The Dollar Exchange Rates in the Covid-19 Era: Evidence from 5 Currencies*

Alexandros Pasiouras[1], Theodoros Daglis[2]

Abstract:

Purpose: In this paper, through a novel Bayesian specification, we test whether the exchange rates are affected by the current crisis caused by the Covid-19 spread.
Design/Methodology/Approach: we set out a novel Bayesian vector autoregressive model and compare it in terms of forecasting ability with the existing literature's econometric models.
Findings: Based on our findings, the novel Bayesian model proposed in the present paper, is better in terms of forecasting ability than the econometric models, and more importantly, it can unveil the impact of the Covid-19 spread on the exchange rates, while the econometric models failed to shed light on this relationship.
Practical Implications: The Covid-19 has affected the overall economic system, in many ways, leading to its disorganization. Such an impact is highlighted by the present paper, examining the exchange rates.
Originality/Value: The Bayesian framework proposed in the present paper has novel technical components and can unveil hidden effects of an exogenous variable on a system of endogenous variables, that the classical econometric approaches fail to unveil.

Keywords: COVID-19, exchange rates, crises, forecasting, Bayesian.

JEL codes: C22, C58, C50, C51, C11.

Paper Type: Research study.

[1]*National Kapodistrian University of Athens, e-mail: pasiouras@windowslive.com;*
[2]*National Technical University of Athens, e-mail: theodagl4@gmail.com;*
**Paper presented in ICABE 2020.*

1. Introduction

During turbulent periods, the exchange rates are affected in a specific, but not always the same way. Such a case were the movements during the global financial crisis of 2007–09, differing than the two previous crises, the Asian crisis of 1997–98 and the crisis following the Russian debt. The first culprit is the typical pattern of crisis-related flows related with the exchange rates. On the other hand, interest rates, being the other culprit, explain during crisis periods, the exchange rate movements, indicating structural changes in the exchange rate dynamics (Kohler, 2010).

Crises impact the exchange rates in many ways. Each crisis period seems to affect in a different way the exchange rates, having economic and political aspects. For instance, the contribution of contagion to the exchange rates during the East Asian currency crisis has been measured by Dungey and Martin (2004), indicating that exists significant contagion to the exchange rates during the crisis. Moreover, during crisis periods, the co-movement between exchange rates and stock prices becomes stronger (Lin *et al.,* 2012), showing that the exchange rates are also affected by crises. Such a case is the Covid-19 spread which has not adequately been examined.

The present paper contributes to the literature since it is among the first to investigate the effect of the Covid-19 in the exchange rates, using a Bayesian framework, and moreover, it accounts for the Covid-19 pandemic in a financial framework. The paper is structured as follows: section (2) sets out the review of the literature; section (3) presents the methodology used; section (4) shows the results and finally, section (5) concludes the paper.

2. Literature Review

Many studies are examining the impact of crises on the exchange rates, using economical and mathematical approaches. In general, there is evidence that credit spreads and stock prices exert significant impacts on exchange rates during financial crises (Gould and Kamin, 2000). Several studies such as Navagasu (2001), Dungey and Martin (2004) have examined the Asian financial crisis through exchange rates and stock insights.

Among the first that examined the exchange rates, were Engel (1992) and Marsh (2000), using a Markov regime-switching technique. Lin *et al.* (2012) investigated the co-movement between exchange rates and stock prices, showing that this co-movement becomes stronger during crisis periods, compared with calm periods. Morales-Arias Leonardo and Moura (2013) used panel methodology to show that exchange rate forecasts improve forecasting precision, leading to better market timing than most single predictors. Furthermore, Caporale *et al.* (2014) showed that the dependence between stock market prices and exchange rates on the banking crisis between 2007 and 2010 increased during the financial crisis.

Several other studies such as the work of Caporale and Spagnolo (2004), Frfmmela Michael and MacDonald (2005), Cheung and Erlandsson (2005), Walid *et al.* (2011), Basher *et al.* (2016) and Nikolsko-Rzhevskyy Alex and Prodan (2012), have investigated exchange rates fairly enough through Switch-Markov technique.

Chen *et al.* (2016) argued that the responses of dollar exchange rates to oil price shocks differ depending on the supply or aggregate demand that may affect the oil prices, highlighting that oil price stocks explain only a small fraction of the volatility in exchange rates. Peng *et al.* (2019) based on a conditional autoregressive value at risk model, showed that the oil prices affect the value at risk (VaR) of the exchange rates of oil-importing and oil-exporting countries in a different way.

3. Methodology

3.1 Econometric Tests

A first step is to check for a potential existence of unit root in the time series, using relevant unit root tests. More analytically, we make use of the Phillips-Perron unit root test. The null hypothesis of the test is that the time-series has a unit root, and if the null hypothesis is rejected, then the time series is I(1).
Johansen co-integration test:
In case of I(1) variables, we have to test for cointegration among the time-series. If cointegrating relationships are present, Error Correction Terms (ECM) must be included in the model. In this work, we implement the Johansen co-integration test.

3.2 Econometric Models

A basic and classical econometric approach is the vector autoregressive model - VAR, or the vector error correction model – VECM in presence of co-integration relationships among the variables. This type of model is used in the present paper, as the baseline model.

3.3 Bayesian Model

In the present paper, we set out a novel Bayesian framework, to capture the simultaneous effect of the trading of the dependent/endogenous variables. In this context, each endogenous variable is affected by its past value and by the past values of the other endogenous variables. Furthermore, we incorporate into our model an exogenous variable that affects all endogenous variables. Finally, we include a discrete version of a stochastic Brownian motion in our model, capturing the random walk effect. This model, appears to be a Vector autoregressive model (VAR) with Bayesian framework, explained bellow.

Model Specification:

We assume that sequence of the time series $\left\{y_j^{(k)}, j \geq 1, k \in \{1,2,\dots,m\}\right\}$ along with the exogenous factor $\{x_j, j \geq 1\}$ are modelled through the system equations:

$$
\begin{cases}
y_j^{(1)} = p_1 \sum_{i=1}^{N} \frac{1}{N} y_i^{(1)} + (1-p_1)\left\{\mu_1 + \sum_{k=1}^{m} a_{1k} y_{j-1}^{(k)} + b_1 x_{j-1}\right\} + \varepsilon_j^{(1)} \\
y_j^{(2)} = p_2 \sum_{i=1}^{N} \frac{1}{N} y_i^{(2)} + (1-p_2)\left\{\mu_2 + \sum_{k=1}^{m} a_{2k} y_{j-1}^{(k)} + b_2 x_{j-1}\right\} + \varepsilon_j^{(1)} \\
\quad \vdots \\
y_j^{(m)} = p_m \sum_{i=1}^{N} \frac{1}{N} y_i^{(m)} + (1-p_m)\left\{\mu_m + \sum_{k=1}^{m} a_{mk} y_{j-1}^{(k)} + b_m x_{j-1}\right\} + \varepsilon_j^{(m)}
\end{cases}
$$
(3.1)

We introduce matrix A in the column form $A = \begin{bmatrix} A_1 \\ A_2 \\ \vdots \\ A_m \end{bmatrix}$, where A_j represents the j-th

row of the matrix, which contains the unknown parameters $\left\{a_{ij}, i \in \{1,\dots,m\}, j \in \{1,\dots,m\}\right\}$. In order to estimate the unknown parameters of the model, we use the multivariate normal distribution as prior setting for the unknown parameters $A_1, A_2, \dots, A_m, b = (b_1, \dots, b_m)$ and the inverse Wishart distribution for the noise's covariance matrix Σ.

For simplicity, we consider that a rational choice for the weights p_j is $p_j = 1 - \frac{N}{D}$, where N represents the total number of data and D represents the number of data that we will use for the Bayesian estimation of the unknown parameters. Using the Gibbs algorithm, we may obtain, and use the posterior distribution of the unknown parameters for forecasting and interpretation.

3.4 Information Criterion and Forecasting Accuracy

In order to choose the appropriate lag order for the modeling of the time-series, we make use of the Schwartz-Bayes Information criterion (SBIC) introduced by Schwarz in 1978, being an optimal selection criterion for finite samples (Breiman and Freedman, 1983; Speed and Yu, 1992). As for the forecasting accuracy, the measures we used, were the mean absolute error (MAE), and the root mean square forecasting error (RMSFE).

4. Empirical Results

4.1 Data and Variables

The data used in our analysis were the exchange rates of the foreign country and the USA dollar, and more precisely, the Australian dollar (AUD), the Swiss Franc (CHF), the Euro (EUR), the British pound or Sterling (GBP), and the Hong Kong dollar (HKD), downloaded from HistData[3], in minute frequency. These were transformed into daily frequency, using the average function. The Covid-19 data, were the confirmed cases, downloaded by Johns Hopkins[4] database. Table 1 presents the descriptive statistics of the timeseries.

4.2 Result Analysis

Based on the literature, in every econometric approach a first level of analysis is a unit root test. In the present paper we make use of the Phillips – Perron test. The results in Table 1 show that all timeseries are I(1), except for the logarithmic transformed timeseries of the confirmed Covid-19 cases.

Table 1. Summary Statistics and Phillips-Perron test results

Variable	Mean	Sd	Min	Max	Phillips-Perron P-value	Order of integration
Confirmed Covid cases	271815.015	402959.073	555.000	1595350.000	0.990	I(1)
Log_Confirmed Covid cases	11.363	1.834	6.319	14.283	0.010	I(0)
AUD	0.644	0.032	0.575	0.685	0.780	I(1)
CHF	0.967	0.014	0.927	0.985	0.580	I(1)
EUR	1.099	0.016	1.070	1.142	0.550	I(1)
GBP	1.268	0.045	1.157	1.317	0.630	I(1)
HKD	7.768	0.012	7.751	7.795	0.710	I(1)

Source: Own study.

In presence of I(1) time-series, we have to examine for cointegration relationships among the variables. The results in Table 2 show that based on the Johansen cointegration test, the variables have 5 cointegration relationships, indicating that we have to incorporate error correction term in the econometric model.

As a next step, we make use of a baseline econometric model, a vector error correction model (VEC) using the exchange rates as the only endogenous variables. Using this model, we forecasted the exchange rates for 1-10 days. As a next step, we set out two alternative models. The first, is the same econometric model, using this time the logarithmic Covid-19 confirmed cases as exogenous variable being a model with an exogenous variable (VECX).

---

[3] https://www.histdata.com/download-free-forex-data/
[4] https://github.com/CSSEGISandData/COVID-19

Table 2. *Johansen cointegration test*

Rank	Test	10pct	5pct	1pct
r<=5	0.430	6.500	8.180	11.650
r<=4	14.670	12.910	14.900	19.190
r<=3	26.670	18.900	21.070	25.750
r<=2	44.210	24.780	27.140	32.140
r<=1	64.740	30.840	33.320	38.780
r=0	83.380	36.250	39.430	44.590

Source: Own study.

As in the baseline model, again, we forecast for 1-10 days. Finally, we make use of our proposed novel Bayesian vector autoregressive model, declaring the exchange rates as endogenous dependent variables and the logarithmic Covid-19 confirmed cases as exogenous independent variable. We then forecasted for 1-10 days. For all models, the autoregressive order was based on the Schwarz-Bayes criterion (Table 3), indicating that the optimal order selection is 1 for all cases. The forecasting ability of the models, we tested under the MAE, and RMSFE forecasting measures are displayed in Tables 4-8.

Table 3. *Schwarz-Bayes criterion for orders 1-8, for the model with and without exogenous variables*

Model / Order	1	2	3	4	5	6	7	8
Without exogenous	-55.272	-54.748	-53.691	-53.003	-52.773	-51.867	-51.489	-50.714
With exogenous	-60.625	-59.653	-58.111	-57.280	-56.507	-55.996	-57.163	-59.065

Source: Own study.

The results depicted in Tables 4-8, indicate that the alternative VECX model is worse in forecasting ability than the VEC model, except for the first 5-6 horizons for the case of HKD exchange rate. These results indicate that the covid-19 spread did not have any impact on the exchange rates in a global manner.

However, the results show that our proposed novel Bayesian model is better in terms of forecasting ability than both other two econometric models, indicating that the Covid-19 provides useful information for the forecasting ability of these exchange rates.

Table 4. *Results of the MAE and RMSFE forecasting measures for both Bayesian and econometric models for the case of the Exchange rate of AUD/Dollar*

MAE_BAYES	RMSFE_BAYES	MAE_VECX	RMSFE_VECX	MAE_VEC	RMSFE_VEC
0.004	0.004	0.095	0.095	0.029	0.029
0.003	0.003	0.077	0.079	0.050	0.054
0.002	0.003	0.084	0.086	0.062	0.066
0.002	0.002	0.142	0.174	0.072	0.078
0.002	0.002	0.175	0.208	0.078	0.083
0.002	0.003	0.184	0.212	0.085	0.090
0.003	0.004	0.253	0.320	0.089	0.094
0.004	0.006	0.315	0.399	0.086	0.091
0.004	0.005	0.316	0.391	0.085	0.089
0.005	0.006	0.393	0.507	0.085	0.089

Source: *Own study.*

Table 5. *Results of the MAE and RMSFE forecasting measures for both Bayesian and econometric models for the case of the Exchange rate of CHF/Dollar*

MAE_BAYES	RMSFE_BAYES	MAE_VECX	RMSFE_VECX	MAE_VEC	RMSFE_VEC
0.006	0.006	0.042	0.042	0.024	0.024
0.005	0.005	0.027	0.031	0.015	0.018
0.005	0.005	0.042	0.048	0.022	0.025
0.005	0.005	0.086	0.117	0.027	0.030
0.004	0.004	0.116	0.149	0.034	0.039
0.004	0.004	0.147	0.183	0.040	0.045
0.004	0.004	0.206	0.271	0.043	0.048
0.004	0.004	0.249	0.320	0.043	0.047
0.004	0.004	0.290	0.364	0.039	0.045
0.004	0.004	0.374	0.498	0.037	0.043

Source: *Own study.*

Table 6. *Results of the MAE and RMSFE forecasting measures for both Bayesian and econometric models for the case of the Exchange rate of EUR/Dollar*

MAE_BAYES	RMSFE_BAYES	MAE_VECX	RMSFE_VECX	MAE_VEC	RMSFE_VEC
0.008	0.008	0.081	0.081	0.024	0.024
0.006	0.006	0.060	0.064	0.016	0.018
0.005	0.005	0.071	0.075	0.022	0.025
0.005	0.005	0.127	0.161	0.029	0.032
0.005	0.005	0.173	0.215	0.037	0.043
0.005	0.006	0.206	0.248	0.044	0.051
0.005	0.005	0.281	0.359	0.047	0.053
0.005	0.005	0.344	0.435	0.045	0.051
0.005	0.005	0.387	0.477	0.042	0.048
0.005	0.005	0.490	0.638	0.038	0.046

Source: *Own study.*

Table 7. *Results of the MAE and RMSFE forecasting measures for both Bayesian and econometric models for the case of the Exchange rate of GBP/Dollar*

MAE_BAYES	RMSFE_BAYES	MAE_VECX	RMSFE_VECX	MAE_VEC	RMSFE_VEC
0.010	0.010	0.104	0.104	0.019	0.019
0.005	0.007	0.054	0.074	0.047	0.055
0.005	0.006	0.079	0.096	0.072	0.083
0.003	0.005	0.176	0.248	0.091	0.103
0.004	0.005	0.224	0.289	0.100	0.110
0.005	0.007	0.251	0.307	0.111	0.122
0.005	0.007	0.364	0.485	0.124	0.137
0.005	0.006	0.449	0.586	0.126	0.137
0.005	0.006	0.484	0.608	0.124	0.134
0.006	0.009	0.621	0.822	0.124	0.133

Source: *Own study.*

Table 8. *Results of the MAE and RMSFE forecasting measures for both Bayesian and econometric models for the case of the Exchange rate of HKD/Dollar*

MAE_BAYES	RMSFE_BAYES	MAE_VECX	RMSFE_VECX	MAE_VEC	RMSFE_VEC
0.001	0.001	0.018	0.018	0.037	0.037
0.001	0.001	0.022	0.023	0.041	0.042
0.002	0.002	0.028	0.029	0.037	0.037
0.002	0.002	0.027	0.028	0.035	0.036
0.002	0.002	0.028	0.029	0.032	0.033
0.002	0.003	0.029	0.030	0.028	0.030
0.003	0.003	0.035	0.039	0.025	0.028
0.002	0.003	0.036	0.039	0.024	0.027
0.002	0.003	0.040	0.043	0.022	0.026
0.002	0.003	0.051	0.064	0.023	0.026

Source: *Own study.*

5. Conclusion

The exchange rates are interdependent but are also affected by external shocks (Dungey and Martin, 2004). Such shocks are caused by economic crises (Kohler, 2010) and more importantly the current crisis caused by the Covid-19 spread.

In this paper, using daily data for major currencies we forecasted the exchange rates using a novel Bayesian vector autoregressive model, using the information of the exogenous variable of the Covid-19 confirmed cases and compared these results with the equivalent derived from respective econometric models. Based on our findings, between the baseline and alternative econometric models, the alternative VECX is worse in forecasting ability than the VEC, except for the first 5-6 horizons for the case of HKD exchange rate. This means that the covid-19 spread did not have any impact on the exchange rates in a global manner, or that the econometric model

cannot unveil a possible "hidden" effect of the Covid-19 spread on the exchange rates.

On the other hand, the results indicate that our proposed novel Bayesian model is better in terms of forecasting ability than the other two econometric models. This implies not only that our novel model is better in terms of forecasting ability by the standard econometric models, but also that it is capable of unveiling "hidden" exogenous information that econometric models fail to unveil. This means that our novel Bayesian model can show that the Covid-19 confirmed cases have affected the exchange rates, a fact that the econometric approach failed to unveil. This information is valuable, as it gives credit to the impact of the Covid-19 spread on the exchange rates

The global pandemic caused by the Covid-19 has significantly changed the operation of the businesses and financial institutions leading to the decrease of the exchange rates. In this context, the Covid-19 spread has an important impact on the exchange rates. The importance of economic and political measures is requisite to avoid economic disaster.

The present paper investigates the effect of the Covid-19 in the exchange rates, using global data on the spread of the pandemic. The results unveil the effect of the Covid-19 on the exchange rates of the major monetary currencies. Future research on the impact of the pandemic on other aspects of the financial and economic activity would be of great interest.

References:

Basher Syed Abul, Haugb Alfred A., Sadorsky, P. 2016. The impact of oil shocks on exchange rates: A Markov-switching approach. Energy Economics, 54, 11-23.

Breiman, L.A., Freedman. D.F. 1983. How many variables should be entered in a regression equation? J. Am. Stat. Assoc., 78, 131-136.

Caporale Guglielmo, M., Hunter, J., Ali Menla, F. 2014. On the linkages between stock prices and exchange rates: Evidence from the banking crisis of 2007-2010. International Review of Financial Analysis, 33, 87-103.

Caporale Guglielmo, M., Spagnolo, N. 2004. Modelling East Asian exchange rates: a Markov-switching approach. Applied Financial Economics, 14(4), 233-242.

Caraiani, P. 2017. Evaluating exchange rate forecasts along time and frequency. International Review of Economics and Finance, 51, 60-81.

Chen, H., Liu, L., Wang, Y., Zhu, Y. 2016. Oil price shocks and U.S. dollar exchange rates. Energy, 112, 1036-1048.

Cheung Yin-Wong, Erlandsson, U.G. 2005. Exchange Rates and Markov Switching Dynamics. Journal of Business & Economic Statistics, 23(3), 314-320.

Dekle, R., Hsiao, C., Wang, S. 2002. High Interest Rates and Exchange Rate Stabilization in Korea, Malaysia, and Thailand: An Empirical Investigation of the Traditional and Revisionist Views. Review of International Economics, 10(1), 64-78.

Dungey, M., Martin, L.V. 2004. A Multifactor Model of Exchange Rates with Unanticipated

Shocks: Measuring Contagion in the East Asian Currency Crisis. Journal of emerging market finance, 3(3), 305-330.

Engel, C. 1992. Can the Markov switching model forecast exchange rates? Journal of International Economics, Volume 36, Issues 1-2, 151-165.

Frfmmela, M., MacDonald, R., Menkhoff, L. 2005. Markov switching regimes in a monetary exchange rate model. Economic Modelling, 22, 485-502.

Gould, M.D., Kamin, B.S. 2000. The impact of monetary policy on exchange rates during financial crises. Board of Governors of the Federal Reserve System, International Finance Discussion Papers, Number 669.

Kohler, M. 2010. Exchange rates during financial crises. BIS quarterly review, 39-50.

Lin Chien-Hsiu. 2012. The comovement between exchange rates and stock prices in the Asian emerging markets. International Review of Economics and Finance, 22, 161-172.

Marsh, W.I. 2000. High-frequency Markov Switching Models in the Foreign Exchange Market. Journal of Forecasting, 19, 123-134.

Morales-Arias, L., Moura, G.V. 2013. Adaptive forecasting of exchange rates with panel data. International Journal of Forecasting, 29, 493-509.

Nagayasu, J. 2001. Currency crisis and contagion: evidence from exchange rates and sectoral stock indices of the Philippines and Thailand. Journal of Asian Economics, 12, 529-546.

Nikolsko-Rzhevskyy, A., Prodan, R. 2012. Markov switching and exchange rate predictability. International Journal of Forecasting, 28, 353-365.

Peng, W., Hu, S., Chen, W., Zeng, Y.F., Yang, L. 2019. Modeling the joint dynamic value at risk of the volatility index, oil price, and exchange rate. International Review of Economics and Finance, 59, 137-149.

Speed, T.P., Yu, B. 1992. Model selection and prediction: Normal Regression. Annals of the Institute of Statistical Mathematics, Vol. 45, Issue 1, 35-54.

Walid, C., Chaker, A., Masood, O., Fry, J. 2011. Stock market volatility and exchange rates in emerging countries: A Markov-state switching approach. Emerging Markets Review, Volume 12, Issue 3, 272-292.