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Book

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Elie Bouri
Lebanese American University
Rangan Gupta
University of Pretoria
Luca Rossini
University of Milan

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Department of Economics
University of Pretoria
0002, Pretoria
South Africa
Tel: +27 12 420 2413

The Role of the Monthly ENSO in Forecasting the Daily Baltic Dry Index

Elie Bouri[a*] Rangan Gupta[b**] Luca Rossini[c***]

[a]Lebanese American University, Lebanon [b]University of Pretoria, South Africa [c]University of Milan, Italy

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Abstract

Using Bayesian Reverse Unrestricted-Mixed Data Sampling (RU-MIDAS) models, we predict the daily Baltic Dry Index (BDI) based on the monthly information content of the El Niño Southern Oscillation (ENSO) from January, 1985 to February, 2022. The results show that the Oceanic Niño Index (ONI) capturing the ENSO produces statistically significant forecast gains in terms of both point and density forecasts for the BDI, relative to a constant-mean benchmark model, at both short and long forecast horizons (i.e., one to twenty one-day-ahead). Notably, these gains primarily emanate from the El Niño rather than La Niña phase of the ENSO.

JEL Classification: C22; C53; Q02; Q54.

Keywords: Baltic Dry Index (BDI); El Niño Southern Oscillation (ENSO); Reverse Unrestricted- Mixed Data Sampling (RU-MIDAS) Models; Forecasting

* e-mail: elie.elbouri@lau.edu.lb

** e-mail: rangan.gupta@up.ac.za

*** e-mail: luca.rossini@unimi.it

1 Introduction

Maritime transport is the backbone of international trade and thus, the global economy. According to the International Chamber of Shipping, the international shipping industry is responsible for the carriage of around 90% of world trade, and of the total freight shipped internationally, dry cargo accounts for nearly 75% of total maritime trade volumes (UNCTAD, 2021). In this regard, the Baltic Dry Index (BDI), which is issued by the Baltic Exchange on daily basis since 1985, is a composite of three sub-indexes based on different vessel sizes (Capesize, Panamax, and Supramax), capturing the freight rate level in the dry bulk shipping market. Understandably, the BDI is an important (high-frequency) barometer of the volume of worldwide trade and has been linked to movements of not only the real economy but also asset markets (see, Han et al., 2020, for a detailed review of this literature). Hence, accurate forecasts of the BDI should be of immense value to both policymakers and investors, especially if they involve the use of weather phenomena as a potential predictor given that they are often blamed for affecting the economy, disrupting shipping patterns, and rising freight costs.

Against this backdrop, the objective of our paper is to forecast the BDI based on the information contained in the El Niño Southern Oscillation (ENSO), which is an irregularly periodic variation in winds and sea surface temperatures over the tropical eastern Pacific Ocean, affecting the climate of much of the tropics and subtropics (Trenberth et al., 2007). The warming phase of the sea temperature is known as El Niño and the cooling phase as La Niña, with the two periods lasting several months each and typically occurring every few years with varying intensity per period. Since the ENSO can cause severe natural disasters (van Eyden et al., 2022) such as droughts, floods, and hurricanes, El Niño and La Niña phases are likely to lead to fluctuations in economic activity (Brunner, 2002; Laosuthi and Selover, 2007; Cashin et al., 2017; Generoso et al., 2020; De Winne and Peersman, 2021), thus affecting global trade volumes and freight rates, and hence the BDI (Bandyopadhyay and Rajib, 2021).

Having outlined the channel through which the ENSO is likely to drive the BDI, we now turn to our methodological framework. Econometrically speaking, we rely on the Reverse Unrestricted-Mixed Data Sampling (RU-MIDAS), as developed by Foroni et al. (2018), for linking the high-frequency (daily) dependent variable with low-frequency (monthly) explanatory variable namely, the Oceanic Niño Index (ONI), which in turn is the most commonly used index to define the El Niño and La Niña events in the climatology and climate economics literature (Hsiang et al., 2011; Hsiang and Meng, 2015). In particular, we rely on the Bayesian prior specification of the RU-MIDAS introduced in Foroni et al. (2019).

Our period of analysis involves both daily and monthly data covering January, 1985 to February, 2022. Given the importance of the BDI for portfolio allocation decisions of asset market participants, it makes sense to forecast the BDI at a daily frequency rather than averaging the daily values over a month, as such aggregation is known to lead to loss of information (Das et al., 2019). Furthermore, note that the future path of the BDI index, which can mimic daily global economic activity, should allow policymakers to nowcast low-frequency real variables using the traditional MIDAS model (Bańbura et al., 2011), and hence design appropriate and timely policy responses. At this stage, we must point out that, we analyze both point and density forecasts. In this regard, note that the point forecast measures the central tendency of the target variable or the best forecast. However, because this is an estimate, there is uncertainty around it. Hence, quantifying this uncertainty is important to capture how "sure" the researcher is regarding the precision of the forecasted value. One way to report the degree of sureness around point forecasts is to use density forecasts. Density forecasts summarize the information regarding the estimated forecast distribution and have become very important for policymakers to estimate and report the degree of uncertainty around their forecasts while making policy decisions (Rossi, 2014).

In the wake of growing concern on the impact of global warming on all aspects of life (Giglio et al., 2021), which is likely to affect the nature of the ENSO (McPhaden et al., 2020), to the best of our knowledge, this paper is the first to forecast the BDI due to El Niño and La Niña events. In the process, our paper adds to the existing literature that has looked at linear and nonlinear univariate models, as well as the role of variables related to the shipping sector, financial and commodity prices, but based on uniform-frequency models (e.g, see Papailias et al., 2017; Zhang et al., 2019; Makridakis et al., 2020; Katris and Kavussanos, 2021; Liu et al., 2022, and references cited therein for earlier works in this area). Note that, in this regard, besides the ENSO capturing business cycle movements, its role in driving commodity prices is quite well-established (Ubilava, 2018; Bouri et al., 2021; Demirer et al., 2022; Salisu et al., 2021). The remainder of the paper is organized as follows: Section 2 presents the data and the models, with Section 3 devoted to the empirical findings, and Section 4 concludes the paper.

2 Data and Models

We use daily BDI as the dependent variable, obtained from Bloomberg, and as stated in the left panel of Figure 1, we provide a logarithmic transformation to ensure stationarity. As a further step for BDI we decide to standardize it, by subtracting the mean and dividing by the standard deviation. Figure 1 provides the daily BDI index and its logarithmic transformation before the standardization.

To capture the ENSO, we use the ONI, with the data obtained from the Climate Prediction Center at the National Oceanic and Atmospheric Administration (NOAA)[1]. The ONI (5 N-5 S, 170 W-120 W) anomalies (with a base period of 1991 to 2020) may be thought of as representing the average equatorial Sea Surface Temperatures (SSTs) across the Pacific from about the dateline to the South American coast. The ONI uses a 3-month running mean, and to be classified as a full-fledged El Niño or La Niña, the anomalies must exceed +0.5 C or -0.5 C for at least five consecutive months. We do not make any transformations to the ONI, with

[1]The data are available from: https://origin.cpc.ncep.noaa.gov/products/analysis_monitoring/ensostuff/ONI_v5.php .

Figure 1: Daily BDI (left) and relative logarithmic transformation (right) from 01 January 1985 to 28 February 2022.

Figure 2 plotting this index, along with the El Niño and La Niña events associated with the ONI. Note that to get El Niño and La Niña phases of the ENSO, we define dummies that take the value of 1 for the months in which the anomalies exceed +0.5C and -0.5C respectively for at least five consecutive months, and zero otherwise, and then multiply them with the ONI.

Based on the availability of data on the variables, our period of analysis involves both daily and monthly data from January, 1985 to February, 2022.

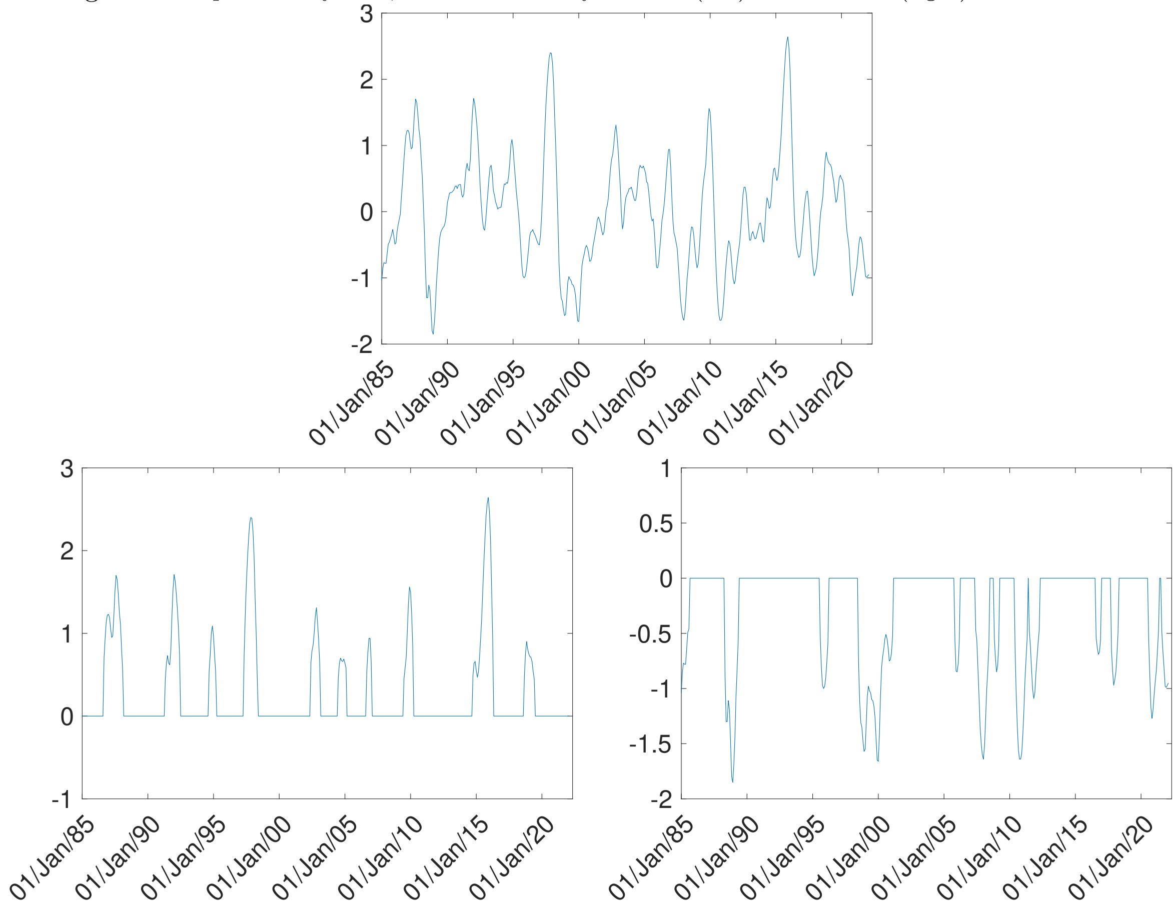
Following Foroni et al. (2018), which show the derivation of the reverse unrestricted MIDAS (RU-MIDAS) regression approach, the high-frequency (HF) variable x for $t = 0; \frac{1}{k}; \dots; 1$ follows an AR(p) process

$$c(L)x_t = d(L)y_t^* + e_{x_t} \tag{1}$$

where y^* is the exogenous unobserved regressor sampled at higher frequency, $c(L)$ and $d(L)$ are the lagged function and the errors are white noise.

Given the data, we consider three different models, where x_t is the daily BDI Index and $y_t; n_t$ and l_t are the monthly predictors of ONI, El Niño, and La Niña, respectively. The decision to disaggregate the ONI into El Niño and La Niña phases are to see which one, if at all matters more in terms of producing more accurate forecasts for the BDI, i.e., if there is an asymmetric predictive effect in the warming and the cooling phases of the ENSO. From Equation 1 and following Foroni et al. (2019), we can represent the RU-MIDAS as a single-equation and we consider 21 dummies since we have an average of 21 trading days per month. For each model, the error term, ε_t, is assumed to follow a Normal distribution with zero-mean and variance as σ^2. We describe the four models below, including also the (constant-mean) benchmark with which comparisons are made:

Figure 2: Top: Monthly ONI; Bottom: Monthly El Niño (left) and La Niña (right) from the ONI.



The first model is the benchmark model (called **Bench**) defined as

$$x_t = \omega + \varepsilon_t.$$

The second model considered is the RUMIDAS with ONI as low frequency variable (called **M1**):

$$x_t = \omega + \alpha_1 \left(1 - \sum_{i=1}^{21} D_i\right) y_{t-\frac{1}{21}} + \alpha_2 D_2 y_{t-\frac{2}{21}} + \ldots + \alpha_{21} D_{21} y_{t-1} + \varepsilon_t,$$

while the third model is the RUMIDAS with El Niño based on the ONI (called **M2**):

$$x_t = \omega + \alpha_1 \left(1 - \sum_{i=1}^{21} D_i\right) n_{t-\frac{1}{21}} + \alpha_2 D_2 n_{t-\frac{2}{21}} + \ldots + \alpha_{21} D_{21} n_{t-1} + \varepsilon_t.$$

In conclusion the forth model analysed is the RUMIDAS with La Niña based on the ONI as low frequency variable (called **M3**), defined as

$$x_t = \omega + \alpha_1 \left(1 - \sum_{i=1}^{21} D_i\right) \ell_{t-\frac{1}{21}} + \alpha_2 D_2 \ell_{t-\frac{2}{21}} + \ldots + \alpha_{21} D_{21} \ell_{t-1} + \varepsilon_t.$$

Contrary to most of the MIDAS literature, which follows a classical estimation approach, in this paper we estimate our models with Bayesian techniques. The Bayesian approach allows for the estimation of complex nonlinear models with many parameters, is useful for imposing parameter restrictions, and, most importantly, allows us to compute probabilistic statements without any further assumption. We define prior information on the vector of coefficients and on the variance, using the independent Normal-Wishart prior (Koop and Korobilis, 2010) adapted to univariate time series, thus a Normal-Gamma prior.

3 Empirical Findings

Though the focus of the paper is on forecasting the BDI based on the ENSO as captured by the ONI, we also estimated M1 to M3 for the full-sample to get an idea about the direction of the relationship. Table 1 provides the posterior mean of the coefficients related to the dummies for each model previously described in Section 2.

Table 1: Posterior Mean of the coefficients of M1 to M3 models for the full sample.

Model	α_1	α_2	α_3	α_4	α_5	α_6	α_7	α_8	α_9	α_{10}	α_{11}	α_{12}	α_{13}	α_{14}	α_{15}	α_{16}	α_{17}	α_{18}	α_{19}	α_{20}	α_{21}
M1								$\omega =$	0.003			$\sigma^2 = 0.972$									
	-0.201	-0.204	-0.203	-0.203	-0.203	-0.197	-0.191	-0.191	-0.186	-0.190	-0.191	-0.191	-0.191	-0.192	-0.193	-0.193	-0.196	-0.199	-0.202	-0.204	-0.203
M2								$\omega = 0.077$				$\sigma^2 = 0.975$									
	-0.288	-0.289	-0.293	-0.293	-0.292	-0.288	-0.283	-0.282	-0.270	-0.274	-0.274	-0.265	-0.270	-0.275	-0.274	-0.274	-0.277	-0.284	-0.285	-0.283	-0.284
M3								$\omega =$	0.076			$\sigma^2 = 0.983$									
	-0.271	-0.273	-0.272	-0.269	-0.267	-0.246	-0.248	-0.255	-0.258	-0.261	-0.264	-0.264	-0.266	-0.262	-0.263	-0.262	-0.259	-0.257	-0.267	-0.271	-0.273

Since for each model we have considered 21 dummies for the monthly predictor, we have decided to average these values and provide these coefficients jointly with the posterior mean of σ^2. In this regard, the posterior mean of ONI (M1) is -0.196, i.e., the BDI decreases by 0.196 when the ONI increases by one; while the posterior mean of the variance is close to unity, i.e., 0.972. Moving to the disaggregated models of the El Niño (M2) and La Niña (M3), we obtain posterior means (posterior mean of σ^2) of -0.281 (0.975) and -0.264 (0.983) respectively. In other words, ENSO cycles negatively impact the BDI by having an adverse effect on economic activity (Generoso et al., 2020; De Winne and Peersman, 2021), and the associated trade of commodities and finished products. In addition, there is also evidence of asymmetry, in the sense that the warming phase of the ENSO, as captured by the El Niño, has a stronger negative effect on the BDI than its corresponding cooling phase, i.e., the La Niña – a feature also observed by Cashin et al. (2017), and Salisu et al. (2021), among others.

Next, we turn our attention to the main focus of the paper, i.e., we provide results for the three models previously considered, relative to the benchmark, in a forecasting exercise, given that in-sample predictability does not guarantee out-of-sample gains, and the latter is undoubtedly a more robust test of predictability in terms of models and predictors (Cambpell, 2008). In particular, we estimate the models to consider one-, two-, three-, five-, and twenty one-step-ahead forecasting horizons, based on a rolling window approach, with 18 years of in-sample and 19 years of out-of-sample. Specifically speaking, the in-sample starts in January, 1985 and ends in December, 2002, while the out-of-sample covers January, 2003 till February, 2022, to provide us both point and density forecasts.

Regarding the accuracy of point forecasts, we use the root mean square errors (RMSEs), whereas to evaluate density forecasts, we use the average continuous ranked probability score (CRPS). The CRPS measure is known to do a better job, relative to the average log predictive score, in rewarding values from the predictive density that are close and not equal to the outcome, thus it is less sensitive to outliers (Gneiting and Raftery, 2007; Gneiting and Ranjan, 2011). Since the models, **M1**, **M2**, and **M3**, nest the benchmark, we use Clark and West (2007) (CW) test of forecast comparison to deduce the statistical gains in the point and density forecasts based on the ENSO indicators relative to the constant mean model, i.e., **Bench**.

As can be seen from Table 2, including the ONI capturing ENSO cycles significantly improves the point forecasts of the BDI at all of the 5 horizons considered, with the highest gain registered at 21-day-ahead. It is also evident, in line with the relatively stronger in-sample influence of the El Niño, that most of the forecast accuracy of the ONI is derived from the El Niño, rather than the La Niña events. Hence, the model **M3**, which includes the latter, i.e., the La Niña part of the cycle as a predictor, though produces lower RMSEs than the benchmark, it fails to statistically outperform it.

Table 2: Point Forecast (RMSE) measures for daily BDI.

Horizon	1	2	3	5	21
RMSEs					
Bench	1.349	1.350	1.350	1.351	1.355
M1	0.989	0.988	0.988	0.988	0.987
M2	0.987	0.986	0.987	0.986	0.985
M3	0.999	0.998	0.999	0.999	0.999

Notes: For the benchmark model, the table reports the RMSEs; for the M1–M3 models, the table reports the RMSE ratios between the current model and the benchmark. , and indicate RMSE ratios are significantly different from 1 at the 1%, 5%, and 10% significance levels respectively according to the CW test.

When we look at the density forecast results reported in Table 3, a similar picture to that of the point forecasts emerges in that, the ONI can produce more accurate forecasts relative to the benchmark in a statistically significant manner, especially at the one-month-ahead horizon. Moreover, as under the case of point forecasts, these significant results emanating from the ONI are driven more by El Niño compared to La Niña events.[2] One difference is that, unlike in the case of the point forecasts, under density forecasting, La Niña phases on their own do also outperform the constant-mean model, i.e., the benchmark.[3]

[2] Interestingly, when we used the average predictive likelihood as a measure of density forecast accuracy, signi cant gains were only observed in the case of the El Niño at horizons of one-, two-, and twenty one-step-ahead. Complete details of these results are available upon request from the authors.

[3] A quantiles-based average CRPS revealed that while the ONI and the La Niña as predictors can outperform the benchmark in a statistically signi cant manner at the left, center, and right quantiles, the La Niña can do so only under the left and center quantiles. Complete details of these results are available upon request from the authors.

Table 3: Density Forecast (average Continuous Rank Probability Score) measures for daily BDI.

Horizon	1	2	3	5	21
Average CRPS					
Benchmark	0.830	0.830	0.830	0.831	0.836
M1	0.990	0.989	0.990	0.989	0.988
M2	0.989	0.988	0.988	0.988	0.987
M3	0.997	0.996	0.997	0.996	0.997

Notes: For the benchmark model, the table reports the average CRPSs; for the three RU-MIDAS models, the table reports the average CRPS ratios between the current model and the benchmark. , and indicate RMSE ratios are significantly different from 1 at the 1%, 5%, and 10% significance levels respectively according to the CW test.

4 Conclusion

In this paper, we estimate Bayesian RU-MIDAS models to forecast the daily BDI based on the monthly information content of ENSO cycles from January, 1985 to February, 2022. Our results show that an index (Oceanic Niño Index (ONI)) capturing the ENSO is able to produce statistically significant gains in terms of point and density forecasts for the BDI, relative to a constant-mean benchmark model, at forecast horizons of one-, two-, three-, five-, and twenty one-day-ahead. We also depict that these gains primarily emanate from the El Niño rather than the La Niña phases of the ENSO. The strength of the El Niño relative to the La Niña in negatively influencing the BDI was also observed in a full-sample analysis. With evidence having shown that BDI leads financial markets and macroeconomic variables, our findings are indeed of tremendous value to both financial investors and policymakers. In sum, economic agents can use low-frequency climate-related information to predict the high-frequency BDI, which in turn is expected to assist in their decision-making involving portfolio allocations and policy. The accurate forecasting of the BDI based on the ENSO should also be of assistance to exporters and importers of bulk commodities and could enable shipbrokers to offer competitive charter rates contingent on climate risks and their associated impact on demand and supply of dry bulk commodities.

As part of future research, it would also be interesting to extend our study to the analysis of the volatility of the BDI due to the ENSO, since accurate forecasting of the second moment of this index is likely to bear important implications for the shipping companies in terms of quantifying and hedging their risks in the freight rate market.

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