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Research Article

Covid-19 Pandemic and Exchange Rate Volatility in Iran: A Markov-Switching Approach

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Abstract

Abstract: This study employs the Markov-Switching model to investigate the impact of the COVID-19 pandemic on exchange rate volatility in Iran using daily data from February 19th, 2020, to March 15th, 2021. The results of our empirical analysis indicate that the COVID-19 crisis has had a significant positive effect on exchange rate fluctuations in both high and low-volatility regimes in Iran. Specifically, a 1% increase in COVID-19 case growth increases exchange rate volatility by 0.526% in the high-volatility regime and 0.483% in the low-volatility regime. Moreover, the high-volatility regime is more persistent, with an expected duration of 4.46 days versus 1.87 days for the low-volatility regime. To address the increased exchange rate volatility triggered by the COVID-19 pandemic, a comprehensive strategy should involve continuous monitoring of the virus's impact, alongside measures like public health interventions and vaccination campaigns. The central bank should also focus on stabilizing exchange rates through interventions and reserve management. Promoting economic diversification, supporting businesses in managing exchange rate risks, fostering international cooperation, and establishing long-term plans that consider prolonged volatility are essential. Additionally, transparent communication about government policies is crucial to reduce market uncertainty during crises.

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1 Introduction

In December 2019, Wuhan, China, identified a surge in cases of a novel coronavirus, marking the world's inaugural encounter with the virus ([1, 2]). Subsequently, other Chinese municipalities and global regions reported escalating cases. This prompted the World Health Organization (WHO) to declare the outbreak of the novel coronavirus, COVID-19, as a pandemic ([3]).

Iran reported its initial COVID-19 cases in February 2020. The rapid spread led to the formation of a committee by the Iranian Ministry of Health and the government to contain the disease, following WHO guidelines ([4]). Swiftly thereafter, nationwide restrictions and quarantines were imposed.

Following the pandemic declaration, most countries globally swiftly escalated restrictions and quarantines. From March 2020, road transport activities in restricted areas saw a 50% reduction compared to 2019, while global aviation activity gradually plummeted by 60% ([5]). The interconnectedness of global economies during recent years of globalization exacerbated the adverse shocks experienced worldwide due to the COVID-19 pandemic. This crisis surpassed the magnitude of prior economic downturns like the 2008 financial crisis or the 2010 Greece crisis ([6]).

The global economy suffered widespread setbacks post the pandemic declaration, significantly altering the global supply and demand for goods and services ([7]). This disruption severely impacted the stability and performance of the global supply chain, especially within the pharmaceutical and medical sectors ([8, 9]). The production downturn in countries like China weakened the global supply chain, resulting in a substantial decline in global trade ([10, 11]).

The financial markets responded swiftly to the crisis, losing stability and facing increased systemic risk. Monetary policy transmission to these markets weakened significantly. Various financial areas, including stock markets, oil price-dependent stocks, and exchange rates, were affected by the daily and weekly rates of coronavirus pandemic ([12, 13, 14]). Consequently, the global spread of coronavirus directly impacted financial markets, resulting in extensive changes in exchange rates, a critical facet of financial markets ([12, 15]).

Exchange rate volatility is a crucial determinant of countries' financial market stability and performance. Literature suggests that higher exchange rate volatility negatively affects economic growth, welfare, foreign investment, export performance, and international trade ([16, 12, 17, 18, 19]). Crises and unpredictable factors often modify exchange rate volatility, as observed with large exchange rate depreciations in 2008 ([20, 21]). Consequently, the global pandemic induced by the coronavirus caused significant fluctuations in exchange rates, leading to varied studies worldwide ([22, 23, 24]).

In Iran, exchange rate fluctuations have been notable historically. Studies attribute these fluctuations to changes in oil prices, sanctions, and external shocks affecting Iran's monetary policy ([25, 26, 27]). Simultaneously embroiled in both widespread sanctions and the global coronavirus pandemic, Iran faced dual crises from external shocks affecting its economy and financial markets. Iran provides a particularly compelling case for studying pandemic-induced exchange rate volatility because the COVID-19 shock coincided with already severe economic sanctions. This combination created a distinctive "dual shock": a health crisis that disrupted domestic activity and an external constraint that limited fiscal space and foreign exchange access. This setting can amplify market sensitivity to pandemic news and strengthens the novelty of the present study. Hence, this study aims to investigate the effect of coronavirus on exchange rate fluctuations in Iran from 19/02/2020 to 15/03/2021 using the Markov-Switching GARCH model.

The structure of this study is as follows: Section 2 provides a literature review, Section 3 details the methodology, Section 4 presents the results and discussion, and finally, Section 5 concludes the study with policy recommendations.

2 Literature Review

The exchange rate, defined as the price of one currency in terms of another, represents a fundamental conversion factor crucial to every economy ([28]). This pivotal metric not only showcases a country's economic conditions but also enables comparative assessments between economies. Research indicates the significant impact of the exchange rate; mismanagement in this area can lead to multifaceted problems within an economy ([29, 30, 31, 32]).

Empirical and theoretical studies emphasize the role of real exchange rate volatility, stemming from real and nominal shocks. Real shocks, rooted in fundamental factors like productivity shifts, technological advancements, alterations in government and private spending, and persistent changes in consumer preferences, influence real exchange rates. In contrast, nominal shocks involve changes in money supply and nominal exchange rates.

The global financial crisis of 2008 stands as evidence of how financial crises impact exchange rates, reflecting countries' foreign exchange policies ([19]). These crises tend to destabilize financial and economic variables, causing significant fluctuations in exchange rates. Similarly, the onset of the COVID-19 pandemic precipitated financial and economic crises worldwide, revealing vulnerabilities tied to global resource dependence.

The pandemic's impact on economies has spurred a burgeoning body of literature employing various methodologies to assess its effects. For example, Pasiouras and Daglis ([33]) utilized Bayesian methods to analyze the Covid-19-induced crisis's influence on the exchange rate. Their study, employing a Bayesian vector model, showcased superior predictive capabilities compared to traditional models. Importantly, it highlighted the Covid-19 impact on the exchange rate, emphasizing the superiority of the Bayesian model in predicting and handling latent data.

Cepoi ([34]) explored the relationship between Covid-19 and stock market dynamics across six heavily impacted countries using a quantitative regression model in a panel structure, affirming the relevance of the stock market to the pandemic. Additionally, Mirza et al. ([35]) examined European investment funds' reactions, returns, and volatilities during Covid-19, observing significant returns among most funds and demonstrating the resilience displayed by social entrepreneurship amidst the crisis.

3 Methodology and Data

This study uses daily data from 19/02/2020 to 15/03/2021. The growth rate of COVID-19 Patients is taken from https://ourworldindata.org/. Additionally, the volatility of the exchange rate is estimated by the GARCH model. In addition, using the Markov-Switching model, the effect of the Covid-19 pandemic on Exchange Rate Volatility in Iran is investigated. Many economic variables over time are affected by financial crises, political crises, Economic decisions, etc. suffer from numerous significant structural failures. As a result, the behavioral relationship between economic variables evolves, forming a new relationship between them. In Behavioral Investigation, these variables use linear methods; It would be normal to use a template for the average instead. The COVID-19 variable (LnCONF) captures the daily growth rate of confirm cases in Iran. Daily case growth is calculated as

$$\left(\frac{\text{New Cases}_t}{\text{New Cases}_{t-1}}\right) - 1.$$

We then use $\ln(1 + \text{Case Growth}_t)$ to reduce skewness. Data are obtained from Our World in Data. LnOIL denotes the natural logarithm of the OPEC crude oil price, a benchmark relevant for Iran's oil-linked external revenues.

The condition of the dependent variable necessitates the utilization of multiple patterns. The Markov Switching Mechanism is a viable tool for modeling endogenous data that exhibit non-linear behavior patterns characterized by transformations or changes in status over time.

Here, to explain the methodology of the Markov-switching model (MS) by Hamilton ([36]), we use a 2-regime Markov-Switching Autoregressive (MS (2) -AR(P)) model:

$$y_t = a_{0.st} + a_{1.st} y_{t-1} + \ldots + a_{p.st} y_{t-p} + \varepsilon_t \tag{1}$$

$$\text{where } \varepsilon_t \sim NID\left(0, \sigma_{s_t}^2\right) \tag{2}$$

$$a_{i.st} = a_{i1}\left(1 - s_t\right) + a_{i2} s_t, \quad i = 1, \ldots, p \tag{3}$$

$$\sigma_{s_t}^2 = \sigma_1^2\left(1 - s_t\right) + \sigma_2^2 s_t \tag{4}$$

$$s_t = 0, 1 \quad (\text{Regime } 0, 1) \quad \text{for } t = 1, \ldots, T \tag{5}$$

In this model, the parameter values depend on the regimes denoted by s_t. To have full dynamics of variables, the transition between regimes is also done with the first-order Markov process:

$$p_{ij} = \Pr(s_t = j \mid s_{t-1} = i) \tag{6}$$

These probabilities can be summarized in matrix P:

$$P = \begin{bmatrix} p_{00} & p_{10} \\ p_{01} & p_{11} \end{bmatrix} \quad \text{with } p_{00} + p_{01} = 1 \wedge p_{10} + p_{11} = 1 \tag{7}$$

For example, p_{00} shows the probability of staying in regime 0 when the initial state of the regime is equal to zero, and p_{01} indicates the probability of any transfer from regime 0 to regime 1 when the regime's initial state is equal to zero. To estimate the parameters of the MS-AR model using the Maximum Likelihood Estimation (MLE), the following probability density function can be assumed based on the previous information Ψ_{t-1}:

$$f\left(y_t \mid \Psi_{t-1}, s_t\right) = \frac{1}{\sqrt{2\pi\sigma_{s_t}^2}} \exp\left(\frac{\left\{y_t - \left(a_{0.st} + a_{1.st} y_{t-1} + \ldots + a_{p.st} y_{t-p}\right)\right\}^2}{2\sigma_{s_t}^2}\right) \tag{8}$$

Since s_t values are not invisible, we have the following conditional function:

$$f\left(y_t \mid s_t, \Psi_{t-1}\right)=\sum_{s_t=0}^{1} f\left(y_t, s_t \mid \Psi_{t-1}\right)=\sum f\left(y_t, s_t \mid \Psi_{t-1}\right) P\left[s_t \mid \Psi_{t-1}\right] \tag{9}$$

Where its likelihood function will be as follows:

$$\ln L=\sum_{t=1}^{T} \ln \left\{\sum_{s_t=0}^{1} f\left(y_t \mid s_t, \Psi_{t-1}\right) P\left[s_t \mid \Psi_{t-1}\right]\right\} \tag{10}$$

Furthermore, $P\left[s_t \mid \Psi_{t-1}\right]$ shows the filtered probabilities, calculated using the Hamilton filter ([36]) for periods $t=1, \ldots, T$ ([37]).

The Markov-switching model can be classified into different types depending on which part of the model is a regime-dependent autoregression and transferred under its influence. What is more important in economic studies include the four modes of Markov-switching models, including Markov-switching mean (MSM), Markov-switching intercept (MSI), Markov-switching autoregressive (MSA) parameters, and Markov-switching heteroscedasticity (MSH) or a combination of them ([38]). Table 1 shows different states of MS models using these symbols:

Table 1: MS-AR models

MSI		**MSM**		
Fixed intercept	Variable intercept	Fixed mean	Variable mean	
Linear AR	MSI	Linear AR	MSM-AR	Fixed variance, Fixed A_i
MSH-AR	MSIH-AR	MSH-AR	MSMH-AR	Variable variance
MSA-AR	MSIA-AR	MSA-AR	MSMA-AR	Fixed variance, Variable A_i
MSAH-AR	MSIAH-AR	MSAH-AR	MSMAH-AR	Variable variance

Note: M: Markov-Switching Mean, I: Markov-Switching Intercepts Term, A: Markov-Switching Autoregressive Parameters, H: Markov-Switching Heteroskedastic.
Source: [39]

4 Empirical Results

4.1 Robustness Check

Before performing and estimating the model, the static mode of variables is checked to detect false regression. In Table 2, the results of the Augmented Dicky-Fuller (ADF) unit root test and Zivot and Andrews (ZA) unit root test are seen with the inclusion of an endogenous structural failure. As seen in Table 2, the variables are stationary at the 1% and 5% levels and can be estimated from conventional patterns methods.

Also, using the Box-Jenkins method and Akaike info criterion in Table 3, the best model for Exchange Rate Volatility, AR(1) model, has been selected as the optimal model. Table 4 also shows the properties of the AR(1) model.

Table 2: Unit Root Test

Variables	**ZA**				**ADF**		
	Result	**Time Break**	**T**	**C**	**Result**	**T**	**C**
Exchange Rate Volatility	$I(0)$	8/26/2020	$\surd$	$\surd$	$I(1)$	x	$\surd$
Growth Rate of COVID-19 Patients	$I(0)$	4/24/2020	x	$\surd$	$I(0)$	x	$\surd$

Note: Standard errors are provided in parentheses. *, **, and *** show significance at 1%, 5%, and 10% levels.
Source: Research finding.

Table 3: Comparison of Akaike info criterion of different ARMA patterns for Exchange Rate Volatility

MA	**AR**		
	0	1	2
0	-	34.810*	34.846
1	34.818	34.817	35.475
2	35.340	34.828	35.831

Source: Research finding.

Table 4: Optimal pattern properties of AR (1)

Variable	**Coefficient**	**Prob.**
C	3.083	0.024
AR (1)	0.962	0.000
F-statistic	1711.132	0.000
Log-likelihood	-450.5006	

Source: Research finding.

4.2 Nonlinearity Test

Before estimating the model, the Likelihood Ratio Test is used according to Equation (8) to check the nonlinearity of exchange rate volatility. Zero probability shows that the null hypothesis stating the linearity of the model is rejected. Therefore, we can use the nonlinear model for exchange rate volatility, and the hypothesis of equality of exchange rate volatility across regimes is rejected. The LR linear statistic test ($\chi^2 = 24$) is used to test the linearity of the model, and the obtained statistic was 42.672, with a probability level of 1%, indicating rejection of the linearity of the model.

$$LR = 2 \times \left| L_{MS(2)-AR(1)} - L_{linearAR(1)} \right| \tag{11}$$

The outcomes derived from the MS(2) - AR(1) model are outlined in Table 6. This table elucidates two distinct regimes, namely regime (1) characterized by a higher intercept value of 9.107, denoting high exchange rate volatilities, and regime (2) with an intercept value of 8.803, indicating lower exchange rate volatilities within Iran.

In regime (1), the phase marked by high exchange rate volatility, and in regime (2), the period

Table 5: Likelihood Ratio Test

Variable	Model	lnL	LR
Exchange Rate Volatility	Linear AR(1)	-450.5006	$\chi^2(2) = 42.672^*$
	MS(2)-AR(1)	-429.1642	

Note: Standard errors are in parentheses. *, **, and *** denote significance at 1%, 5%, and 10% levels.
Source: Research finding.

associated with lower exchange rate volatility, the correlation between the growth rate of Covid-19 patients and exchange rate volatility is starkly evident. In regime (1), a 1% increase in Covid-19 patients corresponded to a 0.526% surge in exchange rate volatility, while in regime (2), a similar increase in Covid-19 patients correlated to a 0.483% escalation in exchange rate volatility. The magnitude of these coefficients is economically substantial, indicating that pandemic news strongly amplifies exchange rate uncertainty. This may reflect heightened market panic, Iran's import dependence, and sanction-induced policy constraints.

Moreover, the self-regression coefficient (AR1) within the model stands notably positive and significant at 0.956. This value signifies that a 1% rise in exchange rate volatility leads to a substantial 95.6% increase in successive periods' exchange rate volatility within Iran.

The estimations for transitioning between the high exchange rate volatility regime (regime 1) and the low volatility one (regime 2) reveal critical insights. The probability of transitioning from regime (1) to regime (2) stands at 0.224, while the likelihood of transitioning from regime (2) to regime (1) is estimated at 0.464. Consequently, the probabilities of remaining in regime (1) and regime (2) stand at 0.776 and 0.536, respectively, signifying a higher probability of persisting in a regime characterized by substantial exchange rate fluctuations.

The negative LOG(SIGMA) estimates represent regime-specific log-variance parameters, consistent with distinct high- and low-volatility states captured by the model.

Furthermore, Table 6 portrays the anticipated duration for staying in regimes 1 and 2, indicating an expected remaining duration of 4.46 days in regime 1 and 1.867 days in regime 2. These estimations provide valuable insights into the anticipated duration of high and low exchange rate volatility periods within the Iranian context.

The evaluation of the MS(2) - AR(1) model's efficacy in delineating the dynamics of exchange rate volatility across high and low volatility regimes is encapsulated in the depiction of transition probabilities within Figure 1. This visual representation serves as a crucial tool in comprehending the likelihood of shifts between these distinct regimes over time.

Figure 1 provides a nuanced understanding of these regimes through smoothed and filtered probabilities. As these probabilities approach unity, signifying closeness to a value of one, it denotes an increasing likelihood of experiencing exchange rate volatility within that period. In essence, the visualization underscores that as these probabilities converge towards unity, the propensity for encountering substantial fluctuations in exchange rates amplifies during that specific timeframe. The insights gleaned from the smoothed and filtered probabilities distinctly delineate regime (1) characterized by heightened exchange rate fluctuations and regime (2) typified by comparatively lower fluctuations.

This graphical representation offers a clear depiction of the evolving probabilities over time, allowing for a comprehensive comprehension of the transitions between these distinct volatility

Table 6: Model Estimation for MS(2) - AR(1)

Regime	Variable	Coefficient	Std. Error	Prob.
Regime (1)	LnCONF	0.526442	0.041194	0.0000
	LnOIL	-0.066515	0.052059	0.0201
	C	8.029748	0.468712	0.0000
	LOG(SIGMA)	-2.855008	0.116378	0.0000
Regime (2)	LnCONF	0.483389	0.036520	0.0000
	LnOIL	0.204138	0.185420	0.0270
	C	7.576336	0.685474	0.0000
	LOG(SIGMA)	-0.695516	0.240568	0.0038
AR(1)		0.9569	0.0065	0.0000
lnL		-429.164		
AIC		33.338		
Constant Expected Durations				
Regime (1): 4.462				
Regime (2): 1.867				
Constant Transition Probabilities				
P_{11}: 0.776				
P_{12}: 0.224				
P_{21}: 0.536				
P_{22}: 0.464				

Source: Research finding.

regimes. By mapping the probabilities, Figure 1 unveils the temporal evolution of these regimes, aiding in the identification of periods marked by pronounced exchange rate volatility (regime 1) and those featuring relatively subdued fluctuations (regime 2). This visualization becomes instrumental in deciphering the temporal patterns and durations of these distinct volatility phases, thereby enriching our understanding of the underlying dynamics governing exchange rate volatilities within the context of the model.

5 Conclusion

The COVID-19 pandemic unleashed economic turmoil globally, with numerous nations grappling with financial crises. Among the predicaments encountered, exchange rate instabilities emerged as a prominent concern for many countries, including Iran. Our comprehensive study delves into the repercussions of the COVID-19 outbreak on exchange rate volatility within Iran, employing the sophisticated Markov-Switching model.

The findings extracted from our analysis yield profound insights. They unequivocally showcase a notable and positive correlation between the pandemic's occurrence and the amplified fluctuations in exchange rates across both high and low volatility periods. This discernible relationship under-

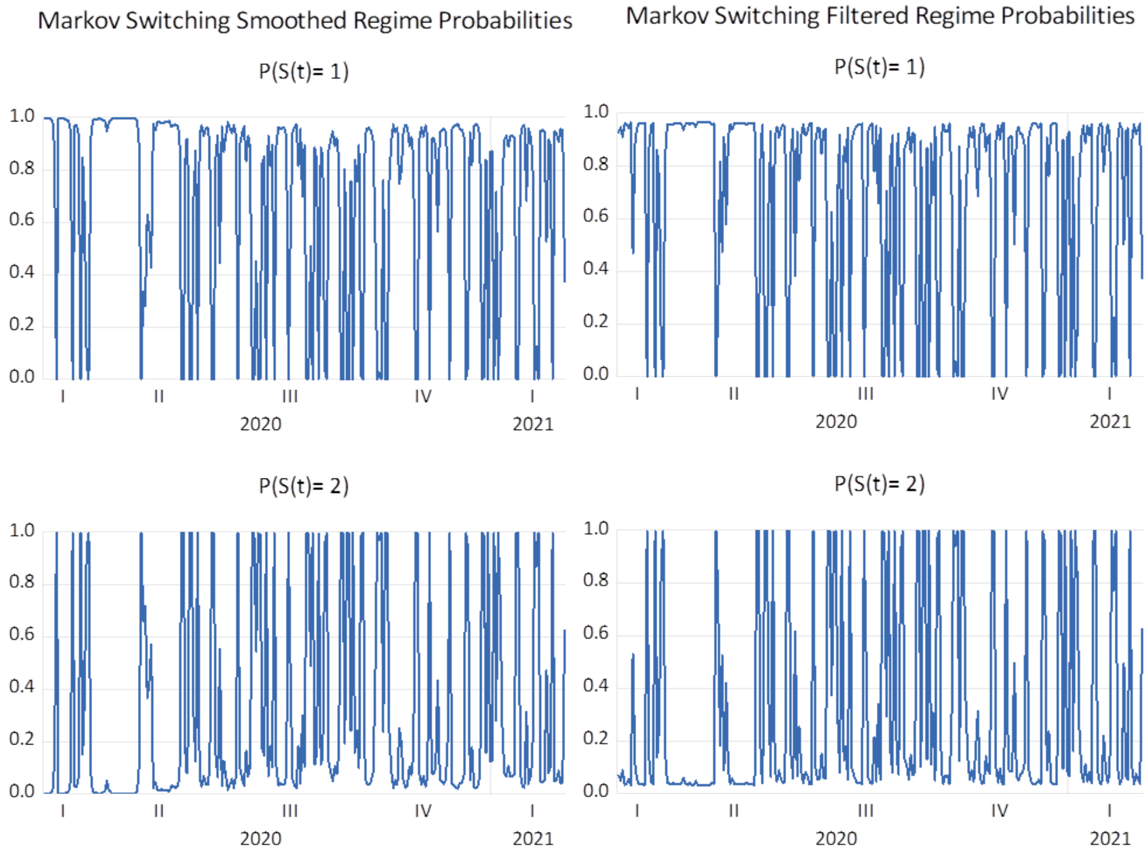

Figure 1: State classification based on the filtered and smoothed probabilities

scores the imperative for policymakers to consider implementing a flexible or floating exchange rate framework. Such a strategic shift is vital to mitigate the adverse ramifications of the pandemic on Iran's economic landscape.

By contributing these empirical findings, our research significantly enriches the prevailing body of literature examining the interplay between pandemics and exchange rates. Moreover, our discoveries carry vital implications, extending beyond Iran's borders, offering valuable guidance to policymakers in other nations grappling with similar challenges stemming from the pandemic's economic upheaval.

Based on the conclusive correlation established between the COVID-19 pandemic and amplified exchange rate fluctuations in Iran, a crucial policy recommendation emerges: the adoption of a flexible or floating exchange rate regime.

This strategic shift holds substantial promise in mitigating the adverse effects of the pandemic on Iran's economic stability. By allowing the currency's value to be determined by market forces, a floating exchange rate system can offer a cushion against the heightened volatility triggered by external shocks, such as global health crises like COVID-19. Policymakers should consider this adjustment as a pivotal measure to safeguard against abrupt and drastic fluctuations in exchange rates, thereby fostering more resilience in the face of economic uncertainty.

Given the strong effect of COVID-19 case growth on volatility in both regimes and the higher persistence of the high-volatility regime, exchange rate flexibility should be complemented by transparent, rule-based stabilization measures and timely policy communication to reduce panic-driven expectations.

Additionally, this recommendation extends beyond Iran's borders. Policymakers worldwide grappling with similar challenges arising from the pandemic-induced economic upheaval can draw valuable insights from this approach. The adoption of flexible exchange rate frameworks may serve as a prudent strategy to navigate the turbulent economic landscapes brought about by global crises, fostering greater stability and adaptability in various economies.

Ultimately, implementing a flexible or floating exchange rate system stands as a proactive measure, offering a means to fortify Iran's economic resilience against unforeseen disruptions and providing a blueprint for other nations to fortify their economic frameworks amid similar tumultuous times.

Declarations

Availability of data and material

The data supporting this study's findings are available from the corresponding author, upon reasonable request.

Competing interests

There are no competing interests between the authors.

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