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Herd behavior and contagion effects of the COVID-19

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Abstract

This work uses structural change tests and the dynamic monitoring method through a new approach to verify whether an exogenous and unexpected event such as the COVID 19 pandemic crisis causes herd behavior and contagion effects. We use 12 indexes of the main world stock markets in daily frequency from 01/02/2019 to 01/22/2021. Initially, structural changes in returns and their volatility apparently had no relationship with the number of cases or deaths from the pandemic. However, between 3 and 13 March this situation changes. Structural breaks, controlled by the market comovement and occurring sequentially, provide evidence of contagion. The statistically significant increase in the correlation between individual and market returns indicates herd behavior in most cases analyzed.

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1. Introduction

Since January 2020, when the first cases of COVID-19 emerged, we observe strong common reactions in different financial markets that have spread to other economies. This fact put in evidence the possibilities of herding behavior and contagion effect between financial markets in response to big unexpected events.

Herding behavior happens when investors imitate the actions of others, even when those decisions are not the result of a profit-optimizing process (see for example, Scharfstein and Stein 1990, Bikhchandani and Sharma 2000). This behavior happens when investors imitate the actions of others, even when those decisions are not the result of a profit-optimizing process Possible explanations for this phenomenon are given by models based on decisions under uncertainty or with imperfect information. For example, investors may be uncertain about the quality of their information.

Financial contagion is usually defined as the propagation of the effects of a crisis from one economy to another, geographically separated, with different economic structures. The main cause of contagion is linked to (major) common or global shocks, such as the one generated by COVID-19. However, other theories seek to explain the determinants of contagion through financial and trade links and investor behavior influenced by liquidity or incentive problems, among others (Forbes and Rigobon, 2002).

In this context, some studies analyze the effects of this exogenous event of large global proportions on stock markets. Zhang, Hu and Ji (2020) use data from twelve stock exchanges and show that the risk (measured by the standard deviation) of the financial market increased from 0.0071 to 0.0196 between February and March 2020. Besides, the systematic risk, measured by weekly correlations, was relatively low in February and increases substantially in March.

Albulescu (2021) shows that the global level of infected people and the worldwide fatality of the virus have a greater impact on S&P500 volatility, than local pandemic numbers. Using Chinese influenza and coronavirus database, Corbet et al (2021) estimate volatility indices based on the decomposition of the forecast error variance and report volatility spillover from the Chinese market for various financial assets.

Okorie and Lin (2021) use the detrended moving cross-correlation analysis (DMCA) and the detrended cross-correlation analysis (DCCM) to analyze the contagion effect of COVID-19 in the stock market of the thirty-two main economies affected by the pandemic. Their results show that there is a significant but short-lived contagion effect on both returns and market volatility.

Based on the connectedness methods of Diebold and Yilmaz (2012) and Baruník and Křehlík (2018), Liu et al (2022) show that the COVID-19 epidemic significantly increases the risk contagion effects in international stock markets. Besides, the risk spillovers from stock markets in European and American regions increase rapidly but those in Asian markets decrease after the outbreak of the COVID-19 pandemic. Finally, the risk contagion among international stock markets caused by the pandemic can last for about 6 to 8 months.

Guo et al (2022) combine the time-varying financial network model and FARM-selection approach to analyze the tail risk contagion between 19 international financial markets during the COVID-19 epidemic. They conclude that the COVID-19 epidemic increases the number of contagion channels in the international financial system, the clustering level of the financial system has a significant growth during the COVID-19 pandemic, and the number of risk drivers is also larger than risk takers.

Akhtaruzzaman et al (2021) examine how financial contagion occurs through financial and nonfinancial firms between China and G7 countries during the COVID‑19 period. They show that firms experience significant increases in conditional correlations between their stock returns, especially in financial companies where this effect is greater than in non-financial ones.

Using data from Eastern European stock exchanges, from January 1, 2010 to March 10, 2021, Fang et al (2021) demonstrate that the COVID-19 pandemic increased herding behavior in all markets in the sample. The authors use the model by Chang et al (2000) which analyzes the (non-linear) relationship between the dispersion of returns and the market return.

Ampofo et al (2020) test herding behavior in the US and UK markets using the quantile regression approach. They find that there is no evidence of herding before the COVID-19 pandemic in either the ups or downs in both markets. However, during the pandemic period, the authors report evidence of this behavior in the US and UK bull markets and the US bear market.

Bogdan et al (2022) investigate the presence of herd behavior during the COVID-19 pandemic in stock markets of European countries with different levels of development. The authors use the model of Chang et al (2000) and a rolling-window regression, and then a logistic model to verify if the herding behavior is caused by the pandemic. The results show that this phenomenon is most pronounced in emerging markets, followed by frontier markets and developed markets.

This work intends to contribute to this theme in 2 different ways. We use structural change tests and the dynamic monitoring method presented by Zeileis et al. (2010), to test the hypothesis of structural breaks in the correlation and variances (ratios) of the main stock indexes of 12 large economies that are among the most affected by the health crisis. This new approach intends to synthesize the definitions of contagion by Forbes and Rigobon (2002) and of herding behavior by Christie and Huang (1995) and Chang et al (2000), and provide empirical evidence about these effects. This methodology allows both endogenous dating and testing for statistically significant changes in correlations and variances.

The basic idea is that a structural break, caused by an exogenous and unexpected event such as the COVID-19 pandemic, in the correlation coefficient between the individual market and the average of other markets returns, resulting in a reduction in dispersion among them, indicates herd behavior. Once these possible comovements are controlled (see for example Corsetti et al, 2005), the change in the (variance) return that spreads to other economies would be evidence of (volatility) contagion (Jung and Maderitsh, 2014, Choi, 2016). In addition to this introduction, this study is organized as follows: Section 2 presents the methodology and model. Section 3 presents the data and results. The last section concludes.

2 Methodology

The approach of Zeileis (2005) and Zeileis et al. (2010) unifies a wide range of parametric methods to detect structural changes or parameter instabilities. This allows a unified methodology that can be applied to different alternatives such as stationary series, random walks, with single or multiple breaks.

However, the most interesting point of the M-fluctuation tests for the problem in question is the direct inclusion and the joint treatment of the variance within the parameter vector subject to structural changes. The possibility of a joint change in the model coefficients and variance is important to contagion analysis. The work by Jung and Maderitsch (2014) is an example of studies that use structural break tests to analyze the contagion effect on volatility.

2.1 The model

Let r_{it} be the return observed in the market i in period t, and $\bar{r}_t$ the average of returns in the other markets in t. The model used in this work can be represented by,

$$r_{it} = \beta_{0t} + \beta_{1t}\,\bar{r}_t + \varepsilon_{it} \quad (1)$$

Forbes and Rigobon (2002) define contagion as a significant increase in cross-market linkages after a shock to one country or group of countries. They propose a correction for the bias in the cross-market correlation coefficients used for contagion tests. The authors estimate the variance-covariance matrices for the entire sample, and only for the troubled period. Then they use a t-test to assess whether there is a significant increase in these correlation coefficients during the turmoil period.

Chang et al (2000) regress the cross-sectional absolute deviation of returns (CSAD) against the market return and its square. There will be herding behavior if, during periods of large price changes, there is a less than proportionate increase or decrease in CSAD. This can be tested from the statistical significance and signs of the regression coefficients.

We use an alternative strategy. Note that the reduction in the dispersion between individual and market returns (herd behavior) and the increase in the correlation between markets (contagion) are related to an increase in the correlation between a market and the average of the markets. In (1), we know that[1]:

$$\beta_{1t} = \rho_t \left(\frac{\sigma_{rt}}{\sigma_{\bar{r}t}}\right) \quad (2)$$

We use GARCH models to estimate σ_{rt} and $\sigma_{\overline{rt}}$. The next step is to test structural changes in (1), and in an AR(1) model for the standard deviation ratio. Breaks only in β_{1t}, but not in $\left(\frac{\sigma_{rt}}{\sigma_{\bar{r}t}}\right)$, are evidence of statistically significant changes in the correlation (ρ_t) and dispersion of individual and (other) market returns.

To distinguish these effects, we use the idea that in contagion, shocks must migrate from one market to another (see Choi, 2016, for example). Therefore, after controlling for these possible co-movements, in the sense of Corsetti et al. (2005), the change in the (variance) mean of (1) that spreads to other economies is evidence of (volatility) contagion.

2.1. Generalized M-Fluctuation Test

Consider a regression model with n observations of a dependent variable y_i and a vector of regressors given by x_t, $y_t = x_t'\theta_t + \varepsilon_t$. Where $t = 1, \dots, T$. The parameters stability hypothesis is given by,

$$H_0\colon \theta_t = \theta_0 \quad (2)$$

Assuming that the stability hypothesis is true, the estimated parameters $\widehat{\theta}$ can be obtained by minimizing the negative log-likelihood $\Psi_{NLL}(y_t, x_t, \theta) = -\log f(y_t|x_t, \theta)$, where $\Psi(.)$ is the objective function and *f*(.) is a (quasi-)likelihood. Alternatively, the first-order conditions can be solved in terms of $\psi(y_t, x_t, \theta) = \delta(\Psi_{NLL}(y_t, x_t, \theta))/\delta\theta$. That means,

$$\underset{\theta\in\Theta}{\operatorname{argmin}} \sum_{i=1}^{n} \Psi(y_t, x_t, \theta) = \widehat{\theta} \quad (3)$$

$$\sum_{i=1}^{n} \psi\left(y_t, x_t, \widehat{\theta}\right) = 0 \quad (4)$$

Let $\hat{J}$ be a consistent and adequate estimator to the covariance matrix of the score function $\psi(.)$. The empirical fluctuation process $efp(.)$ is formally defined as:

[1] See Forbes and Rigobon (2002) for example.

$$W_T(g,\theta) = T^{-1/2} \sum_{t=1}^{[Tg]} \psi\left(y_t, x_t, \widehat{\theta}\right) \tag{5}$$

$$efp(g) = \hat{J}^{-1/2} W_n\left(g, \hat{\theta}\right) \tag{6}$$

The efp is governed by the functional central limit theorem (FCLT) under the null hypothesis of stability in the parameters. The basic idea of the M-fluctuation tests is that deviations from the stability can be obtained by evaluating deviations of the empirical functions $\psi\left(y_t, x_t, \widehat{\theta}\right)$ from their zero mean. Zeileis *et al* (2010) suggested four useful functionals:

$$S_{dmax} = \sup_{g \epsilon [0,1]} ||efp(g)||_\infty \tag{7}$$

$$S_{CvM} = T^{-1} \sum_{t=1}^{T} ||efp(t/T)||_2^2 \tag{8}$$

$$S_{MOSUM} = \sup_{g \epsilon [0,1-h]} ||efp(g+h) - efp(g)||_\infty \tag{9}$$

$$S_{\sup LM} = \sup_{g \epsilon [\pi, 1-\pi]} \frac{||efp(g)||_2^2}{g(1-g)} \tag{10}$$

If a stable model can be established for $t = (1, \dots, T)$, the monitoring process checks whether this model remains stable for $t = (T+1, T+2, \dots)$. More formally, the monitoring test consists of sequentially testing whether:

$$H_0 \colon \theta_t = \theta_0 \ (t > T) \tag{11}$$

For this, it is enough to extend the empirical fluctuation process $efp(g)$ in the monitoring period, calculating the empirical estimation function for each new observation and updating the cumulative sum process. This process is still governed by an FCLT over an extended interval $[0, T]$, with $T > 1$. In this way, the functional $\lambda\left(efp(g)\right)$ can be recalculated for each new observation. The H_0 rejection in (11) occurs if the calculated value exceeds some critical value of $b(t)$ for any $t > 1$. So, in this sequential test, there is not a single critical value, but a boundary function $b(t)$ for the empirical fluctuation process. In this application, a maximum functional function and a linear boundary function $b(t) = \pm c \cdot t$ are adopted, which according to Zeileis (2005) gives a certain uniformity level in the power of the test.

Suppose that there are $j = 1, \dots, m$ regimes. To date the breaks, a segmented regression model can be used to determine the m breakpoints and the specific parameters in the $m+1$ regimes. The overall segmented objective function based on ψ is given by:

$$PSI(t_1, \dots, t_m) = \sum_{j=1}^{m+1} psi\left(t_{j-1}+1, t_j\right) \tag{12}$$

$$psi\left(t_{j-1}+1, t_j\right) = \sum_{t=t_{j-1}+1}^{t_j} \psi\left(y_t, y_{t-1}, \hat{\theta}^{(j)}\right) \tag{13}$$

$$(\hat{t}_1, \dots, \hat{t}_m) = \underset{t_1, \dots, t_m}{\operatorname{argmin}} \, PSI(t_1, \dots, t_m) \tag{14}$$

Where $psi(t_{j-1}+1, t_j)$ is the minimum value of the objective function in the jth segment. Solving (14) subject to a minimal segmental size constraint $t_j - t_{j-1} + 1 \geq T_h \geq k$, gives the global optimizers $\hat{t}_1, \dots, \hat{t}_m$. This procedure is based on Bai e Perron (2003), and the minimum segment size is chosen directly or derived from T_h. We follow the recommendations in Zeileis et al (2010) and use the information criterion in (15) with $\alpha = 0.299$, $\delta = 0.1$.

$$IC(m) = 2 \cdot NLL(l_{m,T}) + \alpha \cdot \log(T)^{2+\delta} \cdot ((m+1)k + m) \tag{15}$$

3 Database and Results

The database contains 12 indexes of the main world stock markets in daily frequency, from 01/02/2019 to 01/22/2021[2]. Daily returns are calculated as $r_t = \ln(p_t) - \ln(p_{t-1})$. Four subperiods were used in the different analyses. Fluctuation tests are performed between 01/02/2019 to 11/30/2019, and between 07/01/2019 to 11/30/2019 to ensure stability. Then, monitoring is carried out in the range from 12/01/2019 to 01/22/2021, while dating through segmented regressions uses the whole sample.

3.1 Testing

The fluctuation tests for the period from 01/02/2019 to 11/30/2019 are presented in table 1, S_{dmax} accepts the null hypothesis of stability in the parameters for ten series, except for Brazil and China. For the S_{CvM}, suggested by Zeileis et al (2010) as more appropriate in the presence of multiple breaks, the stability hypothesis is rejected for three series at 10%: Brazil, Canada and China.

Table 1- Fluctuation Tests 01/02/2019 – 11/30/2019

Country	Index	S_{dmax}	P-value	S_{CvM}	P-value
Argentina	MERV	1.0775	0.4802	0.4468	0.4704
Brazil	BVSP	1.5627	0.0447	1.0528	0.0395
Canada	GSPTSE	1.1413	0.3809	0.9731	0.0560
China	SSEC	1.5268	0.0556	1.3888	0.0087
France	CAC40	1.0026	0.6065	0.3121	0.6301
Germany	DAX	0.8540	0.8418	0.3328	0.6055
Italy	FTSEMIB	0.9594	0.6801	0.4091	0.5151
Japan	NIKKEI	1.2854	0.2046	0.5824	0.3097
Russia	MOEX	1.1203	0.4124	0.2972	0.6477
Spain	IBEX	0.9529	0.691	0.2197	0.7396
United Kingdom	FTSE	1.2065	0.2922	0.3881	0.5400
USA	SP500	1.0682	0.4955	0.4567	0.4587

Looking for a stable period for these three series, the possible points of instability calculated for these indexes were determined. Excluding this period, the test is repeated for the period from 07/01/2019 to 11/30/2019, with results favorable to accept the stability hypothesis as shown in table 2.

[2]The data are provided by Investing.com – Accessed on 01/31/2021

Table 2- Fluctuation Tests 07/01/2019 – 11/30/2019

Country	Index	S_{dmax}	P-value	S_{CvM}	P-value
Brazil	BVSP	1.1830	0.3224	0.3817	0.5476
Canada	GSPTSE	1.0383	0.5456	0.5193	0.3845
China	SSEC	1.2248	0.2699	1.0040	0.6042

3.2 Monitoring

Appendix 1 presents the monitoring process plots. Between December 2019 and mid-February 2020, despite initial indications of the pandemic in China and its spread to other countries, there is no evidence of structural changes. Even in the Chinese stock market, there is only a non-significant change in the variance process.

This scenario changes between late February and early March. Except in Argentina with changes only in the slope, in other markets, there is evidence of structural breaks in $\hat{\beta}_1$ and in the volatility (variance) of returns. Table 3 shows the dating results of the monitoring process. In all series, structural changes are detected between 02/03/2020 and 03/24/2020, with the first date referring to the Chinese market (SSEC) and the last one to the French market (CAC40).

Break dates do not seem to have a pattern related to internal pandemic numbers. There are changes even in countries with just a few cases. In the case of Brazil, the break is detected on 02/22/2020, with no confirmed case. While in China and France, changes occur after several confirmed cases. Once market comovements are controlled, the temporal sequence (domino effect) observed on the dates of the breaks is evidence of a contagion effect.

Table 3 – Monitoring 12/01/2019 – 01/22/2021

Country	Index	Break detected	COVID-19*	COVID-19 Deaths**
Argentina	MERV	03/13/2020	31	1
Brazil	BVSP	02/22/2020	0	0
Canada	GSPTSE	03/06/2020	62	0
China	SSEC	02/03/2020	80261	361
France	CAC40	03/24/2020	19856	860
Germany	DAX	03/12/2020	1567	3
Italy	FTSEMIB	03/09/2020	7375	366
Japan	NIKKEI	03/09/2020	488	7
Russia	MOEX	03/03/2020	3	0
Spain	IBEX	03/09/2020	1527	5
United Kingdom	FTSE	03/09/2020	412	2
USA	SP500	03/04/2020	125	9

Note: * Number of cases by country on the date of the break.
** Number of deaths by country on the date of the break
Source: https://www.worldometers.info/coronavirus.

3.3 Segmented Regressions

A procedure similar to that of Bai and Perron (2003) is used for the whole sample to determine and estimate regression models with multiple breaks. In this process, the maximum number of breaks allowed was 10 with a minimum segment size of $n_h = 20$. The associated segmented NLL and LWZ criteria are then calculated by selecting the number of breaks and, consequently, the number of optimal segments pictured in table 4. The results show no significant changes in the pandemic period to three series: Germany, Argentina and China.

It is worth mentioning that the results in tables 3 and 4 differ due to their methodology and purpose. Even with different results and dates, there is evidence of structural breaks in β_1 that happened in a short period in a sequential way (domino effect), indicating the existence of a contagion effect between several markets.

Table 5 shows the results of the break test following the methodology of Bai and Perron (2003) for the volatilities ratio described in (2). These results complement those of table 4 and show that in most markets there is evidence of an increase in the correlation (statistically significant increase in β_1 and unchanged volatilities ratio) between the individual returns and the market, featuring herd behavior.

Table 4 – Segmented regressions 01/02/2019-01/22/2021

Index	Period	$\widehat{\beta}_0$	$\widehat{\beta}_1$	σ^2	R^2	$Adj\ R^2$
Argentina (MERV)	01/02/2019-08/08/2019	0.0012 (0.0015)	**1.0661 (0.2612)**	0.0003	0.0965	0.0907
	08/09/2019-09/05/2019	-0.0258 (0.0279)	3.9745 (3.6649)	0.0137	0.0613	0.0092
	09/06/2019-01/22/2021	0.0013 (0.0014)	**1.0469 (0.1012)**	0.0007	0.2276	0.2276
Brazil (BVSP)	01/02/2019-02/25/2020	0.0005 (0.0006)	**0.6499 (0.0849)**	0.0001	0.1643	0.1615
	02/26/2020- 04/09/2020	-0.0020 (0.0061)	**1.6541 (0.1683)**	0.0011	0.7628	0.7549
	04/10/2020- 01/22/2021	0.0010 (0.0009)	**0.775 (0.0899)**	0.0002	0.2669	0.2633
Canada (GSPTSE)	01/02/2019-02/21/2020	**0.0004 (0.0002)**	**0.4040 (0.0286)**	0.0000	0.4014	0.3994
	02/24/2020-05/04/2020	0.0027 (0.0023)	**1.3269 (0.0745)**	0.0002	0.8662	0.8434
	05/05/2020-01/22/2021	0.0002 (0.0005)	**0.5155 (0.0504)**	0.0000	0.3584	0.3549
China (SSEC)	01/02/2019-01/22/2021	0.0006 (0.0005)	**0.2523 (0.0371)**	0.0001	0.0794	0.0777
France (CAC40)	01/02/2019-02/21/2020	0.0001 (0.0003)	**0.8997 (0.0494)**	0.0000	0.5287	0.5271
	02/24/2020-01/22/2021	-0.0005 (0.0005)	**1.1531 (0.0326)**	0.0001	0.8399	0.8392
Germany (DAX)	01/02/2019-01/22/2021	-0.0000 (0.0003)	**1.1011 (0.0277)**	0.0001	0.7469	0.7464
Italy (FTSEMIB)	01/02/2019-02/21/2020	0.0004 (0.0004)	**0.9062 (0.0624)**	0.0001	0.4161	0.4141
	02/24/2020-03/25/2020	-0.0012 (0.0063)	**1.1646 (0.1478)**	0.0008	0.7473	0.7353
	03/26/2020-01/22/2021	-0.0008 (0.0005)	**1.2501 (0.0502)**	0.0001	0.7427	0.7415
Japan (NIKKEI)	01/02/2019-02/24/2020	0.0004 (0.0005)	**0.2452 (0.0683)**	0.0001	0.0416	0.0383
	02/25/2020-05/01/2020	-0.0018 (0.0036)	**0.4193 (0.1076)**	0.0006	0.2441	0.2280
	05/04/2020-01/22/2021	**0.0015 (0.0007)**	**0.4011 (0.0700)**	0.0001	0.1488	0.1443
Russia (MOEX)	01/02/2019-02/24/2020	**0.0007 (0.0004)**	**0.3786 (0.0529)**	0.0000	0.1471	0.1442
	02/25/2020-04/15/2020	-0.0022 (0.0046)	**0.5744 (0.1247)**	0.0007	0.3773	0.3595
	04/16/2020-01/22/2021	0.0006 (0.0006)	**0.6600 (0.0549)**	0.0001	0.4192	0.4162
Spain (IBEX)	01/02/2019-02/19/2020	-0.0001 (0.0003)	**0.7898 (0.0048)**	0.0000	0.4730	0.4712
	02/20/2020-01/22/2021	**-0.0012 (0.0007)**	**1.1639 (0.0408)**	0.0001	0.7723	0.7714
UK (FTSE)	01/02/2019-02/21/2020	-0.0002 (0.0003)	**0.7247 (0.0468)**	0.0000	0.4472	0.4453
	02/24/2020-01/22/2021	-0.0006 (0.0005)	**0.9983 (0.0333)**	0.0001	0.0014	-0.0034
USA (SP500)	01/02/2019-02/21/2020	0.0004 (0.0003)	**0.8107 (0.0462)**	0.0000	0.5096	0.5080
	02/24/2020-04/08/2020	0.0034 (0.0053)	**1.1574 (0.1426)**	0.0008	0.6800	0.6696
	04/09/2020-01/22/2021	**0.0006 (0.0007)**	**0.7667 (0.0634)**	0.0001	0.4166	0.4137

Note: Significant coefficients (at 10% level) are printed in **boldface**.

Table 4 shows a second breakpoint for some indexes. These third segments are associated with a recovery period (lower variance) and it is noted that there is a greater dispersion of dates for this breakpoint. Among the nine stock exchanges that had the first break between 02/20/2020 and 02/26/2020, the Italian starts a recovery segment as early as 03/26/2020, just over a month after the first break, coinciding with the period of reduction in the expansion of the pandemic in the country. In April, three more countries were on the path of recovery: the United States (04/09), Brazil (04/10) and Russia (04/16). Subsequently, Japan and Canada followed this recovery trajectory, respectively on May 4th and 5th.

An interesting exercise is to analyze the relationship between these dates and the economic packages adopted by the governments to mitigate the negative effects of public health controls on the economy and to sustain public welfare. On March 15, 2020, the Federal Reserve announced a zero-percent interest rate policy and declared a USD700 billion quantitative easing (QE) program.

Aguilar et al (2020) summarize the measures adopted by European Central Bank with a triple aim: (i) ensuring that the overall stance of its monetary policy was sufficiently accommodative; (ii) underpinning the stabilization of the financial markets to safeguard the monetary policy transmission mechanism; and (iii) providing ample liquidity, especially to keep bank lending flowing.

Thereby, the rapid recovery of stock markets can be associated with quick actions by central banks. Broadly governments were able to act quickly and with the injection of large amounts of resources, these measures have helped shore up economic agents' confidence, with the subsequent expected beneficial effects on economic activity and employment.

Table 5 shows the results of the structural break tests on the volatility (standard deviation) ratio of equation 2. Comparing to the results of table 4, a statistically significant (structural) change in $\hat{\beta}_1$ near the beginning of the pandemic, together with the lack of breaks in the standard deviation ratio indicate herd behavior. This behavior happened in 7 of the 12 (58%) analyzed markets.

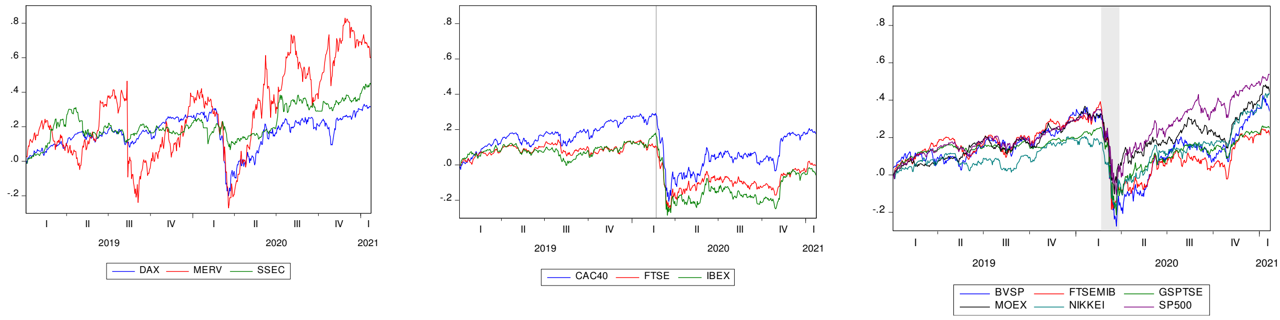
Table 5 – Breaks in standard deviation ratio ($\sigma_{r_{it}}/\sigma_{\bar{r}t}$)

Country	**Index**	**Break detected**	
Argentina	MERV	08/09/2019; 12/27/2019	
Brazil	BVSP	No breaks	Herd behavior evidence
Canada	GSPTSE	02/21/2020	
China	SSEC	No breaks	
France	CAC40	No breaks	Herd behavior evidence
Germany	DAX	No breaks	
Italy	FTSEMIB	No breaks	Herd behavior evidence
Japan	NIKKEI	No breaks	Herd behavior evidence
Russia	MOEX	No breaks	Herd behavior evidence
Spain	IBEX	05/04/2020	
United Kingdom	FTSE	No breaks	Herd behavior evidence
USA	SP500	No breaks	Herd behavior evidence

To facilitate visualization, the return series are divided into three groups: those with no breaks, those with one break, and those with two breaks. Markets with a single break (CAC40, FTSE and IBEX) show a slower recovery than the others.

Figure 1 – Graphics of accumulated return 01/02/2019 to 01/22/2021

a) No breaks b) One break c) Two breaks



4 Conclusion

This work analyzes the effect of the COVID-19 pandemic on the main stock market indices of 12 countries, through dynamic monitoring, structural break tests, and segmented regressions. The suggested methodology allows not only to date the occurrence of these changes, but also to contribute with evidence of herd behavior and financial contagion.

The results show that structural changes in returns and their volatilities were not related to the number of cases or deaths from the pandemic. However, between March 3 and 13, this situation changes and the detected breaks in nine indices coincide with the increase in cases across Europe. Changes, controlled by the average movement (comovement) of markets, which occur sequentially (domino effect) in the individual return and/or its volatilities (variances), provide evidence of (volatility) contagion. Furthermore, structural changes in the increased correlation between individual and market returns indicate herd behavior in most cases analyzed.

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