, threshold-based methods are inherently sensitive to values near the boundary. Moreover, the threshold rule does not incorporate temporal persistence, despite the well-documented tendency of ENSO phases to evolve gradually over time. To address these limitations and validate the robustness of our classification scheme, we implement a Bayesian HMM that infers latent ENSO regimes directly from the data, accounting for both observation likelihood and state dynamics.

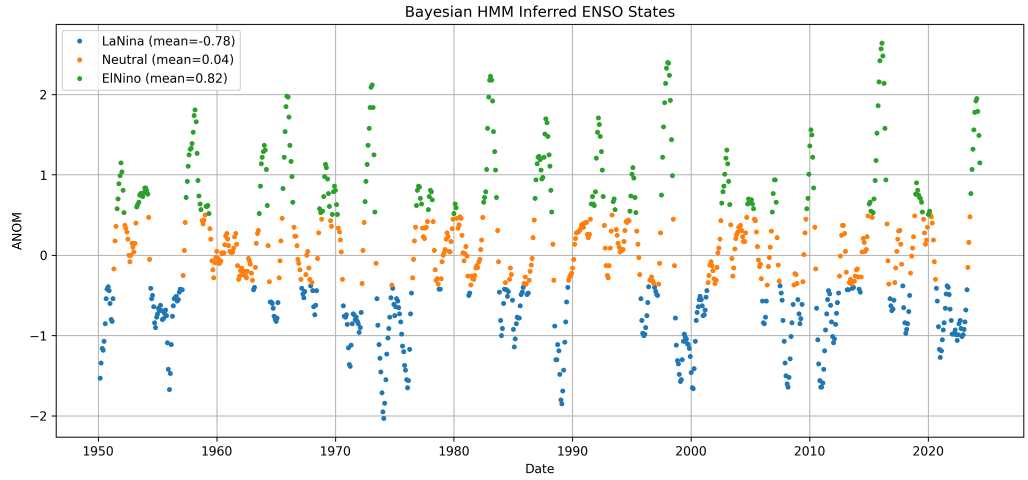
The Bayesian HMM is specified as a three-state model corresponding to La Niña, Neutral, and El Niño regimes. Observed SST anomalies are modeled as emissions from latent states, where each regime is characterized by a Gaussian distribution with distinct mean and standard deviation. The model also includes a Markovian transition structure, where the probability of transitioning between states is governed by a data-driven transition matrix. Crucially, we adopt a Bayesian framework, assigning informative priors to both the emission parameters (with means anchored at -1.0, 0.0, and +1.0) and the transition probabilities (reflecting the tendency of regimes to persist). Parameter estimation is conducted using Markov Chain Monte Carlo (MCMC), specifically the No-U-Turn Sampler (NUTS), which efficiently samples from the posterior distribution over all model parameters.

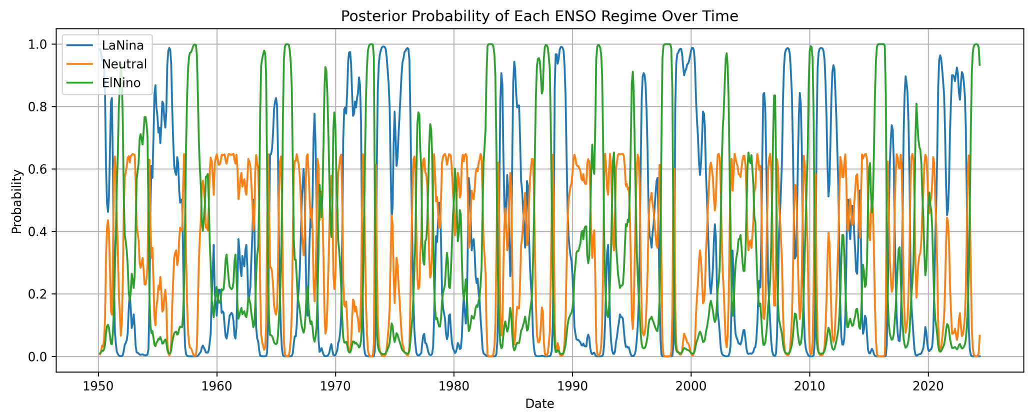
This estimation procedure updates beliefs about state-dependent means, variances, and transitions based on the observed SST anomalies. Unlike classical (frequentist) HMMs estimated via the Baum-Welch algorithm, the Bayesian approach yields full posterior distributions rather than point estimates. This allows for quantifying parameter uncertainty and naturally incorporates prior knowledge. Moreover, the Bayesian model produces a posterior distribution over the latent state sequence, enabling us to compute both the most likely regime at each point in time and the uncertainty (entropy) associated with each assignment. These features distinguish the Bayesian HMM from both hard thresholding rules and standard likelihood-based HMMs.

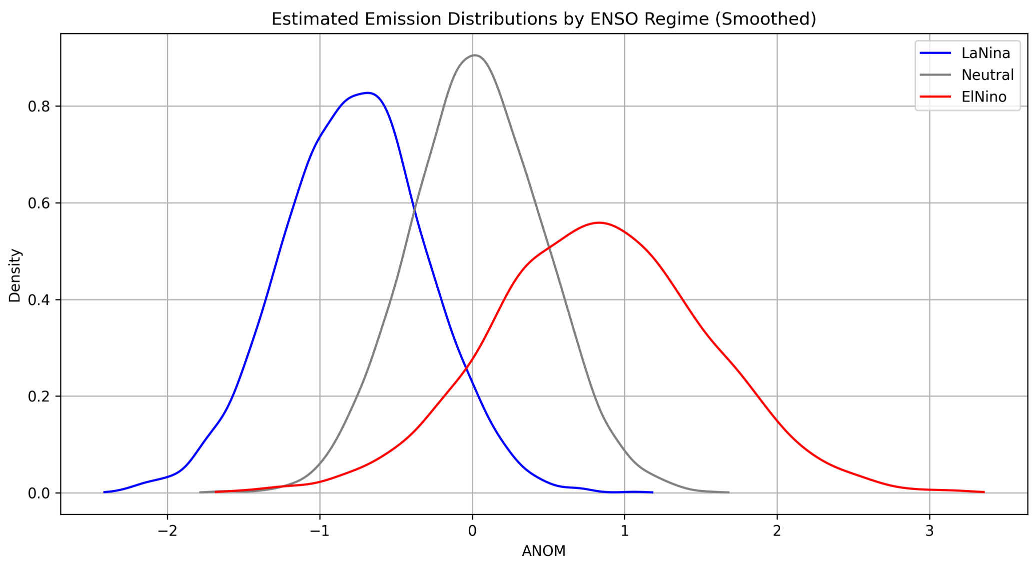
To assess the comparability of the threshold-based ENSO series and the model-inferred ENSO^{HMM}, we examine their joint distribution and rate of agreement. Approximately 94% of monthly observations are assigned to the same regime under both definitions. Discrepancies primarily occur near the cutoff boundary, where the HMM may reclassify borderline observations based on temporal context and overall regime coherence. For instance, months with SST anomalies close to -0.5°C may be classified as Neutral by the threshold rule but as La Niña by the HMM if surrounding observations exhibit strong persistence. Similarly, some near-threshold El Niño months are assigned to the Neutral regime by the HMM due to low transition likelihoods or emission uncertainty.

These differences, while modest, highlight the value of using a Bayesian HMM to smooth transitions and incorporate information from the full time series. At the same time, the high overall agreement lends support to the robustness of the ±0.5°C cutoff rule, reinforcing the credibility of the ENSO classification used in the main specification. Importantly, when we replicate our main empirical regressions using ENSO^{HMM} in place of the threshold-based ENSO variable, the results remain statistically and economically similar. This confirms that our core findings are not driven by arbitrary classification decisions, but rather reflect systematic linkages between ENSO phases and international asset returns.

In summary, the Bayesian HMM serves both as a robustness check and as a theoretically grounded alternative to fixed-threshold classification. By incorporating probabilistic reasoning, regime persistence, and posterior uncertainty, it offers a comprehensive lens through which to understand ENSO dynamics. The consistency between t at the observed return patterns are closely tied to the evolution of ENSO cycles.







C. 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 $e_0 = [I_N - 1_N(1_N' W 1_N)^{-1} 1_N' W]\mu_R$.

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,

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

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

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

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

where $\theta_t=[\gamma_{0t},(\gamma_{1t}-f_t)^{'}]^{'}$, $\theta=[\gamma_0,\ (\gamma_1-\mu_f)^{'}]^{'}$, $u_t=e^{\prime}W(R_t-\mu_R)$, $w_t=\gamma_1^{'}V_f^{-1}(f_t-\mu_f)$, 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.

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

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.

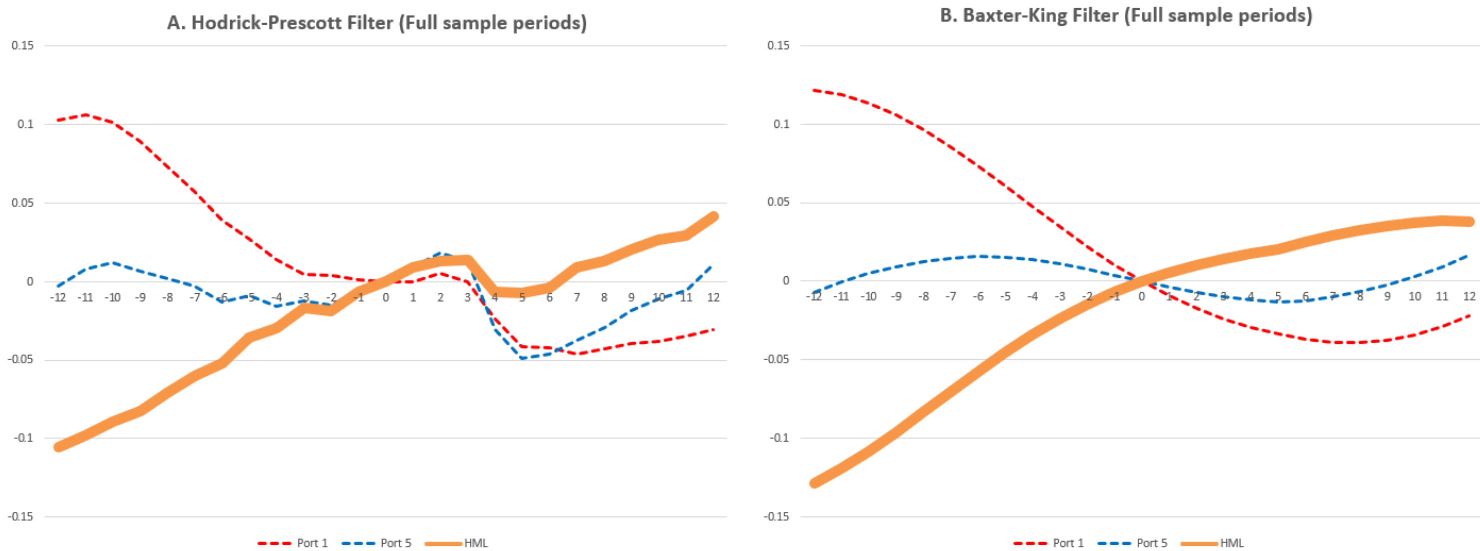


Fig. A1: Cumulative Output Gap Before and After El Niño (Full Sample)

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: 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 $100 \times (f_{t-1}^k - s_t^k)$, where: s_t^k is the log spot rate (foreign currency units per USD) for currency k, and f_{t-1}^k 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 $100 \times (f_t^k - s_t^k)$, where f_t^k and s_t^k 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 A2: 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 A3: 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 A4: 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 A5: Portfolio Results with ENSO based on Bayesian HMM Estimation

This table presents the average returns and t-statistics of θ-sorted portfolios, where θ is estimated using the ENSO^{HMM} variable derived from a Bayesian Hidden Markov Model (HMM). We examine model variations with alternative controls to assess the robustness of the portfolio results to the method of ENSO classification. 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	-1.24%	0.39%	0.13%	-0.06%	-1.58%	-0.76%	-1.70%	-1.31%
	tval	(-0.35)	(0.14)	(0.04)	(-0.03)	(-0.43)	(-0.25)	(-0.50)	(-0.67)
Port_2	mean	-2.01%	0.57%	-2.22%	-1.09%	-1.21%	2.86%	0.19%	0.93%
	tval	(-0.66)	(0.28)	(-0.79)	(-0.72)	(-0.42)	(1.43)	(0.07)	(0.64)
Port_3	mean	0.30%	3.38%	-0.40%	1.22%	-0.17%	2.60%	-1.01%	0.57%
	tval	(0.11)	(1.56)	(-0.15)	(0.81)	(-0.06)	(1.23)	(-0.36)	(0.38)
Port_4	mean	1.50%	2.52%	0.39%	1.46%	2.44%	1.90%	2.37%	2.20%
	tval	(0.47)	(1.02)	(0.14)	(0.90)	(0.75)	(0.79)	(0.87)	(1.38)
Port_5	mean	6.08% *	3.81%	3.95%	4.35% **	5.36% *	3.84%	1.61%	3.27% *
	tval	(1.93)	(1.22)	(1.23)	(2.30)	(1.83)	(1.29)	(0.53)	(1.83)
Port_{HML}	mean	7.32% **	3.42%	3.82%	4.41% ***	6.93% **	4.60% *	3.32%	4.58% ***
	tval	(2.33)	(1.33)	(1.47)	(2.78)	(2.12)	(1.74)	(1.21)	(2.78)

		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	-2.00%	-0.04%	-1.27%	-0.95%	-1.85%	-0.08%	-1.49%	-1.02%
	tval	(-0.54)	(-0.01)	(-0.36)	(-0.47)	(-0.51)	(-0.03)	(-0.42)	(-0.51)
Port_2	mean	-1.70%	1.60%	-0.07%	0.23%	-0.57%	2.28%	-1.36%	0.22%
	tval	(-0.60)	(0.84)	(-0.03)	(0.16)	(-0.20)	(1.27)	(-0.52)	(0.16)
Port_3	mean	0.53%	2.70%	-1.05%	0.74%	-0.27%	2.48%	0.37%	1.06%
	tval	(0.20)	(1.23)	(-0.38)	(0.49)	(-0.10)	(1.13)	(0.14)	(0.71)
Port_4	mean	2.15%	2.12%	1.24%	1.78%	2.65%	2.38%	1.70%	2.16%
	tval	(0.64)	(0.90)	(0.48)	(1.14)	(0.80)	(1.00)	(0.65)	(1.39)
Port_5	mean	5.82% **	4.12%	2.63%	3.89% **	4.88%	3.37%	2.37%	3.29% *
	tval	(2.10)	(1.37)	(0.84)	(2.15)	(1.64)	(1.11)	(0.74)	(1.78)
Port_{HML}	mean	7.82% **	4.16%	3.90%	4.83% ***	6.73% **	3.45%	3.86%	4.31% ***
	tval	(2.41)	(1.56)	(1.38)	(2.88)	(2.16)	(1.34)	(1.34)	(2.60)

Table A6: Fama-MacBeth Regression

This table reports Fama-MacBeth regression results. The dependent variable is the currency excess return (RX_{ct}). The main explanatory variable is θ^{ENSO}, the return sensitivity of each currency to the ENSO cycle, estimated from time-series regressions. The specification is: $RX_{ct} = \alpha_t + \beta\ \theta_c^{ENSO} + \gamma\ \text{Controls}_{ct} + \varepsilon_{ct}$. The control variables include interest rate differentials (Carry), short-term and long-term momentum (MomST and MomLT), currency value (Value), net foreign assets (NFA), liabilities in domestic currencies (LDC), term spread (Term), short-term and long-term yields (SYld and LYld), and the output gap (GAP). Panel A includes all months, Panel B includes only El Niño periods, Panel C includes only La Niña periods, and Panel D includes only Neutral periods. All regressions are run cross-sectionally in each month, and the reported coefficients are the time-series averages of these estimates.

Panel A. All Time

Model	Variable	Intercept	θ^{ENSO}	Carry	MomST	MomLT	Value	Term	GAP	NFA	LDC	SYld	LYld
Model 1	coef	0.002	0.294 **										
	tstat	(1.43)	(2.33)										
Model 2	coef	0.001	0.219	0.850 ***									
	tstat	(0.50)	(1.58)	(4.74)									
Model 3	coef	0.003	0.006	0.522	0.035	-0.004	-0.002						
	tstat	(1.26)	(0.02)	(0.68)	(0.49)	(-0.23)	(-0.25)						
Model 4	coef	-0.002	-1.007	2.332	-0.615	0.020		0.000					
	tstat	(-0.75)	(-0.80)	(1.51)	(-1.56)	(0.29)		(0.10)					
Model 5	coef	0.000	0.225	0.521 *					-0.042				
	tstat	(0.10)	(1.14)	(1.80)					(-1.17)				
Model 6	coef	0.006	2.077 *	-1.402	-0.025	0.090				0.000	-0.013		
	tstat	(0.45)	(1.80)	(-0.64)	(-0.19)	(1.20)				(1.04)	(-0.47)		
Model 7	coef	0.003	1.065	-0.061			-0.015	0.001	0.008				
	tstat	(0.85)	(1.15)	(-0.04)			(-0.60)	(1.06)	(0.45)				
Model 8	coef	-0.013	0.398 **				0.007 *		0.009			0.000	0.002
	tstat	(-1.25)	(1.98)				(1.93)		(0.48)			(-0.08)	(1.10)

Panel B. El Niño

Model	Variable	Intercept	θ^{ENSO}	Carry	MomST	MomLT	Value	Term	GAP	NFA	LDC	SYld	LYld
Model 1	coef	0.002	0.632 **										
	tstat	(0.94)	(2.46)										
Model 2	coef	0.000	0.598 **	0.999 ***									
	tstat	(-0.05)	(2.01)	(3.41)									
Model 3	coef	-0.001	0.743 **	1.122 ***	-0.004	0.010	0.010 *						
	tstat	(-0.55)	(2.49)	(2.70)	(-0.06)	(0.71)	(1.68)						
Model 4	coef	-0.001	0.583 **	0.258	-0.045	0.007		-0.001					
	tstat	(-0.45)	(2.01)	(0.47)	(-0.69)	(0.46)		(-1.22)					
Model 5	coef	0.000	0.675 **	0.207					-0.022				
	tstat	(0.15)	(2.04)	(0.40)					(-0.52)				
Model 6	coef	-0.002	0.423 *	1.449 ***	0.021	-0.015				0.001	0.006		
	tstat	(-0.49)	(1.79)	(3.16)	(0.31)	(-0.71)				(1.39)	(0.91)		
Model 7	coef	0.000	1.116 **	0.724			0.012	0.000	-0.017				
	tstat	(0.14)	(2.27)	(0.94)			(1.52)	(0.27)	(-0.43)				
Model 8	coef	-0.001	1.295 ***				0.013		-0.014			0.000	0.000
	tstat	(-0.35)	(2.62)				(1.55)		(-0.37)			(0.29)	(0.31)

Panel C. La Niña

Model	Variable	Intercept	θ^{ENSO}	Carry	MomST	MomLT	Value	Term	GAP	NFA	LDC	SYld	LYld
Model 1	coef	0.001	0.161										
	tstat	(0.53)	(0.65)										
Model 2	coef	0.000	0.042	1.113 ***									
	tstat	(0.22)	(0.16)	(3.16)									
Model 3	coef	0.004	0.501	-0.878	0.095	-0.022	-0.020						
	tstat	(0.73)	(0.57)	(-0.41)	(0.67)	(-0.56)	(-1.25)						
Model 4	coef	-0.013	-2.879	5.887	-1.931 *	0.085		0.001					
	tstat	(-1.47)	(-0.79)	(1.29)	(-1.66)	(0.41)		(1.18)					
Model 5	coef	0.004	-0.084	0.990 **					-0.068				
	tstat	(1.20)	(-0.28)	(1.98)					(-1.04)				
Model 6	coef	0.033	2.767	-6.095	-0.427 *	0.257				0.002 *	-0.073		
	tstat	(0.98)	(1.14)	(-0.92)	(-1.66)	(1.07)				(1.67)	(-1.05)		
Model 7	coef	0.008	2.037	-1.660			-0.059	0.001	0.009				
	tstat	(0.66)	(0.75)	(-0.39)			(-0.76)	(1.06)	(0.49)				
Model 8	coef	-0.039	0.219				-0.001		0.017			-0.001	0.008
	tstat	(-1.28)	(0.65)				(-0.12)		(0.88)			(-0.65)	(1.15)

Panel D. Neutral

Model	Variable	Intercept	θ^{ENSO}	Carry	MomST	MomLT	Value	Term	GAP	NFA	LDC	SYld	LYld
Model 1	coef	0.002	0.232										
	tstat	(1.12)	(1.34)										
Model 2	coef	0.001	0.168	0.584 **									
	tstat	(0.60)	(0.89)	(2.19)									
Model 3	coef	0.004	-0.710	1.270 **	0.009	0.003	0.006						
	tstat	(1.33)	(-1.58)	(2.24)	(0.08)	(0.11)	(0.66)						
Model 4	coef	0.005 **	-0.382	0.696	0.086	-0.022		0.000					
	tstat	(2.21)	(-0.54)	(1.58)	(0.71)	(-0.91)		(-0.15)					
Model 5	coef	-0.002	0.239	0.324					-0.031				
	tstat	(-0.91)	(0.69)	(0.70)					(-0.53)				
Model 6	coef	-0.006	2.371	0.238	0.203	0.033				-0.001	0.015		
	tstat	(-0.32)	(1.29)	(0.13)	(0.95)	(0.88)				(-0.81)	(0.40)		
Model 7	coef	0.002	0.323	0.746			0.003	0.000	0.019				
	tstat	(0.76)	(0.88)	(1.14)			(0.54)	(0.48)	(0.61)				
Model 8	coef	0.001	0.102				0.009 *		0.014			0.001	0.000
	tstat	(0.16)	(0.36)				(1.74)		(0.42)			(0.83)	(-0.19)

Table A7: 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 A8: 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 A9: 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