The infernal couple China-Oil Price and the Responses of G7 Equities: A QQ Approach

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Abstract: China's growingly sluggish economy and collapsing oil prices sent ripples through global equities, and G7 countries (United States, United Kingdom, Germany, Canada, Japan, France, Italy) are no exception in this regard. In this article, we address how react G7 stock markets to oil price under potent uncertainty encompassing the extent of China's slowdown. The main feature of this study is its use of an unwonted method, dubbed the quantile-on-quantile (QQ) approach. Even though this method is based on the quantile regression paradigm, it departs from the conventional framework as the exogenous variable may be itself a quantile. This technique is devoted to unsettled context where standard methods are malapropos. Captivating findings have been shown. First, the QQ approach views the G7 stock markets responses to oil price as highly heterogeneous among tail-distributions, where consistent with the notion of asymmetry. Second, the equities of Germany, Italy, Canada and United Kingdom (in this order) are typically more responsive than France, Japan and United States towards oil price. Third, even if the fears over China's worsening outlook sends G7 countries into a deeper slowdown, United Kingdom, Japan, France and United States appear better positioned to weather the storm. The oil-dependence profile, the dominance of companies belonging to cyclical industries in the stock market index, the role of monetary policy in containing speculative bubbles, and the forceful quantitative easing have been offered to spell out the convolution of the focal issue.

Keywords: Oil price; China's slowdown; G7 equities; QQ approach.

JEL classification: F30; F36; G11; G15.

1. Introduction

Investors and traders nowadays are not in a snug situation as they are facing a fervent uncertainty. Global market volatility sparked by fears over geostrategic turmoil such as wars, terrorist attacks, and also economic considerations such as the price war triggered by Saudi Arabia to keep its position as leader in the global oil market, the currency war, the uncoordinated central bank policies, the deflation and the China's worsening outlook. It is difficult in these conditions to optimally allocate the investments. The ongoing valuation of financial markets reflects these fears and explains why financial markets are seemingly more responsive to bad news. Given the extremely expansionary monetary policies currently in vogue in the world, we realize that they favor the crash risk premium (retail banking, sovereign bank, corporate banking, etc.). Indeed, when interest rates (risk) are too weak, investors purchase riskier assets without receiving corresponding risk premium (Arthus and Virad 2016). The premium no longer covers the actual risk. A crash would obviously prompt adverse effects (realizing inefficient investments and maintaining expansionary policy over long periods, etc.).

Bearing these considerations in mind, it may be hard for an econometrician to explain what happens exactly in turbulent times. We believe that the traditional methods (OLS, VECM, cointegration, Granger causality, among others) are incongruous and unbefitting to properly depict a vacillating framework. These techniques seem unable to give satisfactory results since they do not account for possible nonlinearity and asymmetry. The novelty of this study lies in carrying out a new method, quantile-on-quantile (QQ) approach that may provide fresh insights into a "complex" relationship in an uncertain context. Using this approach, we can look further into hidden factors driving the focal linkages which the standard econometric techniques seem unsuitable to accommodate. It complements a rich body of existing methodologies for estimating the correlation. The QQ method consists on regressing one quantile on another quantile. Therefore, the main econometric challenge in the present research is to develop a quantile regression model having a conditional quantile regressor. The simple intuition behind this empirical strategy is that this flexibly enables to see the distribution of G7 stock returns to have distinct responses to oil price and untoward crisis (China's slowdown). In addition to analyze the asymmetric response of stock markets to oil price, employing QQ approach allows probing how the performance of stock markets influence the relation between stock returns and oil price (Sim and Zhou 2015). This is exactly relevant to real adjustments for companies' strategies especially in turbulent times.

It is clear that nowadays China encounters a period of hefty stock market turbulence worsened by economic slow-moving and financial trepidation. In response, the prices of many commodities started to fall markedly; the global surplus of output in many commodity markets and expectations of a continuous slowdown in demand from China bolsters the current market weakness and drive prices down. In addition, the markets around the world have been roiled the unrivalled uncertainty surrounding the faltering pace of economic growth and the insufficient response of Chinese authorities to the rambling turmoil. It is no longer a matter of debate whether the economy is slow-moving, but of suitably determining its effects. China consumes about 50 percent of some raw materials, and so far, its economic slowdown has therefore had a conspicuous influence on commodity-related sectors. Also, while investors have taken most of the pain so far, there is spacious more sneaking effect that is spreading to industries far behind China's shores. As Chinese economy falters, so do those of its neighbors, trading partners and its potential suppliers; of course, G7 (United States; United Kingdom, Japan, Germany, France, Italy, Canada) are no exception in this respect.

In this light, this article examines the impact of oil price on G7 stock market returns in an unstable context (in particular, the case of China's slowdown[1]). This idea is recognized by the fact that most of empirical research supports that the economy is the key fundamental of companies' earnings which are a substantial component in equity pricing. Thus, one could expect that changes in oil prices influencing the economy would also significantly yield to changes in equity prices. Accordingly, Huang et al. (1996) argued that oil price increases exert a negative influence on real output, and then on stock prices due to business operating costs and low corporate earnings. This theoretical evidence has been underpinned by Jones and Kaul (1996), who revealed a negative effect of oil shocks on stock market returns in Canada and the United States. Nevertheless, the negative linkage between oil price and stock returns does not usually hold, especially when new methods are carried out. While some analyses showed a positive connection between oil price fluctuations and equity markets (see, for example, Narayan and Narayan 2010, Ono 2011), other studies suggested that oil prices ambiguously affect stock market returns (for instance, Maghyereh 2004, El Charif et al. 2005, Park and Ratti 2008, Apergis and Miller 2009, Al Janabi et al. 2010, among others). Using wavelet approach, Jammazi and Aloui (2010) found a time-variant relationship between oil

[1] We focus on G7 countries as increasing energy efficiency has been one of the main goals targeted by their policy makers. These countries could be also largely affected by the China's slowdown to the great trade relationship with China regarding demand and supply. Although these economies have close levels of economic development, different energy and financial policy alternatives may be available.

price and real stock returns in France, Japan, and United Kingdom; a negative relationship is likely to be more pronounced over the pre-1999 period. More recently, Jammazi and Nguyen performed an improved regime-switching model to assess the dynamic interactions between oil price surges and stock markets in a sample of oil dependent countries. They showed that equity returns strongly exhibit a regime-switching behaviour, and respond dissimilarly to oil price increases. They also deduced that the impact of oil price surges on conditional volatility of equities is less pronounced during the bear than the bull market phases. Such complexity in the focal linkage makes assessing this relationship difficult with conventional methods. The recent China's slowdown and collapsing oil price strengthened the focus on models that are able to detect 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 price and stock returns Correlation asymmetries are crucial, as these dependences will impact the decisions-making by investors, traders and regulators. To be able to exploit compulsive knowledge of the reaction of G7 stock markets to the infernal couple China-oil price, reliable information on how evolve this relationship across heavily tailed-distributions uncovering different nuance features may be meaningful; hence the usefulness of QQ approach.

The results from our QQ estimates over a weekly period from January 1999 to July 2015 inconvertibly reveal the occurrence of asymmetric responses of G7 equities to changes in oil price, underscoring the complexity of the issue. Beyond the nuance of asymmetry, the responses of G7 equities to the couple China-oil appear heterogeneous. First, we show that the stock market returns of Germany, Italy Canada and United Kingdom (in this order) react more strongly to oil price variability; the latter exerts moderate influence on the equities of France, Japan and United States. Second, we note that the seriousness of China's slowdown is not uniform among the investigated countries. Indeed, Germany, Italy and Canada suffered the most.

The remainder of the paper is organized as follows. Section 2 outlines the methodology used, which explains the main advantages of a new approach, called QQ approach. In the same section, we provide a brief data overview. Section 3 reports and discusses our results. Finally, Section 4 concludes and offers some policy implications.

2. Methodology and data

The empirical examination of the oil price effects on equities was widely explored on the entire period generally through OLS regression. This method consists essentially on estimating the conditional mean of the dependent variable, giving therefore inaccurate information about the investigated linkage. Compared to the standard estimation of the conditional mean function, quantile regression (QR) provides an unerring analysis of each relationship among random variables (Koenker and Xiao 2002). It provides a complete description of asymmetric samples, which is a distinguishing feature of financial data. 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. QR may be viewed as an extension of conventional least squares estimation. It may bring scrupulous information on the average dependence between time series on the one hand and the upper and lower tail dependence on the other hand. This method enables to estimate multiple ranges of changes (i.e., slopes) from the minimum to the maximum responses. It bestows a broader picture in helping assess the correlation between current returns and various parts of the lagged conditional returns which presents outstanding when extreme values are present.

This paper contributes to this literature by fortifying conditions for consistency and asymptotic normality of series estimators of conditional quantiles in the presence of generated regressors. While a quantile regression is benefitting and suited to determine how evolves time series for all portions of a probability distribution (i.e., slopes from the minimum to the maximum responses), the application of quantile-on-quantile (QQ) approach involves estimating two linear quantile regressions. In other words, the problem of modeling the quantile of G7 equities as a function of the quantile of oil price shocks gives rise to the practicality and the functionality of QQ model. This technique allows relating the quantile of the G7 stock returns with the quantile of oil price, so that the relationship between them could vary at distinct and well specific points in their respective distributions. In their seminal work, Ma and Koenker (2006) asserted that a triangular system of equations can be denoted as a QQ approach, expressing the connection between quantiles. Although Ma and Koenker (2006) constructed a QQ model via triangular system of equations, Sim and Zhou (2015) carried out the same technique within single equation regression. This new method consists on linking the distribution of the dependent variable to the distribution of the regressors. This method is based on the standard quantile regression as the explanatory variable may be itself a quantile.

Then, each estimated quantile focuses its attention to a specific segment of the conditional distribution, resulting on a comprehensive description of the reaction of G7 equities to oil price in vacillating context, missed by the classic methods.

In practice, let θ superscript denotes the quantile of the G7 stock returns (*STR*), we first postulate a model for the θ-quantile of *STR* as a function of history STR_{t-1} and oil price changes (*Oil*), expressed as follows:

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

where ε_t^{θ} is an error term that has a zero θ-quantile. The history of the time series can reflect the explanatory variables not taken into account in the estimate (or more accurately the STR fundamentals) because of their unavailability[2]. We allow the relationship function $\beta^{\theta}(.)$ to be unknown, since we don't have a prior on how the G7 equities and oil price changes are inter-linked. To examine the linkage between θ-quantile of the G7 stock return and the θ-quantile of oil price shocks, denoted by Oil^{τ}, we linearize the function $\beta^{\theta}(.)$ by taking a first order Taylor expansion of $\beta^{\theta}(.)$ around Oil^{τ}, which yields to:

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

Based on Sim and Zheng (2015)'s study, 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:

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

Another novelty in this study lies on accounting for the China's slowdown to see how respond stock markets returns to oil prices in an unstable context, with special reference to G7 equities. Hence, a further analysis consists on incorporating an interaction term (IT to our regression model). The interaction term links the oil price to a Chinese crisis dummy variable that makes the value 1 since 2011 and 0 otherwise.

[2] As we use weekly data, some variables data are unavailable.

In this article, the QQ model has been applied using weekly data for over the period from January 1999 to July 2015[3] (with a total of 760 observations) for stock prices of France (CAC 40), Germany (DAX 30), Japan (Nikkei 225), UK (FTSE 100), United States (Dow Jones), Italy (MIB 30) and Canada (SP-TSX). The stock market prices data are collected from Datastream. For crude oil price (*Oil*), we use the real national price for each country as a proxy for the oil price. The real national price is computed as the product of the nominal oil price and the exchange rate deflated by the consumer price index of each country, coming from Energy Information Administration (EIA) and Econstats™. We prefer use weekly rather than daily or monthly data to avoid possible econometric pitfalls that may occur including 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 analysis for effectively detecting the responses of stock returns quantiles to oil price quantiles. All the investigated variables have been transformed by taking natural logarithms to correct for potential heteroskedasticity and dimensional differences among time series.

3. Results

3.1. Standard techniques results

As mentioned at the outset, the relationship between oil price and equities has come to the forefront of public attention over the past decades. Most of studies, however, ignore the possibility that this linkage could produce different dependence pattern along the distribution. We address this issue by performing quantile regression estimator[4], which is robust to outlying observations on the dependent variable. We start our investigation by the use of some standard techniques (OLS and quantile regression) while accounting for the possible effects of China's economic downturn. The idea here is to have a case of benchmarking to compare the

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[3] The period of the study is motivated by the availability of the Italian data and the fact that we required a common sample period for all the G7 countries.

[4] Quantile regression was introduced in the seminal paper by Koenker and Bassett (1978). It is a generalization of median regression analysis to other quantiles. The coefficients of the τ^{th} conditional quantile distribution is estimated as:

$$\hat{\beta}\ (\tau) = \arg\min \sum_{t=1}^{\tau} (\tau - 1_{\{y_t \prec x'_t \beta(\tau)\}}) \left| y_t - x'_t\ \beta(\tau) \right|$$

where the quantile regression coefficient $\beta(\tau)$ determines the connection between the vector of independent variables and the τ^{th} conditional quantile of the dependent variable. To determine endogenous time series in function of specific exogenous variables, the values of quantile coefficients could be constant where the values of $\beta(\tau)$ do not change substantially for the values τ. It should be symmetric (asymmetric) where the values of $\beta(\tau)$ seem similar (dissimilar) for lower and higher quantile levels; $1_{\{y_t \prec x'_t \beta(\tau)\}}$ is the usual indicator function.

OLS and QR with the new method in order to highlight the practicality and the effectiveness of QQ approach discussed above.

The QR estimation and OLS (i.e., the mean) findings of the oil price coefficients are reported in Table 1. At the 5% level of significance (and even 10%), the OLS estimates of the effects of oil price on STR of the majority of G7 countries seem insignificant (except the case of Japan and Germany). Accordingly, we are unable to draw a clearer conclusion from this method. It should be noted that OLS estimator focuses only on the central tendency of profitability distribution. This standard technique does not allow to properly examining the interdependence between oil price changes and G7 equities in non-central regions. To address this issue, we explore the conditional quantile estimates for the focal relationship by performing the QR model. We obtain heterogeneous outcomes. In particular, we can distinguish four groups of countries. The first one includes Unites States, France and Italy where there exists a negative interdependence between oil price and stock returns at low quantiles (0.1, 0.2 and 0.3, i.e., when the stock market perform worse). The second group is formed by Canada and United Kingdom where a negative connection is found at low quantiles), while a positive oil price effect on equity returns is well shown at medium and upper quantiles (i.e., when the stock market perform normally or are in a better performance). The third group contains Germany where oil price is negatively correlated to stock return when the performance of STR is good (upper quantiles). The fourth group includes Japan where a positive and weak linkage between oil price and equity is revealed at all quantiles.

Table 1. The link between oil price and G7 equities: OLS vs. Quantile regression

		STR-USA	STR-UK	STR-Canada	STR-Japan	STR-Germany	STR-France	STR-Italy
C	0.100	-2.3456* (-1.9589)	-1.5327 (-1.5688)	-0.4150*** (-9.7089)	0.0175*** (3.7759)	-0.0688*** (-7.2444)	-0.0424*** (-7.2771)	0.0123 (0.6351)
	0.200	-1.3689 (-1.1672)	-1.7345 (-1.5518)	-0.3108*** (-7.5565)	0.0197*** (7.1506)	-0.0580*** (-5.3633)	-0.0325*** (-5.3163)	0.0127 (1.0119)
	0.300	-2.1578* (-1.8694)	0.2762 (1.1356)	-0.2128*** (-4.5323)	0.0212*** (7.0206)	-0.0418*** (-4.4970)	-0.0170*** (-3.0795)	0.0108 (1.5684)
	0.400	-1.2029* (-2.0308)	0.9567 (1.2463)	-0.1081 (-1.6240)	0.0215*** (9.1084)	-0.0203** (-2.3489)	-0.0072 (-1.3236)	0.0113 (1.4676)
	0.500	-1.5894* (-1.8962)	0.6381 (1.1858)	0.0553 (0.6289)	0.0217*** (9.2449)	-0.0023 (-0.2685)	7.35E-05 (0.0135)	0.0232 (1.2270)
	0.600	-1.6581** (-2.9651)	-1.2567* (-1.8962)	0.2094** (3.2906)	0.0217*** (9.4129)	0.0047 (0.5519)	0.0070 (1.3199)	0.0528*** (10.030)
	0.700	-1.2638** (-2.6931)	-1.8965* (-1.6998)	0.3345*** (7.7011)	0.0218*** (9.3134)	0.0253*** (3.0324)	0.0170*** (3.2373)	0.0534*** (11.5751)

	0.800	-1.2625** (-2.8989)	-1.8961** (-2.7214)	0.4188*** (10.5855)	0.0219*** (10.2678)	0.0454*** (4.8679)	0.0255*** (4.9731)	0.0578*** (8.8204)
	0.900	-1.2812** (-3.3119)	-0.9557 (-1.1698)	0.4384*** (14.1182)	0.0219*** (8.5439)	0.0861*** (5.4162)	0.0377*** (6.9942)	0.0695*** (6.0063)
STR_{t-1}	0.100	-0.9634*** (-7.5590)	-0.1195*** (-10.630)	0.0107 (0.3021)	0.0113* (1.8988)	-0.1194*** (-4.6175)	-0.0481*** (-7.2980)	-0.323*** (-7.7569)
	0.200	-0.9332*** (-7.1589)	-0.0992*** (-8.4667)	0.0119 (0.6190)	-0.0014 (-0.2210)	-0.1207*** (-3.6401)	-0.0309*** (-4.9359)	-0.287*** (-5.7582)
	0.300	-0.8936*** (-5.2160)	-0.0728*** (-5.1001)	0.0194* (2.0242)	0.0048 (0.7232)	-0.0822* (-1.9781)	-0.0168** (-2.8752)	-0.161** (-2.7119)
	0.400	-0.8595*** (-4.7498)	0.0491*** (3.2613)	0.0196* (1.9913)	0.0054 (0.8152)	-0.0857* (-1.8612)	-0.0061 (-1.0695)	-0.1401* (-1.9589)
	0.500	-0.8224*** (-5.6754)	0.0243 (1.8906)	-0.0155* (-2.2286)	0.0065 (0.9995)	-0.0179 (-0.3632)	0.0019 (0.3562)	-0.0040 (-0.0568)
	0.600	-0.8025*** (-5.1338)	-0.0122 (-0.8774)	-0.0144* (-1.9889)	0.0070 (1.0605)	-0.0420 (-0.9048)	0.0126** (2.3914)	-0.1228* (-2.3178)
	0.700	-0.7846*** (-4.4234)	-0.0016 (-0.1026)	-0.0149* (-2.0922)	0.0076 (1.1686)	-0.0948*** (-3.2775)	0.0226*** (4.2847)	-0.193*** (-4.0094)
	0.800	-0.7630*** (-3.5561)	0.0184 (0.9851)	-0.0133* (-1.9105)	0.0163* (2.0219)	-0.0912*** (-3.7104)	0.0288*** (5.7113)	-0.294*** (-6.4377)
	0.900	-0.5545 (-1.5669)	0.1579*** (4.2218)	-0.0125* (-1.9113)	0.0149** (2.3820)	-0.0919*** (-3.6536)	0.0467 (7.6612)	-0.340*** (-8.2729)
Oil	0.100	-0.001*** (-3.1422)	-0.0410** (-6.4018)	-0.0905*** (-5.2580)	0.0091*** (17.983)	0.0393 (1.0929)	-0.0070*** (-4.2392)	-0.0015 (-1.2525)
	0.200	-0.003*** (-3.8761)	-0.0263** (-3.6752)	-0.0803*** (-3.4353)	0.0083** (13.640)	-0.0192 (-0.3162)	-0.0023*** (-4.3602)	-0.0022** (-2.5564)
	0.300	1.1678 (1.5519)	-0.0106** (-2.7880)	-0.0514 (-1.3305)	0.0071*** (11.021)	-0.0462*** (-6.0226)	0.0047 (0.7075)	-0.002*** (-4.0392)
	0.400	0.9542 (0.6312)	-0.0054 (-1.4960)	0.0239 (0.4451)	0.0063*** (13.183)	-0.1339*** (-4.5420)	0.0043 (0.6463)	-0.002*** (-3.1541)
	0.500	-1.5735 (-1.0017)	-0.0015 (-0.4469)	0.1435 (0.9340)	0.0065*** (11.429)	-0.1248*** (-3.1776)	0.0015 (0.2200)	-8.07E-05 (-0.045)
	0.600	-0.0321 (-1.0000)	0.0037 (1.1244)	0.2481*** (4.4736)	0.0059*** (8.6836)	-0.1203** (-2.6784)	0.0019 (0.2748)	0.0059 (1.4509)
	0.700	-0.0176 (-0.3861)	0.0126*** (3.5746)	0.3188*** (7.9571)	0.0055*** (7.2568)	-0.0064 (-0.8893)	-0.0013 (-0.1884)	0.0091 (1.6083)
	0.800	-0.0248 (-1.2645)	0.0165*** (4.7365)	0.3717*** (10.2602)	0.0052*** (6.7602)	0.0078 (1.0366)	0.0013 (0.2025)	0.0121 (1.5016)
	0.900	-0.0256 (-1.4924)	0.0230*** (5.8843)	0.3538*** (12.239)	0.0037*** (5.4561)	-0.0369** (-2.9696)	0.0008 (0.1218)	0.0143 (1.0003)
OLS(Oil)		-0.0108 (-1.5381)	0.0055 (0.1187)	0.0782 (1.3100)	0.0112** (2.4931)	-0.1061*** (-4.7857)	-0.007 (-1.2119)	-0.0922 (-0.6454)

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

These first results underscore the usefulness and the functionality of QR. They also show heterogeneous situations. Recall that QR evaluates to what extent the key variables are correlated across different quantile levels in order to explore the role of different rhythms in the connectivity between oil price changes and equity returns. By accounting for the recent China's economic downturn, the relationship between oil price and STR has raised considerably for all the countries (Table 2). At the same time, it is apparently difficult to group countries into coherent groups. In fact, we note that the impact of oil price on United States STR is negative and positive in low and upper quantiles. For the UK, oil price shocks exert a negative influence on stock returns when the market performs in low and medium quantiles. For Germany, oil price exhibits a negative impact on STR at lower quantiles, while for France the Oil effect seems positive at low and medium quantiles. Ultimately, Oil-STR linkage is seemingly negative at upper quantile for Italy. In brief, the obtained outcomes evidently highlight the upheavals in financial markets in the wake of China's slowdown. Now we will see how and to what extent the combined effect of the China economic downturn and changes in oil price (variable IT) influence the G7 equities. Whatever the considered quantile, the "infernal couple" China-Oil price affects negatively and significantly all the G7 markets. But apparently Germany suffered the most from this economic downturn. It should be noted that OLS estimates are statistically significant for only three countries (USA, Canada and France), spotlighting the limitation of this method.

Table 2. The link between oil price and G7 equities: OLS vs. Quantile regression (with interaction term)

		STR-USA	STR-UK	STR-Canada	STR-Japan	STR-Germany	STR-France	STR-Italy
C	0.100	-0.0729*** (-8.5944)	-0.0302*** (-6.0421)	-0.022*** (-10.931)	0.0058*** (17.580)	-0.0153*** (-4.5974)	-0.0193*** (-7.865)	-0.0360*** (-4.5218)
	0.200	-0.0600*** (-7.3180)	-0.0181*** (-4.2727)	-0.0206*** (-8.4763)	0.0061*** (17.968)	-0.0107*** (-3.9673)	-0.0117 (-5.0577)	-0.0168*** (-3.5350)
	0.300	-0.0427*** (-4.7143)	-0.0088** (-2.6769)	-0.0188*** (-6.8851)	0.0066*** (19.557)	-0.0040 (-1.4148)	-0.0076*** (-3.0855)	-0.0070** (-2.3395)
	0.400	-0.0204** (-2.2559)	-0.0035 (-1.1342)	-0.0140*** (-4.6571)	0.0070*** (89.881)	0.0003 (0.2136)	-0.0037 (-1.4545)	-0.0023 (-0.7903)
	0.500	-0.0014 (-0.1714)	0.0022 (0.7064)	-0.0029 (-0.7367)	0.0071*** (81.985)	0.0021 (1.5864)	0.0005 (0.2166)	0.0008 (0.3314)
	0.600	0.0097 (1.1453)	0.0039 (1.2832)	0.0057* (1.8131)	0.0072*** (67.4012)	0.0038** (2.9437)	0.0054** (2.0234)	0.0050* (1.8635)
	0.700	0.0315*** (3.6151)	0.0086** (2.7960)	0.0133*** (4.3165)	0.0072*** (70.568)	0.0059*** (4.5953)	0.0119*** (4.165)	0.0105*** (3.6648)
	0.800	0.0485*** (4.9476)	0.0166*** (4.1055)	0.01834*** (6.3566)	0.0073*** (72.319)	0.0081*** (6.6229)	0.0158*** (5.4479)	0.0195*** (5.6976)
	0.900	0.0867*** (5.8761)	0.0361*** (3.5913)	0.0232*** (8.9097)	0.0072*** (71.814)	0.0128*** (6.3259)	0.0257*** (4.5468)	0.0278*** (6.5910)
STR_{t-1}	0.100	0.0142 (0.9395)	-0.0407*** (-6.3718)	0.1247*** (8.0849)	-0.3225*** (-18.507)	-0.4008*** (-9.7300)	-0.18222 (-5.2023)	0.0268*** (5.7613)
	0.200	-0.0148 (-0.9091)	-0.0204** (-3.3302)	0.1401*** (7.5729)	-0.2994*** (-14.503)	-0.3178*** (-7.8926)	-0.1297*** (-3.8128)	0.0885*** (4.2235)
	0.300	-0.0162 (-2.2470)	-0.0092** (-2.4594)	0.1875*** (8.4555)	-0.2407*** (-9.74258)	-0.2174*** (-5.0634)	-0.0562 (-1.6417)	0.0154* (2.2273)
	0.400	-0.0190* (-2.3498)	-0.0036 (-1.0520)	0.2100*** (7.5279)	-0.2115*** (-6.7707)	-0.1185* (-1.8598)	0.0144 (0.2888)	0.0456 (0.3280)
	0.500	-0.0170 (-1.0903)	0.0007 (0.2185)	0.2691*** (9.5173)	-0.1352*** (-4.1152)	0.0513 (0.5610)	-0.0419* (-1.8722)	-0.0780 (-1.3721)
	0.600	-0.0095 (-0.5755)	0.0056* (1.7346)	0.3101*** (15.695)	-0.0675** (-2.7514)	0.2012*** (3.1124)	-0.0372*** (-4.3394)	-0.0702*** (-3.9402)
	0.700	0.0056 (0.2005)	0.01336*** (3.9060)	0.3320*** (18.7893)	-0.0240 (-1.0660)	0.3150*** (8.1382)	0.0174*** (8.8332)	-0.0507*** (-8.0763)
	0.800	0.0226 (0.9339)	0.0209*** (5.4583)	0.3623*** (20.3946)	0.0430** (2.0776)	0.4041*** (12.244)	0.0610*** (11.583)	-0.0934*** (-11.163)
	0.900	0.0808** (3.0417)	0.0274*** (6.6716)	0.3786*** (23.0777)	0.0760*** (4.0719)	0.4391*** (15.755)	0.0686*** (14.054)	-0.0319*** (-13.958)
Oil	0.100	0.0029 (0.7911)	-0.0156* (-1.9441)	-0.1348*** (-5.6720)	-0.0002 (-0.2553)	-0.1160* (-1.7616)	-0.0044* (-1.8497)	-0.0079 (-1.0542)
	0.200	-0.0048*** (-4.4041)	-0.0228*** (-3.4780)	-0.1138*** (-4.4947)	-0.0003 (-0.2896)	-0.0159* (-1.9061)	0.0005 (0.2033)	-0.0006 (-0.1045)
	0.300	-0.0048*** (-5.9072)	-0.0243** (-2.8491)	-0.1123*** (-3.5725)	-0.0001 (-0.1073)	-0.0152 (-0.9933)	0.0021 (0.7220)	0.0038 (0.8855)
	0.400	-0.0011*** (-3.8934)	0.0025 (0.5119)	-0.1286 (-1.3851)	-0.0003 (-0.4919)	-0.0089 (-0.7366)	0.0029 (0.9591)	0.0024 (0.6768)
	0.500	-0.0093*** (-4.1259)	-0.0447*** (-4.9287)	-0.0001 (-0.0318)	0.0003 (0.3059)	-0.0076 (-0.6664)	0.0061* (1.8155)	0.0026 (0.7959)
	0.600	-0.006*	-0.0330***	0.0060	0.0009*	-0.0078	0.00470	0.0020

		(-2.1444)	(-3.6133)	(0.5173)	(1.8878)	(-0.6012)	(1.511663)	(0.6032)
	0.700	-0.0010 (-0.1418)	0.0001 (0.0272)	0.0095 (1.3583)	0.0009* (1.8799)	-0.0050 (-0.3158)	-0.0070* (-2.2196)	0.003614 (1.087358)
	0.800	0.0106 (1.3523)	-0.0004 (-0.0664)	0.0081 (0.8468)	0.0007* (1.7758)	-0.0046 (-0.5082)	0.0045 (1.3316)	-0.009** (-2.9720)
	0.900	0.0013** (3.2128)	0.0094 (0.9672)	0.0037 (1.2253)	0.0005* (1.9920)	-0.0017 (-0.6722)	-0.0102* (-2.0127)	-0.0091* (-2.3561)
IT	0.100	-0.0098* (-1.843286)	-0.0272*** (-5.8690)	-0.0547*** (-8.7099)	-0.0041*** (-13.771)	0.0194 (1.4760)	-0.0472*** (-5.2371)	-0.0036 (-0.1507)
	0.200	-0.0049*** (-10.0229)	-0.0643** (-2.7999)	-0.0517*** (-6.9635)	-0.0045*** (-12.434)	0.0223 (1.4107)	-0.0553*** (-4.1047)	-0.0095 (-0.5594)
	0.300	-0.0091*** (-9.3014)	-0.0101 (-0.5058)	-0.0484*** (-5.8230)	-0.0045*** (-9.610001)	0.0109 (1.2276)	-0.0439** (-2.5697)	-0.0126 (-1.9019)
	0.400	-0.0022*** (-7.16304)	-0.0077 (-0.4403)	-0.0385*** (-4.3428)	-0.0048*** (-14.129)	0.0019 (0.4080)	-0.0172 (-0.8835)	-0.0151* (-1.9804)
	0.500	-0.0089*** (-6.2164)	0.0001 (0.0109)	-0.0162 (-1.5596)	-0.0048*** (-12.946)	-0.0001 (-0.0403)	-0.0245 (-1.2058)	-0.0028 (-0.2168)
	0.600	-0.0138*** (-5.6573)	0.0028 (0.1662)	0.00249 (0.3589)	-0.0047*** (-11.293)	0.0002 (0.0425)	0.0057 (0.2992)	-0.0019 (-0.1522)
	0.700	-0.0923*** (-4.0105)	-0.0370 (-1.7761)	-0.0077 (-1.1698)	-0.0041*** (-6.7986)	-0.0908 (-0.1597)	0.0246 (1.3765)	-0.0043 (-0.4196)
	0.800	0.06798 (1.65392)	-0.0335* (-1.7283)	-0.0076 (-1.2209)	-0.0039*** (-7.2812)	-0.1141* (-1.8400)	-0.044** (-2.7828)	-0.0158* (-2.4903)
	0.900	-0.0092 (-0.2778)	-0.0220 (-0.4918)	-0.0055 (0.0062)	-0.0031*** (-5.1831)	-0.1263*** (-3.3718)	0.0257 (1.4139)	-0.0113 (-0.5142)
OLS(Oil)		-0.0024** (-2.8716)	-0.0405* (-1.8954)	0.0002 (1.1867)	0.0003 (0.4258)	-0.0018 (-0.5234)	0.0023* (1.6942)	0.0043 (1.1567)

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

Noteworthy, a systematic pattern exists for the quantile-varying estimates of the oil coefficient among G7 countries, that the OLS unknown. However, quantile regression is not flexible enough for uncovering the complexity of the linkage between oil price changes and equities, especially in an unstable context; QQ approach can shed light on whether the same quantile of stock returns respond differently to distinct quantiles of oil price shock, and then provide better paths into the focal issue. In principle, what the QQ approach does is to disentangle the QR estimates so that they are specific for various quantile levels of the exogenous variable (here oil price). While the QR regresses the quantile of the US stock return on oil price, the QQ regresses the quantile of the US stock return on the quantile of oil price shocks. Thus, the QQ approach could convey better information about the nexus between G7 equities and changes in oil prices than the QR technique.

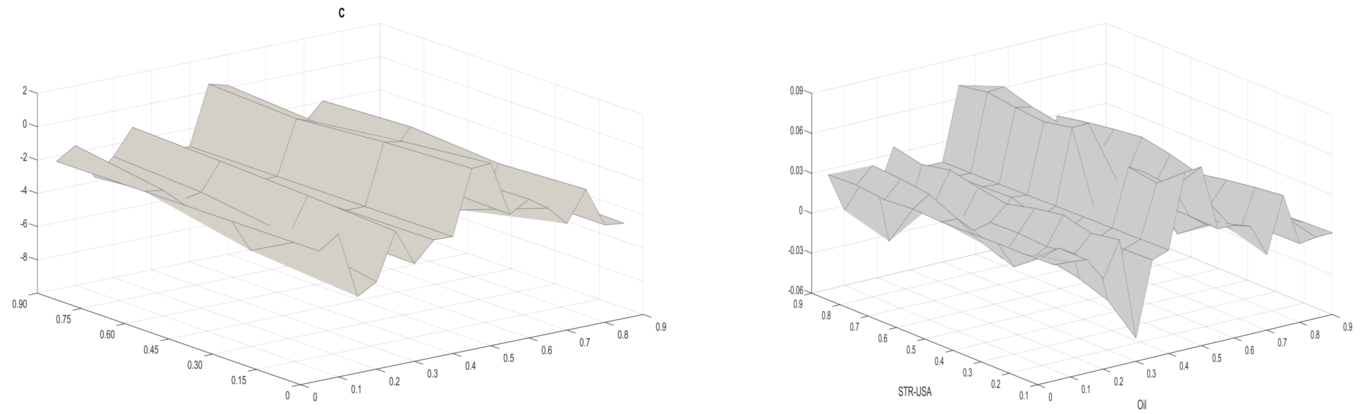
3.2. QQ results

Aware by the fact that the quantiles may contain information about the state of G7 equities, we perform QQ approach to examine the various behaviors of G7 stock markets in response to oil price shocks and the uncertainty surrounding the China slow-moving. To get a sense of what these quantiles look like, Figure 1 plots the surface of the intercept term and the oil price's coefficient for the investigated G7 countries. Unlike the intercept term of the QR in Tables 1 and 2 that are seemingly insensitive to STR quantiles. Figure 1 reports the intercept estimate in the z-axis against both the quantiles of G7 equity returns in the Y-axis and oil price in the X-axis.

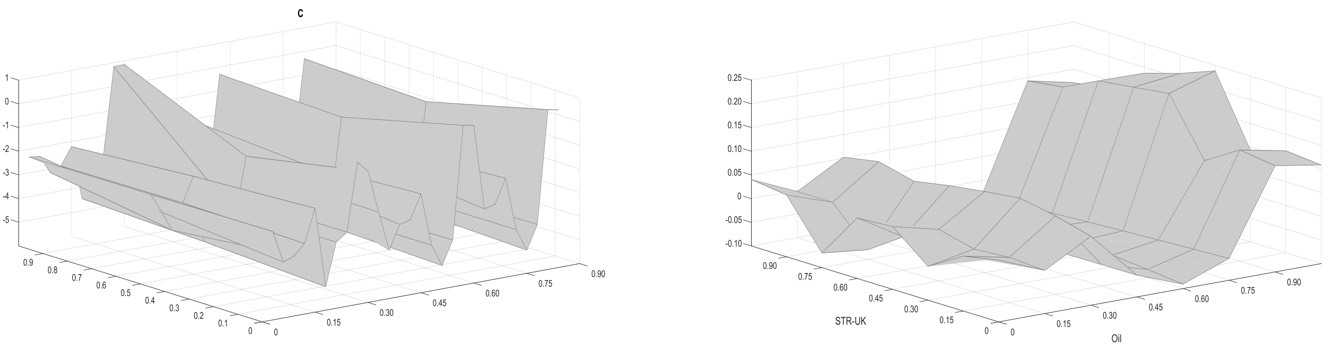
What appears intuitive in the figure below is the fact that the severity of oil price influence was not uniform among all the G7 equities. Specifically, we distinguish two main groups of countries. The first includes Germany, Italy, Canada and United Kingdom (in this order), where the oil price effect seems prodigious. The second group is formed by France, Japan, and USA (by respecting this hierarchy), where a weak effect is shown (the STR responses move within -0.10 and 0.20 in France, -0.10 and 0.12 in Japan and -0.05 and 0.07 in USA). Normally, one could expect that low oil price (i.e. low quantiles) could have a positive impact on stock returns of United States, Germany, Japan, France and Italy (oil importers). The inverse is true for Canada and United Kingdom (oil exporting countries). Similarly, if we consider the share of oil sector in the overall stock market index, we find that it was Canada which ranks first with 27%, followed by United Kingdom with 19% and then Japan with 18%. In principle, it is in these countries that the correlation between STR and Oil must be strong. But what we find is far from these general evidences. QQ outcomes highlight the complexity of the focal relationship. For USA, when oil price is in the medium or high (Oil quantiles 0.5, 0.6 and 0.7), the equity returns react positively; but when oil price is low (Oil quantiles 0.1 and 0.2), the reaction appears negative or neutral. Similarly, when oil price is in upper quantile, the response of equity return is neutral. Close results are found for Japan. When focusing on the nexus between oil price and stock return in UK, the prevailing trend is bullish or upward- moving; but, oil price shocks in low quantile exert a negative influence on STR when the market performs highly (i.e., quantile 0.9). In the upper quantiles, the correlation appears negative; likewise for Germany and Italy. For Canada, the reaction of stock returns to oil price is often positive either when investors are optimistic (STR high quantiles) or pessimistic (STR low quantiles), which is theoretically unanticipated. However, the correlation is neutral or negative at lower medium quantile levels when investors are moderately optimistic. For France, when investors are pessimistic (for STR quantiles 0.3 and 0.4), the equity response to oil price changes seems negative, while it appears positive when traders are optimistic (for STR quantiles 0.8 and 0.9). Distinct outcomes are found for Italian case. In particular, the equity response to oil price variability does not seem sensitive to investors' behaviors since it is usually negative, except when the price of oil is heavier (quantiles 0.8 and 0.9).

Figure 1. QQ estimates: The link between oil price and G7 equities

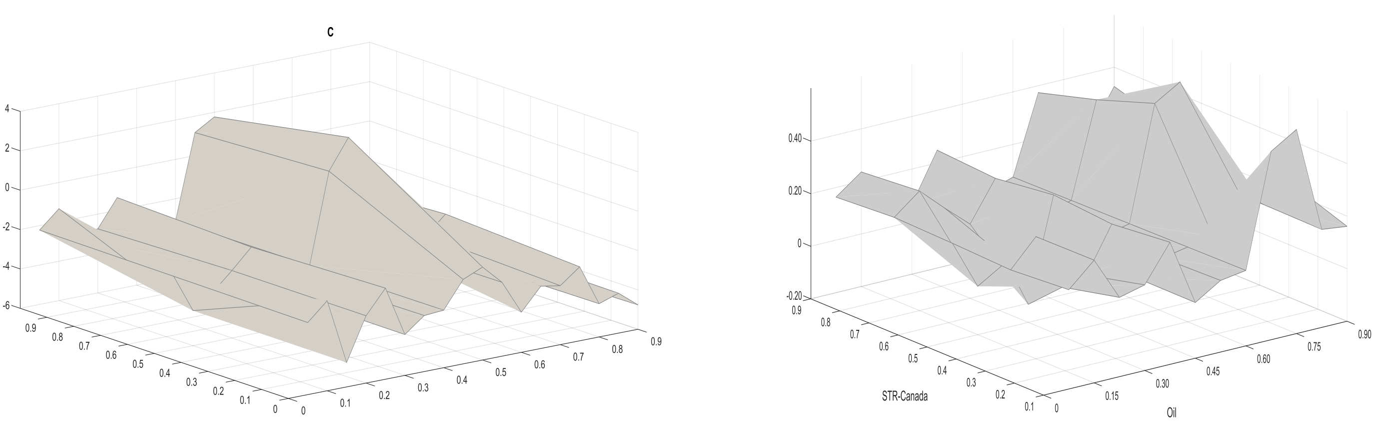
United States



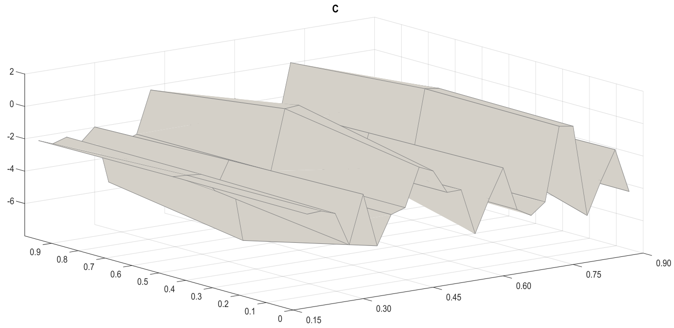
United Kingdom

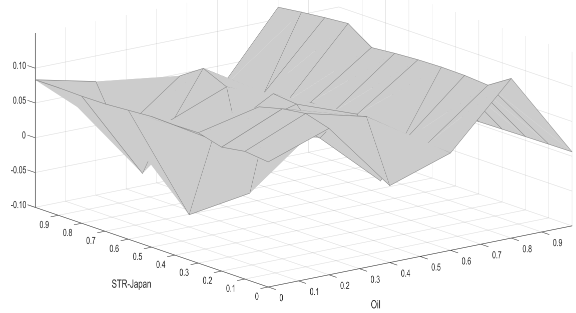


Canada

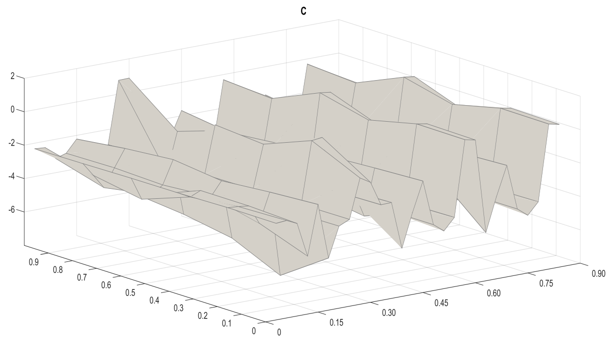


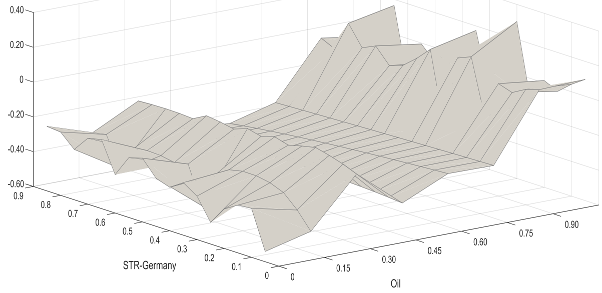
Japan



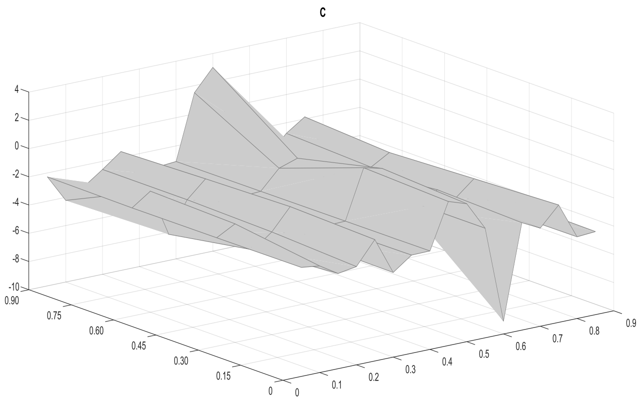


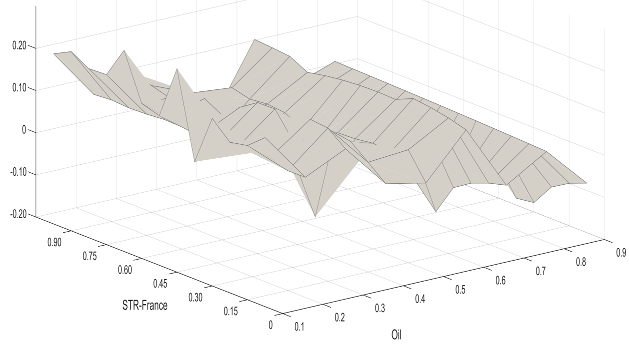
Germany



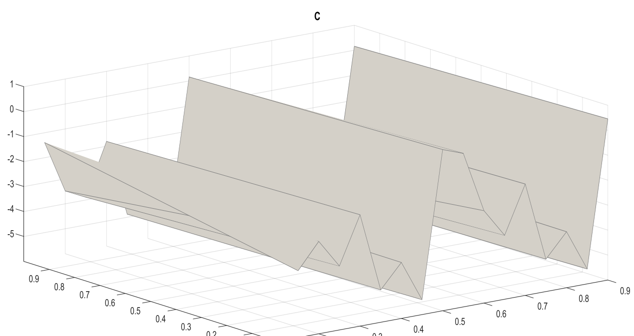


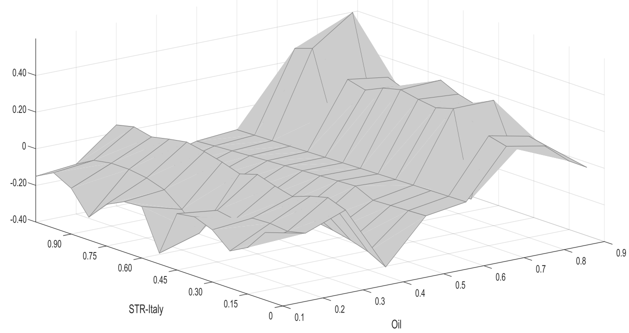
France





Italy



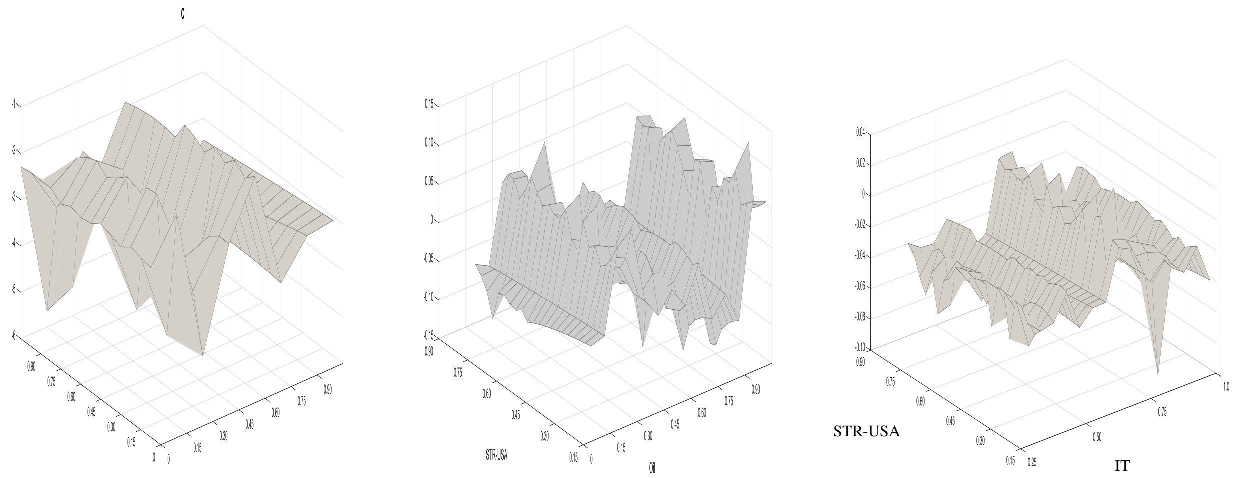


Interesting findings have been drawn when accounting for the period of the faltering pace of Chinese economic growth. First, the interdependence between oil price and stock returns exacerbated markedly for the countries under investigation, with the exception of Italy where the strength of the link fell and France where the linkage appears unchangeable. Second, we keep the same group composition (as the analysis without IT) with slight changes regarding the order pattern. Hence, the response of STR to Oil is strong for the group of countries formed by Germany, Canada, United Kingdom and Italy (by respecting this order). Nevertheless, the focal relationship appears weaker for the group constituted by Japan, USA and France. Third, the consideration of China's slow-moving (combined with oil price) does not change substantially our results with respect the distinction between the two groups, although Italy seems to suffer most from this economic meltdown. But we usually find that Germany (i.e., the reaction of STR to Oil moves within -0.30 and 0.70) is likely to be more jeopardized than Italy and Canada (the responses of STR to Oil vary, respectively, among -0.60 and 0.40 for Italy and -0.50 and 0.50 for Canada). These three countries are the most affected by the infernal couple China-oil price. Ultimately, the combined effect China-oil price on equities is negative for all the G7 countries.

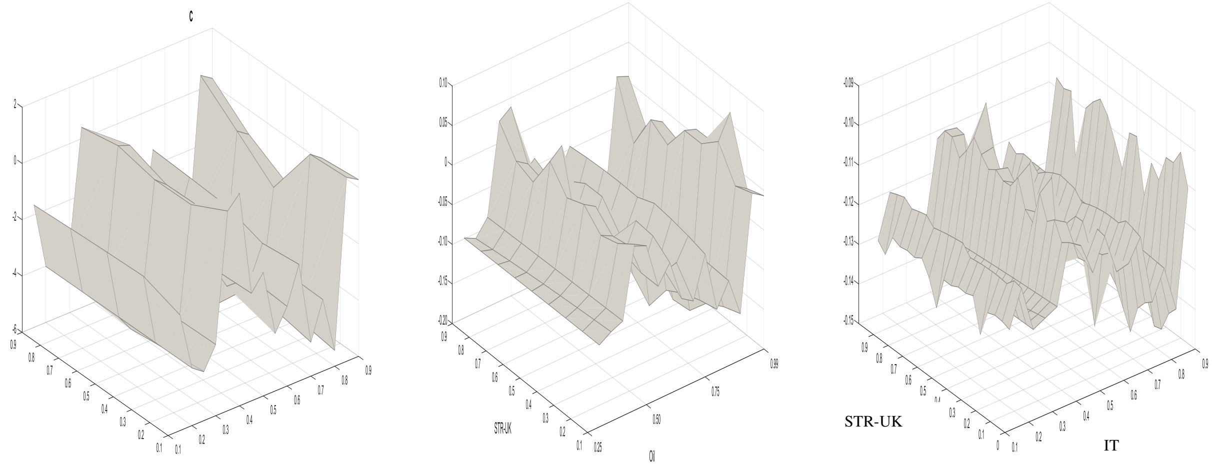
From the aforementioned findings, we can clearly see the ability of QQ approach to uncover some characteristics in the linkage between G7 stock market returns and oil prices that are not apparent if standard methods such as OLS or quantile regression are employed. For example, using OLS regression, we find that the effect of oil price on the G7 equities is insignificant or very weak. Likewise, by carrying out quantile regression, we find that oil price have variant influence on the stock returns quantiles for all the G7 countries. Nevertheless, when the QQ approach is applied, we notice certain features about the relation between G7 equities and changes in oil prices (and then the couple China-oil price) that markedly elude OLS and quantile regressions. Interestingly, the QQ outcomes deeply suggests that the link between G7 stock returns and the couple China-oil price is contingent on the specific quantile of oil price (and the quantile of IT) as well as the quantile of G7 equities. Therefore, this relationship seems sensitive to both the sign and size of the couple China-oil price and the state of the G7 stock markets.

Figure 2. QQ estimates: The link between oil price and G7 equities (with interaction term)

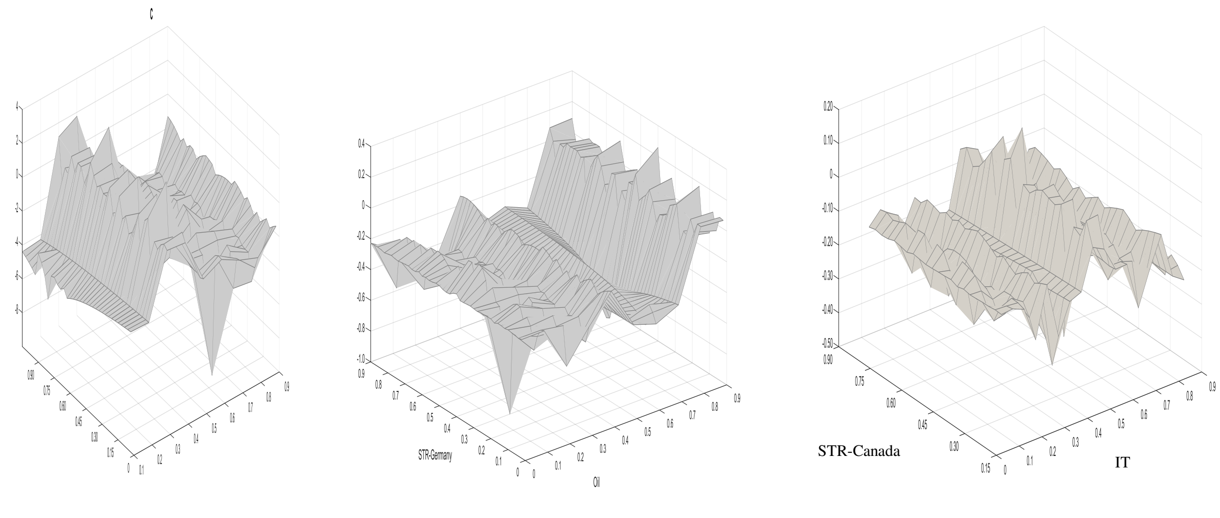
United States



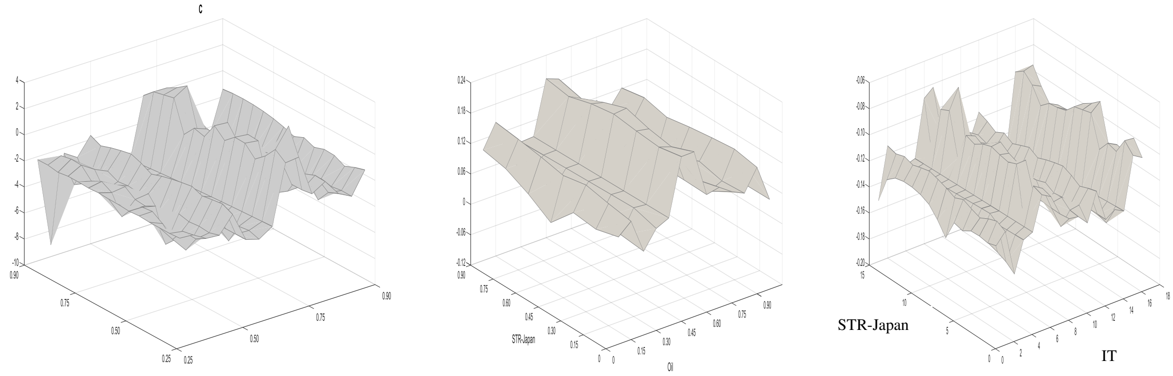
United Kingdom



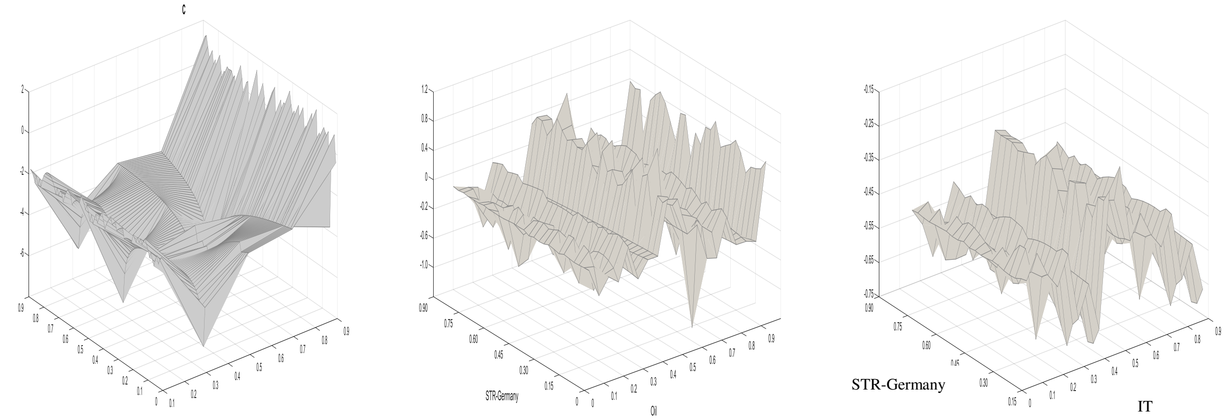
Canada



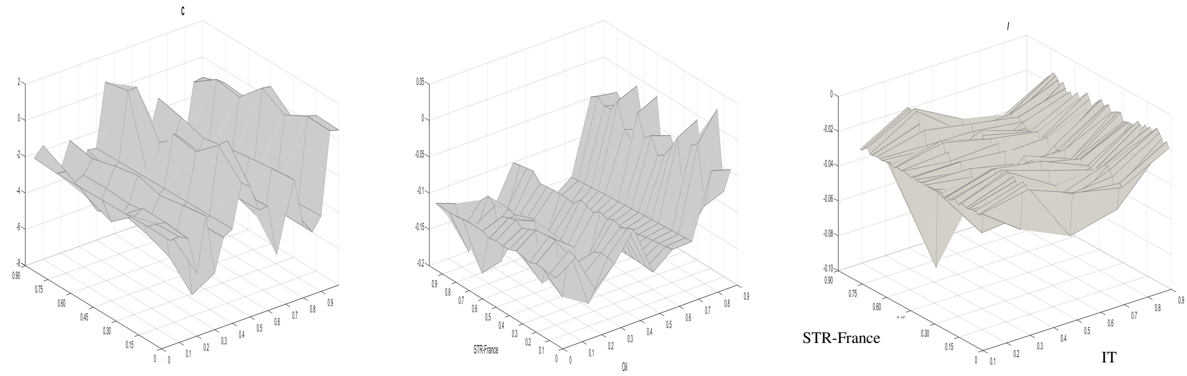
Japan



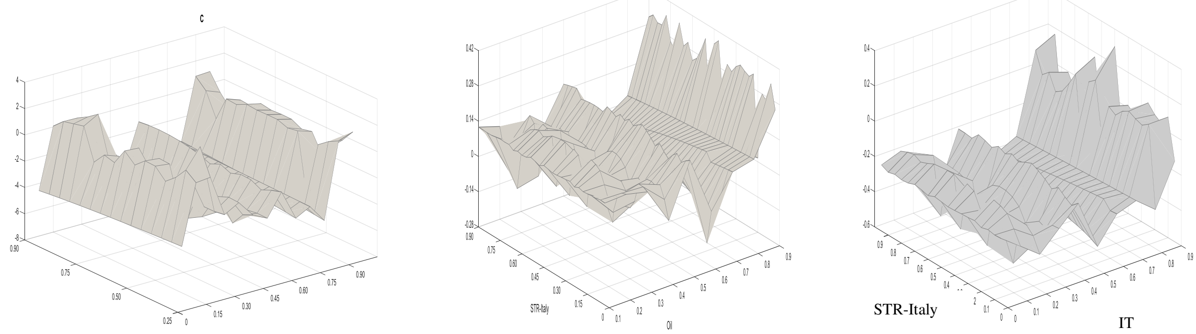
Germany



France



Italy



3.3. Discussion of results

At the average level (quantile means for STR and oil price), the findings do not appear meaningful. This is why the OLS estimates are unsuited or inoperable. The STR-Oil relationships are more significant in the tails (low and high quintiles). Indeed, the extreme stock market performances cause a wider influence on the interaction between oil price and stock returns. Similarly, when the global oil price is in the upper quantile and whatever the market behavior is, the oil price effect on G7 equities seems positive (except in the cases of France and United States). Accurately, it is the price of oil that dictates the stock market mood and not the opposite. In addition, the consideration of the China's slowdown does not fundamentally upset the results. We usually show that Germany, Canada and Italy are the countries suffer most from the current vacillating situation. A vexing question arises here: *what are the main channels through which the slow-moving of the Chinese economy may exert a great effect on developed countries (in particular, Germany, Canada and Italy)*? To effectively address this question, it is necessary to take in mind the problem of sincerity of the Chinese data on economic growth. Indeed, some studies (Arthus and Virad 2016, among others) have raised doubts about these statistics. We leave this debate, also very interesting, aside. But this question shouldn't be overlooked when gauging the relationship between China economic growth and G7 equities. Based on Heyer (2016)'s study, the China's economic downturn can be mainly transmitted to developed countries through the trade channel. Obviously, the remarkable slow-moving of industrial production in China would lead to a drop in Chinese imports and then affect the position of some countries as main exporters. We shouldn't overlook the indirect effect that might occur via the steep fall in imports from the major commodity producers (e.g. Brazil, Russia and South Africa). The pass-through of China's downturn on developed countries can be also via the financial channel. In fact, the Chinese slowdown and the current financial crash are exacerbating the panic across much of the world, as countries on nearly every continent clearly see the sizeable risks of slumps and financial losses. A sharper than expected China's economic slow-moving could prompt an abrupt adjustment in global asset markets, as investor risk aversion adjusts. We shouldn't neglect the importance of commodity channel. It is well known that Chinese economy is one of the major absorbers of global commodity consumption. In particular, China purchases the half of all metals traded in the world. It buys about an eighth of the world's oil, a quarter of its gold, a third of its cotton and up to half of all the major base metals. In countries specializing in crucial commodities, including oil, iron ore and coal, the sharp fall of Chinese demand yielded to a decrease of commodity prices, threatening government tax revenue and fostering trade deficits. Retaining only the trade channel and with reference to developed countries, Heyer (2016) showed heterogeneous responses to Chinese slowdown. The most affected countries are Germany, Japan and to a lesser extent United Kingdom and Italy[5], whereas the least damaged countries are France and the United States. With the exception of Japan, we find almost the same hierarchy. In addition to the differences in oil-dependence profile that has been largely advanced in literature to explain different equities reactions to oil price (Park and Ratti 2008, Kilian and Park 2009; Nandha and Brooks 2009 and Jammazi and Nguyen 2015), this study suggests that the stock prices of the companies belonging to cyclical industries appear more sensitive China's slowdown (Table A.1, Appendix). Accordingly, Damodaron (2014) argued that cyclical companies have volatile earnings, with the volatility coming from global economic and financial factors that are not in the control of these industries. As the economy weakens and strengthens in response to domestic and external shocks, cyclical companies will see their earnings go up and down, providing higher returns in periods of economic boom or expansion. It must be noted here that, the stock market returns of United States and France which experienced weak influence are dominated by non-cyclical or defensive industries. These sectors are those that do well in economic downturn, since demand for their products and services continue to grow regardless of the economic and financial situation.

Beyond the channels through which China-oil price can be transmitted to G7 stock markets, the coincidence of the two phenomena (i.e., China's slowdown and collapsing oil prices) must have contradictory effects. If the first phenomenon may have a detrimental influence on the growth of all the G7 countries, the second may rather exert a positive impact on oil-importing countries (for companies and households) mainly due to the redistribution of gains (reduction of production costs for businesses and gain purchasing power for households). But for the exporting countries, the effect is seemingly opposite. This shows the heavier complexity of the exercise.

Clearly, the different outcomes reached in this paper inconvertibly underscore the difficulty of understanding the behavior of financial markets in turbulent times. Among the

[5] We should mention that these countries are the top export destination of China. For details about the imports, exports and the main trade partners of China, please visit the following link: http://atlas.media.mit.edu/en/profile/country/chn/

potential elements that complicate the analysis, there is the quantitative easing (QE). It corresponds to a large scale asset purchases plan, called also quantitative easing or QE, thereby the Central Banks buy government bonds and in so doing put money base into circulation. Although a conventional monetary tool allows reaching good inflation outcomes, it did not effectively avoid asset market bubbles from occurring. A strand of literature investigated the role of monetary policy in containing speculative bubbles (Joyce et al. 2012). They argued that the more appropriate monetary policy measure, in turbulent period, is that enable to mop up the aftermath of a burst bubble rather than to tackle its build-up. The QE can help to mitigate the adverse effects of sudden shocks. For example, the quantitative easing (or QE) pursued by the Federal Reserve has strengthened the United States equity in the onset of global financial collapse (Bernanke 2012). But it is difficult to generalize this evidence to all countries. It is also hard to determine exactly how or to what extent QE may affect the stock markets (Kuttner 2005, Basistha and Kurov 2008 and Verleger 2015). QE can almightily create multiple risks since no one knows how much QE is too much and how much is not enough. Eventually, a central bank can lose money on its purchases, money that will finally have to be underwritten by taxpayers generating higher future inflation. The latter enables to predict an economic downturn which negatively affects the future corporate profits and pushes investors to require heavier risk premiums to cover the additional risk and hence, lowers stock prices (Fama 1981, 1990). It is not easier to gauge the appropriateness of central bank measures undertaken because the pass-through to economy is complex and opaque. Several factors influence market conditions and the effect of individual policies is hard to isolate, especially over turbulent times.

4. Concluding remarks

The hypothesis that external shocks exert wider influence on stock returns has enthralling appeal but lack solid empirical support. This article focus is twofold: First, we attempt to capture overall quantile dependence structure across different stock market conditions, even if we account for various kinds of oil price movements. Second, it attempts to flesh out the role that may play the China's slowdown in strengthening this relationship. To the extent that global investors increasingly use portfolio diversification as effective strategy to lighten risks, a meticulous investigation of the equities' responses to the couple China-oil price is of paramount importance and relevance for the investor's optimal asset allocation decisions. To address this issue, the paper develops the QQ approach. This novel estimation method may offer accurate information about the convoluted relationship between oil price changes and G7 equities, by shedding light on how the quantiles of explanatory variable could affect the conditional quantile of the endogenous time series. In other words, the QQ model can efficaciously address whether the same quantile of oil price, hence representing the same behavior, influence equities distinctly depending on which quantile of stock returns is of interest. The key methodological challenge in this research is to perform a quantile regression model having a conditional quantile regressor. A principal advantage of the QQ approach is in its ability to model economic relationships more efficaciously than is possible with OLS or quantile regression. While OLS regression is only able to estimate the impact of the couple China-oil price on the conditional mean of the G7 equities; quantile regression goes further by disentangling this influence on the conditional mean into distinct effects on the conditional quantile. In sum, this new method generalizes the quantile regression approach by highlighting how the quantiles of oil price changes could impact the conditional quantile of the G7 stock returns. Among the three estimation approaches used throughout this article, the QQ approach offers the most information possible about the linkage between China-oil price and G7 stock returns. Our findings fortify the practicality and the efficacy of QQ econometric tool in assessing complex linkage in vacillating framework, i.e., during periods of economic downturn and financial stress. Indeed, by performing QQ approach, we have gathered fresh insights on how "complex" the equities responses to the couple China-oil price might be:

(i) The G7 stock returns respond differently to a same quantiles of oil price, underscoring the occurrence of asymmetry.
(ii) The stock markets of Germany, Italy, Canada and United Kingdom (in this order) are seemingly more reactive to oil price changes than France Japan and United States.
(iii) By considering the potent uncertainty surrounding the recent China's economic slow-moving, we found that the G7 stock markets reactions to oil price changes seem more pronounced.
(iv) The severity of Chinese crisis on G7 equities is not uniform. Germany, Italy and Canada suffered the most, while United Kingdom, Japan, France and United States experienced a moderate influence.

So what have we learnt? The consensus of the research here is that the transmission mechanisms of the infernal couple China-oil price to G7 equities is heavily "complex". Some elements have been put forward to explain such complexity and sharp heterogeneity among

G7 countries including the oil dependency, the efficaciousness of monetary policy measures undertaken, the quantitative easing, the unlimited offers of liquidity by major central banks and the distribution of companies belonging to cyclical and non-cyclical industries in the stock market indices. Interestingly, our results suggest that diversification possibilities may be even larger. The evidence that the correlation changes markedly in both low and high quantiles may have deeper consequences for portfolios that trade with different rebalancing horizons. In particular, the relatively dissimilar equity reactions can markedly reflect the fact that oil consumers, oil producers and traders in the oil markets view the oil prices denominated in distinct currencies (dollar, Yen, euro, etc.) differently regarding hedging performance and diversification strategy (Chang 2009).

As a matter of policy implications, regulators should work effectively to build a long-run international investors' confidence in the stock markets by protecting and safeguarding their interest against risk. Last but not least, the traders who hope investing in G7 countries whose equities suffered most from the Chinese crisis (Germany, Canada and Italy) should be cautious about the significant dependence between stock returns and China downturn, and also should give great attention to the volatile behavior of oil price. For instance, an appropriate hedging strategy should be involved to secure the oil-related input which in turn allows efficaciously mitigating the excessive volatility of accounting earnings and stock returns. Importantly, the fact that the fears over China's worsening outlook sends G7 countries into a slowdown indicates, to some extent, that QE does not work satisfactorily or has not been done in sufficient scale. To be more effective, it needs to be supplemented with further monetary measures.

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Appendix

Table A.1. Sectoral Distribution of the Stock Market Index (in percent)

Sectors	USA	UK	Canada	Germany	Japan	France	Italy
Cyclical companies							
-Oil and raw materials	13	19	27	6	18	9	7
-Financials and Banks	17	27	15	16	4	18	30
-Industrial and manufacturing	8	11.5	15	40	16	18	17.5
-Information technology	5	0.2	14	11	34	4	3
Total	43	57.7	71	73	72	49	57.5
Non-cyclical companies							
-Consumer goods	10	9	16	12	16	27.5	31
-Telecommunications	5	8	12	8	8	3.5	6
-Others	32	25	-	7	4	20	5.5
Total	46	42	28	27	28	51	42.5

Source: Datastream.