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Assessing systemic risk of Moroccan banks during Covid-19 pandemic using Marginal expected shortfall

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Abstract: The objective of this work is to assess the systemic risk of the main Moroccan listed banks in the context of the current health crisis and to analyze the impact of the epidemiological evolution of Covid-19 in Morocco on the banking sector. We use the Marginal Expected Shortfall (MES) proposed by Brownlees and Engle (2012) to identify the Moroccan banks mostly exposed to systemic risk. The MES estimates the exposure and contribution of each bank to systemic risk, allowing us to rank Moroccan banks according to their participation in systemic risk. On the other hand, we proposed the multivariate GARCH model DCC-GARCH to estimate the conditional volatility of Moroccan banks' stock returns caused by the high uncertainty of the financial situation following the health crisis and also to estimate the conditional correlation between each bank and the market returns. The results obtained suggest that during the pandemic crisis, the stock returns of the main institutions of the Moroccan banking sector followed the same trend of the stock index of the banking sector which reported a negative shock and a significant decline in its performance from the beginning of 2020.This decline is followed by a period of gradual and partial recovery during the year 2021. The results also show that the Attijari wafa Bank occupies the first place in terms of systemic importance. The other banks seem to be less sensitive to the financial difficulties of the banks in place and the most important factor in the difficulties of other banks. In fact, it is necessary to point out that health crises can trigger financial crises and the stakeholders of the financial system must question the way the current financial system works.

Keywords: *Covid-19; Systemic risk; MES; Conditional correlation; DCC-GARCH; Financial Contagion.*

1. Introduction

In the subprime crisis, the banking sector was the first sector to report huge losses. Then it mutated into a stock market crisis, after having affected the main stock markets, first in the United States, then in Europe via the contagion effect. Finally, it spread to the entire world economy to become a systemic crisis affecting the real economy.

In the last two years, the volatility of financial assets in international financial markets has increased due to the high level of uncertainty about the impact of the epidemic. The history of health pandemics (SARS in 2002, H1N1 in 2010, Ebola in 2014, MERS in 2019) has not negatively affected the performance of financial markets, but the Covid-19 epidemic is an extreme case due to its magnitude. The risk of bank failures has risen sharply since the beginning of the health crisis, according to the European Systemic Risk Board (ESRB), which announced that the probability of default of at least two of the largest European banks has exceeded 5%. March 2020.

The health crisis has prompted countries to assess the negative impact on their economies, especially individual financial institutions, and to seek the best solutions to deal with the crisis.

The measures taken by health authorities, called containment measures, led to a reduction in economic interaction, which in turn led to a decline in financial asset prices. The downside was a loss of investor confidence in the financial markets due to the pandemic, which underperformed.

In Morocco, the impact of the pandemic is, in addition, to the adverse effect of the drought recorded in 2019. On March 2, 2020, Morocco confirmed its first case of COVID-19. To learn from the international fight against the virus, Moroccan authorities took a number of measures, the main one being the implementation of containment on March 16, 2020. This decision has reduced the amount of pollution throughout the containment period, but it has had an undeniable impact on the macroeconomic performance of the Moroccan economy. To this end, the Moroccan financial authorities have intervened by putting in place a set of measures to ensure the stability of the financial system.

In this paper, we propose to use the Marginal Expected Shortfall (MES) Acharya, Pedersen, Phillipon, and Richardson (2012) and follow the MES measurement procedure developed by Brownlees and Engle (2017) to approximate systemic risk for the Moroccan financial system and detect the sensitivity of each institution to the decline in the performance of the group of institutions in the market portfolio. We will exploit the DCC-GARCH model introduced by Engle (2002) to model conditional volatility and dynamic correlation.

The main idea of this paper is to use the systemic risk measure MES (Marginal Expected Shortfall) to capture the interactions between the evolution of the epidemic and the performance of financial assets of financial institutions. In the modeling proposed, we argue that the epidemic has negative effects on the volatility of the financial market. We study the systemic risk through the Moroccan interbank market first by analyzing the evolution of the daily returns of the shares of the main Moroccan listed banks.

The rest of the paper is organized as follows: The next section describes the econometric methodology of our work and presents the data used in this work. In the third section, we present, interpret, and compare the empirical results obtained in our paper. The last section concludes our paper and summarizes the main conclusions.

2. Literature Review

The quest to understand and measure risk has been at the heart of academia since the discipline's inception. But given the number of crises in recent years, the focus has shifted to understanding and managing the measurement of systemic risk. Although this multidimensional concept is widely discussed in a growing number of articles, there is still no consensus on a single definition of systemic risk. Chapra (2008) identified three fundamental factors that led to the recent financial crisis (2007-2008). First, there is a lack of market discipline in the current financial system, which is caused by the misuse of risk sharing tools. In fact, financial innovation led to indiscriminate lending and excessive risk taking. Second, derivatives have grown considerably, especially credit default swaps. Finally, the concept of "too big to fail" is prevalent, which tends to reassure large banks that the central bank will always help to avoid failure and systemic disruption. All of these factors have contributed to a financial environment characterized by unhealthy credit expansion, excessive leverage and unsustainable asset price increases. As a result, the onset of a crisis is inevitable.

According to Blanchard (2014), the global economy was getting closer and closer to the brink, without economists, executives, and financial institutions realizing it. The main difficulty for systemic risk measures is that there is generally no access to some data to measure interdependence at the level of bank balance sheets (Cerutti, Claessens, and McGuire, 2014).

Chan-Lau (2010) measured the risk of default from one institution to another institution or the entire financial system by studying the risk of interdependence between different banks in the system. Brunnermeier et al (2011) proposed a "risk topography" measure based on the liquidity needs of institutions, which have a stronger systemic dimension than solvency indicators. Brownlees and Engle (2011) developed a new systemic risk indicator SRISK (ShortRISK) that measures an institution's contribution to systemic risk and systemic risk in the financial system as a whole. Acharya et al (2012) develop the concept of Expected Shortfall and measure and Marginal Expected Shortfall (MES).

The original idea of MES was combined with techniques proposed by Brownles and Engle (2012) to result in the SRISK indicator that distinguishes between recapitalization needs for an individual institution and for the financial system as a whole. It measures the amount of capital an institution would need to raise in the event of a "crisis" (a decline in the price of a benchmark stock index by at least 40% over six months) without making its origin explicit. Beraich et al (2021) studied the impact of the COVID-19 pandemic crisis on the volatility of the Moroccan financial market by applying GARCH models and noticed that the volatility of the MASI stock index increased during the crisis period. Beraich and S.E El Main (2022) applied the DY’s methodology to the daily stock prices of the Morrocan. financial institutions to construct a volatility index. Their empirical results indicate that the volatility spillover index increased during the COVID-19 crisis. They also find varying degrees of interdependence and spillover effects between the six publicly traded Moroccan banks and the Moroccan banking sector stock index before and during the COVID-19 pandemic crisis.

Perea et al. (2019) use the MES and VaR to determine whether investors are properly rewarded for the expected risk exposures they would face by holding the different tranches of a securitization. The MES, reveals the performance of an asset in terms of expected return when the entire market is likely to experience a tail event.

In this paper, on the one hand, we propose to use the Acharya, Pedersen, Phillipon and Richardson (2012) Marginal Expected Shortfall (MES) to approximate the systemic risk for the Moroccan banking system.On the other hand, we will exploit the dynamic correlation model DCC-GARCH introduced by Engle (2002) to estimate time-varying volatility and conditional correlation.

3. Data and Methodology

3.1. Data

In this paper, we apply the spillover index on a daily series of log-returns of the Moroccan banking sector index and the stocks of the six listed Moroccan banks: (Attijari-Wafa-Bank (ATW), Popular Bank (BCP), Moroccan Bank for International Trade (BMCI), Bank of Africa (BMCE), loan Estate and Hotel Bank (CIH) and Moroccan mortgage loan (CDM)).

The period we have chosen in our document is from 1 January 2012 to 31 December 2021. Because the stock markets are closed on weekends and holidays, non-business days are not taken into account.

The data were downloaded from the website of the Casablanca Stock Exchange (www.casablanca-bourse.com).

3.2. Description of the Models

3.2.1. Marginal Expected Shortfall

We follow the econometric methodology developed by Brownlees and Engle (2017) to estimate the dynamic TSS.

Our study involves estimating the sensitivity of the bank's stock price when market conditions are sensitive. This measure called Marginal Expected Shortfall (MES) allows us to take into account many dimensions of risk as it takes into account investors' perception of the bank's situation, the bank's exposure to the market, and also the volatility of the stock. In a second step, this measure is extrapolated by considering a financial crisis scenario. Then in a third step, the capital losses of the bank during a crisis are combined with the current value of the firm and the amount of debt in order to determine the amount of capital needed to face the crisis.

The MES can be seen as a natural extension of the VaR concept proposed by Jorion (2007) to the ES, which is a consistent risk measure (see Artzner et al., 1999). It measures the increase in system risk (as measured by the ES) induced by a marginal increase in the weight of firm i in the system.

The higher the firm's ES, the higher the firm's individual contribution to the risk of the financial system.

The Expected Shortfall is a function of the portfolio loss distribution, the confidence level chosen and the time horizon.

$$ES(R_{Mt}, \alpha) = E_{t-1}(R_{Mt} | R_{Mt} < C) \tag{1}$$

Where C is a specific shock to the given market return and α is a given threshold
Consider that this shock C is equal to the VaR, $(C = VaR)$ (Jorion, 2007)
So we have:

$$ES(R_{Mt}, \alpha) = E_{t-1}(R_{Mt} | R_{Mt} < VaR(R_{Mt}, \alpha)) \tag{2}$$

$$ES(R_{Mt}, \alpha) = \sum_{i=1}^{N} X_{it} E_{t-1}(R_{it} | R_{Mt} < VaR(R_{Mt}, \alpha)) \tag{3}$$

Where
N : shows the number of financial institutions that make up the financial system,
R_{it} : denotes the geometric profitability of institution i at time t.
R_{Mt} : is the geometric return of the market index of this system at time t.
X_{it} : denotes the relative market capitalization of firm i within this system.

The MES is the marginal contribution of an institution i to systemic risk proportional to the Expected Shortfall (ES) of the system at α%.

After being proposed by Acharya et al.(2010), the MES was developed by Brownlees and Engle(2012).The MES is the partial derivative function of the Expected Shortfall (ES) with respect to the weight X_{it} of institution i in the system (Scaillet, 2004)

$$MES(R_i, \alpha) = \frac{\partial ES(R_{Mt}, \alpha)}{\partial X_{it}} \tag{4}$$

This gives us the following formula:

$$MES(R_i, \alpha) = E_{t-1}(R_{it} | R_{Mt} < VaR(R_{Mt}, \alpha)) \tag{5}$$

Higher levels of TSS imply that institution i is more likely to be undercapitalized in bad economic states and contribute more to the overall risk of the financial system. Acharya, Pedersen, Phillipon, and Richardson (2012) use a market return threshold of 5% and estimate the TSS by taking an average of examined samples. Brownlees, Engle and Acharya (2017) use dynamic volatility and correlation models to estimate the MES from firm and market outcomes.

Under the assumptions that we will specify next, the MES of a financial institution i is proportional to its Expected Shortfall (ES). The proportionality coefficient is the beta of the financial institution's stock:

$$MES(R_{it}, \alpha) = \beta_{it} ES(R_{Mt}, \alpha) \tag{6}$$

Where:

$$\beta_{it} = \frac{cov(R_{it}, R_{Mt})}{\sigma^2(R_{Mt})} \quad (7)$$

β_{it} is the CAPM beta of institution i at time t ;
$cov(R_{it}, R_{Mt})$ is the covariance between R_{it} and R_{Mt} ;
$\sigma^2(R_{Mt})$ the variance of market returns.

Our estimation of the marginal expected shortfall follows the work of Brownlees & Engle (2010) in the following three steps:

Estimation of (i) volatility, (ii) correlation and (iii) conditional tail expectation.

3.2.2. DCC-GARCH Model

The uni-variate GARCH models with conditional volatility presented above simply analyze the financial series individually while ignoring the interdependence with the other series. Thus, the analysis of volatility, as a proxy for risk, must be done from a multiple risk perspective. As long as univariate GARCH models do not take into account the correlation between assets, we will switch to multivariate models in order to capture the dynamic links between these assets. These models also allow us to analyze the potential interdependencies between financial institutions and to identify the transmission mechanisms of shocks.

Multi-variate GARCH models with conditional correlations decompose the correlation matrix into two components: standard deviations and conditional correlations. Bollerslev (1990) introduces the first correlation model which is the constant conditional correlation model (CCC-GARCH). He proposes a model where the conditional variances and co-variances vary in time and the conditional correlations remain constant.

Engle (2002) introduces the dynamic conditional correlations model, the DCC-GARCH, by allowing the conditional correlations matrix to vary in time. This model is a generalization of the DCC-GARCH model of Bollerslev (1990).

In fact, the DCC model we use to estimate the TSS is slightly modified since we also introduce skewness into its specification following Capiello et al. (2006).

Brownlees and Engle (2012) model linear dependencies of variables over time and use a multi-variate GARCH-DCC model to calculate the MES.

The DCC-GARCH model is defined as:

$$r_t = \mu_t + \varepsilon_t \quad (8)$$

$$\varepsilon_t = H_t^{1/2} \ \eta_t = \ \sigma_t \, \eta_t \quad (9)$$

$$H_t = D_t R_t D_t \quad (10)$$

Where :
r_t : Vector of returns of n assets at time t;
μ_t : Vector of conditional expected returns of n assets at time t;
ε_t : Vector of conditional errors i.i.d at time t;

The conditional residuals ε_t are distributed according to a normal distribution with mean 0 and variance H_t. $E[\varepsilon_t] = 0$ and $Var[\varepsilon_t] = H_t$;
H_t : Conditional variance matrix of ε_t at time t;
D_t : Diagonal matrix of conditional standard deviations of ε_t at time t;
R_t : Conditional correlation matrix of ε_t at time t;

And the vector η_t is an i.i.d white noise of mean zero and variance equal to 1. With $E(\eta_t) = 0$ and $Var(\eta_t) = 1$

The Matrix H_t is divided into two matrices D_t and R_t .The elements of the matrix D_t come from the univariate GARCH models estimated for each of the series.

This is a two-stage estimation model. The first step is estimating the conditional variance with a uni-variate GARCH model for each of the series. In the second step, the standardized residuals obtained in the first step are used to estimate the parameters of the dynamic correlation matrix. This model includes conditions allowing the covariance matrix to be positive at all times and the covariance to be stationary.

The matrix H_t is the conditional variance-covariance matrix:

$$H_t = \begin{pmatrix} \sigma_{Mt}^2 & \sigma_{it}\sigma_{Mt}\rho_{it} \\ \sigma_{it}\sigma_{Mt}\rho_{it} & \sigma_{it}^2 \end{pmatrix} \tag{11}$$

where σ_{it} and σ_{Mt} denote the conditional standard deviations and ρ_{it} the conditional correlation.

Time-varying conditional correlations ρ_{it} are assumed to fully capture the dependence between firm and market profitability. Formally, this assumption implies that the innovations $\xi_{it}$and ε_{Mt} are independently distributed at time t.

The matrix H_t is divided into two matrices, D_t and R_t.

The elements of D_t matrix come from the uni-variate GARCH model estimated for each of the series:

$$D_t = \begin{pmatrix} \sqrt{h_{Mt}} & 0 \\ 0 & \sqrt{h_{it}} \end{pmatrix} \tag{12}$$

Where

$$h_t = \sigma_t^2 = \omega_0 + \sum_{i=1}^{q} \alpha_i \, \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j \, \sigma_{t-j}^2 \tag{13}$$

where p and q $\in \mathbb{N}^*$

and (η_t) is white noise with mean zero and variance equal to 1.

To guarantee the positivity of the variance, it is sufficient to assume that $\omega_0 > 0, \alpha_i \geq 0$ for $1 \leq i \leq q$ and $\beta_j \geq 0$ for $1 \leq j \leq p$.

The conditional variance equations are obtained by a GARCH (1,1) model:

$$h_{M,t} = \sigma_{M,t}^2 = \omega_M + \alpha_M \varepsilon_{t-1}^2 + \beta_M \sigma_{t-1}^2 \text{ (market variance)} \tag{14}$$

$$h_{i,t} = \sigma_{i,t}^2 = \omega_i + \alpha_i \varepsilon_{t-1}^2 + \beta_i \sigma_{t-1}^2 \text{ (variance of bank i)} \tag{15}$$

The matrix R_t that of the dynamic conditional correlations of the standardized residuals:

$$R_t = \begin{pmatrix} 1 & \rho_{it} \\ \rho_{it} & 1 \end{pmatrix} \tag{16}$$

In order to ensure that the matrix H_t is positive definite, it is necessary that R_t is also positive definite, because $H_t = D_t R_t D_t$

The diagonal matrix D_t is always positive because its elements are always variances.

We must also make sure that the elements of R_t must be between 0 and 1, because they are correlations.

In order to ensure the positivity of R_t , it is decomposed into two matrices:

$$R_t = Q_t^{*-1} Q_t Q_t^{*-1} \tag{17}$$

and

$$Q_t = (1 - \alpha_{DCC} - \beta_{DCC})\overline{Q} + \alpha_{DCC}\varepsilon_{t-1}\varepsilon'_{t-1} + \beta_{DCC}Q_{t-1} \quad (18)$$

Where

$$Q_t^* = \begin{pmatrix} \sqrt{q_{11,t}} & 0 \\ 0 & \sqrt{q_{22,t}} \end{pmatrix} \quad (19)$$

$$Q_t = \begin{pmatrix} q_{11,t} & \sqrt{q_{11,t}}\sqrt{q_{22,t}} \\ \sqrt{q_{11,t}}\sqrt{q_{22,t}} & q_{22,t} \end{pmatrix} \quad (20)$$

The matrix Q_t must be defined positive so that R_t is also defined positive.

$$\overline{Q} = Cov(\varepsilon_t, \varepsilon'_t) = E(\varepsilon_t \varepsilon'_t) \quad (21)$$

Let be the unconditional covariance of the standardized residuals obtained by the univariate GARCH model. Note that α_{DCC} and β_{DCC} are scalars.

The following conditions must be satisfied to ensure that H_t is defined positive:

$$\alpha_{DCC} \geq 0 \quad (22)$$

$$\beta_{DCC} \geq 0 \quad (23)$$

$$(\alpha_{DCC} + \beta_{DCC}) \prec 1 \quad (24)$$

The general DCC-GARCH (p,q) dynamic correlation structure is as follows:

$$Q_t = \left(1 - \sum_{i=1}^{p} \alpha_{DCC,i} - \sum_{j=1}^{q} \beta_{DCC,j}\right)\overline{Q} + \sum_{i=1}^{p} \alpha_{DCC,i}\,(\varepsilon_{t-i}\varepsilon'_{t-i}) + \sum_{j=1}^{q} \beta_{DCC,j}Q_{t-j} \quad (25)$$

However, in our research work we will use a bivariate DCC-GARCH (1,1) to analyze the volatility transfer relationships between the bank stock index and the listed banks, this is the simplest form of the DCC-GARCH model.

The bi-variate model $DCC - GARCH\ (1,1)$ is presented by:

$$h_{M,t} = \sigma^2_{M,t} = \omega_M + \alpha_M \varepsilon^2_{t-1} + \beta_M \sigma^2_{t-1} \quad (26)$$

$$Q_t = (1 - \alpha_{DCC} - \beta_{DCC})\overline{Q} + \alpha_{DCC}(\varepsilon_{t-1}\varepsilon'_{t-1}) + \beta_{DCC}Q_{t-1} \quad (27)$$

$$R_t = Q_t^{*-1} Q_t Q_t^{*-1} \quad (28)$$

The parameters to be estimated are:

ω_M and ω_i representing the average conditional volatility of market and financial institution i returns, respectively;

α_M, α_i called ARCH parameters measuring the sensitivity of geometric returns to market shocks;

β_M and β_i are the GARCH parameters that measure persistence.

The advantages of the DCC-GARCH model are the direct modeling of co-variance as well as its flexibility. We will try to apply this model to identify the mechanisms of volatility transmission between the banking sector index and individual banks.

4. Preliminary Analysis

Analyzing the evolution of the value of the banking index during the health crisis presented in Figures 1 and 2 and the values of the six banks that make up our sample, we see that these stock prices were affected by the health crisis in early 2020. As can be seen, the charts are characterized by a downward trend in the first months of 2020 (the period when Morocco experienced its first cases of covid-19), followed by a recovery during late 2020 and 2021.

Figures 3 and 4 display the evolution of the daily log returns of the bank index and the six financial institutions before and during the COVID-19 health crisis, respectively. By analyzing the evolution of the log-return of the banking sector index and the values of the six individual banks during the period of the pandemic crisis presented in figures 3 and 4, we notice that these returns were affected by the effect of the health crisis at the beginning of the year 2020. We note that these graphs are characterized by low volatility between 2012 and the end of 2019. at the beginning of 2020 all these graphs recorded a shock in their value, this shock is followed by a partial recovery of the volatility of profitability in 2021.

Tables 1 and 2 summarize the selected descriptive statistics for the two defined sub-period geometric yield series. All series have kurtosis well above 3, indicating that the distribution of returns is leptokurtic. In addition, the Jarque-Berra normality test ($p < 0.0001$) revealed a statistically significant departure of the data from a Gaussian distribution. The Ljung-Box (1978) test statistic shows that the log return series have autocorrelation.

For all financial geometric return series, the standard ADF (Augmented Dickey-Fuller) unit root test (1979) is performed and presented in Table 1 (pre-crisis period) and Table 2 (crisis period), and the ADF statistic for all log return series are below their critical values at the 1% significance level. This allows us to conclude that these series do not have unit root and are stationary, making them suitable for further analysis.

Figure 1. Evolution of the bank index price before and during the crisis COVID-19.

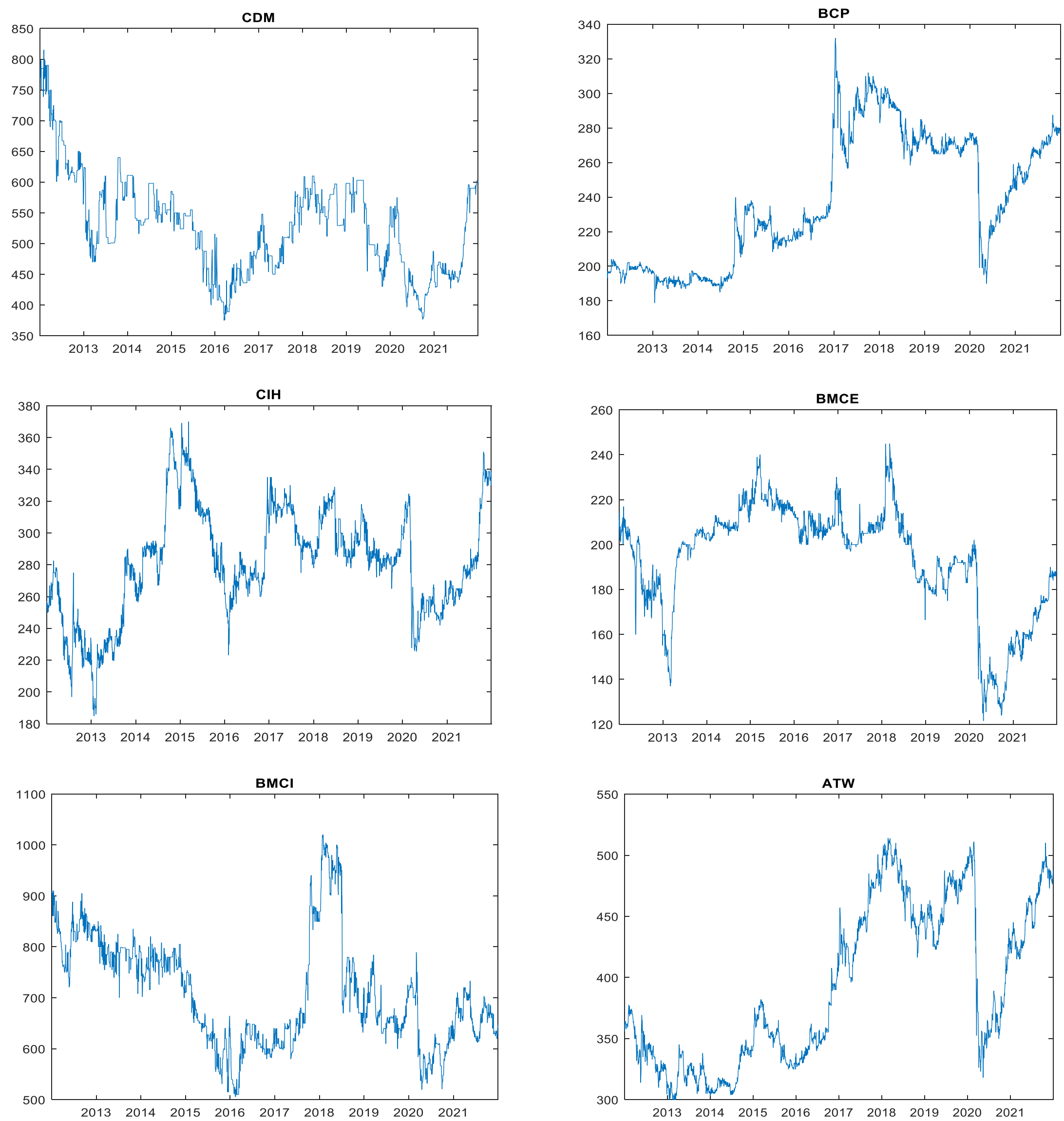

Figure 2. Evolution of bank share prices before and during the crisis COVID-19.

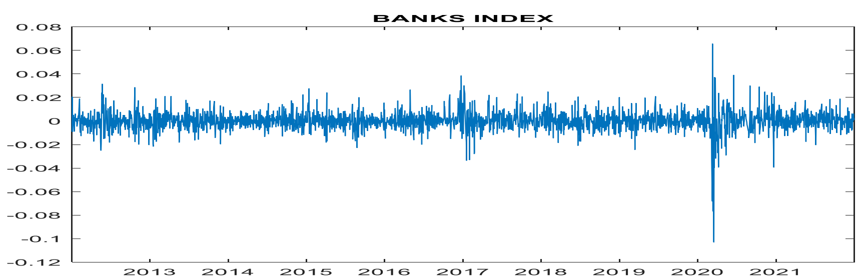

Figure 3. Daily return of the bank index before and during the crisis COVID-19.

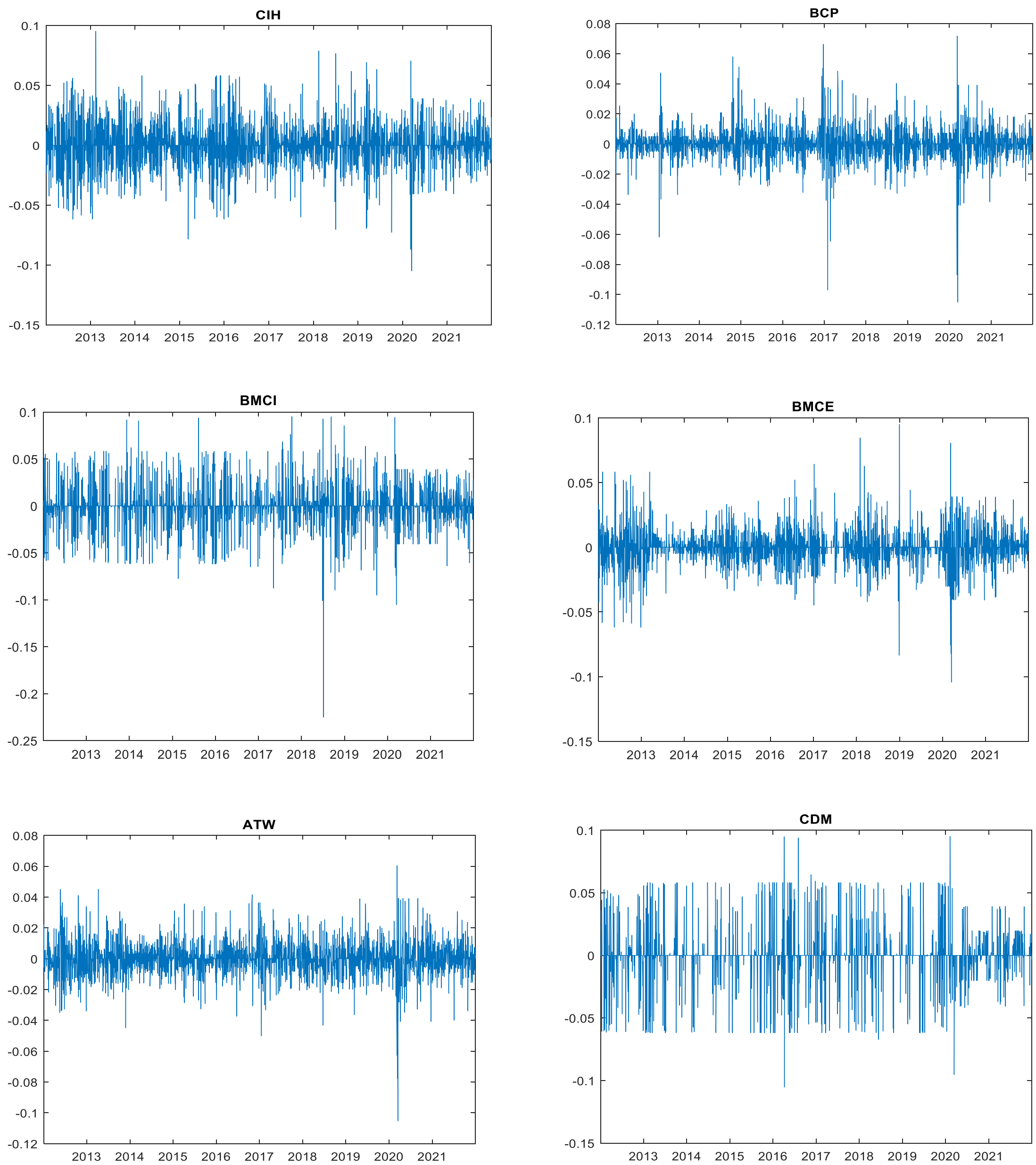

Figure 4. Daily returns on bank shares before and during the crisis COVID-19.

Table 1. Descriptive statistics and stationarity results (before the COVID-19 crisis).

	Banks Index	**ATW**	**BMCE**	**BMCI**	**BCP**	**CIH**	**CDM**
Mean	0.000095	0.000158	−0.000054	−0.000094	0.000168	0.000062	−0.00026
Median	0.0000375	0	0	0	0	0	0
Maximum	0.038563	0.04512	0.095037	0.095191	0.066273	0.09531	0.094856
Minimum	-0.033636	−0.0501	−0.0835	−0.10096	−0.09706	−0.07841	−0.10528

Std. Dev.	0.007109	0.010261	0.013211	0.021749	0.01028	0.018819	0.02038
Skewness	0.285814	0.178666	0.371141	-0.09192	-0.02052	0.054067	-0.25119
Kurtosis	5.466875	5.447024	9.693836	6.621677	12.21747	5.19444	7.42255
Normality test: Jarque Bera	523.6657	499.4417	3704.271	1073.944	6938.677	394.2262	1617.926
Probability	0	0	0	0	0	0	0
Unit root test (ADF test)	−45.58105	−50.192	−52.2934	−31.0853	−48.9221	−39.1363	−22.494
Probability	0	0	0	0	0	0	0

Table 2. Descriptive statistics and stationarity results (**during** COVID-19 crisis).

	Banks Index	**ATW**	**BMCE**	**BMCI**	**BCP**	**CIH**	**CDM**
Mean	0.000026	0.0000079	−0.000020	−0.000498	0.000041	0.0003	0.000502
Median	0.000646	0	0	0	0	0	0
Maximum	0.065637	0.060433	0.080503	0.094297	0.071744	0.070543	0.095132
Minimum	−0.103011	−0.105230	−0.104332	−0.105281	−0.10513	−0.104933	−0.09531
Std. Dev.	0.011529	0.013703	0.016639	0.018420	0.012708	0.016153	0.015292
Skewness	−2.017844	−1.26736	−0.629172	−0.375028	−1.89044	−0.767847	0.138628
Kurtosis	23.39902	13.38928	8.575254	7.34.434	21.00118	9.045455	11.4270
Normality test:	9386.834	2482.609	709.1437	421.1840	7344.744	844.5819	1543.491
Jarque-Bera Probability	0	0	0	0	0	0	0
Unit root test: ADF	−20.88472	−20.65237	−25.9065	−24.20456	−23.9102	−26.01147	−23.2273
Probability	0	0	0	0	0	0	0

5. Empirical Results

5.1. Static analysis

In this section we will analyze the sensitivity of each bank's stock returns to fluctuations in the return of the banking sector index.

The main objective of this section is to exhibit the statistical properties commonly observed in most financial markets. To do so, we will proceed to the empirical study of the evolution of the Moroccan banking index during the period from 01/01/2012 to 31/12/2021, i.e. 2482 daily closing prices as well as on its daily returns.

5.1.1. Static Analysis of Sensitivity Risk:

Table 3 displays the Variance-Covariance Matrix of the geometric return series of the six banks and the banking sector index.

Table 3. Variance-covariance matrix of the geometric return series of the six banks and the banking sector index.

	Banks Index	**ATW**	**BMCE**	**BMCI**	**BCP**	**CIH**	**CDM**
Banks Index	0.000068	0.000079	0.000063	0.000041	0.00006	0.000046	0.000014
ATW	0.000079	0.00012	0.000033	0.000021	0.00005	0.000039	0.0000047
BMCE	0.000063	0.000033	0.000197	0.000024	0.00003	0.000025	0.0000031
BMCI	0.00004	0.000021	0.000024	0.000461	0.00002	0.000030	0.0000253
BCP	0.00006	0.000049	0.000034	0.000020	0.00017	0.000037	0.000011
CIH	0.00005	0.000039	0.000025	0.000031	0.00004	0.000334	0.000004
CDM	0.00001	0.000005	0.000031	0.000025	0.00001	0.000004	0.000377

Table 4 displays the Unconditional Correlation Matrix of the geometric return series of the six banks and the banking sector index.

Table 4. Matrix of unconditional correlations of the geometric return series of the six banks and the banking sector index.

	Banks Index	**ATW**	**BMCE**	**BMCI**	**BCP**	**CIH**	**CDM**
Banks Index	1	0.86597	0.5432	0.23181	0.67201	0.305489	0.08751
ATW	0.86597	1	0.21285	0.0871	0.4081	0.19107	0.02189
BMCE	0.5432	0.21285	1	0.07916	0.2235	0.09743	0.01123
BMCI	0.23181	0.0871	0.07916	1	0.08479	0.07742	0.06059
BCP	0.67201	0.4081	0.2235	0.08479	1	0.185158	0.0521
CIH	0.305489	0.19107	0.09743	0.07742	0.1835158	1	0.01116
CDM	0.08751	0.02189	0.01123	0.06059	0.0521	0.01116	1

The unconditional correlation analysis presented in table 4 shows that there is a positive correlation between the geometric returns of the stocks of the six banks and the returns of the bank index, which confirms the transmission of volatility between the bank index and the individual banks. Indeed, the selected financial assets vary in the same direction with the market and they have a positive correlation with the market.

Moreover, the highest correlation is 0.86597 between the bank index and the ATW stock, while the lowest correlation coefficient is that of the CDM and the bank index which is 0.08751. These results confirm the results of the graphical analysis of the evolution of the daily values of the different stocks.

Table 5 displays the sensitivity coefficients of the return series of the geometries of the six banks with the banking sector

Table 5. Sensitivity coefficients of the six banks' geometric return series with the banking sector index.index.

Institution	**Beta**
ATW	1.16
BMCE	0.92
BMCI	0.6
BCP	0.88
CIH	0.68
CDM	0.21

Table 6 displays the Ranking of the six banks according to the interdependence with the banking sector index.

The objective is then to identify the top banks in terms of their contribution to the risk of the banking system.

Table 6. Ranking of the six banks by interdependence with the banking sector index.

Ranking	Correlation with the market index	Sensitivity coefficient Beta
1	ATW	ATW
2	BCP	BMCE
3	BMCE	BCP
4	CIH	CIH
5	BMCI	BMCI
6	CDM	CDM

5.1.2. Static analysis of Systemic Risk:

We will try to make a static analysis of the systemic risk in the Moroccan interbank system based on the marginal expected shortfall.

Table 7 shows the MES values of the banks

Table 7. MES of Banks.

Bank	MES
ATW	0.0245
BMCE	0.0178
BMCI	0.0054
BCP	0.0137
CIH	0.014
CDM	0.0094

Table 8 shows the ranking of the six banks according to their systemic importance, the objective is to identify the systemic banks in the banking system.

Table 8: Ranking of the six banks according to their systemic importance.

Ranking	MES
1	ATW
2	BMCE
3	BCP
4	CIH
5	BMCI
6	CDM

This table displays the ranking of banks according to their risk contribution based on the results of the MES. ATW bank is considered as the bank with the highest systemic risk and CDM bank is the bank with the lowest systemic risk.

In what follows, we will try to make a dynamic analysis of the different measures treated in the static analysis.

5.2. Dynamic Analysis

In this section, we will present and analyze the results obtained from the MES by applying the estimation method of Brownlees and Engle (2012). Before presenting the results of the

MES, We use ap geometric returns of the market and individual banks between 2012 and mid-2021 to calculate the dynamic beta for each bank as follows:

$$\hat{\beta}_{it} = \frac{\hat{\rho}_{it}\hat{\sigma}_{it}}{\hat{\sigma}_{Mt}} \qquad (1)$$

Where:
$\hat{\beta}_{it}$: Sensitivity coefficient of bank i estimated at time t.
$\hat{\rho}_{it}$: Correlation coefficient between bank i and the market estimated at time t.
$\hat{\sigma}_{it}$: Standard deviation of bank i's estimated return at time t.
$\hat{\sigma}_{Mt}$: Standard deviation of the estimated market return at time t.
Nous allons mettre en œuvre après la méthode d'estimation de Brownlees et Engle (2012)
We will implement after the estimation method of Brownlees and Engle (2012) to calculate the TSS to compare banks in terms of their systemic importance. The conditional volatility and time-varying correlation are modeled by the DCC-GARCH model.

The following graphs illustrate the fluctuations of the estimated dynamic betas of individual banks.

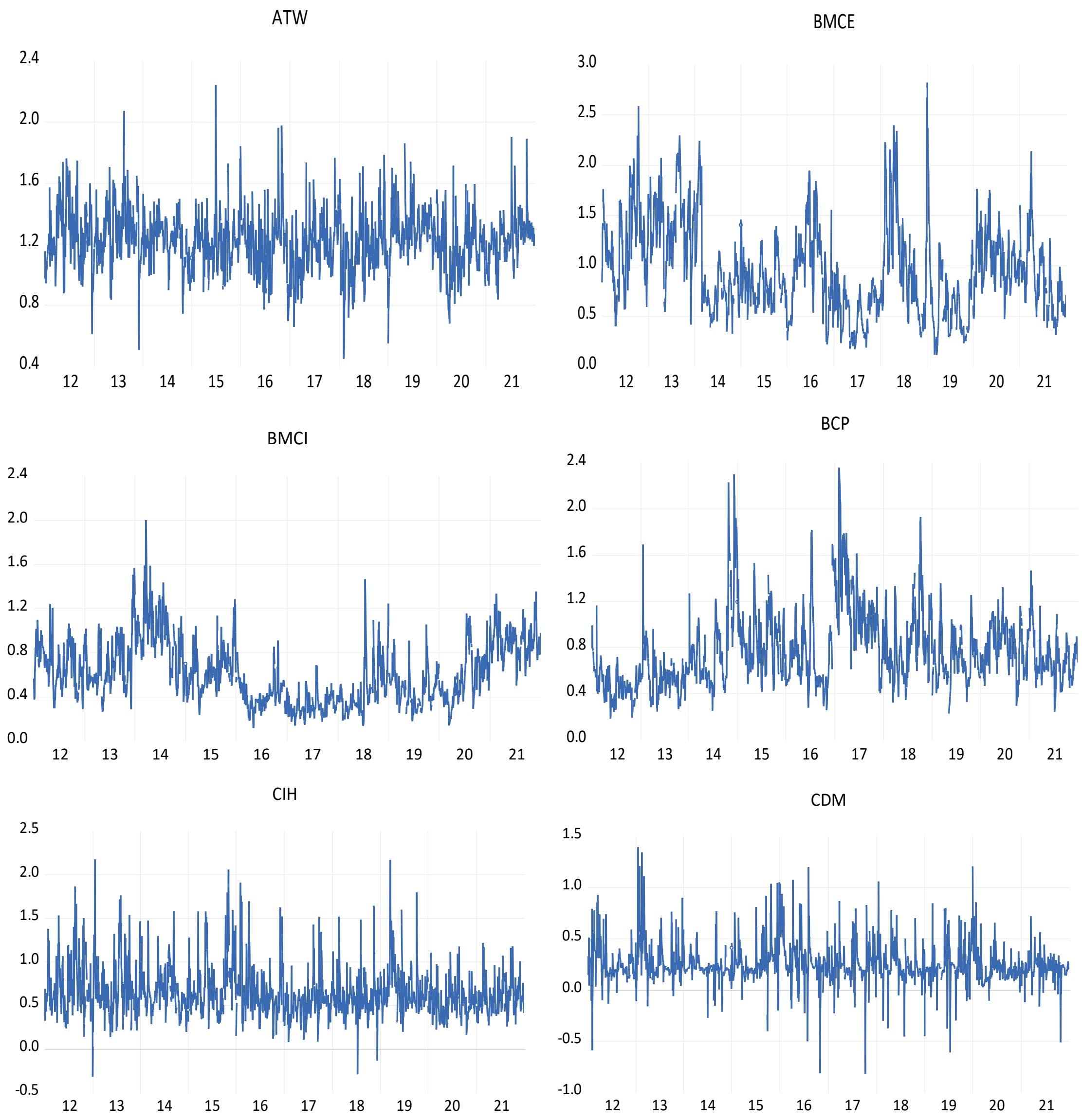

Figure 5. : Dynamic beta of Banks.

By analyzing the previous graphs in figure 5, we notice that the betas of individual banks reported volatile movements during the study period, the sensitivity of bank returns to market return shocks was found to be variable over time with small trends sometimes up and sometimes down.

The change in beta can be considered an indicator of sensitivity risk for individual institutions. This results prove the existence of a strong sensitivity between the index of the banking sector and the various securities of the six banks (ATW, BMCE, BMCI, CIH, BCP and CDM).

The graphs show us that the degree of sensitivity of the geometric return of each bank to the variations of the return of the banking index varies from one bank to another, we are going to calculate the averages and the minimum and maximum values of the sensitivity coefficients to inform us about the level of systematic risk for each bank.

In Table 7 we present the descriptive statistics (mean, minimum and maximum) of the dynamic betas for each of the six banks.

Table 7: Degree of bank awareness.

	ATW	**BMCE**	**BMCI**	**BCP**	**CIH**	**CDM**
Mean	1.216753	0.953770	0.614760	0.76612	0.64166	0.251386
Maximum	2.241446	2.822087	2.002310	2.35889	2.17677	1.395115
Minimum	0.449203	0.116692	0.120382	0.18581	−0.31918	−0.818823

The results presented in table 7 show us that the average sensitivity is quite evident for ATW, followed by BMCE, BCP and BMCE while the lowest average sensitivity was recorded by CDM bank. However, the only stock that is offensive on average (Beta higher than 1) is ATW, all other stocks are on average defensive.

The average value of the sensitivity coefficient for the ATW stock is 1.216753. It is an offensive stock which implies that the systematic risk is high for this bank. The results of the dynamic beta estimation highlight a significant sensitivity of ATW returns to market shocks. The dynamic beta of this bank's stock fluctuates between 0.45(Min) and 2.24(Max) which shows that this stock has a high dynamic sensitivity to market fluctuations.

All the other banks are on average less sensitive to the market compared to ATW, these banks have an average of less than 1 so the market shocks are dampened when arriving at their stocks.

The average value of the sensitivity coefficient for the BMCE share is 0.953770. It is a defensive share which implies that the systematic risk is not high enough for this bank as the case of the ATW bank. The Dynamic Beta of this bank's stock fluctuates between 0.11(Min) and 2.82(Max). For the BMCI bank, the dynamic Beta fluctuates between 0.12 and 2 with an average lower than 1 (0.61).

The BCP and CIH shares have respectively an average Beta of 0.77 and 0.64 and close to that of BMCI. Finally, the CDM bank has the lowest value of beta with an average of 0.25 varying between -0.82 and 1.4 which shows that this bank is the least sensitive to market variations.

We have shown in the theoretical part of this section that the MES is expressed as the product between the dynamic beta β_{it} and the conditional VaR (Expected Shortfall) of the market return $ES(R_{Mt}, \alpha)$.

$$MES(R_{it}, \alpha) = \beta_{it} ES(R_{Mt}, \alpha) \quad (2)$$

The graphs presented below illustrate the estimated MES of each bank.

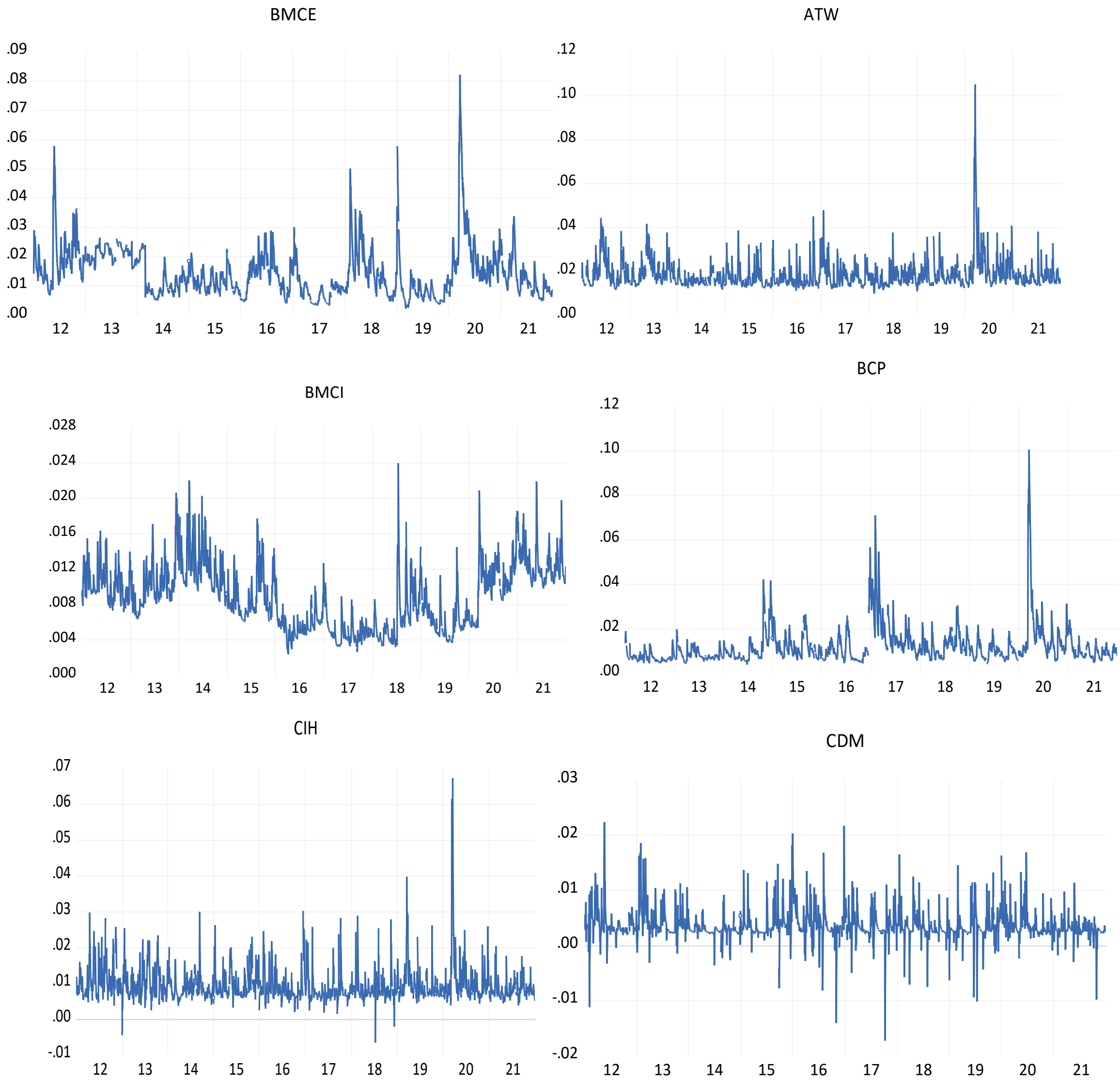

Figure 6: MES of Banks.

By analyzing the previous graphs in figure 6, we notice that the dynamic MES of the different banks are characterized by significant fluctuations during the period studied, the systemic importance of each bank, therefore, varies over time by reporting peaks.

We focus in our dynamic analysis on two measures of risk for banks, the MES and the standard measure of systemic risk, Beta from the Market Model, whose results are presented above.

Table 8 shows the summary statistics (average, minimum and maximum) of the systemic risk of Moroccan banks measured by the MES

Table 8: Descriptive statistics of the MES of banks.

	ATW	BCP	BMCE	BMCI	CDM	CIH
Mean	0.018488	0.012039	0.014556	0.00889	0.003625	0.009520
Maximum	0.105145	0.100536	0.082165	0.02398	0.022374	0.067378
Minimum	0.010007	0.003898	0.002382	0.00236	−0.01721	−0.00654

This table contains some descriptive statistics of the MES. The highest average MES value is recorded by ATW bank with 1.85%, this value can be interpreted as follows: ATW bank loses on average 1.85% of its return value when the market is in its left tail of the VaR. BMCE bank presents an average TSS of 1.45% followed by BCP with an average TSS of 1.2%, CIH bank (0.95%), 0.89% for BMCI and finally the lowest average TSS value was recorded by CDM bank (0.36%). We also examine the systemic importance between the six banks according to their systemic weight. These financial institutions have different average TSS values. The results of this section confirm that the ATW bank is the most systemically risky.

Table 9 displays the Ranking of the six banks according to their contribution to systemic risk as measured by the average TSS value.

Table 9. Ranking of the six banks according to their systemic importance.

Ranking	Mean of MES
1	ATW
2	BMCE
3	BCP
4	CIH
5	BMCI
6	CDM

The highest average value of the MES corresponds to the ATW bank, which puts this bank at the head of the systemic banks of the Moroccan interbank system, followed by the BMCE, then the BCP, CIH and BMCI banks. For the CDM bank, it has the lowest average MES and, therefore, we can consider this bank as a non-systemic bank.

6. Conclusion

We used the MES to analyze the impact of the pandemic crisis on the Moroccan interbank system, in particular the stock index of the banking sector and the listed Moroccan banks. Our sample of geometric returns of the stocks of these banks ranges from January 2012 to the end of 2021 (before and during the COVID-19 crisis). We characterized the static and dynamic systemic risk of the interbank system. Dynamically, we found that the systemic risk of the banks' shares is variable over time with a trend sometimes increasing and sometimes decreasing with significant peaks, the dynamic TSS recorded a significant increase during the COVID-19 health crisis in 2020 and it recovered its levels in 2021.

The level of systemic risk varies from bank to bank, but in general all the measures discussed in this paper give the same systemic ranking of Moroccan banks. In addition, there is significant sensitivity of individual banks' geometric return shocks to market shocks. ATW bank can be considered the most sensitive market bank due to the significant degree of market sensitivity of this bank as well as its systemic importance.

This work aims at analyzing the systemic risk of the Moroccan listed banks in order to identify the institutions mostly exposed to systemic risk. In this paper, we used the DCC-

GARCH model to estimate the conditional variance and the dynamic correlation in order to calculate the marginal Expected Shortfall. We performed a static and dynamic analysis of systemic risk and found that ATW bank's systemic risk is elevated not only by the MES, but also for the other risk measures calculated in this paper. The results suggest that ATW bank is highly involved in systemic risk as it represents large Beta and TSS values. On the other hand, CDM bank has the lowest contribution and exposure values, and is therefore the least involved in systemic risk. These six banks are the main actors in the Moroccan banking sector system. This makes the MES's estimates less accurate because it is impossible to measure systemic risk accurately. Moreover, the MES, as a measure of systemic risk, cannot distinguish between contagious and infected banks. However, this measure is very sensitive to current developments in VaR and ES estimates and does not take into account banks' balance sheet data. Better estimates are needed to fill these gaps. And can be considered as an interesting roadmap study in the future.

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