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Abstract

This research conducts an in-depth econometric analysis of key economic indicators in Madagascar, with a specific focus on Gross Domestic Product (GDP) and the USD exchange rate (USD/MGA). Employing the rigorous Box-Jenkins methodology with ARIMAX modeling, we meticulously examine historical trends, model time series data, and provide forecasts for the year 2023. Our analysis notably highlights a projected decline in Madagascar's GDP for the year 2023, shedding light on the potential repercussions of various factors such as impending presidential elections and ongoing challenges like electricity shortages. These factors have the potential to exert a significant influence on the trajectory of the country's economy.

While ARIMAX models constitute invaluable tools for forecasting, we underscore the necessity of incorporating a more expansive array of econometric methodologies to bolster economic resilience and inform policymaking. This study underscores the critical importance of combining data-driven modeling with a profound understanding of the contextual intricacies that characterize Madagascar's intricate economic landscape. Moreover, it extends its relevance to other emerging economies facing similar complexities and challenges.

Keywords: Econometrics, ARIMAX modeling, ARIMA modeling, Madagascar, Gross Domestic Product, USD exchange rate, Forecasting, Economic Analysis, Box-Jenkins methodology, Time Series Data.

1 Introduction

Economic forecasting plays a pivotal role in the strategic planning and decision-making processes of nations and organizations. Accurate predictions of economic variables, such as Gross Domestic Product (GDP) and exchange rates, are essential for formulating effective policies, optimizing resource allocation, and navigating the complex terrain of international trade. In this context, econometric models have emerged as indispensable tools, offering insights into the intricate dynamics of economic systems.

This study delves into the realm of economic forecasting with a specific focus on Madagascar, a country endowed with unique economic challenges and opportunities. Our aim is to employ an econometric approach, specifically the AutoRegressive Integrated Moving Average (ARIMA) to analyze and forecast Madagascar's annual GDP and exchange rate dynamics. We add the variable CRISIS to GDP model as dummy exogenous variable. The dataset at our disposal spans from 1990 to 2021 and is generously provided by the World Bank, offering a comprehensive historical perspective.

The ARIMA model, renowned for its efficacy in time series analysis, serves as the cornerstone of our investigation. Through a systematic process encompassing data selection, model identification, and rigorous evaluation, we seek to unravel underlying patterns and relationships within the economic data. Our ultimate goal is to provide valuable insights that can inform economic policy, guide investment decisions, and enhance our understanding of Madagascar's economic landscape.

However, recognizing that economic dynamics are not isolated from external influences, we go beyond the numbers. Madagascar, like many nations, grapples with a multifaceted economic context shaped by political events, global uncertainties, and sector-specific challenges. To attain a comprehensive understanding, we integrate these external factors into our analysis, elucidating how they may impact the economic outlook.

2 Literature Review

Within the domain of time series forecasting, the Autoregressive Integrated Moving Average (ARIMA) model has emerged as a venerable and highly influential methodology. This section undertakes a comprehensive review of pertinent literature, delineating key methodologies, and elucidating the diverse applications inherent in ARIMA models.

2.1 ARIMA Model Components

At the core of ARIMA modeling are the Autoregressive (AR), Integrated (I), and Moving Average (MA) components. The AR component, denoted as 'AR(p),' serves to explicate the temporal dependencies by meticulously modeling the intricate interplay between current observations and their antecedent counterparts. Formally, this relationship is represented as:

$$X_t = c + \phi_1 X_{t-1} + \phi_2 X_{t-2} + \cdots + \phi_p X_{t-p} + \varepsilon_t, \tag{1}$$

In this formulation, $(X_t)_t$ is time series, ϕ_i embodies the autoregressive coefficients, and ε_t encapsulates the error term.

The I component, demarcated as 'I(d)', offers a robust mechanism for the alleviation of stationarity concerns by way of differencing. Mathematically, differencing of order 'd' is succinctly articulated as:

$$Y_t = \Delta^d X_t, \tag{2}$$

In this equation, Y_t represents the differenced series, and Δ^d constitutes the differencing operator applied iteratively 'd' times, thereby imbuing the series with the desired stationarity. In other word, d is the least positive integer such that $(Y_t)_t$ is stationary.

The MA component, manifested as 'MA(q)', serves as a pivotal reservoir for encompassing the historical influence of prior prediction errors upon the contemporary observation. Its formal representation is encapsulated within:

$$X_t = \mu + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \cdots + \theta_q \varepsilon_{t-q}, \tag{3}$$

In this expression, μ signifies the mean of the series, ε_t denotes the white noise error terms, and θ_i constitutes the moving average coefficients. The ARIMA model combines equations 1, 3, 2, and defined by the equation:

$$\begin{aligned} Y_t = \mu &+ \phi_1 Y_{t-1} + \cdots + \phi_p Y_{t-p} \\ &+ \theta_1 \varepsilon_{t-1} + \cdots + \theta_q \varepsilon_{t-q} + \varepsilon_t. \end{aligned} \tag{4}$$

Sometimes, adding an exogenous variable (real valued or dummies) to the ARIMA model improves the accuracy of predictions. This extension model is called ARIMAX, and defined by:

$$\begin{aligned} Y_t = \mu &+ \phi_1 X_{t-1} + \cdots + \phi_p X_{t-p} \\ &+ \theta_1 \varepsilon_{t-1} \cdots + \theta_q \varepsilon_{t-q} \\ &+ \beta R_t + \varepsilon_t, \end{aligned} \tag{5}$$

where $(R_t)_t$ is the exogenous variable time series, β is its coefficient in the model [14]. The properties and analysis method of ARIMA described in the following sections are also applicable to ARIMAX.

2.2 Model Identification and Estimation

The critical juncture of ARIMA modeling resides within the meticulous identification of suitable orders for 'p,' 'd', and 'q'. This pursuit is characteristically guided by the judicious scrutiny of the autocorrelation and partial autocorrelation functions (ACF and PACF). These discerning functions, originally posited by Yule [16] and contemporaneously elaborated upon by Tsay [12], impart discerning insights into the underlying structure of the time series .

Mathematically, the autocorrelation function (ACF) assumes the role of quantifying the degree of correlation exhibited between the time series and its antecedent lags, thus facilitating the discernment of the 'q' value within MA(q). Simultaneously, the partial autocorrelation function (PACF) delves into the isolated elucidation of the direct relationship between the prevailing observation and its predecessor lags, thereby instrumentalizing the determination of 'p' in AR(p).

In a methodological resonance, the estimation of ARIMA model parameters is most commonly administered through the prism of Maximum Likelihood Estimation (MLE). This prescriptive approach mandates

the maximization of the likelihood function, thereby engendering the most optimal parameter estimates. Formally, the likelihood function is articulated as:
ARIMA:

$$L(\theta) = \prod_{t=p+1}^{T} f(x_t, x_{t-1}, \cdots, x_{t-p}|\theta) \tag{6}$$

ARIMAX:

$$L_{xreg}(\theta, \beta) = \prod_{t=p+1}^{T} g(x_t, x_{t-1}, \cdots, x_{t-p}, r_t)|\theta, \beta) \tag{7}$$

In these formulations, θ (resp. β) embodies the ARIMA (resp. exogenous) parameters. f and g denote the conditional probability density function governing the observed data and the data with an exogenous variable, respectively. p is the AR order and T signifies the number of observations. These likelihood functions are computed under the assumption that the vector $(x_t, x_{t-1}, \cdots, x_{t-p})$ is Gaussian for $p+1 \leq t \leq T$.

In summation, ARIMA modeling, as substantiated through these mathematical constituents, epitomizes a robust and meticulously structured framework underpinning its versatility and efficacy in the realm of time series forecasting.

3 Empirical Review

This section embarks on an empirical exploration, drawing discerning insights from practical applications of ARIMA models within various domains.

3.1 Meteorological Insights

The meteorological domain has greatly benefited from the deployment of ARIMA models in weather forecasting. Empirical studies, epitomized by the work of Wilks [13], have consistently revealed ARIMA's capacity to make precise predictions of weather patterns and climatic phenomena . The empirical validation of ARIMA's effectiveness in enhancing our comprehension of atmospheric dynamics and elevating the precision of weather forecasts underscores its indelible importance within meteorology.

3.2 Supply Chain Management

ARIMA models, when empirically deployed within supply chain management, have ushered in optimization within inventory management and the streamlining of logistics operations. Research conducted by Chopra and Meindl [5] substantiates the practical benefits of ARIMA-based demand forecasting. The empirical evidence garnered from this study serves as a testament to the efficacy of ARIMA models in effecting resource allocation efficiencies and in the meticulous fulfillment of consumer demands with heightened precision .

3.3 Healthcare Resource Allocation

In the realm of healthcare, the empirical application of ARIMA models has ushered in substantial advancements in resource allocation strategies. Empirical studies, including those conducted by Hyndman and al. [7], offer empirical validation of the utility of ARIMA-based forecasts in predicting patient admission rates and anticipating disease outbreaks . These empirical findings resonate as pragmatic affirmations, facilitating healthcare providers in optimizing resource allocation and elevating the quality of patient care.

3.4 Gold price forecasting

Nanthiya and al. [6] conducts comprehensive evaluation of diverse machine learning methodologies for the precise prediction of gold price rates, encompassing Linear Regression, the Autoregressive Integrated Moving Average (ARIMA) Model, and Random Forest Regression. The robustness of these methodologies is assessed utilizing established performance metrics, notably the Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE). Intriguingly, the empirical results prominently underscore the exceptional accuracy exhibited by the ARIMA model in forecasting gold prices, as evidenced by impressively low MAE and RMSE values of 0.040 and 0.046, respectively. Moreover, this research maintains a focal point on ensemble-based machine learning techniques, shedding light on the ARIMA model's superior performance when juxtaposed with alternative methods such as Linear Regression and Random Forest Regression, distinctly in terms of forecasting precision. These findings decisively accentuate the vast potential of machine learning algorithms and methodologies for the predictive modeling of financial variables, with specific pertinence to the domain of gold price rate prediction, thus augmenting the existing body of knowledge in this field.

3.5 Predicting peak electrical energy consumption

Pierre and al. [2] conducts a comprehensive comparative analysis of various methodologies for forecasting peak electrical energy consumption, encompassing ARIMA, Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), as well as hybrid models ARIMA-LSTM and ARIMA-GRU. Notably, the hybrid ARIMA-LSTM approach emerges as the top-performing model, demonstrating superior prediction performance with a root-mean-square error (RMSE) of 7.35. In contrast, the ARIMA-GRU hybrid approach yields an RMSE of 9.60. The individual methods, GRU, LSTM, and ARIMA, exhibit relatively higher RMSE values of 18.11, 18.74, and 49.90, respectively. These findings collectively underscore the substantial advantage of employing hybrid approaches, such as ARIMA-LSTM and ARIMA-GRU, over their single-method counterparts in the context of predicting peak electrical energy consumption, signifying their potential for enhancing forecasting accuracy .

3.6 Climate Change Prediction Using ARIMA Model

Navaneetha and al. [9] employs univariate statistical methodologies encompassing seasonal and non-seasonal unit root testing, ARIMA, and Seasonal ARIMA (SARIMA) modeling to construct an economical and parsimonious forecasting model for global mean temperature change. This ARIMA-based predictive framework, as articulated in the paper, holds the potential to facilitate predictions of air temperature and the consequent implications of climate change on monthly mean maximum and minimum temperatures, particularly within the context of Tamil Nadu. Remarkably, the applicability of this model extends beyond the realm of global temperature trends, offering utility in the analysis of temperature data at more localized scales . The overarching objective of this research is to furnish accurate and cost-effective forecasting tools, vital for the effective management of climate change's multifaceted impacts on a global scale .

3.7 Give the best score for Quarterly GDP Forecasting in Madagascar

Andrianady, in this study [1], evaluates the effectiveness of three popular econometric models: ARIMA, MIDAS, and VAR for forecasting quarterly GDP in Madagascar. Our analysis reveals that ARIMA provides the most accurate forecasts among the three models, indicating its superiority in predicting the country's economic performance. However, we also argue that combining multiple models can offer additional benefits for forecasting accuracy and robustness. By leveraging the strengths of each model, such an approach can provide more reliable forecasts and reduce the risk of errors and biases associated with using a single model. Our findings have important implications for policymakers, economists, and investors who rely on GDP forecasts to make informed decisions about economic policies and investments in Madagascar

3.8 Less effective in stock Market Prediction

Alotabi [11] examines the forecasting performance of ARIMA and an artificial neural network model with published stock data obtained from the New York Stock Exchange. The empirical results obtained reveal the superiority of the neural network model over the ARIMA model. The findings further resolve and clarify contradictory opinions reported in the literature over the superiority of neural networks and the ARIMA model and vice versa .

4 Methodology

4.1 Data and Sources

This study employs an univariate econometric approach, specifically the AutoRegressive Integrated Moving Average (ARIMA) modeling technique, to analyze the annual Gross Domestic Product (GDP) and the USD exchange rate (USD/MGA). The dataset comprises 31 observations spanning the years 1990 to 2021 and has been sourced from the World Bank, a reputable and widely recognized institution for economic data.

4.2 Time Series Analysis

The analysis of time series data in this research adheres to the well-established Box-Jenkins methodology [8]. This approach involves a systematic procedure for preprocessing, modeling, and forecasting time series data, encompassing model identification, estimation, diagnostic checking, and forecasting. In preprocessing, we apply log transformation to GDP, creating the variable $LGDP$. We add to selected model an exogenous dummy variable denoted $CRISIS$ which valued to 1 for year witch presented a political or socio-economic crisis (1991, 2002, 2009, 2020) and 0 for others. So, we estimate a ARIMAX model with $CRISIS$ as exogenous variable for $LGDP$ and ARIMA for USD.

4.3 Stationarity Testing

Prior to modeling, we conducted a crucial step in time series analysis known as stationarity testing. The Augmented Dickey-Fuller (ADF) test was employed to assess the presence of unit roots in the series. This test is fundamental in determining whether differencing is necessary to make the series stationary, a prerequisite for ARIMA modeling.

4.4 Model Selection

Several competing ARIMA models were estimated for each economic indicator, and the model selection process relied on the Akaike Information Criterion (AIC). The AIC serves as a crucial criterion for model selection, as it balances model fit with complexity, aiming to find the most parsimonious yet effective model for explaining the underlying data.

4.5 Model Evaluation

Once the final ARIMAX and ARIMA models were selected ,respectively, for GDP and the USD exchange rate, we conducted various diagnostic tests to ensure the validity of these models. These tests included checks for white noise in the residuals (utilizing the Box-Pierce test) and normality of residuals (evaluated through the Jarque-Bera test). Model performance was quantified using commonly accepted metrics, including the Root Mean Squared Error (RMSE) and the coefficient of determination (R^2).

4.6 Forecasting

To provide insight into future trends, we utilized the chosen ARIMA models to generate forecasts for the year 2023. These forecasts are valuable for economic planning and decision-making, offering an indication of the expected trajectories of GDP and the USD exchange rate.

In summary, this study adopts a robust methodological framework rooted in ARIMA modeling, following the Box-Jenkins methodology. We rigorously tested for stationarity, selected the most suitable models based on the AIC criterion, conducted thorough model diagnostics, and generated forecasts. These methodological steps ensure the reliability and validity of our analysis and contribute to a comprehensive understanding of the dynamics of GDP and the USD exchange rate.

5 Results

In this section, we present the results of our ARIMAX modeling for the annual Gross Domestic Product (GDP) and ARIMA modeling for the USD exchange rate (USD/MGA) based on data spanning from 1990 to 2021, sourced from the World Bank. We estimate the ARIMAX model corresponding to GDP by using $LGDP$ variable. Our analysis adheres to the Box-Jenkins methodology, encompassing time series transformation, model identification, estimation, diagnostic checking, and forecasting [8].

Table 1 presents the results of the Augmented Dickey-Fuller (ADF) test, which is used to assess the stationarity of the series. It is evident that both the $LGDP$ and the exchange rate (USD) are integrated to order one, denoted as $\Delta LGDP$ and ΔUSD, respectively. This indicates that the orders of two models to estimate takes the form of (p,1,q).

Table 1: Results of Augmented Dickey-Fuller Test (ADF)

	Constant		With Trend	
$LGDP$	-0.7303		-2.2823	
$\Delta LGDP$	-5.0341	***	-4.9379	***
USD	-2.1799		0.2924	
ΔUSD	-4.5203	***	-4.4898	***

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

The GDP is modeled by a ARIMAX(1,1,5) with $CRISIS$ as exogenous variable. And we selected the ARIMA(1,1,1) to modeled USD exchange rate (USD). The model selection process was guided by the Akaike Information Criterion (AIC) . The results of the selected models, including, parameter estimates for the selected models, AIC, Bayesian Information Criterion (BIC), Box-Pierce p-value , Jarque-Bera p-value, Root Mean Squared Error (RMSE), and the coefficient of determination (R^2), are summarized in Tables 2 and 3.

For the GDP estimated model, the coefficients of the autoregressive term (ar1), moving average terms (ma1, ma5) and exogenous terms (crisis) are all highly significant, with p-values close to zero, indicating a strong fit to the data. The R^2 value of 0.969 suggests that the model explains a substantial portion of the variation in GDP.

Similarly, for the USD estimated model , the autoregressive and moving average coefficients are highly significant. The selected model explain the data with a R^2 value of 0.970.

Table 2: Parameter Estimates for LGDP: ARIMAX(1,1,5)

	AR(1)	MA(1)	MA(2)	MA(3)	MA(4)	MA(5)	CRISIS
	0.7645	-0.7739	0.3079	-0.3575	-0.3937	0.6916	-0.1508
s.e.	0.2127	0.2486	0.2409	0.2728	0.2185	0.2042	0.0249
t-stat	3.5946	-3.1132	1.2783	-1.3103	-1.8016	3.3868	-6.0484
p-val	0.0003	0.0019	0.2011	0.1901	0.0716	0.0007	0.0000
R^2	0.969						
$RMSE$	0.0951						
AIC	-35.492						
BIC	-24.019						
Box-Pierces	0.861	(p-value)					
Jarque-Bera	0.903	(p-value)					

Table 3: Parameter Estimates for USD: ARIMA(1,1,1)

	AR(1)	MA(1)
	0.9996	-0.9829
s.e.	0.0031	0.0605
t-stat	318.7575	-16.2576
p-val	0.0000	0.0000
R^2	0.970	
$RMSE$	181.302	
AIC	419.347	
BIC	523.649	
Box-Pierce	0.903	(p-value)
Jarque-Bera	0.12	(p-value)

Table 4 provides forecasts for the year 2023 for both GDP and the USD exchange rate. These forecasts serve as valuable insights for economic planning and decision-making.

Table 4: 2023 Forecasts

	Date	Units	2021	2022	2023
GDP	Forecast	[Billions USD]	14.582	14.781	14.366
	Actual Value	[Billions USD]	14.554	14.954	–
USD	Forecast	[MGA]	3894.45	3935.05	4206.21
	Higher-bound	[MGA]	–	–	4582.18
	Actual Value	[MGA]	3829.98	4096.12	–

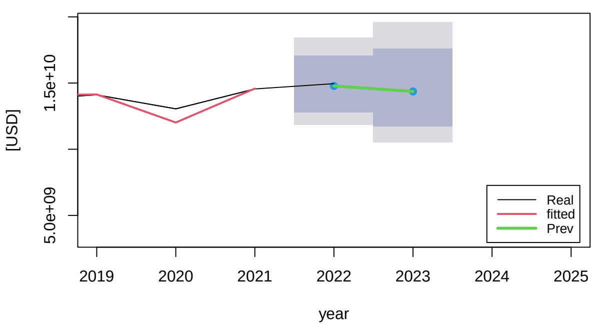

Figure 1: Forecast of Madagascar GDP for 2023

These ARIMA model are adapted than VAR model to forecast GDP and USD. Indeed We notice in the VAR estimation result that the coefficient of determination is low: 0.22 for LGDP equation and 0.21 for that of USD (Tables 5, 6).

Table 5: Parameter Estimates VAR(1) : LGDP

ΔLGDP	ΔLGDPC(-1)	ΔUSD(-1)	CRISIS
	0.2090	0.0003	-0.1048
s.e.	0.2021	0.0001	0.07555
t-stat	1.034	2.588	-1.387
p-val	0.3102	0.0154	0.1766
R^2	0.222		

Table 6: Parameter Estimates VAR(1) : USD

ΔUSD	ΔLGDPC(-1)	ΔUSD(-1)	CRISIS
	569.7621	0.4403	64.3434
s.e.	339.5421	0.1966	126.9266
t-stat	1.678	2.240	0.507
p-val	0.1049	0.0335	0.6163
R^2	0.211		

In conclusion, our ARIMA and ARIMAX models, based on robust methodology, provide valuable insights into the dynamics of GDP and the USD exchange rate. The models exhibit good fit to the data, as indicated by significant parameter estimates and diagnostic tests. The forecasts for 2023 offer a glimpse into the expected trends of these economic indicators. However, it is essential to consider external factors and potential unexpected events in economic analysis.

6 Discussion

In this section, we delve into the implications of our ARIMAX model for Madagascar's Gross Domestic Product (GDP) and ARIMA model for the USD exchange rate (USD/MGA), shedding light on the economic dynamics within the country.

6.1 GDP Modeling and Implications

Our ARIMAX(1,1,5) model for Madagascar's GDP (by $LGDP$) yields valuable insights into the economic performance of the nation. The model's goodness-of-fit measures, including an AIC of -35.492, a BIC of -24.019, a Box-Pierce test p-value of 0.861, and a Jarque-Bera test p-value of 0.903, suggest that the model captures the underlying data patterns. The exogenous part of the estimated model is consistent. The presence of CRISIS in the year affect negatively and significantly the contemporary GDP value.

The model's parameter estimates provide further clarity. The autoregressive terms (AR) capture the influence of past GDP values, while the moving average terms (MA) account for short and middle-term fluctuations. The significant coefficients with p-value close to zero indicate the statistical significance of these terms. The R^2 value of 0.969 implies that the model explains approximately 96.9% of the variance in GDP, signifying a robust explanatory power.

6.2 USD Exchange Rate Modeling and Implications

Our ARIMA(1,1,1) model for the USD exchange rate (USD/MGA) unveils insights into the dynamics of Madagascar's foreign exchange market. With an AIC of 419.347, BIC of 523.649, a Box-Pierce statistic of 0.903, and a Jarque-Bera statistic of 0.120, the model demonstrates its ability to capture the exchange rate's movements.

The parameter estimates for the model reveal that both the autoregressive (AR) and moving average (MA) terms are statistically significant with extremely low p-value. This underscores the model's appropriateness for explaining the fluctuations in the USD exchange rate. The high R^2 value of 0.970 signifies that the model accounts for approximately 97% of the variability in the exchange rate.

Turning to the 2023 forecast (Table 4), we anticipate the USD/MGA exchange rate average to reach approximately 4206.21 MGA; and in the worst case, its can reach to 4582.18 MGA. This forecast offers valuable information for businesses engaged in international trade and foreign investments. However, similar to GDP forecasting, it is essential to consider external factors and global economic events when interpreting this prediction.

6.3 GDP for 2022

On the one hand, the year 2022 was marked by economic momentum, despite the challenges posed by the disruption caused by tropical storms and cyclones, as well as the conflict between Russia and Ukraine. This momentum can be partly attributed to the strength of the mining sector, mainly due to the rise in global commodity prices. These higher prices are the result of the acceleration of the energy transition which has generated substantial growth in global demand .Particularly for graphite,cobalt and nickel due to their usefulness in electric car bateries in the context of the electric vehicle market.(figure3, figure2)

More specifically, cobalt and nickel exports expanded significantly over this period, both in terms of value and volume (figure 4, Figure 5). In 2022, revenues generated by cobalt exports reached 896 billion Ariary, while those linked to nickel reached 3,570 billion Ariary. By comparison, these figures were 406 billion and 1,943 billion Ariary respectively in 2021. This remarkable rise testifies to the growing importance of these raw materials in today's economic landscape, despite external circumstances that may have influenced the course of events.

It should also be noted that the expansion of exports of plant-based products, in particular cloves, can also be seen as a factor contributing to this increase. Indeed, the value of these exports has risen to 1,121 billion Ariary in 2022, compared with 432 billion Ariary in 2021.

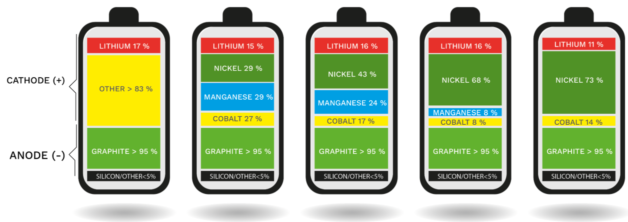

Figure 2: Components of the lithium battery

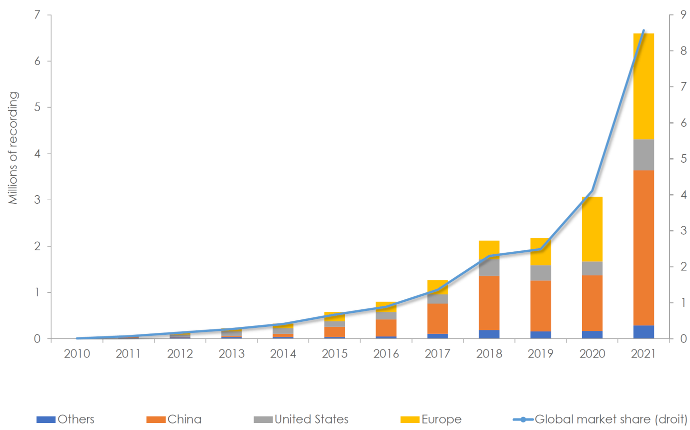

Figure 3: Global sales and market share of electric cars,2020-2021 in %

6.4 GDP Forecast for 2023

Our ARIMAX(1,1,5) model projects a GDP of 14.366 billion USD for the year 2023, while the actual GDP for 2022 stood at 14.954 billion USD. This projection

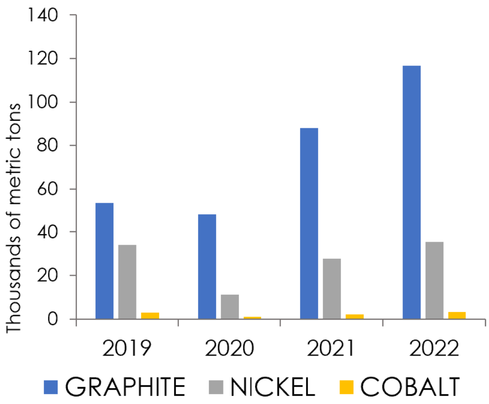

Figure 4: Mineral exports in Madagascar
source: Direction Générale de la Douane-Madagascar

suggests a decrease in GDP for the upcoming year, a phenomenon that warrants a closer examination in the context of Madagascar's economic landscape (Figure 1).

There are several economic factors contributing to this forecasted decrease:

6.4.1 Political Context with Upcoming Presidential Elections

Madagascar is currently gearing up for presidential elections, a critical event that often introduces political uncertainty. As elections draw near, the private sector tends to adopt a cautious stance, delaying investments and economic activities until the political landscape stabilizes. This cautious approach can potentially hamper economic growth and create uncertainty in the business environment.

6.4.2 Extension of the Conflict in Ukraine

The protracted conflict in Ukraine continues to cast a shadow of uncertainty on the global stage. Its ramifications extend far beyond geopolitical boundaries, affecting international trade, commodity prices, and financial markets. Madagascar, as an active participant in the global economy, is not immune to these uncertainties, which can have far-reaching effects on its economic prospects.

6.4.3 Electricity Shortages

Madagascar has long grappled with frequent electricity shortages, a chronic issue that disrupts the nation's production capabilities especially in the first half of 2023. These interruptions can have adverse effects on manufacturing and industrial sectors, posing challenges to GDP growth.

6.4.4 Decline in Exports of Cash Crops

There has been a decline in the exports of cash crops, with a notable drop of 16.8% in volume and a more substantial decline of 39.8% in value[1], especially in vanilla and cloves for the first half of 2023 compare to last year (figure 5 [2]). This decline in cash crop exports can be attributed to various factors, including international market dynamics and agricultural challenges.
Indeed, it is clear that the value of vanilla exports has fallen considerably, in terms of both value and volume. While the first half of 2022 recorded 2,064 billion Ariary, it was only 950 billion Ariary in 2023, a phenomenon engendered by the significant reduction in the quantity exported, a direct result of the postponement of the launch of the export campaign during the first quarter.
In the case of cobalt, there was also a decline in exports, particularly in terms of price, as the first half of 2023 was worth 189 billion Ariary, compared with 516 billion Ariary in 2022, highlighting a significant contraction in this market segment.

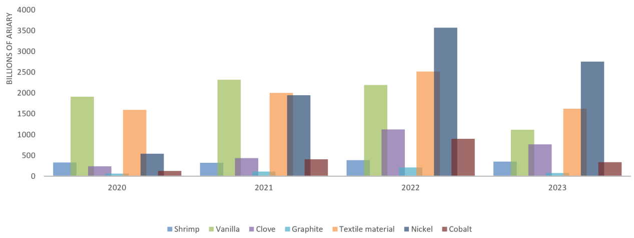

Figure 5: Exports of Madagascar in Billions of Ariary (2020-2021-2022-2023)
source: Direction Générale de la Douane-Madagascar

6.4.5 Risk of Recession in Key Sectors

The potential risks of recession loom over key sectors such as mining and textiles. Technological advancements, like sodium-ion technology, may reduce the demand for minerals like graphite, impacting the mining industry. Additionally, the closure or judicial reorganization of clothing and textile brands in Europe and France can negatively affect Madagascar's textile exports and industrial activities.

[1]Source: MEF Direction générale de la douane, Madagascar
[2]Data 2023: january to august

6.4.6 Possibility of contraction in Transportation Activities

There is a potential contraction in transportation activities, as the Madagascar Oil Marketing Hub (OMH) anticipates a 3% reduction in diesel consumption, which constitutes a significant portion (77%) of the total fuel consumption in Madagascar. This decline in fuel consumption can affect transportation and logistics sectors.

6.4.7 Possibility of neutrality effect on GDP for the Indian Ocean Island Game

The indian Ocean island Games, hosted by Madagascar in 2023,an event that had a multifaceted impct on its economy. In the short term, the games stimulated tourism,leading to increased revenue in the hospitality and restaurant sectors, thereby contributing to temporary economic growth. However, the long-term effects hinged on the management of investment in infrastrucutre and sports facilities post-event. If handled effectively, these assets could have bolstered the country's tourism and sports capacities, potentially supporting sustained economic growth. Nonetheless, its's essential to acknowledge the possibility that the games had no significant effect on Madagascar's GDP, as various economic factors could have offset any short-term gains.

7 Conclusion

In this study, on the one hand, we employed an extension of ARIMA (ARIMAX) with CRISIS variable as exogenous modeling to analyze and forecast Madagascar's Gross Domestic Product (GDP). On the other hand, we used ARIMA model for the USD exchange rate (USD/MGA). We used data from 1990 to 2021 to estimate the models. Our investigation, rooted in the Box-Jenkins methodology, yielded valuable insights into Madagascar's economic dynamics.

The analysis of GDP revealed a consistent growth trend with short-term fluctuations. The selected ARIMAX(1,1,5) model exhibited strong statistical performance with R-squared value of 0.969, indicating its effectiveness in capturing GDP variations. The 2023 GDP forecast, while suggesting a modest decline, warrants consideration alongside external factors, including the potential impact of political uncertainties surrounding Madagascar's upcoming presidential elections, global instability stemming from the ongoing Ukraine conflict, and persistent challenges such as electricity shortages. These external factors can play a crucial role in influencing economic outcomes beyond the scope of the ARIMAX model's historical data.

For the USD exchange rate, the ARIMA(1,1,1) model demonstrated relative stability. With a high R-squared value of 0.970, the model accurately captured exchange rate movements. The projected appreciation of the Malagasy Ariary (MGA) against the USD in 2023 is noteworthy. However, it should be interpreted cautiously, considering potential external shocks and the upcoming presidential elections, both of which may introduce economic and political uncertainties.

While ARIMA and his extension ARIMAX models have proven valuable, it's essential to acknowledge the broader landscape of econometric forecasting tools. Beyond ARIMA, other econometric methods, such as Vector Autoregression (VAR), GARCH models, or machine learning algorithms, can offer complementary perspectives for forecasting economic variables. Combining diverse methodologies can enhance the robustness of predictions and provide more comprehensive risk assessments.

In summary, our ARIMA models offer valuable tools for economic analysis and forecasting in Madagascar. They provide a quantitative foundation for understanding economic trends. However, we encourage policymakers and researchers to explore a spectrum of econometric tools to gain a more holistic view of economic dynamics. Such an approach can help in better anticipating and preparing for the intricacies of Madagascar's evolving economic landscape.

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