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PAPER

Early warning models for the financial crisis in the Covid19 era: Guidelines for an effective interception in Morocco and Egypt

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Abstract This article provides a couple of models for financial crisis detection better to intercept early signals for Moroccan and Egyptian FX Markets. Using publicly available monthly data and a Markov autoregressive switching model, we suggested two models containing the most relevant variables for each country. The results show the Moroccan case model's outstanding detection ability as it revealed both endogenous and exogenous occurring during the study period. On the other hand, even though the Egyptian case model showed promising results, it failed to spot significant disturbances due to various economic and domestic monetary policy issues.

Keywords: Crisis detection, Markov switching regime, Foreign exchange, COVID 19.

JEL classification: F31, G15, E52, C58.

Introduction

Following the collapse of the Bretton Woods order, financial crises have grown in frequency, intensity, and complexity, whatever their form: currency, banking, or debt version. Due to their unpredictable nature, these episodic crises represent permanent challenges for monetary authorities' abilities to conduct sound and sustainable policies. This unique context led to costly and prolonged economic downturns and abrupt financial market instability during the last quarter of the 20th century.

Against this background, economic researchers started to investigate the various types of crises and develop early shocks' detection models to mitigate or at least

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reduce their havoc impacts. Further to the theoretical framework, empirical research on predicting currency crises has multiplied, especially in the 90s of the last century with the upheavals of the successive Mexican, Brazilian, Russian, and then Asian crises. The literature has since produced three models intended to provide early warning systems with various predictive power for crisis detection.

However, most of those models were designed primarily for mature financial markets of the developed economies. They require the availability of high-frequency data and the timely monitoring of various macroeconomic variables. Such statistical data systems are relatively short in most developing countries like Morocco and Egypt, whose economies integrate the global economy increasingly. Furthermore, as both countries are recently embarking on different flexibilization processes and navigating the challenging economic context of the COVID19 pandemic, they would inevitably need to set up systems to identify currency crises long before their occurrence to avoid economically and socially damaging shocks.

This paper suggests a couple of models for crisis detection using publicly available data to intercept early financial crisis signals for the Egyptian and Moroccan cases.

The article is organized as follows: first, we will present a literature review of various detection models in section 2, our data in section 3, and the theoretical framework in section 4. We will then expose our empirical findings in section 5 before ending with a conclusion and policy implication of the study in section 6.

Literature review

In the early 1960s, efforts to detect struggling corporations led to the creation of the early crisis detection models. One of the first models is the z-score based on Beaver (1966) scoring for the single and multiple discriminant analysis Altman (1968). Then researchers as Deakin (1972) and Altman et al. (1977) began introducing statistical models using multiple discriminations in their studies, followed by the use of logistic (logit) and binomial (probit) regression models by Zmijewski (1984), Jones (1987) and Pantalone & Platt (1987).

Regarding the severe fallout of the Asian crisis and the burst of the Internet bubble on the global economic landscape, academics focused on developing models that could detect potential financial crises to allow monetary authorities and market participants to preemptively and effectively address them. One of the early studies on this topic is Fernandez (2004), which uses the ICSS algorithm introduced by (Inclán & Tiao (1994) and wavelet analysis to recognize changes in volatility regimes often associated with stress in financial markets. These two methods effectively caught the interest rate market's attention during the 1997 Asian crisis and after the 2001 terrorist attacks in the United States.

The author elaborates on his previous results (Fernandez, 2006), by adding a heteroskedastic filter. The paper also shows that wavelet analysis offers more accurate results than the ICSS algorithm for emerging countries. Crisis detection models based on the ICSS algorithm are also present in studies such as Wang & Moore (2009) for the Višegrad countries, Duncan & Liu (2009) for South Africa, Kim (2013) and Bouhali et al. (2020) for the case of several developed countries. Simultaneously, another line of research has focused its work on early warning systems (EWS). Abumustafa (2006) provided one of the first foreign exchange crisis EWS for Egypt, Jordan, and Turkey. The proposed model is based on the real effective exchange rate, exports, imports, trade balance, current account, Gross Domestic Product (GDP), foreign currency assets and liabilities, real exchange rate, international oil prices, and government expenditures. However, despite the model's superior detection abilities, its main shortcoming is the lack of data, especially for developing countries such as Egypt and Jordan. A similar approach based on logit and signal processing is proposed by Davis & Karim (2008) for the case of several emerging countries. The same authors presented an improved version of their work using the binomial tree to anticipate crises in the United States and United Kingdom economies Davis & Karim (2008). In the same vein, Koyuncugil & Ozgulbas (2012) introduced an approach based on data processing using a decision support model called CHAID (Chi-Square Automatic Interaction Detector). However, as with previous models, the large number of variables required and the lack of real-time data make it challenging to implement such systems in emerging and developing countries.

Over the last few years, Markov chains have been introduced into crisis detection models, which have led to the optimization of parameters numbers. In this vein, Baumohla et al. (2011) developed a multivariate heteroskedastic model using a Markov chain (DCC MV-GARCH) to detect the excess volatility linked to crises in Central European countries. Cao et al. (2013) presented a similar approach by using a Hidden Markov Chain model to predict economic crises. The authors demonstrated this model's superiority over logit models, signal processing models, and artificial neural networks. Another perspective is presented by Jutasompakorn et al. (2014), which effectively detected various domestic and international crises and their duration for several developed countries via a Markov autoregressive model.

As we notice, the economic literature contains various crisis detection models that are generally suited for developed countries characterized by excellent transparency regarding financial data and monetary policies. In recent years, new studies such as Abumustafa (2006), El-Shazly (2009), Budsayaplakorn et al. (2010), Ari & Cergibozan (2018), Metwally (2019) and Abdelsalam & Abdel-Latif (2020) developed crisis detection models for developing countries with various sets of data and different econometric approaches. While most of those studies yielded promising results, when we thoroughly investigated the authors' data sources, we could not reach out to it at the official website of the Egyptian Central Bank and the IMF online database, making it challenging to reproduce the model's results.

This paper will propose two crisis detection models for Morocco and Egypt that can be used by various market actors using monthly public data from both countries and the Markov autoregressive switching model.

Data

Presentation

One of the main challenges for econometric modeling in developing countries is the lack of reliable and up-to-date data. Therefore, we started our data analysis by gathering all the monthly economic variables available on monetary and trade authorities' websites and the IMF database for Morocco and Egypt. We then determined the most relevant variables for each country based on empirical studies in the literature and the IMF country reports for both countries.

Our second step was to test the autocorrelation between all the selected data to avoid cross-correlated variables that may hamper our model's integrity. After constituting the second pool of independent variables for both countries, we examined various combinations to pick up the best reliable data set based on the Akaike information criterion (AIC) and listed them in Table 1 alongside their sources. To provide more insight, we present in Tables 2 and 3 a quick explanation of each variable's importance for both countries' exchange ecosystems.

Table 1. Variables used in MS AR models

	Period	Variable	Source	Definition
Morocco	Monthly DATA 2004-M01 2020-M06	YIELDS	Authors, based on Data from CBOM[1]	The gap between the highest and the lowest daily closing rate during the month
		MIS	IMF[2]	Misalignment
		RES	IMF	Official foreign exchange reserves in USD
		FIAT	IMF	Fiduciary money
		BoT	ODC[3]	Balance of trade
		MM_VM	CBOM	Volumes on the domestic monetary market
		MRE	ODC	Remittances from Moroccan diaspora

Egypt	Monthly DATA 2004-M01 2020-M06	YIELDS	Authors, based on Data from CBE[4]	The gap between the highest and the lowest daily closing rate during the month
		RES	IMF	Official foreign exchange reserves in USD
		WAMR	IMF	Weighted average money market rate
		EGX30	CBE	The main index in the Cairo Stock Exchange
		FIAT	IMF	Fiduciary money

[1] Central Bank of Morocco (Bank al Maghrib)

[2] International Monetary Fund

[3] The « Office des changes »

[4] Central Bank of Egypt

Table 2. Motivations for variable choices in the case of Morocco

	Variable	Choice's motivations
Morocco	Yields	Exchange rates are a crucial indicator in every economy, especially in developing countries, impacting significantly international trade, competitiveness, and external debt. For Morocco, the exchange rate regime is intermediate, as monetary authorities initiated a smooth transition to a floating regime in the medium/long term. Therefore, detecting perturbations in the domestic foreign exchange market will be one of our model's most important goals.
	MIS	Due to Morocco's strict capital controls, the misalignment of the dirham's exchange rate concerning its real value is always problematic for monetary authorities. Indeed, a significant increase in misalignment will directly impact the country's competitiveness and could lead to a decline in exports, hence its importance in our model.
	RES	Monetary authorities use foreign exchange reserves as the primary instrument for defending the fixed exchange rate regime. Therefore, a significant drop in reserves is a meaningful sign of a possible foreign exchange crisis in 2012 in Morocco.
	FIAT	Moroccan fiduciary money has grown significantly during the last years due to the central bank easing stance and the high demand for cash by domestic economic participants.
	BoT	Morocco's trade balance is structurally in deficit and dependent on energy and food imports (especially oil and wheat). An increase in trade deficit can embolden the risks of a currency crisis.
	MM_VM	Money market trading volumes are an essential proxy for the banking system's liquidity. Severe stress on the money market is usually a sign of endogenous crisis.
	MRE	Remittance from the Moroccan diaspora is an essential source of foreign currency for Morocco as it's relatively constant through time. A perturbation in this variable can be a sign of challenging economic context on the international level and can significantly affect official foreign exchange reserves.

Table 3. Motivations for variable choices in the case of Egypt

	Variable	Choice's motivations
Egypt	YIELDS	Exchange rates have been a crushing problem for the Egyptian economy and monetary authorities during recent years. Therefore, detecting stress on the domestic foreign exchange market will be one of our model's main objectives.
	RES	Same as in Morocco, foreign exchange reserves have been used by monetary authorities as the primary instrument to defend the chosen exchange rate regime to counter speculative attacks. Those reserves are characterized by high volatility as they are mainly built on Gulf countries' deposits in hard currency. Therefore, stress on this variable can contribute significantly to the economic and financial crisis in the country.
	WAMR	The weighted average money market rate is another critical metric in Egypt's case, as it provides considerable information on the country's money market situation. Large variations in the WAMR are associated with significant shocks to the Egyptian economy.
	EGX30	The Egyptian stock exchange is one of the most influential African stock exchanges after South Africa. This leading status allows it to attract significant capital seeking higher returns on equity assets. Its main index, the EGX30, is the main gauge of market participants' expectations of Egypt's economic situation.
	FIAT	Inflation is one of the persisting problems of the Egyptian economy. Its significant variations have strongly impacted wages and living standards in the country. While this problem is partly linked to the Egyptian pound's sharp depreciation in recent years, the Egyptian central bank's accommodating policy is also a substantial factor in this issue.

2. Graphical analysis and descriptive statistics

2.1 Morocco

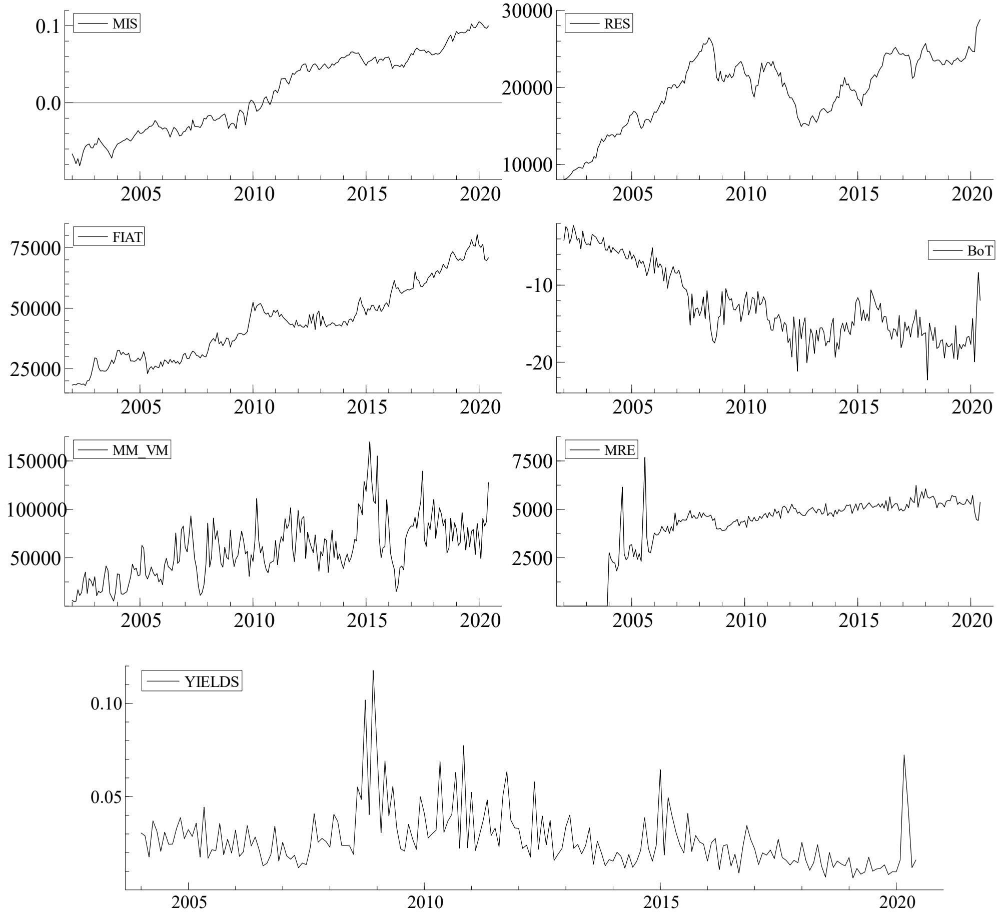

Figure 1. Plot of MS AR Model variables for the case of Morocco
Source: Plotted by authors based on Data from the sources listed in Table 1

The graphs of selected economic variables for the Moroccan model shown in Figure 1 exhibit important information. The first observation is the lagging effect of the 2008 financial crisis on the Moroccan economy. The negative fallout of this external shock took longer to materialize noticeably. Indeed, the economic slowdown was not undisputedly felt until the fourth quarter of 2009.

Although decelerating, the GDP growth overwhelmingly driven by a vivid domestic demand before the 2008 shock was robust to resist the international crisis's early negative repercussions. The downward trend cycle was perceptible in early 2010, with the increasing misalignment of the domestic currency linked to the substantial deepening of the trade balance deficit.

Another observation is the elevated stress on foreign exchange reserves since 2008, resulting in the significant decline of 2012 due to the 2008/2009 financial crisis's shockwaves and the 2011 sovereign debt worries in the Eurozone area. Following the substantial financial grants received from the Gulf monarchies to alleviate the Arab spring political and social challenges in 2011, Morocco succeeded in reestablishing a comfortable international reserve level which held until mid-2017, when the announcement of the gradual flexibilization of the exchange rate regime triggered an abrupt meltdown of these reserves.

Another feature is the significant growing pace of fiduciary money. It almost tripled over 15 years, boosted by the central bank monetary policy's markedly accommodative stance after the 2008 financial crisis. Also, we notice important movements in money market volumes, reflecting the liquidity shortages linked to the persistent current account deficit and reliance on refinancing from the central bank. Finally, the remittance graph exhibits a relatively resilient trend over the years, except for a short-lived fall during the 2008/2009 economic crisis.

Table 4. Descriptive statistics of MS AR Model variables for Morocco

	YIELDS	MIS	RES	FIAT	BoT	MM_ VM	MRE
Mean	0.027608	0.014587	19584.42	43990.90	-12.42651	58546.00	4154.598
Median	0.023701	0.021927	20491.74	43183.95	-13.82525	55178.50	4746.550
Maximum	0.117641	0.105263	28803.44	80386.66	-2.246500	169709.0	7685.100
Minimum	0.006358	-0.081862	8040.456	18070.59	-22.30920	4532.000	0.000000
Std Dev	0.015744	0.051714	4633.867	15472.34	4.729050	29963.26	1664.971
Skewness	2.058036	-0.037335	-0.661304	0.393707	0.480109	0.600985	-1.572563
Kurtosis	9.664859	1.618045	2.706865	2.298007	2.141267	3.599181	4.535989

Descriptive statistics for Morocco are listed in Table 4 shows an asymmetry in all the data sets with different signs.

We also note that all the variables are platykurtic except Yield, Money Market volumes, and the Remittances series.

2.2 Egypt

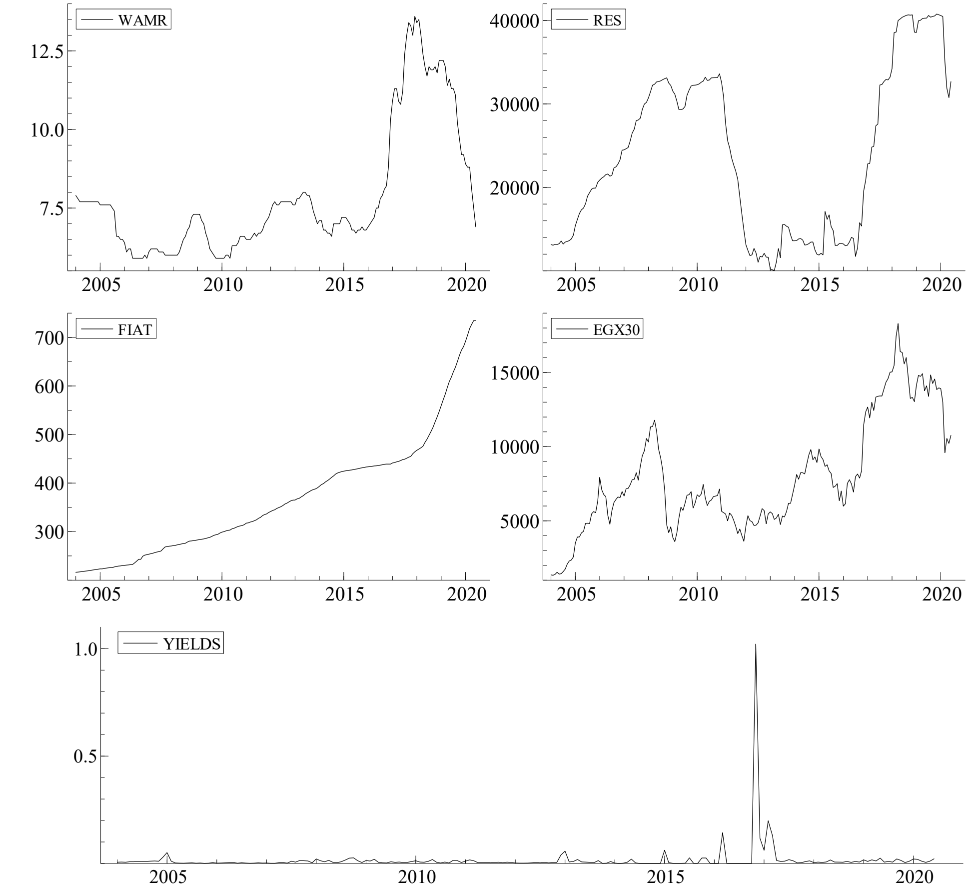

Figure 2. Plot of MS AR Model variables for the case of Egypt
Source: Plotted by authors based on Data from the sources listed in Table 1

We observe a substantial decline in Egypt's foreign exchange reserves after the 2011 popular uprising due to the country's difficult economic situation at the time. Political instability and security problems contributed to the Egyptian economy's pronounced slowdown and the total collapse of the touristic sector revenues. Following the forced transition to floating in 2016, foreign exchange reserves recovered, given the competitiveness boost from the domestic currency's historic free fall. We observe a similar impact on the Egyptian stock exchange index, which improved considerably after 2016. Simultaneously, a substantial rise in the fiduciary currency further magnified the Cairo stock market index's performance and pushed up the Weighted Average Money Rate level.

Unlike Morocco, The Egyptian economy immediately felt the 2008 global financial crisis headwinds as the international reserves fell sharply. Their level reached a record low in the aftermath of the 2011 popular uprise; this dire state of the economy is the main driver for the forced EGP floating, which triggered the 2016 currency crisis. They gradually clawed back to a comfortable level afterward. During the Pandemic crisis in 2020, they decreased back. The Egyptian stock exchange index's performance tracked the same path as the international reserves position. Market liquidity was closely linked to the global capital inflows and reflected investors' high-risk aversion during this politically and socially unstable context.

Simultaneously, the fiduciary money evolution was characterized by an interrupted, rising trend despite the high level of the Weighted Average Money Rate. This outcome resulted from the monetary authorities' failure to halt the speculative attacks against the EGP before the forced transition to floating in 2016 and the government's exceptionally loose fiscal policy to tackle the widespread disastrous uprise fallout in 2011. The drastic deceleration of The Weighted Average Monetary Rate in 2020 was the direct consequence of the Egyptian Central Bank to mitigate the pandemic crisis's adverse effects on the economic and social levels.

Table 5. Descriptive statistics of MS AR Model variables for Egypt

	YIELDS	**RES**	**WAMR**	**EGX30**	**FIAT**
Mean	0.016390	0.006519	-0.000273	0.015104	0.006241
Median	0.005665	0.003014	0.000000	0.014472	0.004073
Maximum	1.021419	0.436572	0.170455	0.366045	0.025647
Minimum	0.000000	-0.154739	-0.108108	-0.331896	0.000000
Std Dev	0.075389	0.064518	0.029012	0.095891	0.005581
Skewness	12.24572	2.583184	0.791332	0.212447	1.473742
Kurtosis	162.2333	17.49432	10.42791	5.043502	4.372818

Descriptive statistics for the Egyptian cases are listed in Table 5 show a positive asymmetry and a strong leptokurticity for all the data sets.

3.Stationarity

The stationarity of the variables is one of the requirements for a suitable autoregressive model. Therefore, we conducted an ADF[1] stationarity test for the Moroccan and Egyptian variables. These tests are listed in Table 6 and show that only Moroccan and Egyptian YILEDS are stationary at the level. At the same time, all the other variables are stationary at the first difference.

[1] Dickey Fuller Augmented

Table 6. ADF stationarity test results for the variables used in Moroccan and Egyptian cases

Country	Variable		Level	1st Diff
Morocco	YIELDS	ADF Statistic	-4.38119	
		P-value	0.00040	
	MIS	ADF Statistic	-0.82770	-12.2389
		P-value	0.80891	0.00000
	RES	ADF Statistic	-1.74811	-12.5819
		P-value	0.40565	0.00000
	FIAT	ADF Statistic	-0.76631	-17.9537
		P-value	0.82613	0.00000
	BoT	ADF Statistic	-2.20058	-17.1831
		P-value	0.20638	0.00000
	MM_VM	ADF Statistic	-3.18636	-16.0300
		P-value	0.52210	0.00000
	MRE	ADF Statistic	-2.72333	-12.3658
		P-value	0.27178	0.00000
Egypt	YIELDS	ADF Statistic	-5.14006	
		P-value	0.00000	
	RES	ADF Statistic	-1.48770	-6.27663
		P-value	0.53791	0.00000
	WAMR	ADF Statistic	-2.61392	-3.29381
		P-value	0.29190	0.01650
	EGX30	ADF Statistic	-1.79887	-12.8080
		P-value	0.38042	0.00000
	FIAT	ADF Statistic	0.57009	-4.36113
		P-value	0.98863	0.00000

3.1 Theoretical framework

3.1.1 Markov Switching Model

The regime-switching Markov model extends the simple framework of exogenous probabilities by specifying a first-order Markov process for the regime probabilities. The first-order Markov hypothesis requires that the likelihood of being in a given regime depends on the initial state, such as:

$$P(s_t = j \mid s_{t-1} = i) = p_{i,j}(t) \tag{1}$$

In general, these probabilities are assumed to be invariant over time so that $p_{i,j}(t) = p_{i,j}$ for any *t*. We can then write the transition matrix with these probabilities in the following form:

$$p(t) = \begin{pmatrix} p_{1,1}(t) & \cdots & p_{1,M}(t) \\ \vdots & \ddots & \vdots \\ p_{M.1}(t) & \cdots & p_{M.M}(t) \end{pmatrix} \tag{2}$$

With $p_{i,j}(t)$ representing the probability of switching from regime *i* in period *t-1* to regime *j* in period *t*. We can parameterize these probabilities according to a multinomial logit specification as in the simple regime-switching model. Since each row of the transition matrix specifies a complete set of conditional probabilities, we define a separate multinomial specification for each row *i* as follows:

$$\begin{gathered} p_{i,j}(G_{t-1}, \delta) = \frac{exp(G_{t-1}{}'\delta_{ij})}{\sum_{k=1}^{M} exp(G_{t-1}{}'\delta_{ik})}, for\ i = 1, \ldots, M\ et\ j = 1, \ldots, M \\ with\ s\tan dardization\ \delta_{iM} = 0 \end{gathered} \tag{3}$$

Markov regime-switching models are usually specified with constant probabilities so that G_{t-1} contains only constants.

3.1.2 Markov autoregressive switching model (MS-AR)

This model was first introduced by Hamilton (1989) for studying econometric time series across different fields. This model was then extended to other time series in various areas.

Let a homogeneous hidden Markov chain $\{s_t\}$ such that transition probabilities $P(s_t = j \mid s_{t-1} = i)$ are constant over time and the evolution of $\{s_t\}$ is regulated by the transition matrix $T = (p_{i,j})_{i,j\in\{1,\ldots,M\}}$ with $p_{i,j} = P(s_t = j \mid s_{t-1} = 1)$.

The MS-AR model of order *p* for a process $\{Y_t\}$ s formulated as follows:

$$Y_t = a_0^{(s_t)} + a_1^{(s_t)} Y_{t-1} + \cdots + a_p^{(s_t)} Y_{t-p} + \sigma^{(s_t)} \varepsilon_t \tag{4}$$

With:

$(a_0^{(s_t)}, a_1^{(s_t)}, \ldots, a_p^{(s_t)}, \sigma^{(s_t)})$ The unknown parameters of the $AR(p)$ model describing the evolution of the process as observed in the regime $s \in \{1, \ldots, M\}$.

$\{\varepsilon_t\}$ Is a sequence of *i.i.d* variables following an independent normal distribution of the Markov chain $\{s_t\}$.

3.2 Empirical results

In line with the work of Hamilton (1989) and the empirical literature regarding the use of Markov switching models for crisis detection such as Chesnay & Jondeau (2001), Gallo & Otranto (2007), Chkili & Nguyen (2014) and Engel et al. (2018), we denote Regime 1 as the calm market state and Regime 2 as the turbulent one.

1. Morocco

Our model's results for the Moroccan case are listed in Equations 5 and 6 for both regimes. The model coefficients and the transition matrix's statistical properties are listed in Tables 9 and 10 in the Appendix. The Ljung Box test results in Table 11 in the Appendix exhibit no autocorrelation between the model's residuals, ensuring our model's reliability and definition.

$$\begin{gathered}\textbf{Regime 1:}\, YIELDS = -0.0399757383086 \times MIS - 2.60480820525e - \\ 06 \times RES + 5.5557927013e - 07 \times FIAT + 3.22222657598e - 06 \times BoT - \\ 5.15050951483e - 08 \times MM_{VM} - 8.38263374688e - \\ 07 \times MRE + \begin{Bmatrix} AR(1) = 0.137398744012 \\ AR(2) = 0.444128753008 \\ AR(3) = 0.280177430084 \end{Bmatrix}\end{gathered} \tag{5}$$

$$\begin{gathered}\textbf{Regime 2:}\, YIELDS = -2.460049053 \times MIS - 5.32928985161e - \\ 06 \times RES + 2.77011996141e - 06 \times FIAT - 0.00320202340342 \times BoT - \\ 1.44444829184e - 07 \times MM_{VM} - 3.41249682214e - \\ 05 \times MRE + \begin{Bmatrix} AR(1) = 0.204937726033 \\ AR(2) = 0.231532642808 \\ AR(3) = 1.05260675007 \end{Bmatrix}\end{gathered} \tag{6}$$

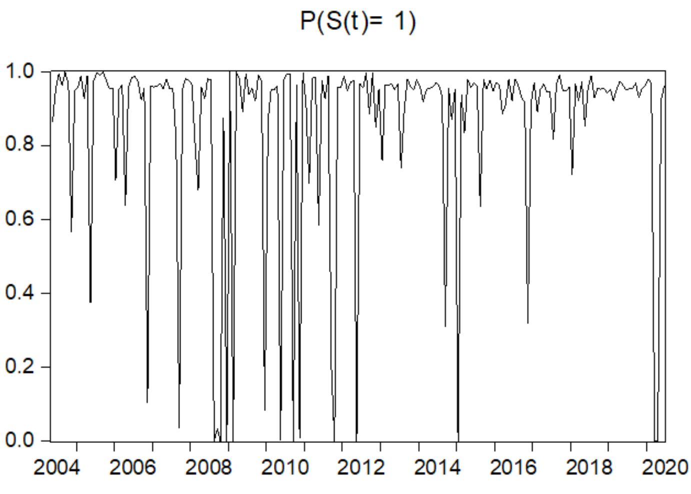

Figure 3. The probability of switching to a calm state in the case of Morocco

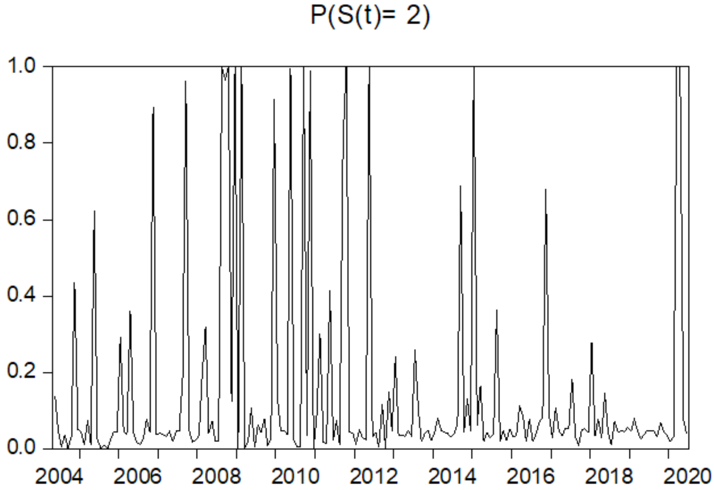

Figure 4. The probability of switching to the turbulent state for the case of Morocco

The graph of switching probabilities to the turbulent state presented in Figure 4 shows significant spikes in the early 2000s due to the economic fallout from the Asian crisis, the internet bubble burst, and the disturbance related to the massive influx of capital into the country.

We also observed significant movements starting in 2007 due to the developing housing bubble and early subprime crisis signals. These perturbations continued in 2010-2011 with the European debt crisis, which heavily impacted Europe and Morocco's respective business cycles. Of interest to notice other spikes between 2015 and 2016 due to the sharp drop in oil prices, leading to a strong appreciation of the USD against world currencies.

Our model also succeeded in detecting the endogenous shocks related to the Moroccan foreign exchange market's panic movement before transitioning to the new exchange rate regime in 2017. Finally, we observe a substantial spike during the first semester of 2020 due to the COVID-19 economic and social impacts on Morocco and the enlargement of the central bank's fluctuation bands. Overall, our model had convincing detecting power capacities. It succeeded in capturing most of the endogenous and exogenous crises over the study period, which will help market participants swiftly assess the economical situation and implement suitable measures to offset the shock effects.

To further examine those shocks, we listed in Table 7 the regime's switches with the most prominent probabilities alongside comments about the Moroccan economic context at the time and the explanatory causes of these perturbations on the FX market.

Table 7. Major perturbations detected by our model in the case of Morocco

	Transition probability	Comments
2005M05	62%	Expected below-average growth due to the severe drought conditions negatively impacting the agricultural output emboldened the probabilities of looming difficulties ahead.
2006M11	89%	Excess liquidity conditions against a backdrop of decelerating growth and high fiscal deficit warned of the incoming economic bumps.
2007M09	96%	The domestic demand's resilience is questionable as the ballooning trade balance deficit is jeopardizing the growth performance.
2008M08	100%	The ripples of the global financial crisis shockwaves on the real economy were limited at this stage. Still, the extreme volatility of capital markets hit the performance of the local interbank currency market.
2008M09	97%	Immediate Strains of the global financial crisis passed through real estate assets valuation and hurt money markets liquidity.
2008M12	100%	Persisting downside risks related to the grim economic outlook forced the public authorities to loosen the fiscal policy through higher spending and lower taxes.
2009M02	100%	The central bank adopted an overtly accommodative stance by lowering its benchmark rate and reserve requirements on local banks to tackle the growing economic risks in the short run.
2009M12	92%	The relative resilience of the Moroccan economy following the 2008 international financial crisis started to fade away through the real channels.
2010M05	100%	Soaring food and energy prices in the international markets ignited inflationary pressures domestically, adding woes to the monetary policy steering in an increasingly adverse environment.
2010M09	100%	Notable deterioration of the public finances, linked to the burdensome subsidy schemes to food staples and oil, added complications to the macroeconomic stability.

2010M11	99%	Gyrations in the Eurozone sovereign debt markets (major trading and financial partner of the country) sent volatility to record levels that influenced the local currency due to its pegging structure dominated by the Euro's heavyweight.
2011M09	81%	Spillovers from the "Arab spring" started directly to impact the country's FDI and tourism receipts which darkened the economic outlook.
2011M10	100%	Declining liquidity was symptomatic of the persistent challenges related to the deterioration in the external balance and the worsening budget deficit.
2012M05	100%	Lagging post-effects of the global financial crisis triggered a pronounced meltdown of the official international reserves putting the Moroccan economy structures under extreme stress.
2014M09	69%	Heightened risks resulting from the exogenous shocks such as the surge of global markets volatility, soaring oil prices, and sluggish growth in the Eurozone represented a heavy toll on the Moroccan economy performance.
2015M01	100%	Deepening external account deficit reached unprecedented levels forcing the authorities to take decisive action to adjust the national currency basket weights
2016M11	68%	Sharp deceleration of the GDP combined with the persisting twin deficits amplified the market liquidity shortage.
2020M03	100%	Monetary conditions worsened significantly, prompting immediate Central bank's response to avert liquidity and exchange crises through widening the dirham fluctuation band from +/- 2,5% to +/-5% and massively injecting funds into the system.
2020M04	100%	Further actions from monetary authorities are desperately needed in response to the recessionary impact of the global pandemic context.

2. Egypt

Our model results for the Egyptian case are listed in Equations 7 and 8 for both regimes. The model coefficients and the transition matrix's statistical properties are listed in Tables 12 and 13 in the Appendix. The Ljung Box test results, listed in Table 14 in the Appendix, exhibit no autocorrelation between the model's residuals, ensuring our reliability.

$$\begin{gathered} Regime\,1: YIELDS = 8.87130530733e-07 \times RES + \\ 0.000235462667779 \times WAMR - 1.03132425395e-06 \times EGX30 + \\ 0.00114216111659 \times FIAT + \{AR(1) = 0.459493209456\} \end{gathered} \tag{7}$$

$$\begin{gathered} Regime\,2: YIELDS = -6.28341153394e-06 \times RES + \\ 0.296932767412 \times WAMR + 8.86630806009e-05 \times EGX30 - \\ 0.00346985171456 \times FIAT + \{AR(1) = -0.354931809591\} \end{gathered} \tag{8}$$

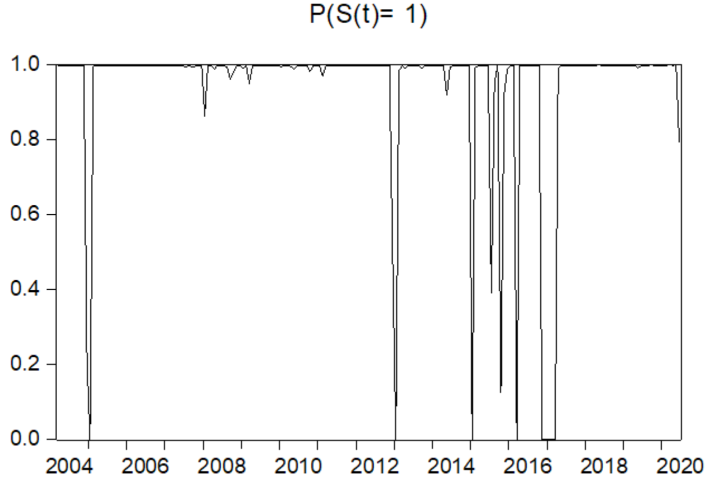

Figure 5. The probability of switching to a calm state in the case of Egypt

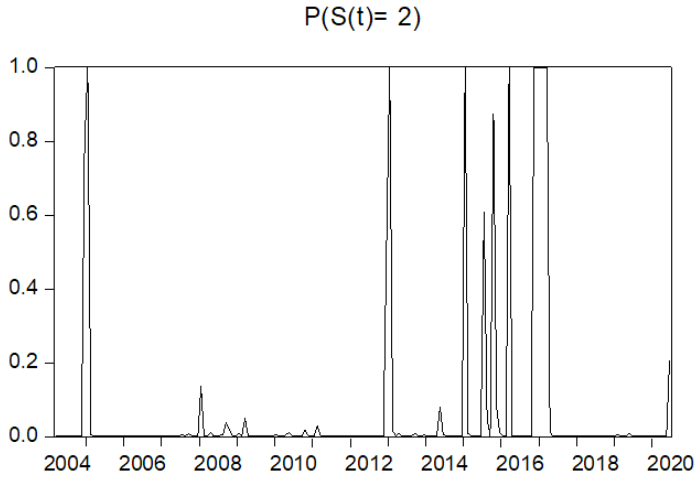

Figure 6. The probability of switching to the turbulent state for the case of Egypt

The switching probabilities to the turbulent state presented in Figure 6 show fewer spikes than in Morocco. This difference may be caused by several factors, such as chronic political instability and the parallel FX market's importance. These factors are complicated to model and often evolve unpredictably, impacting the model's ability to detect shocks. Another factor is the Egyptian central bank stance before 2016. It desperately tried to maintain the fixed regime at any cost, which significantly distorted shocks' impact on the domestic foreign exchange market, fueling the remarkable development of the parallel market. Similar behaviors are exhibited by Bonser-Nea (1996) et Beine et al. (2002).

However, with most switchover probabilities significantly higher than 50%, our model captured most signals of the significant perturbations in the Egyptian economy, especially after the "Arab Spring" events. We notice that the 2012 and 2015 spikes are due to the political instability and the liquidity squeeze on the FX market, leading to the forced transition to floating. We also observe a modest spike in the 2020 first semester, mainly caused by the COVID19 situation in the country and the decline of export activities. Our model's promising detection abilities will provide market participants with valuable information about the different types of shocks on the country's economy, which will allow them to implement efficient and timely remediation plans. We listed the switches with the most prominent probabilities in Table 7 alongside the Egyptian economic context and the perceived events leading to these shocks to analyze further those various perturbations.

Table 8. Major perturbations detected by our model in the case of Egypt

<table>
<tr><th></th><th>Transition probability</th><th>Comment</th></tr>
<tr><td>2004M12</td><td>78,52%</td><td rowspan="2">The steep decline in inflation took the discount rate from 15.9% in late 2004 to 5.1% in January 2005. The government embarked on a loose fiscal approach to boost the living standard, especially in low-income brackets, and improve service quality. Those policies doubled the deficit in government finance, going from 2.4% in 2004 to 5.7% of the GDP in 2005.</td></tr>
<tr><td>2005M01</td><td>100,00%</td></tr>
<tr><td>2012M12</td><td>53,20%</td><td rowspan="2">The Egyptian economic growth and foreign reserves are in free fall as political and social instability reaches its climax. The country is forced to adopt harsh austerity measures to secure a USD4.8 billion loan from the IMF. This significant economic shock will precipitate the popular uprising that led to the change of the political ruling wing in the following months</td></tr>
<tr><td>2013M01</td><td>100,00%</td></tr>
</table>

	Transition probability	Comment
2015M07	60,75%	The political instability and the increasing number of terrorist attacks significantly impacted the tourism sector, accounting for around 10% of Egypt's GDP.
2015M10	87,55%	The central bank imposed bold currency restrictions to help preserve foreign exchange reserves and mitigate the parallel market's disturbing impact. The unsustainable fixed exchange rate regime combined with the recently set of measures worsened the economic situation. Later it accelerated the switch to free-floating of the Egyptian pound the following year.
2017M02	100,00%	The economic outlook darkened further, fueled by the massive effects of monetary authorities' forced floating in November 2016. The domestic currency lost more than half its value, and the inflation rate hit a decade record of 28.1% in February.
2020M06	20,54%	Large capital outflows in the early stage of the global pandemic exposed the official reserves to renewed pressures.

4. Conclusion

This article presented two crisis detection models for Morocco and Egypt using publicly available data and Markov switching models. We introduced the selected data set to emphasize their importance in both countries' foreign exchange ecosystems. We then backtested the models to evaluate their adequacy and ability to detect crises over more than 15 years.

The results show the Moroccan case model's outstanding detection ability as it intercepted both endogenous and exogenous occurring during the study period. On the other hand, the Egyptian case model showed promising results, catching most of the significant crises emerging after the 2012 popular uprising, including the forced switch to free-floating and the economic disruptions in 2016-2017. However, it failed to detect significant disturbances before 2012 except for the inflation shock in the late 2004/ early 2005 period. We believe this lack of detection is likely linked to the Egyptian central bank's frequent interventions on the domestic forex market, significant capital control policies, and the country's crucial parallel market.

Our study's models offer investors and banks a valuable tool for risk management and crisis detection to navigate Morocco and Egypt's flexibilization process challenges efficiently.

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Appendix

Morocco

Table 9. Results of MS AR modeling for the case of Morocco

Variable	Coefficient	Std. Error	z-Statistic	Probability
1st Regime				
MIS	-0.039976	0.122605	-0.326053	0.0444
RES	-2.60E-06	1.19E-06	-2.183724	0.0290
FIAT	5.56E-07	3.05E-07	1.818673	0.0390
BoT	3.22E-06	0.000305	0.010556	0.0416
MM_VM	-5.15E-08	2.86E-08	-1.798363	0.0321
MRE	-8.38E-07	7.74E-07	-1.082408	0.0291
AR(1)	0.137399	0.047029	2.921573	0.0035
AR(2)	0.444129	0.051071	8.696238	0.0000
AR(3)	0.280177	0.049563	5.652925	0.0000
2nd Regime				
MIS	2.460049	0.690278	3.563853	0.0004
RES	5.33E-06	3.25E-06	1.641402	0.0007
FIAT	-2.77E-06	1.45E-06	-1.915249	0.0355
BoT	-0.003202	0.001369	-2.338332	0.0194
MM_VM	1.44E-07	1.66E-07	0.871403	0.0335
MRE	-3.41E-05	1.55E-05	-2.197758	0.0280
AR(1)	0.204938	0.548710	0.373490	0.0288
AR(2)	0.231533	0.285296	0.811553	0.0170
AR(3)	1.052607	0.526483	1.999319	0.0456

All variables in the MS AR model for the Moroccan case are significant during both regimes.

Table 10. Transition matrix for the case of Morocco

		Colonne j	
		1	2
Ligne i	1	0.845459	0.154541
	2	0.845459	0.154541

$$P(i,k) = P(s_t = k \mid s_{t-1} = i)$$

Table 11. Autocorrelation plot of MS AR model residuals for the case of Morocco

	AC	PAC	Q-Stat	Probability
1	0.030	0.030	0.1782	
2	-0.067	-0.068	1.0783	
3	-0.151	-0.147	5.6029	
4	0.033	0.037	5.8143	0.116
5	-0.069	-0.093	6.7815	0.134
6	-0.092	-0.109	8.4831	0.137
7	-0.011	-0.007	8.5071	0.175
8	0.045	0.005	8.9167	0.212
9	-0.029	-0.061	9.0867	0.269
10	-0.082	-0.084	10.477	0.263
11	-0.038	-0.051	10.770	0.215
12	0.095	0.060	12.656	0.279
13	0.022	-0.011	12.755	0.238
14	0.025	0.024	12.892	0.300
15	-0.073	-0.070	14.017	0.300
16	0.054	0.037	14.650	0.330
17	-0.015	-0.014	14.696	0.399
18	-0.051	-0.055	15.257	0.433
19	-0.132	-0.120	19.020	0.268
20	0.090	0.067	20.776	0.236

It is necessary to ensure the absence of autocorrelations among the residuals to validate the model. The Autocorrelation plot in Table X shows no correlation between the residuals with a 95% confidence level, thus confirming our model's validity.

Egypt

Table 12. Results of MS AR modelling for the case of Egypt

Variable	Coefficient	Std. Error	z-Statistic	Probability
1st Regime				
RES	8.87E-07	4.41E-07	2.011645	0.0443
WAMR	0.000235	0.002272	0.103633	0.0175
EGX30	-1.03E-06	6.69E-07	-1.540778	0.0234

FIAT	0.001142	0.000202	5.645959	0.0000
AR(1)	0.459493	0.061154	7.513661	0.0000
2nd Regime				
RES	-6.28E-06	6.13E-06	-1.024763	0.0055
WAMR	0.296933	0.067037	4.429388	0.0000
EGX30	8.87E-05	7.24E-06	12.23827	0.0000
FIAT	-0.003470	0.007045	-0.492521	0.0224
AR(1)	-0.354932	0.279401	-1.270330	0.0140

All the MS AR model variables for Egypt's case are 95% significant in both regimes.

Table 13. Transition matrix for the case of Egypt

		Colonne j	
		1	2
Ligne i	1	0.936979	0.063021
	2	0.936979	0.063021

$$P(i,k) = P(s_t = k \mid s_{t-1} = i)$$

Table 14. Autocorrelation plot of MS AR model residuals for the case of Egypt

	AC	**PAC**	**Q-Stat**	**Probability**
1	-0.116	-0.116	2.6913	
2	0.156	0.144	7.5566	0.106
3	0.183	0.223	14.285	0.121
4	0.043	0.074	14.668	0.122
5	-0.025	-0.081	14.793	0.125
6	-0.017	-0.101	14.852	0.141
7	-0.018	-0.044	14.919	0.161
8	0.114	0.161	17.581	0.144
9	-0.030	0.057	17.765	0.123
10	0.009	-0.026	17.780	0.138
11	-0.001	-0.086	17.780	0.159
12	0.016	-0.020	17.831	0.186
13	0.001	0.043	17.831	0.161
14	-0.013	0.034	17.868	0.173

	AC	PAC	Q-Stat	Probability
15	-0.028	-0.034	18.039	0.205
16	0.019	-0.033	18.114	0.257
17	-0.027	-0.027	18.273	0.308
18	-0.014	0.005	18.315	0.369
19	-0.023	0.001	18.430	0.428
20	-0.022	-0.025	18.540	0.487

The Autocorrelation plot of residuals presented in Table X shows no correlation between yields with a 95% confidence level, which indicates that our model is valid and well defined.