EQUITY MARKET VOLATILITY IMPACT ON S&P 500 SECTOR INDEXES, 1989-2021

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Abstract

This paper analyzes the relationship between the Equity Market Volatility Index and the nine S&P 500 sectors indexes, as well as investigating which of the 42 category-specific Equity Market Volatility (EMV) trackers has a greater impact on each sector index. To achieve this purpose, ARDL and NARDL models are proposed to measure the sector index response to EMV index. To examine which categories of EMV trackers most influence the dynamics of each sector index, an artificial neural network is employed. Findings suggest that there is a symmetric, negative, and significant impact of the EMV on all sector indexes. Energy, materials, and financials are the sectors most sensitive to changes in EMV. The ANN results demonstrate that EMV Categorical Trackers describe accurately the sector indexes return. Although each sector reacts to different categories, the factors that affect two or more sectors are: commodity markets, financial regulation, exchange rates, and trade policy

Key words: S&P 500 Indexes, Equity market

JEL Codes: C58; G11; D87; C22

1. Introduction

According to Bhowmik (2013) a country's depression turned into serious volatile stock market which cannot disappear in the short run. Political instability, bad news and chaos have an adverse effect on stock market which spreads volatility. In the light of the recent crises and turmoil events during the last three decades: emerging markets (1994-Mexico, 1997-Asia, 1998-Russia, and 1999-Brazil), dot com, subprime, sovereign debt and COVID 19 recessions, researchers, practitioners, and economic authorities raised their interest for studying the relationship between volatility and stock indexes.

The stock market is a crucial space for companies and, therefore, for the economy. This market allows companies to finance their operations, expanding their resources through initial or subsequent public offerings. Theoretically, a negative relationship is recognized between the stock market and volatility, which is a measure of risk associated with it. If the risk associated with the price of their stock's increases (higher volatility), two reactions may occur: i) investors will expect higher returns or ii) shareholders will change the composition of their investment portfolios, favoring other less risky assets. Both mechanisms will negatively affect the situation of companies: smaller demand for equities tends to lower stock prices and an uncertain environment generates higher financing costs, increasing the cost of capital. This last idea is the base of the volatility feedback hypothesis, which states that high volatility tends to raise expected stock market returns, diminishing asset prices (Campbell and Hentschel, 1992 and French, Schwert and Stambaugh, 1987).

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Due to stock market volatility importance, several literature has been developed around this topic. Initial studies address the augmented volatility since 1980 and its causes (Schwert, 1990), volatility drivers over time (Schwert, 1989), the relationship between volatility and business cycle (Hamilton and Ling, 1996), volatility and macrofundamentals (Engle & Rangel, 2008; Asgharian, Hou & Javed, 2013; Engle, Ghysels & Sohn, 2013).

In terms of how measure volatility numerous indicators and models have been developed to capture in a better way stock market returns variations. One of the most popular volatility indexes is the Chicago Board of Exchange market Volatility Index (VIX). It was introduced in 1993 and is an average of the S&P500 option (OEX) implied volatilities. It represents a market-consensus estimate of future stock market volatility over the next 30 calendar days (Whaley, 2009).

Based on VIX index, empirical studies have examined the volatility impact on international equity markets (Bagchi, 2012; Dutta, Nikkinen & Rothovius, 2017; Cheuathonghua, 2019). Some other research has focused on the relation between VIX and stock index ETF (Chen & Huang, 2014 and Chang, Hsieh & McAleer, 2016 and 2018). VIX and portfolio management is another related line of investigation, Berkowitz & DeLisle (2018) analyze the index as an asset and evaluates its incorporation in a portfolio, Copeland & Copeland (1999) develop rotation strategies using VIX, Deng, McCann & Wang (2012) analyze VIX futures in the hedging designing.

More recently, Baker *et al.* (2019) created the Equity Market Volatility (EMV) tracker which is a newspaper-based index, and it moves with CBOE Volatility Index (VIX) and with the realized volatility of returns on the S&P 500. The EMV is a risk measure which reflects the expected investors' market sentiment (optimism-pessimism) and it is employed to design investment strategies both to prevent losses, as well as to maximize profits. One useful index to trail market sentiment is the Equity Market Volatility (EMV) created by Baker *et al*. (2019).

The EMV index is designed based on newspaper headlines, employing text mining techniques. To estimate the EMV overall tracker Baker *op cit* proposed 42-category specific EMV trackers. Those variables are helpful to describe the weight of each category in the level of the U. S. capital market volatility and its time-varying performance.

Because of the level of detail provided by EMV category-specific trackers and because according to Zhu, *et al* (2019) the EMV index is superior to VIX in forecasting volatility. EMV index have been selected to: i) analyze the impact of volatility on sector index returns and ii) investigate which category-specific trackers are more relevant to describe the dynamics of each sector.

Due to its advantages, EMV index and its category-specific trackers have been extensively employed to analyze the impact of policy news on stock market volatility (Baker, *et al.* (2019), to investigate the relationship between the equity market uncertainty and crude oil volatility (Dutta, Bouri & Saeed, 2021), to measure the impact of EMV on international stock markets (Algahtani *et al.,* 2020), to study the COVID-19 impact on stock markets (Baker *et al.,* 2020).

In terms of sector index research, vast literature has been developed above all about volatility spillovers among different sectors. Feng, *et al.* (2018) analyzes the spillover relations among sector indexes in the Chinese stock market. Evidence suggests there are direct and indirect connections among sectors and depending on the time scale, the most influential and sensitive sector is different. Tarazi & Hazan (2015) examine the influence of volatility of six foreign exchange rates in six Australian sectors. Results show an important and significant effect of exchange rate volatility on sectors dynamics, except for the health care sector during global financial crisis (GFC) and banks before the GFC. Kirkpinar (2020) investigates the volatility spillover between to major sector indexes in Borsa Istanbul, employing multivariate GARCH model and Granger causality. Findings corroborate a spillover phenomenon and bivariate causal relationship. Malik (2021) studies the volatility spillover among the main US equity sectors (Financial, Technology, Energy, Health, Consumer and Industrial) with bivariate GARCH models during April 2006-March 2021. Spillover is corroborated as well as the importance of incorporate structural breaks to improve the estimation results.

Closely related to this research, Nogueira and Pinho (2020) analyzes the impact of covid-19 and investor sentiment on the US and European sector returns. They applied random-effects robust panel estimation. Results show that the US returns are more sensitive to sentiment compared to Europe, and that country factors influence the returns differently. A general conclusion is that negative sentiment (volatility) is associated with returns in the US global index and in tourism and real estate. In Europe that sectors were also affected but in a lower level than in the US, being the automobile industry also negatively impacted.

Another research with a strong relationship to this paper is developed by Alqahtani *et al.*, (2020) analyze the long-run impact of EMV on nine major international stock markets employing during the period december/2001-August/2018. As in our case, they employ the Non-Linear Auto Regressive-Lag Distributed Model (NARDL). Results indicate there is a significant, symmetric, and negative relationship between stock market returns and volatility.

Based on previously mentioned, this paper aims to analyze the long-run effects of Equity Market Volatility (EMV) Index on nine S&P 500 sectors indexes: Information Technology, Energy, Health Care, Industrials, Materials, Consumer Discretionary, Consumer Staples, Financials and Real Estate. To achieve that purpose, we used monthly data from October/1989 to August/2021. We proposed an ARDL and NARDL models to measure the sector index response to EMV index. Once the long-run relationship between EMV and each sector index is evidenced, a Neural Network Approach is applied to examine whether the 42 category-specific trackers accurately explain the sector index returns and which are the main drivers for each of the nine sectors.

The empirical framework, first, allows us to determine the magnitude, sign, and significance of the long-run relationship between EMV and each of the nine sectoral indexes, considering asymmetric effects, and second, the ANN model evidences whether the 42 category-specific trackers describe sectoral index returns and which categories are the main determinants of sectoral index performance.

This study contributes in a number of ways, it studies the long-run relationship between the volatility and nine S&P 500 sector indexes, including possible asymmetric effects. Second, analyzes the main determinant categories of sector indexes returns. Third, the data sample is innovative, we employed a EMV text-based index. Fourth, the sample data considered in the research includes several crisis periods (1994,1997, 1998, 2001, 2007-2008, 2012 and 2020-2021) which significantly affected in performance of financial market. As far as known, there is none existing study which analyzes the asymmetric risk-return relationship in the US sector indexes, using the EMV index as volatility proxy, as well as the influence of specific categories in sector index dynamics.

This research is structured in 4 sections, the second part presents the data and describes methodology. Section three analyzes the research findings and, the fourth section concludes the paper.

2. Data and methodology

Monthly data from the EMV tracker have been available since January 1985, but the availability of sector indexes is less and varied (see Table 1). Thus, the data were used based on their accessibility. Therefore, in the ARDL and NARDL models, the global EMV tracker[1] was the independent variable, and the return of each sector index[2] was the dependent variable, i.e., for the information technology sector the period studied was October 1989 to August 2021, while the real estate sector was analyzed from November 2001 to August 2021.

Table 1. Data

Series		Period
EMV[1]		October, 1989
S&P 500 Sector Index	Information Technology	October, 1989
	Energy	October, 1989
	Health care	January, 1990
	Industrials	January, 1991
	Materials	January, 1992
	Consumer discretionary	January, 1991
	Consumer staples	January, 1991
	Financials	January, 1991
	Real Estate	November, 2001

Source: Own elaboration

[1] Equity Market Volatility Index and the 42 category specific trackers were obtained from: https://www.policyuncertainty.com/EMV_monthly.html

[2] Sector Indexes data were download from investment webpage: https://mx.investing.com/indices/us-spx-500

Once NARDL and ARDL models analyze the long-term relationship between stock market volatility and each sector index. ANN models are used to investigate whether the 42 category-specific EMV trackers accurately describe the performance of the sector index and what are the main determinants of each sector's performance. For each ANN model, the dependent variable is the sector index, and the input variables (exogenous variables) are the data from the 42 category-specific trackers. As in the ARDL and NARDL models, according to the data availability (see Table 1), each ANN model is executed.

The 42 category-specific EMV trackers are shown in Table 2, they include diverse indicators related with Policy, Macroeconomic, Regulation, Financial markets, Commodity prices, Health and Pandemics.

Table 2. 42 category-specific EMV trackers

Policy-Related	Macro – Consumer Spending and Sentiment	Government Spending, Deficits, and Debt	National Security Policy
Infectious Disease	Commodity Markets	Entitlement and Welfare Programs	Government-Sponsored Enterprises
Macroeconomic News and Outlook	Financial Crises	Monetary Policy	Trade Policy
Macro – Broad Quantity Indicators	Exchange Rates	Regulation	Healthcare Policy
Macro – Inflation	Healthcare Matters	Financial Regulation	Food and Drug Policy
Macro – Interest Rates	Litigation Matters	Competition Policy	Transportation, Infrastructure, and Public Utilities
Macro – Other Financial Indicators	Competition Matters	Labor Regulations	Elections and Political Governance
Macro – Labor Markets	Labor Disputes	Energy and Environmental Regulation	Agricultural Policy
Macro – Real Estate Markets	Intellectual Property Matters	Lawsuit and Tort Reform, Supreme Court Decisions	Petroleum Markets
Macro – Trade	Fiscal Policy	Housing and Land Management	
Macro – Business Investment and Sentiment	Taxes	Other Regulation	

Source: Own elaboration based on Baker *et al.* (2019)

Graph1 shows a comparison with other international indexes.

Index	Period	Return for the period
Nikkei	feb/1989-dec/2021	677%
HSI	feb/1989-dec/2021	677%
S&P 500	feb/1989-dec/2021	1550%
NASDAQ	feb/1989-dec/2021	3814%
DJIA	feb/1989-dec/2021	1509%
CAC	mar/1990-dec/2021	250%
FTSE	feb/1989-dec/2021	260%
IBEX	ago/1993-dec/2021	255%

Sectoral Composition

3. Methodology

The stock market index provides evidence of general market conditions, showing the average performance of the main companies in a given economy. However, there are several economic sectors, and their performance differs according to their nature (intrinsic characteristics) and sensitivity to common factors, such as, for example, market volatility. Therefore, this paper aims to analyze how each sector index reacts to changes in volatility and to the specific trackers of each category. For this purpose, a combined methodology is proposed. First, a nonlinear autoregressive distributed lags (NARDL) model is proposed to analyze whether EMV has a significant and long-run relationship with each sector index, and if the response of each sector index is asymmetric, i.e., whether positive and negative news have a different impact.

Once the long-run relationship between EMV and each sector index is evidenced, a Neural Network Approach is applied to examine whether the 42 category-specific trackers accurately explain the sector index returns and which are the main drivers for each of the nine sectors.

NARDL model

The NARDL model was selected because of the advantages it offers. The estimation of the NARDL model allows estimating considering different integration orders, allowing mixing I(1) and I(0) series. Second, it measures the cointegration relationship that may exist between sectoral indexes and the EMV Tracker. Third, this approach allows measuring the linear and non-linear relationships that usually exist between financial and economic series. Fourth, it is composed of a single explanatory equation that differentiates the short- and long-term effects of the explanatory variables on the dependent variable. Finally, it captures the asymmetric effect of positive and negative news of the explanatory variables on the dependent variable. Compared to other models such as the VECM, the introduction of additional variables considerably increases the number of parameters, since the VECM is a system and not a single equation, as in the NARDL model.

The linear ARDL model is described for the following equation

$$\Delta s_t = \alpha + \rho_s s_{t-1} + \rho_x x_{t-1} + \sum_{i=1}^{r} \theta_i \Delta s_{t-i} + \sum_{i=0}^{s} \pi_i \Delta x_{t-i} + \varepsilon_t \quad (1)$$

This paper aims to analyze the impact of the expected investors' market sentiment represented by EMV Tracker on specific sectors of the S&P 500 index: ICT, Energy, Health Care, Materials, Financials, Consumption Discretionary, Consumer Staples and Real Estate. Thus, s_t are the US Sector indexes and x_t is the explanatory variable EMV Tracker; the Δ symbol denotes price changes.

El modelo ARDL tiene varias ventajas sobre los modelos de cointegración convencionales, es parsimonioso y se mantiene simple incluso si las relaciones entre las variables del sistema son no lineales y/o asimétricas. El modelo de cointegración NARDL desarrollado recientemente por Shin *et al.* (2014) permite medir el efecto asimétrico del EMV Tracker en los índices bursátiles a corto y largo plazo. This model measures the independent variable x_t into its positive Δx_t^+ and negative Δx_t^- partial sums for rises and reduces such as:

$$x_t^+ = \sum_{j=1}^{r} \Delta x_j^+ = \sum_{j=1}^{r} \max(\Delta x_j, 0) \ and\ x_t^- = \sum_{j=1}^{t} \Delta x_j^- = \sum_{j=1}^{t} \min(\Delta x_j, 0)$$

The addition of short- and long-term asymmetries in the model represented in equation 1, results in the following NARDL model with long- and short-term asymmetries

$$\Delta s_t = \alpha + \rho_s s_{t-1} + \rho_x^+ x_{t-1}^+ + \rho_x^- x_{t-1}^- \sum_{i=1}^{r} \theta_i \Delta s_{t-i} + \sum_{i=0}^{s} (\pi_i^+ \Delta x_{t-i}^+ + \pi_i^- \Delta x_{t-i}^-) + \varepsilon_t \quad (2)$$

In Equation (2), (+) and (-) terms denote the positive and negative partial sums decompositions previously calculated. The long-run asymmetry is measure by ρ^+ and ρ^-, while the short-run asymmetry is represented by π^+ and π^-. Hence, long-run asymmetry is evidenced using Wald test of the null $\pi^+ = \pi^-$, for $i = 0,1, \dots s$. Some of the advantages of ARDL-type models are that they allow us to assess the sign, magnitude and significance of changes in the EMV on the returns of U.S. sectoral indexes. In addition, the speed of adjustment to long-run equilibrium is also evaluated using the NARDL framework.

The long-run effect of EMV variations on sector indexes returns are estimated utilizing the long-run coefficients $L_{c+=}\rho_c^+/\rho_s$ and $L_{c-=}-\rho_c^-/\rho_s$ following a positive and a negative change of EMV change, respectively.

Artificial Neural Network

The artificial neural network (ANN) model is a flexible structure that attempts to represent a biological neural system. It can perform nonlinear approximation and classification processes (Fischer, 2015). In this paper, a Multi-Layer Perceptron (MLP) network based on the backpropagation learning rule is employed to analyze whether the category specific EMV trackers accurately describe the performance of the sector index.

Multilayer perceptron

Multilayer perceptron (MLP) is one of the most popular ANN in the case of non-linear mapping, it is also called “Universal Approximator”. It consists of three types of layers: input layer, hiding layer and output layer. Input nodes receive data values and pass them to the hidden layer nodes. Each collects the input from all input nodes after multiplying each input value by a weight, assigns a bias to this sum, and transmits the results through a nonlinear transformation such as the sigmoidal transfer function. The resulted transformed output from each output node is the network output (see Figure 1).

The network needs to be trained using an algorithm i. e. back propagation, cascade correlation and conjugate gradient. This training task aims to reduce the global error.

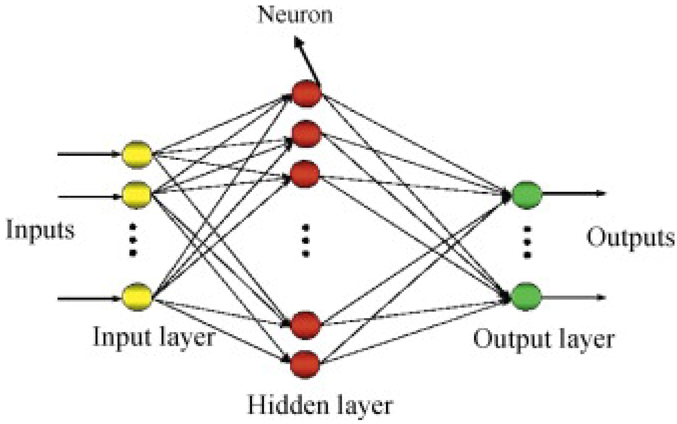


Figure 1 Caption. MLP network structure. Figure 1 Alt text. A diagram showing all the layers of the ANN and the interconnections between them

The ANN separates the data into three different subsets: training, test, and reserve subsamples. The training subsample is used to run the model in the hidden layer; the test subsample allows confirming the adequate learning process, in terms of minimizing the function error; and the reserve subset is not considered in the previous two subsets; it is used to verify the closeness between the data estimated by ANN and the real data to reduce the bias in the estimation (Paule-Vianez, *et al.,* 2019). To measure the overall error, the Mean Absolute Error (MAE) is estimated as follows for each observation:

$$MAE = \frac{1}{n}\sum_{j=1}^{n}\left|y_j - \hat{y}_j\right| \tag{3}$$

Where n is the number of observations, y_j is the target output and $\hat{y}_j$ is the predicted output.

Normalized importance analysis

The ANN approach, unlike econometric models, does not allow us to observe what occurs inside the hidden layers, in terms of the coefficients obtained. Nevertheless, ANN models allow us to obtain information related to the importance of the effect of the exogenous variables on the dependent variable. This analysis is known as variable significance analysis.

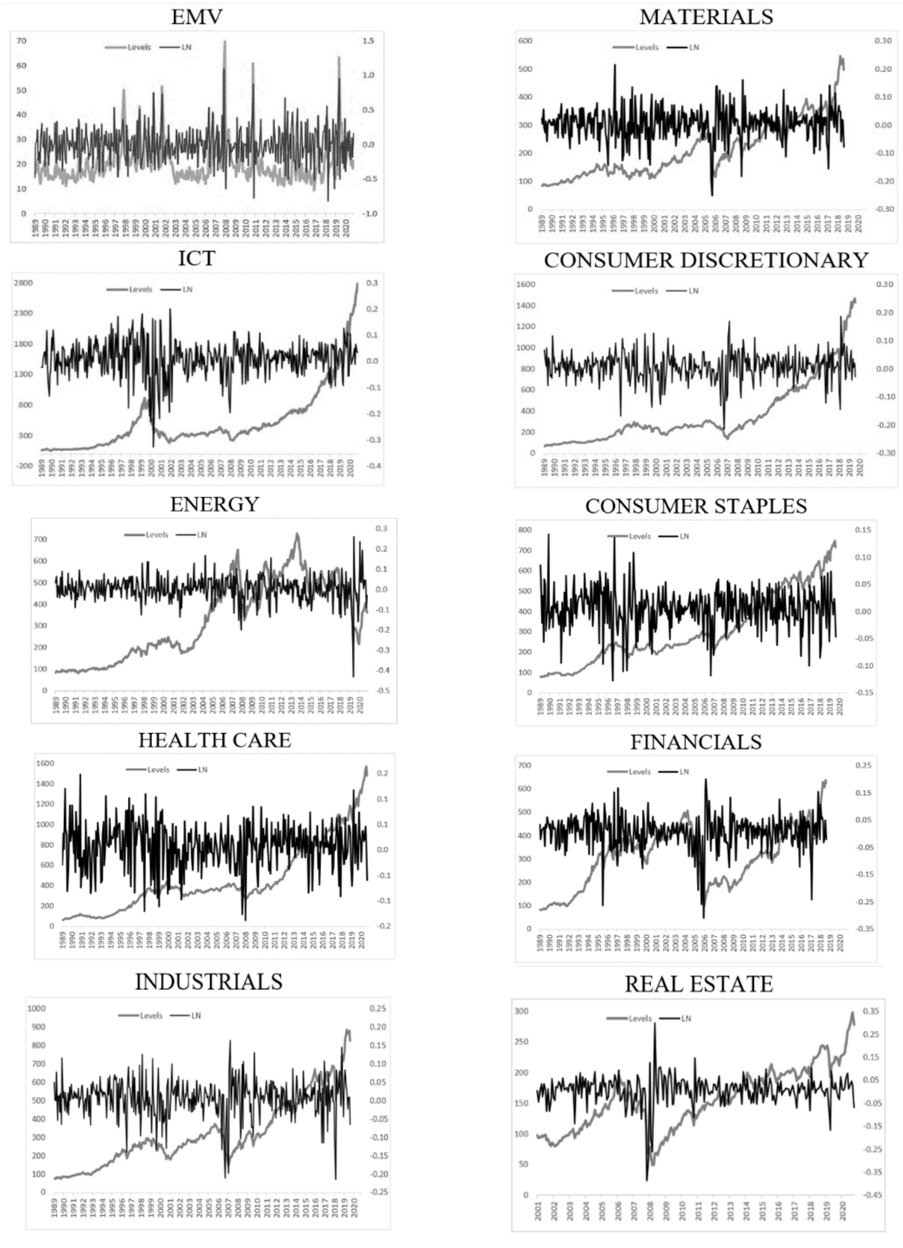
The following function allows the measuring of the synaptic weights of the variables and its impact on the output (Montaño *et al.*, 2002):

$$Q_{ik} = \frac{\sum_{j=1}^{L}\left(\frac{W_{ij}V_{jk}}{\sum_{r=1}^{N}W_{rj}}\right)}{\sum_{i=1}^{N}\left(\sum_{i=1}^{L}\left(\frac{W_{ij}V_{jk}}{\sum_{r=1}^{N}W_{rj}}\right)\right)} \tag{4}$$

The normalized importance is estimated by dividing the importance value of each variable by the highest value of the variables themselves; the result is then multiplied by 100. Hence, the highest value divided by itself is equal to 100; the most important factor has a value of 100.

4. Results

Figure 2 shows the time-series evolution in levels and log-returns. EMV series exhibits extreme variations during 2008, 2011 and at the beginning of 2020. Those dates are consistent with the global financial, sovereign debt and covid-19 crisis. It is important to mention that during the period over study EMV has displayed increasing values and higher variations.



Source: Own elaboration with EPU and Investing web sites

In terms of sector indexes, certain sectors were impacted during 1998 due to the turmoil generated by the Russian and Asian crisis: materials, consumer discretionary, energy, consumer staples, consumer discretionary, financials and industrials. During 2008 all indexes showed important fells produced due to the subprime and the further global financial crisis.

It is important to mention that the trade war and changes in interest rates during 2018 generated certain sectors to fall sharply: materials, consumer discretionary, energy, financials, and industrials. Other important phenomenon was the Covid-19 pandemic which, apparently, has important effects in the following sectors: consumer staples and health care.

Table 3 Shows the descriptive statistics, EMV is the only variable which exhibits negative returns, it means volatility index on average has experienced higher negative changes than positive ones. Index sectors displayed positive average returns, it means that, despite of the pandemics and some other negative and unexpected news, stock market positions resulted in profits for investors; sectors with better results are Information and Communication Technologies (ICT) and Consumer Discretionary (CD). Consistently with the average return sign, EMV index shows positive skewness, while the rest of the series present negative skewness.

Table 3. Descriptive Statistics, ADF and ARCH-LM Test

	EMV	ICT	EN	HC	IND	MAT	CD	CS	FIN	RS
Mean	-0.0009	0.0086	0.0025	0.0058	0.0052	0.0058	0.0077	0.0052	0.0026	0.0047
Median	-0.0104	0.0156	0.0070	0.0086	0.0106	0.0093	0.0096	0.0084	0.0121	0.0100
Max	1.0904	0.2015	0.2597	0.1178	0.1632	0.1621	0.1866	0.0743	0.2003	0.2984
Min	-0.8236	-0.1962	-0.4303	-0.1374	-0.2143	-0.2507	-0.2140	-0.1175	-0.3085	-0.3869
Std. Dev.	0.2693	0.0580	0.0707	0.0384	0.0532	0.0578	0.0512	0.0323	0.0641	0.0643
Skewness	0.4688	-0.5735	-0.8858	-0.5283	-0.9193	-0.6092	-0.4632	-0.7396	-1.2044	-1.5333
Kurtosis	4.8070	4.3208	9.3681	3.8999	5.9347	5.0825	5.0709	3.9973	7.5802	12.71
JB	40.922	30.219	431.454	19.020	118.42	57.486	50.826	31.429	264.45	1024.47
ADF	-12.04*	-19.59*	-20.27*	-20.24*	-18.68*	-18.69*	-18.53*	-18.71*	-16.98*	-6.51*

Source: Own elaboration with estimation results. Note: Jarque-Bera (JB), Standard Deviation (Std. Dev.), Equity Market Volatility (EMV), Information and Communication Technologies (ICT), Energy (EN), Health Care (HC), Industrials (Ind), Materials (Mat), Consumer Discretionary (CD), Consumer Staples (CS), Financials (FIN), Real Estate (RS).

In terms of uncertainty, EMV index was the variable which displayed higher changes (standard deviation of 0.27), fairly followed by Energy (EN) (0.07) and Real Estate (RS) (0.06). Thus, the higher maximum and minimum levels are presented by the EMV index. Real Estate is the sector with the higher maximum level of return and Energy the sector with the lower return (minimum value).

Kurtosis values are above 3. It indicates, series are leptokurtic; distributions are peaky and with heavy and long tails. Jarque-Bera and Augmented Dickey Fuller tests results evidence non-normality and stationarity

As part of the previous analysis, Table 4 presents the correlation matrix between the EMV index and the sectorial indexes. As expected, based on the theoretical framework, the linear relationship between volatility and sector indexes is negative. The Energy sector has the highest level of correlation (-0.3589), followed by Materials (-0.3549) and Industrials (-0.3274). According to this preliminary analysis, Energy, Materials and Industrials are the sectors most affected by nervousness or negative investor sentiment, which is reflected in increased volatility in the overall market.

Table 4 Linear Correlation EMV vs Sector Indexes

INDEX	ICT	EN	HC	IND	MAT	CD	CS	FIN	RS
COEF	-0.3178	-0.3589	-0.2387	-0.3274	-0.3549	-0.3259	-0.2560	-0.2466	-0.1546

Source: Own elaboration with estimation results

As a preliminary analysis, this research performs the Phillips-Perron (PP) and Augmented Dickey Fuller (ADF) unit root tests to test each variable for any second or higher order integrated variables. This test is important because the NARDL model is not suitable if there are any I(2) variables in the estimation.

In Table 5, in the Annex, the unit root tests results are presented for each variable. Results assume variables at levels and first differences (FD), considering constant term (intercept), constant and trend (I&T) and none. In all the cases variables are stationary at levels and first differences. Unit result tests allows us to be sure that there are no I(2) variables.

Once the stationarity is tested in series. Table 6, in the Annex, show the ARDL bound tests for both standard and non-linear specifications.

The Wald-F statistics of the linear and nonlinear models point to a similar finding. The result of the bounds test concludes that sectoral indexes and volatility are cointegrated at the 1% significance level; in other words, there is a significant long-term relationship between the volatility and stock indexes.

Once the cointegration relationship is evidenced, Table 7 presents the long-run relationships estimated by the linear and non-linear ARDL models. As expected theoretically and confirming the results of the linear correlation (Table 4), the relationship between the volatility index and the sector index is negative and statistically significant for all series at 1%. Energy, Financials, and Materials are the sectors with the strongest relationship with volatility changes.

Table 7 also presents the results of the diagnostic tests. The LM test is used to confirm the presence of serial correlation in the error term, while the CUSUM and CUSUM^2 tests allow testing the stability of the parameters ("S" means stable "U" unstable). The LM results are significant in all models, rejecting the null hypothesis of the presence of serial correlation. CUSUM and CUSUM^2 indicate that there is stability in the parameters.

Table 7. Long run relations of ARDL models

	ICT	EN	HC	IND	MAT	CD	CS	FIN	RS
EMV	-0.155*	-0.268*	-0.041*	-0.159*	-0.266*	-0.093*	-0.030*	-0.266*	-0.0910*
LM (2)	0.48604	0.10932	0.16410	0.47838	0.40974	1.12794	0.59218	0.40974	0.093061
CUSUM	S	S	S	S	S	S	S	S	S
CUSUM^2	S	U	S	S	S	S	S	S	S

Source: own elaboration with estimation results. "S" means stable and "U" unstable

Table 8 presents the NARDL model results, to test asymmetry: positive and negative news have a differential impact in sector indexes. NARDL evidence a negative and statistically significant long-run linkage between EMV- and EMV+. Nevertheless, Wald-F results suggest there is a symmetric relationship for most of the indexes, except for Real Estate.

Diagnostic tests, as in the case of linear model, reject the hypothesis of the presence of serial correlation in the error term and confirm the stability in the parameters.

The ARDL and NARDL results are alike and consistent with those obtained by Alqahtani *et al.*, (2020), EMV has a negative and symmetric impact on sector indexes.

Table 8. Long run relations of nonlinear ARDL models

	ICT		EN		HC		IND		MAT		CD		CS		FIN		RS	
EMV+	-0.252	*	-0.107	*	-0.063	*	-1.536	*	-0.101	*	-0.097	*	-0.031	*	-1.432	*	0.168	*
EMV-	-0.006		-0.107	*	-0.078	*	-0.099	*	-0.101	*	-0.097	*	-0.031	*	-0.104	*	-0.018	*
WALD-F	0.524		0.251		0.029		0.840		0.593		1.615		0.213		0.417		3.518	*
LM (2)	0.105	*	0.332	*	0.332	*	0.493	*	0.342	*	1.179	*	0.620	*	0.622	*	0.015	*
CUSUM	S		S		S		S		S		S		S		S		S	
CUSUM2	U		U		U		S		S		S		U		S		S	

*, **, * denote rejection of null hypothesis at 1%, 5%, and 10%, respectively. The letter "S" and "U" denote stable and unstable estimates from CUSUM and CUSUM^2 tests

Artificial Neural Network Analysis

Once a negative and symmetric long-run relationship between the EMV and sector indexes is validated, the ANN model is employed to confirm whether the components of the EMV accurately describe the performance of each sector, and which specific trackers in each category are the most relevant drivers of each sector's return.

Table 9. ANN Results

		ICT	EN	HC	IND	MAT	CD	CS	FIN	RS
Sample	Reserve set	26	26	23	22	24	22	22	24	17
	Testing set	110	110	105	100	108	100	100	108	92
	Training set	189	189	187	180	174	180	180	174	117
Input layer	Exogenous vars	The 42 EMV Category Specific Trackers								
	Endogenous var	Corresponding Sector Index								
	Number of units	7520	7632	7548	7258	7012	7258	7258	7012	4670
Hidden layer	Hidden layers	1								
	Units first layer	10	7	8	6	12	11	7	6	12
	Activation function	Hyperbolic tangent								
Output layer	Number of units	1								
	Change of scale method	Standardized								
	Activation Function	Identity								
	Error Function	Squared Sum								
Error (%)	MAE	0.0001	0.0223	0.026	0.014	0.004	0.013	0.040	0.001	0.036

Source: own elaboration with estimation results

Table 9 summarizes the ANN results. It shows how the total sample was subdivided in the: reserve set, testing set, and training set. It also indicates which are the exogenous variables (the 42 EMV category trackers), endogenous variable (sector index) and the number of units which are the sample observations, according to the period of study considered for each index. The ANN structure suggests there is one hidden layer, and the activation function is “hyperbolic tangent”. In the output layer, the change of scale method employed is standardized, the activation function is “identity” and the error function “squared sum”.
To test the accuracy of the models, the Mean Average Error confirms the high level of fit, especially in ICT, Financials and Materials sectors, where the error is less than 0.005%. Results also reveal the relevance of the 42 category-specific trackers in explaining the sector indexes returns. The goodness of fit can also be visually verified in Figure 3, where the scatter plot shows the similarity between the "estimated" ANN results and the "real" data; in all cases, R^2 is greater than 0.99.

Once the level of accuracy of the model has been verified, the normalized importance analysis is developed to know which are the main sector index drivers. Table 10 shows the results for each sector. In terms of the pandemics and how the phenomenon impacts the sectors activity, surprisingly ICT sector is the only which this category is relevant. Other relevant factors for ICT sector are related to interest rates, intellectual property, healthcare policy and legal matters.

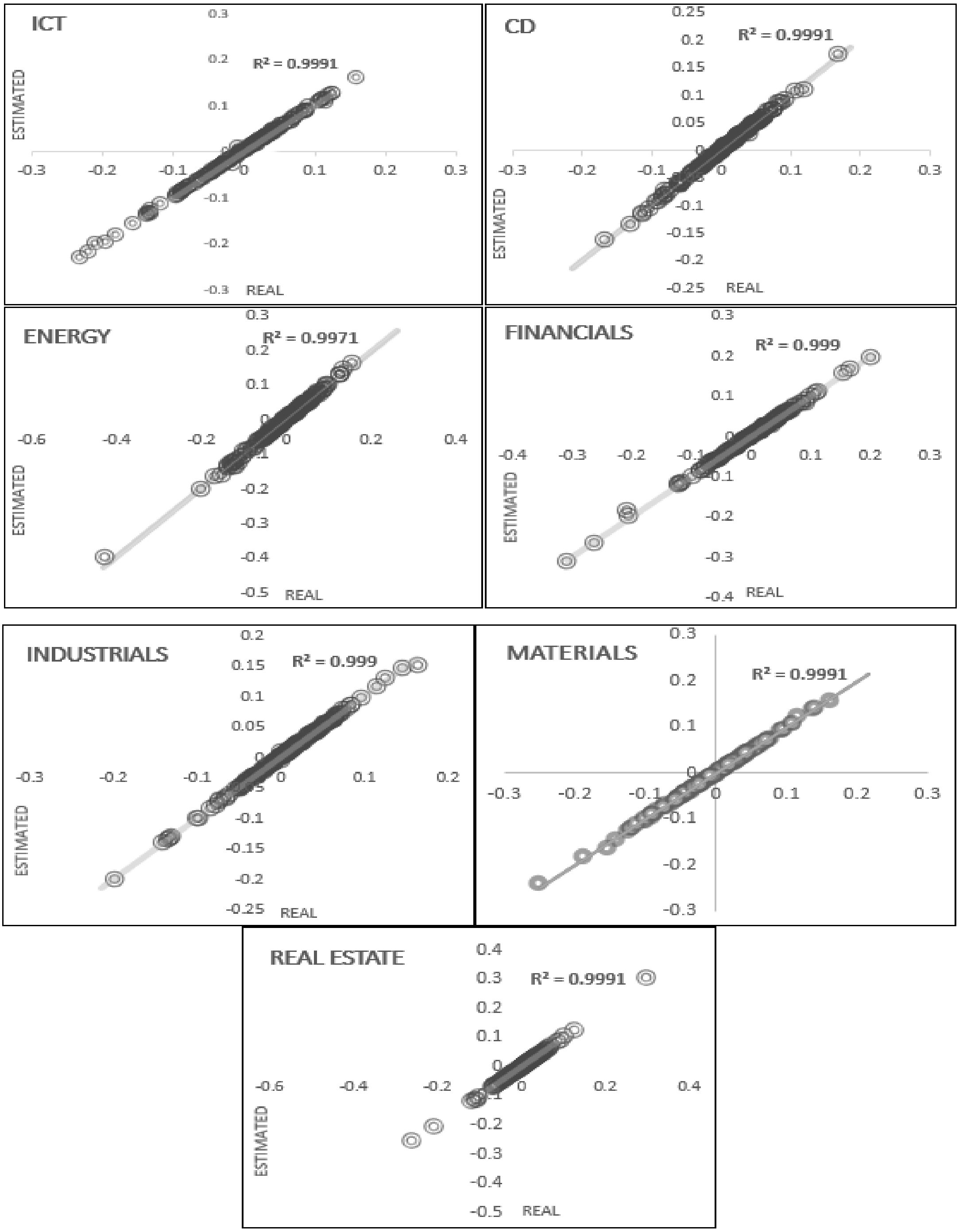


Figure 3 Caption. ANN Estimated vs Real values
Figure 3 Alt text: scatter plots shown how similar are the estimated and the real data. In all the cases, data exhibits a linear and positive relationship, close to 90°.
Source: own elaboration with estimation results

Table 10. Normalized importance analysis results – 5 main determinants

#	ICT	EN	HC	IND	MAT	CD	CS	FIN	RS
1	Macro – Interest Rates	Lawsuit and Tort Reform, Supreme Court Decisions	Exchange Rates	Financial Regulation	Financial Crises	Labor Disputes	Commodity Markets	Labor Disputes	Transportation, Infrastructure, and Public Utilities
2	Intellectual Property Matters	Commodity Markets	Macro – Real Estate Markets	Other Regulation	Trade Policy	Monetary Policy	Government Spending, Deficits, and Debt	Macro – Interest Rates	Entitlement and Welfare Programs
3	Healthcare Policy	Macro – Broad Quantity Indicators	Other Regulation	Labor Disputes	Regulation	Taxes	Food and Drug Policy	National Security Policy	Macro – Broad Quantity Indicators
4	Lawsuit and Tort Reform, Supreme Court Decisions	Exchange Rates	Labor Disputes	Elections and Political Governance	Agricultural Policy	Entitlement and Welfare Programs	Competition Policy	Entitlement and Welfare Programs	Trade Policy
5	Infectious Disease	Financial Regulation	Agricultural Policy	Intellectual Property Matters	Macro – Labor Markets	Financial Regulation	Immigration	Lawsuit and Tort Reform, Supreme Court Decisions	Competition Matters

Source: Own elaboration with estimation results

The energy sector is very sensitive to legal issues, commodity markets, general quantitative indicators, exchange rates and financial regulation. These results highlight the vulnerability of energy index returns due to changes in financial variables and international markets; this fact could be related with the liberalization of energy sector internationally (Tulloch, Diaz-Rainey & Premachandra, 2018).

The main drivers for health care (HC) index are exchange rates, real estate markets, regulation, labor disputes and agricultural policy. Findings are consistent with other studies which identifies the importance of exchange rate (Chowdhury y Tiwari, 2020) and real estate (Terris & Myer, 1998) for health care stocks.

The more important categories to explain industrials sector performance are financial regulation, other regulation, labor disputes, elections and political governance and intellectual property matters. It seems to be a very sensitive sector to legal and regulation matters. Literature identifies that regulation about pollution (Wen, Wu & Gong, 2020; Pham, Ramiah & Moosa, 2020), capital structure (Muradoğlu & Sivaprasad, 2012) and labor flexibility (Edmans, Li and Zhang, 2014) has important effects on industry profits and on industrials stock returns.

Materials index returns are sensitive to financial crisis, trade policy, regulation, agricultural policy and labor markets. These results are in line with expectations since the materials sector is made up of companies focused on discovering, developing, and processing raw materials. The materials sector is deeply related to the economic cycle (crisis) and construction sector, and is exposed to foreign trade, being the agricultural policy basic for its performance; because it is a labor-intensive sector, the labor market is key to develop the above-mentioned activities (Considine, 1991).

Consumer discretionary returns mainly respond to labor disputes, monetary policy, taxes, entitle and welfare programs and financial regulation. All those categories affect the employment rate, yield and prices, factors that theoretically impact the level of consumption.

The categories which better explain the consumer staples sector performance are: i) commodity markets, which are an important part of basic basket products, ii) government spending that impacts the level of income, iii) food and drug policy, laws, regulations, policies and procedures related to basic products, iv) competition policy, that impacts the markets structure and, v) migration, the U.S. economy is made up of a large number of immigrants; changes in immigration policy lead to changes in expectations that affect the level of consumption.

Financial sector returns are affected by labor disputes, interest rates, national security policy, aid and welfare programs, and lawsuit and tort reform, Supreme Court decisions. The interest rate is one of the most important drivers of financial income and a relevant source of risk. On the other hand, social welfare programs are related to income and living conditions that determine people's indebtedness. Regarding legal and labor issues, financials sector is very sensitive to the news generated in those categories.

The real estate sector returns are affected by: a) transportation, infrastructure and public utilities, which are determinants of access; b) entitlement and welfare programs, measures focused on increasing the purchasing power and well-being of the population, which includes housing and basic rights infrastructure; c) broad quantity indicators, including those related to the expansion or contraction of the credit which has an impact on mortgage rates and home sales; d) trade policy, which basically affects the economy's expectations and the cost of imported raw materials used in construction; e) competition matters, which enhance general changes in markets: innovation, prices, market structure, etc.

Despite of the fact that, each sector has proper dynamics and is driven by different categories, there are key factors which impacts more than one sector. Those common factors are: i) commodity markets which are important to describe energy and consumer stables indexes; ii) financial regulation is relevant for industrials, energy and consumer discretionary; iii) exchange rates category has important effects on energy and health care; iv) trade policy is of importance for materials and real estate. Those categories most be of especial interest for economic authorities and policymakers because changes in common categories could have a systematic impact.

5. Summary and Conclusions

This research aims to analyze the long-term relationship between the Equity Market Volatility index, as market sentiment *proxy*, and nine sector index of the S&P 500, as well as, to examine which category-specific EMV trackers are the main determinants of the index sector performance. Methodology employed consists of ARDL and NARDL models to investigate EMV influence on sector indexes. Artificial Neural Network is also applied to determine if category-specific EMV trackers explain accurately the sector index behavior, and which are the main drivers for each sector.

Results evidence a significant, negative, and symmetric long-run linkage between the volatility index and the sector indexes. ANN empirical findings suggest EMV trackers are factors which describe the index sector returns with a high level of accuracy (error lower than 0.001%). The normalized importance analysis point to the categories that affect two or more sectors are: commodity markets, financial regulation, exchange rates, and trade policy.

Results are of outmost importance for investors, policy-makers, financial and economic authorities. First, it is analyzed the possible asymmetric risk-return relationship in the US sector indexes, using the EMV index (market sentiment). Second, results allow us to identify systematic risk categories for each sector.

Future research agenda might include other volatility, uncertainty, or investor sentiment index, broaden the country sample, and propose other approaches to compare results.

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Annex on line: https://www.usc.gal/economet/eaat.htm

Annex:

Table 5. Unit Root Test Augmented Dickey Fuller and Phillips Perron

Variable		ADF				PP			
		Levels		FD		Levels		FD	
EMV	Intercept	-12.041	*	-13.082	*	-132.982	*	-189.828	*
	I & T	-12.024	*	-13.063	*	-132.418	*	-189.675	*
	None	-12.056	*	-13.100	*	-130.788	*	-190.039	*
CD	Intercept	-18.536	*	-11.030	*	-18.529	*	-144.742	*
	I & T	-18.520	*	-11.016	*	-18.512	*	-145.035	*
	0.None	-18.101	*	-11.046	*	-18.090	*	-145.006	*
CS	Intercept	-18.716	*	-13.230	*	-18.715	*	-101.490	*
	I & T	-18.701	*	-13.209	*	-18.701	*	-101.393	*
	None	-18.272	*	-13.249	*	-18.257	*	-101.611	*
ENERGY	Intercept	-20.275	*	-15.446	*	-20.281	*	-142.807	*
	I & T	-20.316	*	-15.426	*	-20.336	*	-142.217	*
	None	-20.215	*	-15.467	*	-20.218	*	-143.039	*
FIN	Intercept	-16.990	*	-12.469	*	-17.064	*	-71.378	*
	I & T	-16.978	*	-12.450	*	-17.048	*	-71.210	*
	None	-16.887	*	-12.487	*	-17.007	*	-71.514	*
HC	Intercept	-20.240	*	-14.876	*	-20.227	*	-101.408	*
	I & T	-20.223	*	-14.849	*	-20.211	*	-100.961	*
	None	-19.562	*	-14.896	*	-19.876	*	-101.547	*
ICT	Intercept	-19.597	*	-14.897	*	-19.597	*	-140.662	*
	I & T	-19.581	*	-14.878	*	-19.581	*	-140.178	*
	None	-19.253	*	-14.918	*	-19.295	*	-140.942	*
IND	Intercept	-18.684	*	-12.625	*	-18.687	*	-100.969	*
	I & T	-18.661	*	-12.604	*	-18.664	*	-100.663	*
	None	-18.419	*	-12.643	*	-18.458	*	-101.192	*
MAT	Intercept	-18.697	*	-12.254	*	-18.699	*	-129.538	*
	I & T	-18.674	*	-12.234	*	-18.676	*	-128.957	*
	None	-18.582	*	-12.272	*	-18.582	*	-129.850	*
RE	Intercept	-6.513	*	-17.660	*	-14.117	*	-39.086	*
	I & T	-6.509	*	-17.622	*	-14.094	*	-38.964	*
	None	-6.445	*	-17.699	*	-14.106	*	-39.199	*

Null hypothesis: time series has unit root test. *, **, * denote rejection of null hypothesis at 1%, 5%, and 10%, respectively.

Table 6. ARDL Bound Test Results

INDEX	Standard ARDL model EMV (K=1)		Standard NARDL model EMV (K=2)	
ICT	91.18027	*	47.44533	*
ENERGY	217.2278	*	29.86201	*
HC	12.88437	*	8.797601	*
INDUSTRIALS	195.2531	*	136.9689	*
MATERIALS	163.0081	*	112.1501	*
CD	193.0408	*	127.7681	*
CS	177.9811	*	118.1724	*
FINANCIALS	163.0081	*	109.7367	*
RS	26.62981	*	20.26764	*

F-statistic values. Null Hypothesis: No long-run relationships exist. *, **, * denote rejection of null hypothesis at 1%, 5%, and 10%, respectively.