The El Niño Ripple: Driving Economic Shifts in Peru

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***Abstract*—The El Niño-Southern Oscillation (ENSO) significantly affects Peru's climate, economy, and financial markets, disrupting local industries and influencing global trade dynamics. This study explores ENSO's far-reaching impacts by analyzing its effects on Peru's fishmeal exports and the S&P/BVL Peru General Market Index, with the Oceanic Niño Index (ONI) serving as a central metric. Through advanced time series modeling, the research uncovers complex relationships between ONI, climatic variations, fishmeal production, and stock market fluctuations. These models effectively capture nonlinear dynamics and temporal dependencies, demonstrating their value in equipping industries and policymakers to anticipate and mitigate climate-induced economic disruptions. The findings offer actionable insights for navigating the challenges posed by ENSO and enhancing resilience in affected sectors. The analysis code can be found on GitHub.**

I. Introduction

The El Niño-Southern Oscillation (ENSO) is a periodic climatic phenomenon that significantly influences global weather patterns, with particularly profound effects in Peru. ENSO events, characterized by warming (El Niño) or cooling (La Niña) of Pacific Ocean waters, disrupt oceanic and atmospheric systems, affecting ecosystems, economies, and industries. Peru's fishmeal industry, the largest in the world, is especially vulnerable to these disruptions due to its reliance on the anchoveta population, which thrives in nutrient-rich upwelling zones. El Niño conditions suppress upwelling, causing anchoveta stocks to decline, while La Niña boosts their productivity. These fluctuations in anchoveta availability create substantial volatility in Peru's fishmeal exports, a vital component of its economy.

The economic impact of ENSO extends beyond fisheries. The S&P/BVL Peru General Market Index, Peru's leading stock market indicator, also exhibits sensitivity to these climatic events, reflecting broader economic ripple effects. The Oceanic Niño Index (ONI), a central metric for monitoring ENSO, provides a foundation for understanding and analyzing these dynamics.

This paper examines the effects of ENSO on Peru from a time series perspective, focusing on three key areas: the climatic variability of ENSO as measured by ONI, its impact on fishmeal exports, and its influence on the stock market. By integrating statistical and time series models, this study bridges the gap between climatic phenomena and economic implications, providing a framework for stakeholders to better understand and respond to climate-induced economic challenges.

II. Datasets

This analysis draws on a diverse collection of datasets, including:

- Monthly Sea Surface Temperature Data from NOAA Physical System Laboratory. [1]
- Monthly Readings of the Southern Oscillation Index from NOAA Climate Prediction Center. [2]
- Daily Precipitation Readings from the Ministry of Environment of Peru. [3]
- Peru's Annual Fishmeal Export Data queried directly from the United States Department of Agriculture Foreign Agricultural Service Database. [4]
- S&P/BVL Market Index data, gathered as a combination of yfinance api queries and from S&P Global website. [5]

III. Part 1: Climate impact of El Niño-Southern Oscillation

A. *El Niño-Southern Oscillation (ENSO)*

El Niño-Southern Oscillation (ENSO) is a recurring climate pattern involving changes in the temperature of waters in the central and eastern tropical Pacific Ocean. On periods ranging from about three to seven years, the surface waters across a large swath of the tropical Pacific Ocean warm or cool by anywhere from $1°C$ to $3°C$, compared to normal.

This oscillating warming and cooling pattern, referred to as the ENSO cycle, directly affects rainfall distribution in the tropics and can have a strong influence on weather across coasts of the Pacific Ocean. ENSO cycles are classified in 3 phases:

- El Niño: A warming of the ocean surface, or above-average sea surface temperature (SST).
- La Niña: A cooling of the ocean surface, or below-average sea surface temperature (SST).
- Neutral: Neither El Niño or La Niña. Often tropical Pacific SSTs are generally close to average.

In Fig.(1), can be found the Oceanic Niño Index (ONI), or ENSO conditions in the Niño 3.4 Region of the tropical Pacific Ocean.

B. *Oceanic Niño Index (ONI)*

The Oceanic Niño Index (ONI) is a sea component of the ENSO phenomenon, and the key measure used to monitor and quantify the ENSO phenomenon, due to smoothness compared to the Southern Oscillation (SOI). The ONI tracks the running 3-month average sea surface temperature in the east-central tropical Pacific (also referred as Niño 3.4, $5°N - 5°S$, $170°W - 120°W$) due its reliability when detecting significant changes in the tropical Pacific Ocean than have global impact.

B.1 Data Preprocessing

Although the monthly Southern Oscillation Index (SOI) and the precipitation data could be used directly, the monthly Sea Surface Temperature (SST) data required further processing. This task can be summarized in the following points:

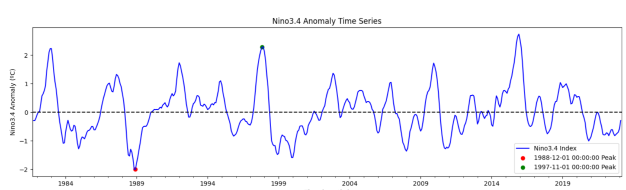
1) Collect the data from the Niño 3.4 region, defined as $5°N - 5°S, 170°W - 120°W$.
2) Compute a 30-year rolling climatological average of SST for each month.
3) Subtract the climatological baseline from the observed SST to obtain monthly anomalies:

$$SST_{Anomaly} = SST_{Observed} - SST_{Climatology} \quad (1)$$

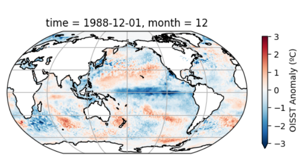
4) Smooth the monthly SST anomalies using a 3-month running mean to reduce short-term variability.
5) Identify El Niño when the 3-month running mean $\geq +0.5°C$, La Niña when $\leq +0.5°C$, and Neutral otherwise.

B.2 Modeling ONI using ARIMA

The ONI can be analyzed and forecasted using ARIMA models. The best results were obtained by ARIMA(3,0,2), which make sense considering that ONI is computed as the SST 3-month running mean. In addition, different ARIMA models were analyzed using both year seasonality and El Niño seasonality, which was put to 5 years. In Tab.(1), results of this analysis is shown, proving that the best model is ARIMA(3,0,2) without considering any kind of seasonality.



(a)



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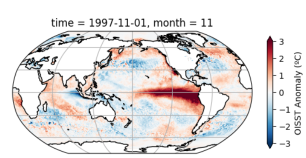


(c)

Fig. 1: (a) Time Series of the temperature anomalies at sea surface in the so-called Niño 3.4 region ($5°N - 5°S$, $170°W - 120°W$). (b) Global temperature anomalies at sea surface on December 1^{st}, 1988. (c) Same as (b) on November 1^{st}, 1997.

ARIMA Models	AIC	BIC
ARIMA(3,0,1)(2,0,0) (auto.arima)	-595.9049	-567.9822
ARIMA(3,0,2)	**-940.6109**	**-911.1507**
SARIMA(3,0,2) (year season)	-858.388	-824.9148
SARIMA(3,0,2) (5-year cycle)	-918.5829	-884.995
LR+ARIMA(3,0,2)	-915.4838	-886.0236
LR+SARIMA(3,0,2) (5-year cycle)	-893.7217	-860.1339

TABLE 1: ARIMA Models with their AIC and BIC values

Moreover, ARIMA(3,0,2) was used in aims of forecasting future values of ONI, see Fig.(2). However, notice the forecast does not provide much information on the long run.

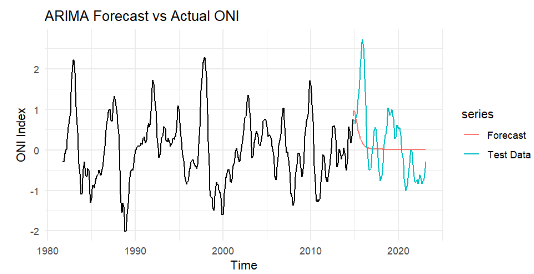


Fig. 2: Forecasting ONI using ARIMA(3,0,2).

B.3 Modeling ONI using GBM

Another interesting model that can predict the complexity of the ONI is the GBM. Notice that GBM might be better at capturing the nonlinearity of on sea surface temperature. For this case, we randomly split the data with ratio 80:20. In Fig.(3), the fit with $RMSE = 0.2097$ on the test dataset is shown.

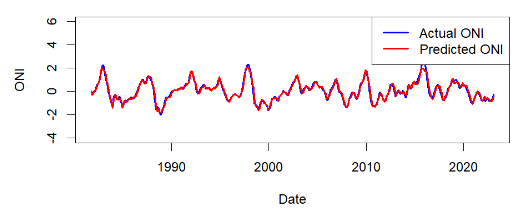


Fig. 3: GBoost fit on the ONI.

In addition, we used GBM to forecast the future of the ONI. See Fig.(4), it can be seen that the forecasting seems to provide more information on future predictions. However, again GBM fails at forecasting future the El Niño/La Niña cycles which happens due to the aperiodic nature of these. In case to achieve better forecasting, more complex models would be needed, loosing with it the interpretability of the data.

C. Influence of ONI on atmospheric behaviour

The Southern Oscillation is the atmospheric component of the ENSO phenomena. It refers to changes in atmospheric pressure patterns between Tahiti (Eastern Pacific), and Darwin,

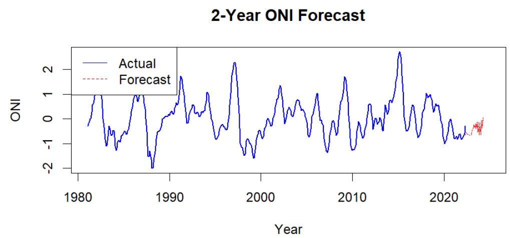


Fig. 4: Forcasting the following 2-Year ONI using GBM

Australia (Western Pacific). Due to its strong relation, the Pearson correlation between ONI and SOI (Southern Oscillation Index) is very high, $corr = -0.6977$. See this correlation in Fig.(5).

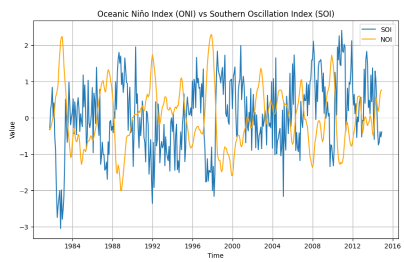


Fig. 5: Relation between the Southern Oscillation Index (blue) and the Oceanic Niño Index (orange).

In fact, given the high correlation, ONI can be used as external variable on predicting SOI. In Tab.(2), the results of different models with and without the external variable are shown. Therefore, the use of ONI would enhance our capability to make predictions on the atmospheric pressure.

ARIMA Models	**AIC**	**BIC**
ARIMA(0,1,2)	888.03	899.99
SARIMA(0,1,2)(2,0,0)	869.99	901.91
ARMAX(0,1,2)	**793.62**	**-**
LR+ARIMA(3,0,2)	862.9	890.82
LR+ARMAX(3,0,2)	776.78	808.69

TABLE 2: ARIMA Models with their AIC and BIC values

D. *Other ENSO influences*

It has been seen how the ENSO produces effects on different climate patterns over different locations on the Pacific. Another example of this can be found in Fig(6), where the Pearson correlation between ONI and the month-average precipitations of the station of Mallares (Peru) is $corr = 0.267$. Therefore, some other non-climate effect would likely appear as well. In fact, Peru is one of the most affected countries by the El Niño patterns as reported in their Statistic Institute [6]. From now on, its effects on Peru's economy will be studied.

IV. Part 2: Modeling Fish Exports from Peru

Peru is the world's largest producer and exporter of fishmeal and fish oil. Fishmeal is a high-protein animal feed primarily derived from small pelagic fish, notably anchoveta (Engraulis ringens), which thrives in the waters along the Peruvian coast. The fish industry relies almost exclusively on Peruvian anchoveta, which represents about 80% of the fish landed in Peru.

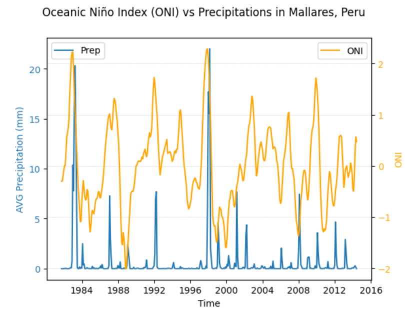


Fig. 6: Relation between the average monthly precipitations in Mallares, Peru (blue), and the Oceanic Niño Index (orange).

Anchoveta stocks fluctuate significantly due to climatic changes, particularly El Niño-Southern Oscillation (ENSO) events. El Niño events (ONI higher than $+0.5°C$) severely disrupts Peru's fishmeal industry by reducing nutrient upwelling, causing anchoveta to migrate or decline, leading to high production losses (e.g., 1997-1998 and 2015-2016). In contrast, La Niña events (ONI less than $-0.5°C$) boost anchoveta populations and therefore, fishmeal productivity.

This section primarily focuses on the effect of El Niño, as measured by the Oceanic Niño Index (ONI), on the fishmeal export of Peru.

A. *Data Preprocessing*

Since Peru's fishmeal export data is available annually, the ONI monthly time series data was aggregated and averaged by year. The two time series were then standardized and aligned to their common years.

In addition to fitting the model to the entire dataset, it is crucial to assess its predictive accuracy. To facilitate this, in a parallel experiment, the data is split into training and testing subsets using an 80:20 ratio. This division enables the evaluation of the model's fit on training set and forecasting performance on test set i.e. unseen data.

B. *Visualizing the Time Series*

B.1 Yearly Averaged ONI Time Series

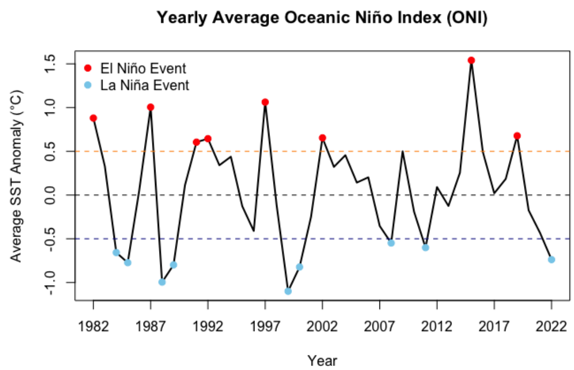


Fig. 7: Yearly Average Oceanic Niño Index

As illustrated in Fig. 7, the same threshold of 0.5 is used to classify moderately strong El Niño and La Niña events, within the Annual ONI time series. This series exhibits a cyclical pattern characterized by recurring peaks and troughs over a span of several years, which shows the presence of periodicity rather than seasonality. Spectral analysis using the Fourier Transform estimates the periodicity to be approximately 4.56 years for the given series.

B.2 Peru Fishmeal Export Time Series

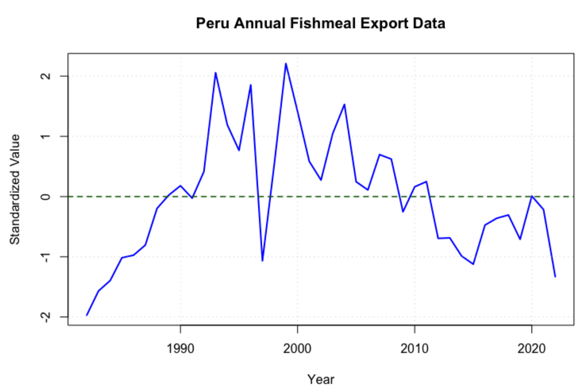


Fig. 8: Peru Annual Fishmeal Export (1982-2024)

Fig. 8 represents the fishmeal exports from Peru. There's a slight upward trend from the 1980's to the late 1990's, followed by a slow, fluctuating decline. Around 1997-98, there's a noticeable sharp drop, followed by a peak, which hints at the influence of external factors. This drop coincides with the 1997-98 El Niño, one of the most significant events on record.

B.3 Relation between ONI and Fish Exports

The influence of El Niño phenomenon, measured through ONI levels is evidently visible on fishmeal exports when they are overlayed on each other, as shown in Fig. 9.

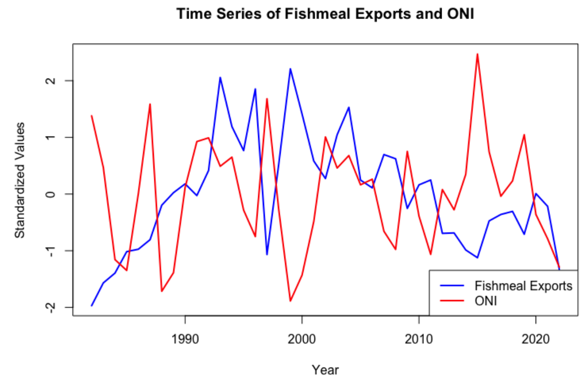
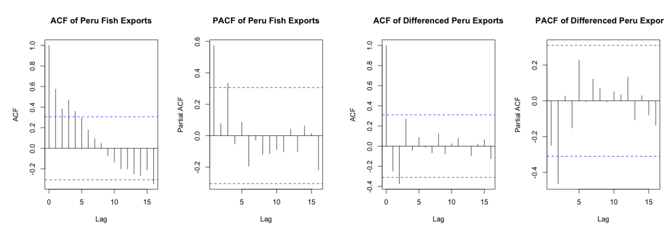


Fig. 9: Superimposed Time Series

The overlay captures the negative correlation between the amount of fish exported annually and the ONI level. This hypothesis is supported by a relatively strong negative correlation i.e. the Pearson correlation of -0.44 between the two series. Therefore, we can model fishmeal exports of Peru, considering ONI as a predictor variable, as seen in the next section.

C. Modeling the Time Series

C.1 Autocorrelations



(a) Original Time Series (b) First Differenced Series

Fig. 10: Autocorrelations for Original & First Differenced Exports Series

The ACF and PACF analysis (Fig. 10) show that the series is non-stationary, which is backed up by the ADF test (p-value = 0.48). To make the series stationary, we applied first differencing. After this, the ACF drops sharply after lag 1, with no significant autocorrelations afterward - clear signs of stationarity. The PACF has a small spike at lag 2, hinting that an AR(2) model might be useful. The updated ADF test on the differenced series (p-value = 0.01) confirms the series is now stationary.

C.2 Modeling Exports without external variable ONI

Several ARIMA models were tested using first differencing to identify the optimal fit. The AutoARIMA function suggested an ARIMA(1, 0, 0) model, which is inappropriate in this case, as stationarity is a prerequisite for ARIMA models, and the series requires differencing (i.e. d is non-zero).

ARIMA Models	AIC	BIC
arima_110	101.16609	104.54385
arima_011	96.36677	99.74453
arima_111	98.11125	103.17788
arima_210	**92.98301**	**98.04965**
arima_211	94.97792	101.73344
arima_113	93.45131	101.89571
autoarima_model (100)	99.99331	103.42045

TABLE 3: ARIMA Models with their AIC and BIC values

The optimal ARIMA model identified is ARIMA(2, 1, 0). Residual diagnostics (checkresiduals) indicate that the ACF values fall within the confidence bounds. The Ljung-Box test also confirms that the residuals resemble white noise, with a p-value of 0.82. After fitting the model to the data, we can generate forecasts for the next 10 years, as seen in Fig. 11.

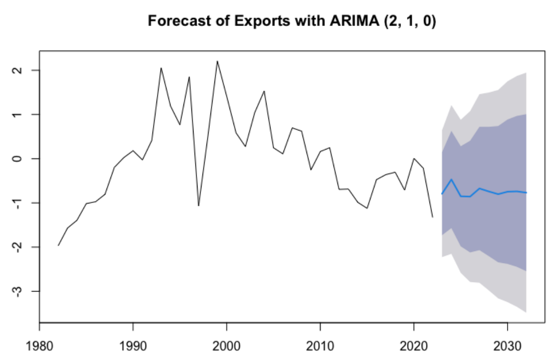


Fig. 11: ARIMA (2, 1, 0) Forecast for next 10 years.

However, since these future events cannot currently be validated, we also assess the model's accuracy by fitting the model on the train data and evaluate how well it predicts the actual values, unseen for the model.

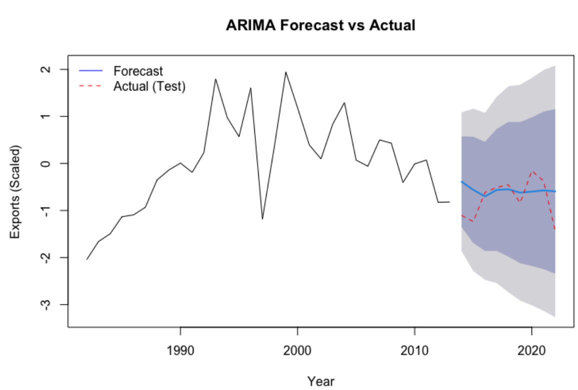


Fig. 12: ARIMA (2, 1, 0) Prediction on Test Data.

As seen in the predictions in Fig. 12, the ARIMA model, with a MAPE of 65.38 and an RMSE of 0.47, shows that it struggles to make accurate forecasts. These high error metrics suggest that the model's predictions are far from ideal.

Similarly, for Exponential Smoothing, although the ACF score is low-indicating that the model captures much of the time series'underlying dynamics-the forecast errors, as reflected by both the MAPE and RMSE, remain relatively high. This means that despite modeling the data well, the model still struggles with accurate forecasting.

We therefore consider next ONI as an external variable, for better forecasting.

C.3 Modeling Exports with External Variable ONI

The linear model with ONI as an external variable, shows a low R-squared value (0.07901) which suggests that the relationship between exports and ONI may not be linear.

A dynamic regression model like ARIMAX, which accounts for both autoregressive patterns and the external influence of ONI, could provide a more accurate and insightful forecast. Below is the ARIMAX model summary.

```
Series: ts_exports_scaled
Regression with ARIMA(2,1,0) errors

Coefficients:
          ar1      ar2  Series 1
      -0.2939  -0.3596   -0.3240
s.e.   0.1623   0.1575    0.1004

sigma^2 = 0.4348:  log likelihood = -38.7
AIC=85.41   AICc=86.55   BIC=92.16

Training set error measures:
                     ME      RMSE       MAE      MPE     MAPE      MASE       ACF1
Training set 0.01451366 0.6264025 0.4585103 94.79418 234.3329 0.7539795 0.03697258
```

Fig. 13: ARIMAX Summary (with ONI as external variable)

The negative coefficient for ONI supports that higher ONI values, associated with El Niño conditions, may lead to reduced exports. However, despite incorporating ONI, the model's high error metrics (such as MAPE) indicate that it still fails to capture the export data effectively. We therefore try to model non parametric regression models with ONI as our external variable to fit the data better.

The Loess Model can capture complex, non-linear relationships between exports and ONI, by using a smoothing approach.

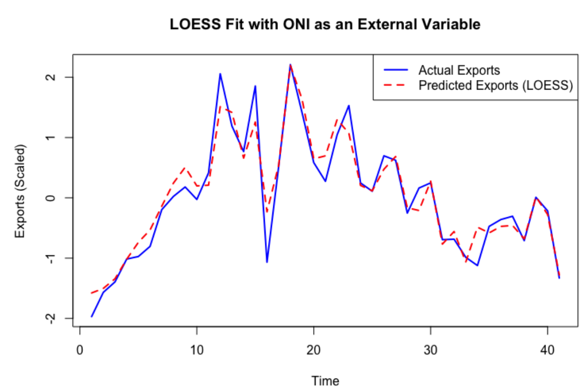
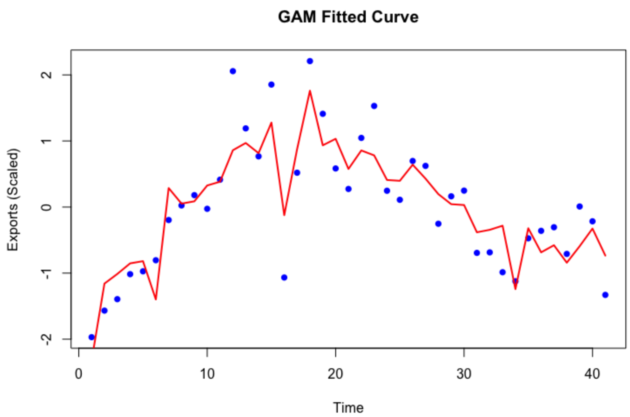


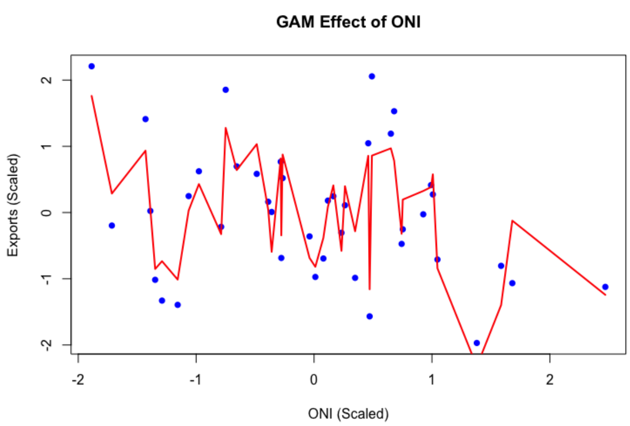
Fig. 14: Loess Model

The LOESS model (Fig. 14) applied to the export data, with ONI as an external variable, provides a smooth, non-linear fit to the data. The low residual standard error suggests that the model captures much of the variation in the data.

We also fit a Generalized Additive Model (GAM), to model the relationship between Peru's exports and two variables: time and the Oceanic Niño Index (ONI), both treated as smooth functions in the model.



(a) GAM Model fit over Time.



(b) GAM Model fit over ONI.

Fig. 15: Illustrating the combined (additive) effect of variables using GAM.

The model (Fig. 15) explains 75% of the variation in exports (adjusted R-squared) and 81.4% of the deviance, which indicates a strong fit.

In conclusion, the Oceanic Niño Index affects Peru's fish exports, which, in turn, which effectively influences its market share - an aspect we explore in the next section.

V. Part 3: Analyzing the Impact of El Niño on the S&P/BVL Peru General Market Index

A. Introduction

Insights gained from the previous sections, where we focused on detecting the El Niño effect using external variables and investigating its influence on fish meal production in Peru, clearly showcased that El Niño could disrupt local industries, creating potential ripple effects on the economy. These ripple effects can present opportunities, such as leveraging this knowledge for investment strategies. Therefore, the final part of our project delves deeper into understanding how this climatic phenomenon specifically impacts Peru's stock market, particularly the S&P/BVL Peru General Market Index.

The S&P/BVL Peru General Market Index is the country's most prominent stock market index, serving as a key indicator of economic performance by tracking the largest and most actively traded stocks on the Lima Stock Exchange.

This deeper examination is crucial because understanding these correlations can enhance our forecasting capabilities and help stakeholders—such as investors, policymakers, and businesses—prepare for future events.

B. Data Extraction & Preprocessing

To extract historical data for the S&P/BVL Peru General Index [7], we faced challenges as free data available online only starts from 2015. While TradingView offers data from 1997, downloading it requires a premium subscription. We explored open-source APIs such as Alpha Vantage, but this specific index was not available. Instead, we used the yfinance [8] library to retrieve data up to 2021 and combined it with the free data starting from 2015, resulting in a more complete dataset.

The preprocessing pipeline involved 1) Identifying and removing null values to ensure data completeness. 2) Aligning timestamp of ONI (collected last day of each month) and S&P/BVL time series (collected first day of each month) for inner join, by shifting one day for inner join 3) Standardizing The ONI index and close values of the market using a StandardScaler to ensure comparability by normalizing them to have zero mean and unit variance. Figure 16 shows combined data that will be used for the analysis in part C.

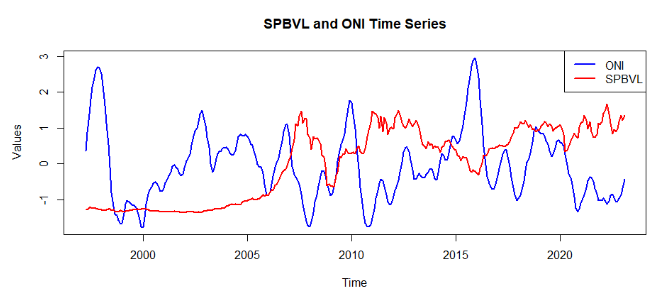


Fig. 16: 1997-2023 S&P BVL - ONI plot

C. Analysis without external variable (ONI)

C.1 Bass Model

The Bass model is applied to the cumulative sum of the S&P BVL stock market index to capture its diffusion process over time. This model is particularly suited for analyzing the adoption and diffusion of innovations but is also effective in modeling cumulative processes in time series data.

Results demonstrated that all parameters (m as market potentia, p as the coefficient of innovation and q as the coefficient of imitation) are highly significant (***).

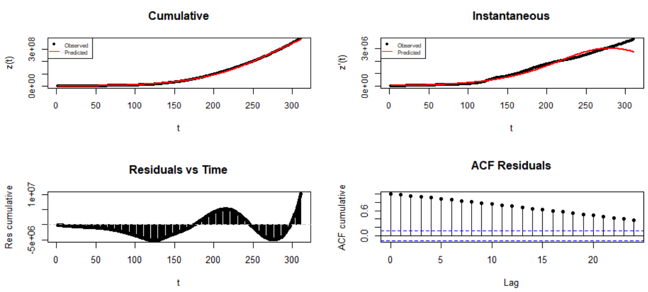


Fig. 17: Bass Model on market index

Figure 17 shows that the diffusion process of the S&P BVL stock market index follows a pattern that can be well-captured by the Bass model.However, The Autocorrelation Function plot of the residuals reveals a high degree of autoregression, suggesting that the current model fails to fully capture the temporal dependencies present in the data. This indicates the necessity of incorporating external information (namely the ONI index) to enhance the model's explanatory and predictive power.

C.2 Generalized Growth Model

Similarly, a Generalized Growth Model (GGM) is applied to the cumulative sum of the S&P BVL stock market index. The GGM successfully identified the coefficients q_c, p_s, and q_s as highly significant (***), whereas the coefficients K and p_c were found to be insignificant.

Fig. 18 illustrates that the GGM managed to better capture the instantaneous form of the data compared to the Bass Model (BM). However, the ACF of the residuals for the GGM revealed a similarly high degree of autoregression. This suggests that, like the Bass Model, the GGM is unable to fully account for the temporal dependencies in the data, reinforcing the need for external variables or additional modeling techniques.

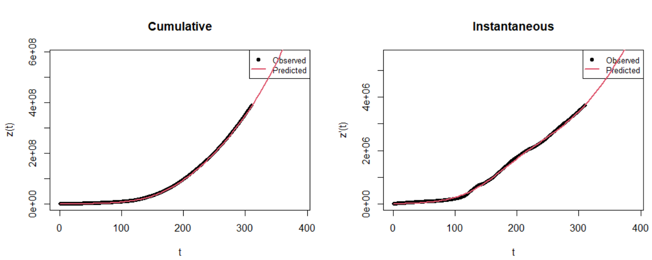


Fig. 18: Generalized Growth Model (GGM) on S&P BVL Market Index

D. Analysis with external variable (ONI)

In the current setup (1997-2023), the Pearson correlation between the S&P BVL index (*spbvl*) and the Oceanic Niño Index (ONI) is calculated as *cor = -0.2150529* with a p-value of 0.0001324. This result suggests a weak negative correlation between the two indices over the entire period.

However, considering that the stock market was relatively unstable during its early years and did not exhibit a stable value due to being newly established, the correlation for this period could be influenced by this instability. To mitigate this effect, we cropped the data to start from 2007, excluding the years of early market volatility, thereby ensuring that the correlation analysis reflects a more stable and relevant relationship between the two indices.

In the cropped data setup, the Pearson correlation between the S&P BVL index (*spbvl*) and the ONI index is calculated as *cor = -0.4382967* with a p-value of 1.641×10^{-10}. This result suggests a moderate negative correlation between the two indices, with a higher level of statistical significance and correlation strength.

Figure 19 shows the cropped plot for the future analysis.

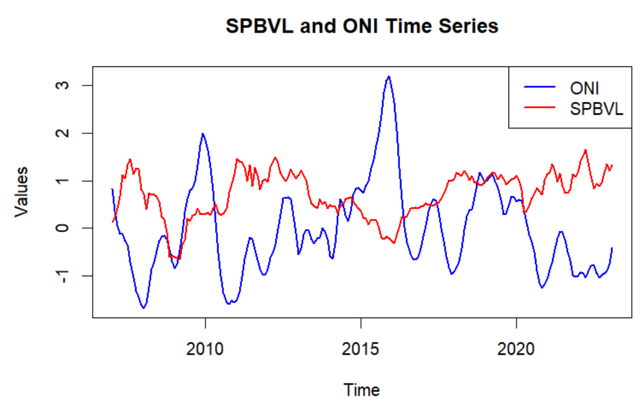


Fig. 19: S&P BVL - ONI Plot 2007-2023

D.1 Lag effect using Cross-Correlation Function (CCF)
Before we continue our analysis with more complex models, we needed to make sure whether there is a need to shift time-series in order to best capture the correlation effect.

The CCF measures the correlation between two time series at different lags. The CCF plot in Fig. 20 shows that there is no significant effect of lag as ACF is centered on 0. Analysis will continue without shifting the data.

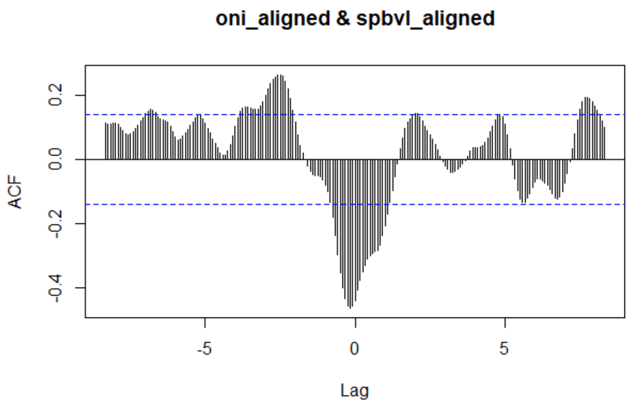


Fig. 20: CCF Plot for lag effect

D.2 Linear Regression

Simple linear regression on stock market index using ONI as regressor provided a coefficient estimate of *-0.2194* with high significance (***), showcasing ONI can be used as a regressor to predict this index.

D.3 Non-linear Regression with GAM Models and AIC Comparison

We evaluated several Generalized Additive Models (GAM) to determine the optimal fit, based on their AIC scores:

TABLE 4: AIC Comparison Between Models

Model	**AIC**
Linear Model(tt + X)	233.18
(GAM) Spline(tt)	192.22
(GAM) Loess(tt) + X	176.04
(GAM) Spline(tt) + X	168.22

The model configuration (GAM) Spline(tt) + X achieved the lowest AIC score, indicating the best fit. Here, X represents the Oceanic Niño Index (ONI) as an external regressor.

We observed that residual plot of (GAM) Spline(tt) + X is not white-noise. We increased the model fit by incorporating an ARIMA fit on residuals into the original predictions.

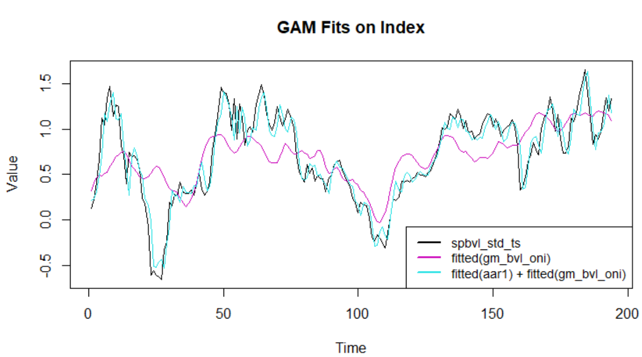


Fig. 21: (fitted(aar1) + fitted(gm_bvl_oni)

D.4 ARIMA Analysis

Upon examining the ACF and PACF plots of the S&P/BVL index (see Fig. 22), we identified that the trend could be effectively removed with a first-degree differencing. Additionally, the autoregressive (AR) and moving average (MA) components were best represented with orders 1 and 4, respectively. We also included the ONI as an external regressor.

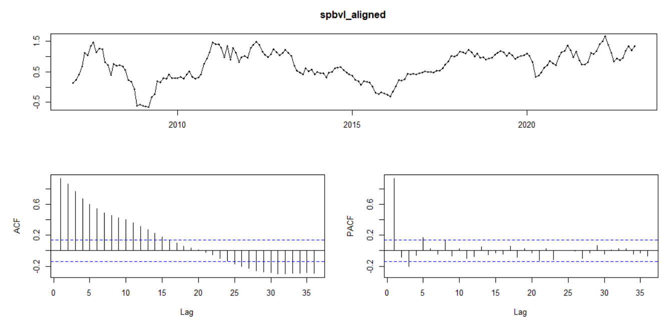


Fig. 22: ACF-PACF Plot of S&P/BVL Index

In comparison, the auto.arima function suggested an AUTO.ARIMA(3,1,1)(2,0,0)[12] configuration, which incorporates a seasonal component and also utilizes ONI as an external regressor too.

Table below illustrates that our manually configured ARIMA model yielded a slightly better AIC value compared to the auto.arima model.

TABLE 5: AIC Comparison Between ARIMA Models

Model	**AIC**
ARIMA [1,1,4]	-154.74
AUTO.ARIMA(3,1,1)(2,0,0)[12]	-149.14

Eventually, we performed a future prediction utilizing ARIMA[1,1,4], assuming the ONI index will exactly repeat itself in the future as it was in the data. Fig 23 below shows this forecast.

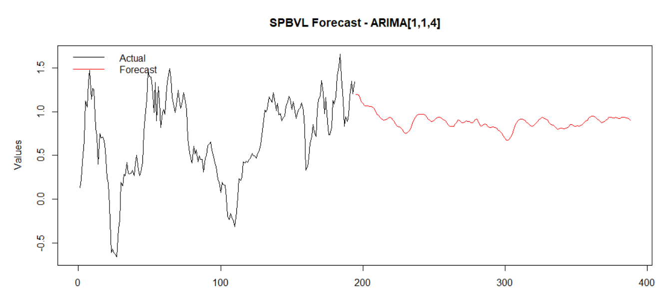


Fig. 23: ARIMA[1,1,4]

D.5 Prophet Model Parameters and Forecast Accuracy

The Prophet model was enhanced by incorporating an additional regressor, `oni`. In line with Meta 's documentation [9], we represented the 2008 financial crisis and the Covid-19 lockdown periods as holiday parameters to improve the model's generalizability.

The dataset was split into training and testing sets with a 90-10 ratio, which we found to be more suitable than an 80-20 split. The latter would have resulted in the Covid-19 period being included in both the training and testing sets, introducing potential instability into the time series.

The best model configuration was achieved using multiplicative seasonality, changepoint.range = 1, n.changepoints = 20, and adding quarterly seasonality, resulting in a Mean Absolute Percentage Error (MAPE) of 16.84.

Fig. 24 shows how the Prophet model captures the drastic changes while still fitting the stock market index.

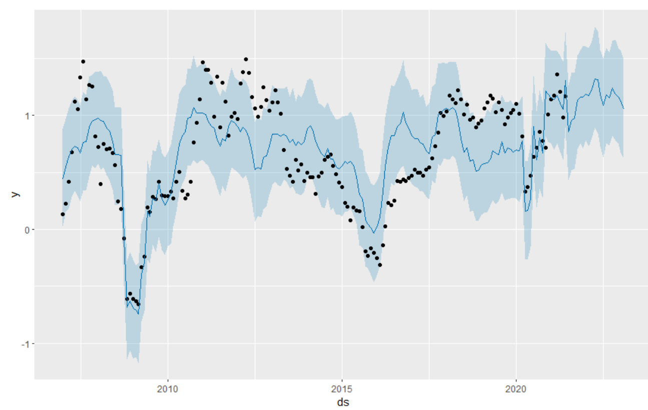


Fig. 24: Prophet model fit

Fig. 25 shows how the prediction of Prophet model aligns with the real-test data.

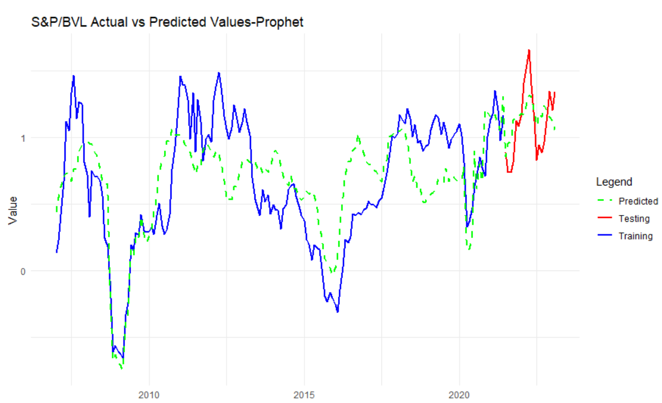


Fig. 25: Prophet Future Prediction

VI. Conclusion

A. Results

The analysis in Part A highlighted the significant impact of the El Niño-Southern Oscillation (ENSO) on various environmental and economic patterns, with a focus on the Oceanic Niño Index (ONI) and its predictive power. Through modeling, it was shown that ARIMA(3,0,2) outperforms other models in forecasting ONI, demonstrating its ability to capture the nuances of this climatic phenomenon. Moreover, the correlation between ONI and the Southern Oscillation Index (SOI) further supports the utility of ONI as an external variable in predicting atmospheric behavior, as evidenced by the improved performance of ARIMAX models. Additionally, the relationship between ONI and precipitation patterns in Peru provides further insights into how ENSO influences local weather conditions, with potential implications for agricultural and economic sectors. These findings underscore the importance of understanding and forecasting ENSO patterns for better preparedness, particularly for countries like Peru, which are highly susceptible to the effects of El Niño events.

Moreover, the ONI index obtained through the analysis of these external variables created a curated dataset to be used for the remaining analysis in this paper.

Then our analysis focused on the economic effect of this observed phenomenon, specifically on Fish Export in Peru. The analysis in part B concluded that the Oceanic Niño Index (ONI) plays a significant role in explaining the fluctuations in Peru 's fishmeal exports. Our analysis revealed a clear negative correlation between the ONI and fish export levels, particularly during El Niño events, which disrupt anchoveta stocks and reduce fishmeal production. Despite challenges with traditional time series models such as ARIMA, incorporating ONI as an external variable improved the model's ability to account for these disruptions. The Loess and Generalized Additive Models (GAM) further enhanced the predictive power by capturing the non-linear relationship between the export data and climatic variables. Ultimately, ONI provided valuable insights for forecasting Peru's fishmeal exports and understanding the broader impact of climatic phenomena on the fishing industry, which is essential for effective market analysis and future planning.

After analyzing these interesting correlations in fish production industry in Peru, we directed our focus on an even more specific financial area, Peru General Stock Market Index, in order to come up with insights for shareholders.

The analysis in Part C clearly demonstrated the value of the Oceanic Niño Index (ONI) as a powerful external regressor for understanding and forecasting the S&P/BVL Peru General Market Index. By comparing the AIC scores, the models ranked from least to most effective in performance are: Prophet Model, Linear Model, GAM with Spline(tt) + ONI, and ARIMA[1,1,4].

Although each model shows varying strengths in explaining the data, certain models excel in different areas. The GAM model with fitted residuals provides the best fit to the data, while the Prophet Model and ARIMA demonstrate greater flexibility and generalization in forecasting. Both these models are particularly effective in capturing the influence of ONI on the stock index, revealing promising opportunities for further exploration. These insights not only enhance forecasting accuracy but also offer valuable information for investors, policymakers, and businesses in preparing for future market movements influenced by climate phenomena like El Niño.

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