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The ENSO cycle and forecastability of global inflation and output growth : evidence from standard and mixed-frequency multivariate singular spectrum analyses

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**The ENSO Cycle and Forecastability of Global Inflation and Output Growth:  
Evidence from Standard and Mixed-Frequency Multivariate Singular Spectrum  
Analyses**

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# The ENSO Cycle and Forecastability of Global Inflation and Output Growth: Evidence from Standard and Mixed-Frequency Multivariate Singular Spectrum Analyses

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## ABSTRACT

In this paper the role of the El Niño-Southern Oscillation (ENSO), measured by the Equatorial Southern Oscillation Index (EQSOI), is used to formally forecast the inflation and GDP growth rates of the United States (US), advanced (excluding the US) and emerging countries, as well as the world economy (barring the US). We rely on univariate and multivariate Singular Spectrum Analyses (SSA), as well as mixed-frequency version of the latter since the EQSOI is monthly, while GDP is available only at quarterly frequency unlike monthly inflation rates. We find statistically significant evidence of the ability of the EQSOI in forecasting inflation and GDP growth rates of the four economic blocs, though there are exceptions in terms of forecasting gains associated with inflation rate of emerging economies and the growth rate of the US. Our results have important implications for policymakers.

## KEYWORDS

GDP growth; Inflation; ENSO; Forecastability; Mixed-Frequency Multivariate SSA; Continuous Wavelet Transform.

JEL : C22; C32; E31, E32; E37; Q54.

## 1. Introduction

The El Niño-Southern Oscillation (ENSO) is an irregularly periodic variation in winds and sea surface temperatures over the tropical eastern Pacific Ocean, which tends to affect the climate of much of the tropics and subtropics [30]. The warming phase of sea temperature is known as El Niño and the cooling phase as La Niña. Each of these two phases can last several months and typically occur every few years with varying intensities per phase. However, it would be a mistake to think of the ENSO as merely affecting climate patterns, but instead, some studies have highlighted its ability to produce downturn phases of the business cycle to some degree, but primarily causing inflationary impacts via increases in agricultural commodity and crude oil prices [1, 2, 5, 6, 9, 23, 25, 28], due to El Niño and La Niña events producing major global rare disaster risks historically [7, 14, 26].

While these studies are of tremendous importance in deducing the empirical link

14 between ENSO and major macroeconomic variables, i.e., growth and inflation, these  
15 primarily being in-sample (causal and structural) analyses are to some degree of limited  
16 value to policymakers in general, and central banks in particular, who would need  
17 accurate predictions of the future path of key economic variables, i.e., out-of-sample  
18 forecasts, while making their policy decisions, following episodes of weather-related  
19 uncertainties. Moreover, from a statistical perspective, it is well-established that in-  
20 sample predictability does not guarantee out-of-sample forecasting gains emanating  
21 from a specific predictor, besides the fact that it is out-of-sample forecasting that  
22 tends to provide a more robust test of the appropriateness of an econometric model  
23 and the predictor [3]. Given this, the objective of this paper is to provide for the first  
24 time an out-of-sample forecasting analysis of output growth and inflation based on the  
25 information content of the ENSO cycle for not only the United States (US), but also  
26 regional blocs involving other advanced (excluding the US) and emerging economies,  
27 besides the overall world (excluding the US).

28 In this regard, as far as the econometric model is concerned, we rely on the Multi-  
29 variate Singular Spectrum Analysis (MSSA). We are motivated to use SSA because it  
30 is a non-parametric technique that works with arbitrary statistical processes, whether  
31 linear or non-linear, stationary or non-stationary, Gaussian or non-Gaussian [27], and  
32 being a versatile approach for modelling and forecasting time series, it has been found  
33 to outperform wide-array of other forecasting models [11, 15, 17, 18]. At this stage, we  
34 must also highlight that, since the ENSO data is available monthly, while the Gross  
35 Domestic Product (GDP) growth data are quarterly, we rely on a mixed-frequency  
36 MSSA model to forecast the growth rate, as recently developed by [20], rather than  
37 averaging the ENSO data over three-months forming the quarter to prevent possible  
38 loss of information [8]. This serves as an additional empirical novelty of our paper.  
39 While forecasting is the primary focus, to highlight the underlying nonlinear and time-  
40 varying relationship between growth and inflation with the ENSO to motivate the SSA  
41 across short-, medium- and long-runs, we also conduct an in-sample-based causality  
42 analysis using the wavelet coherence approach.

43 The remainder of the paper is organized as follows: Section 2 outlines the method-  
44 ologies, while Section 3 presents the data and Section 4 discusses the results. Finally,  
45 Section 5 concludes.

## 46 2. Methods

47 The investigation of the impact of the ENSO on GDP growth and inflation is carried  
48 out in two stages. First a wavelet coherence analysis is used to investigate the complex  
49 relationship between the economic series and the ENSO. Next, we use a data driven  
50 forecasting method (mixed-frequency and standard multivariate SSA), and a nonpara-  
51 metric test (KSPA) to test for the role of monthly ENSO for quarterly GDP growth  
52 and monthly inflation. Following is a brief review of the employed methods.

### 53 2.1. Continuous Wavelet Transform and Coherence Analysis

54 A Continuous Wavelet Transform, CWT, uses a mother wavelet  $\psi(\cdot)$  to transform  
55 a discrete-time time series  $y_t g_1^n$ , to wavelet daughters  $W(\cdot; s)$ , for time localizing  
56 parameter  $t$  and scale parameters. The wavelet daughters  $W(\cdot; s)$  are defined as  
57 convolution of time series  $y_t g_1^n$  with the localized (in time and frequency space by

58 and  $s$ ) mother wavelet  $\psi(t)$  [4]:

$$W(\tau; s) = \sum_t y_t \frac{1}{s} \psi\left(\frac{t-\tau}{s}\right);$$

59 where  $\psi^*(\cdot)$  is the complex conjugate of  $\psi(\cdot)$ . Larger values of scale parameters, reveal  
 60 the long term periodic behavior (with low frequency) and smaller values of scale pa-  
 61 rameter reveal the details in short term periodic patterns (with higher frequencies).  
 62 One common choice for mother wavelet is the Morlet wavelet [24]:

$$\psi(t) = \frac{1}{\sqrt{2\pi}} e^{j\omega t} e^{-t^2/2};$$

63 where  $\omega$  is dimension less frequency, also known as angular frequency. According to  
 64 the literature, the  $\omega = 6$  is the proper choice, since it makes the Morlet wavelet  
 65 approximately analytic [4].

66 Large absolute values of  $W(\tau; s)$  show the powerful periodic pattern in time  $\tau$  and  
 67 period  $s$ . The wavelet power spectrum of time series  $y_t$  is defined as

$$\text{Power}(\tau; s) = \frac{1}{s} |W(\tau; s)|^2;$$

68 The power spectrum can be used to map the periodic patterns in the time series  $y_t$ ,  
 69 through time. The wavelet power spectrum can be tested against white noise spectrum,  
 70 using asymptotic chi square statistic [10, 29] or Monte Carlo simulation [10, 29]. The  
 71 Monte Carlo simulation approach is used in this paper.

72 In the bivariate case, the cross wavelet transform can be used to investigate the  
 73 relation between two time series,  $x_t$  and  $y_t$  [4]:

$$W_{xy}(\tau; s) = \frac{1}{s} W_x(\tau; s) W_y^*(\tau; s);$$

74 where  $W_x(\tau; s)$  and  $W_y(\tau; s)$  are the wavelet daughters in time series  $x_t$  and  $y_t$ , re-  
 75 spectively and  $W^*$  denotes complex conjugate. The wavelet cross power spectrum can  
 76 be used to map the similarities between two time series' periodic behavior:

$$\text{Power}_{xy}(\tau; s) = |W_{xy}(\tau; s)|^2;$$

77 Using the wavelet cross power spectrum, we can map the localized correlation between  
 78 two series, through time and scale. Coherence between two time series  $x_t$  and  $y_t$  is  
 79 defined as the local correlation between the series, localized at time  $\tau$  and scales [4]:

$$\text{Coherence}_{xy}(\tau; s) = \frac{|W_{xy}(\tau; s)|^2}{\text{Power}_x(\tau; s) \text{Power}_y(\tau; s)};$$

80 Like power spectrum, wavelet Coherence between two series can be tested using Monte  
 81 Carlo simulation [29].

82 **2.2. Standard and Mixed Frequency Multivariate Singular Spectrum**  
83 **Analyses**

84 Following is a brief review of implementing standard and mixed frequency MSSAs.  
85 Since the bivariate version of the method is used in this research, the notation is  
86 adapted to the two-variable case. Consider the bivariate time series  $\mathbf{X}_t := (\mathbf{x}_t; \mathbf{y}_t) \mathbf{g}_{t2\mathbf{S}}$ ,  
87 which takes values in  $\mathbf{R}_{\mathbf{X}} \times \mathbf{R}^2$ . The index set  $\mathbf{S}$  can be subset of either  $\mathbf{Z}$  or  $\mathbf{N}$ . It is  
88 assumed that both series are already scaled appropriately and expressed in commensu-  
89 rable units of measurement. Using a observed time series of length  $n$  (i.e.  $\mathbf{X}_1; \dots; \mathbf{X}_n$ )  
90 and embedding dimension  $L$ , MSSA follows these steps [19]:

- 91 (1) We apply the hankelization operator  $\mathbf{H}_L(\cdot)$  to each of the component series of  
92  $\mathbf{X}_t$ , and obtain the trajectory  $(m \times L)$  matrices  $\mathbf{T}_i$  as:

$$\mathbf{T}_i := \mathbf{H}_L(\mathbf{X}_{1i}; \dots; \mathbf{X}_{ni}); \quad i = 1; 2$$

93 where  $\mathbf{X}_{t1} = \mathbf{x}_t$ ,  $\mathbf{X}_{t2} = \mathbf{y}_t$  and  $m = n - L + 1$ . Concatenate the trajectory matrices  
94 horizontally, and build the  $(m \times 2L)$  MSSA trajectory matrix  $\mathbf{T}_{\mathbf{X}} := [\mathbf{T}_1; \mathbf{T}_2]$   
95 which will be used for decomposition and reconstruction in next steps.

- 96 (2) We build the sample covariance matrix  $\mathbf{C} := m^{-1} \mathbf{T}_{\mathbf{X}}^0 \mathbf{T}_{\mathbf{X}}$ , which is block sym-  
97 metric matrix, containing covariance and cross-covariance matrix for both com-  
98 ponent series of  $\mathbf{X}_t$ .  
99 (3) Obtain eigenvalues  $\lambda_1, \dots, \lambda_{2L}$  and eigenvectors  $\mathbf{v}_1; \dots; \mathbf{v}_{2L}$  of sample covari-  
100 ance matrix  $\mathbf{C}$ . Using eigenvalues and eigenvectors, one can decompose sample  
101 covariance matrix as:

$$\mathbf{C} = \sum_{j=1}^{2L} \lambda_j \mathbf{v}_j \mathbf{v}_j^0 = \mathbf{V} \mathbf{\Lambda} \mathbf{V}^0;$$

102 where  $\mathbf{V}$  is a  $(2L \times 2L)$  matrix containing all eigenvectors of  $\mathbf{C}$ .

- 103 (4) Partitioning  $\mathbf{V}$  appropriately in to  $\mathbf{V} = [\mathbf{V}_1^0; \mathbf{V}_2^0]$ , estimate the individual tra-  
104 jectory matrices as:

$$\hat{\mathbf{T}}_i(\mathbf{k}) := \mathbf{T}_i \mathbf{Q}(\mathbf{k}); \quad i = 1; 2;$$

105 where  $\mathbf{Q}(\mathbf{k}) := \sum_{i=1}^P \mathbf{v}_{ij} \mathbf{v}_{ij}^0$  for a subset of eigenvectors in  $\mathbf{V}$ , i.e.  $i \in \{1; \dots; L\}$ .

- 106 (5) Obtain the reconstructed series by applying diagonal averagein operator  $\mathbf{D}_{(L;n)}(\cdot)$   
107 to the estimated trajectory matrices:

$$\hat{\mathbf{X}}_{t;i}(\mathbf{k}) := \mathbf{D}_{(L;n)} \hat{\mathbf{T}}_i(\mathbf{k})$$

108 Now, suppose the  $\mathbf{x}_t$  is the time series observed in lower frequency (say quarterly)  
109 and  $\mathbf{y}_t$  is the time series observed in higher frequency (say monthly). The mixed-  
110 frequency MSSA introduced by [20] follows these steps:

- 111 (1) We build the initial observation matrix in higher frequency by repeating the val-  
112 ues in lower frequency. For instance, if  $\mathbf{x}_t$  is observed quarterly (each observation  
113 is belongs to the end of the quarter) and  $\mathbf{y}_t$  is monthly, the initial observation

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matrix in monthly sampling frequency will be:

$$H^{(0)} = \begin{matrix} & \begin{matrix} 0 & 1 \end{matrix} \\ \begin{matrix} x_1 & y_1 \\ x_1 & y_2 \\ x_1 & y_3 \\ x_2 & y_4 \\ x_2 & y_5 \\ x_2 & y_6 \\ \vdots & \vdots \end{matrix} & \begin{matrix} \\ \\ \\ \\ \\ \\ \\ \end{matrix} \\ \textcircled{A} & \end{matrix}, I = \begin{matrix} & \begin{matrix} 0 & 1 \end{matrix} \\ \begin{matrix} 0 \\ 0 \\ 1 \\ 0 \\ 0 \\ 1 \\ \vdots \end{matrix} & \begin{matrix} \\ \\ \\ \\ \\ \\ \\ \end{matrix} \\ \textcircled{A} & \end{matrix},$$

115

where  $n$  is the number of observations in time series with higher frequency. As it can be seen, in each quarter, the monthly values in quarterly observed series, are filled-in with the end-of-the-quarter observation. The Matrix  $I$  shows which rows in matrix  $H^{(0)}$  are actual quarterly observations (denoted as ones) and which ones are filled with end-of-the-quarter observation (denoted as zeros).

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- (2) Using a standard MSSA [19] on matrix  $H^{(0)}$  to obtain the predicted values in higher frequency, namely  $\hat{H}^{(0)}$ . Initialize the root-mean-squared measure as the root mean square of first column in  $\hat{H}^{(0)}$  (the column associated with the time series with lower sampling frequency):

$$RMSE^{(0)} = \sqrt{\frac{1}{n} \sum_{t=1}^n \hat{h}_{t,1}^{(0)2}},$$

124

where  $\hat{h}_{t,1}^{(0)}$  is the  $t$ th element in first column of  $\hat{H}^{(0)}$ .

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- (3) In  $i$ th iteration, we substitute actual observations (that is the second column of  $H^{(0)}$  and the elements in first column which are the associated with ones in  $I$  matrix) into  $\hat{H}^{(i-1)}$  and build the new  $H$  matrix:

$$H^{(i)} = \begin{matrix} & \begin{matrix} 0 & 1 \end{matrix} \\ \begin{matrix} \hat{h}_{t,1}^{(i-1)} & y_1 \\ \hat{h}_{t,2}^{(i-1)} & y_2 \\ x_1 & y_3 \\ \hat{h}_{t,4}^{(i-1)} & y_4 \\ \hat{h}_{t,5}^{(i-1)} & y_5 \\ x_2 & y_6 \\ \vdots & \vdots \end{matrix} & \begin{matrix} \\ \\ \\ \\ \\ \\ \\ \end{matrix} \\ \textcircled{A} & \end{matrix}.$$

128

- (4) Applying standard MSSA to  $H^{(i)}$  to obtain the new predicted values in higher frequency, namely  $\hat{H}^{(i)}$ .

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- (5) Obtaining a new root-mean-squared measure:

$$RMSE^{(i)} = \sqrt{\frac{1}{n} \sum_{t=1}^n \hat{h}_{t,1}^{(i-1)} - \hat{h}_{t,1}^{(i)2}}.$$

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- (6) For some predefined small value  $\varepsilon$ , while  $RMSE^{(i)} \leq RMSE^{(i-1)}$  and  $|RMSE^{(i)} - RMSE^{(i-1)}| > \varepsilon$ , we repeat steps (3) to (5).

- 133 (7) If  $RMSE^{(i)} > RMSE^{(i-1)}$ , consider the  $\hat{H}^{(i-1)}$  as the final estimation for high  
134 frequency observation matrix and if  $|RMSE^{(i)} - RMSE^{(i-1)}| \leq \varepsilon$ , put  $\hat{H}^{(i)}$  as  
135 final estimation for high frequency observation matrix.  
136 (8) Applying standard MSSA on  $\hat{H}$ , the final estimation for high frequency obser-  
137 vation matrix obtained in step (7),for out-of-sample forecasting.

### 138 2.3. Forecasting Evaluation

139 Suppose  $E(y_{t+h}|\mathcal{F}_t)$  is the  $h$  step ahead forecast from MSSA and the  $\eta_{t+h}$  is the  
140 forecasting square error of the conditional mean model at time  $t$ :

$$\eta_{i+h} = (y_{t+h} - E(y_{t+h}|\mathcal{F}_t))^2.$$

141 Kolmogorov-Smirnov Predictive Accuracy, KSPA, test [16] is used for comparing  
142 the forecasting accuracy of different models. Let  $F_{\eta_{i+h}}^{(k)}(\cdot)$  be the distribution function  
143 of square error corresponding to  $k$ th forecasting model. One tailed KSPA, tests the  
144 following hypothesis:

$$\begin{cases} H_0 : F_{\eta_{i+h}}^{(1)}(z) \leq F_{\eta_{i+h}}^{(2)}(z) \\ H_1 : F_{\eta_{i+h}}^{(1)}(z) > F_{\eta_{i+h}}^{(2)}(z) \end{cases}.$$

145 Rejection of the null hypothesis implies that the forecasting error of second model,  
146  $\eta^{(2)}$  is stochastically smaller than the forecasting error of the first model,  $\eta^{(1)}$ , i.e., the  
147 second forecasting model is significantly more accurate than the first one.

### 148 3. Data Description

149 As far as the metric of the ENSO cycle is concerned, traditionally the Southern Os-  
150 cillation Index (SOI) index is used.<sup>1</sup> The SOI gives an indication of the development  
151 and intensity of El Niño or La Niña events in the Pacific Ocean. The SOI is calculated  
152 using the pressure difference between Tahiti and Darwin. Sustained negative (positive)  
153 values of the SOI below (above) 7(+ 7) often indicate El Niño (La Niña) episodes.  
154 Low atmospheric pressure tends to occur over warm water and high pressure occurs  
155 over cold water, in part because of deep convection over warm water. El Niño episodes  
156 are defined as sustained warming of the central and eastern tropical Pacific Ocean, and  
157 La Niña episodes are defined as sustained cooling of the central and eastern tropical  
158 Pacific Ocean, resulting in a decrease and an increase in the strength of the Pacific  
159 trade winds, respectively.

160 The reliability of the SOI, however, is considered limited due to both Darwin and  
161 Tahiti being well south of the equator, resulting in the surface air pressure at both lo-  
162 cations being less directly related to ENSO. To overcome this issue, a new index called  
163 the Equatorial Southern Oscillation Index (EQSOI) has been created.<sup>2</sup> To generate  
164 the data for this index, two new regions centered on the equator are delimited, with

<sup>1</sup>See: <http://www.bom.gov.au/climate/enso/soi/>

<sup>2</sup>See the discussion of Anthony Barnston of the National Oceanic and At-  
mospheric Administration here: <https://www.climate.gov/news-features/blogs/enso/why-are-there-so-many-enso-indexes-instead-just-one> for further details.



165 the western one located over Indonesia and the eastern one located over the equa-  
166 torial Pacific, close to the South American coast. The EQSOI is obtained from the  
167 Climate Prediction Center (National Weather Service) of the National Oceanic and  
168 Atmospheric Administration (US Department of Commerce).<sup>3</sup> In our analysis, we use  
169 the EQSOI index to capture the ENSO.

170 As far as our macroeconomic variables are concerned, data on year-on-year growth of  
171 quarterly real GDP and monthly inflation rates of the US, other advanced barring the  
172 US and emerging market economies, as well as the overall World economy excluding  
173 the US are obtained from the Global Economic Database maintained by the Federal  
174 Reserve Bank of Dallas.<sup>4</sup> Data on 18 advanced (excluding the US, Japan, Germany, the  
175 United Kingdom (UK), France, Italy, Spain, Canada, South Korea, Australia, Taiwan,  
176 The Netherlands, Belgium, Sweden, Austria, Switzerland, Greece, Portugal, and Czech  
177 Republic, in order of Purchasing Power Parity (PPP)-adjusted GDP shares in 2005)  
178 and 21 emerging (China, India, Russia, Brazil, Mexico, Turkey, Indonesia, Poland,  
179 Thailand, Argentina, South Africa, Colombia, Malaysia, Venezuela, Philippines, Nige-  
180 ria, Chile, Peru, Hungary, Bulgaria, and Costa Rica, in order of PPP-adjusted GDP  
181 shares in 2005) countries are used to compile the aggregates for the blocs, by using  
182 trade weights with the US in weighting the country-level data. The reader is referred  
183 to [13] for further details.

184 Based on latest data availability at the time of writing this paper, the monthly  
185 analysis involving the inflation rates and the EQSOI cover the period of February  
186 1981 to July 2021, while the real GDP growth and EQSOI span the period of June  
187 1981 (1981:Q2) to June 2021 (2021:Q2) for the US, the advanced and world economies  
188 excluding the US, but the same for emerging markets starts a bit later from March  
189 1984 (1984:Q1), but also ends in June 2012 (2012:Q2).

#### 190 4. Empirical Results

191 Before testing the role of EQSOI in forecasting inflation and GDP growth , we use  
192 CWT to investigate the underlying time-varying relation between EQSOI and the  
193 macroeconomic variables for each of the four economic areas. As a measure of de-  
194 pendency, EQSOI's wavelet coherence with inflation and GDP growth is estimated  
195 using CWT. For the GDP growth case, since we are interested in coherence between  
196 the monthly EQSOI and the quarterly GDP growth, the sampling frequency for the  
197 monthly series is set to 3 (i.e., 3 samples during each quarter), so the time unit in  
198 the wavelet figures will correspond to a quarter. Latter, in mixed-frequency MSSA  
199 (MFMSSA), we will use the original monthly data to forecast the quarterly GDP.

200 We use MSSA to forecast inflation and MFMSSA to forecast GDP growth when  
201 EQSOI is included as a predictor. For each economic area, two sets of forecasts are  
202 produced: one without using any predictor, and one using EQSOI as a predictor.  
203 Specifically, following is the list of forecasting models:

- 204 • Model 1: Forecasting inflation without any predictors; i.e., univariate forecasts  
205 using SSA.
- 206 • Model 2: Forecasting inflation using EQSOI as a predictor; i.e., bivariate forecasts  
207 using MSSA.
- 208 • Model 3: Forecasting GDP growth without any predictors; i.e., univariate fore-

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<sup>3</sup><https://www.cpc.ncep.noaa.gov/data/indices/>

<sup>4</sup><https://www.dallasfed.org/institute/dgei/gdp.aspx>

209 casts using SSA.

- 210 • Model 4: Forecasting GDP growth using SOI as predictors; i.e., bivariate fore-  
211 casts using MFMSSA.

212 Since SSA can be used with even non-stationarity data [11, 21, 22], unit root tests are  
213 not necessary to be conducted to ensure stationarity before resorting to forecasting  
214 using SSA. The KSPA test is employed to compare the accuracy of the forecasts  
215 with and without the predictor. In this regard, the null and alternative hypotheses,  
216 for comparing univariate and bivariate models associated with the KSPA test are as  
217 follows:

- 218 (1) For comparing Model 1 and Model 2 (testing for EQSOI’s role in inflation fore-  
219 casting):

$$\begin{cases} H_0 : F_{\eta_{i+h}^{(1)}}(z) \leq F_{\eta_{i+h}^{(2)}}(z) \\ H_1 : F_{\eta_{i+h}^{(1)}}(z) > F_{\eta_{i+h}^{(2)}}(z) \end{cases} ; \quad (1)$$

- 220 (2) For comparing Model 3 and Model 4 (testing for EQSOI’s role in GDP growth  
221 forecasting):

$$\begin{cases} H_0 : F_{\eta_{i+h}^{(3)}}(z) \leq F_{\eta_{i+h}^{(4)}}(z) \\ H_1 : F_{\eta_{i+h}^{(3)}}(z) > F_{\eta_{i+h}^{(4)}}(z) \end{cases} ; \quad (2)$$

222 where  $\eta_{i+h}^{(i)}$  is the  $h$ -step ahead forecasting square error corresponding to “Model  $i$ ”.

223 In each case, half of the data is used for estimating the SSA/(MF)MSSA, and  
224 the rest is used for out-of-sample forecasting, with the KSPA test applied to the  
225 out-of-sample forecasting results (with significance level set at:  $\alpha = 0.05$ ). Rejecting  
226 the null hypothesis in 1 implies that Model 2 (inflation forecasting model containing  
227 EQSOI as predictor) dominates Model 1 (univariate inflation forecasting) significantly.  
228 In the same manner, rejecting the null hypothesis in 2 implies that Model 3 (GDP  
229 growth forecasting model containing EQSOI as predictor) dominates the null model  
230 (univariate GDP growth forecasting) significantly.

#### 231 4.1. In ation Forecasting Results

232 Figures 1 and 2 show the monthly EQSOI and inflation time series for the four eco-  
233 nomic blocs. As can be seen, there are resemblance among the inflation time series,  
234 especially around 2008 during the Global Financial Crisis (GFC).

235 In order to better understand the similarities in the periodic behavior of EQSOI and  
236 inflation, a CWT is used to estimate their power spectrums over time. The estimated  
237 power spectrums are shown in figures 3 and 4. Black contours present significant  
238 power spectrums. EQSOI’s power spectrum shows significant periodic behavior with  
239 the periodic length falling between 16 and 64 months, as well as periods with length  
240 around 128 months. The significant periods of EQSOI are almost steady (i.e., almost  
241 the same) over time.

242 Figure 4 shows the wavelet power spectrum for inflation in advanced economies (with  
243 US excluded) (top left), emerging economies (top right), the US economy (bottom  
244 left) and the world economy (with US excluded) (bottom right). As Figure 4 shows,  
245 the inflation in advanced, the US and the world economies have significant periodic

Figure 1. Monthly Equatorial Southern Oscillation Index time series.

Figure 2. Top Left: Monthly Inflation time series in “Advanced Economies” (US excluded); Top Right: Monthly Inflation time series in “Emerging Economies”; Bottom Left: Monthly Inflation time series in “US Economy”; Bottom Right: Monthly Inflation time series in “World Economy” (US excluded).

246 behavior mostly between 32 and 128 month periods, which overlaps with those of the  
247 EQSOI’s significant periods. For emerging economies however, there is no evidence of  
248 significant period in recent years (i.e., after 2011).

249 According to wavelet power spectrums, EQSOI and inflation have resemblance in  
250 their periodic behavior, in three economic areas i.e., advanced (without the US), the  
251 US and the world (with the US excluded) economies. Given this, we can suggest  
252 that, if significant correlation between the EQSOI and inflation is observed in same  
253 periods (i.e., the location where the power spectrum is significant for both EQSOI and  
254 inflation), we may be able to use one time series as a predictor to forecast the other  
255 one.

256 As a measure of correlation between the inflation and EQSOI, the wavelet coher-  
257 ences are presented in Figure 5. According to these results, there is significant wavelet

Figure 3. Equatorial Southern Oscillation (EQSOI) Index continuous monthly wavelet power spectrum. The thick black contour designates the 10% significance level.

Figure 4. Top Left: Inflation's wavelet power spectrum in "Advanced Economies" (US excluded). Top Right: Inflation's wavelet power spectrum in "Emerging Economies". Bottom Left: US Inflation's wavelet power spectrum. Bottom Right: World Inflation's wavelet power spectrum (US excluded). The thick black contour designates the 10% significance level.

258 coherence between EQSOI and inflation (green, yellow and red areas show coherence  
259 above 0.94), though not significant in most of the periods over time. The significant  
260 wavelet coherence between EQSOI and Inflation occurs mostly around 32- and 64-  
261 month periods, in all four economic areas. However, as it is evident from Figure 5,  
262 the significant coherence between EQSOI and inflation does not always correspond to  
263 the location (i.e., for time and periods) with highest power spectrum. For instance,  
264 in emerging economies, inflation's power spectrum around the 32-month period is not  
265 significant after 2000. This means that the period in which EQSOI and inflation have

266 significant coherence, is a period which has low power (and hence low impact) on infla-  
 267 tion's periodic pattern. In the case, where significant coherence between inflation and  
 268 EQSOI fall in the periods with high values of wavelet power spectrum in both series,  
 269 we may use EQSOI as a potential predictor for inflation forecasting (provided oscilla-  
 270 tions in EQSOI occur before inflation). But as is well-known, existence of in-sample  
 271 causality cannot guarantee that the same will hold over an out-of-sample, since the  
 latter is stronger test of predictability, and we consider this next.

Figure 5. Top Left: Wavelet coherence between Inflation in "Advanced Economies" (US excluded) and SOI.  
 Top Right: Wavelet coherence between Inflation in "Emerging Economies" and SOI. Bottom Left: Wavelet  
 coherence between US Inflation and SOI. Bottom Right: Wavelet coherence between World Inflation (US  
 excluded) and SOI. The 10% significance level is shown as a thick black contour.

272  
 273 KSPA p-values for testing the role of EQSOI in forecasting inflation (i.e., hypothesis  
 274 (1)), for four economic areas, are presented in Table 1. According to KSPA test results,  
 275 using EQSOI as predictor can significantly improve inflation forecasting accuracy (i.e.,  
 276 rejects the null hypothesis in (1)) for medium- and long-term forecasting horizons, in  
 277 advanced and world economies (with US excluded), as well as for the US economy (i.e.,  
 278  $h \geq 10$  in advanced economies,  $h \geq 9$  in the US economy and  $h \geq 7$  in world economy).  
 279 In emerging economies, however, using EQSOI as predictor does not improve inflation  
 280 forecasting accuracy (i.e., the null hypothesis in (1) is not rejected).

#### 281 **4.2. GDP Growth Forecasting Results**

282 Figure 6 shows the quarterly GDP growth for the four economic areas. As it can be  
 283 seen, there are similarities between the EQSOI (as presented in Figure 1) and the  
 284 GDP growth rates, again especially during the GFC, just as in case of the inflation

**Table 1.** KSPA test p-values for testing the EQSOI effect on inflation forecasting accuracy, Hypothesis (1).

Forecasting Horizon	Advanced Economies (US excl.)	Emerging Economies	US Economy	World Economy (US excl.)
$h = 1$	1.0000	1.0000	0.9299	0.8926
$h = 2$	0.9820	0.9955	0.8926	0.5197
$h = 3$	0.9955	1.0000	0.5769	0.7476
$h = 4$	1.0000	1.0000	0.4103	0.6920
$h = 5$	0.8926	0.9955	0.2293	0.2293
$h = 6$	0.6920	1.0000	0.0729	0.0584
$h = 7$	0.6347	1.0000	0.1623	<b>0.0127</b>
$h = 8$	0.2688	1.0000	0.0584	<b>0.0007</b>
$h = 9$	0.0903	1.0000	<b>0.0127</b>	<b>0.0167</b>
$h = 10$	<b>0.0052</b>	1.0000	<b>0.0127</b>	<b>0.0167</b>
$h = 11$	<b>0.0014</b>	0.9955	<b>0.0002</b>	<b>0.0071</b>
$h = 12$	<b>0.0000</b>	1.0000	<b>0.0000</b>	<b>0.0020</b>
$h = 13$	<b>0.0001</b>	1.0000	<b>0.0014</b>	<b>0.0007</b>
$h = 14$	<b>0.0000</b>	1.0000	<b>0.0001</b>	<b>0.0038</b>
$h = 15$	<b>0.0000</b>	1.0000	<b>0.0003</b>	<b>0.0005</b>
$h = 16$	<b>0.0000</b>	1.0000	<b>0.0002</b>	<b>0.0001</b>
$h = 17$	<b>0.0000</b>	1.0000	<b>0.0000</b>	<b>0.0002</b>
$h = 18$	<b>0.0000</b>	1.0000	<b>0.0000</b>	<b>0.0001</b>
$h = 19$	<b>0.0000</b>	1.0000	<b>0.0000</b>	<b>0.0000</b>
$h = 20$	<b>0.0000</b>	1.0000	<b>0.0003</b>	<b>0.0000</b>
$h = 21$	<b>0.0000</b>	0.9955	<b>0.0003</b>	<b>0.0000</b>
$h = 22$	<b>0.0000</b>	0.9599	<b>0.0000</b>	<b>0.0000</b>
$h = 23$	<b>0.0000</b>	0.9599	<b>0.0002</b>	<b>0.0001</b>
$h = 24$	<b>0.0000</b>	0.9599	<b>0.0002</b>	<b>0.0000</b>

: EQSOI improves the inflation forecasting accuracy, significant(at  $\alpha = 0:05$  level).

285 rates.

286 Figure 7 shows the quarterly measured wavelet power spectrum for the EQSOI (with  
 287 the sampling frequency set to 3 in time unit, since there are three monthly observations  
 288 in each quarter). Significant power spectrums are shown with black contour lines. As  
 289 the EQSOI's wavelet power spectrum shows, there are significant mid- and long-range  
 290 (longer than 8 quarters) periodic pattern in the EQSOI, which is basically the same  
 291 as the monthly measured power spectrum (presented in Figure 3).

292 Figure 8 shows the wavelet power spectrum for GDP growth in "Advanced  
 293 Economies (US excluded)", (top left), "Emerging Economies" (top right), "US Econ-  
 294 omy" (bottom left) and "World Economy (US excluded)" (bottom right). As it can  
 295 be seen in Figure 8, steady GDP growth significant periodic patterns mostly fall in  
 296 the midrange (between 8 and 16 quarters) and long periods (around 32 quarters),  
 297 which overlaps with the EQSOI's periodic pattern, especially in mid-range periods. In  
 298 general, the GDP growth power spectrums in all four economic areas show significant  
 299 periodic behavior that has similarities with the EQSOI through time.

300 The wavelet coherences between the GDP growth rates and the EQSOI are pre-  
 301 sented in Figure 9. Figure 9, shows that there is high wavelet coherence between the

**Figure 6.** Quarterly GDP growth time series for “Advanced Economies (US excluded)”, top left; “Emerging Economies”, top right; “US Economy”, bottom left; “World Economy (US excluded)”, bottom right.

**Figure 7.** Equatorial Southern Oscillation (EQSOI) Index continuous quarterly wavelet power spectrum; The thick black contour designates the 10% significance level.

302 EQSOI and GDP growth rates (green, yellow and red areas show coherence above  
303 0.94). However, the significant wavelet coherence between the EQSOI and the GDP  
304 growth occur mostly in midrange periods (around 8 and 16 quarters), in all economic  
305 areas. Furthermore, according to Figure 9, the coherence between EQSOI and the  
306 GDP growth is observed to be stronger before 2000s in the “Advanced Economies”,  
307 the “US Economy” and the “World Economy”, as evident from large red areas on  
308 the left side of time axis in the top left, the bottom left and the bottom right panels  
309 of Figure 9. According to CWT results, as is evident from figures 8 and 9, the GDP  
310 growth have similarities with EQSOI in power spectrums, and there exist significant  
311 wavelet coherence between them. Since the significant coherence between the two se-  
312 ries is located in the areas with significant power spectrum in both series, the EQSOI  
313 can be considered as a potential predictor in forecasting GDP growth rates, but for

**Figure 8.** GDP growth wavelet power spectrum for “Advanced Economies (US excluded)”, top left; “Emerging Economies”, top right; “SU Economy”, bottom left; “World Economy (US excluded)”, bottom right; The thick black contour designates the 10% significance level.

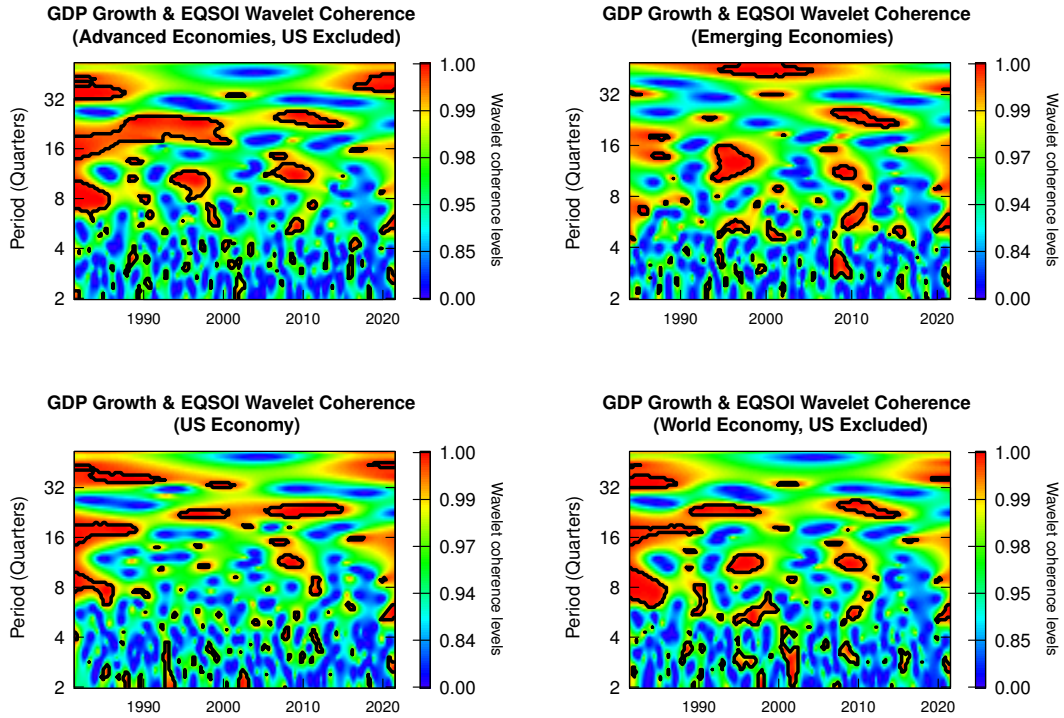
314 this to happen, the oscillation in the EQSOI need to occur well enough before it is  
 315 observed in the GDP growth rates. But again in-sample predictability is no guarantee  
 316 for out-of-sample forecasting gains, and it is the latter which we turn to next.

317 Table 2 show the results of quarterly GDP growth forecasting using SSA and  
 318 MFMSSA with and without EQSOI as predictor respectively. As can be seen, the  
 319 bivariate forecasting model (the model using EQSOI as a predictor) significantly im-  
 320 proves the GDP growth forecasting accuracy in advanced and world economies (with  
 321 US excluded), mostly at the short-term, and also at certain medium- and long-run  
 322 horizons (i.e.  $h = 1, \dots, 6, 16, 24$  for the former, and  $h = 1, \dots, 8, 15$  and  $16$  for  
 323 the latter). For emerging economies, EQSOI significantly improves GDP growth fore-  
 324 casting accuracy at very short ( $h = 1$ ) and medium-term ( $h = 14, \dots, 17$ ) horizons.  
 325 Interestingly for the US GDP growth forecasting, EQSOI as predictor does not provide  
 326 significant forecasting gains at any horizon.

## 327 5. Conclusion

328 In this paper, for the first time, the role of the ENSO, as captured by the EQSOI index  
 329 is used to formally forecast the inflation and GDP growth rates of not only the US  
 330 economy, but advanced (excluding the US) and emerging countries, as well as for the  
 331 world economy (barring the US). For our purpose, we use univariate and multivariate  
 332 SSA, as well as mixed-frequency version of the latter since the EQSOI is monthly,  
 333 while GDP growth is available only at quarterly frequency unlike monthly inflation  
 334 rates.





**Figure 9.** Wavelet coherence between GDP growth and SOI. “Advanced Economies (US excluded)”, top left; “Emerging Economies”, top right; “SU Economy”, bottom left; “World Economy (US excluded)”, bottom right; The 10% significance level is shown as a thick black contour.

335 As a preliminary analysis to motivate the use of the SSA method which is a model-  
336 free approach, we also use the wavelet coherence to depict complex time-varying rela-  
337 tionships between the macro variables and the EQSOI. Since in-sample predictability  
338 does not guarantee the same for the out-of-sample, we then turned to the SSA method  
339 to show that the EQSOI significantly improves the forecasting accuracy of the inflation  
340 rates at medium- and long-runs for the advanced and world economies (when the US is  
341 excluded), as well as for the US economy. For inflation rate of the emerging economies  
342 however, the use of the EQSOI as predictor does not produce forecasting gains. At the  
343 same time, GDP growth forecasting results show that using the EQSOI as predictor  
344 significantly improves accuracy in advanced (with US excluded) and emerging coun-  
345 tries, as well as for the world economy (excluding the US). For these country groups,  
346 the improvement is mostly evident in short horizons, as well as certain medium and  
347 long-runs for advanced and world economies (when US is excluded), and very short as  
348 well as for the medium-term associated with emerging economies. Interestingly, using  
349 EQSOI as predictor does not improve the forecasting accuracy of US GDP growth. In  
350 sum, the ENSO tend to predict both in- and out-of-sample inflation and GDP growth  
351 rates globally, though there are exceptions in terms of forecasting of the inflation rate  
352 of emerging economies and the growth rate of the US. These contrasting results for  
353 the emerging markets and the US in terms of forecastability of output growth and  
354 inflation respectively emanating from the EQSOI, seems to be indicative of the strong  
355 reliance of emerging countries on agriculture (and its corresponding high share in  
356 GDP), and the US being the highest importer in the overall of commodity market.

**Table 2.** KSPA test p-values for testing the SOI effect on GDP growth forecasting accuracy, Hypothesis (2).

Forecasting Horizon	Advanced Economies (US excl.)	Emerging Economies	US Economy	World Economy (US excl.)
$h = 1$	<b>0.0034</b> *	<b>0.0000</b> *	0.6449	<b>0.0000</b> *
$h = 2$	<b>0.0018</b> *	0.0594	0.4233	<b>0.0063</b> *
$h = 3$	<b>0.0063</b> *	0.6125	0.6449	<b>0.0009</b> *
$h = 4$	<b>0.0002</b> *	0.3826	0.1730	<b>0.0034</b> *
$h = 5$	<b>0.0034</b> *	0.4937	0.4233	<b>0.0002</b> *
$h = 6$	<b>0.0321</b> *	0.4937	0.4233	<b>0.0009</b> *
$h = 7$	0.2415	0.4937	0.6449	<b>0.0063</b> *
$h = 8$	0.5318	0.6125	0.4233	<b>0.0321</b> *
$h = 9$	0.6449	0.4937	0.3254	0.0516
$h = 10$	0.6449	0.2851	0.7553	0.0516
$h = 11$	0.7553	0.2043	0.6449	0.0516
$h = 12$	0.3254	0.1407	0.6449	0.0516
$h = 13$	0.2415	0.0932	0.9322	0.0516
$h = 14$	0.3254	<b>0.0364</b> *	0.8539	0.0516
$h = 15$	0.3254	<b>0.0364</b> *	0.8539	<b>0.0018</b> *
$h = 16$	<b>0.0193</b> *	<b>0.0364</b> *	0.4233	<b>0.0112</b> *
$h = 17$	0.0800	<b>0.0214</b> *	0.4233	0.0516
$h = 18$	0.1197	0.1407	0.4233	0.1197
$h = 19$	0.5318	0.3826	0.6449	0.1197
$h = 20$	0.6449	0.2043	0.8539	0.2415
$h = 21$	0.3254	0.3826	0.9322	0.4233
$h = 22$	0.3254	0.3826	0.9322	0.7553
$h = 23$	0.1730	0.2851	0.9322	0.5318
$h = 24$	<b>0.0321</b> *	0.2043	0.8539	0.6449

\* EQSOI improves GDP growth forecasting accuracy, significant (at  $\alpha = 0.05$  level).

357 Clearly, these findings associated with forecasts of inflation and growth due to the El  
358 Niño and La Niña events will allow policymakers to design monetary policy decisions  
359 to circumvent business cycle downturns and inflationary episodes.

360 As part of future research, it would be interesting to extend our analysis to study  
361 individual countries rather than advanced and emerging economies as blocs, since there  
362 is lot of heterogeneity within these countries. Furthermore, one can also analyze the  
363 role of the ENSO cycle for forecasting asset prices, given that climate risks are known  
364 to affect financial markets [12].

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