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Examining the Impact of Covid-19 and Economic Indicators on US GDP using Midas- Simulation and Empirical Evidence

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Abstract

In this study, we demonstrate the impact of the COVID-19 pandemic on the US GDP growth rate for the period 2000–2020. Other economic variables of different frequencies such as consumer price index, crude oil prices, exchange rate, unemployment rate, interest rate, export, import, government expenditure, and consumer confidence are considered in this study. In carrying out the analysis, we compare three approaches—the autoregressive distributed lag-unrestricted mixed data sampling (ADL-UMIDAS) model and autoregressive distributed lag-restricted mixed data sampling (ADL-RMIDAS) model with both exponential Almon and beta functions to the autoregressive distributed lag (ADL) model. Using a comprehensive simulation study, we examine the sensitivity of forecasting approaches to model misspecification. The efficiency of the ADL-UMIDAS model and ADL-RMIDAS model with both exponential Almon and Beta functions to the ADL model is computed throughout the simulation processes using the root mean square error (RMSE). Out-of-sample empirical and simulation analysis showed that the ADL-RMIDAS (Exponential Almon) model outperforms other competing models. The main finding shows that the COVID-19 pandemic has had a statistically significant positive effect on the US GDP growth rate.

Keywords: *Forecasting; MIDAS; ADL; ADL-RMIDAS; Simulation; GDP.*

1. INTRODUCTION

Estimating and predicting the future of economic time series, particularly significant variables like gross domestic product (GDP), presents a formidable challenge. GDP, which serves as a measure of a country's economic progress in terms of output and earnings over a given period, is typically calculated annually or quarterly in some cases. However, its frequency clashes with that of other economic indicators employed in forecasting. While GDP figures are released quarterly, other indicators may follow different publication schedules. Furthermore, accurate forecasts often necessitate estimating multiple parameters, leading to potential over-parameterization and further complexity. Effectively forecasting economic time series demands skillful navigation of

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these challenges to inform sound economic policymaking, especially for fast-paced economies like the United States (US), where GDP plays a vital role in evaluating the overall economic system (Hassan, 2011).

In measuring the GDP, it is important to consider the changes that occur to the price levels in the economy as measured by the consumer price index (CPI). The CPI is a key indicator of the country's inflation, deflation, and stagflation. Consequently, GDP and CPI significantly impact one another, according to another (Katircioglu, Sertoglu, Candemir, & Mercan, 2015). The CPI and the GDP price indexes represent alternative measures of inflation in the US economy, as stated by the Bureau of Labor Statistics (BLS). Therefore, the use of the CPI or GDP deflator is likely determined by the set of goods and services whose price changes are being measured. The two measures have a direct relationship, and only steady growth can offset their long-term effects on each other. Inflation also plays a vital role in tracking interest rates, as an increase in interest rates encourages higher savings compared to spending, leading to a decline in the Consumer Price Index (CPI) which then impacts Gross Domestic Product (GDP), according to (Saymeh & Orabi, 2013). (Wesołowski, 2018) empirically demonstrates the substantial impact of interest rates on GDP, especially in small economies. Similarly, there is a positive, albeit nonlinear, relationship between oil prices and GDP, as stated by (Jiménez-Rodríguez & Sánchez, 2005). Oil price fluctuations directly influence GDP, notably in oil-producing countries, given oil's significant role in the global and US economies. Although crude oil prices declined during the COVID-19 period, they are currently rebounding rapidly. Per (Arezki, Jakab, Laxton, & Matsumoto, 2017), short-term oil prices are elastic while long-term effects on GDP growth are substantial due to the time needed to meet oil demand. Unemployment also notably impacts GDP, as Okun's law (Okun, 1992) suggests a 1% decrease in unemployment leads to a 3% increase in Gross National Product (GNP) according to (Prachowny, 1993). However, these trends have varied over time, prompting proposals that GDP must exceed the employment rate to effectively reduce unemployment, as stated by (Mussida & Zanin, 2022). In the long run, increased unemployment detrimentally affects GDP growth by limiting expansion, as explained by (Hjazeen, Seraj, & Ozdeser, 2021).

The import and export activity of a country can affect its GDP, exchange rate, inflation, and interest rates. A trade deficit occurs when imports exceed exports; usually, when a country runs a trade deficit, it must borrow money from other countries to cover the additional imports (Kallianiotis, 2022). In the case of COVID-19, the pandemic increased demand for medical supplies and encouraged export growth, and government intervention boosted imports and exports (Wei, Jin, & Xu, 2021). This clearly demonstrates the effect of imports and exports on GDP for a short period of time. (Macek, 2014) shows that government expenditure has a negative long-run effect on GDP, whereas (Kneller, Bleaney, & Gemmell, 1999) show that government expenditure has a positive long-run effect on GDP. This contradiction stems from the fact that these authors studied "non-productive" and "productive" expenditures separately (Kutasi & Marton, 2020). They also emphasize that productive expenditures have both short- and long-term positive effects on GDP, whereas non-productive expenditures have a short-term positive effect and a long-term negative effect; therefore, the sign of government expenditure is ambiguous. According to (Islam & Mumtaz, 2016), the consumer confidence index has a direct relationship with GDP and can be used to predict GDP in the short run. In the long run, however, consumer behavior fluctuates greatly due to external and global factors, making it a poor predictor of GDP (Mourougane & Roma, 2003).

COVID-19 has had a profound effect on all levels of the economy. (Andersen, Emil, Niels, & Adam, 2020) and (Teresiene, et al., 2021) investigated its effects on the economy as a whole and on consumer sentiment. COVID-19 made several industries volatile, including oil (Bourghelle, Jawadi, & Rozin, 2021), and caused fluctuations in commodity prices (Ahmed & Sarkodie, 2021). The COVID-19 pandemic positively impacted inflation expectations and price volatility in the US and other countries, according to (Apergis & Apergis, 2021), (Safi, Sanusi , & Tabash, 2022) and (Sanusi, Safi, Adeeko, & Tabash, 2022). According to (Fezzi & Fanghella, 2020), the negative COVID-19 effect on GDP is only temporary. Although certain industries like tourism and hospitality were severely affected, the situation stabilized as governments supported medium and heavy industries during lockdowns, allowing production continuity that benefited GDP and minimized the pandemic's impact, as explained by (Taylan, Alkabaa, & Yılmaz, 2022).

(Chang, Baloch, Saydaliev, Hyder, & Dilanchiev, 2022) examined GDP, CPI, and unemployment rates in China, Europe, and the US, concluding their economies had recovered from COVID-19's negative effects. Interestingly, inflation has been higher in the US than in other countries, as stated by (Jordà, Liu, Nechio, & Rivera-Reyes, 2022). However, many countries still suffer COVID-19 effects. According to (Mustaffa, Zainal Abidin, Ahmad, & Ogundare, 2021) and (Zulkarnain & Nawi, 2023), COVID-19 significantly impacted unemployment, GDP, CPI, and the foreign exchange rate in Malaysia.

Despite the world recovering from COVID-19, there have been short-, medium-, and long-term consequences for the global economy (Chen, 2022), an issue policymakers are currently focused on. GDP forecasting is a major government and policymaker responsibility since it is key for macroeconomic forecasting (Roubini & Sachs, 1998). GDP changes reflect a country's economic situation and primarily track real overall economic growth and inflation (Landefeld, Seskin, & Fraumeni, 2008). However, major challenges in GDP forecasting studies include the different reporting times of explanatory variables and diverse economic and non-economic crises occurring globally (Lu, Ma, Bouri, & Fei, 2022). With less information, the forecasting error enlarges (Dias, Pinheiro, & Rua, 2015). Forecasters face significant challenges due to varied data frequencies of numerous economic variables used to estimate and predict GDP. Unlike classical linear models requiring equal variable frequencies, the Mixed Data Sampling (MIDAS) model introduced by (Ghysels, Santa-Clara, & Valkanov, 2004) and (Ghysels, Sinko, & Valkanov, 2006b) is widely applicable in macroeconomics and finance because it effectively samples macroeconomic variables with different frequencies without losing information to data aggregation. In some cases, using common and alternative GDP measures can provide evidence to validate or invalidate researcher claims. Using the most appropriate model, this study investigates developing predictive relationships between various macroeconomic variables and GDP. Recently, research has focused on the US, European countries, and China's economies.

This study makes three key contributions, especially to the US as the world's leading economic engine. First, we use various MIDAS approaches to estimate COVID-19's impact on quarterly US GDP, not just to determine MIDAS forecasting performance as in many previous studies, but to present the best model's coefficient estimation, which no known previous study has done. Second, in addition to identifying the characteristics of economic variables most likely to influence GDP growth, we determine which indicators significantly impact US GDP growth and quantify their effect. Third, while previous studies only used empirical data to find the best model, we conducted a simulation study to validate the empirical best model based on simulation forecasting accuracy and coefficient estimation. The simulation investigates and compares the effectiveness and robustness of different MIDAS techniques.

This paper is structured as follows: Section 2 presents the literature review. Section 3 outlines the MIDAS model methodologies. Section 4 provides the data description. Section 5 covers the simulation study. Section 6 presents the empirical study findings. Finally, Section 7 offers conclusions and suggestions for future work.

2. LITERATURE REVIEW

Several researchers have used various methods to estimate GDP, but the results have been largely inconclusive due to methodological limitations. (Agu , Onu, Ezemagu, & Oden, 2022) forecast GDP using principal component regression (PCR), ridge regression (RR), lasso regression (LR), and ordinary least squares (OLS). (Pradhan, Arvin, & Ghoshray, 2015) use a panel vector autoregressive model to determine the direction of Granger causality for GDP, oil prices, stock prices, exchange rate, inflation rate, and real rate of interest in the G-20 countries. They demonstrate that, in the long run, GDP converges to its equilibrium path in response to changes in its regressors, and that most variables, including GDP, have bidirectional causality in the short run.

(Kembe & Onoja, 2017), used a two-step non-hierarchical cluster analysis to predict the combination of 13 macroeconomic variables that are significant in estimating Nigeria's GDP. They discover that all cluster combinations are nearly equally successful in determining GDP. (Oluwafemi & Laseinde, 2019) used the auto regressive distributed lag method to investigate the impact of foreign direct investment, interest rates, government expenditure, inflation rate, exchange rate, and trade openness on real GDP. They demonstrate that differences in estimating real GDP are caused by variations in the independent variables examined. (Chowdhury, Hamid, & Akhi, 2019) used correlation and multiple regression analysis to estimate the GDP of Bangladesh, and showed that 75.6% of the variation in GDP is explained by the macroeconomic variables considered in the study.

(Michael & Ana, 2008) investigate whether a mixed data-frequency sampling (MIDAS) approach can improve GDP growth forecasts. They discovered that using monthly data on the current quarter improves forecasting of current and next quarter output growth significantly and that MIDAS is an effective way to exploit monthly data when compared to alternative methods. Most of the time, the dependent variable is sampled at a lower frequency, but in some cases, such as (Ghysels, Santa-Clara, & Valkanov, 2006a), MIDAS has been used for high-frequency financial data. (Clements & Galvão, 2008) extended the distributed-lag MIDAS specification to include an AR term (the MIDAS-AR) and demonstrated how this model can be used in forecasting. Following this, several combinations and variants of the MIDAS model, particularly with ARCH and GARCH models, have been used, according to a detailed review by (Petropoulos, et al., 2022). (Lu, Ma, Bouri, & Fei, 2022) forecast the GDP growth rate using the MIDAS-LASSO model and a large number of economic indicators. The results show that the MIDAS-LASSO model performs significantly better than other competing models.

A simple linear lag polynomial underpins the Unrestricted MIDAS (UMIDAS) model. It has more flexibility than the polynomials functional in the standard MIDAS approach, according to (Armesto, Engemann, & Owyang, 2010). They demonstrated that, in some cases, simply averaging the higher-frequency data produces no disadvantage. In other cases, using the MIDAS model may be more beneficial to researchers, particularly when creating intra-period forecasts. However, if the lag order is large, UMIDAS must estimate many parameters, which increases the difficulty of interpretation. By introducing the Markov-switching mixed data sampling model with unrestricted lag polynomial model, (Barsoum & Stankiewicz, 2015) incorporated the business cycle effect in the forecasting of US GDP (MS-UMIDAS). They discovered that when the frequency difference is small, such as when detecting the dynamic relationships between monthly and quarterly data, a few lags are required—also see (Claudia, Marcellino, & Schumacher, 2011).

Factor MIDAS was proposed by (Marcellino & Schumacher, 2010) as a mixed-data sampling method. They used monthly indicators to forecast quarterly GDP growth in Germany. MIDAS with exponentially distributed lag functions performed similarly to MIDAS with unrestricted lag polynomials, according to the results. Furthermore, (Andreou, Ghysels, & Kourtellos, 2013) forecasted GDP in the US using financial data and the MIDAS model. They discovered that MIDAS regression models based on daily financial data via daily financial assets or factors improved quarterly forecasts of US real GDP growth, particularly during crisis periods.

(Rusnák, 2016) uses the dynamic factor model to forecast the Czech GDP, considering the lag in predictor variables. They did not, however, compare the forecasting performance of their model to the MIDAS model. (Jiang , Guo, & Zhang, 2017), forecast China's GDP using a combination of the dynamic factor model and the MIDAS regression. The dynamic factor model is used to choose appropriate monthly and daily indicators, while MIDAS is used for forecasting. They demonstrate that selecting factors produces better results than using single indicators, and that MIDAS works better in combination than simple linear regression for a single indicator.

According to (Kim & Swanson, 2018), factor-MIDAS prediction models outperform various linear benchmark models. (Mariano & Ozmucur , 2020) used various versions of MIDAS to estimate the Philippine GDP. Their results were inconclusive, indicating that there was no clear winner among the various models. However, (Gunay, Can, & Ocak, 2020) discovered that the MIDAS-Almon method provides better accuracy when testing the effect of the COVID-19 pandemic on China's GDP, considering factors such as export sales, China's foreign-exchange reserves, the US dollar-Chinese yuan exchange rate, and the Brent crude oil price.

Unlike previous studies that determine the best model empirically, we carried out a simulation study to validate the best model based on forecasting accuracy and to compare the effectiveness of various MIDAS techniques.

3. METHODOLOGY

The time-averaging model is the simplest method for time aggregation, according to (Armesto, Engemann, & Owyang, 2010). It converts higher-frequency data to match the observations of the lower-frequency data by computing the simple average of the observations of the high-frequency variable that occur between samples of the lower-frequency variable.

The regression model of Y_t on its own lags (p) with $\overline{X}_t$ and its lags (q) is called the autoregressive distributed lag model of order p and q (ADL(p,q)) as suggested by (Elena, Ghysels, & Kourtellos, 2010); it is given by:

$$Y_t = \alpha + \sum_{i=1}^{p} \beta_i L^i Y_t + \sum_{k=0}^{q} \gamma_k L^k \overline{X}_t + \varepsilon_t,$$

where, γ_k are the coefficients of the time-averaged X's, and ε_t is the white noise process (independent identically distributed random variables with zero mean and constant variance).

$$\overline{X}_t = 1/m \sum_{k=0}^{m-1} L^{k/m} \; X_t^{(m)}, \quad \text{where:} \qquad L^{\frac{k}{m}} X_t^{(m)} = X_{t-(k/m)}^{(m)}.$$

The time-averaging model discards a lot of potentially useful information because of equal-weights assigning; as a result, the relationship between the variables will be less accurate, (Arthur, 2008). (Armesto, Engemann, & Owyang, 2010) presented the step-weighting or unrestricted mixed data sampling regression (U-MIDAS) model that gives each lag of the high-frequency regressor a different weight; it is given by:

$$Y_t = \alpha + \sum_{i=1}^{p} \beta_i L^i Y_t + \sum_{k=0}^{m-1} \gamma_k L^{k/m} X_t^{(m)} + \varepsilon_t.$$

This equation is called an autoregressive distributed lag model (ADL(p,m)-UMIDAS) because the low-frequency regressand is regressed on its own lags with the high-frequency regressor and its lags.

(Ghysels, Santa-Clara, & Valkanov, The MIDAS Touch: Mixed Data Sampling Regression Models, 2004) propose the MIDAS model, which is based on a distributed lag model: instead of estimating the coefficient on each lag of the high-frequency regressor, the model assigns weights to the lags according to a polynomial function as follows:

$$Y_t = \alpha + \sum_{i=1}^{p} \beta_i L^i Y_t + \gamma \sum_{k=0}^{m-1} \phi(k;\theta) L^{k/m} X_t^{(m)} + \varepsilon_t,$$

where, $\phi(k;\theta)$ is a polynomial function of the lag number k, and θ is a small set of hyperparameters that determine the shape of the function. For the same reason as mentioned above, this equation is called an autoregressive distributed lag model (ADL(p,m)-RMIDAS).

In practice, the function $\phi(k;\theta)$ can be any type of polynomial function but two common functional forms are the exponential Almon function and the beta formulation. The proper selection of the polynomial functional allows for the assignment of few parameters to a large number of lags, implying a simple interpretation of results (Armesto, Engemann, & Owyang, 2010).

(Ghysels, Santa-Clara, & Valkanov, 2005) and (Ghysels, Sinko, & Valkanov, MIDAS Regressions: Further Results and New Directions, 2006b) suggest an exponential Almon specification:

$$\phi(k;\theta_1,\theta_2) = \frac{\exp(\theta_1 k + \theta_2 k^2)}{\sum_{j=1}^{m} \exp(\theta_1 j + \theta_2 j^2)}.$$

Here, simple time averaging is obtained when $\theta_1 = \theta_2 = 0$.

Empirical applications are usually based on two parameters, which simplifies the model but still ensures flexibility in the specification of the shape of the polynomial. The most used function for the lag polynomial in MIDAS models is the exponential Almon function.

Once the model is extended to multiple lags of the predictor X, the most general model is given by:

$$Y_t = \alpha + \sum_{i=1}^{p} \beta_i L^i Y_t + \gamma \sum_{k=0}^{n*m-1} \phi(k;\theta) L^{k/m} X_t + \varepsilon_t .$$

In this generalization, lags of the predictor are included by expanding the weighting polynomial. The second polynomial specification is the Beta function, with its formulation as follows:

$$B(k;\theta_1,\theta_2) = \frac{f(k/m;\theta_1,\theta_2)}{\sum_{k=0}^{m} f(k/m;\theta_1,\theta_2)},$$

where,

$$f(x;\theta_1,\theta_2) = \frac{x^{\theta_1-1}(1-x)^{\theta_2-1}\Gamma(\theta_1+\theta_2)}{\Gamma(\theta_1)\Gamma(\theta_2)} \quad , \quad \Gamma(\theta) = \int_0^\infty e^{-x} x^{(\theta-1)} dx.$$

We empirically perform in-sample and out-of-sample analysis and compare various techniques—autoregressive distributed lag-unrestricted mixed data sampling regression (ADL-UMIDAS) model and autoregressive distributed lag-restricted mixed data sampling regression (ADL-RMIDAS) model with the exponential Almon and beta functions to our bench-mark model, namely the autoregressive distributed lag (ADL) model, and discuss in detail the best model based on the simulation and the empirical study.

4. DATA DESCRIPTION

In this study, we build a quarterly GDP growth model with US data for the period 2000 to 2020, collected from the fred.stlouisfed.org website. Included in this model are the COVID-19 dummy variable as well as monthly and quarterly economic variables. The monthly economic variables are CPI, crude oil price, exchange rate, unemployment rate, interest rate, export, and import. The quarterly economic variables are government expenditure and consumer confidence. The analysis is performed using the midasr R package created by (Ghysels, Kvedaras, & Zemlys, 2016). Table 1 describes the different variables used in the study to construct the MIDAS models. The growth of the world economy has shown a declining trend since the COVID-19 pandemic. At the start of 2020, the pandemic caused a sharp decline in the US GDP growth rate, followed by recovery.

Variables	Abbrev.	N	Min.	Max.	Mean	SD.
Gross domestic product	GDP	84	10002	21707	15555	3426.57
Government expenditure	Expend	84	768599	2727605	1361640	368550
Consumer confidence	CC	84	57.7	110.1	85.58	11.897
Exchange rate	Exch	252	0.85	1.577	1.206	0.16
Unemployment rate	Unem	252	3.3	14.4	5.987	1.99
Interest rate	Int	252	0.62	6.66	3.311	0.163
Export	Exp	252	53149	150361	103694	29242.89
Import	Imp	252	82542	237646	162770	39550.22
Consumer price index	CPI	252	168.8	260.4	217.4	26.53
Crude price	Cru	252	16.6	133.9	60.67	26.07
COVID-19	Dummy variable: 0 for the period Jan. 2000 – Jan. 2020 1 for the period Feb. 2020 – Dec. 2020					

Table 1: Descriptive statistics for the variables

Figure 1 shows the US GDP growth rate before COVID-19 (Jan. 2000 – Jan. 2020) and after COVID-19 (Feb. 2020 – Dec. 2020). At the start of 2020, the pandemic caused a sharp decline in US GDP growth rate, but it has since recovered.

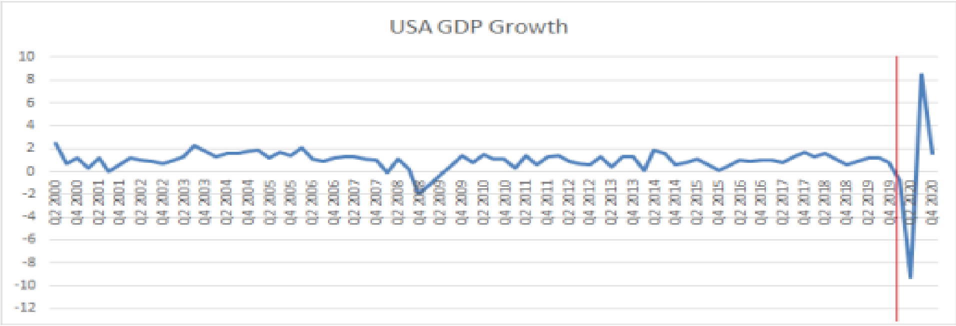

Figure 1: US GDP growth rate before and after COVID-19

Net export variable (NetExp) has been used, rather than the export and import variables each separately, due to the existence of high correlation between them. The growth rate for the GDP (GDPG) is calculated as follows:

$$\mathrm{GDPG_t} = \log\left(\frac{\mathrm{GDPG_t}}{\mathrm{GDPG_{t-1}}}\right) * 100\%.$$

Similarly, we take the growth rate for the CPI variable. The first lag of the growth GDP is considered using the equation $\mathrm{DGDG1L_t} = \mathrm{GDPG_{t-1}}$. In addition, the second lag of the growth rate GDP is implemented using the equation $\mathrm{DGDG2L_t} = \mathrm{GDPG_{t-2}}$.

The Phillips-Perron test of (Peter, Phillips, & Perron, 1988) is used to examine the variables' stationarity. The null hypothesis states that the variable under study contains a unit root, as opposed to the alternative hypothesis, which states that the variable does not contain a unit root. If the probability is lower than 0.05, the null hypothesis is rejected, indicating that the variable is stationary.

The results show that the GDP and CPI growth rates are stationary at the 0.05 significant level, and all other variables are stationary after controlling for the first difference, as shown in Table 2.

Variable	P-value	Integrated Order
GDPG	< 0.01	I (0)
CPIG	< 0.01	I (0)
Cru	< 0.01	I (1)
Exch	< 0.01	I (1)
NetExp	< 0.01	I (1)
Int	< 0.01	I (1)
Unem	< 0.01	I (1)
CC	< 0.01	I (1)
Expend	< 0.01	I (1)

Table 2: P-value of Phillips-Perron test and the integrated order for the variables

When choosing models, it is common to use a portion of the available data for estimating (or training) the model, and the rest of the data to measure the forecasting performance. Therefore, we divide the data into in-sample training data and out-of-sample testing data. We take 75% of the data as in-sample period from Jan. 2000 – Sep. 2015, and the remaining 25% is considered as the out-of-sample period from Oct. 2015 to Dec. 2020.

First, we estimate the in-sample GDP growth rate using time trend, first and second lag of GDP growth rate, CPI growth rate, and the other independent variables. Then we use the in-sample coefficients' estimations to forecast the out-of-sample GDP growth rate. Second, we compare the forecasts of these models with the true observed GDP growth rate values using the forecasting criteria. Third, we use the best model to estimate the variables' coefficients for the overall period and determine their significant effects on the GDP growth rate.

The selection of the best forecasting model is chosen by adopting the mean absolute error (MAE), root mean standard error (RMSE), residual standard error (RSE), and the relative efficiency (ρ).

RMSE is considered an appropriate criterion if the data is free of extreme values, while MAE is superior in the presence of outliers, (Hyndman & Koehler, 2006). The relative efficiency of the ADL-MIDAS models to the ADL bench-mark model in terms of the MAE, ρ, is given by:

$$\rho = \frac{\mathrm{MAE_m}}{\mathrm{MAE_b}}$$

where $\mathrm{MAE_m}$and $\mathrm{MAE_b}$ are the MAE from the different ADL-MIDAS models to the ADL bench-mark model. The same is applicable to the RMSE relative efficiency.

5. SIMULATION STUDY

To assess the predictive performance of the MIDAS model, we simulate the data from the ADL benchmark model using the simulate function from the midasr package. It simulates the responses from the distribution corresponding to a fitted model, and assumes that the independent variable and coefficients are fixed; only the regression innovators are simulated via bootstrap. We use this simulation design not only to assess the forecasting performance but also to compare the empirical and simulation results. Most previous studies test the forecasting performance solely using empirical data, and to the best of our knowledge, there is no simulation study applying the MIDAS models—except (Babii, Ghysels, & Striaukas, 2020), who implemented simulation for the MIDAS-LASSO model. Here, we conduct 1000 simulations using the same sample size as the initial empirical study.

Table 3 shows the RSE, RMSE, MAE, relative efficiency, and the p-value of the Kolmogorov-Smirnov (KS) test of the four models for the simulated out-of-sample period. Based on the p-value of the KS normality test, the residuals of the ADL-UMIDAS model are not normal; therefore, the MAE forecasting criterion is used for the best model selection. Depending on the MAE criteria, the ADL-RMIDAS (Exp. Almon) is the best model for the out-of-sample analysis. Considering MAE, the relative efficiency of the ADL-RMIDAS (Exp. Almon) to the ADL model equals 0.81, this indicates that the relative efficiency for ADL-RMIDAS (Exp. Almon) equals 81% that of the ADL model and an improvement in performance by 19%.

Out-of-sample	RSE	RMSE	MAE	R.E. (ρ)	KS
ADL Model	4.684	4.214	2.168	-	0.33
ADL-UMIDAS	4.214	3.792	2.409	1.11	0.02
ADL-RMIDAS (Exp. Almon)	3.863	3.475	1.751	0.81	0.23
ADL-RMIDAS (Beta)	4.788	4.308	2.071	0.96	0.22

Table 3: The RSE, RMSE, MAE, relative efficiency, and the p-value of KS test

6. EMPIRICAL STUDY

After estimating the in-sample GDP growth rate using time trend, first and second lag of GDP growth rate, CPI growth rate, and the other independent variables (except COVID-19 dummy variable) and using the in-sample coefficients estimations to forecast the out-of-sample GDP growth rate, we compare the forecasting values of these models with the true observed GDP growth rate values using the forecasting criteria; see Table 4. Based on the p-value of the KS normality test, the residuals of the ADL-UMIDAS model and the ADL-RMIDAS (Beta) model are not normal. Therefore, the MAE forecasting criterion is used for the best model selection.

Table 4 presents the RSE, RMSE, MAE, relative efficiency, and the p-value of the KS test of the four models for the out-of-sample period. Depending on the MAE criteria, the ADL-RMIDAS (Exp. Almon) is the best model for the out-of-sample analysis. This result is consistent with (Gunay, Can, & Ocak, 2020), who show that the RMIDAS (Almon) method offers better accuracy when testing the effect of the COVID-19 pandemic on GDP. Considering MAE, the relative efficiency of the ADL-RMIDAS (Exp. Almon) to the ADL model equals 0.992; this indicates that the relative efficiency for ADL-RMIDAS (Exp. Almon) equals 99.2% of the ADL model, and the performance is improved by 0.8%. Therefore, it is regarded the best model, and its estimated coefficients are discussed in detail. The best model ADL-RMIDAS (Exp. Almon) has been estimated for the overall period, and the COVID-19 dummy variable is included.

Out-of-sample	RSE	RMSE	MAE	R.E.	KS
ADL Model	5.349	3.502	1.559	-	0.27
ADL-UMIDAS	5.095	3.335	2.169	1.39	< 0.001
ADL-RMIDAS (Exp. Almon)	5.059	3.312	1.547	0.992	0.47
ADL-RMIDAS (Beta)	4.838	3.167	1.575	1.01	0.04

Table 4: RSE, RMSE, MAE, relative efficiency, and the P-value of the KS test

To assess multicollinearity in the ADL-RMIDAS (Exp. Almon) model, which is a weighted model, the variance inflation factor (VIF) used for the unweighted model can be used to provide an estimate. Accordingly, the VIF for the unweighted benchmark (ADL) model is calculated in Table 5 to obtain an idea about the VIF for the ADL-RMIDAS model. The findings indicate that all variables in the ADL model have a VIF of less than 10, indicating a low level of correlation.

Variable	VIF	Variable	VIF	Variable	VIF	Variable	VIF
Trend	1.3	CPIG	3.4	NetExp	2	CC	1.6
GDPG1L	1.4	Cru	4	Int.	1.5	Expend	9.4
GDPG2L	2.9	Exch.	1.8	Unem.	7.8	COVID-19	2.3

Table 5: The VIF for the ADL-RMIDAS model (Exp. Almon)

The estimated coefficients for all variables over the entire data period in the ADL-RMIDAS (Exp. Almon) model are presented in Table 6. The residuals' autocorrelation was assessed using the Durbin-Watson (D.W.) test, which indicated no serial correlation, as the D.W. value was close to 2 at 1.7. The R-square value of 0.92 suggests that approximately 92% of the variance in the GDP growth rate can be explained by the selected independent variables. The selected model's residuals were found to be stationary, with a p-value less than 0.01, as confirmed by the Phillips-Perron (PP) test. Furthermore, the homoscedasticity of residuals was confirmed, as indicated by the ARCH test's p-value of 0.31.

Parameters	Estimate	Std. Error	P-value
Intercept	1.141	0.169	0.3e-8 ***
Trend	- 0.007	0.002	0.005 **
GDPG1L	- 0.104	0.043	0.008 **
GDPG2L	0.185	0.085	0.018 *
CPIG (1)	0.793	0.373	0.019 *
CPIG (2)	1.51	1.64	0.18
Cru (1)	0.005	0.026	0.42
Cru (2)	0.989	9.277	0.46
Exch (1)	- 0.692	3.24	0.42
Exch (2)	5.293	661	0.5
NetExp (1)	0.97e-5	0.395e-4	0.41
NetExp (2)	0.384	2.876	0.45
Int (1)	0.838	0.366	0.013 *
Int (2)	-7.677	807	0.5
Unem (1)	-3.376	0.56	0.5e-7 ***
Unem (2)	0.02	0.076	0.4
CC	0.02	0.014	0.07
Expend	-0.31e-5	0.24e-5	0.098
COVID-19	1.379	0.486	0.003 **
R square	0.923		
RSE	0.491		
RMSE	0.43		
MAE	0.35		
PP test (p-value)	< 0.01		
D.W. test	1.7		
ARCH test (p-value)	0.31		

Table 6: The estimated coefficients of ADL- RMIDAS (Exp. Almon)

Significance levels: ‘***’ 0.001, ‘**’ 0.01, ‘*’ 0.05

The symbols (1) and (2) in Table 4 indicate the parameter of the exponential Almon function.

In general, all variables used in the analysis are significant, except the crude oil price, exchange rate, and net export, which have an insignificant effect on the GDP growth rate in the chosen model. According to (Jokubaitis, Celov, & Leipus, 2021), CPI is driven by crude oil prices; therefore, it already includes the effect of the crude oil prices. Moreover, the change in oil prices was not noticeable in the past—crude oil price has grown in recent years, which may explain why the oil price is insignificant for the forecasts of GDP growth rate, given the estimation is performed for the overall period. The correlation between the GDPG and the exchange rate is positive but small at 0.18. The correlation between the GDPG and the net export is negative and smaller at 0.12. The mean of the net export is equal to -59076 and the minimum and maximum value are -93851 and -27440, respectively, indicating that the US has a trade deficit in this period.

The first lag of the GDP growth rate has a negative significant effect on the current GDP growth rate at 0.1%, whereas the second lag has a positive significant effect on the current GDP growth rate at 0.19%. This statement indicates that the change in GDP growth rate from one period to the next (first lag) has a negative impact on the current period's GDP growth rate, while the change in GDP growth rate two periods ago (second lag) has a positive impact on the current period's GDP growth rate. The negative impact from the first lag suggests that a decrease in GDP growth rate from the previous period will likely lead to a lower GDP growth rate in the current period. The positive impact from the second lag suggests that an increase in GDP growth rate two periods ago will likely lead to a higher GDP growth rate in the current period. The CPI growth rate has a significant effect on GDP growth rate similar to (Katircioglu, Sertoglu, Candemir, & Mercan, 2015), and, as expected, it positively affects GDP growth rate.

Although an increase in prices translates to a decline in purchasing power, the consumer’s perception of further increase in price increases consumption; therefore, the GDP growth rate increases. In other words, an increase in prices is likely to result in an increase in the growth rate of the economy, and vice versa. This relationship may reflect the influence of inflation on consumer purchasing power, which can drive changes in the overall level of economic activity.

A possible explanation could be the role of investment. The negative effect of the first lag could be due to a decline in investment as the economy reaches full capacity, while the positive effect of the second lag could be due to increased investment in response to the initial slowdown in growth. Additionally, international factors could also be at play. The negative effect of the first lag could be due to global economic conditions, such as a recession in major trading partners, while the positive effect of the second lag could be due to improved global conditions leading to increased exports and investment.

The interest rate has a significant positive effect on the GDP growth rate, as reported by (Wesołowski, 2018) and in contrast to (Saymeh & Orabi, 2013). The data considered in this study show a positive effect of the interest rate on the GDPG, equal to 0.84%. This implies that the two variables are positively related, and changes in interest rates have a noticeable impact on the growth of the economy. This relationship may reflect the influence of monetary policy, where a higher interest rate makes borrowing and investing more expensive, which can lead to lower levels of spending and investment, and thus a lower GDP growth rate. However, the positive effect in this case suggests that, under certain conditions, higher interest rates can actually stimulate economic growth. The unemployment rate is significantly negatively correlated with the GDPG, which is consistent with the general economic understanding (according to (Okun, 1992)) and other studies such as (Prachowny, 1993) and (Hjazeen, Seraj, & Ozdeser, 2021). The negative impact of the unemployment rate is 3.38%, and this is the most significant variable in our chosen model; the p-value is less than 0.00001. This implies that higher levels of unemployment lead to lower levels of economic growth, as measured by GDP. This relationship may reflect the influence of the labor market on economic activity, as a higher unemployment rate indicates a weaker labor market with fewer job opportunities, which can lead to lower levels of consumer spending and overall economic growth.

Consumer confidence has a significant relationship with the GDPG, as also shown by (Islam & Mumtaz, 2016). However, it is a poor determinant (p-value is 0.07) of the GDPG, as shown in (Mourougane & Roma, 2003), because consumer behavior fluctuates extensively because of external and global factors. Here, consumer confidence has a positive significant effect on GDP growth rate at 0.02%. This relationship may reflect the influence of consumer sentiment on consumer spending, which is a major driver of economic growth. When consumers feel confident about their personal finances and the overall economy, they are more likely to spend money, which can drive demand for goods and services and boost economic activity.

As stated in the literature, the government expenditure correlation sign is ambiguous because the sign of the "non-productive” and “productive” expenditures is different (Kutasi & Marton, 2020). Our results are consistent with (Macek, 2014), which shows that government expenditure affects GDP negatively, but inconsistent with (Kneller, Bleaney, & Gemmell, 1999), who argue that government expenditure affects GDP positively. Here, the government expenditure has a negative significant effect on GDP growth rate at 0.000003%, however the significance is low, the p-value is 0.098. This indicates that increases in government expenditure that are financed through higher taxes on economic activities, and an increase in government debt that can crowd out private investment, may lead to lower overall economic growth.

During the COVID-19 pandemic, the GDP growth rate increased by 1.38%; this effect is statistically moderately significant (the p-value is 0.003) and consistent with (Mustaffa, Zainal Abidin, Ahmad, & Ogundare, 2021), who showed a moderate, positive correlation between the COVID-19 pandemic and GDP. This relationship may reflect the influence of government stimulus measures and changes in consumer behavior in response to the pandemic. For example, governments around the world implemented large-scale fiscal stimulus packages to support households and businesses during the pandemic, which were considered to boost economic activity and increase GDP growth.

The effects of the CPI growth rate, unemployment rate, consumer confidence, and government expenditure are approximately the same as in the previous model. The effect of the second lag of the GDP growth rate, the interest rate, and COVID-19 increase from 0.195%, 0.838%, and 1.379% to 0.27%, 0.9%, and 1.76%, respectively. It is evident that the second model maintained its efficiency despite the exclusion of some variables and the residuals are still not autocorrelated, stationary, and homoscedastic.

The findings show that the empirical data and simulation are consistent. The findings from both the empirical study and simulation agree with those of existing literature, and the ADL-RMIDAS (Exp. Almon) model outperforms other competing models in terms of mean absolute error (MAE) in the out-of-sample analysis.

7. CONCLUSION AND FUTURE WORK

This study analyzed the impact of COVID-19 and economic indicators on the US GDP by applying various MIDAS approaches. The findings show that the COVID-19 pandemic has significantly impacted the US economy. The results also indicate that key economic indicators, such as inflation, unemployment, and consumer spending, play a significant role in determining the growth of the US economy. The study highlights the importance of monitoring and addressing the impact of both COVID-19 and economic indicators to maintain economic stability and promote growth in the future. Our findings are consistent with those in the literature.

For mixed-frequency data, it is difficult to estimate parameters accurately because the high-frequency data may contain more noise and may not be directly comparable to the low-frequency data.

Based on both the empirical and simulation studies, and as expected, the out-of-sample analysis shows that the ADL-RMIDAS (Exp. Almon) model outperforms other competing models in terms of mean absolute error (MAE); its residuals are uncorrelated, stationary, and homoscedastic; and the variance inflation factor is small for most variables and acceptable for others.

According to the empirical study, all variables used in the analysis are significant, with the exception of the crude oil price, exchange rate, and net export, which have an insignificant effect on the US GDP growth in the chosen model (RMIDAS Exp. Almon). All significant variables have the expected coefficient sign.

The exponential Almon function is the most commonly used function for the lag polynomial in MIDAS models because it allows a small number of parameters to be assigned to a large number of lags, simplifying the interpretation of results. In the empirical applications, we use two parameters of the exponential Almon function to simplify the model while still ensuring flexibility in the specification of the shape of the polynomial.

The ADL-RMIDAS model with exponential Almon weights is a useful modelling framework for analyzing time series data that includes mixed-frequency variables and autoregressive dynamics. Moreover, the exponential Almon weights enable flexible weighting of the mixed-frequency variables, allowing the model to capture different patterns in the data. This can improve the accuracy of the estimates, particularly if the data exhibit structural changes or nonlinear relationships.

The ADL-RMIDAS model addresses this issue by using a weighted regression approach, where the weights are determined by an exponential Almon function that depends on the frequency of the data. Overall, the ADL-RMIDAS model with exponential Almon weights provides a powerful tool for analyzing time-series data that includes mixed-frequency variables and autoregressive dynamics and can lead to more accurate and robust parameter estimates.

Other techniques such as principal component regression (PCR) and ridge regression (RR) are avenues to explore in future work. Finally, future research can explore the effect of the significant variables in this study on GDP growth rates in different countries or a panel of countries.

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