UNIVERSIDAD COMPLUTENSE DE MADRID

FACULTY OF ECONOMICS AND BUSINESS

DEGREE IN FINANCE, BANKING AND INSURANCE

The Dynamic of News. How Information Affects Financial Variables.

BACHELOR'S THESIS

Author: *Rafael Storni Santiago Corrêa*

Supervisor: *Juan Ángel Jiménez-Martin*

ACADEMIC YEAR: 2015-2016

MADRID

Index

Abstract

The transmission of new information among financial markets can be detected by the analysis of causality links between the financial variables related to them. This paper aims to explain the movements of financial assets after experiencing external shocks during the last 16 years: Is there any class of assets reacting faster than others to the generation of financial information? How could they be used in order to forecast the behavior of other series to these shocks? All these are important matters to investors, markets agents and policy makers.

Information was considered to flow across returns and volatility of daily price series. The concept of Granger causality was used to detect links between these magnitudes in the evaluation of vector autoregressive (VAR) models. Empirical evidence reveals different transmission patterns during periods of relative serenity and financial crisis, with gold and euro playing important roles in all the analyzed period. Additionally, during economic turmoil shocks, Brent crude appeared to be an important step in the information flows through international financial markets.

Acknowledgements

A.M.D.G.

To all those who made these University years a period of hope, friendship and true Science.
To my parents, grandparents, brother and sister, for the inestimable support – affective and material – without which it would not have been possible to achieve this academic goal.
To V.M., for the immense generosity of assuming all my projects as if they were her own.
To R.H., for helping me, with infinite patience, to choose those values which guide an entire life.
To all the Complutense lecturers, for their contribution in my realization as student and economist.
To professor Jiménez-Martin, for the solid guidance in the development of this work.

Methodological advice

When Greek mathematician Euclides set the basis of Hellenistic geometry in his «Elements», not a single habitant of Alexandria could imagine that this way of reasoning through a system of axioms and demonstrations would become, many centuries later, the seed of all modern epistemology. Nowadays, however, on very few subjects is the consensus of specialists so extended as on the affirmation of the influence exerted by such speculative orientation over all the science produced since the beginning of rationalism until the most critical schools of 20th century.

The History of Financial thought gives testimony of the several means by which the mentioned geometric logic have also been introduced in the very heart of modern Financial theory: the influence of classical Economics – which provides an analytical approach to the problem of capital accumulation and consume – and the first equilibrium models – derived from the characterization of stock prices as random walk processes carried by Louis Bachelier in the early 1900's – are just some examples of the above mentioned. Be that as it may, what is certain is that, wherever the existence of an object heads the speculation about its causes, there the spirit of Euclidean geometry can be discerned, and Finance most actual emphasis on the numerical consideration of the issue of value creation is not an exception to that schema.

All innovations of the study here introduced can be gathered in two main groups. Firstly, a rigorous structure of principles, postulates and hypothesis was sought according to the nature of an University dissertation. Based on the methodology employed, several propositions were stated in a logical process which main intention was to preserve the totality of the evidence collected and a general interpretative coherence. Some of the contributions of Karl Popper to the theory of knowledge were consciously applied, in special the importance provided to the demarcation of all the presented propositions. Datasets were also object of extensive testing and modelling in order to improve the degree of falsiability of such hypothesis and to provide an exit to the empirical problem of induction. Importance given to the consistency of all paper's structure aims to open a new path for the hypothesis testing in Economics, supported by some interpretative methodology. A second group of innovations, containing all the conclusions related to the empirical analysis, will be extensively discussed along the following sections.

Introduction

The purpose of the present work is to provide an empirically based explanation for the changes occurred, since the beginning of the 2000's, in the flow of information across financial variables, supplying investors with a clearly suitable tool when predicting the future behavior of their portfolios. Such achievement can only be reached through the study of large series of market data. Hence, as innovations are expected to affect the *prices* of financial assets, and once price modelling may sometimes become an extremely difficult task, a first obligatory step in the conception of the introduced investigation seems to be determining an appropriate *space* where such changes of information flows may occur, or what is the same: to fix the correct constraints to the manifestation of the *phenomenon* in discussion.

Consider that all relevant information produced in financial markets successively affects the assets negotiated in these markets: it is possible thus to recognize each stage of the generated information flow by the predictive capacity of one asset's price over the one subsequently reacting to these news. Such predictive connection can be considered as *causal* from a very particular point of view, notoriously formalized by Granger (1969). Even if a more complete theoretical development will be afterwards carried, for the moment, it is enough to know that a popular context for the detection of Granger causality is that of vector autoregressive models, a simple but effective resource when evaluating the interaction of time series.

It is a consensus amongst financial authors that any conclusion about random financial prices can be more easily inferred from its rates of variation, which leads empirical analysis to be performed around the concept of *returns*. Therefore, shifts in the patterns of information transmission trough financial prices are considered to affect first or second moments (*central tendency* and *dispersion* measures¸ respectively) of returns' statistical distribution, which attend to the financial concepts of an asset's return and risk (or volatility, henceforth indistinctly used), respectively. Of all methods available to calculate the mean and variance of daily returns, the use of logarithmic difference for the former and a GARCH-GJR estimation of the latter were selected. These are the magnitudes to be introduced in fifth-order VAR models.

Related financial literature has already employed VAR-based structures when examining the relation of specific variables in markets. For instance, Broadstock, Cao & Zhang (2012), and Kilian & Park (2007) applied similar methods to the dynamics of international oil prices and stock markets, whereas Cologni & Manera (2008) used cointegrated VAR models to measure the influence of oil prices over monetary variables. Other linear methodology will be found in Batten, Ciner & Lucey (2010) when assessing the conditional determinants of precious metals volatilities, and in the evaluation of safe haven properties carried by Ranaldo & Söderlind (2010) with high frequency data. Also, several GARCH variants were used in order to detect volatility links in financial assets: Satkhivel, Bodhe & Kamaiah (2012) opted for bivariate GARCH analysis of the different stock indices, and DCC-GARCH-GJR and BEKK models were respectively applied by Filis, Degiannakis & Floros (2011) and Broadstock & Filis (2014) to the relation existing between oil conditional volatility and stock markets. Any of the described methodologies, however, were applied to the same goals of the paper here introduced.

The particularity of this study lays on the different time spaces used to the estimation of autoregressive models, being the periods comprised in 2000-2015, 2000-2007, 2007-2015, 2009-2010 and 2015-2016 considered to provide distinct patterns in the transmission of news. The analysis of 2000-2007 and 2007-2015 brings into discussion possible structural changes before and after the beginning of the financial crisis, whilst in 2009-2010 strong changes in oil prices were observed, as further discussed. Also, variables belonging to three main categories were chosen (stock and volatility indices, commodities and exchange rates), in order to provide a more global view over the movements of information in international financial markets, with no constancy of similar data selection in all revised literature. Granger causality analysis on price dynamics among the study series is believed to remit to several future interesting lines of investigation, mainly on the linkage between gold and EUR/USD volatilities, gold and VIX returns and the role played by oil prices during global turmoil.

❖❖❖

The upcoming structure of the paper will be as follows: Section I is centered in the theoretical development of the methodology applied in the empirical block. Section II aims to provide a feedback to data modeling based on univariate and bivariate analysis. Sections III and IV apply VAR models to different periods: 2000-2007, 2007-2015, 2015-2016 and 2009-2010. Section V is dedicated to conclusions.

Section I: Methodology

Determination of daily returns first and second moments

A very important methodological issue in Financial literature refers to the possibility of obtaining any conclusion related to the behavior of financial assets price series, empirically proved to work as random walk processes and, consequently, barely compliant to be modelled. Therefore this study, in line with most financial researchers, chooses to infer prices' behavior from the analysis of its rates of change (R_t), considered to replicate the comportment of a random process with defined features.

According to the conceptual framework exposed in the introductory section, new information is believed to affect first and second moments (mean and variance, respectively) of returns' statistical distribution, it means: the return and risk of financial assets. Such assumption can be justified by the well-known linkage existing between riskier securities and the risk premium required by investors when acquiring them. Given the speed of news transmission in highly developed financial markets, analysis will focus on high frequency (daily) returns and volatility.

Daily returns were calculated as the logarithmic difference of daily prices, which matches the definition of instant rate widely accepted in financial literature. Hence, considering $\ln P_t$ and $\ln P_{t+1}$ are i.i.d, it holds that

$$E(R_t) = E[\ln P_{t+1} - \ln P_t] = 0 \ , \qquad [1.1]$$

and that

$$var(R_t) = E\big[[\ln P_{t+1} - \ln P_t]^2 - E[\ln P_{t+1} - \ln P_t]\big] = R_t^2, \qquad [1.2]$$

which are the parameters of a $N(0, R_t^2)$ distribution.

Once an appropriate measure for daily returns is achieved, a next stage would be determining the estimation method of daily volatilities. According to Glosten, Jagannathan & Runkle (1993), given the possibility of volatility clustering during large periods of time, «**[..] a positive as well as a negative sign for the covariance between the conditional mean and the conditional variance of the excess return on stocks would be consistent with theory**», for what «**it is important to empirically characterize the nature of the relation between the conditional mean and the conditional variance [...] as a group**» (p.1780). Such is the main reason to select forecast models based on historical data rather than other models, for instance, those related to option prices. Therefore, in order to heed the possible asymmetries generated by daily returns in the distribution of conditional volatility in each specific market, let

$$E(R_{t+1}|\Omega_t) = \propto + \beta var(R_{t+1}|\Omega_t) \ , \qquad [1.3]$$

given an information set Ω_t.

Consider now a subset G_t with investor's limited information related to the variance of returns. Hence:

$$R_{t+1} = \propto + \beta var(R_{t+1}|G_t) + \varepsilon_{t+1} \ , \qquad [1.4]$$

being $\varepsilon_{t+1} = u_t + \epsilon_{t+1}$, where $u_t = \beta[R_{t+1}^2 - var(R_{t+1}|G_t)]$, it means, the error associated to the prediction of future variance given a lack of information; and $\epsilon_{t+1} = R_{t+1} - E(R_{t+1}|\Omega_t)$ the error associated to the prediction of future returns.

It is known, by definition, that:

$$E(\varepsilon_{t+1}|G_t) = E[u_t + \epsilon_{t+1}] = E[u_t] = 0\ . \qquad [1.5]$$

Therefore, applying in [1.4]:

$$var(\varepsilon_{t+1}) = \varepsilon_{t+1}^2 \qquad [1.6]$$

which will be the specification used for the estimation of a conditional variance model.

[Model specification]

Assume that only effect of new information over the variance of R_{t+1} would be linked to the error observed in this period. Therefore, recalling [1.6], the model to the forecast of daily volatility would be:

$$var(R_{t+1}|G_t) = \omega + \alpha\ var(R_t|G_{t-1}) + \delta var(\varepsilon_{t+1}) + \gamma I_t var(\varepsilon_{t+1}),$$

$$\rightarrow var(R_{t+1}|G_t) = \omega + \alpha\ var(R_t|G_{t-1}) + \delta\varepsilon_{t+1}^2 + I_t\varepsilon_{t+1}^2 \qquad [1.7]$$

where I_t is an indicator which takes value 1 when R_t is negative. The estimation of all parameters is carried through the method of maximum likelihood.

Cross Correlation and Riskmetrics® methodology

As already exposed, shifts in the information course are related, in this study, to the changes observed in the causality patterns of daily returns and volatility of financial variables. Before applying any methodology to detect such changes, however, Section II provides some previous bivariate analysis of returns in order to obtain some evidence which could support the conclusions afterward stated. To this end, contemporary, cross and conditional correlation of daily returns were analyzed in 2000-2015, 2000-2007 and 2007-2015. Contemporary correlation is a broadly recognized measure which does not require further explanation. Notwithstanding, the concepts of cross and conditional correlation chosen will be described below.

Firstly, given two series of daily returns, x and z, related as follows,

$$x_{t+1} = \alpha + \beta z_t, \qquad [1.8]$$

the least square estimation of α and β implies that:

$$\hat{\beta} = \frac{\sum_{t=0}^{n}[(x_{t+1}-\bar{x})(z_t-\bar{z})]}{\sum_{t=0}^{n}(z_t-\bar{z})^2}\ . \qquad [1.9]$$

Assuming i.i.d:

$$\sum_{t=0}^{n}(z_t-\bar{z})^2 = \sum_{t=0}^{n}(z_t-\bar{z})(x_{t+1}-\bar{x})\ , \qquad [1.10]$$

which makes:

$$\hat{\beta} = \frac{\sum_{t=0}^{n}[(x_{t+1}-\bar{x})(z_t-\bar{z})]}{\sum_{t=0}^{n}(z_t-\bar{z})(x_{t+1}-\bar{x})} = \rho_{x_{t+1},z_t} \qquad [1.11]$$

being $\rho_{x_{t+1},z_t}$the definition of cross correlation between x_{t+1} and z_t.

It has also been exposed that the forecast of conditional magnitudes can be better performed by using historical data rather than other implicit measures. Some similar argument may be used when calculating conditional correlation of returns, to which end exponentially weighted moving average (EWMA) based RiskMetrics® methodology is applied.

Assume the EWMA formula of daily variance:

$$var\left(x_{t+1|t}\right) = (1-\lambda)\sum_{s=0}^{\infty}\lambda^s\, var(x_{t-s}) = (1-\lambda)\sum_{s=0}^{\infty}\lambda^s\, E[(x_{t-s} - E(x_{t-s})^2)\ . \qquad [1.12]$$

Recalling [1.1], it is known that $E(x_t) = 0$. Hence:

$$var\left(x_{t+1|t}\right) = (1-\lambda)x_t^2 + \sum_{s=1}^{\infty}\lambda^s\, x_{t-s} = (1-\lambda)x_t^2 + var(x_{t|t-1}), \qquad [1.13]$$

which is written in recursive form.

A similar reasoning can be applied to daily covariance:

$$covar_{t+1|t}(x,z) = (1-\lambda)\sum_{s=0}^{\infty}\lambda^s\, cov_{t+1|t}(x,z) = (1-\lambda)\sum_{s=0}^{\infty}\lambda^s\, E[\big(x_{t-2} - E(x_{t-s})\big)\big(z_{t-s} - E(z_{t-s})\big) \qquad [1.14]$$

$$\rightarrow covar_{t+1|t}(x,z) = (1-\lambda)x_{t-s}z_{t-s} + \sum_{s=1}^{\infty}\lambda^s\, x_{t-s}z_{t-s}$$

$$\rightarrow covar_{t*1|t}(x,z) = (1-\lambda)x_t z_t + cov_{t|t-1}(x,z)\ . \qquad [1.15]$$

Applying the same method to daily variance, it is possible to conclude that:

$$\rho\left(x_{t+1|t}, z_{t+1|t}\right) = \frac{(1-\lambda)x_t z_t + cov_{t|t-1}(x,z)}{\left[(1-\lambda)x_{t-s}^2 + var\left(x_{t|t-1}\right)\right]\left[(1-\lambda)z_{t-s}^2 + var\left(z_{t|t-1}\right)\right]} \qquad [1.16]$$

where $\rho\left(x_{t+1|t}, z_{t+1|t}\right) = \phi(\lambda)$.

[Estimation of λ]

The requirement now is to explore in the most efficient way the relation existent between observed conditional correlation and unknown parameter λ in order to estimate its value.

Recall from [1.2] that $var(x_t) = x_t^2$. Hence,

$$\varepsilon_{t|t-1} = x_t^2 - var(x_{t|t-1})\ , \qquad [1.17]$$

which expected value:

$$E\left(\varepsilon_{t|t-1}\right) = \sqrt{x_t^2 - var\left(x_{t|t-1}\right)^2} = 0. \qquad [1.18]$$

Therefore, the most resourceful value of λ would be, under a minimum MSE criterion:

$$Min_{(\lambda)}\sqrt{\left[n^{-1}\sum_{i=1}^{n} x_t^2 - var\left(x_{t|t-1}\right)\right]^2}, \qquad [1.19]$$

subject to $var\left(x_{i,t|t-1}\right) \geq 0$ and $\lambda \leq 1$.

An analogous process would be set to conditional covariance. Empirical testing assigns a value of 0.94 to λ when using daily data.

VAR estimation and Granger causality

Sections III and IV are the dedicated to the detection of Granger causality between conditional returns and volatilities in the context of vector autoregressive models. Since information is believed to flow, in developed markets, within a maximum period of one week, fifth order models (VAR(5)) were estimated to daily returns and volatilities of a set of six financial assets: Dow Jones, VIX, Brent, Gold (3 p.m. fixing), EUR/USD and JPY/USD exchange rates. Granger causality implies that daily returns and volatilities of one asset are explainable by the returns or volatilities of other asset if the parameters associated to them in vector autoregression are significant. Hence, according to the generation process:

$$x_t = \alpha + \beta_{1(1x5)}z_{1(5x1)} + \beta_{2(1x5)}z_{2(5x1)} + \cdots + \beta_{6(1x5)}z_{5(5x1)} + \varepsilon_t, \qquad [1.20]$$

where $\beta_{(1x5)}$ correspond to the vector containing all the parameters related to the delays of each causing variable, including the delays of x, and $z_{(5x1)}$ is the column containing the corresponding delays of the exogenous and endogenous variables; it holds that:

$$E_t(x_{t+h}|\Omega_t) = E(x_{t+h}|\{z_s|s \leq t\}) , \qquad [1.21]$$

Recall now the definition of Granger causality already presented. By definition, a *cause* is the precursor of an *effect* somehow attached to it.. In the specific case of our paper, however, that daily returns and GARCH-GJR estimated volatilities of any financial asset could anticipate changes in other asset's same magnitudes does not necessarily imply that the *origin* of the latter will be found in the former: in fact, being both assets the links of a same information transmission chain, as previously stated, one could arrive to assume that, not only one series cannot be originated in the other, but also that both are the product of similar subjacent stochastic processes. In more appropriate terms, a process z_t is said to Granger-cause x_t if, given a set Ω_t containing all the information relevant to the behavior of such series at period *t*, it holds that:

$$MSE_x(h|\Omega_t) < MSE_x(h|\Omega_t \backslash \{z_s|s \leq t\}), \qquad [1.22]$$

being $MSE_x(h|\Omega_t)$ the lower mean squared forecast errors of a h-step predictor of x_t and $\Omega_t \backslash \{z_s|s \leq t\}$ the complete information set excepting past and present information of z_t. It is hence possible to infer that not rejecting the null hypothesis to x_t in a T-test of the estimated VAR(5) model would imply that:

$$MSE_x(h|\Omega_t) = MSE_x(h|\Omega_t \backslash \{z_s|s \leq t\}) , \qquad [1.23]$$

which does not attend to the definition previously stated.

Empirical analysis in Sections III and IV departs from this characterization of Granger causality suggesting, however, that the robustness of the conclusions would be improved by applying a F-test to all lags of each daily volatilities and returns before evaluating individually the significant parameters associated to them.

Section II: Data Analysis

Dataset was obtained from Datastream and the Saint Louis FED database. A daily frequency was selected after taking into account the trade-off between accuracy of the information provided and the difficulty to manage it. The main features of the series obtained are exposed in Table 1. It is worth mentioning that the closing hour of the series an element of big importance to the purposes of this investigation, due to the possibility of overlapping markets: GMT+2h refers to Continental Europe time zone, GMT-4h to New York, GMT-5h to Chicago, and GMT+1 to London. All analysis were carried with Gretl.

Table 1. Data description.

	Source	Beginning of the sample	End of the sample	Closing hour
IBEX35	Datastream	2000-1-4	2015-1-20	5:30 p.m. (GMT+2h)
DOW JONES	Datastream	2000-1-4	2015-1-20	4 p.m. (GMT-4h)
SP500	Datastream	2000-1-4	2015-1-20	4 p.m. (GMT-4h)
VIX	St. Louis FED	2000-1-4	2015-1-20	3:15 p.m. (GMT-5h)
BRENT	St. Louis FED	2000-1-4	2015-1-20	4 p.m. (GMT+1h)
TEXAS	St. Louis FED	2000-1-4	2015-1-20	4 p.m. (GMT+1h)
GOLD 10:30 a.m.	St. Louis FED	2000-1-4	2015-1-20	10:30 p.m. (GMT+1h)
GOLD 3 p.m.	St. Louis FED	2000-1-4	2015-1-20	3 p.m. (GMT+1h)
EUR/USD	Datastream	2000-1-4	2015-1-20	4 p.m. (GMT+1h)
JPY/USD	Datastream	2000-1-4	2015-1-20	4 p.m. (GMT+1h)
CHF/USD	Datastream	2000-1-4	2015-1-20	4 p.m. (GMT+1h)
GBP/USD	Datastream	2000-1-4	2015-1-20	4 p.m. (GMT+1h)

2.1. Univariate Analysis

Daily returns were organized under three categories – *stock and volatility indices, commodities* and *exchange rates* – in order to allow a sectorial analysis (Table 2).

Table 2. Descriptive statistics of data.

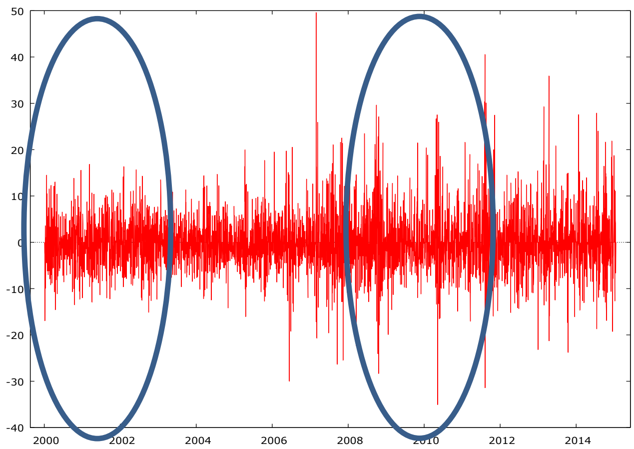
CLASS		EXP. VALUE	C.V.	KURT. EXCESS	SKEW.
Stock and volatility índices	**IBEX35**	-0.0021886	686.937	5.05305	0.0970850
	DOW JONES	0.011853	99.1102	8.44443	-0.060871
	SP500	0.0093811	134.096	8.45176	-0.180566
	VIX	-0.12007	49.2723	4.07362	0.623606
Commodities	**BRENT**	0.010328	202.250	5.28110	-0.411457
	TEXAS	-0.0037577	591.338	5.05140	-0.322215
	GOLD 10:30 a.m.	0.027123	41.1672	6.93941	-0.234965
	GOLD 3 p.m.	0.026491	40.7939	5.64907	-0.360465
Exchange rates	**EUR/USD**	-0.0029622	209.998	2.65866	-0.142368
	JPY/USD	0.0018789	181.070	3.89113	-0.255305
	CHF/USD	0.0035410	48.4468	25.9503	-0.908288
	GBP/USD	-0.014606	306.382	4.41982	0.0548241
CLASS		**5% QUANT.**	**JARQUE BERA**	**LB (1)**	**LB(5)**
Stock and volatility índices	**IBEX35**	-2.47478	4181.93***	-0.0015	-0.0431***
	DOW JONES	-1.84286	11664.3***	-0.0785***	-0.0301*
	SP500	-1.96492	11703.5***	-0.0845***	-0.0341**

	VIX	-9.61061	2757.27***	-0.0951***	-0.0295*
Commodities	**BRENT**	-3.57789	4430.3***	-0.0053	0.0098
	TEXAS	-3.73310	3934.09***	-0.0442***	-0.0407**
	GOLD 10:30 a.m.	-1.77553	7478.16***	-0.0463***	0.0238
	GOLD 3 p.m.	-1.79042	4975.56***	-0.0094	-0.0019
Exchange rates	**EUR/USD**	-1.00647	1169.24***	0.0118	-0.0003
	JPY/USD	-1.01913	2518.8***	-0.0272*	0.0026
	CHF/USD	-1.12236	110672***	0.0172	0.0041
	GBP/USD	-0.899348	3196.72***	0.0357**	-0.0251

Source: own elaboration

Stock indices experienced similar average returns over the study period, even though dissimilar dispersion measures were observed: coefficient of variation for Spanish IBEX 35, the most volatile of all series, appeared to be well above 600, a rather high value if compared to S&P500 and Dow Jones (99 and 134, respectively). Some parallel can be found, however, between the daily returns of IBEX35 and oil as to volatility: Texas returns post the second-highest coefficient of variation (591.338) and both Texas and Brent present a 5% value-at-risk higher than the average (-3.57789 and -3.57789, respectively), the same as the Spanish index (-2.4747). *It is clear how risk patterns change according to the market to which a particular index belongs.* Skewness coefficients are negative for all cases, excepting Spanish markets. All series present high kurtosis excesses, and the Jarque-Bera test undoubtedly rejects the normality hypothesis. Ljung-Box test reveals the presence of serial correlations for both 1 day (excepting IBEX 35) and 5 days. *General conclusion points to the inexistence of significant differences between time series due to the classes to which they belong.*

Figure 1. VIX returns. Time series



Source: own elaboration

As to the Chicago Board Options Exchange Markets Volatility Index (VIX) returns, coefficient of variation indicates one of the lowest variation per unity of return among all studied series (49.27). *High probability of extreme values and strong serial correlations point towards the existence of volatility clusters* (see Figure 1). As mentioned in Mandelbrot (1963), **«large changes [in prices] tend to be followed by large changes – of either sign – and small changes tend to be followed by small changes [...]»**, being the reason why

«one cannot argue that they are "causally" explainable» (p.419). This is an important conclusion when studying price movements since, as demonstrate Brunnermeier & Pedersen (2009) for some reserve assets, liquidity (which is inversely related to risk aversion) may be a priced factor.

2.2. Bivariate Analysis

Table 3 contains unconditional correlations of all pairs of daily returns between 2000 and 2015, ordered from lower to higher values. The table also displays Spearman's rank correlations for each pair, as well as the results of a simple T-statistic significance test. Table 4 depicts the resumed results of the analysis of cross correlations and some conditional correlations to the complete sample and 2000-2007 and 2007-2015 subperiods. As already stated, such previous study is performed in order to provide some support to the evidence found in the next sections.

Table 3. Correlations between returns.

NEGATIVE CORRELATIONS				POSITIVE CORRELATIONS			
			Spearman's rank correlation				*Spearman's rank correlation*
S&P 500	VIX	-0.7482	-0.7650***	VIX	GOLD 3 PM	0,0169	0.0321**
DOW JONES	VIX	-0.7203	-0.7251***	VIX	GOLD 10:30	0,0178	0.0229
IBEX 35	VIX	-0.4305	-0.3771***	BRENT	JPY/USD	0,0364	0.0247
GOLD 3 PM	EUR/USD	-0.3799	-0.3791***	S&P 500	CHF/USD	0,0457	0.0371**
GOLD 3 PM	CHF/USD	-0.3728	-0.3811***	TEXAS	JPY/USD	0,0459	0.0281*
GOLD 3 PM	GBP/USD	-0.3039	-0.3071***	IBEX 35	CHF/USD	0,0512	0.0777***
GOLD 10:30 AM	EUR/USD	-0.2398	-0.2343***	DOW JONES	CHF/USD	0,0555	0.0498**
GOLD 10:30 AM	CHF/USD	-0.2129	-0.20074***	VIX	EUR/USD	0,0719	0.0356**
GOLD 3 PM	JPY/USD	-0.2087	-0.1969***	TEXAS	GOLD 10:30 AM	0,0745	0.0784***
BRENT	GBP/USD	-0.2069	-0.1659***	DOW JONES	BRENT	0,0845	0.0704***
TEXAS	GBP/USD	-0.1938	-0.1548***	VIX	GBP/USD	0,0876	0.0386**
GOLD 10:30 AM	GBP/USD	-0.1918	-0.1913***	S&P 500	BRENT	0,1084	0.0927***
BRENT	EUR/USD	-0.1887	-0.1694***	BRENT	GOLD 10:30 AM	0,1223	0.1074***
TEXAS	EUR/USD	-0.1827	-0.1739***	JPY/USD	GBP/USD	0,1388	0.1960***
IBEX 35	GBP/USD	-0.174	-0.0800***	TEXAS	GOLD 3 PM	0,1534	0.1483***
VIX	JPY/USD	-0.1683	-0.1470***	DOW JONES	TEXAS	0,1667	0.1224***
VIX	TEXAS	-0.1634	-0.1431***	IBEX 35	BRENT	0,1672	0.1317***
BRENT	CHF/USD	-0.1384	-0.1333***	S&P 500	JPY/USD	0,1749	0.1430***
IBEX 35	EUR/USD	-0.1308	-0.0623***	DOW JONES	JPY/USD	0,1775	0.1453***
S&P 500	GBP/USD	-0.1266	-0.0632***	BRENT	GOLD 3 PM	0,1946	0.1886***
DOW JONES	GBP/USD	-0.1142	-0.0513***	S&P 500	TEXAS	0,2023	0.1556***
TEXAS	CHF/USD	-0.1009	-0.1250***	IBEX 35	TEXAS	0,2037	0.1587***
GOLD 10:30 AM	JPY/USD	-0.0953	-0.0845***	EUR/USD	JPY/USD	0,2554	0.2714***
VIX	BRENT	-0.0931	-0.0756***	IBEX 35	JPY/USD	0,2638	0.2232***
S&P 500	EUR/USD	-0.0862	-0.0580***	JPY/USD	CHF/USD	0,368	0.3869***
DOW JONES	EUR/USD	-0.0745	-0.0497**	IBEX 35	DOW JONES	0,4993	0.4416***

DOW JONES	GOLD 3 PM	-0.0543	-0.0334**	IBEX 35	S&P 500	0,5097	0.4505***
VIX	CHF/USD	-0.0407	-0.0486**	CHF/USD	GBP/USD	0,5179	0.5699***
S&P 500	GOLD 3 PM	-0.038	-0.0186	BRENT	TEXAS	0,5715	0.5199***
IBEX 35	GOLD 10:30 AM	-0.0325	-0.0073	GOLD 10:30 AM	GOLD 3 PM	0,652	0.5880***
DOW JONES	GOLD 10:30 AM	-0.0311	-0.0221	EUR/USD	GBP/USD	0,6674	0.6486***
IBEX 35	GOLD 3 PM	-0.0216	-0.01937	EUR/USD	CHF/USD	0,7815	0.8556***
S&P 500	GOLD 10:30 AM	-0.0146	-0.0027	DOW JONES	S&P 500	0,9686	0.9453***

Source: own elaboration

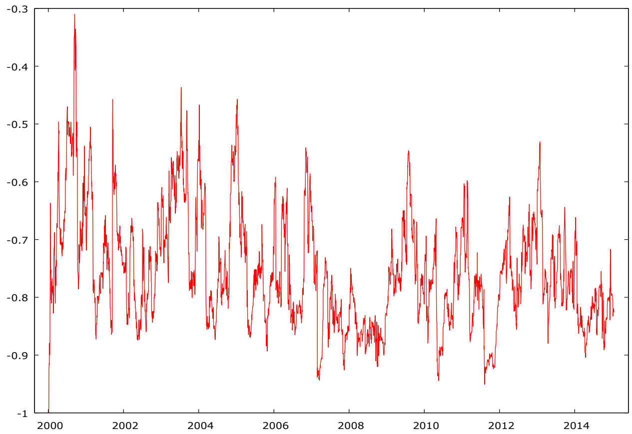
Table 4. Resumed information of Section II.

Variables	Effect	2000-2015	2000-2007	2007-2015
Dow Jones/S&P500 and VIX returns	Contemporary correlation: Negative correlation	✓	✓	✓
Dow Jones and EUR/USD returns	Negative cross correlation: Dow Jones´ reaction to price shocks 1 day before EUR/USD	✓	✗	✓
EUR/USD and Gold returns	Negative cross correlation: Gold returns reaction to price shocks 1 day before EUR/USD	✓	✓	✓
VIX and Gold returns	Negative cross correlation: VIX returns reaction to price shocks 1 day before gold’s 3 p.m. fixing	✓	✓	✓
Dow Jones and Brent returns	Positive cross correlation: Dow Jones’ reaction to price shocks 1 day before Brent	✓	✗	✓

As firstly depicted in Table 4, *it is obvious that changes in American stock returns are strongly related to contemporary increases and decreases in volatility in option markets*, as indicates significant Spearman’s correlation between Dow Jones and S&P500 and VIX (-0.7251 and -0.7650, respectively). Similar results are found in 2000-2007 and 2007-2015. Conditional correlation (see Figure 2) appeared to be varying: as expected, volatility clusters were observed. Experienced values appeared, however, to be always below zero. Once illiquidity measures like VIX are considered to be very sensible to information updates in financial sector, *evidence of the negative impact of market shocks on American stock markets is thus provided*. Such conclusion comes to reinforce papers like Sakthivel, Bodkhe & Namaiah (2012), which affirms that external news are first received by US stock markets volatility and afterward transmitted to other countries.

The table also indicates negative contemporary between Dow Jones and EUR/USD (-0.0497, 10% significant Spearman’s coefficient). Cross correlation analysis shows Dow Jones reacting to news 1 day before EUR/USD does (-0.04897, 1% significant 1 day correlation). *Subperiod analysis, however, suggests* *this affirmation is only correct during the recession years (2007-2015), with no significant evidence of such behavior found during the previous period.*

Figure 2. VIX and Dow Jones returns. Conditional correlation.

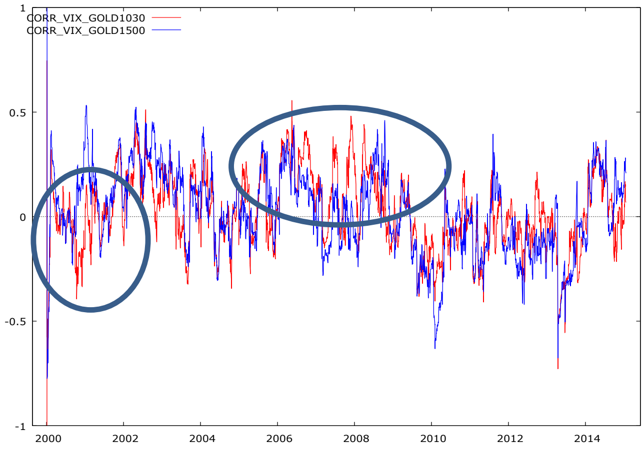


Source: own elaboration

Contemporary correlation between daily returns on gold and exchange rates of European currencies (euro, Swiss franc and GBP) to dollar seems much more negative at 3 p.m. quotation (-0.3799, -0.3728 and -0.3039, respectively) than they are at 10:30 a.m. (-0.2398, -0.2129 and -0.1918, respectively). Spearman's coefficient for each pair of returns are similar and significant to correlation coefficients, as depicts Table 3. *It is clear that the last gold fixing price discounts all the information related to currency markets along the session*. Conversely, cross correlation of gold and European currencies systematically reveals high 1 % significant negative effects of currencies on 10:30 a.m. gold's fixing 1 day after (around -0.32 for all EUR/USD, CHF/USD and GBP/USD), whereas lagged effect over 3p.m. fixing is rather low (around -0.08 for all currencies, 1% significant). The evidence suggests that all information accumulated in currency markets after the closing of London's fixing will be immediately incorporated by gold's first auction of the following day. Previous results were enhanced during 2007-2015, when the currencies' effect over 3 p.m. gold's fixing arrived to disappear. Information provided in the third line of Table 4 refers only to EUR/USD, since it is believed to run the behavior of all other European currencies.

Investigation also reveals low positive contemporary correlation (0.0321 Spearman's coefficient, 5% significant) of gold fixing returns at 3 p.m. and the VIX index, whereas no significant contemporary correlation can be found between VIX and 10:30 fixing (0.0229 Spearman's coefficient, with a 0.1511 p-value). Additionally, cross correlation analysis of VIX returns and gold clearly shows negative dependence of gold's 3 p.m. fixing on the Chicago Board' returns 1 day before (-0.01474, 1% significant), when 10:30 a.m. fixing dependence is null. *Such results point to a higher sensibility of gold's last auction to general illiquidity measures as the VIX, probably associated to the closing positions of European investors*. Parameters keep significant in subperiod analysis, as exposed in Table 4. Remark that estimated conditional correlations for both 10:30 a.m. and 3:00 p.m. gold fixing and the Chicago Board's (VIX) index reveals countercyclical movement and detachments during critical periods (2001 and 2008), as depicts Figure 3, standing for different reactions to risk according to the fixing hour.

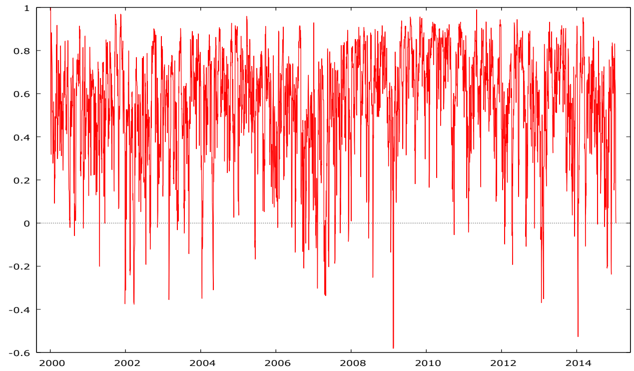
Figure 3. VIX and Gold returns. Conditional Correlation.



Source: own elaboration

Significant Spearman's rank correlation (0.5199, 1% significant) between Texas and Brent oil varieties was observed in the study period. Estimation of dynamic correlation coefficients, however, shows that such interaction can be very unstable along time: in concrete, for those periods associated with financial crisis, estimated correlations are negative, owing for possible speculative movements relating short and long positions in different oil varieties as part of hedging strategies (see Figure 4). It is worth mentioning that the *lambda* coefficient used in the estimation of conditional correlations through the RiskMetrics® methodology is 0.8 instead of 0.96: the impact of past returns is thus increased. *Changeable behavior of oil may be due to different types of price shocks (whether supply or demand shocks), a recently introduced hypothesis in financial literature* (to this regard, see Kilian & Park (2009) and Filis, Degiannakis & Floros (2011)).

Figure 4. Texas and Brent returns. Conditional Correlation.



Source: own elaboration

Lastly, positive contemporary correlation between Brent and Dow Jones returns (0.0704 Spearman's coefficient, 1% significant) suggests that both series react in the same direction to information updates. At the same time, cross correlation analysis of the complete sample also indicates Dow Jones reacting to news 1 day before Brent (0.16, 1% significant). *Higher absolute value of parameters indicates that forecasting effect of Dow Jones over Brent is stronger than contemporary effect.* As indicated in the bottom line of Table 4, however, no evidence of such interaction was found during 2000-2007, leading to the conclusion of *enhanced positive connection between oil and equity sector in face of aggregated demand shocks like the one caused by 2007 crisis*. Broadstock & Filis (2014) – affirming time varying correlations between oil markets and equity sector - and Broadstock, Cao & Zhang. (2012) – standing for an increased relation of Chinese stock markets with oil after 2008 -, can be quoted as influential papers on this matter.

Section III: Data modelling

3.1. Granger causality in returns

Six representative sets of daily returns - those on Dow Jones, VIX, Brent, Gold (3 p.m. fixing), EUR/USD and JPY/USD exchange rates – were extracted from the overall data in order to estimate a fifth-order vector autoregression ($VAR_{(5)}$). Such series are believed to contain all important information related to the three studied categories of assets (stock and volatility indices, commodities and exchange rates). Each column of Table 5 represents an unique model including all those variables represented by the table rows. Significant F-statistics[1], as well as all 5% significant individual terms are also displayed. Plus or minus signs indicate the direction of the relation between endogenous and exogenous variables for each delay (from 1 to 5 days). Only significant delays are kept in the table. Vector autoregression was also estimated for both 2000-2007 and 2007-2015 subperiods, although its results are not displayed below.

Table 5. Series of returns. VAR(5) (2000-2015).

Lagged variable	DOW JONES		VIX		BRENT	
	F-statistic	T-statistic (5%)	F-statistic	T-statistic (5%)	F-statistic	T-statistic (5%)
All variables	**		***			
DOW JONES	**	-(1)				+(1)
VIX			***	-(1,4)	**	-(2)
BRENT						
GOLD 03:00	*		*	+(5)		
EUR/USD	*	-(4)				
JPY/USD	*	-(5)				
Lagged variable	**GOLD 3:00**		**EUR/USD**		**JPY/USD**	
	F-statistic	T-statistic (5%)	F-statistic	T-statistic (5%)	F-statistic	T-statistic (5%)
All variables						
DOW JONES			***	-(1)		
VIX	*	-(1)				
BRENT						
GOLD 03:00			**	-(2)		-(5)
EUR/USD		-(1)				-(4)

[1] (*) indicates 10% significant parameter; (**) indicates 5% significant parameter; (***) indicates 1% significant parameter.

JPY/USD				-(2)		-(1)

Source: own elaboration

Looking at the first column of the table, Dow Jones serial correlation in returns appeared to be relevant for all 5 periods (F-statistic 2.3502) and particularly negative for 1 day. The same was observed for VIX returns in the second column (F-statistic 3.8690 and negative 1-day autocorrelation). Significant F-statistics were estimated to "all variables" in both Dow Jones and VIX associated models (2.1717 and 2.8938, respectively).

Even if no causality was found between American equity sector and Brent in the complete sample (see third column), *during 2007-2015 Dow Jones returns seemed to forecast the reaction of Brent's returns to news* (1% significant F-statistic and 1% significant 1-day correlation of 0.31).

Relevant negative correlation between lagged Dow Jones and EUR/USD (F-statistic 3.0251) was observed in the fifth column of Table 5. Similar results were found in 2007-2015. *1% significant parameter provides evidence of Dow Jones containing information about future movements of EUR/USD*. Notice that, although Forex market works in a continuous time, exchange rates used in this study are based on London closing time, meaning that all the information accumulated by Dow Jones index between 10 a.m. (end of London's session in New York, approximately) and its own closing hour would be discounted by EUR/USD in the next opening session.

Cross correlation analysis in Section II (see Table 4) had already provided evidence of the described interaction between Dow Jones and both Brent and EUR/USD: a plausible conclusion is hence that, based on the employed methodology, *there is evidence of strengthened information flows in daily returns between American equity sector and oil market and European currency after the beginning of 2007 financial crisis*.

❖❖❖

3 p.m. gold's returns (see Table 5) *appeared to be forecasted by VIX returns (2.0308 F-statistic, 10% significant), also in line with Section II, pointing to higher sensibility of gold's last auction to volatility expectations, on the go of European investors closing positions* (see Table 4). In spite of the above-mentioned, no other important evidence of causality between returns series has been found.

3.2. Granger causality in volatility

Table 6 displays the results of conditional volatility estimation for the studied series with GARCH and GARCH-GJR models. As expected, GJR *gamma* parameter appeared to be significant at 5% for several assets, providing a more accurate approach to asymmetries in dynamic variance. In line with Mandelbrot (1963): «**If one succeeded in eliminating all large changes [in prices] […], one would have a Gaussian-like remainder which, however, would be devoid of any significance**» (p.419).

Following a common practice in financial research, according to which the volatility structure of assets provides important evidence about information flows, Table 7 depicts the results of vector autoregression models ($VAR_{(5)}$) for GJR estimated volatility of six sets of returns: Dow Jones, VIX, Brent, Gold (3 p.m. fixing), EUR/USD and JPY/USD exchange rates. Once GJR models introduce, by definition, the effect of past volatilities in the estimation of dynamic variance, significant serial correlations observed to all series are not surprising. Other important statistics about changes in daily volatility are however observed.

Table 6. Series of returns. GARCH and GJR.

		omega	Alpha	beta	Gamma
IBEX 35	GARCH	0.0199769***	0.0929070***	0.900897***	-
	GJR	0.0199838***	8.069e-07	0.922029***	0.134696***
DOW JONES	GARCH	0.0138998***	0.0905055***	0.898874***	-
	GJR	0.142988***	2.474e-07	0.908512***	0.157233***
SP 500	GARCH	0.0149103***	0.0859189***	0.903141***	-
	GJR	0.0165555***	2.3823-07	0.909071***	0.152609***
VIX	GARCH	2.71092***	0.112510***	0.816013***	-
	GJR	2.33771***	0.165682***	0.849803***	-0.16567***
BRENT	GARCH	0.0115862*	0.0494738***	0.950164***	-
	GJR	0.00893253	0.0244560***	0.956804***	0.0367319***
TEXAS	GARCH	0.0343795	0.611039***	0.934535***	-
	GJR	0.0339941	0.0449370**	0.937569***	0.0249013
GOLD 10:30	GARCH	0.0217034	0.568424*	0.926522***	-
	GJR	0.0189984	0.0687904**	0.931840***	-0.0293658*
GOLD 03:00	GARCH	0.0325193	0.0785274**	0.896874***	-
	GJR	0.0276575	0.0891324***	0.906262***	-0.0305849
EUR/USD	GARCH	0.000972287*	0.300494***	0.967770***	-
	GJR	0.000870841	0.0352750***	0.969571***	-0.0134152**
JPY/USD	GARCH	0.00403881**	0.0391078***	0.951755***	-
	GJR	0.00484048**	0.0314175***	0.948352***	0.0174832
CHF/USD	GARCH	0.00552093	0.0389711***	0.953456***	-
	GJR	0.00403622*	0.0586181***	0.952939***	-0.0297442
GBP/USD	GARCH	0.00175198**	0.0397146***	0.954746***	-
	GJR	0.00194629**	0.0525710***	0.955396***	-0.028969***

Source: own elaboration

Table 7. Conditional variances. VAR-5 (2000-2015).

Delayed variable	DOW JONES		**VIX**		BRENT	
	F-statistic	T-statistic (5%)	F-statistic	T-statistic (5%)	F-statistic	T-statistic (5%)
All variables						
DOW JONES	***	+(1)		-(1)	**	
VIX			***	+(1)		
BRENT			**		***	+(1,3) -(2)
GOLD 03:00						

EUR/USD	**	+(3)				
JPY/USD						+(4)
Delayed variable	GOLD 3:00		EUR/USD		JPY/USD	
	F-statistic	T-statistic (5%)	F-statistic	T-statistic (5%)	F-statistic	T-statistic (5%)
All variables	***		**		**	
DOW JONES	**		*	+(5)		
VIX						+(4)
BRENT	**					
GOLD 03:00	***	+(1)				
EUR/USD	***	-(1)	***	+(1)		
JPY/USD	***	+(5) -(4)	**	+(5)	***	+(1,5) -(3)

Source: own elaboration

Negative causality of EUR/USD over gold (3.1276, 1% significant F-statistics), observed in the fourth column of Table 7, may indicate the volatility of EUR/USD rate as a predictor of 3 p.m. fixing's volatility reactions to financial news. In this case, evidence would be suggesting that, once received by European currency volatility, information updates in Forex markets are afterwards transferred to the risk of maintaining gold reserves. Similar result seems not to be observable during 2007-2015, however. *All the obtained information may indicate gold's emergence as a safe haven against the risk of exchange market after the beginning of the financial crisis,* in an extension of the definition stated by Ranaldo & Söderlind (2010) when observing high frequency returns, according to which any asset considered to offer hedging benefits « **[...] is uncorrelated or negatively correlated with its reference asset**» (p.2). *The important point here is thus to notice how safe haven characteristics can be also observed in dynamic variances*.

Additionally, it is important to observe that, even if there is evidence of Dow Jones volatility reactions to information prior to Brent in the complete period (2.7523 F-statistic, 5% significant), during the recession years such interaction seemed to be more robust (0.0792 p-value in 2000-2007 and 0.0087 in 2007-2015), indicating *oil market as more responsive to risk in American equity sector after the beginning of the financial crisis*. Another point to mention is that, regardless of what have been said about causality in returns, there is no meaningful evidence of links in volatilities between Dow Jones and EUR/USD[2], either in the overall sample or in subperiod analysis. These and all previous results will be furtherly discussed in the next epigraph.

[2] Even if significant correlation in volatility was observed for Dow Jones and EUR/USD in a 5-day prospect, such information is excessively weak for the purposes of the present work: causality hypothesis would only be acceptable under the existence of successively correlated periods, in which case, e.g., if returns of asset A could forecast those of asset B after 3 days, significant correlation would also be observed 2 days and 1 day before.

3.3. General considerations in causality

Several conclusions were suggested in the previous lines, which deserve deeper reasoning. Evoking the objective of this paper, as to know, the identification of information flows through international financial markets, daily returns and volatility were considered to provide important insights in market dynamics. The main conclusions of Section III are displayed in Table 8.

a) Granger causality in returns: Dow Jones and EUR/USD

Table 8.1. Resumed information of Section III. Granger causality in returns.

Variables	Effect	2000-2015	2000-2007	2007-2015
Dow Jones and EUR/USD	Negative causality in returns: Dow Jones' reaction to shocks 1 day before EUR/USD	✓	×	✓

Negative causality found between daily returns of Dow Jones and currencies in the first epigraph of Section III (see the commentaries following Table 5) comes to indicate *the emergence of EUR/USD returns as an important path for the transmission of news from US equity sector returns to Europe after the beginning of 2007 crisis*. In fact, evidence seems to suggest that any losses in American stocks during this periods imply the depreciation of euro against dollar, standing for an increase in the precautionary demand of the latter relative to European currency. Remark, however, that this connection is never a sign of inefficient markets: as already stated in Section II, since exchange rates used are based on London closing time, all the information accumulated by Dow Jones index between 10 a.m. (end of London's session in New York, approximately) and its own closing hour would be discounted by EUR/USD in the next opening session.

b) Granger causality in volatility: EUR/USD and Gold

Table 8.2. Resumed information of Section III. Granger causality in volatility.

Variables	Effect	2000-2015	2000-2007	2007-2015
EUR/USD and Gold returns	Negative causality in volatility: EUR/USD reaction to price shocks 1 day before 3 p.m. gold's fixing	✓	✓	×

A next finding to discuss is the causality link in daily volatilities of EUR/USD and 3 p.m. gold's fixing in London[3]. As already exposed in the second epigraph of Section III (see commentaries following Table 7), evidence suggests that the impact of market surprises over EUR/USD volatility is transferred to the risk of maintaining gold reserves through a negative causality link[4]. The contribution of the present

[3] Results from both bivariate analysis in Section II and autoregressive vectors in the first section of Section III are consistent with the conclusion that such connection is not observable in returns.

[4] To this respect, Savva, Osborn & Gill (2009) conclude that, when studying European and American markets, foreign financial shocks could affect both volatility and returns.

paper on this topic is to determine how such class of risk transmission, however, seems to occur uniquely during relatively stable periods, with gold more likely to be traded like any other asset[5]: *when gold reserves are predictably used in risk covering strategies during financial crisis, volatility connections between these two series tend to disappear*. Analogical reasoning support the similarity of the mentioned effect and the one observed in returns for the relation of safe assets with its reference. In such case, hypothesis raised in Batten, Ciner & Lucey (2010) – sustaining evidence of the influence of macroeconomic factors, such as inflation and exchange rates, over the volatility dynamic of precious metals – would only be applicable in those periods of relative serenity in markets.

c) Granger causality in returns and volatility: Dow Jones and Brent

Table 8.3. Resumed information of Section III. Granger causality in returns and volatility.

Variables	Effect	2000-2015	2000-2007	2007-2015
Dow Jones and Brent returns	Positive causality in returns and volatility: Dow Jones' reaction to shocks 1 day before Brent.	✓	✓	✓

Substantial evidence obtained from Sections II and III (see Table 4 and commentaries after Table 5 and Table 7) evoke the link between Dow Jones and Brent crude's reactions to new information: study on series revealed positive effects of Dow Jones over Brent's performance in both daily returns and volatility during the whole study period, which became more robust in 2007-2015. *In this case, during critical years, oil prices would appear as most likely to absorb the effect of new information over American equity sector, a behavior not expected for an asset presenting hedging benefits to this sector*. In effect, Deggianakis *et al.* (2014) affirm that during fluctuations of business cycles and global turmoil oil market *cannot* be viewed as a safe haven against losses in stock markets.

Such observations are widely illustrative in view of the most actual deterioration of financial conjuncture, occurred during 2015 and 2016, when myriad of analysts would find consensus in relating recent losses in European stock markets, the decline of global demand and an increasing need for liquidity to big movements in oil's prices.

❖❖❖

In order to present a complete study on the patterns of information flows in financial markets the important question to answer now is thus: how could the most recent financial situation be reacting to the dynamic observed in the empirical analysis of this paper? Did any structural change occur during the last months? The following section will look over additional data since 2015 until the beginning of 2016, in an attempt to suitably respond the problems presented. Results will be also compared with the one obtained from analyzing 2009-2010 data, in order to provide a point of reference to the stated conclusions.

[5] Sjaastad (2008) could demonstrate how between 1998 and 2004 gold seemed not to be used as a stores against market inflation.

Section IV: Sampling extension

The main goal of the present section is to compare the causality patterns obtained in the previous analysis of the dynamic of financial markets with the one found by using 2015 and 2016 daily information. Moreover, in an attempt to improve conclusions' robustness, results will be compared to the one observed in 2009-2010, when oil (which prices fell from above 140 dollars per barrel to below 40) experienced a shock in its demand similar to the one currently being experienced. Conclusions from both periods are expected to be alike. In line with the methodology already applied, vector autoregression models were estimated for returns and conditional volatilities. To avoid overloading empirical analysis, the outcome of data modelling is presented in Appendix 1.

Table 9. Data description.

	Source	Beginning of the sample	End of the sample	Closing hour
DOW JONES	Datastream	2015-1-20	2016-2-29	4 p.m. (GMT-4h)
VIX	St. Louis FED	2015-1-20	2016-2-29	3:15 p.m. (GMT-5h)
BRENT	St. Louis FED	2015-1-20	2016-2-29	4 p.m. (GMT+1)
GOLD 3 p.m.	St. Louis FED	2015-1-20	2016-2-29	3 p.m. (GMT+1)
EUR/USD	Datastream	2015-1-20	2016-2-29	4 p.m. (GMT+1)
JPY/USD	Datastream	2015-1-20	2016-2-29	4 p.m. (GMT+1)

a) Granger causality in returns: Dow Jones and EUR/USD

Cross correlation analysis in Section II (see Table 4) and VAR models in Section III (see Table 8.1) provided evidence of an enhanced negative connection between American equity sector and European currency returns after the beginning of 2007 financial crisis, enabling Dow Jones as an important predictor of euro's behavior during this period. *Such dynamic seemed to disappear during 2015, however, with no significant F-statistic being found for the period (0.22787 F-statistic, with a 0.9502 p-value). A similar behavior was observed in 2009 (1.3071 F-statistic, with a 0.2617 p-value).* In an attempt to explain this *phenomenon*, several papers regarding the performance of exchange rates were revised.

In line with Brunnermeier & Pedersen (2009), sudden exchange rates movements in 2015 and 2009 could be associated to the reduction of currency carry trades (selling low interest-rate currencies to invest in high interest-rate currencies): in effect, interest rate differential (allowing arbitrage) between Europe and US were minimal during these years, providing evidence on the previous affirmation. Even if this explanation may be partially satisfactory, however, one would be persuaded to look for the links existent between shocks in oil prices and unwinding carry trades, an important issue in order to evaluate future economic movements. Although limited recent literature on this matter was found, some remarkable papers can be quoted. For instance, Cologni & Manera (2008) show evidence of expanding monetary policy as a response to deflationary stress due to falling oil prices, and Nordhaus (2007) describes the impacts of the overreaction of monetary authorities to oil-price shocks in global economy. This can be the subject of an interesting line of future investigation.

b) Granger causality in volatility: EUR/USD and Gold

Conclusions presented in Section III (see Table 8.2) were persistent in relating observed causality of European currency in 3 p.m. gold's daily volatility to relatively calm periods. Therefore, non-significant F-statistics were found between EUR/USD and gold in vector autoregression of daily volatilities during 2007-2015, suggesting that, in episodes of financial crisis, gold prices cease reflecting currency markets expectations and becomes an important reserve in risk hedging strategies. *These are also the results found in 2015-2016 (1.4099 F-statistics, with a 0.2209 p-value) and 2009-2010 (0.42898, with a 0.8282 p-value).* As expected, gold maintains its category of a highly esteemed commodity when covering currency markets risk.

c) Granger causality in returns and volatility: Dow Jones and Brent

Dow Jones appeared to be an important predictor of the reactions of both Brent's daily returns and volatilities to price surprises during all studied periods, with important evidence pointing to the enhancement of such interaction after 2007, as indicate Section II (see Table 4) and Section III (see Table 8.3). *Similar results were extracted for dynamic volatilities in 2015-2016 (3.5277 F-statistic, 1% significant) and 2009-2010 (4.3486 F-statistics, 1% significant), but not in returns.* It is worth mentioning, however, that several remarkable factors exist, that could be affecting these numbers.

Figure 5. Dow Jones and Brent Returns. Conditional correlation (2015-2016)

Source: own elaboration

For instance, a period of high uncertainty over the development of the global economic conjuncture, occurred between January 2015 and June 2015, caused oil returns to cease responding to the movements of American stock markets. As described by estimated conditional correlation in Figure 5, the fear of a Chinese default started in Summer 2015, however, quickly restored the positive interaction between the returns of these two variables, which acquired a positive tendency, in line with the patterns previously observed. General uncertainty in 2009 may explain the absence of links in returns observed in this period.

Be that as it may, the clear point is that, during shocks in oil prices, *consistent evidence exists of the positive causality exerted by Dow Jones volatility over oil's conditional variance*.

❖❖❖

Table 10 describes the results of the analysis carried in the present section, and its comparison with the crisis years.

Table 10. Main conclusions of Section 4. Granger causality.

<table>
<tr><th>Variables</th><th>Effect</th><th>2007-2015</th><th>2009-2010</th><th>2015-2016</th></tr>
<tr><td rowspan="2">Dow Jones and EUR/USD</td><td rowspan="2">Negative causality in returns: Dow Jones' reaction to shocks 1 day before EUR/USD</td><td rowspan="2">✓</td><td>×</td><td>×</td></tr>
<tr><td colspan="2">(periods of expanding monetary policy as a response to deflationary stress due to falling oil prices)</td></tr>
<tr><td>EUR/USD and Gold returns</td><td>Negative causality in volatility: EUR/USD reaction to price shocks 1 day before 3 p.m. gold's fixing</td><td>×</td><td>×</td><td>×</td></tr>
<tr><td rowspan="2">Dow Jones and Brent returns</td><td rowspan="2">Positive causality in returns and volatility: Dow Jones' reaction to shocks 1 day before Brent.</td><td rowspan="2">✓</td><td>×</td><td>×</td></tr>
<tr><td colspan="2">(causality in volatility)</td></tr>
</table>

Although ongoing precautionary demand of gold against risk in currency markets and unwinding carry trades seem to "break" the causality patterns already observed in financial markets, what is certain is that information can never cease to flow: it is hence logical to determine that, in replacement of gold and European currency, some other series was suffering, during 2015, the impact of the news generated in this sector. Since, according to Sakthivel *et al.* (2012), US markets volatility are the first to absorb new information, *evidence of a strengthened causality of Dow Jones over Brent's daily volatility can be an indicator of the above mentioned.* It remains to clarify, however, if this this effect is somehow caused by any changes in the economic environment. To this respect, important insights of the interaction of oil and other variables during turmoil periods can be found in Ewing and Thompson (2007) -affirming crude oil's procyclical behavior with industrial performance -, the already quoted Filis *et al.* (2011) [**«during fluctuation business cycles oil cannot be viewed as a safe haven against losses in stock markets»**], and the OPEC's (2015) World Oil Outlook - according to which oil's falling demand was greatly caused by the deceleration of world's economies.

Section V: Conclusions

The main goal of this paper was to answer an unique question concerning the information flow in global financial markets. Identifying such patterns provides an important tool to investors and policy makers interested in predicting possible future changes in their portfolios. Insights on the above mentioned are considered to be found either in daily returns and volatilities, for whose purposes a methodological approach based on vector autoregressive models was applied. Contemporary and cross correlations and univariate volatility models were also used to provide a feedback to the conclusions stated.

The investigation started with a set of prices of 12 financial variables belonging to three categories - stock and volatility indices, commodities and exchange rates - which were reduced to 6 in order to estimate the $VAR_{(5)}$ models in Section III. The smaller dataset is believed to contain all important information related to the studied categories of assets. The main sample contained daily information from 2000 to 2015. In all sections, subperiod analysis (2000-2007 and 2007-2015) was also performed in order to test the robustness of the causality patterns identified. $VAR_{(5)}$ models were replicated in the last section to smaller samples (2015-2016 and 2009-2010) in order to contrast the obtained results to those periods of demand shocks in oil prices. All employed tools are considered to be appropriated to the object of this study. The conclusions stated are consistent with the evidence found, as exposed below:

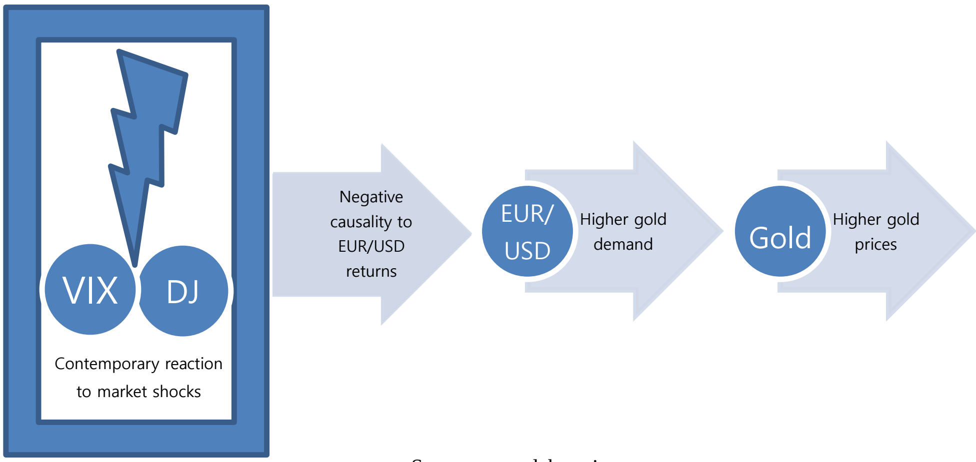
1. Strong contemporary interaction of Dow Jones with the VIX index (see Table 3), as well as the natural assumption about the important role played by American financial market in the creation information flows, point undoubtedly to the avowal of Dow Jones reactions to market updates prior to other series, as any volatility index like the VIX is considered to be highly sensible to news in financial markets.
2. Negative causality in returns observed between Dow Jones and EUR/USD during the crisis years stands for the role played by American equity sector as a predictor of European currency, as stated in Section III (see table 8.1). However, some interferences in the interaction of these variables during periods of intense lack of oil's demand - namely those occurred in 2009-2010 and 2015-2016 - provide signs of the impact of oil prices on the monetary policy of Central Banks, which could affect arbitrage in currency markets. This point is an object of discussion in epigraph «a» of Section IV (see Table 10).
3. Increasingly robust evidence of Dow Jones interaction with Brent in both returns and volatility indicates strengthened information flows between these two variables, as stated in Section III (see Table 8.3). High sensitivity of Brent's volatility to stock returns after 2007 crisis and during 2015 can be caused by negative demand shocks related to turmoil periods, as suggested by Ewing & Thompson (2007), Filis *et al.* (2011), and the OPEC's (2015) World Oil Outlook (see commentaries after table 8 in Section IV).
4. Additionally, the paper brings into discussion the existing links between EUR/USD and gold daily prices. According to the analysis presented in Section III (see Table 7.2), the absence of causality among the volatility of these two series provides evidence of the use of gold as a safe haven against the risk of currency market after the beginning of 2007 financial crisis. It

is logical to think that higher demand of gold in critical periods would cause its price to increase.

❖❖❖

The output of the investigation carried in this paper makes possible to establish a complete path relating, for the years of crisis, VIX and gold returns, with interesting impacts in the field of policy recommendations.

Figure 6. Causal path between VIX and gold returns.



Source: own elaboration

In line with Figure 6, increasing illiquidity (increases in VIX index) and negative returns in American stock markets caused by market shocks would imply next day's devaluation of euro against dollar, which, according to the theory presented, is one of the causes of gold's precautionary demand in London commodity market in its subsequent session. Such relation could be somehow related to the significant negative impact of illiquidity measures and gold price already observed in Section II (see Table 4) for a one-day outlook. Therefore, empirically testing this effect for a two-days' time horizon, as suggested, could be the object of a further study. In case it would confirmed the proposition of liquidity as a priced factor, postulated for currencies in Brunnermeier & Pedersen (2009), would also demonstrate to be true in the case of gold.

Some strengthened information flows were also identified between Dow Jones and Brent's daily returns during 2015. As a digression from the topics presented in this section and as an interesting feature to be observed by market authorities, an additional hypothesis can be added in view of some punctual movements causing Brent and Texas conditional correlation of daily returns to be negative, as observed in the analysis of Section II: instead of representing a single asset, these two varieties may be being used simultaneously, during critical periods, in taking long and short positions. The study of oil varieties not as an homogeneous class of commodity, but rather as distinct assets responding differently to surprises in financial markets in the presence of economic could guide to an investigation similar to the one realized by Batten *et al.* (2010) for precious metals. Other possible innovations of this paper lay on the identification of increasing role of oil's volatility as a driver of monetary variables, as stated in the first epigraph of the present section.

Once all the causality relations found in $VAR_{(5)}$ models relate variables with a maximum 24 hours delay, a reasonable advance in the work presented could be the estimation of first order vectors in order to validate the conclusions stated. Other possible extensions may include the use of more sophisticated methodology in order to capture non lineal causality in variables, specially relating those of safe haven assets and illiquidity indices such as VIX as suggest Batten *et al.* (2010). Further investigations on the role of oil as a predictor of monetary markets and the behavior of JPY/USD in relation to market shocks would also be interesting, given the constrained space dedicated to this variable in the paper. Lastly, any other contribution to the coherence of the postulates and hypothesis used and the deductive process of this investigation would be highly appreciated.

References

Batten, J. A., Ciner, C., & Lucey, B. M. (2010). The macroeconomic determinants of volatility in precious metals markets. *Resources Policy*, *35*(2), 65-71.

Cologni, A., & Manera, M. (2008). Oil prices, inflation and interest rates in a structural cointegrated VAR model for the G-7 countries. *Energy economics*,*30*(3), 856-888.

Broadstock, D. C., Cao, H., & Zhang, D. (2012). Oil shocks and their impact on energy related stocks in China. *Energy Economics*, *34*(6), 1888-1895.

Broadstock, D. C., & Filis, G. (2014). Oil price shocks and stock market returns: New evidence from the United States and China. *Journal of International Financial Markets, Institutions and Money*, *33*, 417-433.

Brunnermeier, M. K., & Pedersen, L. H. (2009). Market liquidity and funding liquidity. *Review of Financial studies*, *22*(6), 2201-2238.

Ewing, B. T., & Thompson, M. A. (2007). Dynamic cyclical comovements of oil prices with industrial production, consumer prices, unemployment, and stock prices. *Energy Policy*, *35*(11), 5535-5540.

Filis, G., Degiannakis, S., & Floros, C. (2011). Dynamic correlation between stock market and oil prices: The case of oil-importing and oil-exporting countries. *International Review of Financial Analysis*, *20*(3), 152-164.

Glosten, L. R., Jagannathan, R., & Runkle, D. E. (1993). On the relation between the expected value and the volatility of the nominal excess return on stocks. *The journal of finance*, *48*(5), 1779-1801.

Granger, C. W. (1969). Investigating causal relations by econometric models and cross-spectral methods. *Econometrica: Journal of the Econometric Society*, 424-438.

Kilian, L., & Park, C. (2009). The impact of oil price shocks on the us stock market*. *International Economic Review*, *50*(4), 1267-1287.

Mandelbrot, B. (1967). The variation of some other speculative prices. *The Journal of Business*, *40*(4), 393-413.

OPEC (Organization of the Petroleum Exporting Countries) (2015). 2015 World Oil Outlook.

Nordhaus, W. D. (2007). Who's afraid of a big bad oil shock?. *Brookings Papers on Economic Activity*, *2007*(2), 219-238.

Ranaldo, A., & Söderlind, P. (2010). Safe Haven Currencies. *Review of Finance*, rfq007.

Sakthivel, P., Bodkhe, N., & Kamaiah, B. (2012). Correlation and volatility transmission across international stock markets: a bivariate GARCH analysis.*International Journal of Economics and Finance*, *4*(3), 253.

Savva, C. S., Osborn, D. R., & Gill, L. (2009). Spillovers and correlations between US and major European stock markets: the role of the euro. *Applied Financial Economics*, *19*(19), 1595-1604.

Sjaastad, L. A. (2008). The price of gold and the exchange rates: Once again.*Resources Policy*, *33*(2), 118-124.

Singh, P., Kumar, B., & Pandey, A. (2010). Price and volatility spillovers across North American, European and Asian stock markets. *International Review of Financial Analysis*, *19*(1), 55-64.

Appendix 1: VAR(5) estimation in Section IV

a) VAR estimation for returns

2015-2016

Delayed variable	DOW JONES		VIX		BRENT	
	F-statistic	T-statistic (5%)	F-statistic	T-statistic (5%)	F-statistic	T-statistic (5%)
All variables					*	
DOW JONES	**	-(1)	**	+(1)	***	-(5)
VIX	***	+(3)	***			+(3)
BRENT			*	-(1)		
GOLD 03:00	*	-(2)		+(2)		
EUR/USD						
JPY/USD						

Delayed variable	GOLD 3:00 (Londond 3pm)		EUR/USD (London 4pm)		JPY/USD (London 4pm)	
	F-statistic	T-statistic (5%)	F-statistic	T-statistic (5%)	F-statistic	T-statistic (5%)
All variables			*			
DOW JONES					*	-(4)
VIX				-(1)		-(4)
BRENT						
GOLD 03:00						-(3)
EUR/USD		+(3)				
JPY/USD			*	-(1,5)		-(5)

2009-2010

Delayed variable	DOW JONES		VIX		BRENT	
	F-statistic	T-statistic (5%)	F-statistic	T-statistic (5%)	F-statistic	T-statistic (5%)
All variables	*		**			
DOW JONES		+(4)	*	-(4)		
VIX			***	-(4)		

BRENT	`*	-(1)				-(3)
GOLD 03:00						
EUR/USD						
JPY/USD	***	+(1) -(2,5)	***	+(2,5)		

Delayed variable	GOLD 3:00 (Londond 3pm)		EUR/USD (London 4pm)		JPY/USD (London 4pm)	
	F-statistic	T-statistic (5%)	F-statistic	T-statistic (5%)	F-statistic	T-statistic (5%)
All variables			*			
DOW JONES						
VIX		+(4)				
BRENT				-(2)		
GOLD 03:00	***	+(4,5) -(1)				
EUR/USD	*	+(4)	**	-(2)		
JPY/USD				-(5)		

b) VAR estimation for volatilities

2015-2016

Delayed variable	DOW JONES		**VIX**		BRENT	
	F-statistic	T-statistic (5%)	F-statistic	T-statistic (5%)	F-statistic	T-statistic (5%)
All variables					*	
DOW JONES	***	+(1)			***	+(1)
VIX		+(1)	***	+(1)		-(3)
BRENT					***	+(1)
GOLD 03:00				-(3)	***	+(1,5) -(2)
EUR/USD					***	-(3,4)
JPY/USD					**	-(1)
Delayed variable	GOLD 3:00 (Londond 3pm)		EUR/USD (London 4pm)		JPY/USD (London 4pm)	
	F-statistic	T-statistic (5%)	F-statistic	T-statistic (5%)	F-statistic	T-statistic (5%)
All variables						
DOW JONES				-(3)		

VIX						
BRENT	*					
GOLD 03:00	***	+(1) -(4)	***	+(1)	**	
EUR/USD			***	+(1,4) -(3)		-(3)
JPY/USD					***	+(1)

2009-2010

Delayed variable	DOW JONES		**VIX**		BRENT	
	F-statistic	T-statistic (5%)	F-statistic	T-statistic (5%)	F-statistic	T-statistic (5%)
All variables	*				*	
DOW JONES	***	+(1)	*	+(3) -(1)	***	+(2) -(1)
VIX			***	+(1)		
BRENT		+(5) -(4)			***	+(1)
GOLD 03:00			**			-(3)
EUR/USD	***	+(1) -(2)		+(1) -(2)	*	
JPY/USD	**	+(1) -(5)			*	-(5)
Delayed variable	GOLD 3:00 (Londond 3pm)		EUR/USD (London 4pm)		JPY/USD (London 4pm)	
	F-statistic	T-statistic (5%)	F-statistic	T-statistic (5%)	F-statistic	T-statistic (5%)
All variables						
DOW JONES			*			
VIX	*					
BRENT		+(2)	***	+(3)		
GOLD 03:00	***	+(1)				
EUR/USD			***	+(1)	***	-(3)
JPY/USD			*	+(1,2)		