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Contaduría y Administración 66 (5), Lecciones de la pandemia Covid-19, 2021, 1-25

The Fama-French multifactor model with market and Pandemic news fear sentiments: a test in the Mexican stock markets

El modelo multifactorial de Fama y French con sentimiento de miedo de noticias de mercados financieros y pandemias: una prueba en las bolsas de valores mexicanas

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Received October 18, 2021; accepted December 2, 2021
Available online December 13, 2021

Abstract

In the present paper, we test the extension of the Fama-French (FF) three-factor model by including Economic, stock market, and Pandemic news uncertainty. For this purpose, we used either Global news or social media (Twitter) sentiment indexes, along with Mexican and U.S. implied volatility (VIX) ones. Using robust panel data regression models in the 72 most traded and biggest companies in the Mexican stock markets from 2017 to 2021, we found that only the Mexican VIX index is helpful to extend the FF model. Contrary to our expectations, the social media and news sentiment indexes have a negligible impact on stock price formation. These results suggest that developing more appropriate sentiment indexes is an essential need in the Mexican stock markets.

JEL Code: C24, C58, G14, G15

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

http://dx.doi.org/10.22201/fca.24488410e.2021.4583

Keywords: Market sentiment; mexican stock market pricing; COVID-19; policy uncertainty index; social media uncertainty index; volatility indexes; factor models

Resumen

En el presente trabajo se extiende el modelo de tres factores de Fama y French (FF) al incluir incertidumbre económica, de mercados financieros y de noticias de pandemias. Para lograr este objetivo, utilizamos índices globales de noticias o de publicaciones en redes sociales (Twitter). Esto junto con índices de volatilidad implícita (VIX) de México y Estados Unidos. Al utilizar modelos robustos de regresión de datos panel en las 72 empresas más grandes y negociadas de las dos bolsas mexicanas de valores (del 2017 al 2021), encontramos que solo el índice VIX mexicano es útil para extender el modelo FF. Contrario a nuestras expectativas, los índices de sentimiento de noticias y redes sociales tienen un impacto bajo en la formación del precio de las acciones estudiados. Estos resultados sugieren la necesidad de desarrollar índices de sentimiento más apropiados para el caso mexicano

Código JEL: C24, C58, G14, G15
Palabras clave: Sentimiento de mercado; valuación de activos en mercados financieros, COVID-19, índice de incertidumbre de política económica; índice de incertidumbre de redes sociales, índices de volatilidad; modelos de factores

Introduction

Asset pricing and the related risk factor models are helpful in the investment and financial industries to estimate the risk or expected return, given the influence of such factors (such as the equity market influence) in price formation.

The development of such models is not new and has had a broad discussion if we depart from a Classical Financial Economics perspective. From this perspective (Classical), the price reflects all the company-specific news and market sentiment information. Given this, the markets are in equilibrium (Sharpe, 1964). As a related assumption, this statement implies that the stock markets are informationally efficient (E. Fama, 1965). These two assumptions (market equilibrium and informational efficiency) are not the main interest of this paper. Several works have studied the validity of these, finding several results. One of the most important results is that the second regression of the Capital Asset Pricing Model (CAPM), which leads to the security market line (SML), does not hold. That is:

$$r_{i,t} = \alpha + \gamma_i \cdot \beta_i + \varepsilon_t, \alpha \neq rf, \gamma_i \neq [r_{m,t} - rf] \tag{1}$$

In the previous expression, rf is the risk-free asset (the 28-day money market CETES rate in Mexico), $r_{m,t}$ is the observed (or expected in an ex-ante context) return of the market portfolio or index

(The MSCI Mexico stock index in local currency for this paper). Following the equilibrium assumptions, this market portfolio is considered the added position of all the investors in the stock market (Sharpe, 1963, 1964). Also, from another perspective, it is regarded as one of several factors of the security's information set in a non-arbitrage or APT context (Ross, 1976). We are not interested in discussing the evolution of factor models from the CAPM or the APT. Our departing point is that the broad literature review in the subject signals a statement of interest: the CAPM and the APT pricing models are part of the asset pricing process if we assume the existence of a rational investor. That is an agent that sets aside her emotions in the pricing and trading of securities. This statement does not hold in real life and questions informational market efficiency. Investors could be informed or "noisy" when they decide, and we can think of security markets as places in which trade two types of agents (Black, 1986; L.A. Smales, 2017): the informed and the uninformed (noisy) traders. This potential group explanation also allows explaining other phenomena unexplained by the CAPM and the efficient markets hypothesis (EMH): the appearance of price bubbles (in their burst) or the potential market crash episodes. Phenomena or disequilibrium should not be happening in the EMH. A noise trader is a market agent that decides following her sentiment and not fundamental information or a proper quantitative analysis about the security's future cash flows (M. Baker & Wurgler, 2007; Black, 1986; De Long et al., 1990; López-Cabarcos et al., 2020; Shiller, 2003). This definition, the questioning proofs about CAPM that lead to multifactor CAPM or APT models, and the equity risk premium puzzle suggest the need to incorporate investor sentiment as an explaining factor. The equity risk premium puzzle relates with (1) because $[r_m - rf]$ is higher than its equilibrium expected value. This has been explained in part with the noisy and informed investors theory and with Behavioral Finance. This led to the development of pricing models with quantitative non-financial risk or sentiment factors (Ang et al., 2006; M. Baker & Wurgler, 2006, 2007; Durand et al., 2011; Luo et al., 2015) or the explicit inclusion of news, social media or internet searches index as proxies of the general market sentiment (Da et al., 2015; Griffith et al., 2020; Preis et al., 2013; Uhl, 2014).

The main studies and tests of the previous behavioral extensions present results in the U.S., Korea, and some European countries. There is scant literature about Mexican stock market sentiment and its relationship with Mexican securities' pricing. Departing from this theoretical and practical need, we present one of the first tests of the use of news sentiment in Mexican stocks. We want to extend the Fama-French (1992) three-factor model by including five market sentiment ones: 1) the U.S. in-the-money and at-the-money S&P500 stock option's implied volatility index (VIX), 2) the Mexican in-the-money and at-the-money S&P/BMV IPC stock option's implied volatility index (VIXMX), 3) the Global Economic policy uncertainty news on (WEUI) of Baker, Bloom, and Davis. (2016), 4) the Global Twitter Economic Uncertainty (TWITUI) index of Baker et al. (2021) and the Global pandemic uncertainty (WPUI) index of Ahir, Bloom, and Furceri (2018)

Our theoretical position is that including the U.S. and Mexican stock market volatility and the market uncertainty given the world Economic policy, Twitter, and pandemic news could enhance the information set of the leading Mexican Public companies. We believe that the statistical relation between WEUI, TWITUI, and WPUI is significant and inverse. We demonstrate the need to include these news and social media indexes as part of a Mexican stock market risk and asset pricing model by proving these relations as true. The practical use of these results is the potential incorporation of news and social media sentiment. More importantly, given the current pandemic times, the news and social media comments related to infectious diseases.

This need is not new, given the 2003 SARS (Chen et al., 2009) pandemic and its impact on global stock markets (predominantly Asian ones). With the 2020 COVID-19 SARS2 Global pandemic outbreak, it is necessary to incorporate the Pandemic, social media, and Economic policy news uncertainty as proxies of agents' feelings in the stock markets. This practical motivation is the one that we pretend to cover with our results by testing if these three uncertainty indexes (WEUI, WPUI, and TWITUI) are good proxies of market sentiment in the Mexican stock exchange. Also, our results will extend the literature about quantitative tests of models that want to incorporate the trade-off between informed and noisy traders. We believe this because the former traders tend to be more prone to their feelings and uncertainty and are the ones that create market bubbles or crashes.

Once we have presented our theoretical position and the aim of our work, we offer, in the next section, a brief review of the previous literature. In the third section, we present how we gathered the data and how we performed our tests. Finally, in the fourth section, we show our conclusions and potential extensions (improvements) to our work.

Literature review

The original single market and CAPM model of Sharpe (1963, 1964) and Lintner (1965) is an initial framework for asset pricing by including a general market sentiment ($r_{m,t}$). In a Classical Economics (Classical Financial Economics) framework, these authors developed a model that used a general market risk security's sensitivity (β_i) as the leading risk factor. Under specific and restricted assumptions, the model has been a cornerstone in asset pricing, risk management, and even project valuation in Corporate Finance. Despite its simplicity, the model fails to explain several phenomena in financial markets, such as asset price bubbles or market crashes. Even the Efficient Markets Hypothesis (E. Fama, 1965), founded in the CAPM, lacks this explanation. Several tests and critiques to the CAPM and several extensions try to explain and model this issue. Still, all of these are made in a Classical, rational, and fully informed investor context. Even some other perspectives, such as the non-arbitrage factor modeling (Ross, 1976), try to enhance the explaining power of factor models.

Several CAPM or APT tests and stock market crisis episodes showed that rationality and equilibrium assumptions do not hold in real life. Departing from this result, the Behavioral approach to Economics and Finance (Kahneman & Tversky, 1979; Shiller, 2003, 2014; Tversky & Kahneman, 1981) made a significant breakthrough to incorporate the not-so-rational behavior of investors. The pre Behavioral works that talk about the not-so-rational behavior are the ones of Black (1986) and DeLong et al. (1990). The former introduces the concept of “noise” as part of the information set used for trading decisions. According to Black, traders decide with the information they believe is correct but is not. Even noise, in the words of Black, is the real support for the market’s liquidity. This result is because noisy traders decide to benefit from the social (and not fundamental) information they have about that trade. In his paper, Black explains the implications of noise in Macroeconomics and Microeconomics. In the latter, Black explains that if two assets (dolls and books) have higher demand, investors will invest in their production if they believe this public demand will hold. This higher demand will potentially increase book publishing and toy companies' stocks higher (even a potential bubble in these). But, if the demand changes to action dolls and Science books, possibly some investors will sell their non-Science editing and non-action dolls companies’ stocks. This last impulse could create a potential burst.

The paper of De Long et al. (1990) uses the noisy trader rationale to explain some paradoxes, such as the Mehra-Prescott (1985) equity premium. An explanation for the higher observed stock risk premium than its expected value with single market factor models (CAPM and its extensions). As part of their explanation, followed Black’s rationale, pointing that the volatility created by noise traders deters the involvement of arbitrageurs, leading to a higher expected return. Their model is a first attempt to explain (in a not efficiently informed market) the presence of several “market anomalies” such as bubbles, the mean reversion of stock returns and the Mehra-Prescott equity risk premium puzzle.

Some papers that test market sentiment with non-behavioral factors and test the trade-off between informed and noisy traders are the ones of Wang (2001, 2003) who use hedgers and speculators S&P500 index or agricultural futures position as sentiment proxies. For the case of both papers, the author found that speculator sentiment is a continuation factor. In both works, the author suggests following speculators’ sentiment and going against hedgers if it is of interest to perform an active trading strategy. The author attributes this result to market friction to hedgers who have to pay significant premiums to speculators to hedge their position. These two works motivate us to test proxy the market sentiment in spot stock positions with uncertainty indexes that cause the current future or spot positions.

With another non-behavioral perspective, the work of Simon and Wiggins III (2001) shows that the S&P500 VIX, the put-call ratio of this index’s options, and the number of stocks growing versus the losing ones (also known as TRIN) are inverse indicators of U.S. stock market returns. In practical terms to our paper, the authors found that the relation of these indicators is inverse in asset pricing or risk factor models. This result is significant because it motivates the inclusion of the U.S. VIX and the Mexican S&PBMV IPC VIX indexes in our tests. It presents proof of the benefit of using volatility indexes as factors.

Ding et al. (2014) test other quantitative proxies of market sentiment such as the turnover rates of trading shares, the trading value, and the number of transactions (market and momentum measures) and compared their benefit with the results of some psychometric tests. Also, the authors tested the use of some fundamental ratios such as the price-to-book value or the short-selling turnover ratio. In their conclusions, the authors proved that only the first three turnover measures are appropriate to proxy market sentiment. This paper motivates ours because some turnover indicators are reasonable but limited to measuring genuine investor sentiment. This last result encourages us to test the benefit of including market sentiment (uncertainty) proxied with social media or news.

Another work that is a real inspiration to ours is the one of Pan (2020), who tests the relation between market sentiment (proxied with consumer confidence indices) and bubble creation or burst. By using a recursive unit-root test for bubbles, the author determined the presence of these and found that positive and increasing sentiment is a cause of bubble creation and its reversal of bubble bursts in the U.S. stock markets. This conclusion led us to test the extension of the conventional Fama-French three-factor model with volatility, social media, and news sentiment. As mentioned previously, our position is that these factors could enhance stock price predictability and risk modeling.

Following the pre-behavioral (quantitative proxies) context, some models include financial, Economic, and even latent factors as market sentiment proxies. The paper of Baker and Wurgler (2007) is a well-known reference because these authors use the first principal component of the correlations of quantitative factors as a fear proxy. Quantitative such as the closed-end fund discount, the turnover in the analyzed stocks, the number of initial public offerings (IPOs), the first-day return in the IPO, and the dividend premium. The authors found that this first principal component is valuable as a market sentiment proxy and motivates other similar works such as the ones of Raddatz and Schmukler (2012), Cambón and Estévez (2016), and Armendaris and Ramírez (2017). These last works replicate the Baker and Wurgler (2007) first principal component methods in their countries and found similar results.

The works of Liu (2015) and Li (2015) are the first to relate a more behavioral factor with stock prices: investors' uncertainty due to Economic policy news. One uncertainty (as a fear sentiment) channel among market agents is newspapers' news. Suppose newspapers publish several notes with words such as recession, economic policy, distress, or similar. In that case, the sentiment transmitted to informed and uninformed investors is of uncertainty about the actions of a given Government (or Governments if we talk in Global terms). Baker, Bloom, and Davis (2016) developed an uncertainty index that uses the count of three-word sets: Economic, stock market, and volatility. The count is made from the leading newspapers in different countries such as the U.S., the U.K, Germany, France, Canada, Japan, and others and normalized with a specific method suggested by the authors. This count leads to a 100 points value, considered the threshold value of the uncertainty index. As an example, suppose the count of words in the previous sets is high. In that case, the index increases its value above 100, suggesting a high level of Economic policy uncertainty due to stock market volatility and Government response.

Liu (2015) and Li (2015) test the relation between stock prices and news sentiment in a two-regime context. They tested this relation in Chinese stock markets. The authors found a strong relationship between stock market volatility and returns in distress periods in their results. This paper motivates ours because it is one of the first papers that relate the WEUI index with stock market return, which we extended for the Mexican stock market.

To strengthen the conclusions about the relation between news sentiment indexes or even quantitative sentiment proxies, Viebig (2020) used machine learning algorithms to detect periods of exuberance. These machine learning algorithms are practical to detect changes in market sentiment and the corresponding "bubble behavior," along with potential reversion periods.

We are not going to extend our literature review to the history of Classical and Behavioral Economics. Also, we are not to discuss the pros and cons of these two research programs. For this purpose, there are specialized journals, and the work of López-Carbacos et al. (2020) could be an interesting and straightforward review. As noted, we are interested in highlighting the literature that relates news and social media sentiment (COVID-19 sentiment) as asset pricing factors.

From the previous references, we want to highlight the one of De Bondt and Thaler (1985). Also, the one of Kahneman and Rieppe (1998). Bu (2019, 2021) discussed these works and tested their results for the case of U.S. mutual funds' flows: Most people overreact to unexpected and dramatic events, given the biases in their judgment and preferences biases (due to sentiment) in their decisions.

Daniel, Hirshleifer, and Teo (2002) confirmed this last result in capital asset pricing models. This work is one of the first behavioral asset pricing models that tested the inclusion of investors' sentiment in asset pricing. After this work and similar ones, others used the benefits of data mining, the availability of Finance lexicons, and the computational capabilities to use artificial intelligence. Among the principal works that motivate the present paper, we can mention the work of Wolff (2013), Zheng (2014), and Smales (2017; 2016). These authors provide empirical evidence about the benefit of using trader sentiment in the trading decision process in stock or commodities. More specifically, Smales shows the advantage of using good investor sentiment to trade stocks and bad feelings to avoid such activity.

A closely related work to ours is Uhl (2014), who tested the use of Refinitiv financial news' sentiment in multifactor models in U.S. stocks. The author found that news sentiment explains better stock returns than macroeconomic factors. The author also found that the negative sentiment has higher predictive power than the positive one. In a similar perspective, the works of Preis, Moat, and Stanley (2013) and Da, Engelberg, and Gao (2015) estimate an index with the number of Google searches of terms such as recession, bankruptcy, unemployment, and related. In their results, these authors find evidence that favors using Google searches volume as an advanced indicator of market sentiment in stocks. In a similar review, Koo, Chae, and Kim (2018) developed an internet search index of financial terms and estimated a sentiment index for the Korean stock market. The authors found that their index predicts a return reversal after three weeks of positive returns. The authors' index increase coincides with the negative returns of the KOSPI stock index.

Finally, Nikkinen and Peltomäki's (2019) work tests news and internet search indexes' influence on stock returns. The authors' position is that internet searches related to market crashes are a fear indicator leading to negative news. The authors present their review in a supply/demand news framework. The number of internet searches oy using multifactor models of crash or stocks negative returns is a "demand" indicator of negative news. Also, the number of news published on the subject is considered a "supply" indicator for the authors. Using multifactor models, the authors found that the number of web searches led to a higher number of negative news but not the opposite. That is, more negative news led to a higher number of internet searches. Also, the authors found that the higher the number of internet searches of negative stock market words, it is expected to have negative stock returns. This relation holds in the short term. For the connection between negative news and stock returns, the authors found that the effect has a lag effect of up to 11 weeks. That is, the negative shock in stock returns appears 11 weeks after the news publication.

From all these previous references, we extended these to the Mexican stock market case. We did this by extending the Fama-French (1992) multifactor model with the U.S. and Mexican VIX volatility indexes and using the global economic policy uncertainty, the world pandemic uncertainty, and the twitter negative terms uncertainty indexes. We used these last three indexes to estimate the relationship between the supply (economic policy and pandemic uncertainty indexes) and the demand (the Twitter uncertainty index) of negative news. That is, the supply/demand channels of the "fear" or uncertainty in the Mexican stock markets. We couldn't make our tests in a Carhart (1997) multifactor context because there is no Public and well-accepted momentum factor (index) for the Mexican stock markets. Also, we used the global or world uncertainty indexes (more specifically, the economic uncertainty one) because the Mexican uncertainty index has been discontinued since 2019.

Departing from these motivations and the work of Nikkinen and Peltomäki (2019), we estimated the next multifactor model. An extension of the Fama-French (1992) three-factor model:

$$r_{i,t} = \alpha + \beta_1 \cdot r_{m,t} + \beta_2 \cdot SMB_t + \beta_3 \cdot HML_t + \gamma_1 \cdot \Delta\%VIX_t + \gamma_2 \cdot \Delta\%VIXMX_t + \lambda_1 \cdot \Delta\%WEUI_t + \lambda_2 \cdot \Delta\%WPUI_t + \lambda_3 \cdot \Delta\%TWITUI_t + \varepsilon_{i,t} \quad (2)$$

In the previous model, r_(m,t) is the Mexican equity portfolio risk premium (we used the MSCI Mexico index in local currency as the benchmark) from the 28-day CETE rate. SMB_t is the small minus big capitalization factor. We estimated this factor as the difference between the MSCI small+mid cap Mexico stock index's risk premium and the MSCI large-cap Mexico one. HML_t is the high minus low book-to-value, estimated with the difference of the MSCI Mexico value stock index with the MSCI Mexico growth one. The fifth and sixth terms are the percentage variation of the implied volatility indexes of the U.S. markets or S&P 500 stock index (VIX) and the S&P/BMV IPC Mexican stock index. Finally, Δ%WEUI_t and Δ%WPUI_t are the world Economic policy news, the World pandemic news uncertainty indexes (our "fear" news supply factors). Our fear news demand factor is the Δ%TWITUI_t, the world Twitter-based uncertainty index.

A model that is an extension of the Fama-French one, with the volatility and the news and Twitter uncertainty indexes.

From our hypothesis, our position is that β_1,β_2,β_3>0 and γ_1,γ_2,λ_1,λ_2,λ_3<0. Being these factor loadings a theoretical mixture of the classical asset pricing and risk modeling framework (β_1,β_2,β_3) and the Behavioral one (γ_1,γ_2,λ_1,λ_2,λ_3).

As mentioned in this and the previous section, we found scant literature about Mexico's behavioral extension of factor models. Only the work of González and Ortiz (2020) makes a first overaction test in such markets. Departing from this theoretical and practical need, we want to test the factor model in (2) by performing panel data regression and individual regressions of the 79 stocks that have been index members of the Refinitiv Mexico price return index from January 2017 to October 2021.

We believe that our results will contribute to investors in the Mexican stock markets and financial institutions determining if it is helpful to include the uncertainty indexes of interest for asset pricing in portfolio selection (in a Black-Litterman (1992) context) or risk measurement.

In a similar practical use, we believe that our results could contribute to the feasibility of adding news sentiment (more specifically, Pandemic news sentiment) in a company valuation rate, such as the weighted average cost of capital (WACC). Suppose it is possible to include sentiment factors in the equity rate of return of the WACC. In that case, an investor could have a more real company value assessment, given the uncertainty in that company or its sector.

Given our theoretical and practical motivations, we will present the data gathering and processing method, our tests parameters, and a review of our main results next.

Behavioral multifactor models tests

Stock universe data gathering and processing

As mentioned in the previous section, we tested the multifactor model (2) for the 79 members of the Refinitiv Mexico price return index. We selected this index because it is estimated with 65 most traded and most valuable companies in the Mexican stock markets. The conventional S&P/BMV IPC stock index includes only 30 stocks with the same capitalization and trading criteria. There is also a well-known 60 stocks index: the S&P/BMV IPC composite. Because the Refinitiv index is a well-known stock index with a broader investment universe, we preferred to use it instead of the other two indexes.

From the databases of Refinitiv, we fetched the weekly historical total percentage return of each stock (Refintiv field code: TR.TotalReturn1Wk) from January 6, 2017, to September 30, 2020 (249 weeks). We used this period for our test because we wanted to include most stocks when forming a balanced panel. Fourteen companies (almost 25% of the sample) would have been set aside had we used more extended time series. Also, the VIXMX index has a starting value from 2015. Despite this, we ran our test from 2015 and, even with 14 companies out of the study, the tests' conclusions are the same as those presented herein (The input data is available upon request).

Once we have downloaded the historical data of these stocks, we conformed balanced panels to have the same time series length in each stock. We eliminated all the shorter time series stocks with this criterion, leading us to a universe of 72 stocks detailed in Appendix A.

To estimate the market factors in (2), we used the historical price of the MSCI Mexico price return stock index, calculated in Mexican pesos. With its price, we estimated the continuous-time return ($\Delta\%\mathrm{P_t} = \ln(\mathrm{P_t}) - \ln(\mathrm{P_{t-1}})$). We did the same process with the MSCI Mexico small+mid cap (MSCIMXSMcap), large-cap (MSCIMXLcap), growth (MSCIMXGrowth), and value (MSCIMXValue) stock indexes. With the historical return of these last five indexes, we estimated their risk premiums by subtracting the weekly equivalent 28-day CETES secondary money market rate (Refinitiv identifier code of RIC: MX1MT=RR).

To estimate the Fama-French factors, we followed the following calculations with the risk premiums of the small minus big capitalization stocks ($\mathrm{SMB_t}$) factor and the high minus low book-to-value (growth minus value stocks) factor ($\mathrm{HML_t}$):

$$SMB_t = \mathrm{MSCIMXSMcap_t} - \mathrm{MSCIMXLcap}$$

$$HML_t = \mathrm{MSCIMXGrowth_t} - \mathrm{MSCIMXValue\_t}$$

Please, remember that we are using the MSCI stock indexes transformations for the calculations.

For the specific case of the implied volatility indexes, we downloaded the weekly historical data of the S&P 500 stock index's options 1-2 months implied volatility index or VIX (RIC: .VIX). For the Mexican case, we downloaded the historical data of the Mexica S&P/BMV IPC 90 days implied volatility index or VIXMX (RIC: .SPBMVVIX). We calculated the deviation values of the VIX and VIXMX indexes from their equilibrium value of 20 (S&P Dow Jones indices, 2017; S&P Dow Jones Indices LLC, 2021). The difference in equilibrium values between the VIX and the VIXMX is because both indexes are estimated with different maturities. The equilibrium values correspond to the long-term yearly implied volatility value.

Instead of using the percentage variation of these indexes, we used the difference of the current value with its equilibrium one. This change comes from the rationale of multifactor models (such as APT) that suggests that the used factors should be estimated as differences from their expected value.

For the case of the $\mathrm{WEUI_t}$, $\mathrm{WPUI_t}$ and the $\mathrm{TWITUI_t}$, we made the same transformation as in the previous indexes, but we used, as an expected value, the 100 points reference in the $\mathrm{WEUI_t}$ and the $\mathrm{WPUI_t}$ and zero in the $\mathrm{TWITUI_t}$.

We used the Backer Economic policy uncertainty indexes because these are available online and because their methodology is plain and replicable. This use sets aside other sophisticated methods, such as using artificial intelligence algorithms or a specific lexicon to measure sentiment. One of our purposes with this paper is to make a first review of the statistical relation between investor's uncertainty (especially in terms of Pandemic news). Departing from our conclusions, we could suggest the necessary extensions and test with other sentiment indexes.

To test our hypotheses in the 72 stocks of interest ($\beta_1, \beta_2, \beta_3 > 0$ and $\gamma_1, \gamma_2, \lambda_1, \lambda_2, \lambda_3 < 0$), we estimated panel data regression models first. We calculated pooled, within fixed-effects and random-effects regression models. We evaluated the random-effects model with the usual Swammy-Arora (1972) method.

To reduce the effect of a potential presence of heteroskedasticity and serial correlation in the residuals, we estimated the three-panel regressions' standard errors with the Newey-West (1987) method.

We estimated the F test to compare the goodness of fit in the fixed-effect model against the pooled regression to determine the best fitting panel data regression model of both. Similarly, we ran the Hausman (1978) test to assess the goodness of fit between the random effects model versus de fixed effects one.

We used panel data regression to summarize the factor loadings values in these 72 stocks. The appropriate steps to follow are to estimate the 72 multivariate regressions with Newey-West robust standard errors or a seemingly unrelated regression (SUR) equation system. After panel data regression, we did the former. We didn't use the SUR model because the regressors are the same for the 72 stocks. It is well-accepted that if the regressors are the same for the K study units in the equation system, there is no benefit of estimating the SUR model against a K number of individual regressions. Once we evaluated the 72 separate regressions using (2), we summarized the results of each factor loading by setting as zero the loading that wasn't significant at a 5% level.

Finally, to determine the effect of the inclusion of each factor, we estimated six different multifactor models or versions of (2). First, we estimated the Fama-French 3 factor model (regression one or simply 1), followed by a pure risk factors regression (2). Also, we estimated two extensions of the Fama-French model: an extension (3) with only volatility indexes (VIX_t and $VIXMX_t$), and another (4) with the three uncertainty (news or social media) indexes. Finally, we estimated an extension with the volatility and uncertainty indexes (5) and a model (6) that used only the pandemic news uncertainty index as an explaining factor. We present the summary of the six-panel data regressions in Table 1.

Table 1
The six-panel data regressions in our tests

(1)	(2)	(3)	(4)	(5)	(6)
$r_{m,t}$		$r_{m,t}$	$r_{m,t}$	$r_{m,t}$	
SMB_t		SMB_t	SMB_t	SMB_t	
HML_t		HML_t	HML_t	HML_t	
	VIX_t	VIX_t		VIX_t	
	$VIXMX_t$	$VIXMX_t$		$VIXMX_t$	
	$\Delta\%WEUI_t$		$\Delta\%WEUI_t$	$\Delta\%WEUI_t$	
	$\Delta\%WPUI_t$		$\Delta\%WPUI_t$	$\Delta\%WPUI_t$	$\Delta\%WPUI_t$
	$\Delta\%TWITUI_t$		$\Delta\%TWITUI_t$	$\Delta\%TWITUI_t$	

Source: Own elaboration.

We show our main results next once we have presented how we gathered, processed the data, and modeled our hypothesis.

Main results and findings

In Table 2, we present the statistical summary of our model's factors. As noted, the market factor (r_(m,t)) has a symmetric behavior because the min and max values are similar in magnitude. The MSCI Mexico stock index paid a weekly mean risk premium of 2.3578% during the 247 weeks of interest. The company size factor (SMB_t) paid one of 1.25% and has a similar symmetric performance than the SMB_t. The book-to-value or value minus growth factor (HML_t) paid a negative risk premium, suggesting that the Mexican stock market created value through growth stocks. This result is consistent with the case of a developing economy such as Mexico. During the period of interest, it is essential to note that the Twitter and economic policy uncertainty indexes were, on average, above their 100 points expected value. This result suggests that our entire study has been subject to some distress or uncertainty periods. Uncertainty periods such as the U.S. commerce policy controversies or other economic/political episodes as the 2018 Mexican election process.

The factor of primary interest in this paper, the pandemic news uncertainty index (WPUI_t) had a mean value of 12.1655 points above its expected value. The VIX_t and VIXMX_t factor had a mean value of 8.5961 and 2.8791 points above its expected value of 20.

Table 2
Statistical summary of the factors used in our tests.

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
$r_{m,t}$	17,854	0.0754	2.3578	-10.4557	-1.1731	1.1848	10.6830
SMB_t	17,854	0.0713	1.2504	-3.6036	-0.7000	0.9606	3.7066
HML_t	17,854	-0.1075	0.9262	-3.8841	-0.6558	0.3984	5.5919
$WEUI_t$	17,854	96.8621	143.3096	-95.9500	9.7300	118.9400	761.1000
$TWITUI_t$	17,854	44.6020	134.9877	-75.2429	-33.0573	69.5627	881.9287
$WPUI_t$	17,854	12.1655	19.9755	0.0000	0.0000	19.9400	112.9300
VIX_t	17,854	-1.9236	8.5961	-10.8600	-7.7900	1.1500	46.0400
$VIXMX_t$	17,854	-4.0807	2.8791	-9.8464	-5.8893	-3.1005	10.7249

Source: Own elaboration with data from the Mexican stock exchange and Refinitiv (2021)

In Table 3, we present the Panel regression and F and Hausman tests of the six regressions of interest. As noted, regressions (2) to (4) weren't feasible in the random-effects method. As pointed out in the p-values of the Hausman test, the best method to estimate (1) and (6) is the random effects. Also, the F test's p-values of Table 3 show that the best approach to estimate regressions (2) to (4) is the fixed effects one.

Table 3
Summary of the F and Hausman test in the

	(1)	(2)	(3)	(4)	(5)	(6)
F test	0.850	0.7587	0.8500	0.8502	0.8508	0.7270
Hausman test	0.0010	Not Feasible	0.0020	Not Feasible	Not Feasible	0.0003

Source: Own elaboration with data from our tests, the Mexican stock exchange, and Refinitiv (2021)

In Table 4, we summarize the six regressions coefficients and significance values. In that Table, we specified which model we used in each regression, given the results of Table 3.

We used the conventional one, two, or three-stars notation to determine the factor loading significance at a 10%, 5%, and 1% level, respectively.

As noted in the Log-likelihood function (LLF) and the Akaike (1974) information criterion (AIC), the best fitting model is (5). The model with the three Fama-French factors, the two volatility indexes', and the news or social media uncertainty indexes. Also, the adjusted R^2 suggest that this model has the highest explanation level. As expected for the Fama-French factor loadings, these were significant in all the regressions that used these. The market factor loading has the expected sign, being the opposite in the size and book-to-value ones. This result is against the expected one because the Mexican stock index of interest has gained value due to growth and mid+small cap stocks and because growth and mid+small cap stocks are less liquid, which could help in terms of general stock market value.

The validity of this last statement is one that we suggest as future research work.

http://dx.doi.org/10.22201/fca.24488410e.2021.4583

Table 4
Summary of the panel-regression models of interest

	(1) Random effects	(2) Fixed Effects	(3) Fixed Effects	(4) Fixed Effects	(5) Fixed Effects	(6) Random Effects
Constant	0.018	---	---	---	---	0.1090**
$r_{m,t}$	0.692***		0.6670***	0.6890***	0.6610***	
SMB_t	-0.439***		-0.4400***	-0.4420***	-0.4420***	
HML_t	-0.314***		-0.3410***	-0.3010***	-0.3290***	
VIX_t		-0.040***	-0.0020		-0.0030	
$VIXMX_t$		-0.0320***	-0.0110***		-0.0120***	
$WEUI_t$		-0.0010***		-0.0004*	-0.0003*	
$WPUI_t$		-0.0060		0.00004	-0.0003	-0.0030
$TWITUI_t$		-0.0100***		-0.0040***	-0.0040***	
LLF	-50,597.12	-51,566.64	-50,559.84	-50,559.94	-50,551.91	-51,979.15
AIC	136,894.25	138,687.29	136,673.68	136,671.88	136,651.82	139,662.3
Adj. R^2	0.1430	0.0380	0.1410	0.1410	0.1420	0.0001

Source: Own elaboration with data from our tests, the Mexican stock exchange, and Refinitiv (2021)

To strengthen our results and check for robustness, we set aside the panel data regression and made the 72 multifactor individual regressions with (2). Also, as we mentioned in the previous section, we used the Newey-West robust standard errors. All the parameters that weren't significant at a 5% level were equaled to zero. In Table 5, we present the summary of the 72 values of the constant (α) and the factor loadings.

As noted in our results, we arrived at almost the same conclusions as in the panel data regression of model (5) in Table 4: is possible to extend, for the Mexican case, the Fama-French three-factor model with the Mexican implied volatility index.

Our results suggest that the impact of news and social media uncertainty indexes is negligible.

Conclusions and guidelines for further research

The Classical, rational, informationally efficient, and arbitrage-free context of the original asset pricing (and factor risk management) models used for decades. Despite their groundbreaking entrance into financial theory and the development of the financial industry, as a result, these models need review.

The most crucial review that is under discussion es the inclusion of investor sentiment in its functional form. That is, to relax the market equilibrium, informational efficiency, and (most of all) rationality assumptions. An observed result is that humans are not so rational as expected. We also decide according to our sentiment, being fear one of the most influential. This feeling has more power because there are two types of traders, as Black (1986) and Ang et al. (2006) primarily suggest: informed and noisy. The former traders tend to have a broader information set and decide, consequently, in a longer investment horizon longer. The latter trade more with short-term information and believe that rising price moves will continue. When they find that this view is wrong, some panic and lower market prices. This type of trader (noisy) is a potential explanation of price bubbles and market crashes. Two phenomena that the Classical asset pricing models do not fully explain.

Several quantitative and Behavioral extensions have been under test. These include using quantitative factors or other financial markets' indicators such as implied volatility indexes (VIX) or the use of sentiment indexes estimated from the text of Economic or financial markets-related news, along with social media posts or internet search volumes.

There is scant literature for the case of this extension in the Mexican stock markets. We extended the well-known Fama-French (1992) three-factor model in the Mexican stock market from this theoretical and practical need. We did this by including the U.S. implied volatility (VIX_t) index and its Mexican counterpart ($VIXMX_t$). We did this to extend the model by incorporating general market "fear" factors measured directly from the option's market prices. That is, the fear that hedgers and traders have of downward moves in the Mexican stock markets, proxied with their stock options positions.

In a parallel perspective, we included market sentiment indexes such as the Global Economic policy uncertainty ($WEUI_t$) and the Global pandemic uncertainty ($WPUI_t$) index. The latter gauges the stock market fear, given epidemic episodes' news such as the 2003 SARS or the 2020 SARS-COV2 of 2020). These two indexes represent the supply and impact of "fear" news related to these topics. To have a demand of fear news channel, we also included the Global Twitter-based uncertainty index that measures the uncertainty level estimated from social media (Twitter) posts and retweets.

We made our tests using weekly panel data of the 79 most traded and biggest Mexican companies traded in the Mexican stock exchange and the Institutional stock exchange. We did this for these companies from January 2017 to September 2021.

Our results suggest that none of the news or social media uncertainty indexes are appropriate to extend the Fama-French model in the Mexican stock markets. Also, the Pandemic news has no significant impact on stock price formation.

The previous results imply, for the Mexican stock markets, that the $\mathrm{WPUI_t}$ is not a good Pandemic news uncertainty proxy. Departing from this result, we suggest developing another pandemic news uncertainty index to estimate the impact of this type of news on Mexican stocks' performance. As a complement to this conclusion, we believe that the performance of Mexican stocks during their earliest stages of the COVID-19 is due to stock market risk contagions among markets. We suggest proving this statement with other pandemic news uncertainty indexes.

From the volatility indexes, only the Mexican $\mathrm{VIXMX_t}$ implied volatility one is appropriate to extend the Fama-French factor model and is helpful to integrate fear in the asset pricing process.

These results are helpful for risk management and asset pricing models, along with their use in active portfolio selection in models such as Black and Litterman (1992) or similar ones that incorporate quantitative views in the asset prices.

Among the guidelines for further research is the test of our results in lower periodicities such as daily. Also, we suggest searching and developing sentiment indexes with different methodologies, along with a more Mexican view. Instead of using global sentiment indexes, it is interesting to create Mexican social media and news sentiment with Mexican social media posts and news.

References

Ahir, H., Bloom, N., & Furceri, D. (2018). The World Uncertainty Index. https://ssrn.com/abstract=3275033

Akaike, H. (1974). A new look at the statistical model identification. IEEE Transactions on Automatic Control, 19(6), 716–723. https://doi.org/10.1016/J.CUB.2017.09.001

Ang, A., Hodrick, R. J., Xing, Y., & Zhang, X. (2006). The cross-section of volatility and expected returns. Journal of Finance, 61(1), 259–299. https://doi.org/10.1111/J.1540-6261.2006.00836.X

Armendáriz, T., & Ramírez, C. (2017). Estimación de un índice de condiciones financieras para México. El Trimestre Económico, 4(336), 899–946.

Baker, M., & Wurgler, J. (2006). Investor sentiment and the cross-section of stock returns. Journal of Finance, 61(4), 1645–1680. https://doi.org/10.1111/J.1540-6261.2006.00885.X

Baker, M., & Wurgler, J. (2007). Investor sentiment in the stock market. Journal of Economic

Perspectives, 21(2), 129–151. https://doi.org/10.1257/jep.21.2.129

Baker, S. R., Bloom, N., & Davis, S. J. (2016). Measuring Economic Policy Uncertainty. The Quarterly Journal of Economics, 131(4), 1593–1636. https://doi.org/10.1093/qje/qjw024

Baker, S. R., Bloom, N., Davis, S. J., & Renault, T. (2021). Twitter-Derived Measures of Economic Uncertainty. http://www.policyuncertainty.com/media/Twitter_Uncertainty_5_13_2021.pdf

Balcilar, M., Demirer, R., & Hammoudeh, S. (2013). Investor herds and regime-switching: Evidence from Gulf Arab stock markets. Journal of International Financial Markets, Institutions & Money, 23, 295–321. https://doi.org/10.1016/j.intfin.2012.09.007

Black, F. (1986). Noise. The Journal of Finance, 41(3), 529–543. https://doi.org/10.1111/J.1540-6261.1986.TB04513.X

Black, F., & Litterman, R. (1992). Global portfolio optimization. Financial Analysts Journal, 48(5), 28–43. https://doi.org/10.2469/faj.v48.n5.28

Bu, Q. (2019). Investor Sentiment and Mutual Fund Alpha. Journal of Behavioral Finance, 21(1), 57–65. https://doi.org/10.1080/15427560.2019.1594814

Bu, Q. (2021). Mutual Fund Alpha: Is It Managerial or Emotional? Journal of Behavioral Finance, 22(1), 46–55. https://doi.org/10.1080/15427560.2020.1716361

Cambón, M. I., & Estévez, L. (2016). A Spanish Financial Market Stress Index (FMSI). The Spanish Review of Financial Economics, 14(1), 23–41. https://doi.org/10.1016/j.srfe.2016.01.002

Carhart, M. M. (1997). On Persistence in Mutual Fund Performance. The Journal of Finance, LII(1), 57–82.

Chen, C.-D., Chen, C.-C., Tang, W.-W., & Huang, B.-Y. (2009). The Positive and Negative Impacts of the Sars Outbreak: A Case of the Taiwan Industries. The Journal of Developing Areas, 43(1), 281–293.

Da, Z., Engelberg, J., & Gao, P. (2015). The Sum of All FEARS Investor Sentiment and Asset Prices. Review of Financial Studies, 28(1), 1–32. https://doi.org/10.1093/rfs/hhu072

Daniel, K., Hirshleifer, D., & Teoh, S. H. (2002). Investor psychology in capital markets: evidence and policy implications. Journal of Monetary Economics, 49(1), 139–209. https://doi.org/10.1016/S0304-3932(01)00091-5

De Bondt, W. F. M., & Thaler, R. (1985). Does the Stock Market Overreact? The Journal of Finance, 40(3), 793–805. https://doi.org/10.1111/J.1540-6261.1985.TB05004.X

De Long, J. B., Shleifer, A., Summers, L. H., & Waldmann, R. J. (1990). Noise Trader Risk in Financial Markets. Journal of Political Economy, 98(4), 703–738. https://doi.org/10.1086/261703

Ding, C. G., Wang, H.-J., Lee, M.-C., Hung, W.-C., & Lin, C.-P. (2014). How Does the Change in Investor Sentiment over Time Affect Stock Returns? Emerging Markets Finance and Trade, 50(sup2), 144–158. https://doi.org/10.2753/REE1540-496X5002S210

Durand, R. B., Lim, D., & Zumwalt, J. K. (2011). Fear and the Fama-French Factors. Financial Management, 40(2), 409–426. https://doi.org/10.1111/J.1755-053X.2011.01147.X

Fama, E. (1965). The behavior of stock-market prices. Journal of Business, 38(1), 34–105.

Fama, E. F., & French, K. R. (1992). Common risk factors in the returns on stocks and bonds. Journal of Financial Economics, 33(1), 3–56.

González, J., & Ortiz, E. (2020). Testing the overreaction hypothesis in the Mexican stock market. Contaduría y Administración, 65(1), 1–23. https://doi.org/http://dx.doi.org/10.22201/fca.24488410e.2019.1794

Griffith, J., Najand, M., & Shen, J. (2020). Emotions in the Stock Market. Journal of Behavioral Finance, 21(1), 42–56. https://doi.org/10.1080/15427560.2019.1588275

Hausman, J. A. (1978). Specification tests in econometrics. Econometrica, 46(6), 1251–1271. https://doi.org/10.2307/1913827

Kahneman, D., & Riepe, M. W. (1998). Aspects of Investor Psychology. The Journal of Portfolio Management, 24(4), 52–65. https://doi.org/10.3905/jpm.1998.409643

Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. Econometrika, 47, 263-291. Econometrica, 47(2), 263–292. https://doi.org/10.2307/1914185

Koo, B., Chae, J., & Kim, H. (2018). Does Internet Search Volume Predict Market Returns and Investors' Trading Behavior? Journal of Behavioral Finance, 20(3), 316–338. https://doi.org/10.1080/15427560.2018.1511561

Li, J. (2015). The asymmetric effects of investor sentiment and monetary policy on stock prices. Applied Economics, 47(24), 2514–2522. https://doi.org/10.1080/00036846.2015.1008770

Lintner, J. (1965). The valuation of risk assets and the selection of risky investments in stock portfolios and capital budgets. The Review of Economics and Statistics, 47(1), 13–37.

Liu, L., & Zhang, T. (2015). Economic policy uncertainty and stock market volatility. Finance Research Letters, 15, 99–105. https://doi.org/10.1016/j.frl.2015.08.009

López-Cabarcos, M. Á., Pérez-Pico, A. M., Vázquez-Rodríguez, P., & López-Pérez, M. L. (2020). Investor sentiment in the theoretical field of behavioural finance. Economic Research-Ekonomska Istrazivanja , 33(1), 2101–2119. https://doi.org/10.1080/1331677X.2018.1559748

Luo, C., Seco, L., & Wu, L.-L. B. (2015). Portfolio optimization in hedge funds by OGARCH and Markov Switching Model. Omega, 57, 34–39. https://doi.org/10.1016/j.omega.2015.01.021

Mehra, R., & Prescott, E. C. (1985). The equity premium a Puzzle. In Journal of Monetary Economics (Vol. 15).

Newey, W. K., & West, K. D. (1987). A Simple, Positive Semi-Definite, Heteroskedasticity and

Autocorrelation Consistent Covariance Matrix. Econometrica, 55(3), 703–708.

Nikkinen, J., & Peltomäki, J. (2019). Crash Fears and Stock Market Effects: Evidence From Web Searches and Printed News Articles. Journal of Behavioral Finance, 21(2), 117–127. https://doi.org/10.1080/15427560.2019.1630125

Preis, T., Moat, H. S., & Stanley, H. E. (2013). Quantifying trading behavior in financial markets using google trends. Scientific Reports, 3, 1684. https://doi.org/10.1038/SREP01684

Raddatz, C., & Schmukler, S. L. (2012). Deconstructing Herding: Evidence from Pension Fund Investment Behavior. Journal of Financial Services Research, 43(1), 99–126. https://doi.org/10.1007/s10693-012-0155-x

Refinitiv. (2021). Refinitiv Eikon. Thomson Refinitiv Eikon Login. https://eikon.thomsonreuters.com/index.html

Ross, S. (1976). Return, Risk and Arbitrage. In I. Friend & J. Bicksler (Eds.), Risk and Return in Finance (pp. 189–218). Ballinger.

Rotta, P. N., & Valls Pereira, P. L. (2016). Analysis of contagion from the dynamic conditional correlation model with Markov Regime switching. Applied Economics, 48(25), 2367–2382. https://doi.org/10.1080/00036846.2015.1119794

S&P Dow Jones indices. (2017). A practitioners guide to reading VIX. S&P Indices. http://www.cboe.com/assets/modules/microsite/vix/documents/SandP A Practitioners Guide to Reading VIX.pdf

S&P Dow Jones Indices LLC. (2021, August). Índice S&P/BMV IPC VIX Metodología. Indices. https://www.spglobal.com/spdji/es/documents/methodologies/methodology-sp-bmv-ipc-vix-index-spanish.pdf

Sharpe, W. (1963). A simplified model for portfolio analysis. Management Science, 9(2), 277–293.

Sharpe, W. (1964). Capital asset prices: A theory of market equilibrium under conditions of risk. The Journal of Finance, XIX(3), 425–442.

Shiller, R. J. (2003). From Efficient Markets Theory to Behavioral Finance. Journal of Economic Perspectives, 17(1), 83–104. https://doi.org/10.1257/089533003321164967

Shiller, R. J. (2014). Speculative asset prices. American Economic Review, 104(6), 1486–1517. https://doi.org/10.1257/aer.104.6.1486

Simon, D. P., & Wiggins III, R. A. (2001). S&P futures returns and contrary sentiment indicators. Journal of Futures Markets, 21(5), 447–462. https://doi.org/10.1002/FUT.4

Smales, L.A. (2017). The importance of fear: investor sentiment and stock market returns. Applied Economics, 49(34), 3395–3421. https://doi.org/10.1080/00036846.2016.1259754

Smales, Lee A. (2016). The role of political uncertainty in Australian financial markets. Accounting &

Finance, 56(2), 545–575. https://doi.org/10.1111/acfi.12107

Swamy, P. A. V. B., & Arora, S. S. (1972). The Exact Finite Sample Properties of the Estimators of Coefficients in the Error Components Regression Models. Econometrica, 40(2), 261. https://doi.org/10.2307/1909405

Tversky, A., & Kahneman, D. (1981). The framing of decisions and the psychology of choice. Science, 211(4481), 453–458. https://doi.org/10.1126/SCIENCE.7455683

Uhl, M. W. (2014). Reuters Sentiment and Stock Returns. Journal of Behavioral Finance, 15(4), 287–298. https://doi.org/10.1080/15427560.2014.967852

Viebig, J. (2020). Exuberance in Financial Markets: Evidence from Machine Learning Algorithms. Journal of Behavioral Finance, 21(2), 128–135. https://doi.org/10.1080/15427560.2019.1663849

Walid, C., & Nguyen, D. K. (2014). Exchange rate movements and stock market returns in a regime-switching environment: Evidence for BRICS countries. Research in International Business and Finance, 31, 46–56. https://doi.org/10.1016/j.ribaf.2013.11.007

Wang, C. (2001). Investor Sentiment and Return Predictability in Agricultural Futures Markets. Journal of Futures Markets, 21(10), 929–952. https://doi.org/10.1002/fut.2003

Wang, C. (2003). Investor sentiment, market timing, and futures returns. Applied Financial Economics, 13(12), 891–898. https://doi.org/10.1080/0960310032000129653

Wolff, A. F. (2013). Investor sentiment and stock prices in the subprime mortgage crisis. Applied Financial Economics, 23(16), 1301–1309. https://doi.org/10.1080/09603107.2013.804163

Wu, P.-C., Liu, S.-Y., & Chen, C.-Y. (2016). Re-examining risk premiums in the Fama–French model: The role of investor sentiment. North American Journal of Economics and Finance, 36, 154–171. https://doi.org/10.1016/j.najef.2015.12.002

Ye, W., Zhu, Y., Wu, Y., & Miao, B. (2016). Markov regime-switching quantile regression models and financial contagion detection. Insurance: Mathematics and Economics, 67, 21–26. https://doi.org/10.1016/j.insmatheco.2015.11.002

Zheng, Y. (2014). The linkage between aggregate stock market investor sentiment and commodity futures returns. Applied Financial Economics, 24(23), 1491–1513. https://doi.org/10.1080/09603107.2014.925073

Appendix

In this Appendix, we summarize the 72 stocks that we studied in our sample. It comprises common stocks, Real state investment trusts, and Prive equity companies trading in the Mexican stock exchange.

Refinitiv RIC	Exchange ticker	Name
AC.MX	AC*	Arca Continental SAB de CV
AEROMEX.MX	AEROMEX*	Grupo Aeromexico SAB de CV
AGUA.MX	AGUA*	Grupo Rotoplas SAB de CV
ALEATIC.MX	ALEATIC*	Aleatica SAB de CV
ALFAA.MX	ALFAA	Alfa SAB de CV
ALPEKA.MX	ALPEKA	Alpek SAB de CV
ALSEA.MX	ALSEA*	Alsea SAB de CV
AMXL.MX	AMXL	America Movil SAB de CV
ARA.MX	ARA*	Consorcio Ara SAB de CV
ASURB.MX	ASURB	Grupo Aeroportuario del Sureste SAB de CV
AXTELCPO.MX	AXTELCPO	Axtel SAB de CV
AZTECACPO.MX	AZTECACPO	TV Azteca SAB de CV
BACHOCOB.MX	BACHOCOB	Industrias Bachoco SAB de CV
BIMBOA.MX	BIMBOA	Grupo Bimbo SAB de CV
BOLSAA.MX	BOLSAA	Bolsa Mexicana de Valores SAB de CV
BSMXB.MX	BSMXB	Banco Santander Mexico SA Institucion de Banca Multiple Grupo Financiero Santander Mexico
CADUA.MX	CADUA	Cadu Inmobiliaria SA de CV
CEMEXCPO.MX	CEMEXCPO	Cemex SAB de CV
CHDRAUIB.MX	CHDRAUIB	Grupo Comercial Chedraui SAB de CV
CMOCTEZ.MX	CMOCTEZ*	Corporacion Moctezuma SAB de CV
CREAL.MX	CREAL*	Credito Real SAB de CV SOFOM ENR

Refinitiv RIC	Exchange ticker	Name
CULTIBAB.MX	CULTIBAB	Organizacion Cultiba SAB de CV
DANHOS13.MX	DANHOS13	Concentradora Fibra Danhos SA de CV
ELEKTRA.MX	ELEKTRA*	Grupo Elektra SAB de CV
FCFE18.MX	FCFE18	CFECapital S de RL de CV
FEMSAUBD.MX	FEMSAUBD	Fomento Economico Mexicano SAB de CV
FHIPO14.MX	FHIPO14	Concentradora Hipotecaria SAPI de CV
FIBRAHD15.MX	FIBRAHD15	FIBRA HD Servicios SC
FIBRAMQ12.MX	FIBRAMQ12	Macquarie Mexico Real Estate Management SA de CV
FIBRAPL14.MX	FIBRAPL14	Prologis Property Mexico SA de CV
FIHO12.MX	FIHO12	Concentradora Fibra Hotelera Mexicana SA de CV
FINN13.MX	FINN13	Administradora de Activos Fibra Inn SC
FORTALE.MX	FORTALE*	Fortaleza Materiales SAB de CV
FRAGUAB.MX	FRAGUAB	Corporativo Fragua SAB de CV
FSHOP13.MX	FSHOP13	Fibra Shop Portafolios Inmobiliarios SAPI de CV
FUNO11.MX	FUNO11	Fibra Uno Administracion SA de CV
GAPB.MX	GAPB	Grupo Aeroportuario del Pacifico SAB de CV
GCARSOA1.MX	GCARSOA1	Grupo Carso SAB de CV
GENTERA.MX	GENTERA*	Gentera SAB de CV
GFINBURO.MX	GFINBURO	Grupo Financiero Inbursa SAB de CV
GFNORTEO.MX	GFNORTEO	Grupo Financiero Banorte SAB de CV
GICSAB.MX	GICSAB	Grupo Gicsa SAB de CV
GISSAA.MX	GISSAA	Grupo Industrial Saltillo SAB de CV
GMEXICOB.MX	GMEXICOB	Grupo Mexico SAB de CV
GNP.MX	GNP*	Grupo Nacional Provincial SAB
GSANBORB1.MX	GSANBORB-1	Grupo Sanborns SAB de CV

Refinitiv RIC	Exchange ticker	Name
HCITY.MX	HCITY*	Hoteles City Express SAB de CV
HERDEZ.MX	HERDEZ*	Grupo Herdez SAB de CV
HOTEL.MX	HOTEL*	Grupo Hotelero Santa Fe SAB de CV
ICHB.MX	ICHB	Industrias CH SAB de CV
IDEALB1.MX	IDEALB-1	Impulsora del Desarrollo y el Empleo en America Latina SAB de CV
IENOVA.MX	IENOVA*	Infraestructura Energetica Nova SAB de CV
KIMBERA.MX	KIMBERA	Kimberly-Clark de Mexico SAB de CV
KOFUBL.MX	KOFUBL	Coca-Cola Femsa SAB de CV
KUOB.MX	KUOB	Grupo KUO SAB de CV
LABB.MX	LABB	Genomma Lab Internacional SAB de CV
LACOMERUBC.MX	LACOMERUBC	La Comer SAB de CV
LALAB.MX	LALAB	Grupo Lala SAB de CV
LAMOSA.MX	LAMOSA*	Grupo Lamosa SAB de CV
LIVEPOLC1.MX	LIVEPOLC-1	El Puerto De Liverpool SAB De CV
MEGACPO.MX	MEGACPO	Megacable Holdings SAB de CV
MFRISCOA1.MX	MFRISCOA-1	Minera Frisco SAB de CV
NEMAKA.MX	NEMAKA	Nemak SAB de CV
OMAB.MX	OMAB	Grupo Aeroportuario del Centro Norte SAB de CV
ORBIA.MX	ORBIA*	Orbia Advance Corporation SAB de CV
PEOLES.MX	PE&OLES*	Industrias Penoles SAB de CV
PINFRA.MX	PINFRA*	Promotora y Operadora de Infraestructura SAB de CV
PINFRAL.MX	PINFRAL	Promotora y Operadora de Infraestructura SAB de CV
Q.MX	Q*	Qualitas Controladora SAB de CV
RA.MX	RA	Regional SAB de CV

Refinitiv RIC	Exchange ticker	Name
SIMECB.MX	SIMECB	Grupo Simec SAB de CV
SITESB1.MX	SITESB-1	Telesites SAB de CV
TERRA13.MX	TERRA13	CI Banco SA Institucion de Banca Multiple FF/00939
TLEVISACPO.MX	TLEVISACPO	Grupo Televisa SAB
UNIFINA.MX	UNIFINA	Unifin Financiera SAB de CV
VESTA.MX	VESTA*	Corporacion Inmobiliaria Vesta SAB de CV
VITROA.MX	VITROA	Vitro SAB de CV
VOLARA.MX	VOLARA	Controladora Vuela Compania de Aviacion SAB de CV
WALMEX.MX	WALMEX*	Wal Mart de Mexico SAB de CV