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# **The Impact of COVID-19 News and Investor Sentiment in European Stock Pricing, a Regional, Country, and Economic Sector Review**

## **O Impacto das Notícias do COVID-19 e o Sentimento dos Investidores no Preço das Ações Europeias, uma Análise Regional, Nacional e do Setor Econômico**

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### **Abstract**

In the present paper we extended the Fama-French (FF), three-factor model, by including the U.S. VIX and European VSTOXX implied volatility indexes. Also, the Baker, Bloom Davis, Kost, and Renault Economic policy (WEUI), pandemics (WPUI) news, and social media (TWITUI) uncertainty index were included. We did this in order to test if, the main Eastern, Northern, Southern, and Western European stock markets could be priced with behavioral biases such as investor sentiment. With a balanced panel data of 659 European companies from January 2017 to Jun 2021, we found that the WPUI could be used in a regional perspective, along with the VIX and TWITUI factors. In a country-specific perspective, only the inclusion of the TWITUI factor led to better-fitting results in Finland, Ireland, the Netherlands, Poland, Spain, and Sweden. Our results suggest that other pandemic news sentiment indexes should be developed and used in the main European stock markets and encourage the use of social media investor sentiment proxies in risk and asset-pricing multifactor models.

*Keywords:* investor sentiment, European stock pricing, economic sector, COVID-19

*JEL Codes:* C24; C58; G14; G15

### **Resumo**

No presente artigo estendemos o Fama-French (FF), modelo de três fatores, incluindo os índices de volatilidade implícita U.S. VIX e European VSTOXX. Além disso, o índice de incerteza da política econômica de Baker, Bloom Davis, Kost e Renault (WEUI), pandemias (WPUI) e mídia social

(TWITUI) foram incluídos. Fizemos isso para testar se os principais mercados de ações da Europa Oriental, do Norte, do Sul e do Oeste poderiam ser precificados com vieses comportamentais, como o sentimento do investidor. Com um painel de dados balanceado de 659 empresas europeias de janeiro de 2017 a junho de 2021, descobrimos que o WPUI poderia ser usado em uma perspectiva regional, juntamente com os fatores VIX e TWITUI. Em uma perspectiva específica do país, apenas a inclusão do fator TWITUI levou a resultados mais adequados na Finlândia, Irlanda, Holanda, Polónia, Espanha e Suécia. Nossos resultados sugerem que outros índices de sentimento de notícias pandêmicas devem ser desenvolvidos e usados nos principais mercados de ações europeus e encorajar o uso de proxies de sentimento do investidor de mídia social em modelos multifatoriais de precificação de risco e de ativos.

*Palavras-chave:* sentimento do investidor, preços de ações europeus, setor econômico, COVID-19

*Códigos JEL:* C24; C58; G14; G15

## 1. INTRODUCTION

Classical Financial Economics has been a cornerstone in the investment industry, given the developments of models for asset pricing and optimal security selection. As in the case of Classical Economics, one of the main assumptions is the one of a rational investor. That is an agent that has complete information set in his mind and proper calculation and information processing capabilities. Also, another important assumption grounded in Classical Financial Economics is the Efficient markets hypothesis (E. Fama, 1965). It proposes that all the necessary information relative to the price of an asset is known (discounted) by the agents almost immediately once it is generated. Given this assumption, there is no space for differences between the price and the real value of a given company's stock. That is, there is no reason to over or under-price stocks in an efficient market.

Given the efficient markets hypothesis, a given investor acts as a utility (satisfaction) maximizer. This conception led to the development of the Financial economic sector, given several asset pricing models. Among the most used is the Capital Asset Pricing (CAPM) model (Lintner, 1965; Sharpe, 1963, 1964) that assumes that the only source of risk in each asset is the one related to systemic risk (market fluctuations or  $r_{m,t}$ ). Departing from this, the price or return of common stocks ( $r_{i,t}$ ) is explained as follows:

$$r_{m,t} = \alpha_i + \beta_i \cdot r_{m,t} + \varepsilon_{i,t} \quad (1)$$

This result allows valuing the expected price or return ( $E(r_{i,t})$ ), given a risk-free asset ( $rf$ ):

$$E(r_{i,t}) = rf + [r_{m,t} - rf] \cdot \beta_i + v_{i,t} = a + b \cdot \beta_i + v_{i,t} \quad (2)$$

According to the CAPM assumptions (supported by the efficient markets theory), the prices in a stock market are in equilibrium and reflect all the information about of a given security. Given this, price deviation ( $r_t$ ) from its equilibrium value ( $E(r_{i,t})$ ) is random and due to diversifiable company's specific risk ( $\sigma(\varepsilon_{i,t})$ ). Also, it assumes the existence of a market portfolio ( $m$ ) that results from the added positions of all the agents in the market.

Given the assumptions of this model, emotions and other “no rational” aspects of the agent's mind are not part of the investment decision process, given the assumed equilibrium or the possibility of no-arbitrage, which led to assuming  $a = 0$  and  $b = 1$  in (2).

From Economic History it is well-known that Classical Economics and Classical Financial Economics have made important contributions but, as theories or research programs, their models lack a sufficient explanation of reality. A well-known historical critique is the one made by Keynes (1936) who observes that equilibrium does not exist and that Economic agents follow either their reasoning or their “animal spirits”. That means they decide also with emotions and are not as rational as the Classical Economic Theory suggests. In a similar discussion, several papers (Grauer & Roll, 2001; Roll, 1977, 1978; Roll & Ross, 1994) showed several limitations about the CAPM, leading to the concepts of “noise” and “noisy trader” (Black, 1986). The latter an agent “causes” market price disequilibrium and

other related phenomena such as the presence of price bubbles or crashes. Episodes that are difficult to explain or to forecast with the traditional CAPM and its later extensions.

Despite this, several of these models lack to explain specific issues of financial (stock) markets: Why do the agents in these markets act as part of a herd? Why do asset bubbles and crashes happen? Why the predicted equilibrium of the CAPM ( $a \neq 0$  and  $b \neq 1$ ) in the in (2) does not hold?

Several extensions of the CAPM and even the emergence of the Arbitrage Pricing Theory (APT) of Ross (Ross, 1976) have been proposed to answer this and other related questions. These extensions are an effort to explain the previous market or equilibrium “anomalies”. Several multifactor CAPM or APT models have been proposed to include other factors such as human capital (Black, 1972) or multiperiod selection (R. Merton, 1969, 1987). Among the most used in the financial practice are the multi-factor model of Fama and French (1996) (FF) and Carhart (1997). The former adds to the CAPM model in (1) a small minus big (in terms of capitalization) company return effect (*SMB*) and a high minus low book-to-market ratio stocks. That is, a value minus growth companies’ factor or *HML*:

$$r_{m,t} = \alpha_i + \beta_{1,i} \cdot r_{m,t} + \beta_{2,i} \cdot SMB_t + \beta_{3,i} \cdot HML_t + \varepsilon_{i,t} \quad (3)$$

This model seeks to explain the so-called “equity premium puzzle” (Mehra & Prescott, 1985). These authors refer to the causes of why the capital asset pricing model (CAPM) assumptions, such as  $\beta = [r_{m,t} - rf]$ ,  $\alpha = rf$  in the second regression of this asset pricing model. That is, if an investor performs a regression model with the first two terms in (3), and given the  $\beta_{1,i}$  value of each asset of interest, she could perform a second regression with the observed return of each asset ( $r_{i,t}$ ). The parameters of that regression should be  $\alpha = rf$ ,  $\beta = [r_{m,t} - rf]$ . In real life, this theoretical CAPM result does not hold, leading to observe that  $[r_{m,t} - rf]$  is higher than its expected value. Despite these improvements, Classical Financial Economics lacks to incorporate (and to accept) the impact of investor sentiment on asset pricing and investing. The debate about information efficiency and noise trade-off in investment decisions led to a new research program: the Behavioral Finance approach (Barberis et al., 2002; Barberis & Thaler, 2005; Kahneman & Tversky, 1979; Tversky & Kahneman, 1981).

In this approach, investor’s sentiment must be measured. This led to several extensions of the Fama-French model in (3) that include the presence of generally perceived volatility (measured with option’s implied volatility indexes or *VIX*) or the direct estimation of investor’s sentiment. Given this, we found that several papers have been written about this issue of informed v.s. noise traders (Black, 1986; de Long et al., 1990; Mehra & Prescott, 1985).

Little has been written about the effect that investor sentiment and risk perception had on the stock price of European stock. Also, none paper makes a review of regional, country, and Economic-specific review of the behavioral patterns that investors have when they price stocks for investment purposes. Our tests are to review if it is possible to use a Behavioral factor model for risk management and portfolio selection models. A model that could incorporate the effect of market sentiment, given the news of future pandemic episodes. Episodes such as the one of the COVID-19 on course from February 2020 to the moment of writing this paper.

Departing from this need, we extend the current literature by extending the Fama-French model by including the VSTOXX (Eurostoxx index option’s volatility index), the U.S. VIX, the index of Global Economic policy uncertainty or *WEUI* (S. R. Baker et al., 2016b), another index of pandemics’ news uncertainty or *WPUI* (S. R. Baker et al., 2019) and the global economic sentiment index (*TWITUI*) measured from social media such as Twitter (S. R. Baker et al., 2021). Our results contribute to the debate of the Noise Trader hypothesis that suggests measuring the impact of noisy investment decisions. That is, we tested the extension of well-accepted asset-pricing models with investor’s sentiment factors. Our perspective contributes to the scant literature on the subject with of European stock markets with a regional, country, and Economic sector-specific review. Given this, the work is structured as follows: in the second section, we present a brief review of the most relevant literature that motivates our work. In the third section, we describe or data gathering and processing method, along with a review of our main findings. Finally, the fourth section concludes and presents the suggestions for further research.

## 2. LITERATURE REVIEW

As mentioned in the previous section, the emergence of Behavioral Finance as a new research program requires including the investor's non-rational aspects such as feelings or emotions. The first efforts were focused on extending multi-factor models (such as the Fama-French or the Carhart ones) with volatility (*VIX*) factors. This rationale came from the work of Ang et. al. (2006), Durand et. al. (2011) and Wu, Lui, and Chen (2016). These works suggest enhancing the FF model with a volatility measure (such as the *VSTOXX* or the *VIX*), by following Merton's (1987) proofs about the influence of the general market volatility level with the risk-premium  $[r_m - rf]$  in (2). These authors found strong evidence of the benefits of including the *VIX* in multi-factor asset-pricing models, that motivate our work by including the European volatility index (*VSTOXX*) and the U.S. *VIX* one. We included the latter by the fact that we want to measure if European stocks are affected by a risk contagion effect in their risk premiums. By following the use of Economic, poll, or statistical proxies of investor sentiment (M. Baker & Wurgler, 2006, 2007; Fisher & Statman, 2000; Pan, 2020; C. Wang, 2001, 2003), we used the *VIX* and *VSTOXX* volatilities as a first (non-psychological) proxy of investor or market sentiment. We did this by following the rationale of the previously cited authors and the financial practice of interpreting these volatility indexes as a sort of "fear gauges" (S&P Dow Jones indices, 2017; STOXX Quontigo, 2021). Why? These two indexes represent the 30-days annualized volatility of the at-the-money and in-the-money put and call options in their respective options market (Chicago Mercantile Exchange or CME in the U.S. and the Eurex in Europe). If Institutional investors or stock portfolio hedgers perceive a higher risk or a lousy perspective in their corresponding stock markets, they will buy more puts. Given the market put prices increased demand, the implied volatility of market options (in a Black-Scholes (1973) and Merton (1973) valuation context) will increase. Given this, the perceived "fear" or uncertainty among investors will be proxied as "high".

From a less quantitative perspective and given the Behavioral Finance developments and the developments in Data Science nowadays, it is possible to estimate investor's sentiment either from the sentiment perceived in the headers and text of news or even in blogs or social networks such as Twitter, Stocktwits and similar. Authors such as Preis, Moat, and Stanley (2015), Da, Endelberg, and Gao (2015), Smales (2016a, 2016b, 2017a, 2017b) and Nikkinen and Peltomäki (2019) tested the impact that the level of Google searches or social media posts had in stock returns. They did this with computer algorithms or financial dictionaries had in the performance of U.S., Australian, Korean, or Chinese stock markets of Agricultural futures. Also, Wolff (2013), Uhl (2014) and Griffith, Najand, and Shen (2020) use the sentiment from Refinitiv's (a well-known financial data, analytics, and news service) news in the main U.S. stock markets. Smales (2016a, 2016b, 2017a, 2017b) and Zheng (2014) do the same test in commodity markets. From all the previously cited authors that test the benefit of news sentiment, practically all extended well-known multi-factor models such as the FF model. In their results, they found that the model had a better explanation if they include either a numerical sentiment proxy such as the *VIX*, or a sentiment-specific index measured from news, social media, or internet searches. Practically all, found that negative feelings, such as fear, are good to forecast future negative returns in the short, mid, and long term. Also, they found that happiness is a good sentiment index for positive future returns, being less powerful its influence, compared with the one of fear. Departing from these works, we want to extend the FF three-factor model by including the *VIX* and *VSTOXX* volatility indexes, along with the Baker, Bloom, and Davis (2016b) Global Economic policy news uncertainty index and the Baker, Bloom, Davis, and Kost (2019) Global Pandemic news uncertainty one. These two indexes are published daily and measure the level of uncertainty (fear) read from the news related to the implementation of Economic policies around the world, along with the uncertainty perceived given the news related to infectious disease' news around the world. News about Ebola, SARS, or SARS-COVID-19 news. We want to add these two indexes by the fact that they measure investor's fear in Global markets, given the news they read from the main newspapers in the U.S., European, Latin American, Asian and African countries. If the number of negative words in these newspapers is high (negative Economics, pandemics, Finance, policy, or politics words, determined in a specific set of words), these indexes will tend to increase to values higher than 100 (in the case of the *WEUI*) or higher than 20 (for the *WPUI*). Given this, the perceived uncertainty about Economic policy or epidemics (also pandemics) is high. This will have an impact on the return of common stocks.

Previous works that motivate ours and test the impact of COVID-19 in the negative performance of stock or commodity markets are the works of Wang and Park (2021), Ahmed et. al. (2021), Dutillo, Gattone and Batista (2021), Størdal, Lien and Trømborg (2021), Iqbal, Manzoor and Bhatti (2021) and Castro and López-Herrera (2021). Some other works extend this review to the impact on pension fund performance (Martínez Preece & Zubieta Badillo, 2020). Departing from these reviews, we want to extend the FF model to include a pandemic's news factor.

Also, we added a Twitter tweets uncertainty index (*TWITUI*). This index measures the level of fear or uncertainty, given the word set of the two previous indexes (specially *WEUI*). This last index uses the published tweets instead of the content and headers of the main newspapers around the world.

Given our interest to include a no psychological or sociological uncertainty or fear index and three Economic policy, pandemic news, and tweets fear ones, we will test the next FF model extension:

$$\begin{aligned}
 r_{i,t} = & \alpha_i + \beta_{1,i} \cdot r_{m,t} + \beta_{2,i} \cdot SMB_t + \beta_{3,i} \cdot HML_t + \\
 & \beta_{4,i} \cdot \Delta\%VIX_t + \beta_{5,i} \cdot \Delta\%VSTOXX_t + \\
 & \beta_{6,i} \cdot \Delta\%WEUI + \beta_{7,i} \cdot \Delta\%WPUI + \\
 & \beta_{8,i} \cdot \Delta\%TWITUI + \varepsilon_{i,t}
 \end{aligned} \tag{4}$$

Our position or hypothesis is that the influence of either the volatility indexes (*VIX* and *VSTOXX*) and the uncertainty indexes (*WEUI*, *WPUI*, and *TWITUI*) is significant and has an inverse relation, leading to a better explanation paid by the European stocks in our study. That is  $H_1: \beta_{4,i}, \beta_{5,i}, \beta_{6,i}, \beta_{7,i}, \beta_{8,i} < 0$  and  $H_2: R_{(3)}^2 < R_{(4)}^2$ .

Given our position, we want to extend the previous literature in two ways:

1. There is scant literature about the benefit of extending a well-known multi-factor model such as the FF in the European context. Especially in the southern, northern, and eastern European stock markets. Most of the current literature is related to western stock markets (Apergis & Pragidis, 2019; Aydogan, 2016; Bai, 2014; Frugier, 2016; Siganos et al., 2014). These works use other quantitative proxies or the news sentiment from central banks' news, but none use a combination of volatility (*VIX* or *VSTOXX*) indexes or news sentiment.
2. Most of the papers that test the relation of news or investor sentiment with stock return or volatility are focused mainly on a single stock type study and none test the effect of this relationship in a region or country-specific sector perspective. Given this, we want to test the leverage effect observed either in  $\alpha_i$  or  $\beta_{4,t}, \beta_{5,t}, \beta_{6,t}, \beta_{7,t}$  or  $\beta_{8,t}$  in (4). Our position is that there could be some region or country-specific effect in the investor sentiment with the expected return.
3. The most important for the current health and economic conditions in the world, we tested the inclusion of a pandemic news uncertainty factor (*WPUI*) in the model. This last test will be of use for asset-pricing, risk management, and portfolio selection purposes in the financial industry. Our position is that the inclusion of *WPUI* must be part of asset-pricing and risk models in the investment industry.

Once we have presented our main motivations for the tests made herein, we will describe or test methodology and observed results.

### 3. EMPIRICAL TEST: METHODS AND RESULTS

#### 3.1 Data gathering and processing

To test the benefit of including investor sentiment in an FF asset pricing context, we selected the stocks that were members of the Refinitiv (2019, 2020) Europe price return index from January 1<sup>st</sup>, 2017, to June 30, 2021. This index is a market capitalization one that measures the performance of the 2,000 biggest and most traded companies of stock exchanges from East, North, South, and West Europe. We prefer to use Refinitiv's Europe index, given the broader stock members sets that these indexes have, compared with well-known indexes such as the ones of the Eurostoxx, the MSCI, or the FTSE families.

From this index, we fetched, from the databases of Refinitiv Eikon, the weekly arithmetic returns of the stock members with a total of  $T = 238$  weeks.

Also from the same database, we fetched the historical weekly returns of the MSCI Europe price return index the MSCI Europe small, mid, and large-cap indexes, and the MSCI Europe growth and value ones. This is to estimate the values of the *SMB* and *HML* FF factors. The index data used are summarized in Table 1.

**Table 1. The MSCI Europe stock indexes used to estimate the Fama-French factors**

<i>RIC</i>	<i>Index</i>	<i>Purpose</i>	<i>Ticker in this paper</i>
.TRXFLDEUPU	REFINITIV Europe price return index	To determine the set of stocks to be tested	The ticker of each stock in the final balanced panel
.MIEU0000PEU	MSCI EUROPE stock index	To determine the SMB or HML factor	MEUR
.MIEU000LGPEU	MSCI EUROPE large-cap growth stock index	To determine the SMB or HML factor	MEURGLC
.MIEU000MGPEU	MSCI EUROPE mid-cap growth stock index	To determine the SMB or HML factor	MEURGMC
.MIEU000SGPEU	MSCI EUROPE small-cap growth stock index	To determine the SMB or HML factor	MEURGSC
.MIEU000LVPEU	MSCI EUROPE large-cap value stock index	To determine the SMB or HML factor	MEURVLC
.MIEU000MVPEU	MSCI EUROPE mid-cap value stock index	To determine the SMB or HML factor	MEURVMC
.MIEU000SVPEU	MSCI EUROPE small-cap value stock index	To determine the SMB or HML factor	MEURVSC

Source: Own elaboration.

All these indexes were measured in local currency. With these historical returns, we estimated the market factor (*MKT*) with the MSCI Europe index's weekly return. We also estimated the small minus big (*SMB*) size and the high minus low (value minus growth) factors of the FF model as follows respectively:

$$SMB_t = \frac{(MEURGLC+MEURVLC)-(MEURGSC+MEURVSC)}{2} \quad (5)$$

$$HML_t = \frac{(MEURVLC+MEURVMC+MEURVSC)-(MEURGLC+MEURGMC+MEURGSC)}{2} \quad (6)$$

Also from the databases of Refinitiv Eikon, we fetched the weekly historical 30-days *VIX* and *VSTOXX* values and we estimated the arithmetic return of these ( $\Delta\%VIX_t$ , and  $\Delta\%VSTOXX_t$ ).

For the news sentiment uncertainty indexes, we fetched the historical data of the *WEUI*, the *WPUI*, and the *TWITUI* from the website of Baker, Bloom, and Davis (2016a). From these, we also estimated their weekly arithmetic return.

To have a proper general analysis, we formed a balanced panel in which we included all the Refinitiv Identifier Codes (RIC) that had a complete return time series from January 1<sup>st</sup>, 2017 to May 30, 2021. Also, we included only the stocks with a European country-based main headquarters. For example, we excluded Arcelor Mittal an Indian-based company with stocks trading in several European stock markets.

This filtering process left our study with a balanced panel of  $T = 238$  weeks and  $K = 659$  companies. The panel includes stocks from eastern, northern, southern, and western stock exchanges from countries such as Austria, Belgium, Czech Republic, Denmark, Finland, France, Germany, Greece, Hungary, the Republic of Ireland, Italy, the Netherlands, Norway, Poland, Portugal, Spain, Sweden, Switzerland, and the United Kingdom. These 659 companies are companies classified according to the Thomson-Reuters (2012) Business Classification (TRBC) methodology used by Refinitiv. Our panel data has companies of the next Economic Sectors: Academic and educational services, basic materials, consumer cyclicals, consumer non-cyclicals, energy, financials, healthcare, industrials, real estate (realtors and not real estate investment trusts or REITS), technology, and utilities.

The panel is concentrated in Northern, Southern, and Western Europe companies (by the number of companies) as shown in the region summary of Table 2. Due to issues of space, we don't present a country or Economic sector-specific representativeness summary table. Those are available upon request. We only mention that, given the filtering process, our balanced panel is properly diversified if we measure the representativeness by the number of companies. The highest representativeness is concentrated in values between 5% and 26% in British, French, German, Swedish, Swiss, Spanish, and Italian companies. Other countries have representativeness between 0.15% to 4.09%. Related to the Economic Sector representativeness, we also found that our panel is properly diversified with mean representativeness of 9.16% in all the Economic sectors, being the Academic and Educational services the one with the lowest concentration (1%) and Industrials the one with the highest representativeness (21.85%).

**Table 2. The region-specific representativeness of our panel data model**

Region	Number of companies	Representativeness	Market capitalization	Market cap. representativeness
Eastern Europe	47	7.132	59,443.370	0.147
Northern Europe	302	45.827	12,808,631.000	31.574
Southern Europe	76	11.533	111,947.800	0.276
Western Europe	234	35.508	27,587,233.000	68.004

Source: Own elaboration with data from Refinitiv (2021).

To test our two hypotheses, we estimated a pooled regression model, along with a within-fixed-effects panel regression and a Swamy-Arora (1972) random effects one. We reduced the impact of potential heteroskedasticity and serial correlation by using the Newey-West (1987) robust standard errors. We estimated these three-panel regression models with the plm R library (Croissant & Millo, 2008). To determine the most suitable model of these three-panel regression ones, we performed the F-test to determine the appropriateness of the fixed-effects model, along with the Hausman (1978) test for the random-effects one.

To test our second hypothesis (the use of investor sentiment increases the explanation of the Fama-French factor model), we estimated 6 panel data regressions with 6 the next versions of (4).

1. A first regression with the FF original factors.
2. A second regression with (4).
3. A third regression of the original FF plus  $\Delta\%VIX$  and  $\Delta\%VSTOXX$  only.
4. A fourth regression with the original FF factors plus  $\Delta\%WEUI$ ,  $\Delta\%WPUI$ , and  $\Delta\%TWITUI$  only.
5. A fifth and sixth regressions using (4) with the region, country-specific effects in  $\alpha_i$  or from  $\beta_{4,i}$  to  $\beta_{8,i}$ . For this purpose, we created, in each regression a dummy variable with a variable of 1 if the current observation in the panel belongs to a specific country, region, or Economic sector or 0 otherwise. This dummy by itself creates a leverage effect in  $\alpha_i$  in (4). Also, we made a product of the dummy variable with  $\Delta\%VIX$ ,  $\Delta\%VSTOXX$ ,  $\Delta\%WEUI$ ,  $\Delta\%WPUI$ ,  $\Delta\%TWITUI$  and used it to estimate the leverage effect in their corresponding factor loadings ( $\beta_{k,i}$ ). For the country effect, we used Austria as the base country and used the dummy variables in the rest. Also, in the region effect, we used Eastern Europe as the base region.

Once we have detailed our data gathering and processing, we will proceed to review our main results and findings.

### 3.2 Main results and findings

In Table 3 we present the F and Hausman test results of each of the 5 panel regressions. The results for all the regression models show that the fixed-effects is the most appropriate model for our balanced panel data. This is so because the p-value of the F-test is lower than 5% (a significance level widely accepted), suggesting that the pooled regression and the fixed-effects, lead to similar fitting results.

**Table 3. F and Hausman test of the panel regressions made (p-values in %)**

	<i>Fama-French</i>	<i>Equation (4)</i>	<i>Fama-French+ VIX+VSTOXX</i>	<i>Fama-French+ WEUI+ WPUI+ TWITUI</i>
<i>F-test</i>	0.954	0.835	0.954	1.192
<i>Hausman test</i>	0	0	0	0
	<i>Equation (4) with region ef- fect</i>	<i>Equation (4) with country ef- fect</i>	<i>Equation (4) with economic sector effect</i>	
<i>F-test</i>	1.192	0.94	0.927	
<i>Hausman test</i>	0	0	0	

Source: Own elaboration with data from Refinitiv (2021) and Baker, Bloom, and Davis (2016a)

Also, the Hausman test suggests that the random-effect and the fixed effects model are not leading to similar fitting results. Given the almost 0% p-value (lower than the expected 5% threshold), we conclude that the within-fixed-effect model is the most appropriate one. Departing from this result, we present, in Table 4, the summary of the 6 regressions of interest, including the region, country leverage effects. Due to space issues, we present only the coefficients that are significant at 10% (1 star), 5% (2 stars), or 1% (3 stars). At the bottom of that table, we present the adjusted R-squared.

As noted, the R-squared improves marginally if the volatility or news uncertainty (investor sentiment) is included in the analysis. The same happens when there is a region or country leverage effect. Given this, we are partly supporting our first hypothesis by the fact that we noted marginal improvements if the FF model is extended with the 5 suggested investor sentiment indexes. The best model (without leverage effects) is the one that extends the FF model with news uncertainty indexes (columns 4 or 5 in Table 4).

If a given investor, risk manager, or portfolio manager wants to include a region or country leverage effect in the model, the explanation level increases marginally. For the Eastern European countries, there is no statistical relationship between the *STOXX* and their stock's price. This could be by the fact that the *VSTOXX* is the implied volatility index of the Eurostoxx50 stock index that doesn't include stocks of these countries (please refer to column 6 of Table 4).

The unexpected positive relationship between the U.S. volatility index (*VIX*) could be explained with Merton's (1987) position of the relationship between the volatility level and the market risk premium. For the case of the Northern Europe region, we found the expected inverse relation with the *VIX* index, suggesting that the higher the fear, their stock prices will move downward.

For the specific case of the news sentiment indexes, we found that the four regions had a significant relation with the Pandemic news index. A result that supports our position of including a pandemic news factor in asset-price models. Except for Eastern Europe, all the regions have the expected negative sign, suggesting that the higher the uncertainty related to pandemics (COVID-19) news, the lower the expected return. This suggests that pandemic news sentiment could be incorporated as part of the risk factors to map in these regions.

For the specific case of social media (Twitter) sentiment, we found that only the Northern, Southern, and Western European countries have a significant relationship but with a sign contrary to our expectation. Despite the factor loading value is significant but close to zero, the sign of this relation is positive.

For the country-specific review, we found that only Sweden has a significant relation (with the expected sign) to the *VIX* volatility index and Poland has it with the pandemic news sentiment. In the latter, the relationship is positive, a result that needs further review by the fact that it means that an increase of fear (given pandemic news) leads to an increment in Polish stock prices.

**Table 4. The results of our 6 panel regression models with region or country -specific leverage effects**

<i>Variable</i>	<i>Fama-French</i>	<i>Equation (4)</i>	<i>Fama-French+ VIX+ VSTOXX</i>	<i>Fama-French+ WEUI+ WPUI+ TWITUI</i>	<i>Equation (4) with region ef- fect</i>	<i>Equation (4) with country ef- fect</i>
<i>MKT</i>	0.843***		0.843***	0.835***	0.835***	0.835***
<i>SMB</i>	0.712***		0.713***	0.716***	0.717***	0.717***
<i>HML</i>	0.373***		0.372***	0.396***	0.396***	0.396***
<i>VIX</i>		-0.011***	-0.006***		0.015**	
<i>VSTOXX</i>		-0.008***	0.005***			
<i>WEUI</i>		-0.001***		0.0001**	0.001**	
<i>WPUI</i>		0.013***		0.008***	0.028***	
<i>TWITUI</i>		-0.007***		-0.002***	-0.008***	
<i>I(Northern Europe):VIX</i>					-0.024***	
<i>I(Southern Europe):VIX</i>					-0.022**	
<i>I(Western Europe):VIX</i>					-0.023***	
<i>I(Northern Eu- rope):VSTOXX</i>					0.014**	
<i>I(Northern Eu- rope):WPUI</i>					-0.023***	
<i>I(Southern Eu- rope):WPUI</i>					-0.020**	
<i>I(Western Europe):WPUI</i>					-0.019***	
<i>I(Northern Eu- rope):TWITUI</i>					0.006**	
<i>I(Southern Eu- rope):TWITUI</i>					0.007**	
<i>I(Western Eu- rope):TWITUI</i>					0.008***	
<i>I(Sweden):VIX</i>						-0.021*
<i>I(Poland):WPUI</i>						0.026**
<i>I(Finland):TWITUI</i>						-0.011**
<i>I(Ireland):TWITUI</i>						-0.016**
<i>I(Netherlands):TWITUI</i>						-0.009*
<i>I(Poland):TWITUI</i>						-0.014***
<i>I(Spain):TWITUI</i>						-0.012*
<i>I(Sweden):TWITUI</i>						-0.012**
<i>Adjusted R<sup>2</sup></i>	0.1260	0.0010	0.1260	0.1270	0.1280	0.1280

Source: Own elaboration with data from our analysis and data from Refinitiv (2021) and Baker, Bloom, and Davis (2016a)

Finally, the impact of uncertainty, given the fear perceived in social media is significant and with the expected sign in countries such as Finland, Ireland, the Netherlands, Poland, Spain, and Sweden. Therefore, the risk and asset pricing models should include the social media news sentiment as part of these.

As a corollary of results, we found that extending the FF factor model with pandemic news volatility indexes leads to marginal benefits in countries such as Sweden. Despite that a full European or region-specific view suggests a significant relation, it only holds in the Swedish case. Therefore, the inclusion of volatility indexes in a FF factor model context is left for further research. This is so by the fact that only Swedish stocks suggest having the expected relation.

Our results also suggest that most of the countries in our sample could use the FF factor model and extend it with social media sentiment factors such as the Twitter uncertainty index used herein (*TWITUI*).

#### 4. CONCLUSIONS

Behavioral Finance has its developments in the need of extending the current Classical Financial Economics models that assume an investor's rational (emotions-free) behavior. Despite this assumption simplifies the use of Classical Financial Economics models, their assumptions have several drawbacks that do not explain phenomena such as asset price bubbles or unexpected crashes. Also, the main assumptions of well-known models, such as the Capital Asset Pricing, have failed to pass empirical tests. This is due to the lack of other non-rational aspects such as feelings or investor sentiment that are not captured or discounted in the asset's price. Departing from this, several improvements have been made to explain and measure the impact of non-informational and rational issues, as is the case of the Fama-French (1996) three-factor model (FF). This model includes a size and capitalization factor, to proxy the not-so-rational investor's decisions. Despite this improvement, this and almost all the Classical models are not enough to explain the phenomena such as bubbles or crashes. Given this, Behavioral Finance has found ways to improve the Classical models by incorporating market sentiment proxies such as volatility indexes, confidence polls, or even news or social-media text-based sentiment indices. In the present paper, we extended and tested, for the main European stock exchanges, the FF model by including the European VSTOXX volatility index and its U.S. counterpart, the VIX. Also, we tested the benefit of using the Baker, Bloom, and Davis (2016b) Global Economic policy news uncertainty index (WEUI), the Baker, Bloom, Davis, and Kost (2019) Global infectious diseases (epidemic and pandemic) uncertainty index (WPUI), and a Global social-media (Twitter) uncertainty index (*TWITUI*) suggested by Baker, Bloom, Davis, and Renault (2021). With a weekly balanced panel of 659 stocks of companies of Eastern, Southern Northern, and Western Europe companies, with 54 weeks, we found that the fixed-effects models were the most suitable in our tests. With a European, regional, and country-specific perspective in our analysis, we found that our suggestion of including these five sentiment factors holds in a European perspective, but when we observed the country-specific one, we found that including the VIX leads to a significant relation only in Sweden. Related to the three news uncertainty indexes, we found that only Twitter or social media should be incorporated in the FF model in Finland, Ireland, the Netherlands, Poland, Spain, and Sweden.

With our results, we conclude, considering our tests and data, the FF factor model could be useful in these last six countries if we extend it with the inclusion of a social media (Twitter) based market sentiment index. Our position that the use of a epidemics or pandemics uncertainty index could enhance the power of the FF model is not proved as true in our results. This suggests that better pandemics news sentiment methodologies should be developed to enhance factor models.

As guidelines for further research, we suggest developing and test the inclusion of other social media, pandemic news, or simply news sentiment indexes and extending our work for risk management or portfolio selection applications. Also, the extension to other regions could be of use.

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