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Contaduría y Administración

Accounting & Management

Contaduría y Administración 65 (5), Especial COVID-19, 2020, 1-29

COVID-19 news and volatility contagion in the Mexican stock market

Noticias del COVID-19 y contagio de volatilidad en la Bolsa Mexicana de Valores

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Received October 1, 2020; accepted December 29, 2020
Available online October 14, 2022

Abstract

In the present work VIX volatility, Economic and trade policy and infectious disease (such as COVID-19) news sentiment indexes. This, to measure their impact in the probability of being in a high volatility episode in the Mexican stock exchange (BMV). With monthly data from January 1996 to August 2020, Markov-Switching models were used to estimate the smoothed high volatility regime probabilities. With these and the market sentiment indexes, logit models were estimated in order to prove that the COVID-19 news uncertainty does not generate high volatility episodes in the BMV. These episodes are a result of a volatility spillover from the U.S. financial markets.

JEL Code: C580, D53, D91, G11, G14
Keywords: markov-switching models; economic policy uncertainty index; behavioral finance; volatility spillover; mexican stock exchange

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Peer Review under the responsibility of Universidad Nacional Autónoma de México.

http://dx.doi.org/10.22201/fca.24488410e.2020.3088

Resumen

En el presente trabajo se utilizan el índice de volatilidad VIX e índices de sentimiento de mercado de noticias de política económica, comercial y de propagación de enfermedades como el COVID-19. Esto para medir el efecto que estos tienen en la probabilidad de ocurrencia de episodios de alta volatilidad en la Bolsa Mexicana de Valores (BMV). Con información mensual de enero de 1996 a agosto del 2020, se utilizaron modelos Markov-Switching para calcular las probabilidades suavizadas de un régimen de alta volatilidad. Con estas y los índices de sentimiento de mercado, se corrieron modelos logit que demostraron que la incertidumbre relativa a noticias del COVID-19 no genera episodios de alta volatilidad en la BMV. La presencia de estos episodios se debe más a una situación de contagio de volatilidad desde los mercados financieros estadounidenses.

Código JEL: C580, D53, D91, G11, G14
Palabras clave: modelos markov-switching; CODIV-19; sentimiento de mercado; finanzas conductistas; contagio de volatilidad; bolsa mexicana de valores

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Introduction and foundation for the crisis warning model studied

The pandemic declared by the World Health Organization (2020) in January of this year led to a widely known sequence of events that generated social, psychological, and political reactions in practically every country worldwide.

As a result of these reactions and the subsequent preventive actions taken worldwide, financial markets underwent an episode of high volatility in their behavior. The above means that, in terms of Financial Econometrics or time series analysis, financial markets had a structural break in their behavior in the context of a high volatility regime.

These episodes are not new in the history of all financial markets. In fact, they are one of the main subjects of study in both Macroeconomics and Financial Economics. These two areas of knowledge had their theoretical development thanks to the need to explain the behavior of investors in episodes such as 1) the Great Depression of 1834, resulting from the euphoria of the Gold Rush in the United States (USA) and the real estate bubble in states such as New York; 2) the long depression in England and the United States in 1873, resulting from the investment bonanza achieved with the industrial revolution and the investment in railroads and steelworks in the USA, as well as the end of the Franco-Prussian war that gave rise to a political change in Germany or the end of the Civil War in the USA; 3) what is still called the Great Depression of 1929 in the USA and the rest of the world; or 5) the world financial crisis of 2008 to 2009, originating in the US financial system. These episodes are among the many that could be cited.

As can be appreciated from the above, the high volatility that occurred in the financial markets (especially stock and currency markets) has some factors in common (Shiller, 2003, 2014). The first is a generalized behavior of collective panic in which there was a massive sell-off of stocks and an abrupt decline in these markets. The latter occurred due to a high level of uncertainty among investors due to the news reports published at their respective times (M. Baker & Wurgler, 2006, 2007; S. R. Baker, Bloom, & Davis, 2016c). The above is coupled with the widespread perception of a "lack of certainty" regarding what would happen in economic and political terms and the actions that the governments of each country would take to resolve the financial or economic crisis.

These crisis episodes generated what is known as a "contagion effect" or "volatility contagion" from the markets where the events originated to the markets of other countries and other types of securities. This work seeks to demonstrate this contagion effect as the main cause of the episodes of volatility in the Mexican Stock Exchange (Spanish: Bolsa Mexicana de Valores, BMV). For this purpose, this cause will be contrasted with other possible causes, such as the level of uncertainty generated by news of economic and trade policy in the USA or that which, potentially, could be generated by the uncertainty resulting from the news of the spread of infectious diseases such as COVID-19.

In addition to this contagion effect, the actions taken by the different governments led to uncertainty regarding the restrictions and legal guidelines that would be implemented. Some examples are the potential bailout of banks and companies of national interest in the United States in 2008, the disruption of production chains and international trade in episodes of uncertainty following the terrorist attacks in the United States in 2001, or the closing of borders and airports in the recent declaration of a pandemic in 2020.

Given the actions above, it is of interest to measure the relationship between the uncertainty generated among investors in the Mexican stock market and the generation of episodes of high volatility. The latter is based on the news related to the US economic policy and its trade policy since 2016.

Moreover, and due to the events sadly observed in the world with the 2020 pandemic, it is of interest to determine whether the uncertainty generated by the news related to infectious contagions around the world also has an impact on the generation of high volatility regimes in this market.

Given the above, this work will use the measures of the volatility level in US financial markets, approximated with the VIX index of the S&P 500, and market sentiment resulting from economic policy news, trade policy, and news of infectious diseases such as that of COVID-19.

Market sentiment is defined as "the attitude (positive, negative, or neutral) that investors have toward investing in the securities of a given market" (Hens & Rieger, 2010). It is a concept typical of so-called behavioral finance. One way to approximate it is through the news published in recognized media. To achieve this measurement, this work uses the Economic Policy Uncertainty Indices (Spanish: Índices de Incertidumbre de Política Económica, IIPE) estimated by Baker, Bloom, and Davis (2016c) at the global level. This is done with the 21 major economies of the planet ($IIPEG_t$), that of the USA ($IIPEUS_t$), the Trade Policy Uncertainty Index ($IIPC_t$), and the Infectious Disease Stock Market Volatility Index ($IVEI_t$). These indices use the text of the headlines and first paragraphs of the news of the main world newspapers in each country studied. This was done to code a level of uncertainty that ranges around 100 points. When the level of each index is greater than 100, it is understood that the level of uncertainty is higher than usual; the opposite is the case when it is lower.

The working hypothesis of this article is that the level of each of these indices has a positive relationship or influence if the Mexican stock market is in an episode of high volatility or crisis.

The practical motivation for measuring this relationship consists in the feasibility of using these news indices to generate a warning system (J. Engel, Wahl, & Zagst, 2018; Hauptmann, Hoppenkamps, Min, Ramsauer, & Zagst, 2014) that makes it possible to forecast episodes of high volatility in the Mexican stock market. This forecast can potentially be useful for financial risk quantification or investment decision-making applications.

Another important motivation for this work is the desire to join the discussion as to whether the episodes of high volatility observed in the BMV are the result of the COVID-19 epidemic and the high uncertainty in economic and trade policy (Ortiz, Cabello, & Sosa, 2020) or if they are the consequence of a volatility contagion effect from the US financial markets.

Among the potential applications of these tests, multiple works use regime-switching models with Markov chains (Markov-Switching models or MS) for investment decision-making (Brooks & Persand, 2001; Kritzman, Page, & Turkington, 2012) or risk quantification (Ardia, 2008; Ardia, Bluteau, & Rüede, 2018; Ardia & Hoogerheide, Lennart, 2013; Ardia & Hoogerheide, 2014; Cabrera, Coronado, Rojas, & Venegas-Martínez, 2017; Sosa, Ortiz, & Cabello, 2018).

With the above perspective, the objective of this work is to quantify the influence that the negative sentiment (level of uncertainty) generated by the economic and trade policies of the United States has on the generation of crisis episodes (high volatility) in the BMV, especially the influence of the uncertainty generated by news of epidemics and massive outbreaks of infectious diseases (such as the current pandemic in the year 2020). This work also seeks to demonstrate that the generation of these episodes in the BMV is due more to a situation of contagion from the US financial markets than to the uncertainty generated by the development and news of the COVID-19 pandemic.

This work's theoretical position or hypothesis is that there is no positive influence on the probability of observing episodes of crisis or high volatility, given the level of uncertainty of economic or trade policies or the level of uncertainty generated by news of infectious diseases (epidemics or pandemics). That said, it is the author's position that the crisis episodes in the BMV are due more to a situation of volatility contagion from the US financial markets.

The applications of these results lie in developing forecasting models of these high volatility episodes for quantifying financial risks or investment decision-making in the BMV. This is done for the potential benefit of multiple institutional investors such as investment companies, pension funds, insurance companies, banks, or brokerage firms.

Specifically, if the analyst were to employ regime-switching models modeled with 2- or 3-regime Markov (Markov-switching or MS) chains (C. Engel & Hamilton, 1990; Hamilton, 1989, 1994), she would be in a position to forecast the probability that, in $t + n$ periods, she would be in a period of "normalcy" (low volatility or s = 1) or in a crisis episode (high volatility or s = 2). In addition, by employing MS models, the analyst will be able to estimate the expected location (mean) and scale (standard deviation) parameters for such regimes or episodes in such time intervals. The latter is done by quantifying and incorporating the influence that the uncertainty of economic, trade, or health policy news has on these probabilities.

MS models are time series analysis methods whose estimate of the probability $P(s = i|r_t, \theta)$ of being in regime s, given the information set r_t and the estimated parameter set θ, is extracted from the data itself. The smoothed probabilities of being in each regime at t ($\xi_{s=i,t}$) are not something that external variables or factors can predict.

For the above, there have been multiple extensions to the original MS model, such as MS models with autoregressive transition probability matrices (Filardo, 1994)[1] or the development of warning systems to forecast the probabilities of each regime, given some financial or economic factors (J. Engel et al., 2018; Hauptmann et al., 2014).

Specifically, and as an extension to the above, this work uses the monthly US economic policy uncertainty index, the US trade policy index calculated by Baker, Bloom, and Davis (2016c), and the uncertainty index given news of infectious disease (Baker, Scott, Bloom, Davis, & Kost, 2019). Monthly periodicity is used because the trade policy index is calculated monthly and not daily, as is the case for other indices.

Once the working hypothesis and the objectives to be achieved have been established, the article's structure is briefly described. The next section presents the literature review that motivates both the practical applications of the results and the objectives and hypotheses. In the third section, a brief description of the method of estimation of uncertainty indices through news by Baker, Bloom, and Davis (2016c) is made, as well as details of the method of obtaining and processing data. In the same section, the observed results are presented. Finally, the last section presents the conclusions and potential extensions for future research work.

[1]Hamilton's original proposal assumes that these are fixed in t.

Review of previous literature that prompted this work

Market sentiment is a variable that has gained interest in the practice of asset valuation, investment management, and even risk management. This is due to the development of Financial Economics theories such as Behavioral Finance. The latter originated with the Prospect Theory (Kahneman & Tversky, 1979; Malkiel, Mullainathan, & Stangle, 2005; Thaler, 1999). As a result of these original proposals, financial theory or the study of financial economics has relaxed, or at least questioned, the assumption of rational choice by investors.

Specifically, the academic research work of these studies has made it possible to propose explanations for behaviors that classical financial economics did not consider. One example is the role played by the individual emotions of the agents in the market and how these can be the same or similar among them.

The latter is possible to the extent that collective behaviors known as "herd behavior" may be generated.

It is not the purpose of this article to discuss or critically review all of these works. In addition, it is out of the scope of this study to discuss the benefits and scope of behavioral finance compared to the research program of classical finance theory.

This work takes the position, at an assumed level and in the light of the evidence of the most recent financial crises, that, although the classical Financial Theory is a solid and complete approach in its postulates and explanations, it has some pending issues such as an adequate quantification of the effect of human feelings (i.e., level of certainty).

Specifically, and as established in the introduction, this work seeks to develop a warning model of episodes (s = 2) of high volatility, starting from external factors such as the uncertainty indices of economic policy news, trade policy, and infectious diseases (COVID-19). This is done for investment decision-making or risk quantification.

The use of MS models and their extension, the MS-GARCH models (with GARCH standard deviation), has been widely studied in modeling time series and contagion effects in stock markets (Bundoo, 2017; Cabrera et al., 2017; De la Torre-Torres, 2021; Dufrénot & Keddad, 2014; Gallo & Otranto, 2007; Rotta & Valls Pereira, 2016; Shen & Holmes, 2013), exchange markets (Chen, 2006; Dueker & Neely, 2006; Mouratidis, 2008; Mouratidis, Kenourgios, Samitas, & Vougas, 2013; Sosa et al., 2018; Wu, 2015; Yang, 2017), or energy or agricultural futures markets (Charlot & Marimoutou, 2014; Herrera, Rodriguez, & Pino, 2017; Hou & Nguyen, 2018; Roubaud & Arouri, 2018).

As previously mentioned, the potential applications of the MS and MS-GARCH models are to forecast the probabilities of each of the studied regimes and, consequently, make investment decisions.

This perspective was originally proposed by Brooks and Persand (2001) and studied from various perspectives in portfolio management (Ang & Bekaert, 2002b, 2004; Kritzman et al., 2012). Even the investment decision-making process proposal with MS models by Brooks and Persand (2001) has been extended to other stock markets or to agricultural and energy futures (De la TorreTorres, Galeana-Figueroa, & Álvarez-Garcia, 2019).

The decision-making method originally proposed by Brooks and Persand (2001) uses the smoothed probabilities ($\xi_{s=i,t}$) of being in a certain regime at t to make the decisions and assumes that the transition probabilities are fixed over time.

Accordingly, Hauptman et al. (2014) and Engel, Wahl, and Zagst (2018) develop models for warning of crisis episodes by employing multivariate models in which they forecast the probability of each regime at t.

This is done with financial variables anticipating an increase in the probability of high (s = 2) and very high (s = 3) volatility regimes. This makes it possible to have an alternative form of smoothed probabilities ($\xi_{s=i,t}$) of each regime and changing transition probabilities at t.

With historical data from stock indices such as the S&P500, Eurostoxx 50, or Nikkei 250, these two works can measure the influence that multiple financial variables have on each regime's smoothed probability and can generate returns that are superior to those of the indices studied.

These last two works are the most influential in this article. The reason for that is because this work seeks to demonstrate that there is a positive relationship between the smoothed probabilities with the crisis or high volatility regime (s = 2), the level of uncertainty generated by economic and trade policy news, and that generated by news related to pandemics and epidemics, and the level of volatility in Mexican financial markets.

The measurement of market sentiment or the quantification of so-called "uncertainty indices" has been a topic of discussion for the last 15 years. The first quantifications were based either on the residuals of multivariate or factor models. That is, a relationship was established between the percentage variation of the market, security, currency, or interest future with various financial or economic factors (M. Baker & Wurgler, 2006, 2007; Blasco, Corredor, & Ferreruela, 2012; Brown, 1999; Fisher & Statman, 2000). Specifically, this work seeks to estimate the statistical relationship (β_k) that each factor x_k has on either the percentage change in the time series of interest (r_t) or in the time series of its volatility or variance:

$$r_t = \alpha + \sum_{k=1}^{K} \beta_k \cdot x_{k,t} + \varepsilon_t \tag{1}$$

Other approaches even use principal component analysis (Armendáriz & Ramírez, 2017) to estimate which variables contribute the most to the joint variability of the system (the market under study and the factors of interest). On estimating the first principal component, there is an indicator that measures the level of uncertainty, given the many financial and economic variables identified.

Despite the above, the two methodologies do not estimate the impact of financial news on the performance of financial markets.

Consequently, multiple data mining and text analysis developments have been applied to quantify market sentiment (Graff, Miranda-Jimenez, Tellez, & Moctezuma, 2020; Hernandez, Miranda-Jimenez, Villaseñor, Tellez, & Graff, 2015). Among multiple proposals that can be cited are the economic policy uncertainty indices or $IIPE_t$ (S. R. Baker et al., 2016c). These measure the level of uncertainty in the markets, given the news published in the main newspapers of the countries where they are quantified. The calculation methodology will be reviewed in the following section. However, to review the literature, many works can be cited that have used these uncertainty indices to measure the impact they have on the percentage variations of different markets or their volatility levels.

Some of the most important works studying the impact of this uncertainty index are those of Pástor and Veronesi (2012, 2013). These two works measure the relationship between the level of the $IIPE_t$ and stock market fluctuations. This measurement is done to the extent that the authors develop an equilibrium model that explains the relationship of the level of political uncertainty with the equity risk premium.

Some works use the $IIPE_t$ to make forecasting models of business cycles (Armendáriz & Ramírez, 2017; Degiannakis & Filis, 2019). Christou et al. (2018) employ this indicator to measure the impact on foreign exchange markets, and the works of Gao and Zhang (2016), Liu, Han, and Yin (2018), and Fang et al. (2018) measure the impact that the global, US, European, Australian, and Chinese $IIPE_t$ have on the behavior of major energy and metal futures. All these authors find a negative influence of the level of political uncertainty on the percentage change of economic growth or the valuation of the studied currency. In other words, there is an inverse relationship between the level of uncertainty in economic policy and the performance of an economy or currency.

For study purposes related to this work, it is possible to cite works that studied the impact of $IIPE_t$ indices in the United States (Brogaard & Detzel, 2015), Australia (Smales, 2016, 2017), and even in Malaysia (Hoque & Zaidi, 2019). Studying the same markets but with a different perspective, Antonakakis, Babalos, and Kyei (2016) measure the impact of political uncertainty on major US socially responsible stock indices. All these works also find an inverse relationship between the level of political uncertainty and the performance of the markets studied.

http://dx.doi.org/10.22201/fca.24488410e.2020.3088

From a similar perspective, measuring the existing relationship with the level of volatility, Fang et al. (2018) use econometric models of heterogeneous frequencies to measure the influence that the IIPE has on the daily volatility levels (standard deviation) in the price of gold traded on the Chicago Mercantile Exchange (CME). These authors find a positive relationship between these factors and the level of volatility, validating the hypothesis where it is established that the greater the uncertainty, the higher the volatility observed in t. Similarly, to forecast volatilities, Shaikh (2020) employs the $IIPE_t$ to forecast the value of the VIX implied volatility index. Using a model-free option valuation method, this index approximates the volatility of all outstanding options on the S&P 500 index with a term to maturity of fewer than or equal to 30 days. With the above, the author is forecasting the level of expected (implied) volatility in the S&P 500 index options market and can measure the relationship or positive influence that economic policy uncertainty has on the level of expected volatility, in the next 30 days, in the S&P 500 stock market. That work influences the efforts of this one in that it seeks to measure the relationship in reverse. That is, how the level of implied volatility in the US financial markets influences the generation of high volatility episodes in the BMV. This is due to a contagion effect.

For the case of the Mexican and North American stock markets, the work of Sum (2012), who estimates models relating the level of political uncertainty measured by the $IIPE_t$ and the index of uncertainty in US trade policy ($IIPC_t$) with the Mexican IPC indices, US S&P500, and the Canadian S&P/TSX-300 (two of the three regressors to be used in this study) is mentioned. In his tests, the author finds that only the US $IIPE_t$ has a positive influence on the Mexican and Canadian stock markets (a conclusion that is not confirmed in this study, as will be seen in the review of results) and that both uncertainty indices have an influence on the US index.

As can be seen, all previous works measure the impact or influence of the global or US economic policy uncertainty index and the US trade policy uncertainty index, either with the percentage variation or the level of volatility of stock indices, currencies, or interest futures. Based on this line of study and paying attention to the application of MS models for investment decision-making or risk quantification, it is of interest to extend the existing literature in three areas:

1. Measure the impact that the global $IIPE_t$ ($IIPEG_t$) and US ($IIPEUS_t$) indices have on the generation of high volatility episodes in the BMV. That is, their impact on the smoothed probability of a high (s = 2) volatility regime in that market.

2. Extend the existing literature to verify whether or not the uncertainty generated by epidemiological news or infectious diseases is really a factor that creates episodes of high volatility in the BMV. None of the previously studied works incorporates epidemiological news's effect on the markets.

3. Demonstrate that high volatility episodes are due more to a contagion effect from the US financial markets. This can be done by demonstrating a positive relationship between the S&P 500 VIX index level and the smoothed probability of the BMV high volatility regime.

The theoretical position concerning the second extension is that the uncertainty generated by epidemiological news does not impact the generation of high volatility episodes (s = 2). That is, the high volatility episode observed in early 2020 results from volatility contagion from US financial markets and not from health or political-economic uncertainty.

A natural question that might come up based on the literature review is the lack of inclusion of the Mexican economic policy uncertainty index ($IIPE_t$). While it is true that this has been used to estimate the global economic policy uncertainty index, Baker, Bloom, and Davis (2016a) stopped publishing results for this index in September 2019. Had this complete information been available to perform the tests, a complete comparison would have been achieved since Mexico also experienced important and interesting fiscal adjustments (from different points of view). These adjustments can be reflected in the generation of episodes of high volatility in the BMV.

That said, the current literature will be extended as mentioned above, and attention will be given to using these uncertainty indices and the VIX. In particular, that of uncertainty generated by news related to infectious disease contagions, including news related to the COVID-19 pandemic.

Following this literature review, a brief explanation of the Baker, Bloom, and Davis (2016a) methodology for estimating the uncertainty indices used in this work will be given. The sources and methods of data processing will be described, followed by the description of the results. The last section will present the concluding comments and guidelines for future research work.

Methodology

This section will explain, in the first subsection and for greater understanding of the methodology to be used, how Baker, Bloom, and Davis (2016a) have proposed to calculate market sentiment through published news. The next subsection will explain the analysis methodology with which the probability of being in each regime was estimated and how the logit model was performed to demonstrate the working hypothesis.

http://dx.doi.org/10.22201/fca.24488410e.2020.3088

Methodology for calculating the economic policy uncertainty and infectious disease news uncertainty indices

As a starting point, Baker, Bloom, and Davis (2016a) calculate the Economic Policy Uncertainty index ($IIPEG_t$ and $IIPEUS_t$) using news published in the top ten newspapers in the United States and countries such as Germany, Australia, Brazil, Chile, China, Colombia, France, Germany, Greece, Holland, India, Ireland, Italy, Japan, Mexico, Russia, South Korea, Spain, United Kingdom, and the United States (21 in total). The number of newspapers used for the calculation of $IIPE_i$ in each country varies according to the availability of source publications in the Newsbank service. Once each $IIPE_t$ is calculated by country, Baker, Bloom, and Davis (2016a) weight each by GDP at current prices (in US dollars) or by purchasing power parity-adjusted GDP. The overall IIPE ($IIPEG_t$) used in the latter method is the one that will be used in this work. This is because each country's weighting is based on an approximation of its real GDP or at constant prices in terms of the exchange parity with the US dollar.

In order to describe the methodology that Baker, Bloom, and Davis (2016a) used for the monthly calculation of each of the $IIPE_i$ by country, how the authors present the same for the case of the United States will be described. This is done with the understanding that the methodology above is specific to each country, and only the number of sources (newspapers) and the words used to measure market sentiment in the local language and based on local monetary policy institutions change.

To calculate the $IIPEUS_t$ of the US, Baker, Bloom, and Davis (2016a, 2016c) consulted multiple articles from the top ten newspapers in that country: USA Today, The Miami Herald, Chicago Tribune, The Washington Post, The Los Angeles Times, The Boston Globe, San Francisco Chronicle, The Dallas Morning News, The New York Times, and The Wall Street Journal. This consultation was done from January 1985. Subsequently, through computer-based methods, validated by a university team for audit with humans (S. R. Baker et al., 2016c), they did a count of articles containing the following triad of word sets:

- V: "uncertainty" or "uncertain"
- E: "economic" or "Economy"
- I: "Federal Reserve," "congress," "deficit," "legislation," "regulation," and "White House"

The previous groups included variants of words such as "Uncertainties," "regulatory," or "The FED" (among multiple possibilities).

http://dx.doi.org/10.22201/fca.24488410e.2020.3088

With this word count, the authors follow a standardization procedure that leads to a smoothed and standardized word count (M_t). Next, the $IIPE_t$ is obtained by standardizing the value of M_t to give it a fluctuating value around 100 with the following operation:

$$IIPE_t = \frac{100}{M_t} \tag{2}$$

This historical value is the one downloaded for the US ($IIPEUS_t$) and globally ($IIPEG_t$) from Baker, Bloom, and Davis (2016a). For the specific case of the infectious disease volatility index ($IVEI_t$) from Baker et al. (2019), the authors followed the same calculation methodology with the following four-word groups (and their variants) for the count per newspaper ($X_{i,t}$):

- E: "Economic," "Economy," "Financial"
- M: "stock market," "equity," "shares," "Standard & Poors" (and variants)
- V: "volatility," "volatile," "uncertain," "uncertainty," "risk," "risky"
- ID: "epidemic," "pandemic," "virus," "influenza," "disease," "coronavirus," "MERS," "SARS," "ebola," "H5N1," "H1N1"

For the specific case of the Trade Policy Uncertainty Index ($IIPC_t$), the same procedure was used, adding terms such as "tariffs," "treaties," "trade policy," "trade war," "protection," "national security," among others.

Once the methodology for calculating the three indices of interest ($IIPEG_t$, $IIPEUS_t$, and $IVEI_t$), has been described in general terms, this work then describes how the data were extracted and processed, and how, employing MS models, the smoothed probabilities of being in each regime or state of nature were estimated.

Obtaining input data, processing, and method of calculating the probabilities of regimes

As a starting point, the following equation or regression model is used to demonstrate the working hypothesis:

$$\xi_{s=i,t} = \alpha + \beta_1 \cdot IIPEG_t + \beta_2 \cdot IIPEUS_t + \beta_3 \cdot IIPC_t + \beta_4 \cdot \Delta IVEI_t + \beta_5 \cdot VIX_{SP500} + \varepsilon_t \tag{3}$$

In the above expression $\xi_{s=i,t}$ is the smoothed probability of being in regime $s = i$ in t. α is a coefficient that estimates the constant value of the smoothed probability of each regime in t, which does not consider the influence of factors such as $IIPEG_t$, $IIPE_t$, $IIPC_t$ e $IVEI_t$. On a complementary basis, VIX_{SP500} is the so-called implied volatility index obtained from all options (at-the-money, out-of-the-money, and in-the-money) listed on the Chicago Mercantile Exchange (CME) that have a maturity equal to or fewer than 30 days. This last indicator has been incorporated to approximate the volatility contagion effect from the US financial markets to the BMV. This index is not specifically a "fear" or "uncertainty" index as is conventionally believed, but rather an indicator of the level of implied volatility with which outstanding options are valued. Given the above, it has been shown that there is an important relationship between this index and uncertainty as measured by news or other financial and economic variables (Armendáriz & Ramírez, 2017; M. Baker & Wurgler, 2006, 2007; S. R. Baker et al., 2016a; Shaikh, 2019).

Finally, ε_t is a value of $\xi_{s=i,t}$ that is not explained by the model given in (3). This term represents a proper random fluctuation of a white noise term with $\varepsilon_t \sim \Phi(0, \sigma_{\varepsilon t})$.

The model given in (3) is a general form that seeks to establish the operationalization of variables in the hypothesis to be demonstrated. However, the estimation of the model can be complex since a linear model such as (3) can lead to values of $\xi_{s=i,t} \in [-\infty, \infty]$, with the values of $\xi_{s=i,t}$ being constrained ($\xi_{s=i,t} \in [0.1]$).

To facilitate the above and simplify estimation against a conventional probit or logit model, this work uses the

logistic transformation of $\xi_{s=i,t}$ to convert (3), which is a potential logit or probit model, into an ordinary least squares model:

$$l_t = \alpha + \beta_1 \cdot IIPEG_t + \beta_2 \cdot IIPEUS_t + \beta_3 \cdot IIPC_t + \beta_4 \cdot IVEI_t + \beta_5 \cdot VIX_{SP500} + \varepsilon_t \tag{4}$$

The definition of all terms to the right of equality is the same for the terms in (3), and l_t is the corresponding logistic transformation of the smoothed probability of the regime of interest:

$$l_t = \frac{\ln(P_{s=i,t})}{1-\ln(P_{s=i,t})} \tag{5}$$

It was decided to use the logistic transformation for two reasons: 1) its simplicity in transforming the smoothed probabilities ($\xi_{s=i,t}$) of each regime[2] into standard variables and 2) the flexibility of this transformation to relax the assumption of using some specific probability function (such as Gaussian, t-Student, or extreme value) to model the cumulative probability.

The model that will be used to estimate the statistical relationship between the regressors of interest and the probability of high volatility episodes will be (4).

One situation that could raise doubts about (4) is the behavior of the regressor time series—specifically their stationarity. Multiple works cited in the literature review (that use these variables) have found that the time series of the uncertainty indices ($IIPEG_t$, $IIPEUS_t$ e $IVEI_t$) and VIX_{SP500} present unit roots. Starting from the same, this work will accept this result as given, and estimate (4) with 3 variants. In the first model, this work incorporates the right of equality (regressors), the variables measured at level (P_t). In the second, their values are replaced by their first differences ($\Delta P_t = P_t - P_{t-1}$). Finally, in the third variant, they are used by their percentage variances or log first differences ($\Delta P_t\% = \ln(P_t) - \ln(P_{t-1})$). This is done to eliminate the non-stationarity of the regressors. In a complementary manner and to reduce the impact of serial correlation on the significance levels observed in each regressor, (4) was estimated using the robust error estimators method of Newey and West (1987).

For the specific case of the smoothed probability $\xi_{s=i,t}$ leading to the logistic standard value l_t in (4), the MS (Markovian with regime switching or Markov-Switching) models proposed by Hamilton (1989, 1990, 1994) were used. This was done with the monthly time series of the CPI index from January 1, 1996, to August 31, 2020. With the monthly levels of the same[3], continuously compounded returns were calculated ($r_{IPC,t}$), and residuals were extracted by subtracting the mean ($\varepsilon_{IPC,t} = r_{IPC,t} - \overline{r_{IPC,t}}$). With these residuals, the following stochastic process was assumed:

$$\varepsilon_{IPC,t} = 0 + \sigma_{s,t} . l_t \tag{6}$$

In the same process, it is assumed that there is a standard deviation or scaling parameter that is different depending on the regime ($s = i$) or state of nature in t. This means that there is one standard deviation for the "normal" or low volatility regime ($s = 1$) and another for the high one ($s = 2$). Given this, it is assumed that $\sigma_{s=2} > \sigma_{s=1}$. To estimate the smoothed probability of being in each regime, the Gaussian likelihood function, the t-Student (with ν_s degrees of freedom in each regime), and the generalized error

[2]These are assumed to be cumulative probabilities from left to right.

[3]Historical data for the CPI and VIX indices were obtained from the Refinitiv (2018) databases.

distribution function (GED with a shape parameter ν_s for each regime) were used. These are defined as follows:

$$\xi_{s=i,t} = P\left(\varepsilon_{IPC,t}, \theta\right) = \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{\varepsilon_{IPC,t}}{\sigma_S}\right)} \tag{7}$$

$$\xi_{s=i,t} = P\left(\varepsilon_{IPC,t}, \theta\right) = \frac{\Gamma\left(\frac{\nu_S+1}{2}\right)}{\sqrt{(\nu_s-2)\pi\Gamma\left(\frac{\nu_S}{2}\right)}}\left(1 + \frac{\frac{\varepsilon_{IPC,t}}{\sigma_S}}{(\nu_s-2)}\right) \tag{8}$$

$$\xi_{s=i,t} = P\left(\varepsilon_{IPC,t}, \theta\right) = \frac{\nu_s e^{-\frac{1}{2}\left|\frac{\nu_S}{\lambda}\right|^{\nu_S}}}{\lambda 2^{\left(1+\frac{1}{\nu_S}\right)}\Gamma\left(\frac{1}{\nu_S}\right)}, \quad \lambda = \left(\frac{\Gamma\left(\frac{1}{\nu_S}\right)}{4^{\frac{1}{\nu_S}}\Gamma\left(\frac{3}{\nu_S}\right)}\right) \tag{9}$$

To estimate the smoothed probabilities, a set of parameters ($\theta = \{\sigma_s, \nu_s, \mathbf{\Pi}, \xi_{s=i,t}\}$)[4]) was estimated in turn. This is according to the case of each function $\xi_{s=i,t}$.

The method of inference of the parameters and of $\xi_{s=i,t}$, was using the Metropolis-Hastings algorithm (Metropolis, Rosenbluth, Rosenbluth, Teller, & Teller, 1953), which is typical of a Markovian Chain Monte Carlo (MCMC) estimation method. The latter uses the MSGARCH R package (Ardia et al., 2017). For comparison purposes and following the objectives of the work, the MS models were estimated with 2 and 3 regimes, as well as with each of the three likelihood functions given in (7) to (9).

To estimate σ_s, GARCH (Generalized AutoRegressive Conditional Heteroscedasticity) variances were not used, which are changeable over t. This is because the periodicities with which they work are monthly. This type of model (GARCH), in all its functional forms, is more appropriate for shorter and "noisier" periodicities such as weekly, daily, and even intraday time intervals (Broda, Haas, Krause, Paolella, & Steude, 2013; Haas, Mittnik, & Paolella, 2004, 2009; Hamilton & Susmel, 1994).

[4]With **Π**, being the transition probability matrix of each regime, given the latent Markovian chain in the stochastic process of CPI returns.

To determine which of the six possible models is the best fit for the CPI time series, the Deviance Information Criterion (DIC), which is typical of models estimated with MCMC methods, was used:

$$DIC = D(\bar{\theta}_i) + 2p_d, \quad D(\theta_i) = -2\ln\left(P(\varepsilon_{IPC,t}, \theta_i)\right), p_d = \overline{D(\theta_i)} - D(\bar{\theta}_i)$$

(10)

In the above expression, what is used is the probability function (7), (8), or (9), given the i Monte Carlo simulations performed (10,000 in the case of this work). From each of these, the set of parameters (θ) estimated for that i-th iteration is used.

With this information criterion, the number of regimes and the smoothed probability function that best describes the stochastic process of CPI returns were determined. Once the best model and the appropriate number of regimes were determined, the smoothed probabilities ($\xi_{s=i,t}$) were used to make the logistic transformation given in (5), and the three regression models (level, first differences, and log first differences) were run. This was done with the functional form given in (4).

To choose which of the three types of regressors is the most suitable for modeling l_t, the Deviance information criterion was used.

Once it was determined which of the three models (level, first differences, or log first differences) is appropriate, a forecast of the regime probability ($\xi_{s=i,t}$) was made and compared to the observed probability ($\xi_{s=i,t}$). Given this, the root mean square error (RMSE) and the mean absolute error (MAE) were estimated:

$$RSME = \sqrt{\frac{\sum_t^T \left(\widehat{P_{s=i,t}} - P_{s=i,t}\right)^2}{T}}$$

(11)

$$EAM = \frac{\sum_t^T |\widehat{P_{s=i,t}} - P_{s=i,t}|}{T}$$

(12)

After describing how the data were obtained and processed, the results observed in the tests will be reviewed.

Observed results

Table 1 presents the results of the goodness-of-fit criterion (DIC) that determines the best MS model to use and the most appropriate number of regimes. It shows that the stochastic process of CPI returns is best modeled with a t-Student MS model with two regimes.

Table 1
Goodness-of-fit of each of the estimated MS models

	Gaussian	t-Student	GED
2 regimes	-742.737	-772.481	-750.76
3 regimes	-669.377	831.5168	6575.655

Source: created by the author with data from Refinitiv (2018)

Based on the above, in the case of the stock market and a monthly periodicity analysis, the existence of two volatility regimes ("normal," s = 1 or "low volatility" or "crisis," s =2 or "high volatility") is considered valid.

This work proceeds to perform the logistic transformation of $\xi_{s=2,t}$, given in (5), and to the three regression models with the regressors expressed at level, first differences, and at returns (log first differences). Table 2 presents the results.

Table 2
Results of the logit regression models performed for the probability of the high volatility regime of the CPI index

	Type of regressor		
	Level	1st. Differences	1st. Logarithmic diff.
Constant	-3.8615***	-0.6885	-0.6999
	(1.0263)	(0.9736)	(0.9502)
	p = 0.0003	p = 0.4683	p = 0.4389
IIPEG	-0.0103*	-0.0074	-0.7886
	(0.0777)	(0.0797)	(1.0266)
	p = 0.0877	p = 0.2469	p = 0.4550
IIPEUS	0.0165	0.0040	0.8435
	(0.1054)	(0.1056)	(0.9184)
	p = 0.1386	p = 0.7169	p = 0.3183
IIPC	-0.0359***	-0.0002	-0.1145
	(0.0836)	(0.0719)	(0.8430)
	p = 0.000001	p = 0.9619	p = 0.8722
IVEI	0.0999	-0.0503	0.0590
	(0.2924)	(0.2132)	(0.4236)
	p = 0.2436	p = 0.2693	p = 0.7425
VIX	0.3062***	-0.0005***	-6.7861***
	(0.2314)	(0.0097)	(1.2009)
	p = 0.000000	p =0.000001	p = 0.000004
Remarks	284	283	283
Adjusted R^2	0.3295	0.0622	0.0521
F Statistic	28.819[6]*** (g.l.= 5; 278)	4.7379*** (g.l.= 5;277)	4.1005*** (g.l.= 5; 277)
Coding level of significance	*p<0.1**p<0.05***p<0.01		

Source: created by the author with data from Refinitiv (2018) and Baker, and Bloom and Davis (2016a)

It can be seen that the model that has the highest degree of explanation (adjusted R^2 coefficient) is the one that uses the regressors at level. From this model and contrary to what would be expected, the level of uncertainty in global economic policy ($IIPEG_t$) has a significant but inverse relationship in sign. That is, as the level of $IIPEG_t$ increases, the value of l_t and the probability of the crisis regime ($\xi_{s=2,t}$) decreases.

On the other hand, it can be seen that the relationship between the VIX (level of volatility in the US financial markets) and the probability of a high volatility episode is significant, positive, and has the most important coefficient. Its value of 0.3062 suggests that, when the VIX is above 20 points (a level considered as delta volatility), the coefficients of $IIPEG_t$ and $IIPC_t$, together with the inertial value of (α)

http://dx.doi.org/10.22201/fca.24488410e.2020.3088

are counterbalanced. This means that the standardized logit value (l_t) is greater than zero, and the probability of having a high volatility episode in the BMV is greater than 50%. This coefficient shows that the volatility of the US financial markets (VIX) is the only variable of sufficient weight and significance to forecast the probability of a high volatility regime in the BMV.

The above shows that neither the uncertainty generated by the COVID-19 news nor that generated by economic or trade policy news are factors that positively influence the probability of high volatility episodes. This makes it possible to demonstrate the validity of the position taken in this work.

Since the adjusted R^2 coefficient gave a positive magnitude and is not always considered a fully reliable parameter for the goodness-of-fit of different models under comparison, the values of the information criterion of Akaike (1974) and that of Schawrz (1978) are presented in Table 3. In addition, the RMSE and MAE for the three regression models are presented. The two information criteria confirm that the best goodness-of-fit is achieved with the model that has the regressors at level.

On the other hand, the RMSE and MAE show that the forecasts made with the first model (level regressors) are those that lead to forecasts closest to the modeled probability. This can be seen more clearly in Figures 1 to 3.

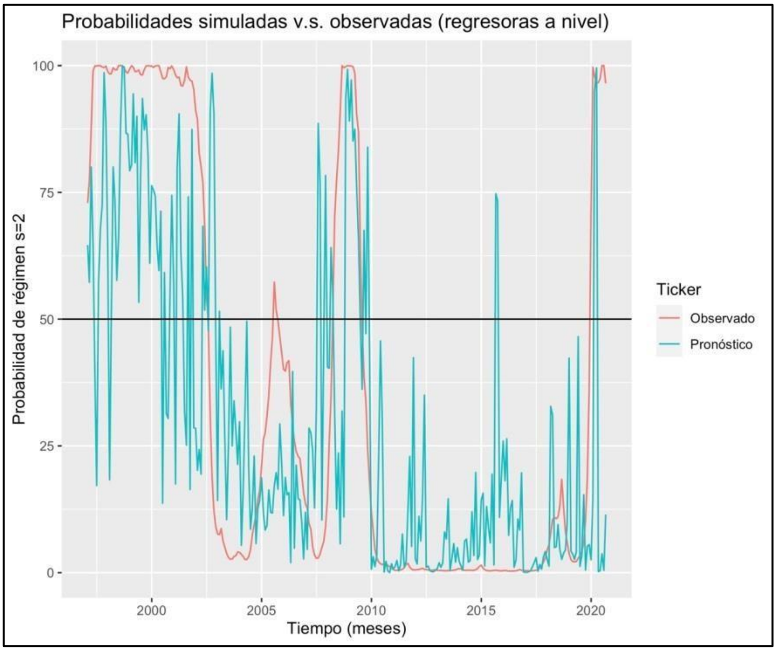

Figure 1. Comparison of the predicted probability of the crisis regime (high volatility) versus that observed with regressors at level
Source: created by the author with data from Refinitiv (2018) and Baker, Bloom and Davis (2016[a])

In these figures, especially Figure 1, it can be seen in graphic form that the forecast of the probability of the high volatility regime (blue line) fits better with the logit model given in (4), the uncertainty indices, and the VIX at level. Moreover, it can be seen that the values at first differences and first logarithmic differences (Figures 2 and 3) have a poorer fit to forecast the probability of the aforementioned high volatility periods.

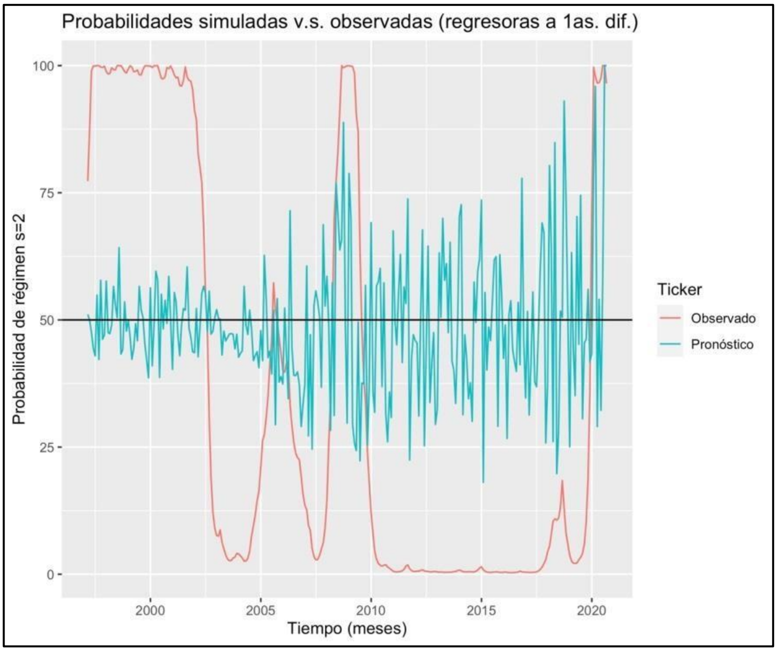

Figure 2. Comparison of the predicted probability of the crisis regime (high volatility) versus that observed with regressors in first differences.
Source: created by the author with data from Refinitiv (2018) and Baker, Bloom and Davis (2016[a])

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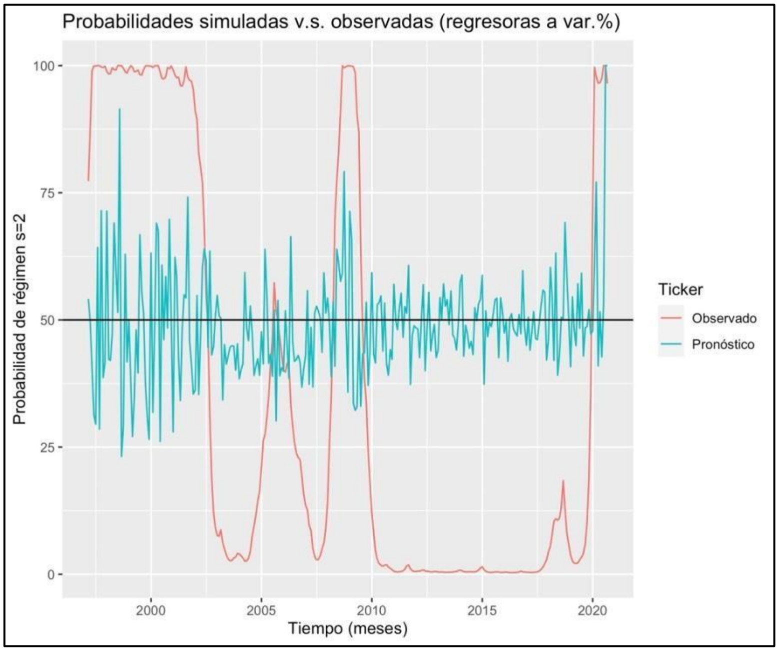

Figure 3. Comparison of the predicted probability of the crisis regime (high volatility) versus that observed with regressors in first log differences (returns or percentage changes). Source: created by the author with data from Refinitiv (2018) and Baker, Bloom and Davis (2016[a])

Despite the above, it is necessary to make an important methodological and econometric note. Based on the value of the adjusted coefficient R^2 (0.3295) of the model and the behavior of the predicted and observed probabilities in this model, both the model and its forecasts are far from complete and accurate.

Table 2
Results of the logit regression models performed for the probability of the high volatility regime of the CPI index

Goodness-of-fit criterion	Level	1st. Differences	1st. Logarithmic differences
Log-likelihood function	-814.4873	-859.5515	-861.0593
Akaike Criterion	1642.9746	1733.103	1736.1187
Schwarz Criterion	1668.5174	1758.6211	1761.6368
RMSE	0.3251	0.4427	0.4421
MAE	0.2178	0.4058	0.4124

Source: created by the author with data from Refinitiv (2018) and Baker, and Bloom and Davis (2016a)

This is because, as suggested by the adjusted R^2 and the behavior of the predicted probability, other economic, financial, social, or uncertainty variables have not been incorporated. This, as will be seen shortly, is a potential area of research beyond the scope of this first review.

Conclusions

The use of Markov-Switching models (MS) for investment decision-making is an application that has gained recent interest. This is due to the ability of these models to forecast episodes (regimes) with different volatility behaviors. Specifically, multiple investigations (Ang & Bekaert, 2002a; Brooks & Persand, 2001; De la Torre-Torres, Aguilasocho-Montoya, Álvarez-García, & Simonetti, 2020; De la Torre-Torres, Aguilasocho-Montoya, & del Río-Rama, 2020; Kritzman et al., 2012) have demonstrated the benefit of these for decision making. They are also a method for estimating financial risks (Ardia, 2008; Ardia et al., 2018; Ardia & Hoogerheide, Lennart, 2013; Ardia & Hoogerheide, 2014; Cabrera et al., 2017; Sosa et al., 2018).

However, most estimation methods focus on studying, in a univariate way, the estimation of the smoothed probabilities of being in each regime or t-volatility behavior. Starting from this premise, the development of warning systems for periods of high or extreme volatility is a subject of interest. That is, warning systems that, with the help of financial and economic variables, make it possible to forecast the probability of entering periods of high volatility in $t + n$. The practical use of these warning systems is their application for investment decision-making.

The first proposals in this regard were made by Hamilton himself (1989, 1990) when he proposed the Markov-Switching models (MS). In proposing these models, Hamilton sought to forecast the probability of the US economy going into recession. The above is based on financial and economic variables that make up the leading indicator of that country.

For the case of forecasting systems in stock markets, the first works with favorable results were those of Hauptmann et al. (2014) and Engel, Wahl, and Zagst (2018). These authors managed to incorporate estimates of up to 3 volatility regimes (low, high, and extreme) in the US (S&P 500), European (Eurostoxx 50), and Japanese (Nikkei 250) indices.

Using multiple financial and economic indicators, such as the slope of the interest rate curve of the respective countries or volatility indices, the authors were able to establish forecasting systems for high and extreme volatility episodes.

These authors were able to make risk estimates (potential losses) and tested investment decision-making systems with favorable results.

This work seeks to become an extension of these last two articles by quantifying the influence that market sentiment, generated by news of economic policies (global and the USA), trade policy, and news of infectious diseases, has on the generation of crisis episodes in the Mexican Stock Exchange (BMV).

With monthly data from the BMV price and quotes index (CPI), this work quantified the probability that this market is in a normal (s = 1) or low volatility, a crisis or high volatility (s = 2), or extreme volatility or crisis period (s = 3). 2- and 3-regime Markov-Switching (MS) models and Gaussian, t-Student, and Generalized Error Distribution (GED) likelihood functions were used. The six MS models were estimated with the Metropolis-Hastings (1953) algorithm, which is a Markov Chain Monte Carlo (MCMC) estimation technique that makes convergence in the inference method possible.

With the Deviance Information Criterion (DIC) and based on monthly CPI data from January 1996 to August 2020, it was determined that the best MS model to model CPI behavior is one with a t-Student likelihood function and two regimes.

Subsequently, the uncertainty indices measured by Baker, Bloom, and Davis (2016c; 2016b) were used to measure market sentiment. Based on news from major newspapers, these measure market sentiment or level of uncertainty on multiple topics. Of these, the indices of global policy uncertainty ($IIPEG_t$), US policy uncertainty ($IIPEUS_t$), trade policy uncertainty in the same country ($IIPC_t$), and that of uncertainty generated by news of the spread of infectious diseases ($IVEI_t$) such as COVID-19 were used.

In addition, the value of the VIX volatility index was used as a proxy for the volatility contagion effect from the US financial markets.

The position taken is that the uncertainty generated by news related to economic and trade policy, as well as news of epidemiological episodes such as COVID-19, does not have a positive and significant influence on the probability of episodes of high volatility in the BMV. The specific position in this regard is that high volatility episodes in the BMV result from a volatility contagion effect from the US financial markets. This situation was approximated by incorporating the VIX index of the implied volatility of the S&P 500 index in the models.

Using a logit regression with these regressors and the VIX volatility index, it was found that political uncertainty ($IIPC_t$) and stock market volatility (VIX) have a significant but negative relationship with the likelihood of the high volatility regime.

On the other hand, the VIX index was found to have a positive and significant relationship, and its coefficient is the highest of all those estimated in the regression model. That said, sufficient evidence was found to conclude that the high volatility episodes in the BMV result from a volatility contagion effect from the US financial markets.

The above demonstrates that the uncertainty generated by the news and events related to the spread of the COVID-19 virus, as well as the uncertainty in economic and trade policies, are factors that do not influence, in the long term, the generation of episodes of high volatility in the BMV.

That said, the volatility contagion effect from the US financial markets is the factor that most influences the generation of high volatility episodes in the BMV.

In order to incorporate the effect that this health crisis has had on the episodes of volatility (crisis) of the BMV, it is suggested to extend this work to tests with lower periodicity and even to incorporate, in the same model, other financial and economic variables as is the case of Hauptmann et al. (2014) and Engel, Wahl, and Zagst (2018).

Finally, another suggested research subject could be using econometric models with heterogeneous periodicities or developing alternative methods of quantifying market sentiment.

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