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Forecasting Economic Growth Based on Systemic Risk for a Sample of Emerging Countries: a MIDAS Approach with Almon Polynomial Lag Distribution

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ABSTRACT

This study aims to study the effect of systemic risk on economic growth and provide GDP growth forecasts for five emerging countries. To do so, Mixed Data Sampling (MIDAS) models are used to incorporate the Emerging Market Bond Index (EMBI) and the Composite Leading Indicator (CLI) as explanatory variables. This methodology combines different time series frequencies and various weighting schemes and lag structures. The main empirical results suggest that MIDAS models provide accurate forecasts, in particular during periods of strong recessions, as in the subprime crisis. Moreover, the results show similarities with many previous studies on emerging countries, which demonstrate the accuracy of MIDAS models. This research provides a deeper understanding of the impact of systemic risk on economic growth and the financial factors that influence the latter, thereby contributing substantially to better economic policy design in developing countries.

Keywords: Emerging Countries, GDP Growth Forecast, Systemic Risk, MIDAS Model
JEL Classifications: C32, C53, G32, O47, O57

1. INTRODUCTION

Emerging market economies have increasingly become significant players in the global economy, attracting investors with their dissimilar characteristics (Tsunekawa, 2019; Yang et al, 2024). In this regard, gaining a deeper understanding of the dynamics of financial markets and their effects on economic growth presents a promising area of focus, particularly in emerging economies. Moreover, conducting comparisons among emerging economies could offer valuable insights and help identify common characteristics in the financial markets among the countries studied. Emerging economies are significant not only due to their share in the global economy, but also because of their vulnerability to crises. In fact, they have been the source of most financial crises in recent decades, with the exception of the subprime crisis (Shil, 2013). In this sense, Sahu (2013) highlights that crises pose substantial risks for emerging economies due to the multiple transmission mechanisms involved and their dependence on foreign capital. For instance, negative movements in G7 financial markets are often felt almost immediately in these economies.

Gross Domestic Product (GDP) is often regarded as an indicator of an economy's performance. However, economic growth is influenced by numerous variables, making its prediction a significant challenge for policymakers. Forecasting GDP requires monitoring the behavior of various economic and financial variables, which introduces additional issues, for istance, the timely availability of data and the relevance of data sampled at different frequencies. Conventional time series models typically rely on data with uniform frequencies, but in many cases, specific and useful data may not be available in that format. This issue is addressed by the introduction of Mixed Data Sampling (MIDAS) models by Ghysels et al. (2004) that allows for the combination of data with both low and high frequencies. Unlike autoregressive models, MIDAS involves regressors with different sampling frequencies. The authors also find that the MIDAS framework is particularly useful for forecasting volatility across various horizons. Additionally, MIDAS regression can be viewed as a reduced-form representation of a linear projection derived from a state-space model, but it does not require a complete system of state-space equations (Ghysels et al., 2016; Andreou et al., 2013). Hence, the primary objective of a MIDAS regression is to aggregate the higher frequency data, align all remaining data to the same frequency, and estimate a standard regression model. This method may provide more efficient estimations compared to approaches that aggregate series to the lowest frequency (Ghysels et al., 2004). The MIDAS approach effectively resolves the challenge of needing to convert or transform data into a uniform frequency and avoids the risk of omitting important variables that contain critical information for explaining the underlying system under study.

On the other hand, Ferreira de Mendonça and da Silva (2018) define systemic risk as a situation that, when in distress, impacts economy in general. Given this definition, it is logical to consider systemic risk as a factor that influences economic growth. Prochniak and Wasiak (2017) argue that the financial system plays a significant role in economic growth, emphasizing the importance of studying and identifying financial factors that affect its performance and stability. The authors also point out that an oversized financial sector, characterized by excessive lending or a high volume of nonperforming loans, can negatively impact GDP growth. Similarly, Buch and Neugebauer (2011) find a correlation between the size of the banking system, idiosyncratic shocks to loan growth, and their effects on real GDP growth. De Nicolò and Lucchetta (2011) find that financial shocks can amplify disruptions in the real sector, a conclusion also supported by Adrian et al. (2019). Additionally, Hryckiewicz and Kozłowski (2017) find that in countries as Belgium, The Netherlands, and Switzerland, the banking sector's size has exceeded that of the GDP, recognizing that bankruptcies in this sector can have catastrophic consequences for a country's real economy.

The main contribution of the present investigation is to provide a deeper understanding and assessment of the impact of systemic risk on economic growth using MIDAS regressions to a sample of emerging economies. Subsequently results across emerging economies are compared as a crucial step toward understanding the financial factors that influence economic growth. This study aims to explore the hypothesis that financial variables and leading indicators can effectively predict GDP growth.

This paper is organized as follows: Section 2 presents a literature review of studies about emerging economies and systemic risk, including those that apply the MIDAS methodology; section 3 presents and describes the data used in this study; section 4 presents the MIDAS methodology; section 5 carries out an analysis of the results; finally, section 6 concludes.

2. LITERATURE REVIEW

2.1. Emerging Economies

Emerging economies are countries that are not yet fully established financially and economically but have undergone significant development since the second half of the 20th century. These countries have reported growth in real GDP per capita and a reduction in global poverty rates and their growth has been largely export-oriented. Much of their growth is dependent on external financing, particularly following the liberalization processes of the 1990s (Aizenman, 2008). Emerging economies can be classified as countries that were considered developing economies before the 1980s but have experienced rapid growth since then, increasing their share in the global economy. Another perspective classifies them as partners of advanced economies rather than mere followers (Tsunekawa, 2019). Countries as Mexico, Brazil, Indonesia, and South Africa are recognized as emerging economies due to their economic size (GDP) and their influence on the global economy (Shiraishi, 2019). Meanwhile, Chile has significantly expanded its economy over the past three decades, achieving high-income status. Chile has developed important industries but remains dependent on natural resource exports, which exposes it to vulnerabilities in global commodity markets (Tsunekawa, 2019; Shiraishi, 2019).

While emerging economies share many common characteristics, it is important not to overgeneralize, as each country possesses unique features that are crucial for understanding its economic dynamics (Pels and Kidd, 2012; Seyf, 2016). Additionally, the presence of multiple emerging economies in certain regions suggests that geographical and regional characteristics play a significant role and require in-depth analysis. In this sense, Pesce (2015) identifies Asia as having the largest number of emerging economies (including Singapore, South Korea, Taiwan, Malaysia, China, Thailand, Indonesia, the Philippines, India, and Pakistan), followed by Latin America (Chile, Brazil, Argentina, Mexico, Venezuela, Colombia, and Peru). The Middle East and North Africa have several emerging economies (Saudi Arabia, Turkey, Iran, Iraq, Algeria, and Egypt). The regions with the fewest emerging economies are the Former USSR, Eastern Europe (Poland, Russia, and Kazakhstan) and Sub-Saharan Africa (South Africa and Nigeria). This classification is based on the size of an economy, specifically where a country's GDP represents at least 1.0% of GDP in USD.

Other notable characteristics of emerging economies include large, attractive domestic markets, abundant natural resources, and technological capabilities (Tsunekawa, 2019). However, many of these economies are stuck in the middle-income trap struggling to become high-income economies due to challenges in increasing productivity and advancing their industrial structures (Sonobe, 2019). Pels and Kidd (2012) also highlighted issues such as: insufficient legislation, inefficient judicial systems, corruption, informal labor markets, large family sizes, socioeconomic inequality, violence, young populations, institutional influence, political barriers, inadequate infrastructure, ineffective education, healthcare systems, low incomes, low financial inclusion, and a large number of small enterprises. While these challenges may seem daunting, emerging markets remain vital for business. For foreign enterprises to succeed, they must understand and navigate these complexities within the large internal markets that these economies offer (Paul, 2020; Tsunekawa, 2019).

2.2. Systemic Risk and Emerging Markets

In the context of emerging economies, Ferreira de Mendonça and da Silva (2018) carry out a study on the Brazilian banking sector using ΔCoVaR (Co-Value at Risk) and panel data analysis. Their findings were consistent with reports from the Central Bank of Brazil, identifying leverage and return on assets as key variables influencing systemic risk. Wang and Li (2020) examine financial conditions in China finding a strong relationship between these conditions and GDP downside risk. They noted that an increase in systemic risk not only reduces GDP growth, but also it has a longer forecasting horizon compared to financial conditions. Prochniak and Wasiak (2017) analyze 28 European countries and 34 OECD members, including some emerging economies, and found a nonlinear relationship between financial sector development and economic growth, emphasizing that a large financial system can negatively impact GDP dynamics. Esterhuysen et al. (2011) find an increase in systemic risk in South Africa due to the 2007 financial crisis, using prices of insurance against distressing losses. Finally, a study on South Africa by Moudud-Ul-Huq (2020) revealed the benefits of diversification, suggesting that during a crisis, emerging economies can use portfolio diversification to manage risk and enhance bank performance.

While diversification can offer advantages to emerging economies, Stolbov (2017) find that advanced economies possess greater resilience to the propagation of systemic risk compared to countries as China, Brazil and Russia. Another vulnerability is identified by Llaudes et al. (2010) that find that increasing financial and trade linkages, coupled with weak fundamentals in emerging economies, affect economic and credit growth, stock market performance, and sovereign spreads. However, the authors also emphasize the importance of reserves in mitigating the decline in growth. Moreover, Andries and Mutu (2016) study banks in 10 Central and Eastern European countries, including emerging economies like Poland and the Czech Republic, the authors find that while banks with stringent risk management structures tend to be less risky, they also contribute significantly to systemic risk. Finally, López-Herrera et al. (2019) and Mongrut and Juárez (2020) deal with systemic risk and EMBI for Latin-American countries.

2.3. MIDAS Models

MIDAS models are effective for short-term forecasting because they incorporate high-frequency data and combine different time series frequencies for estimation. In most studies, researchers predominantly focused on using the MIDAS method to forecast or nowcast GDP growth or the S&P 500 Index. For GDP-related studies, researchers such as Kuzin et al. (2011), Schumacher (2016), Chernis and Sekkel (2017), Siliverstovs (2017), Claudio et al. (2019), and Gorgi et al. (2019) applied MIDAS models and their variations to the euro area, Canada, Switzerland, East Germany, and the United States. Generally, these studies reported improvements in predictions and a more accurate model with the MIDAS approach. The analysis of volatility in the S&P 500 index is covered in studies by Engle et al. (2013), Asgharian et al. (2013), Pan et al. (2017), Conrad and Kleen (2020), and Wang et al. (2020). These studies consistently concluded that MIDAS models are suitable for short-term forecasting and emphasized that including high-frequency data enhances prediction accuracy, a conclusion also supported by Kiygi-Calli et al. (2017).

The applications of MIDAS models extend beyond GDP growth and financial index predictions, as shown by the following contributions. These include studies on Bitcoin (Ma et al., 2020), inflation rates (Breitung and Roling, 2015; Götz et al., 2014), computing density forecasts (Aastveit et al., 2017), modeling joint distributions of returns for portfolio selection among three Chinese indexes (Jiang et al., 2020), and predicting gold futures market volatility (Fang et al., 2017). The MIDAS models have also been used to measure volatility in oil prices, stock markets, futures, and exchange rates (Mei et al., 2020; Wang et al., 2020; Liu et al., 2021; Zhou et al., 2020), as well as to predict tourism flows and bank failures (Liu et al., 2021; Audrino et al., 2018). Generally, these studies reach the same conclusion as those focused on GDP growth, namely, MIDAS models often outperform traditional models and are particularly accurate for short-horizon predictions.

MIDAS models are complementary to various prediction models and can be easily combined with them. Some examples include the MIDAS autoregressive (MIDAS-AR) model developed by Clements and Galvão (2008), the combination of an Unrestricted MIDAS (U-MIDAS) model with a LASSO-type approach to create the MIDASSO model (Siliverstovs, 2017), the multiple output support vector machine unrestricted mixed data sampling (MSVM-UMIDAS) model proposed by Pan et al. (2017), and the integration of generalized autoregressive score (GAS) models with MIDAS models; the MIDAS-GAS model (Gorgi et al., 2019). Additionally, GARCH-MIDAS models have been employed by Engle et al. (2013), Asgharian et al. (2013), Fang et al. (2017), Conrad and Kleen (2020), and Wang et al. (2020). Finally, Jiang et al. (2020) introduce a time-varying multivariate copula-MIDAS-GARCH (TVM-Copula-MIDAS-GARCH) model, while Ma et al. (2020) design a Markov regime-switching MIDAS (MRS-MIDAS) model.

On the other hand, Franta et al. (2016) use a MIDAS model to compare the Czech National Bank's real-time GDP forecasts, concluding that mixed-frequency data models serve as a valuable complement to other forecasting methods. This approach has also been applied to nowcast and forecast GDP for Turkey (Şen Doğan and Midiliç, 2016), proving to be a better alternative than static Stock and Watson factor forecasts using time-aggregated data for Bahrain's GDP growth (Naser, 2015). Moreover, Gómez-Zamudio and Ibarra-Ramírez (2017) estimate a MIDAS model for Mexico, finding that incorporating daily financial data enhances GDP forecasts compared to models that use only quarterly data and flat aggregation. Also, Santos and Ziegelmann (2014) employ a combination of heterogeneous autoregressive MIDAS (GARCH-MIDAS) models for forecasting the Brazilian IBOVESPA index over various horizons but found no significant statistical difference between this combination and the individual methods. Ersin et al. (2022) carry out another GARCH-MIDAS study, using the Composite Leading Indicator (CLI) to forecast stock market volatility in G7 countries and highlighting the importance of including the CLI in policy decisions. Gao and Yang (2017) focus on forecasting stock indices and futures stock sentiment in emerging markets. Research on the relationship between systemic risk and GDP using MIDAS is limited. Xu et al. (2018) propose a Dynamic Conditional Correlation MIDAS model, incorporating the Student's *t*-distribution to create the DCC-MIDAS-*t* model, which is more accurate in predicting volatility CoVaR, outperforming other models in both in-sample and out-of-sample-forecasts. In the context of emerging economies, Kim and Swanson (2017) use a factor-MIDAS model for backcasting, nowcasting, and forecasting South Korea's GDP showing that their real-time model surpasses linear models and excels across all forecast horizons.

3. NATURE OF DATA AND DESCRIPTIVE STATISTICS

This study uses data on GDP growth (quarterly) and the Composite Leading Indicator (CLI) (monthly) from the OECD, and the Emerging Market Bond Index (EMBI) (daily or monthly depending on the country) from JP Morgan. The latter is considered an indicator of country risk (López-Herrera et al., 2013). The analysis focuses on the following countries: Mexico, Brazil, Chile, Indonesia, and South Africa. GDP is a widely used proxy for economic development and is relatively easy to obtain for most countries. The OECD developed the CLI by estimating the trend and cycle of each component time series individually, then aggregating the de-trended components to form the composite indicator using a growth cycle or deviation-from-trend approach (OECD, 2006). The components of the CLI are selected based on several criteria. For instance, they must be significant economic indicators, statistically robust, not subject to substantial revisions, and consistently align with the peaks and troughs of the business cycle. Additionally, the components should reflect general cyclical movements, not be dominated by erratic or non-cyclical influences, and be available promptly and regularly at intervals such as monthly or quarterly (Ojo et al., 2024).

The GDP in all OECD member countries is tracked using this CLI growth cycle approach. This tool predicts economic cycles by analyzing time series relevant to a country's aggregate economy. The Index of Industrial Production (IIP) serves as a reference series within the CLI, acting as a leading indicator of GDP and encompassing various economic indicators related to industrial production, manufacturing, commodities, labor markets, financial variables, exchange rates, consumer and business surveys, interest rates, and monetary aggregates. The EMBI measures the spread between the interest rate a bond issuer from an emerging country pays to issue a bond in a foreign market and the interest rate a U.S. bond pays. It is viewed as a measure of country risk or the probability of a country defaulting, and it serves as a proxy for the stability and confidence a market can project. Table 1 presents the frequency, sample length, source, and dates of the data used for each country studied. The data samples are sufficient to capture significant periods of growth and the economic behavior of these countries before and after the subprime crisis.

The descriptive statistics in Table 2 show that all the countries have negative skewness, suggesting the significant impact of the economic crisis, as indicated by the mean values being lower than the medians in all cases. The time series data used in this study are stationary, a condition that was confirmed through the KPSS test. The methodology for this study is based on the approach used by Gómez-Zamudio and Ibarra-Ramírez (2017), which considered GDP growth as the dependent variable and daily returns from the Mexican stock price index as the independent variable. In this study, GDP remains the dependent variable, while the Composite Leading Indicator (CLI) and the Emerging Markets Bond Index (EMBI) are the independent variables. The model also incorporates the growth rate of these variables from the previous period. The GDP data is sampled quarterly, the CLI monthly, and the EMBI either daily or monthly, depending on the country being analyzed.

In equation (1), GDP growth is represented by Y_t^Q where Q stands for quarterly frequency, $X_{m,t}^M$ represents the CLI with M indicating

Table 1: Data description

Variable	Number of observations	Frequency	Dates	Source
México				
GDP	49	Quarterly	2007Q4-2019Q4	www.oecd.org
CLI	147	Monthly	2007M10-2019M12	www.oecd.org
EMBI	3042	Daily	10/30/2007-31/12/2019	www.jpmorganchase.com
Brazil				
GDP	47	Quarterly	2007Q4-2019Q4	www.oecd.org
CLI	139	Monthly	2007M10-2019M04	www.oecd.org
EMBI	2874	Daily	30/10/2007-30/04/2019	www.jpmorganchase.com
Chile				
GDP	49	Quarterly	2007Q4-2019Q4	www.oecd.org
CLI	147	Monthly	2007M10-2019M12	www.oecd.org
EMBI	3042	Daily	10/30/2007-12/31/2019	www.jpmorganchase.com
South-Africa				
GDP	48	Quarterly	2007Q4-2019Q3	www.oecd.org
CLI	144	Monthly	2007M10-2019M9	www.oecd.org
EMBI	144	Monthly	2007M10-2019M9	www.databank.worldbank.org
Indonesia				
GDP	49	Quarterly	2007Q4-2019Q3	www.oecd.org
CLI	144	Monthly	2007M10-2019M9	www.oecd.org
EMBI	144	Monthly	2007M10-2019M9	www.databank.worldbank.org

Source: Authors' own elaboration with data from OECD and JP Morgan

Table 2: Descriptive statistics

Country	GDP	CLI	EMBI
Mexico			
Mean	0.4489	0.0052	−0.0005
Median	0.5631	0.0107	0.0007
Std. Desv.	1.1326	0.2813	0.0761
Variance	1.2829	0.0791	0.0058
Skeweness	−2.2917	−1.3277	0.0695
Kurtosis	13.5385	8.9015	18.4360
Chile			
Mean	0.6661	0.0141	-7.54×10^{-5}
Median	0.8730	0.0243	0.0010
Std. Desv.	1.1398	0.3182	0.0413
Variance	1.2992	0.1012	0.0017
Skeweness	−1.2128	−0.4192	−1.3051
Kurtosis	7.8927	4.7260	20.5882
Brazil			
Mean	0.3896	0.0068	−0.0002
Median	0.4252	0.0093	0.0015
Std. Desv.	0.6179	0.2889	0.0867
Variance	0.3818	0.0834	0.0075
Skeweness	−0.8128	0.9462	−1.4613
Kurtosis	3.6919	6.9388	34.8904
Indonesia			
Mean	1.3176	−0.0037	-3.76×10^{-1}
Median	1.2722	0.0405	−2.0476
Std. Desv.	0.2587	0.2055	47.2936
Variance	0.0669	0.0422	2236.6934
Skeweness	1.0923	−0.5012	4.7740
Kurtosis	12.1733	3.4305	50.1504
South Africa			
Mean	0.3771	0.0162	-1.28×10^{-1}
Median	0.4227	0.0204	−1.0114
Std. Desv.	0.6174	0.1411	36.7084
Variance	0.3811	0.0199	1347.5083
Skeweness	−0.7557	0.9516	−2.5115
Kurtosis	3.5790	4.9237	23.4543

Source: Authors' own elaboration with data from OECD and JP Morgan

monthly frequency, and $Z_{m,t}^{D}$ represents the EMBI, with D indicating daily frequency (monthly frequency for South-Africa and Indonesia), m denotes trading days within a quarter.

$$Y_{t+h}^{Q,h} = \mu^{h} + \sum_{j=0}^{p_Y^Q-1} \rho_{j+1}^{h} Y_{t-j}^{Q} + \beta^{h} \sum_{j=0}^{q_X^M-1} \sum_{i=0}^{m-1} w_{i+j*m}^{\theta^h} X_{m-1,t-j}^{M}$$

$$+\beta^{h} \sum_{j=0}^{q_Z^D-1} \sum_{i=0}^{m-1} w_{i+j*m}^{\theta^h} Z_{m-1,t-j}^{D} + u_{t+h}^{h} \quad (1)$$

To forecast GDP growth h periods ahead. In the framework of equation (1), a usual autoregressive terms include p_Y^Q quarterly lags of the dependent variable Y_t^Q. In addition, q_X^M and q_Z^D introduce m monthly or daily lags for the independent variables included in the model. The term $w_{i+j*m}^{\theta^h}$ that multiplies the monthly and daily variables serves as a weighting scheme. This scheme reduces the number of parameters to estimate and assists in determining coefficients for each high-frequency lag (Gómez-Zamudio and Ibarra-Ramírez, 2017). To simplify, the dependent variable Y_t^Q has a quarterly frequency, while its regressor $X_{m,t}^{M}$ has a monthly frequency. As a result, each Y_t^Q s explained by three instances of $X_{m,t}^{M}$. Similarly, for daily regressors, the EMBI provides daily data at 5 days/week that explains Y_t^Q, using 20 business days/month or 60 days/quarter. This logic leads to a fixed set of monthly and daily lags, as outlined by Ghysels et al. (2016) where they assume each month has exactly 4 weeks, and each week contains 5 business days to generate daily data. The term θ is a low-dimensional vector containing unknown hyper-parameters that helps prevent the proliferation of parameters (Andreou et al., 2013).

There are several weighting schemes for assigning lag coefficients, with the Polynomial Distributed Lag (PDL) or Almon PDL being the most straightforward providing a simpler estimation process. Other weighting schemes include Unrestricted MIDAS (U-MIDAS), normalized Beta probability functions, normalized exponential Almon lag polynomials, Multiplicative MIDAS (M-MIDAS), iterative MIDAS, and step functions. U-MIDAS and the Almon lag polynomial are typically estimated using nonlinear least squares (Gómez-Zamudio and Ibarra-Ramírez, 2017). The purpose of the weighting scheme is to allow the data to determine the aggregation weights while ensuring the model remains parsimonious. This approach applies polynomial distributed lag functions to weight high-frequency data. The weights in an Almon polynomial distributed lag are described in the following equation, as outlined by Şen Doğan and Midiliç (2016);

$$\omega(\theta, i) = \sum_{p=0}^{n_p} \theta_p i^p \quad (2)$$

where the weight of the i^{th} lag is calculated by (n_p+1) hyperparameters $\theta = (\theta_0, \ldots \theta_p)$. For this investigation, the most accurate estimates were obtained using the Almon polynomial lag distribution. Polynomial lag structures are constructed through nonlinear functional specifications (Ghysels et al., 2007). After selecting the appropriate lag for each variable, the resulting model is used to forecast GDP growth. To assess the accuracy of these forecasts, we conducted a test of equality of the medians between the actual GDP series and the forecasted GDP series. Additionally, we calculated the percentage of correct signs by comparing the original GDP series with the predicted series and counting how many of the forecasts match the sign of the actual data.

4. EMPIRICAL RESULTS

As a first general finding, the Almon polynomial lag distribution was identified as the most suitable model for all the studied economies, aligning with the results of Şen Doğan and Midiliç (2016) for the Turkish economy. This suggests that the Almon polynomial lag distribution may be the most effective model for emerging economies. The second key finding is that the estimated models successfully captured the peaks and troughs described by Ojo et al. (2024), even when considering the impact of the COVID-19 pandemic. These results also confirm the influence of the EMBI as noted by López-Herrera et al. (2013). The Wilcoxon test for equality of medians indicated that all forecasts were statistically similar to the observed series, as shown in Table 3. The results for the percentage of correct signs in the predicted series are presented in Table 4. In all cases, the percentage of correct signs (indicated by a value of one) was significantly higher than the number of incorrect signs, demonstrating that the models are appropriate for all countries. Additionally, the estimations consistently reflected the fluctuations of the subprime crisis. The following subsections provide detailed results for each country studied.

4.1. Results for México

For Mexico, the optimal number of lags for the regressors is 2 for the CLI and 12 for the EMBI, with a degree 1 polynomial (Table 5). The resulting model effectively captures the GDP decline during the subprime crisis and the subsequent recovery, as well as downturns observed in 2013 and 2017; see Figure 1. The prediction is statistically significant when compared to the original series (Table 3), and the percentage of correct directional predictions is 72.91% (Table 4). The sensitivity and vulnerability reflected by this model align with findings reported by Sahu (2013) and Llaudes et al. (2010). The inclusion of daily data suggests model improvements, as also highlighted by Gómez-Zamudio and Ibarra-Ramírez (2017). Finally, the integration of CLI in the MIDAS models supports the findings of Ersin et al. (2022), emphasizing the importance of CLI not only for policy decisions but also for economic forecasting.

Table 3: Test for equality of medians between series

Wilcoxon/MannWhitney		
Country	**Value**	**Probability**
Mexico	0.4286	0.6681
Chile	0.0463	0.9630
Brazil	0.4517	0.6514
Indonesia	0.5003	0.6168
South-Africa	0.4358	0.6629

Source: Authors' own elaboration with data from OECD and JP Morgan

Table 4: Percentage of correct signs

Country	Total observations after adjustments	Zeros	Percentage	Ones	Percentage
Mexico	48	13	27.0833	35	72.9166
Chile	41	2	4.8780	39	95.1219
Brazil	42	7	16.6666	35	83.3333
Indonesia	45	0	0	45	100
South-Africa	41	6	14.6341	35	85.3658

Source: Authors' own elaboration with data from OECD and JP Morgan

4.2. Results for Chile

For Chile, the optimal lags chosen for the CLI are 3, while for the EMBI are 8, resulting in a model with a degree 2 polynomial (Table 6). This model successfully captures the economic fluctuations throughout most of the study period. Notably, it accurately reflects the declines and recoveries from 2014Q3 to 2017Q2 and anticipates the 2013Q2 downturn as early as 2012Q4, demonstrating a forward-looking capability of two quarters, as shown in Figure 2. The model also mirrors the downturns in 2015Q3 and 2016Q3. Although the model does not capture the post-subprime crisis recovery with high precision, it still follows the general trend. The percentage of correct directional predictions for Chile is the second highest among the studied countries, at 95.12%, while the R-squared value is 55%. These results support the findings of Gómez-Zamudio and Ibarra-Ramírez (2017) and Ersin et al. (2022) regarding the benefits of including CLI and daily data for improved forecasting.

4.3. Results for Brazil

For Brazil, the optimal model is a degree 1 polynomial with 3 lags for the CLI and 60 lags for the EMBI (Table 7). This model effectively tracks the behavior of the original GDP series during the subprime crisis and demonstrates a forward-looking capability from 2010Q4 to 2012Q4. It also successfully predicted the increase in 2017Q2, showing an uptick a quarter in advance; see Figure 3. While the model generally follows the actual trend of the series, it failed to estimate the downturn in 2018. Despite some inaccuracies across different periods, the model is statistically significant (Table 3) and correctly predicts 83.33% of the signs (Table 4). The R-squared value is 0.38, and the CLI is marginally significant at the 0.10 level, indicating it

Table 5: Estimation for Mexico

Adjusted sample: 2007Q4-2019Q3				
Included observations: 48 affter adjustment				
Method: PDL/Almon (polynmial degree: 1)				
Automatic lag selection, max lags 1 2				
Chosen selection 1 2				
Variable	**Coefficient**	**Standard error**	**t-Statistic**	**Probability**
CLI/CLI	−2.7310	0.6639	−4.1132	0.0001
EMBI	−2.9750	1.7496	−1.7003	0.0962
C	0.5070	0.1176	4.3087	9.37×10^{-5}
Series: CLI (1) Lags: 1				
PDL01	3.7879	0.6320	5.9931	3.74×10^{-7}
Series: EMBI (12) Lags: 12				
PDL01	3.7176	1.1890	3.1266	0.0031
R-squared	0.5639		Mean dependent variable	0.4611
Adjusted R-squared	0.5234		S.D. dependent variable	1.1413
S.E. of regression	0.7879		Akaike information criterion	2.4595
Sum Squared residuals	26.6980		Schwarz criterion	2.6545
Log Likelihood	−54.0303		Hannan-Quinn criterion	2.5332
Durbin-Watson stat.	1.7034			

Source: Authors' own elaboration with data from OECD and JP Morgan

Table 6: Estimation for Chile

Adjusted sample: 2009Q3-2019Q3				
Included observations: 41 affter adjustment				
Method: PDL/Almon (polynmial degree: 2)				
Automatic lag selection, max lags 16				
Chosen selection 16 16				
Variable	**Coefficient**	**Standard error**	**t-Statistic**	**Probability**
CLI/CLI	−4.2369	1.1207	−3.7806	0.0006
EMBI	4.0882	2.3259	1.7576	0.0878
C	0.4822	0.1262	3.8199	0.0005
Series: CLI (3) Lags: 16				
PDL01	0.7679	0.2465	3.1154	0.0037
PDL02	−0.0629	0.0198	−3.1677	0.0032
Series: EMBI (8) Lags: 16				
PDL01	−2.1831	1.7174	−1.2711	0.2122
PDL02	−0.0735	0.1612	−0.4559	0.6513
R-squared	0.5561		Mean dependent variable	0.8715
Adjusted R-squared	0.4778		S.D. dependent variable	0.7897
S.E. of regression	0.5706		Akaike information criterion	1.8702
Sum Squared residuals	11.0726		Schwarz criterion	2.1628
Log Likelihood	−31.3401		Hannan-Quinn criterion	1.9767
Durbin-Watson stat.	2.5919			

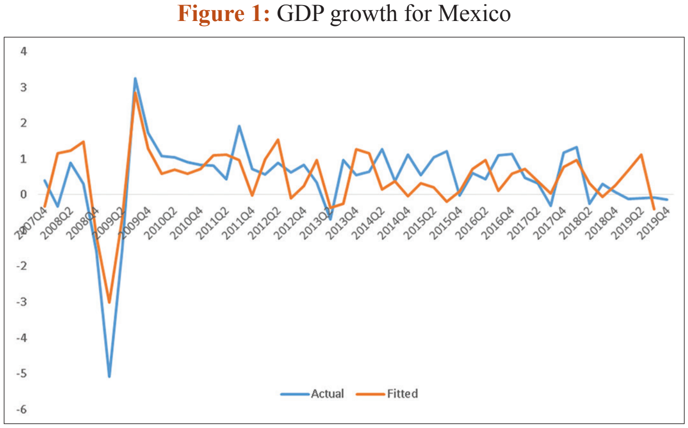
Source: Authors' own elaboration with data from OECD and JP Morgan

Table 7: Estimation for Brazil

Adjusted sample: 2008Q3-2018Q4				
Included observations: 42 affter adjustment				
Method: PDL/Almon (polynmial degree: 1)				
Automatic lag selection, max lags 1 2				
Chosen selection 1 2				
Variable	**Coefficient**	**Standard error**	**t-Statistic**	**Probability**
CLI/CLI	0.6529	0.3876	1.6842	0.1005
EMBI	−2.1149	0.9884	−2.1396	0.039
C	0.4994	0.0873	5.7203	0
Series: CLI (3) Lags: 14				
PDL01	−0.1529	0.0456	−3.3508	0.0019
Series: EMBI (60) Lags: 16				
PDL01	3.7176	1.1890	3.1266	0.0031
R-squared	0.3827		Mean dependent variable	0.3628
Adjusted R-squared	0.3160		S.D. dependent variable	0.5880
S.E. of regression	0.4863		Akaike information criterion	1.5075
Sum Squared residuals	8.7520		Schwarz criterion	1.7144
Log Likelihood	−26.6594		Hannan-Quinn criterion	1.5834
Durbin-Watson stat.	1.8662			

Source: Authors' own elaboration with data from OECD and JP Morgan

Figure 1: GDP growth for Mexico



Source: Authors' own elaboration with data from OECD and JP Morgan

is less influential in the model compared to the EMBI, which contrasts with the findings of Ersin et al. (2022) regarding the crucial importance of CLI.

4.4. Results for Indonesia

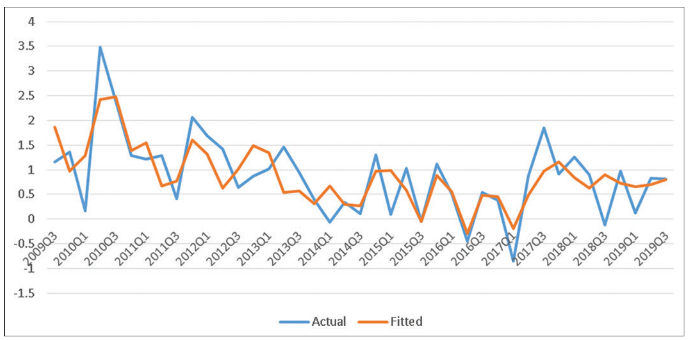
The optimal model accurately predicts the decline and recovery associated with the subprime crisis and continues to effectively track subsequent economic behavior, achieving 100% correct signs (Table 4), the highest percentage among all studied economies. The inclusion of different frequencies led to this perfect accuracy suggesting that such models are both useful and precise, as observed in Kiygi-Calli et al. (2017). Although the model is more sensitive than actual observations, it generally follows the behavior of the actual series, with the fitted series closely mirroring

Table 8: Estimation for Indonesia

Adjusted sample: 2008Q2-2019Q2				
Included observations: 45 after adjustment				
Method: PDL/Almon (polynomial degree: 1)				
Automatic lag selection, max lags 11 5				
Chosen selection 11 5				
Variable	**Coefficient**	**Standard error**	**t-Statistic**	**Probability**
CLI/CLI	−0.7153	0.3354	2.1326	0.0391
EMBI	−0.0046	0.0009	4.9641	0
C	1.3147	0.0258	50.8651	0
Series: CLI (3) Lags: 11				
PDL01	0.0785	0.0431	1.8225	0.0759
Series: EMBI (12) Lags: 12				
PDL01	0.0005	0.0002	1.9538	0.0577
R-squared	0.458331		Mean dependent variable	1.313701
Adjusted R-squared	0.404165		S.D. dependent variable	0.224094
S.E. of regression	0.172979		Akaike information criterion	−0.566854
Sum Squared residuals	1.19687		Schwarz criterion	−0.366113
Log Likelihood	−17.75421		Hannan-Quinn criterion	−0.49202
Durbin-Watson stat.	1.534238			

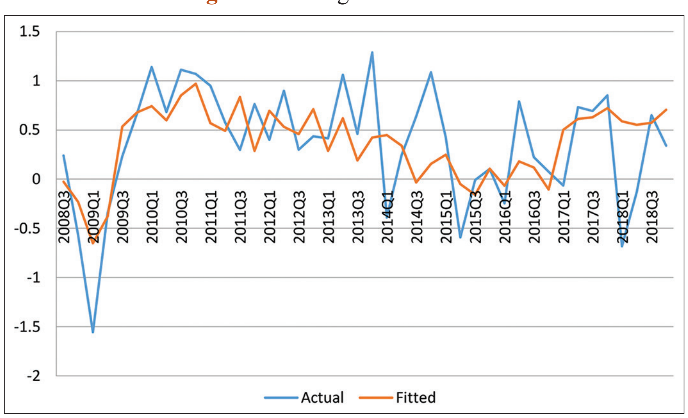
Source: Authors' own elaboration with data from OECD and JP Morgan

Figure 2: GDP growth for Chile



Source: Authors' own elaboration with data from OECD and JP Morgan

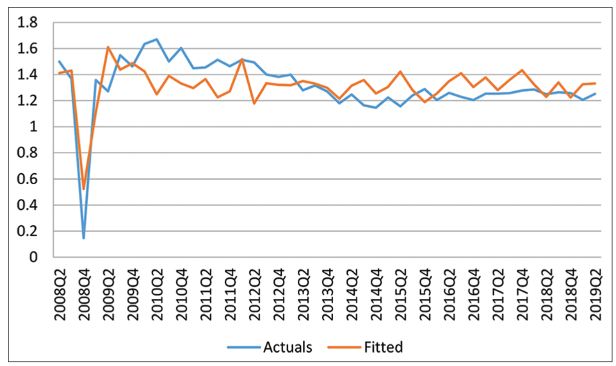
Figure 3: GDP growth for Brazil



Source: Authors' own elaboration with data from OECD and JP Morgan

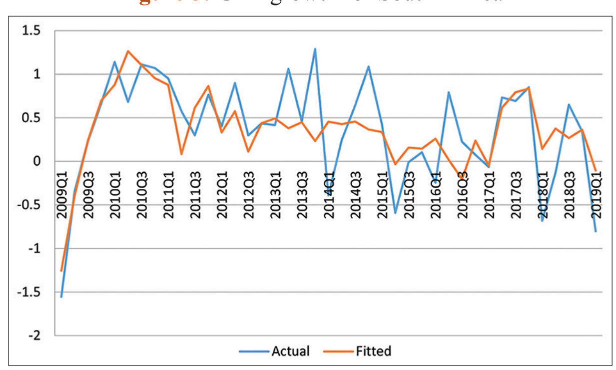
movements throughout the sample, though with no clear trend. The model's R-squared value is 0.45, and both the CLI and EMBI are significant contributors. The estimation employed a degree-1 polynomial with 3 lags for both the CLI and EMBI (Table 8). These results align with the findings of Ersin et al. (2022) and Gómez-Zamudio and Ibarra-Ramírez (2017). The model captures the dynamic of GDP (Figure 4).

Figure 4: GDP growth for Indonesia



Source: Authors' own elaboration with data from OECD and JP Morgan

Figure 5: GDP growth for South-Africa



Source: Authors' own elaboration with data from OECD and JP Morgan

4.5. Results for South Africa

The optimal model utilizes 4 lags for the CLI and 3 lags for the EMBI, with a degree 1 polynomial (Table 9). The resulting forecast effectively tracks the recovery following the subprime crisis and anticipates the 2010Q3 downturn two quarters in advance, as well as the economic behavior from 2011Q1 to 2013Q1. The model also captures the rise in 2017Q2 and the decline in 2017Q4 (Figure 5). Toward the end of the sample,

Table 9: Estimation for South-Africa

Adjusted sample: 2009Q1-2019Q1				
Included observations: 41 after adjustment				
Method: PDL/Almon (polynmial degree: 1)				
Automatic lag selection, max lags 21 5				
Chosen selection 21 5				
Variable	**Coefficient**	**Standard error**	**t-Statistic**	**Probability**
CLI/CLI	−1.8299	0.8850	−2.0675	0.0459
EMBI	−0.0168	0.0066	−2.5283	0.016
C	0.3199	0.0717	4.4578	0.0001
Series: CLI (4) Lags: 21				
PDL01	−0.2190	0.0714	−3.0673	0.0041
Series: EMBI (12) Lags: 12				
PDL01	0.0029	0.0017	1.7412	0.0902
R-squared	0.5290		Mean dependent variable	0.3601
Adjusted R-squared	0.4767		S.D. dependent variable	0.6053
S.E. of regression	0.4378		Akaike information criterion	1.3001
Sum Squared residuals	6.9026		Schwarz criterion	1.5090
Log Likelihood	−21.6523		Hannan-Quinn criterion	1.3762
Durbin-Watson stat.	2.1017			

Source: Authors' own elaboration with data from OECD and JP Morgan

the model accurately follows the downturn in 2019Q1. While it doesn't perfectly mirror all the ups and downs, the general trend of the actual series remains similar to that of the fitted series. The model achieves 85.36% correct signs (Table 4), ranking third among all models. The R-squared is 0.52, and both the CLI and EMBI are significant within the model. The use of higher-frequency predictors supports the assertions made by Kiygi-Calli et al. (2017) regarding the utility of including data at different frequencies.

5. CONCLUSION

This research applied the MIDAS models for predicting GDP growth in a sample of emerging countries. The variables, EMBI and CLI, proposed in this study proved to be significant predictors of economic performance across all countries, particularly during sharp declines and increases in GDP. This conclusion aligns with the findings of Gómez-Zamudio and Ibarra-Ramírez (2017) regarding the EMBI. The results also corroborate López-Herrera et al. (2013) that highlighted the role of EMBI in capturing risk in these countries.

The Almon polynomial lag distribution was the best weighting scheme for all models, consistent with the findings of Şen Doğan and Midiliç (2016), suggesting that it is the most suitable approach for emerging markets. The results demonstrated superior accuracy in capturing abrupt changes in GDP growth, making MIDAS models particularly effective for predicting economic crises. The high percentage of correct directional predictions further supports the assertion that the estimates closely follow the actual behavior of the original series.

Finally, future research could focus on examining more elaborated weighting schemes and lag structures (Tsunekawa, 2019), comparing the resultant optimal models against benchmark models and exploring a broader set of independent financial variables.

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