Universidade de São Paulo
Faculdade de Economia, Administração e Contabilidade de Ribeirão Preto
Departamento de Economia
Programa de Pós-graduação em Economia - Área: Economia Aplicada

Rodrigo Rodrigues Branco de Moraes

Nonlinear dependence between the US banking and insurance market during COVID-19 epidemic

Orientador: Prof. Dr. Márcio Poletti Laurini

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Coordenador do Programa de Pós-Graduação em Economia - Área: Economia Aplicada

RODRIGO RODRIGUES BRANCO DE MORAES

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Dissertação de Mestrado submetida ao Programa de Pós-Graduação em Economia da Faculdade de Economia, Administração e Contabilidade de Ribeirão Preto da Universidade de São Paulo

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1. Modelo de volatilidade estocástica, 2. Saltos, 3. COVID-19

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Resumo

BRANCO, R. M. **Dependência não linear entre bancos e seguradoras americanas durante a epidemia de COVID-19**. 2022. Dissertação (Mestrado) - Faculdade de Economia, Administração e Contabilidade de Ribeirão Preto, Universidade de São Paulo, 2022.

Propomos um modelo estocástico multivariado de salto duplo de volatilidade para capturar a presença de saltos na média e variância condicional nos ativos de retorno dos nove maiores bancos norte-americanos por capitalização de mercado e nove das seguradoras norte-americanas mais relevantes foram consideradas durante o período do início de março de 2020, quando se inicia o COVID-19, até meados de 2021. Dividimos nossas amostras em três grupos diferentes, um grupo apenas com seguradoras, outro com bancos e um com todos os ativos de dezoito empresas. Para todas as três amostras, os fatores comuns estimados mostram precisão suficiente para capturar características e fatos estilizados dessas séries financeiras em um período de crise no mercado de ações, como saltos na média, volatilidade e volatilidade condicional.

Palavras-chaves: Modelo de volatilidade estocástica, Saltos, COVID-19.

Abstract

BRANCO, R. M. **Nonlinear dependence between the US banking and insurance market during COVID-19 epidemic.**Dissertação (Master Degree) - School of Economics, Business Administration and Accounting at Ribeirão Preto, University of São Paulo, Ribeirão Preto, 2022.

We propose a multivariate stochastic volatility-double jump model to capture the presence of jumps in mean, and conditional variance in the returns assets of the nine largest North American banks by market capitalization and nine of the most relevant North American insurance companies were considered during the period from the beginning of march 2020, when starts the COVID-19, to mid-2021. We divide ours samples in three different groups, a group with insurance companies only, another with banks and one with all eighteen companies assets. For all the three samples, the common factors estimated shows enough precision to capture characteristics and stylized facts of these financial series in a period of crisis in the stock market, such as jumps in mean, volatility and conditional volatility.

Key-words: Stochastic volatility model, Jump, COVID-19.

Lista de ilustrações

Sumário

1 Introduction

The novel coronavirus (COVID-19) had it's first recorded appearance in early December 2019 in Hubei province, China. Since then, it has spread around the world, being classified as a pandemic by the world health organization in March 2020. In fact, most countries have taken restrictive measures with the objective of mitigating the number of infected people and, consequently, avoiding a collapse in the health system. However, such measures have not stopped the proliferation of COVID-19 in more than 220 countries, with more than 200 million infected and 4 million dead by September 2021. The restrictive measures coupled with uncertainty about how COVID-19 would develop had a major economic impact on the world economy. Zhang (2020) highlights the link between the severity of the outbreak in each country and the stock market in each region. It is also evidenced that economic losses make markets highly volatile and uncertain.

Specifically in the North American financial market, many studies have been carried out to determine the effect of the pandemic. Some studies like Baker, Bloom, Davis, Kost, Sammon and Viratyosin (2020) showed that no pandemic had such an effect on the North American stock market, in this study they highlighted the increase in the level of volatility in March 2020 being higher than those detected in October 1987, Black Monday and December 2008 during the international financial crisis. Onali (2020) investigate the north American stock markets and identified the increased volatility related to the disclosure of cases and deaths by COVID-19 in several countries. Thorbecke (2020) evidence how banks and insurance companies can be impacted by the U.S. stock market.

In this context, this study aims to assist the development of the literature specifically considering how the insurance and banking market in U.S. was affected by the pandemic. For this study, the close daily log returns, between August 1, 2018 and March 28, 2021, of the nine most relevant insurance companies, namely: UnitedHealth Group(UNH), CVS Health(CVS), NorthWestern Corporation(NWE), MetLife(MET), Prudential Financial(PRU), Lincoln National Corporation(LNC), MassMutual(MEFZX), State Farm(STFGX) and Aegon(AEG); and the nine largest banks by market capitalization, namely: JPMorgan Chase(JPM), Bank of America(BAC), Wells Fargo(WFC), Citigroup(C), Goldman Sachs(GS), First Republic Bank(FRC), Huntington Bancshares(HBAN), Fifth Third Bank(FITB) and Ally(ALLY) were considered. In the next session, we will illustrate some descriptive statistics that make clear the impact of COVID-19 on both markets. Some characteristics, such as the increase in the level of unconditional volatility, the presence of negative skew and high kurtosis in the distribution of asset returns in the period starting in December 2019, when its first case was announced, and in March 2020, when has been classified as a pandemic by the World Health Organization (WHO) and such behavior patterns remain until today. Being able to choose an appropriate model to capture all these characteristics of these companies in such unstable times is crucial for financial planning, both in risk management and portfolio allocation. The multivariate stochastic volatility model incorporated in the literature by Laurini, Mauad, and Auibe (2016) is the model we choose to apply in this study and it's able to model common jumps, both in the mean and in the conditional volatility between the log returns of insurance companies and banks. In addition to this benefit, this model is able to identify which jumps are common between these two sectors, and also allows decomposing the permanent and transitory effect caused by the pandemic during this period. In simple terms, it is a regime switching model, however is capable to model regimes with common shocks and regimes with only specific shocks for each asset. Due to the high number of latent variables in this model, we will use the Bayesian estimation method by mixed Markov Chain Monte Carlo.

The remainder of this paper is organized as follows: Section 2 reviews literature about COVID-19 and the stock market. Section 3 introduces the utilized data and the descriptive statistics. Section 4 describes the model and estimation procedure. Section 5 explains the empirical results. Section 6 concludes.

2 Literature Review

Since the beginning of 2020, it began to be investigated how COVID-19 are affecting the stock market. The high impact of the COVID-19 pandemic both in the international market and in the US market is becoming a consensus in the literature. Chan and Marsh (2020) compared the Dow Jones index between the periods of February and March 2020, with other historical crashes such as the period of the Great Depression in 1929 and the Spanish Flu in 1919, similarly with Baker (2020). They show that the falls in the recent period had more impact on the financial market than these two historical periods, and they justify such characteristics by the lack of information about COVID-19, in addition to the policies adopted by governments. Ramelli and Wagner (2020) applied the standard asset pricing model and the factorial model of Fama and French (1993) for asset returns, and found evidence that the high negative impact caused between January and March 2020, mainly assets of US companies closer with the Chinese market. Furthermore, in the same period they showed that assets of companies with less money and greater leverage were most affected overall. Tiberiu (2020) also analyzes how US financial market volatility behaved during the start of COVID-19 using the S&P 500 as a proxy. He found evidences that global new infections amplify the US financial volatility in this period.

In the context of studying specific markets, Liu, Wang, and Lee (2020) examines the relationship between the pandemic and crude oil returns and stock returns utilizing the time-varying parameter vector autoregression (TVP-VAR) model; and find that COVID-19 pandemic can have a positive influence on the crude oil market and stock market during January and March 2020. Seungho (2020) use a Markov Switching AR model to identify regime changes and how volatility in US asset markets is affected by economic indicators and COVID-19 deaths and recovery. This study showed an increase in risk for 30 different sectors of the industry, in particular increases in systematic risk for defensive industries, such as telecom and health care, but there were decreases in systematic risk for aggressive industries, such as automobiles and business equipment. Sharif (2020) used the wavelet method and wavelet-based Granger causality tests in the data between January 2020 and March 2020 to investigate the relationship between the beginning of the COVID-19 pandemic, the U.S. Dow Jones and the West Texas Intermediate (WTI) crude oil. They measure of economic uncertainty and among the world risk. Their study showed that the U.S. stock market, economic uncertainty, and risk between countries are all affected by both the Coronavirus and falling oil prices. Gharib et al. (2020) used the bootstrap techniques in daily data from January 2010 to May 2020 to analyze if there are common bubbles between WTI oil prices and gold prices. They concluded that during the beginning of COVID-19 these two series shared explosivity, with oil prices behaving like a negative bubble and stock prices behaving like a positive bubble. Granger causality tests show that there was bilateral contagion between the two markets. Their findings indicate that gold has been functioning as a safe haven asset during the pandemic.

In this context, our study aims to show a model capable of capturing characteristics of volatility in times of crisis, such as the presence of jumps and regime changes, both in the average and in the volatility of assets for the North American banking and insurance market. Studies on the impact of COVID-19 on the insurance market can be highlighted as Yating Wang (2020) focuses on how the Chinese market has been affected using the provincial level panel data and the fixed-effects model. The findings reveal that COVID-19 has had a significant negative impact on China's insurance market in the short term due to the limitation of insurance marketing channels and the suppression of household insurance demand. Thorbecke (2020) uses daily stock returns of 125 sectors to investigate how such sectors are affected when COVID-19 is seen as an exogenous shock between February and July 2020. In particular, for the banking and insurance market they found highly exposed to the aggregate U.S. market.

3 Database

For our database, the assets of the nine largest North American banks by market capitalization and nine of the most relevant North American insurance companies were considered. The number of Banks and insurance companies was determined by the amount of relevant data available and no missing data,the data begins in a stable period of the economy and goes until the middle of the pandemic. Considering these criteria, regarding insurance companies, we have UnitedHealth Group(UNH), CVS Health(CVS), NorthWestern Corporationn(NWE), MetLife(MET), Prudential Financial(PRU), Lincoln National Corporation(LNC), MassMutual(MEFZX), State Farm(STFGX) and Aegon(AEG); for banks, JPMorgan Chasee(JPM), Bank of America(BAC), Wells Fargo(WFC), Citigroup(C), Goldman Sachss(GS), First Republic Bankk(FRC), Huntington Bancsharess(HBAN), Fifth Third Bank(FITB) and Ally(ALLY) were considered. The basis was converted to daily log-returns of closing prices, between the periods 2018-08-04 to 2021-05-28, our sample has a total of 1091 observations.

In figure 1 and 2 we have plots daily log returns from both markets an increase in volatility from the moment that COVID-19 was classified as a pandemic on March 11, 2020. Apparently, volatility in both markets has not yet returned to the previous pattern to the pandemic, this is due to many factors observed by the market, such as: high number of deaths, total lack of knowledge about the effects of the disease, among others.

The Table 4, representing the bank's assets, and Table 5, representing the Insurance assets, show the descriptive statistics used in this study. In both tables we can see some the presence of some stylized facts present in financial data. The mean in almost all data set is close to zero, high volatility, negative skewness and fat tails distribution. These characteristics together with high maximum and minimum values are signs of volatility varying over time and the presence of jumps. In the presence of negative skewness and high minimum values show how the COVID-19 crisis had a negative impact on both markets. In the presence of negative skewness and high minimum values show how the COVID-19 crisis had a negative impact on both markets, this fact was already expected since the fundamental function of insurance is to protect people from risks and a catastrophic event such as COVID-19 can cause big losses for these companies that are reflected in the value of their assets. The banking market, in times of crisis, has suffered heavy losses, therefore, with the announcement of the start of the pandemic, a large drop in its assets is expected.

Table 6 shows correlation between contemporaneous daily returns of our assets. All assets have a high positive correlation with each other, especially among stocks with the highest market capitalization such as JPMorgan and Banks of America. This is preliminary evidence that these markets' returns show movements in these periods of increased volatility.

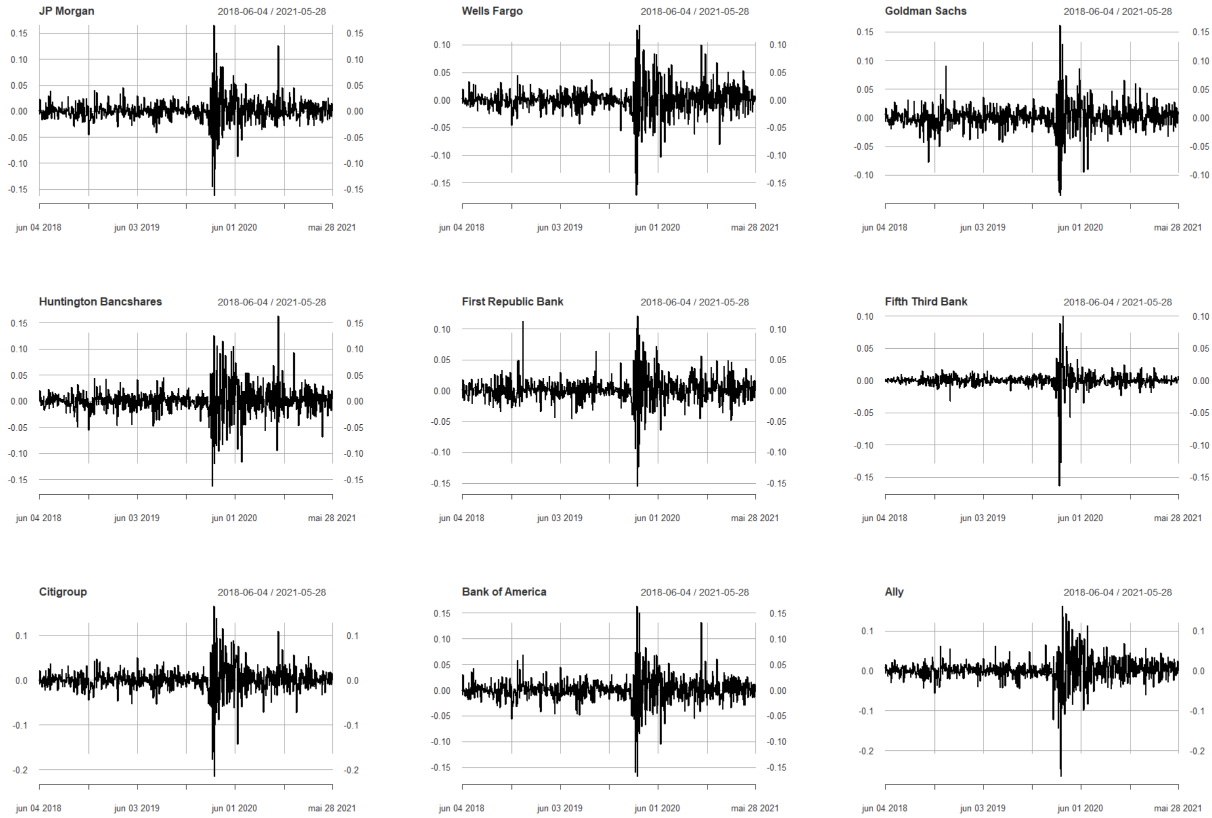


Figura 1 – Figure plots daily log returns of the nine bank assets in our sample, from 2018-08-04 to 2021-05-28.

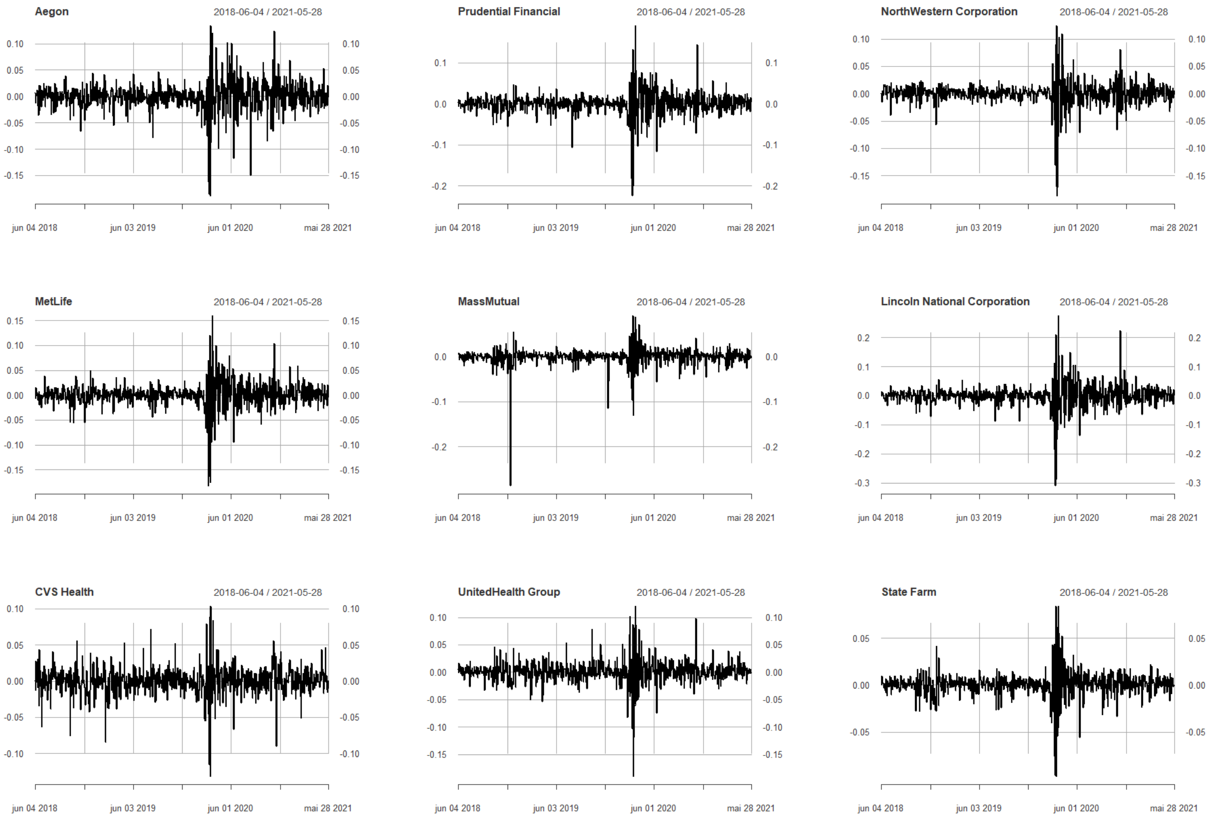


Figura 2 – Figure plots daily log returns of the nine insurance company's assets in our sample, from 2018-08-04 to 2021-05-28.

4 The Model

In our study we will going to use the multivariate stochastic volatility model proposed by Laurini, Mauad, and Auibe (2016), that captures jumps in the average and volatility of asset returns. Such model is capable of capture the permanent and temporary volatility and mean return of the sample. Furthermore, it's capable of capture regime changes and jumps in mean and volatility.These characteristics are essential to get more information about the sample in such a critical event as COVID-19 where the parameters are extremely difficult to capture with standard models like standard SV model and MGARCH (citações). This model has the following description:

$$
\begin{gathered}
y_{i,t} = \exp\left(\frac{h_{i,t}}{2} + \frac{s_i^{\nu}\mu_t}{2}\right)\epsilon_{i,t},\ \epsilon_{i,t} \sim N(\gamma_{i,t}, 1) \\
h_{i,t} = \phi_i h_{i,t-1} + \sigma_i^h z_{i,t}^h,\ z_{i,t}^h \sim N(0,1) \\
\mu_t = \mu_{t-1} + \delta_t^v \sigma^v z_t^v,\ z_t^v \sim N(0,1) \\
\gamma_{i,t} = s_i^m \delta_t^m \sigma^m z_t^m,\ z_t^m \sim N(0,1) \\
\delta_t^v \sim Bernoulli(p_v),\ \delta_t^m \sim Bernoulli(p_m), \\
h_{(i,j),t} = s_i^v s_j^v \mu_t
\end{gathered}
$$

Where $y_{i,t}$ represents the observed log return of the i-asset for each period of time t. In the first equation, which represents the behavior of conditional volatility is separated into two components, $h_{i,t}$ representing the transient part, which is characterized as a first order autoregressive process persistence ϕ_i, and standard deviation error given by σ_i^h; and μ_t is the permanent part, being multiplied by a scaling factor s_i^v . The μ_t can also be understood as a common factor in conditional variance with the compound Binomial process, with δ_t^v, being a sequence of Bernoulli processes with parameter p_v, representing the probability of jumps in the variance, similar to what is suggested by Qu and Perron (2013).Another source of the temporary jumps in the mean is the parameter $\gamma_{i,t}$, which is represented by an independent Bernoulli process δ_t^m with parameter p_m; $\gamma_{i,t}$ is incorporated through the average of the error $\epsilon_{i,t}$. Note that differently, the process of jumps in the mean does not show persistence, that is, it only generates an impact in the period t, unlike the jumps present in the conditional variance, where it is permanent.

It is worth noting that, in this formulation μ_t depends on the performance of the process δ_t^v. If δ_t^v has a value of zero, there will be no jump and, consequently, the value the μ_t will not change from period t to period $t-1$. On the other hand, if δ_t^v is equal to one, a jump will have occurred and the process μ_t will depend on its value in the period $t-1$, μ_{t-1} added a Gaussian innovation with volatility σ^v, which represents the intensity of the jump. This model fits well in crisis scenarios such as COVID-19, as it does not assume a fixed number of regimes and allows an analysis of several assets. In addition, it allows for both transitory and permanent effects on the common and specific volatility of each asset.

The second component of the model is the structure of common jumps in mean. This structure is represented by $\gamma_{i,t}$, which is dependent on three components, the first component being δ_t^m which is a Bernoulli process with parameter p_m and represents the jumps in mean; the second component is the σ^m factor, which represents the bounce impact and the third component s_i^m which represents the bounce impact for each asset. Distinct from the process of jumps in conditional variance, the jump process in mean is not persistent and only impacts the log returns in period t. The covariance between assets is represented by $h(i,j),t$, and depends on the scale factors s_i^v and s_j^v that characterize the sensitivity to the jump in volatility, and the permanent component of volatility u_t. The estimation procedure selected for this model is analogous to the one proposed by Laurini and Mauad (2016), that is, a Bayesian estimation using the mixed Markov Chain Monte Carlo. The δ_t^m and δ_t^v jump processes will be estimated using the threshold exceedance methodology proposed by Albert and Chib (1993). In this procedure, the jump occurs if the value if an auxiliary variable exceeds a threshold, this procedure depends on the jump probabilities p_m and p_v. The inference procedure is based on a burn-in of 3000 samples, and calculating the all-posterior distributions using 1200 additional samples

5 Results

The estimated results for the model described in the previous section are presented in the tables 5 to 8 and figures 3 to 7. We have separated the figures related to the common jumps in volatility, the mean and the permanent component of volatility into three groups: the first group refers to the estimation of the model with both assets types, both from US banks and US insurance companies and such graphs can be seen in figure 3 and figure 4, the second group consists of the estimated model only considering bank assets and these results are available in figure 5; the third group refers to the assets of insurers and the graphs are available in figure 6.

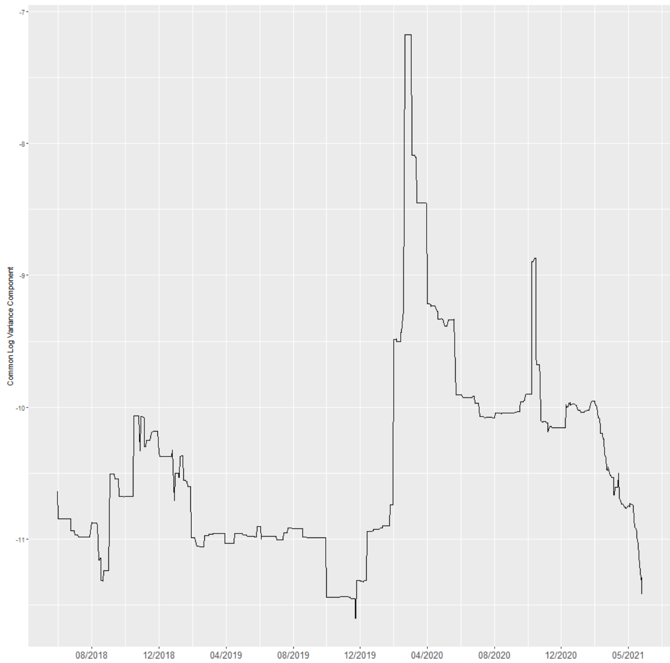
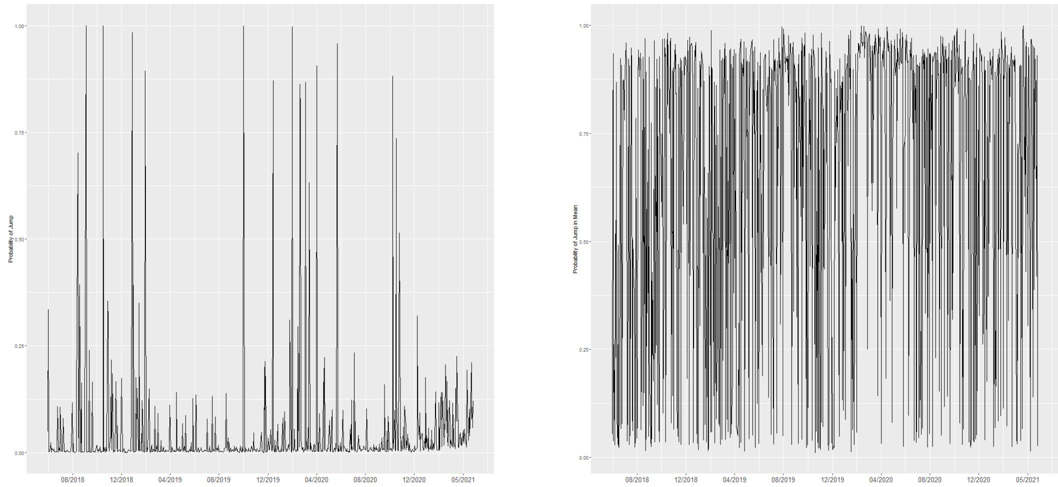


Figura 3 – Permanent commom Volatility component for all eighteen assets.

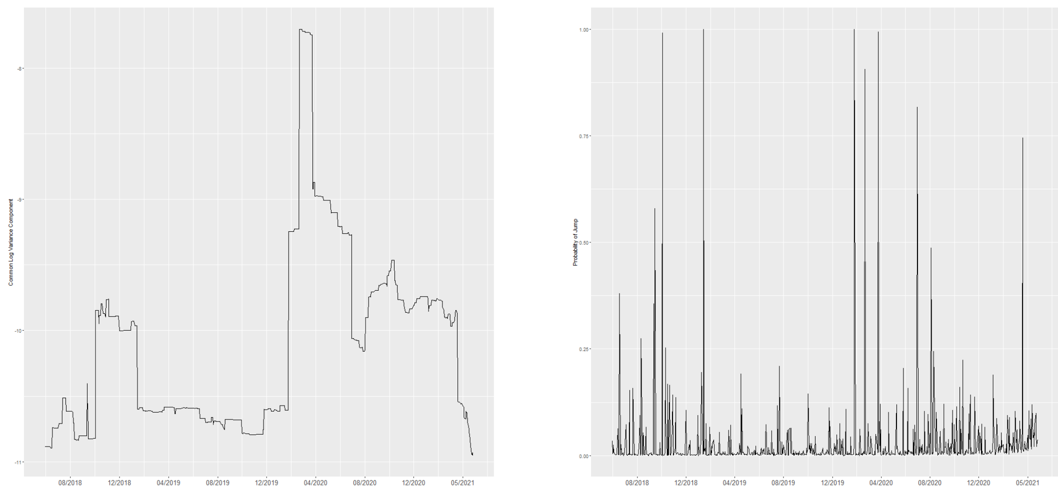
The figure 3 we see the plots the common permanent volatility component, and in figure 4 the probability of a volatility jump (a) and Probability of Jumps in Mean (b). The common permanent volatility and the Probability of Jumps in Mean show that from the beginning of our sample, between August 2018 and march 2020, the permanent component of volatility μ_t remained stable. After March 2020, when the World Health Organization(WHO) classified COVID-19 as a pandemic, there was a high jump in volatility that remains persistent until October 2020 where we can see another jump in volatility not as high as in March, this result shows the high uncertainty of the market and governments regarding this disease. The graphic (b) on figure 4 shows the posterior probability of jumps on mean, connected to the Bernoulli process δ_t^m.



(a) Probability of a volatility jump. (b) Probability of Jumps in Mean.

Figura 4 – probability of jumps in volatility and jump in mean for all eighteen assets.

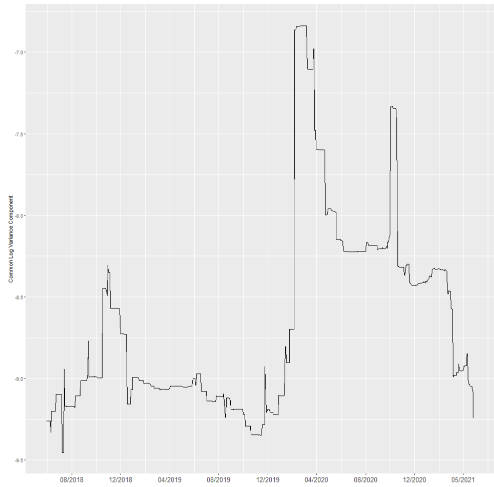
The figure 5 shows plots analogous to figure 3 and 4, but now estimated using the common permanent volatility component and the probability of a volatility jump exclusively for the nine US bank assets. We can notice a similar behavior to that found in the estimation with all 18 assets, the big difference is a drastic decrease in volatility in the period of August 2020, but after this period the behavior pattern remained similar to that seen in figure 3 and 4. Finally, in figure 6, where we consider only the assets of insurers, we see the behavior of the common permanent volatility component and the probability of volatility jump similar to the estimated model considering both markets, that is, the same pattern.



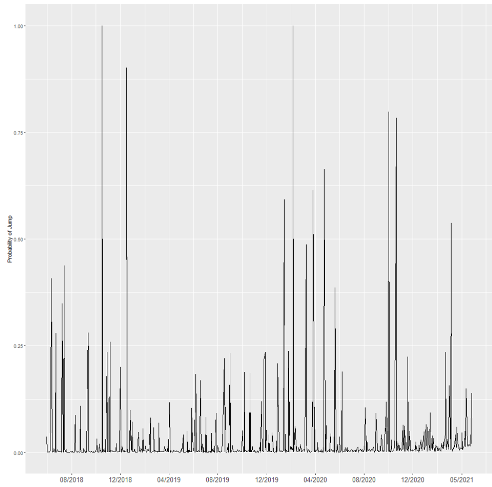
(a) Probability of a volatility jump. (b) Probability of Jumps in Mean.

Figura 5 – Volatility component, probability of jumps in volatility for nine bank assets.

As an example, figure 7 show panels with the observed returns, a comparison between the absolute returns and the volatility adjusted by the model fitted for the



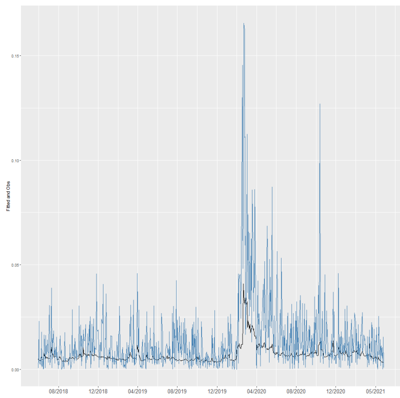
(a) Probability of a volatility jump.



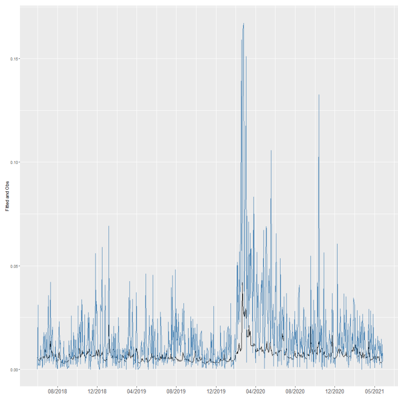
(b) Probability of Jumps in Mean.

Figura 6 – Volatility component, probability of jumps in volatility for nine insurance assets.

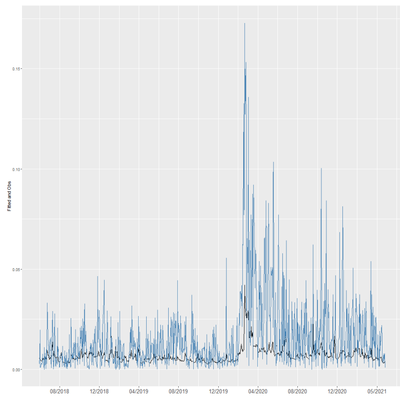
eighteen assets. We can observe that the volatility model with latent factors achieves a good fit when compared to the absolute returns for all 5 assets, being able to capture the impact of regions of high volatility observed at the beginning of the pandemic.



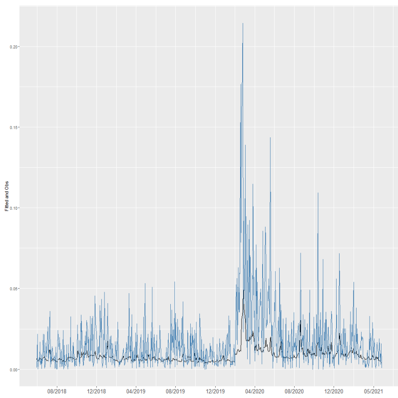
JP Morgan



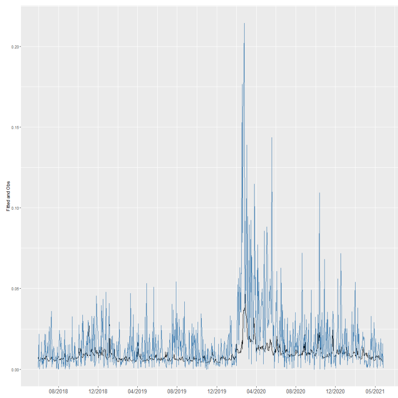
Bank of America



Wells Fargo



Citigroup



Goldman Sachs

Figura 7 – Abs. Returns and Estimated Volatility for the 5 US bank assets.

Table 1 summarizes the descriptive statistics of all individual parameters for each asset using the double jump model for the eighteen assets. This table contains s_i^v, ϕ_i and σ_i^h. Being, respectively, the scale factor for volatility, the volatility persistence parameters and standard deviation of idiosyncratic volatility. Among banking assets, the posterior means of the persistence of volatility for the vast majority, was estimated between 0.36 and 0.58, with Fifth Third Bank being the only bank out of this range with 0.91 posterior mean. On the other hand, the insurance company's assets showed high persistence in volatility, with the posterior average of most assets between 0.56 and 0.74. The only exception outside this range is Aegon, which presents a posterior average of 0.28, that is, low persistence of transient volatility. These results indicate, in general, that most assets present a partial autonomy of the conditional volatility dynamic in relation to the common factor μ_t. The confidence interval between all assets was between 0.14 and 0.94 so we could not find evidence of nonstationarity. Insurance companies, in general, show greater independence in the behavior of conditional volatility in relation to banks, such factor can be justified by the greater impact of COVID-19 on insurance companies compared to banks.

Tabela 1 – Posterior distributions individual parameters for the model with eighteen assets.

	1. Quartile	3. Quartile	Mean	Median	Stdev	Skewness	Kurtosis
s_1^v	1.00	1.00	1.00	1.00	0.00	0.00	0.00
σ_1^h	1.94	8.45	5.66	2.47	5.92	1.59	1.59
ϕ_1	0.33	0.92	0.58	0.52	0.30	0.07	-1.37
s_2^v	0.96	1.01	0.97	0.99	0.05	-1.23	0.22
σ_2^h	1.16	1.80	1.53	1.43	0.50	1.02	0.89
ϕ_2	0.42	0.59	0.50	0.51	0.13	-0.18	0.17
s_3^v	0.89	0.94	0.91	0.92	0.04	-2.53	23.17
σ_3^h	1.05	1.53	1.36	1.23	0.46	1.75	3.67
ϕ_3	0.33	0.52	0.43	0.43	0.16	0.35	0.44
s_4^v	0.92	0.96	0.93	0.95	0.05	-1.55	1.87
σ_4^h	1.67	2.55	2.30	2.05	1.00	2.39	7.62
ϕ_4	0.43	0.59	0.52	0.51	0.14	0.39	0.99
s_5^v	0.91	0.95	0.92	0.93	0.04	-1.23	0.51
σ_5^h	1.28	1.87	1.60	1.53	0.45	0.72	0.21
ϕ_6	0.25	0.47	0.36	0.36	0.16	-0.02	-0.49
s_6^v	0.88	0.92	0.88	0.91	0.06	-1.78	4.99
σ_6^h	1.64	4.03	3.03	2.07	2.01	1.37	0.91
ϕ_6	0.40	0.77	0.58	0.54	0.24	0.17	-0.92
s_7^v	0.87	0.91	0.89	0.90	0.03	-0.94	-0.44

σ_7^h	2.53	5.14	4.00	3.48	1.94	1.21	1.79
ϕ_7	0.33	0.73	0.53	0.59	0.24	-0.54	-0.93
s_8^v	0.97	1.01	0.99	0.99	0.03	-1.05	4.58
σ_8^h	5.41	8.92	7.25	7.03	2.55	0.35	0.03
ϕ_8	0.89	0.94	0.91	0.92	0.04	-4.95	63.20
s_9^v	0.84	0.88	0.86	0.87	0.03	-0.71	0.14
σ_9^h	1.18	1.55	1.42	1.32	0.38	1.85	4.58
ϕ_9	0.25	0.47	0.36	0.35	0.17	0.42	-0.12
s_{10}^v	0.83	0.85	0.84	0.84	0.02	-4.37	71.93
σ_{10}^h	1.77	3.02	2.55	2.30	1.07	1.18	1.07
ϕ_{10}	0.59	0.77	0.67	0.68	0.13	-0.75	0.43
s_{11}^v	0.82	0.85	0.83	0.84	0.02	-0.86	0.27
σ_{11}^h	1.22	2.04	1.81	1.53	0.91	2.10	4.82
ϕ_{11}	0.38	0.64	0.51	0.50	0.19	0.00	-0.38
s_{12}^v	0.84	0.86	0.85	0.86	0.02	-1.59	7.72
σ_{12}^h	2.85	5.22	4.26	3.71	1.91	1.00	0.42
ϕ_{12}	0.28	0.68	0.46	0.43	0.23	0.06	-1.09
s_{13}^v	0.93	0.97	0.94	0.96	0.04	-1.22	1.58
σ_{13}^h	2.08	3.32	2.87	2.61	1.15	1.38	2.22
ϕ_{13}	0.52	0.68	0.59	0.61	0.14	-1.07	1.59
s_{14}^v	0.94	0.99	0.95	0.98	0.07	-2.32	5.78
σ_{14}^h	1.33	2.13	1.89	1.64	0.91	2.39	7.35
ϕ_{14}	0.46	0.67	0.56	0.56	0.16	0.03	0.13
s_{15}^v	0.87	0.92	0.89	0.91	0.05	-1.52	1.77
σ_{15}^h	1.90	3.23	2.65	2.46	0.97	0.80	0.33
ϕ_{15}	0.59	0.73	0.65	0.66	0.12	-0.95	1.32
s_{16}^v	0.90	0.93	0.91	0.92	0.02	-2.13	20.51
σ_{16}^h	1.58	2.37	2.03	1.98	0.63	1.15	2.83
ϕ_{16}	0.57	0.73	0.64	0.66	0.15	-1.19	1.87
s_{17}^v	0.97	1.01	0.99	1.00	0.03	-2.73	30.37
σ_{17}^h	6.13	11.39	9.61	8.25	5.40	1.84	4.23
ϕ_{17}	0.66	0.84	0.74	0.77	0.14	-0.97	0.85
s_{18}^v	0.81	0.85	0.83	0.84	0.03	-0.82	-0.66
σ_{18}^h	1.57	2.05	1.86	1.79	0.44	1.11	1.45
ϕ_{18}	0.14	0.40	0.28	0.25	0.18	0.69	0.08

The scale factor for the volatility s_i^v which indicate how each asset i reacts to the global common volatility μ_t. The larger the average of s_i^v will indicate an increase in the contribution of the common factor μ_t in the conditional volatility of each asset i.

As expected, all assets in both markets had estimated parameters with a posterior mean lower than one, this fact shows the high exposure of the volatility common factor to the jump effect. In periods of financial market uncertainty, such jumps are often observed.

Table 2 summarizes the posterior descriptive statistics of the parameters common to all assets. The parameter that captures the probability of common jumps in mean and it can also be interpreted as a regime switching is p_m. This parameter was estimated with posterior mean of 0.53 and such value is considered very high. As such jumps occurred close to the beginning of the pandemic in March 2020, we can see a high interconnection between the jumps of assets in periods of financial instability, explaining the high correlation observed in table 5. The parameter σ^m, which measures the intensity of the jumps in common factor for mean was estimated with posterior mean of 0.75, such high value indicate that factor explain significant part of the volatility for all this asset series in this period.

Tabela 2 – Posterior distributions common parameters for the model with eighteen assets.

	1. Quartile	3. Quartile	Mean	Median	Stdev	Skewness	Kurtosis
σ^v	0.19	0.74	0.47	0.47	0.31	0.07	-1.28
σ^m	0.68	0.89	0.75	0.79	0.20	-1.27	1.44
p_v	0.03	0.06	0.05	0.04	0.02	0.97	-0.11
p_m	0.44	0.67	0.53	0.62	0.19	-1.16	-0.10

Tables 3 and 4 present the descriptive statistics of all individual and common parameters for each asset type, with table 9 representing the model parameters considering only the bank assets and table 10 representing the model parameters considering only 9 insurance companies. The posterior means of the persistence of volatility for the banks, ϕ_i, has a larger range of values, with the lowest value being 0.433 for Bank of America and 0.919 for Fifth Third Bank. As this parameter represents the autonomy of the conditional volatility dynamic in relation to the common factor μ_t, we can see that the Banks with the highest market capitalization tend to be independent of volatility in relation to the common factor, with the exception of Ally, which has a parameter value of 0.443. In the case of insurance companies, we observed a range between 0.492 and 0.831 for later means of the persistence of volatility. In the case of insurance companies, we observed a range between 0.492 and 0.831 for later means of the persistence of volatility. Indicating greater autonomous dynamics of conditional volatility in relation to the common factor for insurers MassMutual, State Farm and NorthWestern Corporation. These facts show that banks with lower market capitalization tend to have greater autonomy from conditional volatility in relation to common volatility in periods of crisis such as COVID-19. Regarding insurance companies, we cannot observe any explicit trend in relation to this parameter.

The scale factor for the volatility s_i^v in both models was considerably high, indicating high exposure to the common factor of variance i.e., greater jump effects. The highlights on bank assets would be s_2^v, which is related to Bank of America and s_1^v, which is related to JP Morgan showing that such companies have the greatest impact on jumps in volatility and are responsible for the greatest impact on the banking sector in this period. The scaling factors for the jumps on mean s_i^m indicate that Bank of America, Citigroup and Huntington Bancshares are most responsible for the amplification of the jumps in the average, with parameters estimated, respectively, at 1.05, 1.11 and 1.08. This result shows that such companies have a tendency to impact the banking market in times of crisis. In the case of insurance companies, we can notice that the six companies are responsible for amplifying the jumps in mean. This evidence shows how most companies amplified the common factor σ^m. Moments of instability drastically affect the results of these companies in the market, as expected.

For the model with all the assets we can list the following most important results: In the beginning of the COVID-10 pandemic until almost the end of 2020; the model was able to capture the high jumps in volatility in the market. This result shows that the model was capable to capture the high uncertainty of the market on both, banks and insurance companies. We found evidences that Insurance companies show more autonomous volatility dynamics compared to banks. All assets in both markets shows high exposure of the volatility common factor to the jump effect on the period of COVID-19, such fact shows that the model was able to capture the market uncertainties in such period, as these types of jumps in volatility are common in these types of periods. This jumps started to occur on the beginning of the pandemic, showing high correlation between the jumps of assets in periods of financial crises, explaining the high linear correlation observed in table 5. In short, we can see that the estimated model using all assets is capable of capturing market characteristics such as the dynamics of jumps and conditional volatility in periods of high instability.

For the model with the nine banks assets and nine insurance companies separately we observe that banks with lower market capitalization present more autonomy from conditional volatility indicating that the process of reversion to the common factor is slower. Also we can see that Bank of America, Citigroup and Huntington Bancshares are most responsible for the amplification of the jumps in the average showing evidence that such banks have a greater ability to impact the banking market compared to others in periods of instability. For the insurance companies, we observe that most companies amplified the common volatility.

Overall, we can see that the model proposed for the three samples was significantly capable of capturing some market characteristics during the COVID-19 pandemic, such as jumps in the mean and variance, switching regime for both common parameters and individual parameters. Proving to be a good alternative model in times of crisis or instability.

	Mean	Stdev	1.Quartile	Median	3.Quartile	Skewness	Kurtosis
σ^v	0.41	0.125	0.264	0.378	0.741	1.26	4.64
σ^m	0.374	0.16	0.212	0.337	0.761	4.29	63.2
p_v	0.0333	0.0269	0.00897	0.0237	0.102	1.53	4.28
p_m	0.456	0.217	0.0424	0.573	0.656	-0.85	2.16
s_1^v	1	0	1	1	1	0	0
s_1^m	1	0	1	1	1	0	0
ϕ_1	0.439	0.237	0.0494	0.443	0.807	-0.13	1.81
σ_1^h	0.41	0.125	0.264	0.378	0.741	1.26	4.64
s_2^v	1	0.0409	0.907	1.01	1.04	-6.62	112
s_2^m	1.05	0.103	0.95	1.06	1.24	4.64	4.27
ϕ_2	0.433	0.218	0.0783	0.441	0.895	0.137	2.45
σ_2^h	0.659	0.136	0.417	0.667	0.888	-0.25	2.4
s_3^v	0.937	0.027	0.91	0.936	0.976	-12.3	299
s_3^m	0.956	0.0967	0.871	0.956	1.03	5.26	75
ϕ_3	0.542	0.173	0.278	0.521	0.89	0.265	2.59
σ_3^h	0.788	0.199	0.35	0.837	1.06	-0.926	3.12
s_4^v	0.949	0.012	0.929	0.949	0.971	0.0514	3.38
s_4^m	1.11	0.114	0.989	1.12	1.2	5.06	72.4
ϕ_4	0.546	0.174	0.232	0.568	0.868	-0.39	2.85
σ_4^h	0.562	0.108	0.42	0.542	0.795	0.55	2.65
s_5^v	0.925	0.0289	0.859	0.933	0.957	-2.23	12.3
s_5^m	0.918	0.127	0.834	0.904	1.29	6.04	53.7
ϕ_5	0.47	0.274	0.0826	0.421	0.969	0.447	2.16
σ_5^h	0.676	0.197	0.269	0.715	0.989	-0.583	2.57
s_6^v	0.92	0.0254	0.891	0.915	0.982	-1.4	63.5
s_6^m	0.762	0.0834	0.671	0.761	0.884	4.48	51.1
ϕ_6	0.663	0.13	0.427	0.679	0.884	-1.13	5.8
σ_6^h	0.652	0.1	0.486	0.651	0.861	0.131	2.93
s_7^v	0.913	0.0169	0.889	0.911	0.951	0.652	3.83
s_7^m	1.08	0.147	0.961	1.07	1.4	5.37	52.2
ϕ_7	0.714	0.127	0.461	0.726	0.926	-0.762	3.8
σ_7^h	0.51	0.116	0.323	0.51	0.778	0.57	4.29
s_8^v	0.996	0.0256	0.965	0.99	1.06	1.16	4.11
s_8^m	0.0638	0.092	0.0298	0.0537	0.121	11.1	138
ϕ_8	0.919	0.0371	0.858	0.924	0.969	-3.23	33.5
σ_8^h	0.381	0.0936	0.286	0.358	0.624	2.9	16.6
s_9^v	0.873	0.0251	0.847	0.868	0.937	-1.21	40.3
s_9^m	0.969	0.0959	0.825	0.98	1.06	-0.144	31.3
ϕ_9	0.443	0.197	0.136	0.427	0.896	0.381	2.9
σ_9^h	0.756	0.13	0.49	0.775	0.969	-0.622	3.31

Tabela 3 – Posterior distributions individual and commom parameters for the model with nine bank assets.

	Mean	Stdev	1.Quartile	Median	3.Quartile	Skewness	Kurtosis
σ^v	0.629	0.123	0.446	0.618	0.875	0.374	2.64
σ^m	0.374	0.155	0.213	0.337	0.765	2.64	18.1
p_v	0.0325	0.0264	0.01	0.0231	0.1	1.59	4.27
p_m	0.351	0.159	0.0921	0.38	0.527	-0.436	1.67
s_1^v	1	0	1	1	1	0	0
s_1^m	1	0	1	1	1	0	0
ϕ_1	0.679	0.159	0.385	0.697	0.913	-0.566	2.73
σ_1^h	0.629	0.123	0.446	0.618	0.875	0.374	2.64
s_2^v	1.01	0.0379	0.914	1.02	1.06	-1.2	4.25
s_2^m	0.602	0.103	0.491	0.583	0.881	2.06	3.13
ϕ_2	0.569	0.187	0.269	0.552	0.895	0.0412	2.51
σ_2^h	0.77	0.169	0.425	0.801	1.03	-0.629	2.65
s_3^v	1.02	0.0352	0.951	1.03	1.07	-1.1	5.79
s_3^m	0.378	0.129	0.263	0.345	0.746	3.14	16.8
ϕ_3	0.705	0.162	0.403	0.743	0.923	-0.751	2.91
σ_3^h	0.431	0.124	0.275	0.406	0.712	0.76	2.94
s_4^v	1.11	0.0882	0.938	1.14	1.22	-0.675	2.23
s_4^m	1.09	0.149	0.964	1.05	1.55	3.17	18.4
ϕ_4	0.557	0.191	0.175	0.598	0.863	-0.696	2.97
σ_4^h	0.498	0.121	0.29	0.493	0.755	0.297	3.17
s_5^v	1.11	0.0981	0.924	1.14	1.24	-0.651	2.2
s_5^m	1.19	0.149	1.06	1.16	1.61	2.86	16.1
ϕ_5	0.492	0.215	0.0765	0.52	0.852	-0.401	2.48
σ_5^h	0.645	0.147	0.42	0.637	0.949	0.319	2.66
s_6^v	1.04	0.076	0.9	1.06	1.14	-0.943	7.07
s_6^m	1.54	0.192	1.36	1.49	2.14	1.97	11.3
ϕ_6	0.528	0.255	0.0779	0.578	0.931	-0.344	2.06
σ_6^h	0.625	0.137	0.362	0.626	0.87	-0.312	2.92
s_7^v	1.1	0.0582	0.961	1.12	1.16	-1.66	4.82
s_7^m	0.594	0.132	0.461	0.564	0.938	2.12	11.1
ϕ_7	0.735	0.124	0.51	0.747	0.936	-0.414	2.77
σ_7^h	0.676	0.144	0.447	0.675	0.964	0.13	2.41
s_8^v	1.2	0.0657	1.03	1.22	1.26	-1.81	5.41
s_8^m	0.539	0.0993	0.439	0.517	0.81	2.06	9.54
ϕ_8	0.831	0.0788	0.69	0.849	0.938	-1.08	4.52
σ_8^h	0.351	0.0974	0.228	0.334	0.567	1.6	8.88
s_9^v	0.974	0.0442	0.883	0.986	1.03	-1.25	9.51
s_9^m	1.04	0.186	0.885	0.998	1.61	2.78	13.8
ϕ_9	0.497	0.214	0.0798	0.542	0.845	-0.558	2.5
σ_9^h	0.603	0.0918	0.465	0.599	0.808	0.437	3.07

Tabela 4 – Posterior distributions individual and commom parameters for the model with nine insurance companies assets.

6 Conclusion

In this paper, we propose a study of the volatility behavior of the major insurance companies and banks in the US, considering the period from the beginning of march 2020, when starts the COVID-19, to mid-2021. For this, a multivariate stochastic volatility-double jump model in three different groups, a group with insurance companies only, another with banks and one with all eighteen companies assets. For all the three samples, the common factors estimated shows enough precision to capture characteristics and stylized facts of these financial series in a period of crisis in the stock market, such as jumps in mean, volatility and conditional volatility. The model estimated for all the assets indicate that banks and insurance companies has high exposure of the volatility common factor to the jump effect during the onset of COVID-19 until mid-year 2021.

Overall, the model was able to capture the shocks caused by the news of the first case of COVID-19 in the world and the declaration of a pandemic by World Health in the banking and insurance sectors. Proving to be a model capable of enabling an economic interpretation.

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Apêndices

APÊNDICE A – appendices1

	JPM	BAC	WFC	C	GS	FRC	HBAN	FITBI	ALLY
Minimum	-0.16211	-0.16720	-0.17278	-0.21441	-0.13588	-0.15487	-0.16273	-0.16361	-0.26411
Maximum	0.16562	0.16379	0.13571	0.16538	0.16195	0.12115	0.16326	0.10032	0.16248
1. Quartile	-0.00845	-0.00943	-0.00981	-0.01035	-0.00899	-0.00864	-0.01080	-0.00324	-0.00965
3. Quartile	0.00946	0.01150	0.00993	0.01218	0.01166	0.01047	0.01148	0.00405	0.01333
Mean	0.00067	0.00057	-0.00008	0.00034	0.00073	0.00087	0.00024	0.00030	0.00109
Variance	0.00050	0.00061	0.00066	0.00078	0.00052	0.00046	0.00074	0.00018	0.00095
Stdev	0.02230	0.02467	0.02564	0.02800	0.02291	0.02146	0.02722	0.01334	0.03087
Skewness	-0.07798	-0.05443	-0.35497	-0.69067	-0.17831	-0.15518	-0.01865	-2.77162	-1.20584
Kurtosis	13.41959	11.06416	8.52772	11.89662	10.17602	9.10715	6.60883	52.04942	15.83613

Tabela 5 – Bank Daily Log Returns Descriptive statistics.

	UNH	CVS	NWE	MET	PRU	LNC	MPGSX	STFGX	AEG
Minimum	-0.18967	-0.13133	-0.18658	-0.18202	-0.22457	-0.31021	-0.28710	-0.09724	-0.18851
Maximum	0.12044	0.10345	0.12412	0.15990	0.19091	0.27536	0.09173	0.08421	0.13420
1. Quartile	-0.00729	-0.00963	-0.00714	-0.00886	-0.00998	-0.01262	-0.00452	-0.00334	-0.01270
3. Quartile	0.00891	0.01095	0.00887	0.01091	0.01194	0.01498	0.00788	0.00613	0.01227
Mean	0.00076	0.00052	0.00039	0.00061	0.00030	0.00017	0.00013	0.00060	-0.00025
Variance	0.00045	0.00039	0.00047	0.00063	0.00078	0.00147	0.00038	0.00018	0.00081
Stdev	0.02125	0.01976	0.02162	0.02508	0.02793	0.03833	0.01945	0.01328	0.02855
Skewness	-0.56692	-0.48950	-1.87040	-0.78792	-0.98847	-0.44731	-4.91105	-0.70400	-0.77220
Kurtosis	14.10836	7.15424	22.35454	12.70894	15.80650	16.88277	68.28333	14.76615	9.06246

Tabela 6 – Insurance Companies Daily Log Returns Descriptive statistics.

	JPM	BAC	WFC	C	GS	FRC	HBAN	FITBI	ALLY	UNH	CVS	NWE	MET	PRU	LNC	MPGSX	STFGX	AEG
JPM	1.00000	0.93535	0.84945	0.89987	0.85816	0.75222	0.85130	0.48503	0.77688	0.54947	0.51551	0.58827	0.85842	0.85680	0.85507	0.54113	0.77659	0.72402
BAC	0.93535	1.00000	0.87441	0.90582	0.86365	0.77374	0.86096	0.40884	0.75012	0.53823	0.52406	0.55041	0.86784	0.87008	0.85999	0.53330	0.77743	0.71486
WFC	0.84945	0.87441	1.00000	0.84966	0.78937	0.71381	0.80956	0.42238	0.72515	0.48881	0.48824	0.57050	0.81998	0.83053	0.82498	0.48349	0.71847	0.68163
C	0.89987	0.90582	0.84966	1.00000	0.86016	0.71264	0.82788	0.50041	0.77772	0.51489	0.49737	0.55417	0.83988	0.85374	0.85744	0.54960	0.76376	0.71644
GS	0.85816	0.86365	0.78937	0.86016	1.00000	0.69918	0.75330	0.48459	0.73339	0.56268	0.48987	0.55530	0.78955	0.78977	0.81038	0.57940	0.77274	0.68403
FRC	0.75222	0.77374	0.71381	0.71264	0.69918	1.00000	0.69968	0.26386	0.66522	0.50322	0.43551	0.55148	0.69587	0.68986	0.69143	0.49250	0.68714	0.59772
HBAN	0.85130	0.86096	0.80956	0.82788	0.75330	0.69968	1.00000	0.37385	0.72945	0.40881	0.45563	0.49483	0.81046	0.82613	0.81630	0.42388	0.64710	0.67590
FITBI	0.48503	0.40884	0.42238	0.50041	0.48459	0.26386	0.37385	1.00000	0.45691	0.44424	0.36322	0.46924	0.46944	0.49285	0.55090	0.42635	0.52739	0.38423
ALLY	0.77688	0.75012	0.72515	0.77772	0.73339	0.66522	0.72945	0.45691	1.00000	0.48792	0.39546	0.55881	0.74354	0.73062	0.77428	0.48589	0.65471	0.63117
UNH	0.54947	0.53823	0.48881	0.51489	0.56268	0.50322	0.40881	0.44424	0.48792	1.00000	0.59191	0.52656	0.53538	0.52229	0.53671	0.57732	0.69803	0.42303
CVS	0.51551	0.52406	0.48824	0.49737	0.48987	0.43551	0.45563	0.36322	0.39546	0.59191	1.00000	0.42147	0.54017	0.55268	0.52692	0.43865	0.60211	0.45607
NWE	0.58827	0.55041	0.57050	0.55417	0.55530	0.55148	0.49483	0.46924	0.55881	0.52656	0.42147	1.00000	0.57053	0.56575	0.61057	0.42903	0.64377	0.44747
MET	0.85842	0.86784	0.81998	0.83988	0.78955	0.69587	0.81046	0.46944	0.74354	0.53538	0.54017	0.57053	1.00000	0.93077	0.91071	0.55513	0.80401	0.70865
PRU	0.85680	0.87008	0.83053	0.85374	0.78977	0.68986	0.82613	0.49285	0.73062	0.52229	0.55268	0.56575	0.93077	1.00000	0.92820	0.53319	0.79639	0.73867
LNC	0.85507	0.85999	0.82498	0.85744	0.81038	0.69143	0.81630	0.55090	0.77428	0.53671	0.52692	0.61057	0.91071	0.92820	1.00000	0.53896	0.77411	0.71814
MPGSX	0.54113	0.53330	0.48349	0.54960	0.57940	0.49250	0.42388	0.42635	0.48589	0.57732	0.43865	0.42903	0.55513	0.53319	0.53896	1.00000	0.76852	0.43929
STFGX	0.77659	0.77743	0.71847	0.76376	0.77274	0.68714	0.64710	0.52739	0.65471	0.69803	0.60211	0.64377	0.80401	0.79639	0.77411	0.76852	1.00000	0.62675
AEG	0.72402	0.71486	0.68163	0.71644	0.68403	0.59772	0.67590	0.38423	0.63117	0.42303	0.45607	0.44747	0.70865	0.73867	0.71814	0.43929	0.62675	1.00000

Tabela 7 – Pearson correlation coefficients between daily log-returns of booth markets