On the reactions of sectoral equity returns to oil price in France: Implications for portfolio allocation

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On the reactions of sectoral equity returns to oil price in France: Implications for portfolio allocation

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Abstract: Instead of conducting overall stock market index analysis, this paper focuses on the reactions of sectoral equity returns (Industrials, Financials and Banks, Health care, Information Technology, Consumer goods, Materials, Oil and Gas, Telecommunications) to oil price changes in France. From a methodological perspective, this study uses a new method, called the quantile-on-quantile (QQ) approach. Even though this technique is based on the quantile regression paradigm, it departs from the conventional framework as the exogenous variable may be itself a quantile. It allows looking further into hidden factors driving the link between oil price and stock returns which the standard econometric methods are unsuitable to accommodate. QQ views the nature and sensitivity of the stock returns responses to oil price shocks change greatly across sectors of activity and tail distributions. Specifically, Industrials, Materials, and Oil and Gas equities are typically more reactive towards oil price shocks. The response of Financials and Banks is relatively weak, while it appears negligible for Health care, Information Technology, Consumer goods and Telecommunications. The frequency domain causality test (relying on signal theory) has demonstrated its functionality and adequacy in this exercise. On the basis of this article' outcomes, market participants could enhance the risk-adjusted return of their portfolios by pursuing a sector-based portfolio investment strategy. Also, introducing oil asset into a diversified portfolio of stocks enables to invigorate its risk-return features.

Keywords: Oil price; stock market; sector indices; France; QQ approach; frequency domain causality test.

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1. Introduction

Oil price has posted very wide swings in recent decades depending on fluctuation in amounts of oil demanded and sold by both OPEC and non-OPEC countries. The abrupt changes in the price of oil have wide-ranging ramifications for both oil-producing and oil-consuming countries. Since the 1970s there has been a huge amount of studies focusing on the synchronization of oil price changes and economic activity. A considerable economic literature has been conducted on studying this impact. The early research as that of Hamilton's (1983) has supported the proposition that oil shocks were a contributing factor in at least some of the U.S. recessions prior to 1972. Subsequent empirical studies have confirmed that oil price volatility has a great influence on economic output in several developed and emerging countries (see Lee et al. 1996; Ferderer 1996). However, other studies have argued that oil price shocks could explain only a modest component of the variance of output growth (Blanchard and Gali 2009). Thus, as mentioned by Blanchard and Gali (2010) since the late 1990s, the global economy has experienced two oil shocks with sign and magnitude comparable to those of the 1970s but, in contrast with the more recent episodes, both economic growth and inflation have remained relatively stable in much of the industrialized world. Still the most evident explanation of the correlation between oil prices and output is that this link results from common dependence on some factors that explain both the increase in oil prices and the subsequent recession (Hamilton 2005). Such factor can be the monetary policy i.e., for maintaining a low and stable inflation rate, monetary authorities raise interest rates in response to a substantial increase in oil prices, slowing growth. Another explanation emphasises the contraction of energy-intensive sectors resulting of oil price drop that reduces the demand for certain goods leading to a decrease in the sectoral production which raises the unemployment. In fact, individual sectors will have dissimilar exposures to oil prices shocks and there may be significant differences in the reactions of the industries to oil shocks (Lee and Ni 2002). Further, as noted Haung et al. (1996), if oil affects real Gross National Product, it will affect earnings of companies for which oil is a direct or indirect cost of operation, in such case a rise in oil prices will decline expected earnings which will bring about an immediate decrease in stock prices if the stock market effectively capitalizes the cash flow implications of this oil price decrease. The present paper extends this empirical work by tackling the possible oil price effects on financial markets at disaggregated level. During the last two decades, some researchers have focused on the response of financial markets to oil price shocks. Unfortunately, the empirical evidence on the impact of oil price fluctuations on stock markets has been inconclusive (Haung et al. 1996; Broadstock and Filis 2014; Apergis and Miller 2009; Kilian and Park 2007). All these studies provide market-level evidence. They are either using time series data on one country (e.g. Haung et al. 1996) or conducting cross-sectional data analysis across countries (e.g. Maghyereh 2004). The sectorial effects of oil price shocks, however, have remained relatively understudied (although there are some exceptions such as Arouri (2011) and Gogineni (2010) and concentrated almost exclusively on some countries like U.S. In fact, while the analysis of the macroeconomic impact of oil price movements has long been the subject of a vast literature, only a very few studies has focused at the disaggregate market level on the effects of oil price shocks on the returns of distinct stock market sectors. Arouri (2011) has found in the case of Europe that the reaction of stock returns to oil price shocks change considerably across sectors. Broadstock and Filis (2014) have suggested in the case of China and the U.S that oil shocks effects differ substantially across industrial sectors, namely Metals and Mining, Oil and Gas, Retail, Technology and Banking. Kilian and Park (2007) have shed more light on whether the response of aggregate U.S. real stock returns may differ greatly depending on the hidden factors driving the price of crude oil (demand or supply shocks). Accordingly, there is evidence that the sectors are typically more responsive towards oil demand shocks than oil supply shocks. Nevertheless, the degree of sensitivity varied across industries. McSweeney and Worthington (2008) have confirmed in the case of Australia that oil prices are an important determinant of returns in the Banking, Energy, Materials, Retailing and Transportation industries. Finally, Gogineni (2010) has attempted to identify the factors that may drive industries' sensitivity to oil prices. For the author, naturally, oil prices affect stock returns of industries that depend strongly on oil, but the stock returns of some industries that do not use oil can also be sensitive to oil price changes, perhaps because the main customers of these industries are influenced by excessive oil price fluctuations. Another strand of literature has focused on specific sectors such as Oil and Gas sector (El-Sharif et al. 2005; Boyer and Filion 2007). Arguably, Boyer and Filion (2007) have assessed the financial determinants of Canadian Oil and Gas company stock returns. They have reported that the returns of Canadian energy stocks are positively associated with the overall Canadian stock market return and with the appreciations of Oil and natural Gas prices.

Given the importance of oil, better understanding how exactly respond market returns to oil price changes may be useful for market participants. In fact, both investors and regulators closely follow financial market evolution, even if each one has different interests, in the sense that investors monitor equities fluctuation to optimize the risk-return profile on their investment, while policymakers employ stock market prices to infer information about market expectations of economic growth and inflation. The primary objective of this article is to test the explanatory power of oil prices on sectoral stock returns. The approach we adopt here is similar to that employed by Zhu et al. (2016) who have examined the question of dependence between crude oil price changes and industry stock market returns in the case of China. In their empirical analysis, Zhu et al. (2016) have used the quantile regression (QR) approach to analyze whether the oil price affect dissimilarly stock market returns across bearish and bullish markets. The volatile behaviour and the speculative bubbles characterizing oil and asset markets strengthened the focus on models that allow efficaciously capturing dynamic dependencies in data. In fact, linear correlation may not be a satisfactory measure of dependence, as it does not account for dependence between tail events. Therefore, the focus is no longer on the mean effect, but on the full distributions of oil prices and stock returns. Obviously, the correlation asymmetries would ensure that market participants (investment advisers, investors, traders and regulators) have the opportunity to make informed decisions. Beyond this contribution, another novelty of this study lies in performing a new method, dubbed quantile- on-quantile (QQ) approach that may provide fresh insights into a “complex” topic. Using this method, we can look further into hidden factors driving the relationship between changes in oil price and the performance of stock market sectors which the standard econometric techniques seem improper or malapropos. The QQ method complements a rich body of existing methodologies for estimating the correlation. It consists on regressing one quantile on another quantile. Therefore, the main econometric challenge in this paper is to develop a quantile regression model having a conditional quantile regressor which allows the relationship between sector stock indices and oil price varying at different points in their respective distributions (Sim and Zhou 2015). It enables to exploit compulsive knowledge of the reactions of different sector stock markets to oil price changes, and a reliable information on how evolve this relationship across tailed-distributions uncovering various nuance features that may be relevant to real adjustments for companies’ strategies. In addition to the correlation variation among tail-distributions, the direction of the Granger causality from oil price to sectoral markets returns has been computed for distinct frequency components (frequency domain causality test). In this case, the stationary process can be depicted as a weighted sum of sinusoidal components with a certain frequency, allowing us to evaluate several cyclical components.

To our best knowledge, there is no study that has analyzed the relationship between the oil price changes and the returns of individual stock market sectors for the case of France. In fact, as most research has concentrated on a few industrialized countries, in particular the United States and the United Kingdom, additional evidence would be provided for some other major world economies like France. This country has a high dependency rate for crude oil[4] and thus a heaviest sensitivity to the variability of oil prices. In fact, France is the Europe's second largest consumer of energy, after Germany and oil is the France's second most important energy source behind nuclear energy. Also, sectors may be differentially affected by oil changes. In this study, we consider eight sectors: Industrials, Financials and Banks, Health care, Information Technology, Consumer goods, Materials, Oil and Gas and Telecommunications.

Our findings via QQ and frequency domain causality over a weekly period from January 2000 to June 2015 suggest the occurrence of asymmetric and nonlinear responses of French sectoral markets to changes in oil price. Beyond the nuance of asymmetry and nonlinearity, the seriousness of oil price impact on French sectoral equities is not uniform. It varies remarkably depending on sectors of activity. Specifically, we show that Industrials, Materials, and Oil and Gas react more strongly than Financials and Banks, Health Care, Information Technology, Consumer goods and Telecommunications towards oil price changes. Regarding the strength of causality, the frequency domain causality test (relying on signal theory) has also proved its practicality and meaningfulness in this respect by sustaining the existence of variant spillovers between Oil market and sectoral equity returns in France. On the whole these results appear of paramount importance for international portfolio management.

The rest of the paper is organized as follows. Section 2 describes the methodology pursued throughout this study. In the same section, we provide a brief data overview. Section 3 reports the main empirical results. Section 4 concludes and offers some portfolio allocation implications.

[4] The nuclear fuels, the petroleum products, the natural gas and renewables are perceived as the main alternative inputs in France (Christie 2008). The intensity calculations determined by IEA Energy Balances (2008) can give us more accurate picture of where exactly French industries' vulnerability may lie: the petroleum product intensity of France's industry is about 8.9 percent, while that of natural gas appears stronger (about 16.8 percent).

2. Methodology and data

2.1. The quantile-on-quantile approach

Compared to the standard estimation of the conditional mean function (OLS regression), quantile regression assesses each link accurately across random variables. Since its introduction by Koenker and Bassett (1978), quantile regression continues to be an interesting tool as it accounts for a set of regression curves that differ across distinct quantiles of the conditional distribution of the dependent variable. It provides a complete description of an asymmetric time series, which is one of the main distinguishing features of financial data. It may bring scrupulous information on the average dependence between time series on the one hand and between the upper and lower tails on the other hand. The quantile method enables to estimate multiple ranges of changes (i.e., slopes) from the minimum to the maximum responses (Koenker and Xiao 2002). It can underscore a broader picture in helping gauge the correlation between current returns and various parts of the lagged conditional returns which presents outstanding when extreme values are present. It bestows the role of different rhythms in the connectivity between the considered variables.One shortcoming of the QR method relies in its inappropriateness to detect dependence in its entirety.While a QR is suited to determine how evolve time series for all portions of a probability distribution (i.e., slopes from the minimum to the maximum responses), the application of QQ approach involves estimating two linear quantile regressions (Sim and Zu 2015). In other words, the problem of modeling the quantile of sectoral French stock market as a function of the quantile of oil prices gives rise to the usefulness of QQ model. This technique allows relating the quantile of the various sectors of French equity with the quantile of changes in oil price, so that the linkage between them could vary at different and well specific points in their respective distributions. Then, each estimated quantile concerns a specific segment of the conditional distribution, resulting on a comprehensive description of the reaction of French sectoral equities to oil price variability, missed by the conventional methods.

Technically, unlike the QR which regresses the θ-quantile of the sectoral stock returns on oil price changes, the QQ regresses the θ-quantile of the investigated equity returns on the τ-quantile of oil price shocks, and as a result, its parameters will be indexed by θ and τ (and not only θ as QR). Thus, one can expect that the QQ approach should convey supplementary information about the central issue.

Let the superscript *SSTR* denotes the quantile of the sectoral level of French equity returns, we first postulate a model for the θ-quantile of *SSTR* as a function of history and oil price changes (*Oil*), expressed as follows:

$$SSTR_t = \beta^{\theta} Oil_t + \alpha^{\theta} SSTR_{t-1} + \varepsilon_t^{\theta} \tag{1}$$

where ε_t^{θ} is an error term that has a zero θ-quantile. It must be recalled here that this investigation considers eight sectors: Industrials, Financials and Banks, Health care, Information Technology, Consumer goods, Telecommunications, Materials and Oil and Gas. The history of *SSTR* is used here since the potential exogenous variables (in particular, the sectoral stock returns fundamentals) are unavailable[5] for our estimates. This time series allows measuring the sensitivity of *SSTR* to its past values. The relationship function $\beta^{\theta}(.)$ is unknown, since we don't have prior insights on how *SSTR* and *Oil* are inter-linked. To rigorously analyze the interdependence between θ-quantile of the sectoral-level stock returns of France and the τ-quantile of Oil price, denoted by Oil^{τ}, we linearize the function $\beta^{\theta}(.)$ by taking a first order Taylor expansion of $\beta^{\theta}(.)$ around Oil^{τ}, which prompts:

$$\beta^{\theta}(Oil_t) \approx \beta^{\theta}(Oil^{\tau}) + \beta^{\theta'}(Oil^{\tau})(Oil_t - Oil^{\tau}) \tag{2}$$

We can redefine $\beta^{\theta}(Oil^{\tau})$ and $\beta^{\theta'}(Oil^{\tau})$ respectively as $\beta_0(\theta,\tau)$ and $\beta_1(\theta,\tau)$. Then, the equation (2) can be re-written as:

$$\beta^{\theta}(Oil_t) \approx \beta_0(\theta,\tau) + \beta_1(\theta,\tau)(Oil_t - Oil^{\tau}) \tag{3}$$

Ultimately, we substitute equation (3) into equation (1) to obtain:

$$SSTR_t = \beta_0(\theta,\tau) + \beta_1(\theta,\tau)(Oil_t - Oil_{\tau}) + \alpha(\theta) SSTR_{t-1} + \varepsilon_t^{\theta} \tag{4}$$

While the correlation examination via QQ may be very useful for market participants to act appropriately to oil price shocks, a computational critical way arises from the fact that correlation does not necessarily imply causality.

[5] Weekly data are unavailable for some variables explaining stock returns such as inflation or industrial production.

2.2 The frequency domain causality test

The majority of previous empirical researches are limited in scope to the application of linear models. However, the change in energy policy, the excessive oil price movements, the great speculation, the hefty uncertainty surrounding energy and financial markets and the " convoluted" asset prices dynamics can prompt structural alterations in the pattern of equities' responses to oil price shocks for a given time period. Bearing in mind these considerations, this study seeks to scrupulously address this issue in a nonlinear framework by utilizing recently developed nonparametric approach of Breitung and Candelon (2006). This technique allows decomposing the Granger causality in the frequency domain. A frequency-by-frequency analysis will make it possible to identify if the predictive power is concentrated at the quickly fluctuating components (high frequencies or short-run) or at the slowly fluctuating components (low frequencies or long-run).

To define the frequency causality test, we start by considering $z_t = [x_t, y_t]$ as a two-dimensional time series vector with t = 1… T. It is supposed that z_t has a finite-order VAR representation $\theta(L)z_t = \varepsilon_t$ where $\theta(L)z_t = 1 - \theta_1 L - ... - \theta_p L^p$ is a 2 × 2 lag polynomial with $L^k z_t = z_{t \to k}$. It is assumed that the vector ε_t is white noise with $E(\varepsilon_t) = 0$ and $E\ (\varepsilon_t \varepsilon_t') = \Sigma$, $E(\varepsilon_t \varepsilon_t') = \sum$ where $\sum$ is a positive definite matrix. The system is stationary expressed as:

$$z_t = \phi(L)\varepsilon_t = \begin{pmatrix} \phi_{11}(L)\phi_{12}(L) \\ \phi_{21}(L)\phi_{22}(L) \end{pmatrix} \begin{pmatrix} \varepsilon_{12} \\ \varepsilon_{21} \end{pmatrix} \tag{5}$$

$$= \Psi(L)\upsilon_t = \begin{pmatrix} \psi_{11}(L)\psi_{12}(L) \\ \psi_{21}(L)\psi_{22}(L) \end{pmatrix} \begin{pmatrix} \eta_{12} \\ \eta_{21} \end{pmatrix}$$

Then, the spectral density can be derived from the previous matrix and denoted as:

$$f_x(w) = \frac{1}{2\pi} \left\{ \left| \psi_{11}(e^{-iw}) \right|^2 + \left| \psi_{12}(e^{-iw}) \right|^2 \right\} \tag{6}$$

Analyzing time series in frequency domain i.e., spectral analysis, allows us to identify the cyclical properties of data. In this study, the Granger causality test-based frequency domain relies on a modified version of the coefficient of coherence. It is estimated in a nonparametric fashion enabling to derive the distributional properties of investigated time series. Let x_t and y_t be two stationary time series of length *T* representing the oil price and the sectoral stock returns, respectively. We test whether x_t (*Oil*) Granger causes y_t (*SSTR*) at a given frequency λ. Accordingly, Geweke (1982) proposed a measure of causality that can be expressed as follows:

$$M_{Oil\rightarrow SSTR}(w) = \log\left[1+\frac{\left|\psi_{12}(e^{-iw})\right|^2}{\left|\psi_{11}(e^{-iw})\right|^2}\right] \quad (7)$$

As $\left|\psi_{12}(e^{-iw})\right|^2$ seems a "complex" nonlinear function of the VAR parameters, Breitung and Candelon (2006), and while attempting to resolve this drawback, argued that the hypothesis $M_{Oil\rightarrow SSTR}(\omega) = 0$ corresponds to a linear restriction on the VAR coefficients.

$$H_0 : R(\omega)\phi(L) = 0 \quad (8)$$

where $R(\omega) = \begin{bmatrix} \cos(\omega)\cos(2\omega)\ldots\cos(p\omega) \\ \sin(\omega)\sin(2\omega)\ldots\sin(p\omega) \end{bmatrix}$

Based on equation (8), we can adequately capture how signals evolve among different frequency bands involved. The significance of the causal relationship can be tested by a standard F-test or by comparing the causality measure for $\omega \in [0, \pi]$ with the critical value of a $\chi 2$ distribution with 2 degrees of freedom, which is 5.99.

2.3. Data

In this article, we empirically gauge the linkages between oil prices changes and stock returns in France from a sectoral perspective using weekly data over the period from January 2000 to June 2015[6] (with a total of 708 observations). Our sample data include eight sector indices of French stock market "CAC40". The sector indices offer some insights of the performance of this market. The selected industries are Financials and Banks (Banks, insurance, reinsurance, real estate and financial services), Oil and Gas (Oil and Gas producers, Oil equipment, and services, distribution and alternative energy), Health Care (Health care equipment and services, and pharmaceuticals and biotechnology), Industrials (construction and materials, and industrial goods and services), Consumer goods (household goods, home construction, leisure goods, and personal goods and tobacco), Technology Information (software and computer services, and technology hardware and equipment), Telecommunications (fixed line and mobile telecommunications), and Materials (chemicals and basic resources). We collect these sectoral stock market data from Datastream database. For crude oil price, we use real oil price (*Oil*) to take into account the level of inflation

[6] The period of the study is motivated by the availability of the data.

coming from Energy Information Administration (EIA) and Econstats™. We use weekly instead of daily or monthly data to avoid possible econometric pitfalls that may occur such as the microstructure effects, the bid-ask bounce and the non-synchronous trading, and possible asymmetrical demeanor, etc. The large sample size can satisfactorily guarantee proper QQ and frequency causality investigations for capturing the responses of sectoral stock returns to oil price changes. In order to analyze whether there is an asymmetric and nonlinear dependence (correlation and causality) among the considered variables, we have transformed them by taking natural logarithms to correct for heteroskedasticity and dimensional differences. Descriptive statistics for return series (first logarithmic differences) are reported in Table 1. On average, *Oil* experiences heavier returns than French sectoral stock returns over our sample period. Oil and Gas have the greatest volatility followed by Industrials stocks and then Materials. Skewness is negative for all the investigated time series and the Jarque-Bera test statistic rejects the hypothesis of normality in the most cases.

[Insert Table 1 about here]

3. Main results

As a preliminary exercise, we first explore what OLS, QR and standard Granger causality test have to say about the influence that oil price has on various sectors of the French stock market. The idea here is to have a case of benchmarking to compare these three methods with new techniques in order to underscore the effectiveness and the functionality of the QQ method and the frequency domain causality test in this exercise.

3.1. Results via standard methods

The OLS findings are summarized in Table 2. They appear significant for only three sectors: Oil and Gas, Financials and Banks and Materials. The reaction to oil price seems negative for Materials, while it is positive for Oil and Gas and Financials and Banks. The sign of these correlations appears predictable and intuitive. Nevertheless, the non-significance of other sectors such as Industrials and Consumer goods are highly unexpected. The mean effect of the exogenous variable on the endogenous time series may be under or over estimate impacts or even fail to properly determine full possible influences (Cade and Noon 2003); hence the need to perform more sophisticated methods.

[Insert Table 2 about here]

QR estimates are presented in Table 3. They give more detailed and finer results. For the Industrials sector, for example, the relationship that was positive and insignificant becomes significantly negative at lower quantiles (i.e. when investors are pessimistic). It is noticeable that the strength of the relationship is likely to be strong when compared with other sectors. For the Oil and Gas sector, the response to oil price variability seems positive when the French market is moderately efficient (i.e., for quantile levels 0.6 and 0.7). The reaction of Financials and Banks sector to oil price changes is positive and weaker at different quantiles. However, this response is stronger when the market is euphoric (i.e., quantile equals to 0.9). For Materials sector, the correlation is negative at θ-quantile around the average, but also when investors are optimistic (i.e., upper θ-quantiles). About the Consumer goods sector, the relationship is also negative, but it is significant only in the lower θ-quantiles (i.e., when the market is underperforming). These observed findings appear encouraging for the main sectors concerned by oil price shocks. For the other sectors, we show an insignificant reaction of Information Technology, a negative Health Care response (i.e., low quantile levels) and a positive Telecommunications' reaction at upper θ-quantiles.

[Insert Table 3 about here]

Table 4 reports a formal test of the equality of the coefficient estimates for various θ-quantiles to evaluate whether the estimated QR relationships are conform to the location shift hypothesis which assumes the same slope parameters for all of the conditional quantile functions[7]. It shows that the coefficient estimates are statistically different from each other if the estimates for lower θ-quantiles are compared with estimates for the higher or intermediate θ-quantiles. These outcomes hold for both coefficient estimates of *Oil* and $SSTR_{t-1}$. The null hypothesis of equal slope is generally rejected[8] at the conventional significance levels for Industrials (40th vs. 60th), Oil and Gas and Consumer goods (20th vs. 80th), Financials and

[7] The Koenker and Xiao (2002) test computes that all the covariate effects satisfy the null hypothesis of equality of the slope coefficients across θ-quantiles. In particular, the difference between slope estimates at the θ and (1-θ) quantiles is examined. A rejection favors the QR.

[8] The rejection of the null hypothesis implies that the magnitude of the slope coefficient, estimated at the various parts of the return distribution, is different and that the difference is statistically significant.

Banks (30th vs. 70th and 40th vs. 60th), Health Care, Telecommunications and Materials (30th vs. 70th) and Information Technology (20th vs. 80th and 30th vs. 70th).

[Insert Table 4 about here]

The Granger causality is also an interesting method since it provides relevant information on the interaction between the concerned variables in a dynamic model. The main results are summarized in Table 5. With respect to the significance of the central relationship, Granger causality reveals close outcomes. The sectors where the dependence (causality) is significant are, respectively, Oil and Gas, Materials, Financials and Banks, Industrials and Consumer goods. Thus, these sectors of French stock market suffered most from the changes in oil price. For the rest of sectors (secondary sectors), only the Telecommunications sector responds significantly to oil price fluctuations.

[Insert Table 5 about here]

Summing up, our analysis of the responses of different sectors of French stock market to changes in oil price via standard econometric techniques (OLS, QR and Granger causality test) has allowed us to reach the following results:

(i) There exist significant dependence (both correlation and causality) between the main sectors of French stock market (Industrials, Oil and Gas, Financials and Banks, Materials and Consumer goods) and oil price changes, with the expected sign.

(ii) These relationships are likely to be sensitive to the mood in central equity market. We distinguish two extreme cases: the relationship is negative and significant for Industrials when the mood toward the market turns pessimistic. It is positive and negative for Oil and Gas sector when pessimism mostly prevailed.

(iii) With respect the strength of causality (maximum Fisher), it appears more significant for Oil and Gas, Consumer goods, Telecom, Materials, Financial and Banks and Industrials (in this order).

These results are globally intuitive. But we want to go beyond and see how exactly the sectoral French equity reacts to the oil price movements. In other words, this study will not be limited in assessing whether the effect of oil price changes is positive or negative or whether such causality exists, but what is more interesting for us is to evaluate if an impact exists when *Oil* is cheap or when it is expensive and if is sensitive to the mood toward stocks and the market turns pessimistic or optimistic (through QQ approach). Similarly, it may be relevant for market participants to be acknowledged by the occurrence of a time-varying causality (via frequency domain causality).

3.2. QQ results

Let's start our interpretations with Oil and Gas, the most concerned sector by oil price changes in the French case. One of the key contributions of the QQ method is that it allows achieving interesting interpretations with respect to the constant term. It is well noticeable that the constant increases with the price of oil and the performance of sectoral stock market (the left side of Figure 1). This implies that the intercept is large at upper Oil and Gas return quantiles and at higher oil price quantiles. But, when the oil price is weak (for τ=0.3), the constant term seems negative, mostly for quantile levels 0.6 and 0.8. Likewise, when the market is very efficient and the price of oil rises markedly (achieving its maximum), the constant also reaches its maximum. This fortifies that large positive oil price shocks can bolster the return of equity further when investors are optimistic. Besides, we show that the behavior of constant term with respect to τ suggests that the effect of oil price variation could be symmetric. For instance, when τ is low, the effect of oil price shocks on stock returns is stronger (constant coefficient equals to -4), and when τ is high, the *Oil* impact is positive, but the correlation (or the constant coefficient) does not exceed 2. In other words, the positive effect of the oil price shock is two times less than its positive effect on the examined sectors. In addition to the intercept term, the effect of oil price chock is also captured by the slope coefficient of the τ-quantile of oil price. The graphs (the right side of Figure 1) represent the values of the slope coefficient for different levels of θ and τ. Our results initially reveal that the relationship is generally positive when investors are optimistic; it is negative when investors are rather pessimistic. The relationship reached its peak when the market is euphoric (θ= 0.9) and the oil price is above the average (τ = 0.6). It attains its minimum when the market is pessimistic (for θ=0.1) and the oil price is low (when τ is around 0.3). And even when the oil price is well oriented, the correlation can be negative if investor mood is not optimistic, where in line with the notion of asymmetry. For Materials sector, a negative influence of *Oil* is validated whatever the performance of equities. It appears at its peak (slope coefficient = -0.24) when investor mood seems optimistic (for θ=0.8) and when the oil price variation is low (for τ=0.3), but also when pessimism mostly prevailed (θ=0.1) and when *Oil* is moderately high (for τ around 0.6 and 0.7). This underpins the occurrence of asymmetry. Industrials sector behaves dissimilarly; we notice that Oil-Industrials nexus is negative regardless of the mood of the market and whatever the prices of oil. However, it is close to zero when the price of oil seems highest (for τ=0.7) and when the market performance is around the average (for $\theta = 0.5$). Remarkably, a strong interdependence (-0.60) occurs when the market is inefficient (lower θ-quantile) and when the oil price vary heavily (for τ=0.7). When focusing on the Consumer goods, we show that the relationship is negative everywhere (as in the QR analysis), but it is positive when the market is rather around the mean ($\theta = 0.5$) and the price of oil increases substantially (upper τ-quantile*)*. Note, nevertheless, that the correlations are weak. While the QR seems suggestive of positive and weak response of Financials and Banks' sector to oil price changes especially at upper θ-quantiles (i.e., when investors are optimistic)the QQ approach views differently this linkage. First, the *Oil*'s effect on Financials and Banks sector is generally negative and small, or close to zero, except when oil prices are at the top (i.e., highest τ). Secondly, the relationship is significantly positive (but weak) whatever the mood of the market. For other sectors (Health Care, Information Technology, and Telecommunications), the correlations are usually negligible.

Based on the aforementioned outcomes, we can deduce the ineffectiveness of the QR in addressing the focal topic, since it overlooks the possibility that the nature of oil price shocks could also influence the dynamic interaction between equity returns and oil price movements.

[Insert Figure 1 about here]

3.3. Frequency domain causality results

As mentioned above, the focus of the use of frequency domain causality test is on detecting cycles in the intensity of *Oil*' s impact on various sectors of French equity. Figure 2 clearly depicts the causal relationships between oil price variability and the eight sectors previously analyzed. The figure contains the test statistic with the 5 percent critical values for the different frequencies involved (solid line) over the interval [0, π]. The frequency (ω) on the horizontal axis can be translated into a cycle or periodicity of *T* by $T = (2\pi / \omega)$ where *T* is the period (weeks in our case).

The results of Granger coefficient for causality between *Oil* and *SSTR* highlight sharp dissimilarity among the investigated sectors regarding the seriousness of oil price's effect. Specifically, we can distinguish four groups of sectors. In the first, the cyclical components appear longer for Materials (when $\omega \in [0.01\pi - 0.76\pi]$, corresponding to a cycle superior to 8.3 weeks), and Financials and Banks (when $\omega \in [0.01\pi - 1.08\pi]$, corresponding to a cycle above 5.8 weeks). Notably, the Oil and Gas is the most sensitive sector to Oil shocks since the cycle seems lengthy (when $\omega \in [0.01\pi - 0.65\pi]$, corresponding to a cycle length above 9.6 weeks). The second group includes Industrials' sector which is likely to be driven by medium and quickly fluctuating components (when $\omega \in [1.52\pi - 3.03\pi]$, corresponding to a cycle within 4.2 weeks). The third group is formed by Consumer Goods and Telecommunications where the causality occurs at highest frequencies (short-run). In particular, a causal link running from oil price changes to Consumer goods is supported when $\omega \in [2.81\pi - 3.03\pi]$ or for a cyclical component less than 2.2 weeks, while it is validated for Telecommunications sector when $\omega \in [2.60\pi - 2.92\pi]$, corresponding to a cycle between 2.1 and 2.4 weeks. The last group includes Health Care and Information Technology where the causality does not occur at any frequency band.

[Insert Figure 2 about here]

It is noteworthy that with the sharp drop of oil prices, the Oil and Gas industry undergoes a difficult situation. The biggest companies (Total[9], for instance) suffered less from this oil price decrease. Not surprisingly, these companies have a great financing capacity and a heavier resilience to the crisis. But small businesses (OEMs[10], particularly) are bearing the brunt of slowdown in investment of the major Oil and Gas clients. Vallourec group ‒specialized in hot rolled seamless steel tubes and the second largest steel tube manufacturer in France‒ has laid off 10 percent of its workforce in 2015 and reduced by one third its European production capacity[11]. The French state ‒as a company shareholder ‒ has decided to participate in strengthening the capital to avoid bankruptcy. Other industries have pursued the same path by rising their capital (GCC and Maurel and & Prom, for example).

[9] Total is a French multinational integrated energy producer and provider. It is the world's fourth-ranked international oil and gas company.
[10] It is short for original equipment manufacturer. It is a company whose products are used as components in another company's product.
[11] Vallourec has lost 80 percent of its value on the stock exchange at the end of January 2015.

4. Conclusions and some portfolio allocation implications

Studying asset prices and the possible oil market spillovers has been and continues to be one of the popular fields of applied research. Several asset classes have been tested, but it seems that the effect of oil price shocks on broad-based indices has been mixed. The distinguishing features of this paper include the focus on the responses of sector equity returns to oil price changes in France and the use of new econometric tools: the QQ approach vs. the frequency domain causality test. The main advantage of these techniques lies in their ability to model the link between oil price and sector stock returns more effectively than is possible with standard methods including the OLS, the QR and the standard Granger causality test. While the OLS regression is only able to estimate the impact of oil price on the conditional mean of French sectoral equities, the QR goes further by disentangling this influence on the conditional mean into different effects on the conditional quantile, accounting therefore for asymmetry. Beyond this nuance, carrying out QQ approach allows probing how both the nature of oil price shocks and the performance of stock market affect the relationship between equity returns and oil price changes. In addition to the correlation analysis, this study applies the frequency domain causality, enabling to test whether the causality between the variables of interest evolves over different cyclical components. By doing so, fresh insights on the French sector returns' responses to oil price changes have been gathered. It must be stressed here that in the case of France, the sectors influenced by oil price movements represent almost 50 percent of the CAC 40. As average for the period 2000-2015, Industrials and Financials and Banks sectors represent each 18 percent, followed by Consumer goods (14 percent), Health care (10 percent), Oil and Gas (almost 9 percent), Information technology (4.5 percent), Materials (presenting 4 percent of overall CAC40 index) and then Telecommunications (3 percent)[12].

The obtained results deeply suggest that the French stock market' response to oil price changes differs substantially among the sector activities and the tail-distributions. Besides, this study provides new evidence that the dependence between oil price and French sector-by-sector stock returns could be specific, asymmetric and nonlinear. Indeed, Industrials, Materials, and Oil and Gas sectors react more strongly to oil price variability than Financials and Banks, Health care, Information Technology, Consumer goods and Telecommunications. These outcomes have far-fetching policy implications in this regard. They may be used for portfolio construction and diversification, as variant sensitivities to oil price have been

[12] For details about the composition of the CAC40 stock market index, please refer to Figure A.1, Appendix.

discovered. The fact that the responses of the French industries to oil price shocks change heavily from lower to upper quantiles and from shortest to longest frequencies may have profound consequences for portfolios that trade with various rebalancing horizons. Holding diversified portfolio could obviously palliate risk management, by lessening the sensitivity of French equity to oil price changes by allocating investment among various industries that would each react differently to oil shocks. In spite of the asymmetry distinguishing the central linkage, investors in Industrials, Materials and Oil and Gas should seek to rebalance their portfolios ease with their views of the sign of coming oil price variation (increase or decrease). In fact, investors who hope investing in French stock market (especially in Industrials, Materials and Oil and Gas sectors) should keep an eye on crude oil market behavior and anticipate their operations. Specifically, market participants who are highly interested in trading in oil-sensitive stocks in France may, when oil prices are expected to raise, select stocks from sectors, such as Oil and Gas sector, with positive sensitivity to oil price changes. However, when oil price is expected to fall, investors may choose sectors with negative sensitivity including Industrials. They can also use oil-related derivatives instruments.

In a nutshell, on the basis of the article' findings, the investors can properly anticipate the evolution of the different sectoral price indices conditioning upon the variation of oil prices. The results show that the relations are neither linear nor symmetric. In other words, investors (traders in particular) can find well specified inflection points (depending to the quantiles of *SSTR* (θ) and oil price (τ)), allowing it to efficaciously judge the pertinence of market structure determined by the entry and exit decisions. Standard methods are completely unbefitting in this respect. From an asset allocation perspective, digging further into the financial stability implications of the rising dependence of oil price changes and sectoral equity returns is a relevant topic for future research.

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Table 1. Descriptive statistics

	Oil	Industrials	Oil and Gas	Financials and Banks	Health Care	Information Technology	Consumer goods	Telecom	Materials
Mean	-0.043886	-1.908514	-2.623529	-2.000827	-2.476462	-3.235433	-1.713637	-3.243677	-3.254033
Median	0.000541	-1.855605	-2.616529	-1.951914	-2.118009	-3.180615	-1.703215	-3.026191	-3.256578
Maximum	0.140247	-1.618215	-2.425748	-1.850336	-2.042876	-3.060841	-1.602369	-2.973971	-3.140758
Minimum	-0.443831	-2.556344	-2.909243	-2.324201	-4.593867	-3.789297	-1.960952	-4.482953	-3.387590
Std. Dev.	0.168909	0.326716	0.435279	0.251931	0.188581	0.184311	0.087808	0.043059	0.276913
Skewness	-0.959173	-1.512853	-0.807922	-1.216954	-2.134424	-1.722326	-1.196311	-1.932192	-0.173964
Kurtosis	2.969950	4.961090	3.110060	3.136414	5.971664	5.783398	4.686048	5.428490	1.967275
Jarque-Bera	12.45391	9.208883	8.858007	14.29280	19.16314	13.89250	9.068573	14.75531	10.84200

Table 2. OLS estimates: the link between oil price and sectoral equities in France

	Industrials	Oil and Gas	Financials and Banks	Health Care	Information Technology	Consumer goods	Telecom	Materials
C	-2.282*** (-19.776)	-0.128*** -4.017119	-0.481*** (-10.242)	-0.0282* (-1.8935)	-1.5942* (-13.598)	-0.278*** (-7.194)	-0.44*** (-6.490)	-0.203*** (-4.258)
$SSTR_{t-1}$	0.251*** (7.1803)	0.9593*** (94.9588)	0.776*** (35.529)	0.991*** (21.149)	0.586*** (20.017)	0.858*** (46.120)	0.888*** (53.490)	0.553 (1.523)
Oil	0.0675 (1.467)	0.0208** (2.2944)	0.008*** (5.1970)	-0.0055 (-1.3153)	-0.0193 (-0.6130)	-0.0124 (-0.9691)	-0.003 (-0.209)	-0.651*** (-5.116)
R^2	0.26	0.92	0.65	0.98	0.34	0.73	0.78	0.91

Note: ***, ** and * imply significance at the 1%, 5% and 10% levels, respectively.

Table 3. QR estimates: the link between oil price and sectoral equities in France

		Industrials	Oil and Gaz	Financials and Banks	Health Care	Information Technology	Consumer goods	Telecom	Materials
Intercept	0.100	-4.61657*** (-10.07311)	-4.96003*** (-13.53617)	-0.37137*** (-5.594970)	-4.33036*** (-4.285185)	-1.19069* (-2.62080)	0.019047 (0.46632)	0.4941*** (9.788064)	-5.7276*** (-7.755769)
	0.200	-3.56348*** (-10.81410)	-4.17932*** (-12.60183)	-0.34326*** (-4.735503)	-3.98579*** (-11.96497)	-0.83177* (-1.94192)	-0.072586 (-0.8201)	0.2719*** (5.325986)	-4.76631*** (-21.54473)
	0.300	-2.81871*** (-11.66203)	-3.61910*** (-14.76543)	-0.27424*** (-4.640707)	-3.23517*** (-10.99059)	-1.09489* (-5.57613)	-0.19774* -(2.0714)	0.137379* (1.74122)	-4.28970*** (-25.82033)
	0.400	-2.42107*** (-11.4242)	-3.21986*** (-17.32207)	-0.31342*** (-4.539322)	-2.87061*** (-10.37225)	-1.05932* (-7.25114)	-0.226*** (-7.0999)	-0.075019 (-1.20183)	-4.14698*** (-25.82274)
	0.500	-2.09634*** (-10.48665)	-2.969260 (-18.56424)	-0.37629*** (-5.262487)	-2.47736*** (-11.21431)	-1.18585* (-8.52449)	-0.2635** (-3.0274)	-0.20098* (-2.35262)	-3.83741*** (-23.96235)
	0.600	-1.83620*** (-9.908312)	-2.70211*** (-17.62503)	-0.44594*** (-7.543814)	-2.39279*** (-12.51097)	-1.2920*** (-10.8533)	-0.286*** (-5.2061)	-0.392*** (-5.97065)	-3.39808*** (-21.78730)
	0.700	-1.45548*** (-8.191780)	-2.33180*** (-15.18424)	-0.45222*** (-8.403698)	-2.09880*** (-12.80783)	-1.3354*** (-11.7024)	-0.293*** (-3.7848)	-0.466*** (-8.16460)	-3.19067*** (-22.24955)
	0.800	-1.23131*** (-6.434784)	-1.98913*** (-10.08604)	-0.39686*** (-8.162114)	-1.83882*** (-12.59389)	-1.6210*** (-10.7400)	-0.359*** (-9.0532)	-0.558*** (-13.9794)	-2.77657*** (-22.32728)
	0.900	-0.85123*** (-4.301304)	-1.657031 (-8.043582)	-0.45195*** (-5.313638)	-1.64844*** (-12.27608)	-1.5557*** (-20.7751)	-0.455*** (-9.5248)	-0.625*** (-20.4604)	-2.25787*** (-18.85851)
$SSTR_{t-1}$	0.100	0.188502 (1.448568)	-0.134329 (-1.222199)	0.847667*** (27.41696	0.206477 (0.856562)	0.95095*** (8.415715)	1.163*** (47.4035)	1.2169*** (66.20755)	0.091534 (0.009728)
	0.200	0.16798*** (3.095479)	-0.110378 (-1.095213)	0.853817*** (25.49866)	0.197304** (2.950143)	0.90620*** (7.426781)	1.041*** (20.2211)	1.1164*** (68.73225)	0.243786 (0.753637)
	0.300	0.22303*** (4.710777)	-0.053214 (-0.702110)	0.879939*** (31.92848)	0.255048*** (4.176888)	0.75531*** (13.87960)	0.941*** (17.3983)	1.0629*** (42.09860)	0.192939 (0.704166)
	0.400	0.253007*** (5.824163)	-0.022574 (-0.390098)	0.857763*** (26.52071)	0.266687*** (4.966201)	0.72591*** (17.50294)	0.897*** (51.1645)	0.9856*** (52.44873)	0.699373* (1.804586)
	0.500	0.270313*** (6.924021)	-0.017970 (-0.363486)	0.824190*** (24.57683)	0.303403*** (6.917263)	0.65492*** (16.30570)	0.855965 (17.5912)	0.941*** (36.84637)	0.577502 (1.518301)

	0.600	0.281864*** (8.005946)	-0.002039 (-0.043307)	0.788432*** (28.52190)	0.287175*** (7.642336)	0.59528*** (17.33810)	0.821805 (27.2965)	0.8742*** (45.45310)	0.597108 (1.681001)
	0.700	0.298460*** (8.956046)	0.040205 (0.883220)	0.781577*** (31.17928)	0.282386*** (8.967892)	0.55163*** (16.50233)	0.794*** (18.2393)	0.843*** (50.43208)	0.334421 (1.193125)
	0.800	0.308107*** (9.408059)	0.046415 (0.761670)	0.802550*** (35.54141)	0.283283*** (11.05057)	0.43445*** (9.476465)	0.724*** (32.8503)	0.8035*** (66.91757)	0.232473 (1.400322)
	0.900	0.25015*** (12.37394)	-0.003444 (-0.053952)	0.768399*** (19.06196)	0.240313*** (9.425751)	0.38576*** (20.66995)	0.595*** (20.6522)	0.7489*** (66.78642)	0.393754** (2.724515)
Oil	0.100	-0.213187* (-1.945522)	0.102937 (0.911491)	0.001283 (0.662925)	-0.001026 (-0.010006)	-0.068994 (-0.76317)	0.000724 (0.05489)	-0.011815 (-1.14562)	-0.290591 (-0.03029)
	0.200	-0.10509*** (-3.431381)	0.084399 (1.023438)	0.003153 (1.654064)	-0.092211* (-1.923181)	-0.006593 (-0.15284)	-0.0221** (-2.4599)	-0.003704 (-0.50121)	-0.361888 (-1.26616)
	0.300	-0.038669 (-0.708304)	0.072074 (0.754742)	0.004694* (2.403697)	-0.035883 (-0.790992)	0.006268 (0.216120)	-0.011048 (-1.1928)	-0.006796 (-0.75032)	-0.263280 (-0.98853)
	0.400	-0.033539 (-0.758260)	0.071956 (1.040313)	0.004045* (2.097392)	-0.029419 (-0.627129)	0.012862 (0.515053)	-0.01674* (-2.1036)	-0.006599 (-1.05078)	-0.82196* (-2.15107)
	0.500	-0.013593 (-0.326721)	0.074916 (1.506812)	0.006090** (3.277359)	-0.036816 (-0.949277)	-0.003108 (-0.13879)	-0.012466 (-1.5450)	-0.008429 (-1.35471)	-0.67628* (-1.81276)
	0.600	-0.008066 (-0.198150)	0.094445* (2.161173)	0.006910*** (4.083948)	-0.048262 (-1.408312)	-0.005157 (-0.25798)	-0.013140 (-1.6317)	-0.006348 (-0.98650)	-0.63940* (-1.84377)
	0.700	0.028123 (0.708842)	0.082893* (1.891457)	0.006055*** (3.552765)	-0.024482 (-0.770284)	-0.005652 (-0.26900)	-0.011210 (-1.2559)	-0.008733 (-1.299407	-0.382188 (-1.39994)
	0.800	0.009626 (0.192022)	0.042618 (0.712381)	0.006491*** (4.319355)	-0.011250 (-0.370604)	0.002065 (0.093688)	-0.0297** (-3.0080)	-0.001366 (-0.17526)	-0.239424 (-1.40213)
	0.900	0.053345 (0.906810)	0.038605 (0.590419)	0.010370*** (5.274175)	0.001766 (0.061472)	-0.015103 (-0.43140)	-0.004779 (-0.3920)	0.016439* (2.044008)	-0.34336* (-2.27447)

Note: ***, ** and * imply significance at the 1%, 5% and 10% levels, respectively.

Table 4. Statistic tests of the equality of slope estimates across various quantiles

	Industrials	Oil and Gas	Financials and Banks	Health Care	Information Technology	Consumer goods	Telecom	Materials
0.100 vs. 0.900	0.38 [0.5497]	0.41 [0.6812]	0.27 [0.8615]	0.86 [0.7534]	1.32 [0.5211]	0.88 [0.8961]	0.39 [0.9574]	0.42 [0.8876]
0.200 vs. 0.800	0.42 [0.7218]	3.68** [0.0096]	0.56 [0.7421]	0.34 [0.6942]	3.74 [0.0094]	10.12*** [0.0000]	0.52 [0.8123]	0.71 [0.9034]
0.300 vs. 0.700	0.61 [0.5350]	0.38 [0.3110]	4.09** [0.0053]	2.71* [0.0813]	1.12 [0.6319]	1.24 [0.7651]	7.76*** [0.0003]	5.06** [0.0012]
0.400 vs. 0.600	2.59* [0.0121]	1.10 [0.1925]	6.13*** [0.0007]	0.62 [0.5593]	4.50** [0.0012]	1.31 [0.6943]	1.18 [0.5641]	1.48 [0.3615]

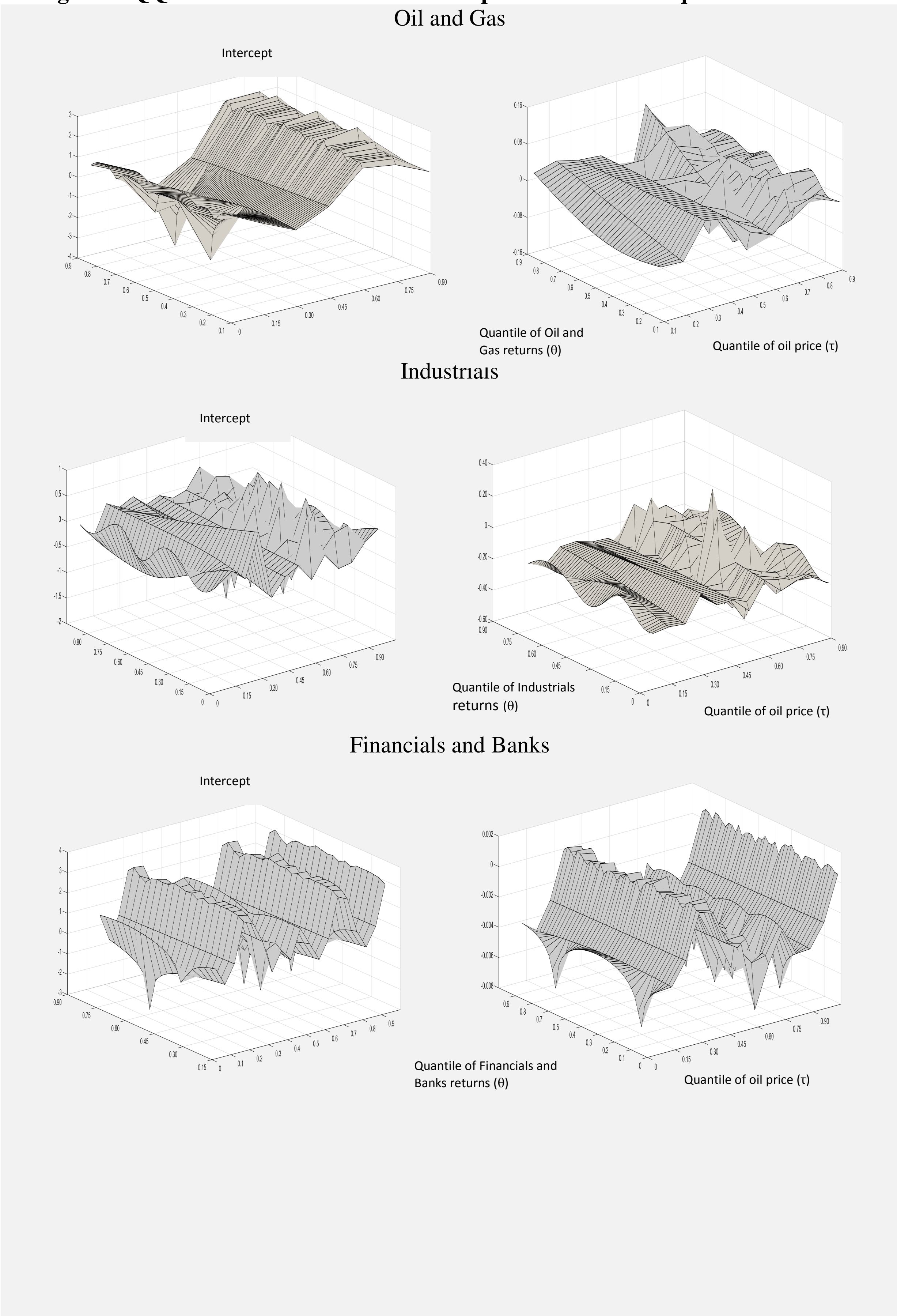
Notes: The table presents the F tests of the equality of slope parameters across various quantiles; [.]: p-values: *, ** or *** denote that the null hypothesis is rejected at the 10%, 5% or 1% significant level, respectively.

Table 5. The Granger causality test: the link between Oil price and Sectoral equities in France

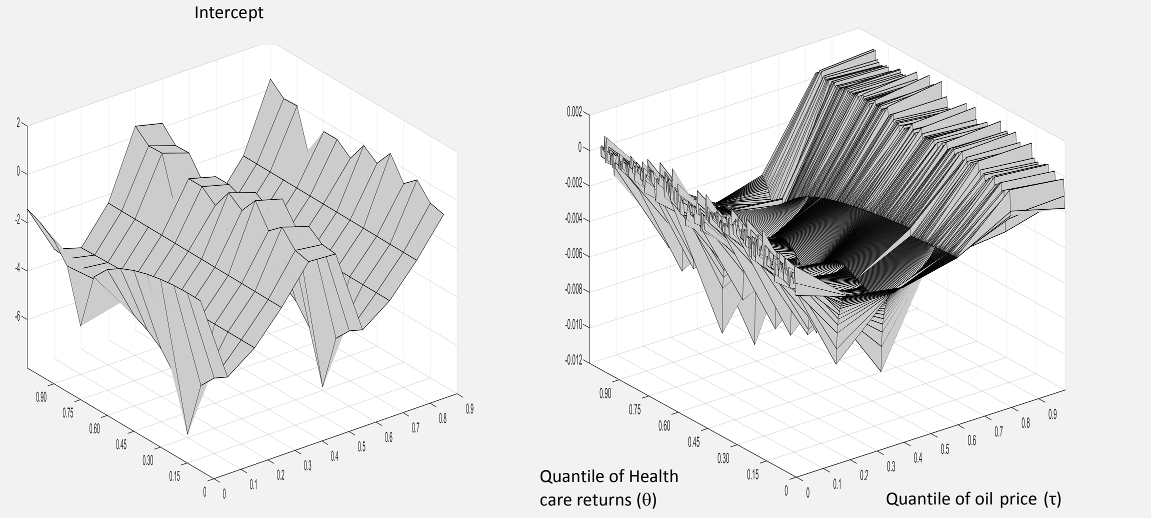
	Industrials	Oil and Gaz	Financials and Banks	Health Care	Information Technology	Consumer goods	Telecom	Materials
Oil	0.0779*	0.0023**	0.0437**	0.2116	0.4934	0.0036**	0.0312**	0.0334**

Note: The table presents the p-values; *, ** or *** denote that the null hypothesis is rejected at the 10%, 5% or 1% significant level, respectively.

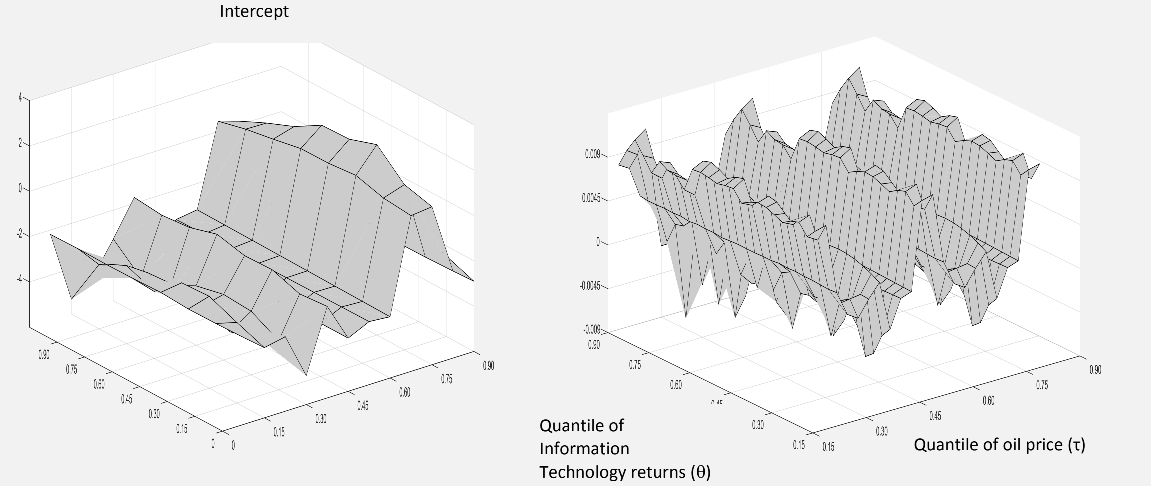
Figure 1. QQ estimates: the link between oil price and sectoral equities in France



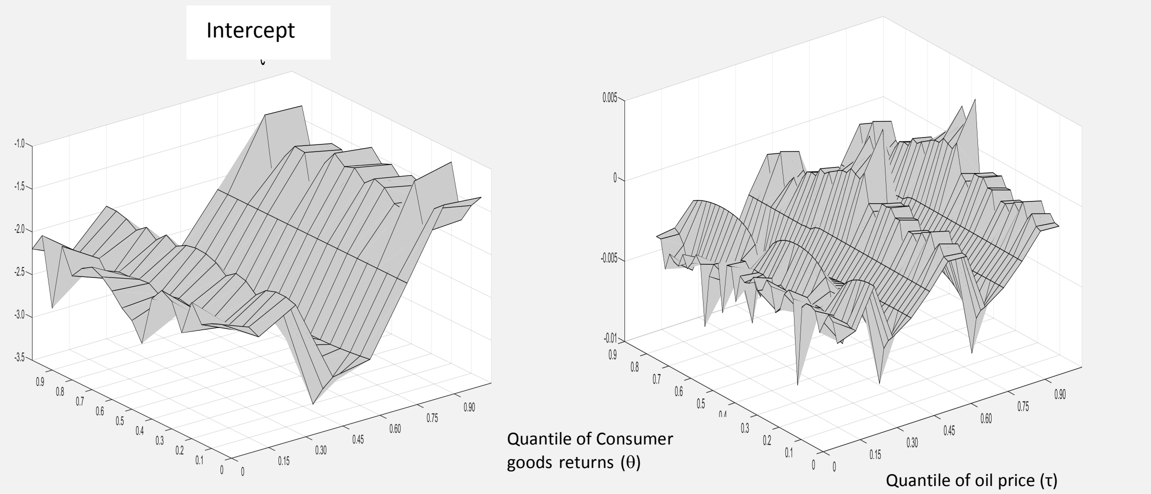
Health Care

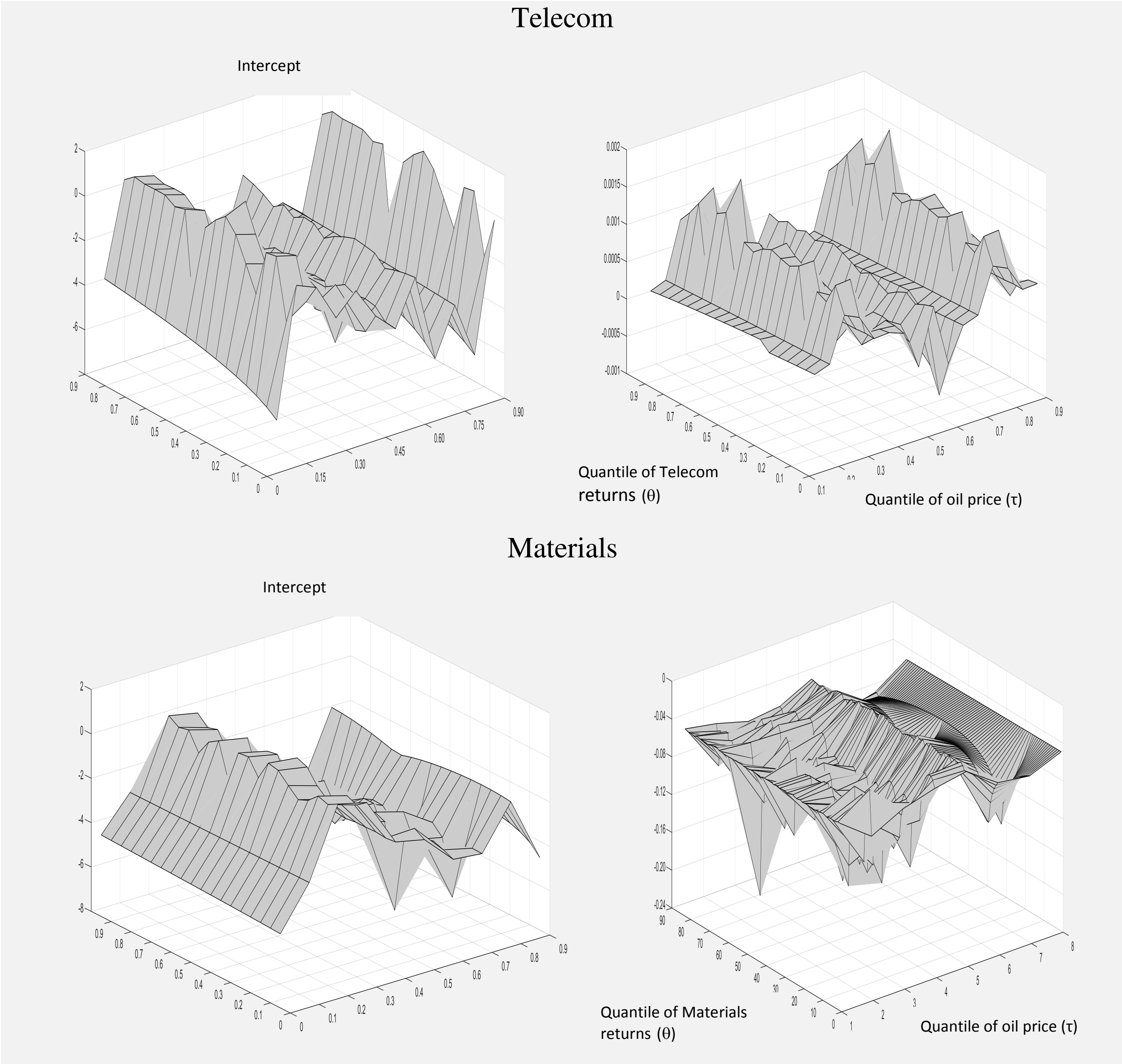


Information Technology



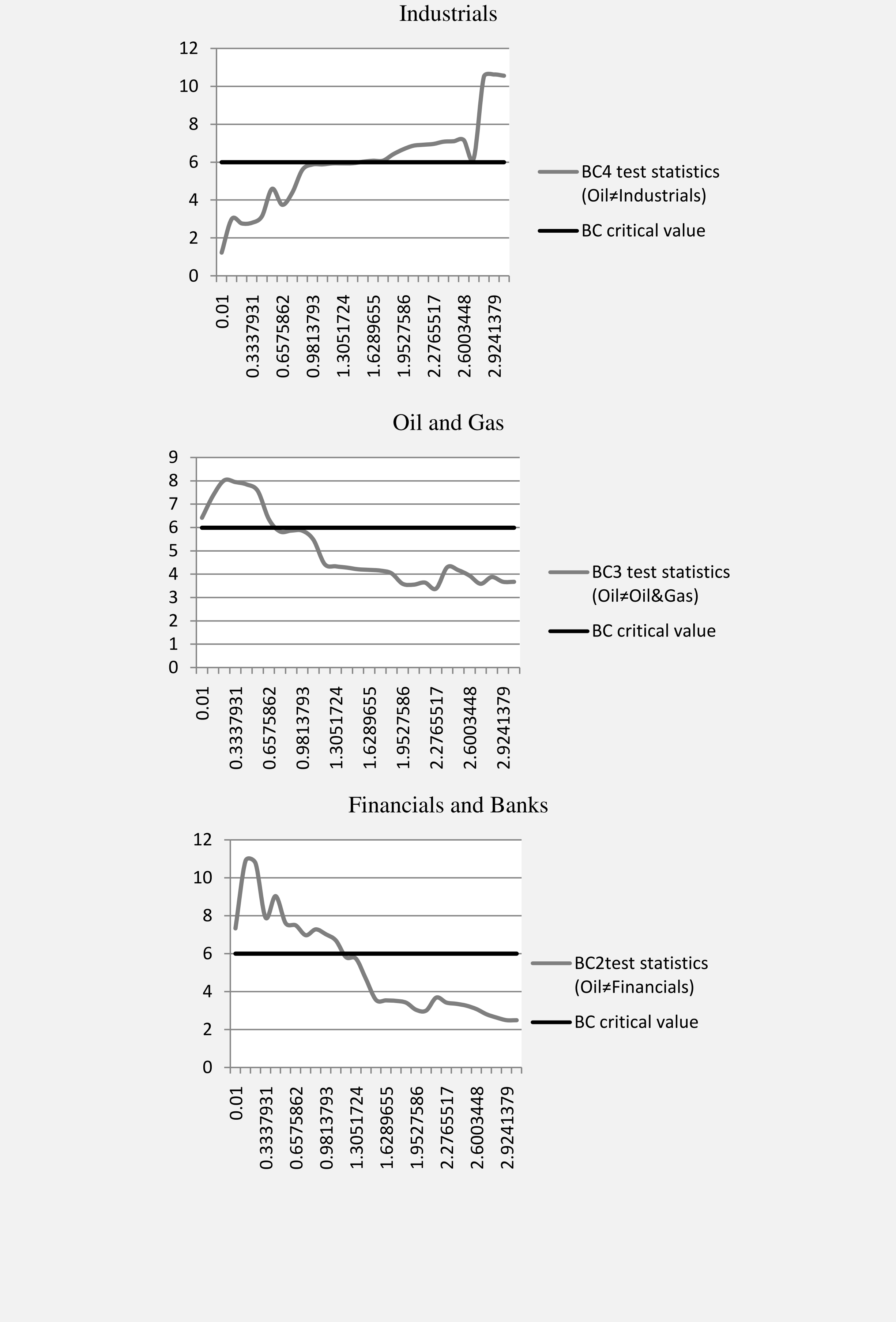
Consumer goods

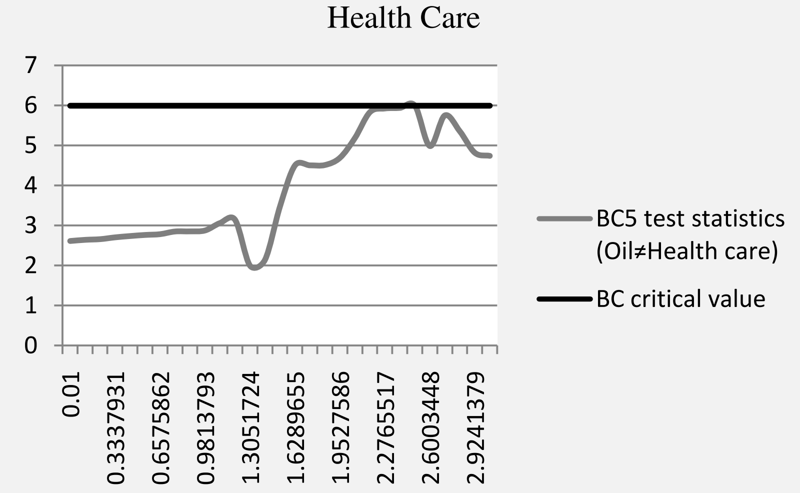


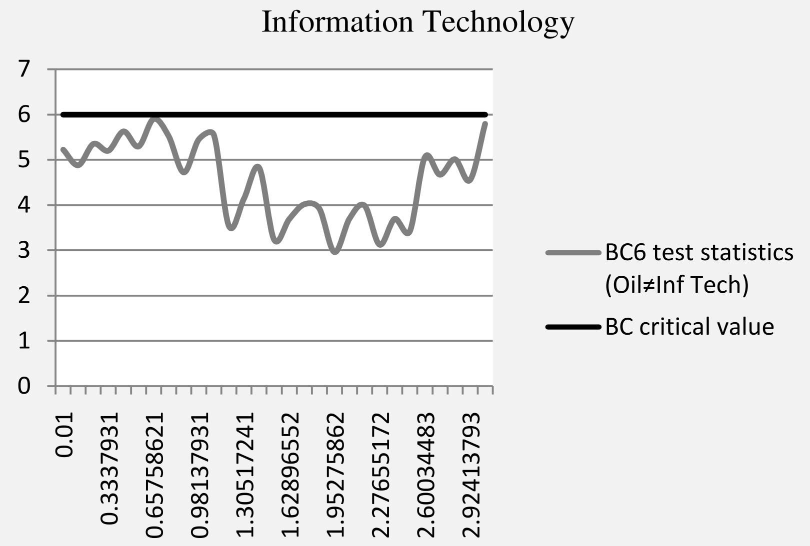


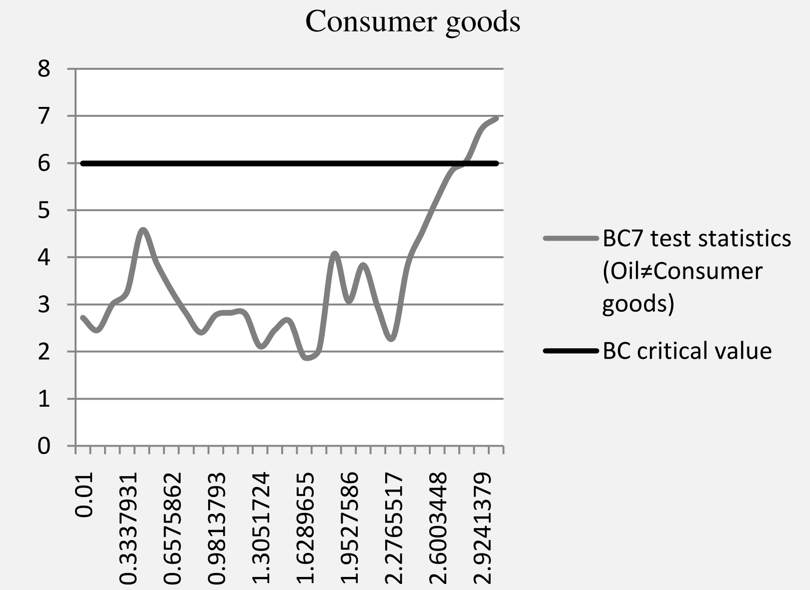
Notes: θ and τ correspond, respectively, to the quantiles of sectoral stock returns and oil price.

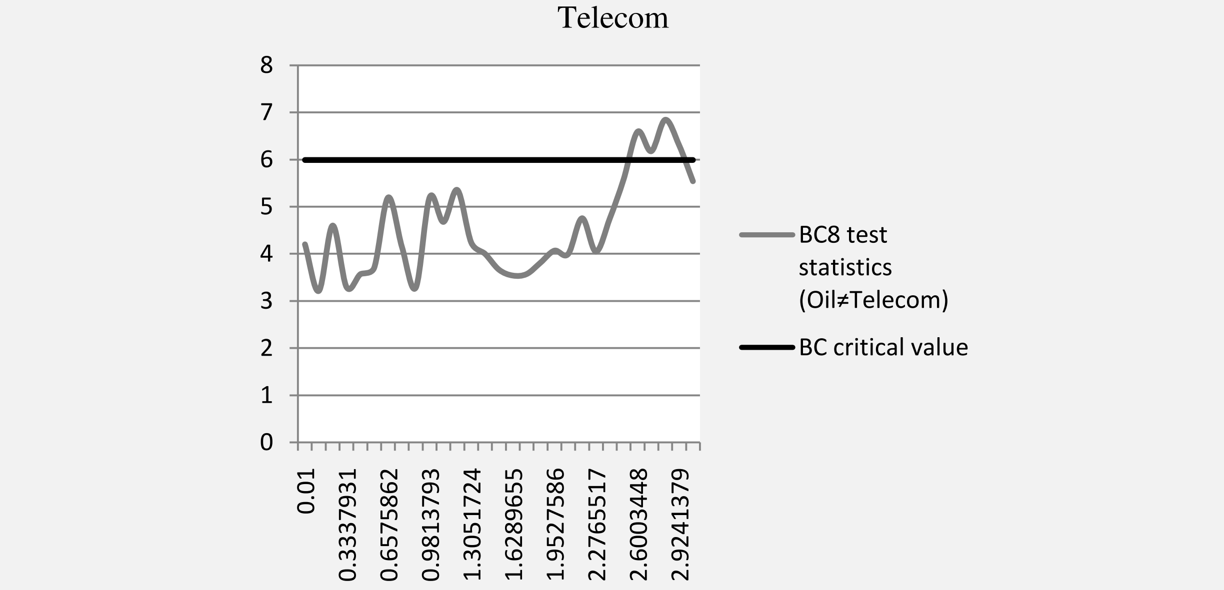
Figure 2. Frequency causality: the link between oil price and sectoral equities in France

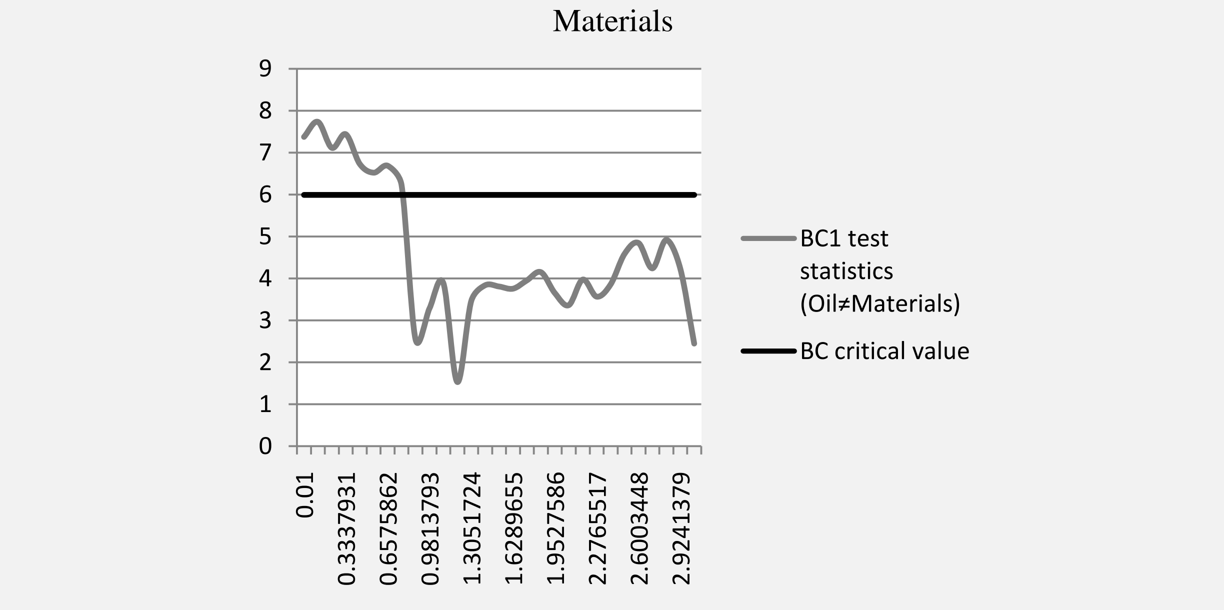



Health Care
7
6
5
4
3
2
1
0
0.01
0.3337931
0.6575862
0.9813793
1.3051724
1.6289655
1.9527586
2.2765517
2.6003448
2.9241379
BC5 test statistics (Oil≠Health care)
BC critical value


Information Technology
7
6
5
4
3
2
1
0
0.01
0.3337931
0.65758621
0.98137931
1.30517241
1.62896552
1.95275862
2.27655172
2.60034483
2.92413793
BC6 test statistics (Oil≠Inf Tech)
BC critical value


Consumer goods
8
7
6
5
4
3
2
1
0
0.01
0.3337931
0.6575862
0.9813793
1.3051724
1.6289655
1.9527586
2.2765517
2.6003448
2.9241379
BC7 test statistics (Oil≠Consumer goods)
BC critical value

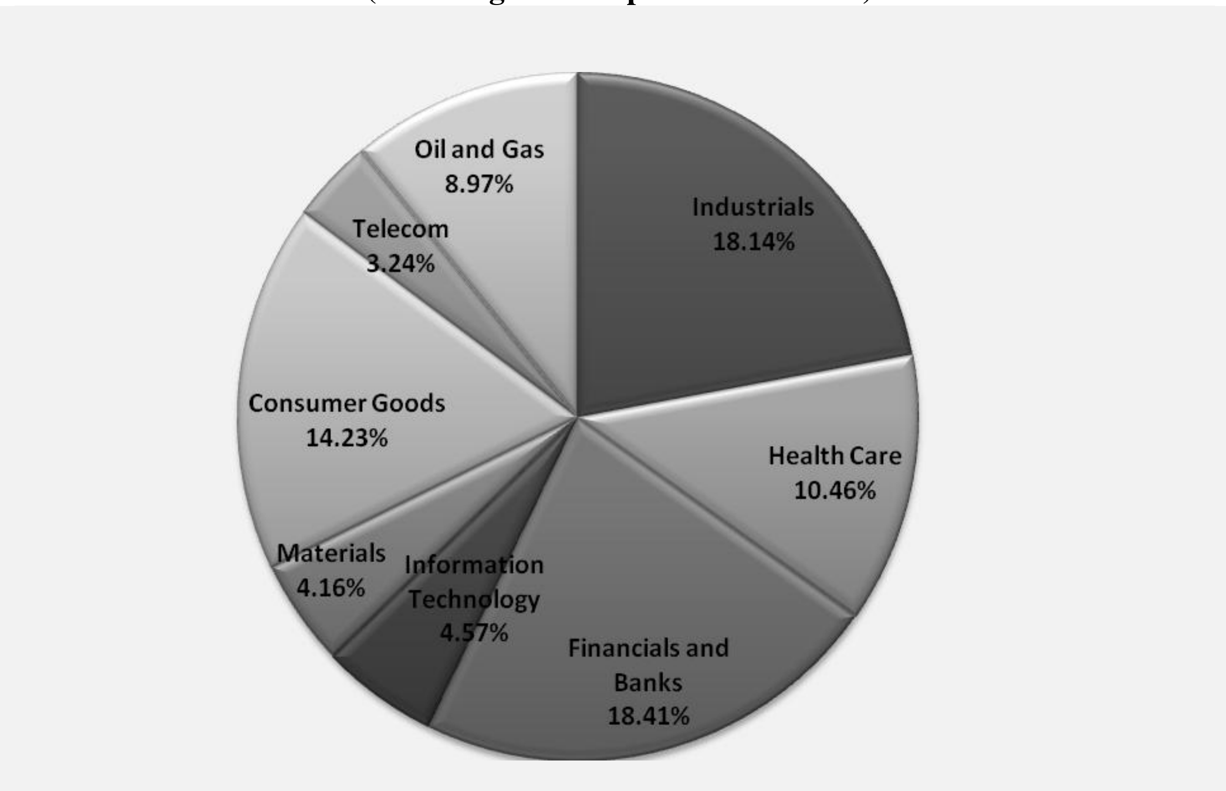




Note: The horizontal line represents the 5% critical value of the null hypothesis test of no Granger causality at frequency *w*.

Appendix

Figure A.1. Sectoral distribution of French stock market (as average for the period 2000-2015)



Source: Datastream.