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ABSTRACT

In this paper, we revisit the debate on the relationship between oil price shocks and stock market returns by replicating the quantile-on-quantile (QQ) regression model for the US stock market in Sim and Zhou (2015, Journal of Banking and Finance), and extending it to 15 countries. The classification of these countries as oil importers or oil exporters depends on their net position in crude oil trade. Our results indicate that the main finding by Sim and Zhou (2015) that large negative oil price shocks can bolster stock returns when markets are performing well is only partially supported by the three largest oil importers in our sample– China, Japan and India– during the period 1988:1–2007:12. However, when extending the study to more recent data (period 1988:1–2016:12), we find that China and India experience higher returns when markets perform well and there is a large positive oil price shock. Also, large positive oil price shocks often lead to higher stock market returns when markets perform well for both oil exporting countries– Canada, Russia, Norway– and moderately oil dependent countries– such as Malaysia, Philippines and Thailand. In most cases large negative oil price shocks depress further already poorly performing markets, as in Sim and Zhou (2015). These findings highlight that the relationship between the distributions of oil price shocks and stock market returns is not stable over time in most countries studied. Furthermore, the asymmetric effect between positive and negative oil price shocks observed in the US market by Sim and Zhou (2015) is less evident in most countries for both the baseline and extended periods.

Key words: Oil prices; stock returns; Quantile regression.

JEL classification: C01, C14, C31, G15.

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1 Introduction

Since the seminal work of Hamilton (1983) several studies have investigated the link between oil price shocks and either the macroeconomy,[1] or financial markets.[2] Yet no clear consensus has emerged as to whether such a link even existed. Our paper revisits this debate by replicating and extending the model proposed for the US by Sim and Zhou (2015, Journal of Banking and Finance) to 15 countries, whose classification as oil importing or exporting depends on their net position in crude oil trade.[3] We show that although the findings by Sim and Zhou (2015) apply to the large oil importing countries of China, India, and Japan, they do not apply to large oil exporting countries such as Mexico, Russia, and Venezuela.

Using a structural vector autoregression (SVAR), Kilian (2009) and Kilian and Park (2009) identify three structural shocks to oil prices in the US; demand, supply and oil-specific demand. They find that precautionary demand shocks are the largest contributor to the relationship between oil price shocks and stock market returns. Sim and Zhou (2015) offer further insights into this relationship by using a quantile-on-quantile (QQ) approach. Stock markets, they argue, may react differently to small, large, positive, or negative oil price shocks (see Figure 13 in the appendix). Their framework thus aims to differentiate the effects of oil prices on the US stock market conditional on the sign and the size of oil price shocks and the performance of the US stock market.

In this paper, we adapt the framework by Sim and Zhou (2015) to account for the impact of the US stock market on other countries, and apply the model to countries that are considered to be either oil importer, oil exporter or moderately oil dependent. Our results corroborate those of Sim and Zhou (2015) when considering large oil importing countries, in that large negative oil price shocks[4] may lead to higher returns when the market is well performing and lower returns when markets perform poorly during the period 1988:1–2007:12. However, when extending the study to more recent data (period 1988:1–2016:12), we find that China and India experience higher returns when markets perform well and there is a large positive oil price shock. Also, we find that large positive oil price shocks often lead to higher stock market returns when markets perform well for both oil exporting countries– Canada, Russia, Norway– and moderately oil dependent countries– such as Malaysia, Philippines and Thailand. Finally, in most cases, large negative oil price

[1]See e.g. Barsky and Kilian (2004), Hamilton (1996), Mork et al. (1994), Lee et al. (1995), and more recently Ratti and Vespignani (2016).

[2]See e.g. Kling (1985), Jones and Kaul (1996), Chen et al. (1986), Sadorsky (1999), and more recently Broadstock and Filis (2014), Kang et al. (2015), Maghyereh et al. (2016), Balcilar et al. (2017), and Zhang (2017).

[3]Aloui et al. (2012) and Wang et al. (2013) adopted a similar classification.

[4]With the exception of Japan where the negative oil price shock is small.

shocks depress further already poorly performing markets, as in Sim and Zhou (2015).

While much of the early literature on oil price shocks and stock market returns focus on the US, there has been an increased interest in developed countries in Europe and Asia, and developing countries across the world. In particular, Wang et al. (2013), and Cunado and de Gracia (2014) suggest that when considering other countries besides the US, the significance of the precautionary demand shocks are lower. Using a Vector Error Correction Model (VECM), Cunado and de Gracia (2014) analyze the impact oil price shocks have on stock market returns in 12 oil importing European countries. They find that the relationship between oil price shocks and stock market returns is negative, and that supply shocks have a greater impact than demand shocks.

Park and Ratti (2008) consider 13 European countries along with the US to conduct a multivariate vector autoregression (VAR) analysis on oil price shocks and stock market returns. They conclude that there is a statistically significant negative impact of oil price shocks on stock market returns in the same month or within one month.[5] They also look at the asymmetric effects of stock returns on oil price shocks. They find some evidence for the US and Norway, but little evidence for any other oil importing European country.

Using a SVAR approach, Apergis and Miller (2009) analyse three types of oil price shocks on stock market returns from eight countries– Australia, Canada, France, Germany, Italy, Japan, the United Kingdom, and the United States – and find that international stock market returns do not respond in a large way to oil market shocks. Using a similar methodology, Abhyankar et al. (2013) show that the Japanese stock market reacts negatively to oil price increases related to oil-market specific demand shocks, and Lin et al. (2010) show that global oil demand and oil specific demand shocks have no significant impacts on China's stock market returns.

Wang et al. (2013) consider the relationship between oil price shocks and stock market returns for a range of oil importing and oil exporting countries, using the SVAR methodology by Kilian (2009). They find that the magnitude, direction, and duration response of an oil price shock impact the stock market returns differently in oil importing countries compared with oil exporting countries. They further show that the nature of the price shock– whether it is driven by supply or demand– affect oil importing countries differently from oil exporting countries.

In their study, Fang and You (2014) analyse whether the stock market returns of the three large Newly Industrialised Economies' (NIE), namely China, India and Russia, can be explained by fundamental oil demand and supply shocks, and find mixed results.

[5]Except for Norway which shows a positive relationship. They attribute this to Norway being a net oil exporter. Bjørnland (2009) confirms this result for Norway showing that following a 10% increase in oil prices, stock returns increase immediately by 2-3% with the effect gradually dying off after 15 months.

More recently, Bouoiyour and Selmi (2016) used a QQ approach to study G7 stock market responses to oil price shocks accounting for China's slowdown. They find responses to be asymmetric and show that markets in Germany, Italy, Canada and the United Kingdom are typically more responsive than those in France, Japan and the United States.

Basher and Sadorsky (2006) use an international multi-factor model to investigate the relationship between oil price shocks and stock market returns for 21 emerging stock markets. While they find strong evidence of such a relationship, their results are inconsistent and vary with the frequencies of data used. For daily and monthly data, they find that an increase in oil prices has a positive effect on stock market returns, while the same effect occurs for a decrease in oil prices using weekly and monthly data.

Aloui et al. (2012) consider emerging countries, which they separate into three groups– net oil exporting countries, net oil importing countries, and moderately oil dependent countries– depending on their net position in crude oil trade. Using the framework of Basher and Sadorsky (2006), they find that the sensitivity of stock market returns in relation to oil price shocks is asymmetric and particularly significant during periods of rising oil prices. They also find that the relationship between oil price shocks and stock returns during bearish periods is positive in moderately oil dependent countries and negative for oil exporting countries. No relationship is found however for oil importing countries during either bullish or bearish periods.

Güntner (2014) examines the relationship between structural oil price shocks and stock market returns in six OECD countries, comprising of four oil importing countries - the United States, Japan, Germany, and France - and two oil exporting countries - Canada and Norway. Using the model developed by Kilian (2009), they find similar results to Kilian and Park (2009). In particular, they find that oil supply shocks have no significant impact of oil price shocks on stock returns, while aggregate demand oil shocks have a positive effect on stock returns, although more persistent for exporters and in particular Norway. They also show that precautionary demand oil shocks have a negative impact on stock returns for importing countries, a positive effect for Norway, but no effect for Canada.

The rest of the paper is organised as follow. Section 2 introduces the model by Sim and Zhou (2015), and the changes we made to extend its application to countries outside the US. Section 3 presents the data used in this study and our results. Section 5 concludes.

2 Model

Let $\left\{(r_{jt}, oil_t)\right\}_{t=1}^{n}$ be a sample of n observations where r_{jt} is the stock returns of country j at time t and oil_t denotes the oil price shock at time t due to variations in precautionary demand.[6] Consider the following quantile-on-quantile framework [similar to Sim and Zhou (2015)]:

$$r_{jt} \quad = \quad \beta_j^{\theta}(oil_t) + \alpha_{1j}^{\theta} r_{j,t-1} + \alpha_{2j}^{\theta} r_{US,t-1} + \upsilon_{jt}^{\theta}, \tag{1}$$

where $\beta_j^{\theta}(\cdot)$ is a possible unknown function that links oil price shocks to the θ-quantile of the stock returns of country j, $r_{US,t-1}$ is the US stock market returns at $t-1$, and υ_{jt}^{θ} is an error term that has zero θ-quantile. Although model (1) is similar to that of Sim and Zhou (2015), focusing on countries other than the US requires controlling for the global influence of the US market in the equation. Indeed, it is highly likely that changes in the US market affect the stock returns in markets worldwide. Therefore the inclusion of $r_{US,t-1}$ in the RHS of (1) is required in order to identify α_{1j} as well as the link function $\beta_j^{\theta}(\cdot)$.

Under the standard regularity conditions on the link function $\beta_j^{\theta}(\cdot)$ [see Sim and Zhou (2015)], the first order Taylor expansion of $\beta^{\theta}(\cdot)$ around oil^{τ}, where τ represents the quantile of oil price shock gives:

$$\beta_j^{\theta}(oil_t) \approx \beta_{0j}(\theta,\tau) + \beta_{1j}(\theta,\tau)(oil_t - oil^{\tau}), \tag{2}$$

where $\beta_{0j}(\theta,\tau) \equiv \beta_j^{\theta}(oil^{\tau})$ and $\beta_{1j}(\theta,\tau) \equiv \partial\beta^{\theta}(oil^{\tau})/\partial oil_t'$ is the score of $\beta^{\theta}(\cdot)$ evaluated at $oil_t = oil^{\tau}$. Now substituting (2) into (1) gives:

$$r_{jt} = \underbrace{\beta_{0j}(\theta,\tau) + \beta_{1j}(\theta,\tau)(oil_t - oil^{\tau}) + \alpha_{1j}(\theta) r_{j,t-1} + \alpha_{2j}(\theta) r_{US,t-1}}_{(*)} + \upsilon_{jt}^{\theta}, \tag{3}$$

where $\alpha_1(\theta) := \alpha_1^{\theta}$ and $\alpha_2(\theta) := \alpha_2^{\theta}$. The term $(*)$ in the RHS of (3) represents the θ conditional quantile of country j's stock returns, and captures the dependence between the θ-quantile of country j's returns and the τ-quantile of the oil price shocks. Clearly both the intercept term, $\beta_{0j}(\theta,\tau)$, and the slope coefficient, $\beta_{1j}(\theta,\tau)$, are functions of θ and τ. As $(\theta,\tau) \in [0,1]^2$, the 3D plots of $\beta_{0j}(\theta,\tau)$ and $\beta_{1j}(\theta,\tau)$ in $[0,1]^2$ inform us on the dependence structure between the distribution of the stock returns and that of oil price shocks for a given country j.

To estimate the parameters of model (3), we employ quantile regression technique. As the oil price shocks oil_t are not observed, we approximate them with the fitted shocks $\widehat{oil_t}$ from the 3 variables SVAR model as in Sim and Zhou (2015), and replace oil^{τ} with the

[6] Following Kilian (2009) and Kilian and Park (2009), oil_t represents the oil price shocks arising from changes in oil precautionary demand filtered from the structural vector autoregressive(SVAR) model. In this study, we approximate oil_t following the same steps as in Sim and Zhou (2015). The details of this estimation are omitted to shorten the exposition of the paper.

empirical quantile of $\widehat{oil}^{\tau}$. We then solve the minimization problem:

$$\min_{b_0,b_1} \sum_{t=1}^{n} \rho_\theta \left[r_{jt} - b_0 - b_1(\widehat{oil}_t - \widehat{oil}_\tau) - \alpha_{1j}(\theta) r_{j,t-1} - \alpha_{2j}(\theta) r_{US,t-1} \right] M\Big(\frac{F_n(\widehat{oil}_t) - \tau}{h} \Big), \quad (4)$$

where $\rho_\theta(\cdot)$ is the tilted absolute value function that gives the θ-conditional quantile of r_{jt} as a solution, and $M(\cdot)$ is the Gaussian kernel function that weighs the observations around the neighborhood of the τ-quantile of oil price shocks. To estimate these weights, we follow Sim and Zhou (2015) and use a bandwidth of $h = 0.05$ and the empirical distribution function of oil price shocks given by:

$$F_n(\widehat{oil}_t) = \frac{1}{n} \sum_{k=1}^{n} \mathbb{1}[\widehat{oil}_k < \widehat{oil}_t], \quad (5)$$

where $\mathbb{1}[C] = 1$ if condition C holds, and $\mathbb{1}[C] = 0$ otherwise. Although we are aware of issues involving kernel regressions, especially the choice of the kernel function and the optimal bandwidth parameter h, we use the Gaussian kernel function with a bandwidth of $h = 0.05$ in order to mimic the methodology of Sim and Zhou (2015).

3 Data and estimation

We use monthly data from Datastream spanning from 1988:1 to 2016:12 for 15 countries.[7] Replication of the main results in Sim and Zhou (2015) are presented in Table 6 and Figure 13 of the appendix, using their US data for the period 1988:1 to 2007:12. Their conclusion that the slope estimates tend to meander around zero in large regions of the parameters space is supported by our replication, but we identify a peak at the lower θ-quantiles of the US stock returns [see Figure 13-(b) in the appendix] rather than the upper θ-quantiles of the US stock returns.

Following Wang et al. (2013), we separate the 15 countries in our sample into three categories depending on their net trade balance in crude oil as shown in Table 1 (where the net positions are for the year 2009[8]).

[7] For China, Colombia, India, and Venezuela, we were only able to get data for the period 1993:1 to 2016:12. Similarly, we could only collect data for Russia for the period 1995:1 to 2016:12.

[8] Aloui et al. (2012) established a similar classification using the average net position between 1997 and 2006. In this study, we follow the one year classification by Wang et al. (2013) as it includes all countries in our sample except Colombia, while the classification used by Aloui et al. (2012) excludes many countries.

	Crude Oil Imports (1000 barrels/day)	Crude Oil Exports (1000 barrels/day)	Net Position (1000 barrels/day)
Oil importers			
China	4,082	104	-3,978
Japan	3,725	0	-3,725
India	3,185	0	-3,185
South Korea	2,348	6	-2,342
Germany	1,980	2	-1,978
Taiwan	946	0	-946
Oil exporters			
Russia	36	4,891	4,855
Norway	20	1,800	1,780
Venezuela	132	1,594	1,462
Mexico	10	1,303	1,293
Canada	818	1,980	1,162
Moderately oil dependent			
Malaysia	115	254	140
Philippines	136	26	-110
Thailand	803	45	-758
Colombia	–	–	–

Table 1: Categorization of countries in our sample

For each country, the stock returns are calculated as the continuously compounded returns of the Morgan Stanley Capital International (MSCI) market index (in US dollars) minus the inflation rate. The inflation rate is calculated as the log difference in the consumer price index (CPI) over time. For oil price shocks, we use monthly data from 1988:1 to 2016:12 on crude oil production and prices (in US dollars) from the US Department of Energy. We then compute the global real activity as formulated by Kilian (2009)[9] using an index of cargo ocean shipping freight rates. Finally, we follow Sim and Zhou (2015) and filter the oil price shocks through their 3 variables SVAR model. To facilitate the comparison with the findings in Sim and Zhou (2015) for the US, we conduct our analysis for: (i) the period 1988:1 to 2007:12 [similar to Sim and Zhou (2015)], and (ii) the extended period 1988:1 to 2016:12. The estimation of the model over the extended period allows us to check the stability of the results over recent years, and whether there are variations in the differences across countries in our sample.[10] For the clarity and readability of our

[9]We thank Professor Kilian for providing us the formula of the global real activity index that we use to extend the data to 2016:12.

[10]We thank an anonymous referee for suggesting the extension of the analysis to more recent data.

results, we thus present for each period (baseline and extended) the estimates $\widehat{\beta}_{0j}(\theta,\tau)$ of the intercept, and that $\widehat{\beta}_1(\theta,\tau)$ of the slope coefficient.

3.1 Intercept estimates

In this section, we analyze the results for the estimates $\widehat{\beta}_{0j}(\theta,\tau)$ of the intercept term in (3). An interesting feature of the quantile-regression (3) is that the intercept coefficient still captures the stock market and oil price shocks movements of country j through its dependence on their respective quantiles, even though on average it measures the predicted level of country j's stock returns when the values of the regressors other than a constant term are set to zero. This is not possible in a standard linear regression setting because the intercept estimate is constant conditional on the sample, and thus is not influenced by the distributions of the stock returns (θ-quantiles) and oil price shocks (τ-quantiles). Therefore, the quantile regression framework allows us to measure the joint impact that the θ-quantiles of the stock returns and the τ-quantiles of oil price shocks exert on the stock market of country j when oil price shocks τ-quantile deviations $(oil_t - oil^\tau)$ and US global influence $(r_{US,t-1})$ are set to zero in (3). This can be achieved, for example, by examining the plots of $\widehat{\beta}_{0j}(\theta,\tau)$ as a function of (θ,τ) in $[0,1]^2$. Our aim is to examine in which regions of $(\theta,\tau)\in[0,1]^2$ the distributions of stock returns and oil price shocks are dependent, and to what extent this dependence impacts on stock returns (through their effect on the intercept estimates $\widehat{\beta}_{0j}(\theta,\tau)$). To investigate this further we believe that a combination of 3D graphical representations [similar to Sim and Zhou (2015)] and summary tables will facilitate the comparison across the categories of countries, and also allows for a more thorough comparison with the results of Sim and Zhou (2015).

For the remainder of the section, results are presented for quantiles ranging from 0.06 to 0.94 in increments of 0.02 for both the stock returns and the oil price shocks. As a consequence, each country has 2025 estimated values of $\widehat{\beta}_{0j}(\theta,\tau)$ corresponding to the different points (θ,τ) in the grid $[0.06 : 0.02 : 0.94]^2$. This grid is similar to that of Sim and Zhou (2015) for the case of the US. We interpret the θ-quantiles of the stock returns greater than to 0.75 as reflective of *positive market conditions*, while those less than 0.25 represent *negative market conditions*. The stock markets with θ-quantiles lying in the interval $[0.25, 0.75)$ are interpreted as neutral. However, no country in our sample exhibits statistically significant coefficients when $\theta\in[0.25,0.75)$, and this classification is thus omitted in the presentation of our results.

Moreover, we also separate the τ-quantiles of oil price shocks into four categories: (**i**) large negative shocks (symbolized by $\mathbf{q_1}$) which correspond to the values of τ less than 0.25; (**ii**) small negative shocks ($\mathbf{q_2}$) corresponding to the values of $\tau\in(0.25,0.5]$; (**iii**) small positive shocks ($\mathbf{q_3}$) corresponding to the values of $\tau \in (0.5, 0.75]$; and finally (**iv**) large positive shocks ($\mathbf{q_4}$) corresponding to the values of τ greater then 0.75.

In the 3D representations (e.g. in Figure 1), $\widehat{\beta}_{0j}(\theta, \tau)$ (the z-axis) is plotted against the θ-quantiles of the stock returns (the x-axis) and the τ-quantiles of the oil price shocks (the y-axis). In the tables however, we report for each country, and for a given market condition (positive or negative) and a given oil price shock type ($\mathbf{q_1}, \mathbf{q_2}, \mathbf{q_3}$ or $\mathbf{q_4}$), the maximum (in absolute term) of the estimated coefficients $\widehat{\beta}_{0j}(\theta, \tau)$ for all (θ, τ) in the specified region in grid $[0.06 : 0.02 : 0.94]^2$. These maxima usually correspond to the peaks of the 3D representations in that region– e.g., see Figure 1. The codification '$*$' in the tables indicates that the absolute value of the difference between the estimate and the sample average of the estimated coefficients $\widehat{\beta}_{0j}(\theta, \tau)$ in the specified region is larger than 2.6 times the standard deviation of the sample average. Although this rule is not a proper statistical test, it can be interpreted as indicating the regions of the parameters where the maximum (in absolute term) estimated coefficient is significantly different from the sample average of the estimated coefficients $\widehat{\beta}_{0j}(\theta, \tau)$ in that region at the 1% nominal level. Finally, for the purpose of clarity, we discuss our results separately for oil importing, oil exporting, and moderately oil dependent countries, as classified in Table 1.

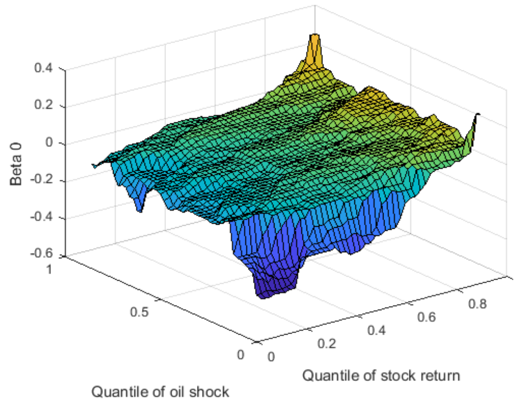
3.1.1 Oil importing countries

Figures 1 & 2 present the results for oil importing countries for both periods, baseline and extended. Figure 1 shows the results for the three largest oil importing countries in our sample– China, Japan, and India, while Figure 2 contains those of medium oil importing countries– South Korea, Germany, and Taiwan. These graphical representations are complemented by Table 2 that summarizes the maximum estimated impact $\widehat{\beta}_{0j}(\theta, \tau)$ for each country, and for a given market condition (Positive or Negative) and a given oil price shock type ($\mathbf{q_1}, \mathbf{q_2}, \mathbf{q_3}$ or $\mathbf{q_4}$). The first part of the table shows the estimates for the baseline period (1988:1–2007:12), while the second part of the Table presents the estimates for the extended period (1988:1–2016:12).

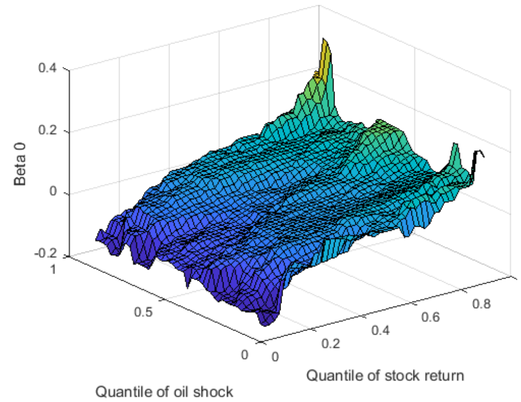
Let us first focus on the baseline period which coincides with the period considered in Sim and Zhou (2015). From Figure 1-(1a), (1c) & (1e) and the first part of Table 2, we see that in general the three largest oil importing countries experience increased returns when the market is performing well (Positive: θ-quantiles of the stock returns greater than 0.75) and there is a large negative ($\mathbf{q_1}$ for China, Japan) or small negative ($\mathbf{q_2}$ for India) oil price shock. This result corroborates the findings by Sim and Zhou (2015) for the US [see Table 6 and Figure 13-(a)]. However, China and Japan also experience higher returns when the market is performing well and there is a large positive ($\mathbf{q_4}$) oil price shock, which is at odds with the findings of Sim and Zhou (2015) for the US. India differs from the other large oil importing countries (China and Japan) as it does not overreact when the market is performing well and there is a large positive ($\mathbf{q_4}$) oil price shock. Finally, when the market performs poorly (Negative: θ-quantiles of the stock returns less than 0.25), all three countries experience lower returns when there is a large negative oil price shock ($\mathbf{q_1}$), which corroborates the findings by Sim and Zhou (2015). For the medium oil importing countries– South Korea, Germany, and Taiwan– the impact of a positive market (θ-quantiles of the stock returns greater than 0.75) is quite similar across all oil price shock types ($\mathbf{q_1}, \mathbf{q_2}, \mathbf{q_3}$ or $\mathbf{q_4}$), with South Korea showing the highest impact at $\mathbf{q_4}$ (large positive oil price shock); see Figure 2-(2a), (2c) & (2e) and the first part of Table 2. Clearly, this contradicts the main conclusion by Sim and Zhou (2015) for the US market. Nevertheless, all medium oil importing countries (South Korea, Germany, and Taiwan) experience lower returns when there is a large negative oil price shock ($\mathbf{q_1}$) and the market is performing poorly (Negative: θ-quantiles of the stock returns less than 0.25), a finding similar to that of China, India and Japan (largest oil importing countries). The latter result is also translated by the peaks at the bottom of each subfigure of Figure 1 & 2, and are also reported in the first part of Table 2 (period 1988:1–2007:12).

We now analyse the results for the extended period which includes both data during the Global Financial Crise (GFC) and post GFC. Looking at the US graphs (see Figure 13), the extension to more recent data does not change significantly the response of the intercept ($\beta_0(\theta, \tau)$) to a large positive ($\mathbf{q_4}$) oil price shock when the positive market is performing well (θ-quantiles of the stock returns greater than 0.75); see Figure 13: (13a) vs. (13b). However, the results have changed drastically for most oil importing countries in our sample. Indeed, while China [Figure 1-(1b)] and India [Figure 1-(1f)] experience higher returns when the market is performing well (θ-quantiles of the stock returns greater than 0.75) and there is a large positive ($\mathbf{q_4}$) oil price shock, the other oil importing countries [Japan: Figure 1-(1d), South Korea: Figure 1-(2b), Germany: Figure 1-(2d), and Taiwan: Figure 1-(2f)] exhibit a relatively uniform impact across all oil price shock types ($\mathbf{q_1}$ to $\mathbf{q_4}$) when the market is performing well. These results are also shown in the second part of Table 2 (period 1988:1–2016:12), and contradict the main findings by Sim and Zhou (2015). When the market is performing poorly (θ-quantiles of the stock returns less than 0.25), all countries experience lower returns across all oil price shock types ($\mathbf{q_1}$ to $\mathbf{q_4}$). However, except for a large oil price shock ($\mathbf{q_1}$), the impact is quite uniform from small negative to large positive oil price shock ($\mathbf{q_2}$ to $\mathbf{q_4}$) for China, India, Japan, and Germany. South Korea experiences a deeper decrease in returns when there is a large or small negative oil price shock ($\mathbf{q_1}$, $\mathbf{q_2}$) but the impact is quite similar for small and large positive oil price shock ($\mathbf{q_3}$, $\mathbf{q_4}$). Taiwan experiences a decrease in returns when there is a large negative oil price shock ($\mathbf{q_1}$), but there is no clear trend for the other types of oil price shocks ($\mathbf{q_2}$ to $\mathbf{q_4}$).

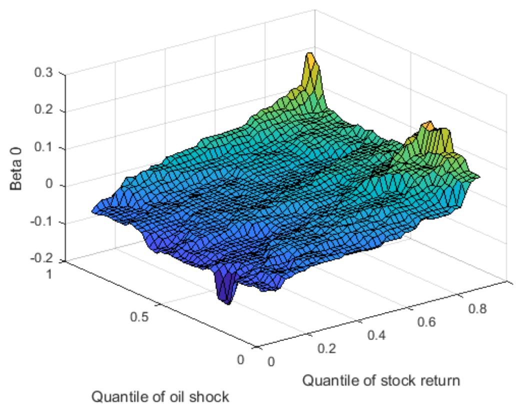
As extending the analysis to GFC and post GFC data seems to alter the results significantly, we can conclude that the relationship between the distributions of oil price shocks and stock market returns is not stable over time. We acknowledge that identifying the possible causes to this instability is important but we leave this analysis to future work. Moreover, due to insufficient data, we are not able to apply the QQ analysis to the post GFC period alone, which makes it difficult to quantify the relationship between the distribution of oil price shocks and that of the stock returns in the post GFC period. Future work could elucidate this question. It is also worth mentioning that the evidence shown in this study is purely descriptive and is far from identifying causal patterns between the distribution of oil price shocks and that of stock market returns. As such, extending the analysis to recent data (including the GFC period) is still informative, although the identification of oil price shocks from the SVAR system may be problematic during the GFC.



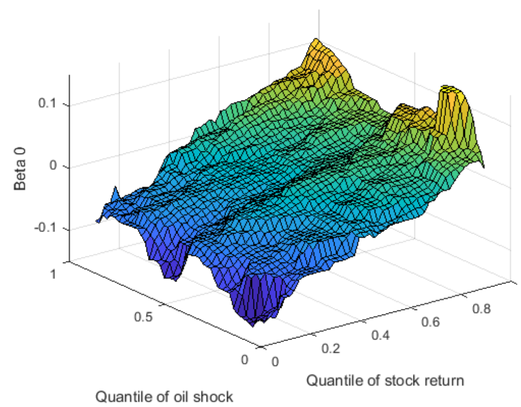
(a) China's β_0: period 1993–2007



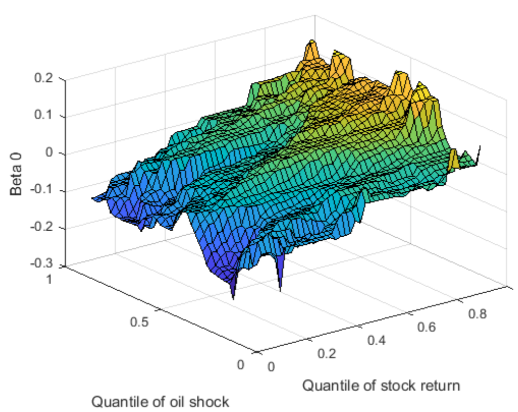
(b) China's β_0: period 1993–2016



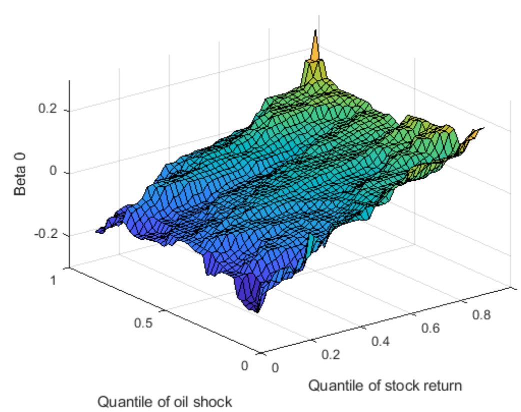
(c) Japan's β_0: period 1988–2007



(d) Japan's β_0: period 1988–2016

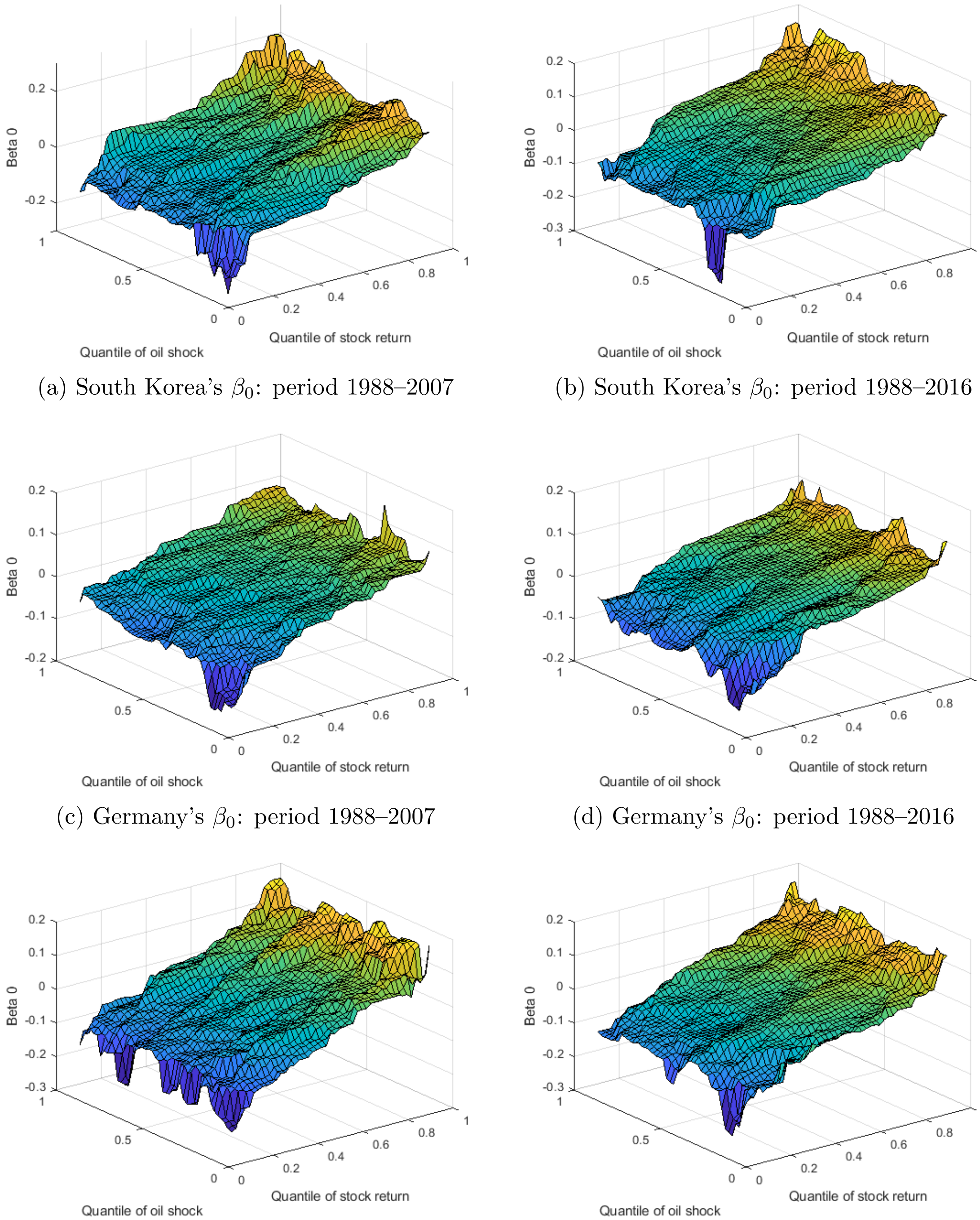


(e) India's β_0: period 1993–2007



(f) India's β_0: period 1993–2016

Figure 1: 3D representation of β_0 as a function of market conditions (θ) and oil price shocks (τ) for the largest oil importing countries.



(a) South Korea's β_0: period 1988–2007

(b) South Korea's β_0: period 1988–2016

(c) Germany's β_0: period 1988–2007

(d) Germany's β_0: period 1988–2016

(e) Taiwan's β_0: period 1988–2007

(f) Taiwan's β_0: period 1988–2016

Figure 2: 3D representation of β_0 as a function of market conditions (θ) and oil price shocks (τ) for medium oil importing countries.

	Period 1988:–2007:12						
Market conditions	Oil price shock	Max impact of β_0					
		China	Japan	India	South Korea	Germany	Taiwan
Positive	$\mathbf{q_1}$	0.266*	0.169*	0.085	0.182	0.103	0.181
	$\mathbf{q_2}$	0.155	0.168*	0.180	0.176	0.164*	0.190
	$\mathbf{q_3}$	0.150	0.073	0.176	0.196	0.107*	0.169
	$\mathbf{q_4}$	0.303*	0.209*	0.158	0.224*	0.099	0.183
Negative	$\mathbf{q_1}$	−0.421*	−0.150*	−0.216*	−0.285*	−0.172*	−0.219*
	$\mathbf{q_2}$	-0.137	−0.147*	-0.175	-0.200	-0.080	-0.197
	$\mathbf{q_3}$	-0.239	-0.097	-0.144	-0.144	-0.080	−0.221*
	$\mathbf{q_4}$	-0.150	-0.064	-0.137	-0.156	-0.058	-0.167

	Period 1988:–2016:12						
Market conditions	Oil price shock	Max impact of β_0					
		China	Japan	India	South Korea	Germany	Taiwan
Positive	$\mathbf{q_1}$	0.207	0.139*	0.209*	0.141	0.125*	0.159
	$\mathbf{q_2}$	0.145	0.137*	0.164	0.138	0.135*	0.135
	$\mathbf{q_3}$	0.153	0.073	0.126	0.173	0.097	0.165
	$\mathbf{q_4}$	0.333*	0.119	0.283*	0.184*	0.117	0.168
Negative	$\mathbf{q_1}$	-0.178	−0.141*	−0.222*	−0.287*	−0.167*	−0.254*
	$\mathbf{q_2}$	-0.168	-0.103	-0.163	−0.269*	-0.115	-0.141
	$\mathbf{q_3}$	-0.165	-0.126	-0.141	-0.119	-0.098	-0.178
	$\mathbf{q_4}$	-0.169	-0.084	-0.182	-0.139	-0.105	-0.131

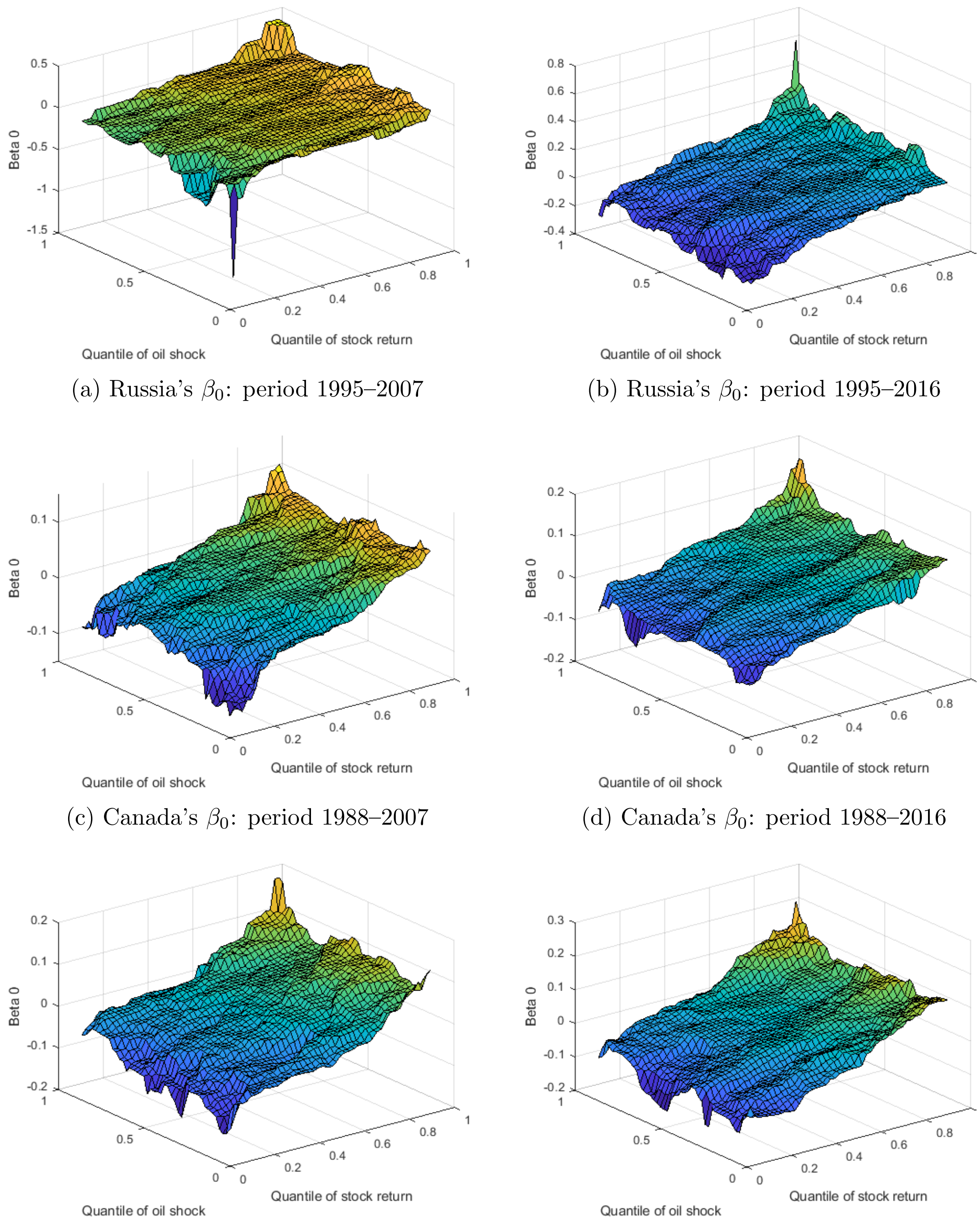
Table 2: Joint effects of market conditions and oil price shocks on the intercept estimate for oil importing countries.

3.1.2 Oil exporting countries

Figures 3 & 4 and Table 3 present the intercept results for oil exporting countries. As before, the analysis is conducted for the baseline period 1988:1–2007:12 (similar to Sim and Zhou (2015)) and the extended period 1988:1–2016:12.

As seen, the results are different from that of the oil importing countries in Table 2 and Figures 1 & 2. First, looking at the baseline period 1988:1–2007:12, we see that a large positive oil price shock ($\mathbf{q_4}$) often leads to the highest returns when the market is performing well (Russia, Canada, and Noway); see Figure 3-(3a), (3c) & (3e) and the first part of Table 3. Mexico and Venezuela experience higher returns when the market is performing well, but the impact is quite similar across all price shock types ($\mathbf{q_1}$ to $\mathbf{q_4}$); see Figure 4-(4a) & (4c) and the first part of Table 3. For Canada, a large negative oil price shock ($\mathbf{q_1}$) does not significantly increase the stock returns when stock markets are performing well. All these findings once again contrast with that of Sim and Zhou (2015). Moreover, Mexico, Russia, Venezuela, and Canada all experience the lowest returns when the market is performing poorly (θ-quantiles of the stock returns less than 0.25) and there is a large negative oil price shock ($\mathbf{q_1}$), while under poor market performance Norway is seeing the lowest returns when there is a small negative oil price shock ($\mathbf{q_2}$). These findings are confirmed by the peaks at the bottom of each subfigure of Figures 3 & 4, and are also reported in the first part of Table 3 (period 1988:1–2007:12).

When considering the estimates of the model for the extend period 1988:1–2016:12, we see that the results have changed drastically for Russia [Figure 3: (3a) vs. (3b)], and in some ways for Canada [Figure 3: (3c) vs. (3d)], Norway [Figure 3: (3e) vs. (3f)], and Mexico [Figure 4: (4a) vs. (4b)]. This highlights once again that the relationship between the distributions of oil price shocks and stock market returns is not stable over time.



(a) Russia's β_0: period 1995–2007

(b) Russia's β_0: period 1995–2016

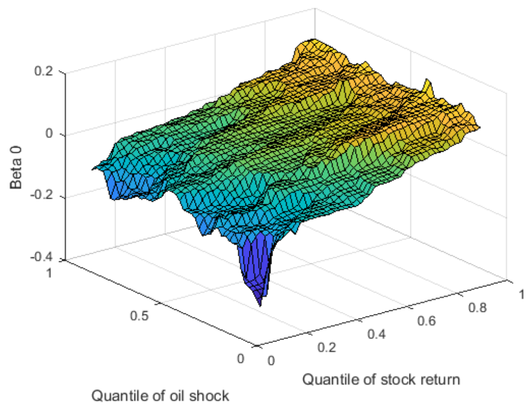
(c) Canada's β_0: period 1988–2007

(d) Canada's β_0: period 1988–2016

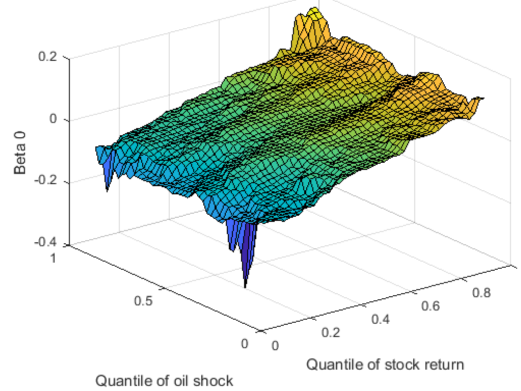
(e) Norway's β_0: period 1988–2007

(f) Norway's β_0: period 1988–2016

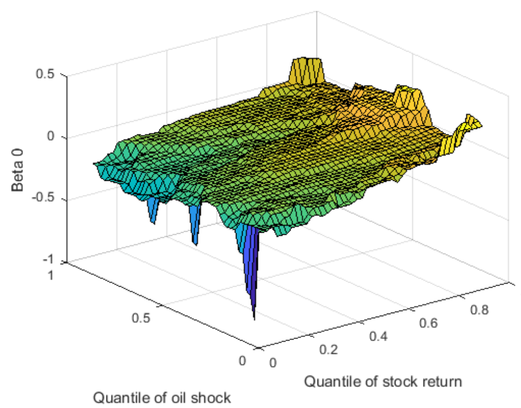
Figure 3: 3D representation of β_0 as a function of θ and τ for oil exporting countries: Russia, Norway, and Canada



(a) Mexico's β_0: period 1988–2007



(b) Mexico's β_0: period 1988–2016



(c) Venezuela's β_0: period 1993–2007

Figure 4: 3D representation of β_0 as a function of θ and τ for oil exporting countries: Mexico and Venezuela.

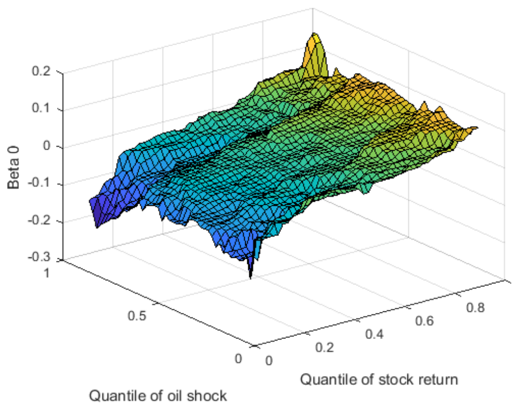
Market conditions	Oil price shock	Max impact of β_0				
		Period 1988:1–2007:12				
		Russia	Canada	Norway	Mexico	Venezuela
Positive	$\mathbf{q_1}$	0.269	0.090	0.127	0.139	0.316*
	$\mathbf{q_2}$	0.346	0.091	0.116	0.168*	0.315*
	$\mathbf{q_3}$	0.302	0.073	0.121	0.135	0.285
	$\mathbf{q_4}$	0.460*	0.113*	0.186*	0.136	0.222
Negative	$\mathbf{q_1}$	−1.218*	−0.128*	−0.153*	−0.303*	−0.875*
	$\mathbf{q_2}$	−0.460*	-0.066	−0.158*	-0.158	−0.485*
	$\mathbf{q_3}$	-0.184	-0.055	-0.139	-0.142	−0.462*
	$\mathbf{q_4}$	-0.186	-0.092	-0.068	-0.170	-0.311
		Period 1988:1–2016:12				
Market conditions	Oil price shock	Max impact of β_0				
		Russia	Canada	Norway	Mexico	
Positive	$\mathbf{q_1}$	0.258	0.083	0.123	0.134	
	$\mathbf{q_2}$	0.246	0.087	0.132	0.143	
	$\mathbf{q_3}$	0.244	0.084	0.118	0.136	
	$\mathbf{q_4}$	0.622*	0.169	0.212*	0.187*	
Negative	$\mathbf{q_1}$	-0.319	−0.102*	-0.137	−0.320*	
	$\mathbf{q_2}$	-0.295	-0.066	−0.159*	-0.143	
	$\mathbf{q_3}$	-0.211	−0.122*	−0.168*	-0.121	
	$\mathbf{q_4}$	-0.260	−0.112*	-0.100	−0.206*	

Table 3: Joint effects of market conditions and oil price shocks on the intercept estimate for oil exporting countries.

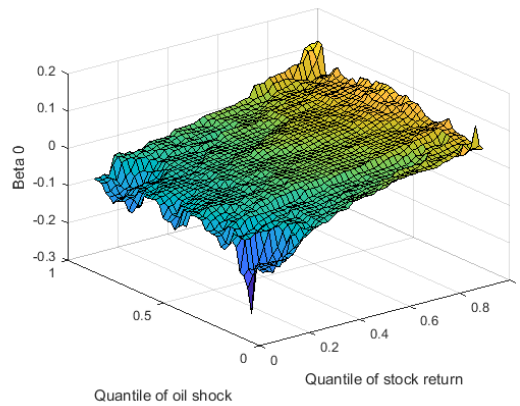
3.1.3 Moderately oil dependent countries

The results for the four moderately oil dependent countries– Malaysia, Philippines,Thailand, and Colombia– are presented in Figures 5 & 6 and Table 4. Consider first the estimates from the period 1988:1–2007:12. As seen from Figure 2: (2a) vs. Figure 5: (5a) & (5c), and Table 2 vs. Table 4, the reaction of the stock market to oil price shocks in Malaysia and Philippines is quite close to that of South Korea under positive market conditions. Colombia mimics Taiwan very well when the market is performing well, while Thailand differs to the other moderately oil dependent countries in the sense that it experiences higher returns when the stock market is performing well, and there is a positive oil price shock (both $\mathbf{q_3}$ and $\mathbf{q_4}$). Thailand and Colombia share the same results under poor market conditions and large negative oil shocks, i.e. when their stock markets perform poorly, a large negative oil shock often results in decreasing their stock returns. However, under poor market conditions and large negative oil shocks, Malaysia and Philippines experience the lowest stock market returns when there is a large positive oil shock ($\mathbf{q_4}$), which is at odds with the findings by Sim and Zhou (2015).

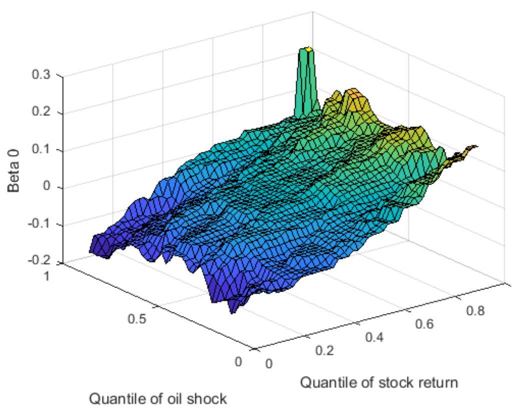
Extending the analysis to the period 1988:1–2016:12 does not drastically change the results for moderately oil dependent countries except for Malaysia and Philippines under poor market conditions; see Figures 5 & 6 and Table 4. Indeed, Malaysia and Philippines experience the lowest returns when the market is performing poorly (θ-quantiles of the stock returns less than 0.25) and there is a large negative ($\mathbf{q_1}$), while the lowest returns for these countries were observed using the sample period 1988:1–2007:12 for a large positive oil shock ($\mathbf{q_4}$). The findings for the remaining moderately oil importing countries are the same as those for the period 1988:1–2007:1, meaning that the relationship between the distributions of oil price shocks and stock market returns can be seen as quite stable over time in those countries, a finding similar to that of the US [Figure 13: (13a) vs. (13b)].



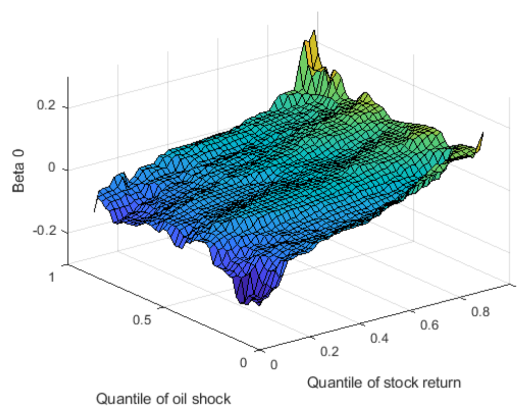
(a) Malaysia's β_0: period 1988–2007



(b) Malaysia's β_0: period 1988–2016

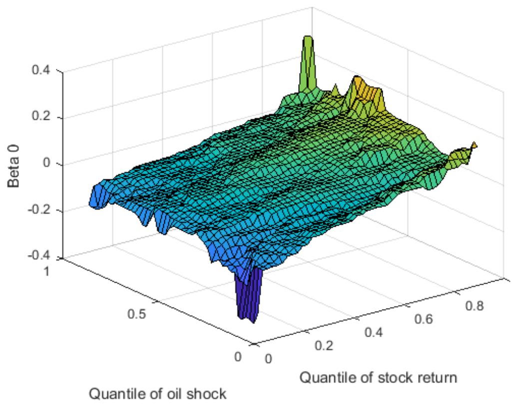


(c) Philippines's β_0: period 1988–2007

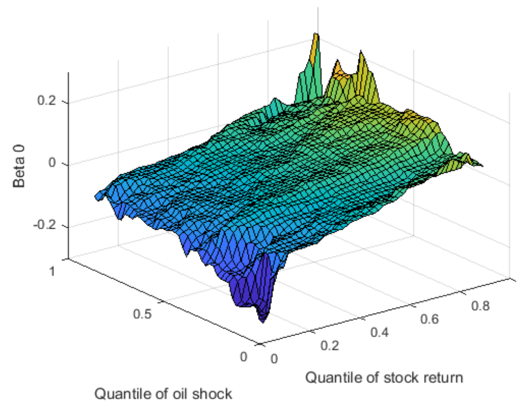


(d) Philippines's β_0: period 1988–2016

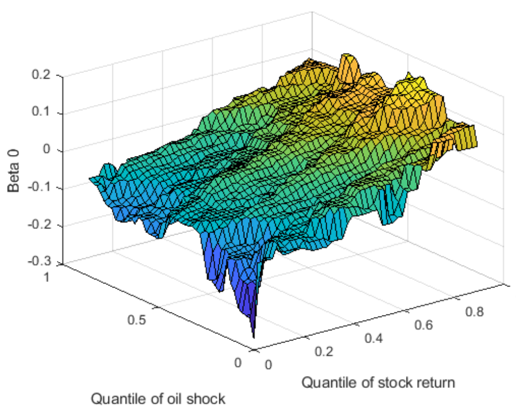
Figure 5: 3D representation of β_0 as a function of θ and τ for moderately oil dependent countries: Malaysia and Philippines



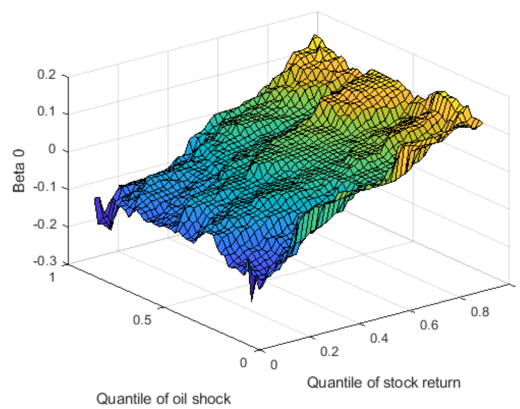
(a) Thailand's β_0: period 1988–2007



(b) Thailand's β_0: period 1988–2016



(c) Colombia's β_0: period 1993–2007



(d) Colombia's β_0: period 1993–2016

Figure 6: 3D representation of β_0 as a function of θ and τ for moderately oil dependent countries: Thailand and Colombia

Market conditions	Oil price shock	Max impact of β_0			
		Malaysia	Philippines	Thailand	Colombia
Period 1988:1–2007:12					
Positive	$\mathbf{q_1}$	0.110	0.164	0.176	0.157
	$\mathbf{q_2}$	0.118	0.150	0.129	0.185
	$\mathbf{q_3}$	0.110	0.174	0.237*	0.158
	$\mathbf{q_4}$	0.164*	0.230*	0.317*	0.145
Negative	$\mathbf{q_1}$	-0.156	-0.161	−0.364*	−0.298*
	$\mathbf{q_2}$	-0.111	-0.155	-0.178	-0.215
	$\mathbf{q_3}$	-0.120	-0.119	-0.148	-0.146
	$\mathbf{q_4}$	−0.202*	-0.169	-0.169	-0.146
Period 1988:1–2016:12					
Positive	$\mathbf{q_1}$	0.102	0.185	0.110	0.160
	$\mathbf{q_2}$	0.102	0.127	0.135	0.168
	$\mathbf{q_3}$	0.106	0.143	0.255*	0.141
	$\mathbf{q_4}$	0.141*	0.271*	0.247*	0.163
Negative	$\mathbf{q_1}$	−0.252*	−0.213*	−0.261*	−0.208*
	$\mathbf{q_2}$	-0.112	-0.133	-0.180	-0.121
	$\mathbf{q_3}$	-0.124	-0.121	-0.115	-0.120
	$\mathbf{q_4}$	-0.124	-0.135	-0.134	−0.196*

Table 4: Joint effects of market conditions and oil price shocks on the intercept estimate for moderately oil dependent countries

3.2 Slope estimates

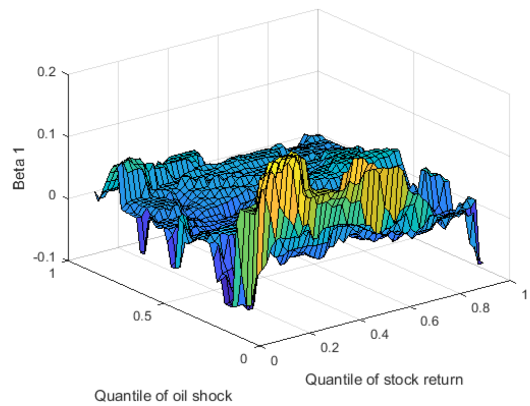
Our analysis in Section 3.1 focuses on the intercept estimates but the dependence between the distributions of stock returns and oil price shocks can also impact on the slope coefficient estimates $\widehat{\beta}_{1j}(\theta, \tau)$. Therefore, it is also important to quantify the impact that the θ-quantiles of the stock returns and the τ-quantiles of oil price shocks exert on the stock market of country j due to changes in $\widehat{\beta}_{1j}(\theta, \tau)$ when (θ, τ) varies in $[0, 1]^2$. As in the previous section, we present the results separately for oil importers, oil exporters, and moderately oil dependent countries.

3.2.1 Oil importing countries

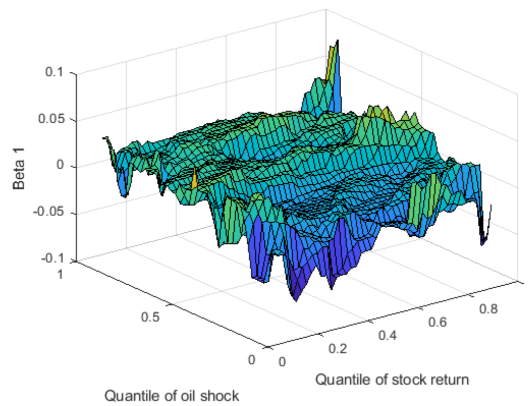
Figures 7 & 8 present the results for the largest (China, Japan, and India) and medium (South Korea, Germany, and Taiwan) oil importing countries respectively for both the periods 1988:1–2007:12 and 1988:1–2016:12. Considering first the the baseline period 1988:1–2007:12, it is obvious from Figure 7: (7a), (7c) & (7e) and Figure 8: (8a), (8c) & (8e) that there are several regions of the parameters $(\theta, \tau) \in [0, 1]^2$ where the estimated $\widehat{\beta}_{1j}(\theta, \tau)$ are statistically different from zero for all countries, which contrasts with the findings of Sim and Zhou (2015, Fig. 4). While well performing stock markets (Positive) tend to increase insignificantly the stock returns in Germany when there is a large negative oil price shock ($\mathbf{q_1}$), it is possible that China, Japan, and Taiwan experience a counter effect depending on whether the negative effect of $\widehat{\beta}_{1j}(\theta, \tau)$ observed here offsets the positive effect on $\widehat{\beta}_{0j}(\theta, \tau)$ in Table 2. For both India and South Korea, well performing stock markets (Positive) do not seem to have a significant impact on $\widehat{\beta}_{1j}(\theta, \tau)$ when there is a large negative oil price shock ($\mathbf{q_1}$), thus the net effect for these countries is reduced to the one observed in the first part of Table 2.

Now, looking at the results for the extended period 1988:1–2016:12 [Figure 7: (7b), (7d) & (7f) and Figure 8: (8b), (8d) & (8f)], we see that for all countries, the shapes have many plateaus and ridges but the slope estimates tend to meander at zero. Therefore, well performing stock markets do not seem to have a significant impact on $\widehat{\beta}_{1j}(\theta, \tau)$ when there is a large negative oil price shock ($\mathbf{q_1}$). This highlights that for the period 1988:1–2016:12 the net effect on the stock returns of all countries due to a positive market news, combines with a large oil price shock, is reduced to the one observed in the second part of Table 2. These findings again illustrate that the relationship between the distributions of oil price shocks and stock market returns is not stable over time. Furthermore, except for India and South Korea, the 3D graphical representation of other oil importers illustrates that the estimated $\widehat{\beta}_{1j}(\theta, \tau)$ do not meander around zero in most of the parameter regions for the baseline period 1988:1–2007:12, unlike what was found by Sim and Zhou (2015, Fig.

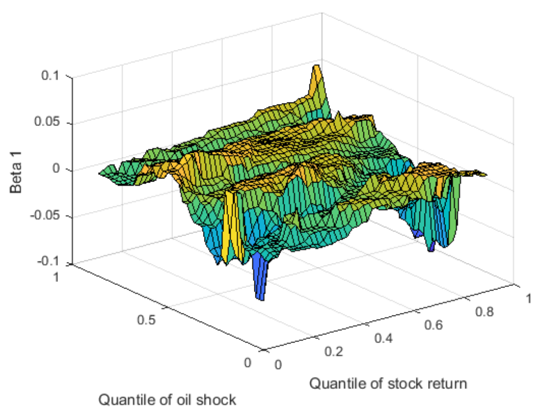
4).



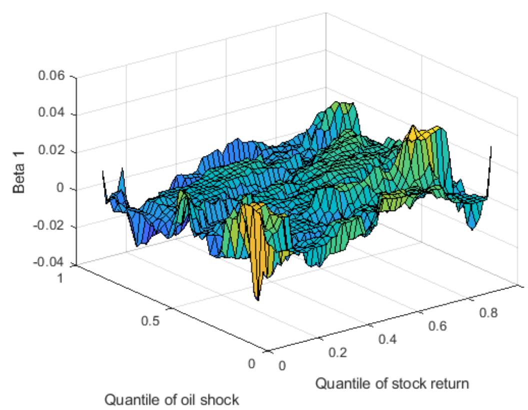
(a) China's β_1: period 1993–2007



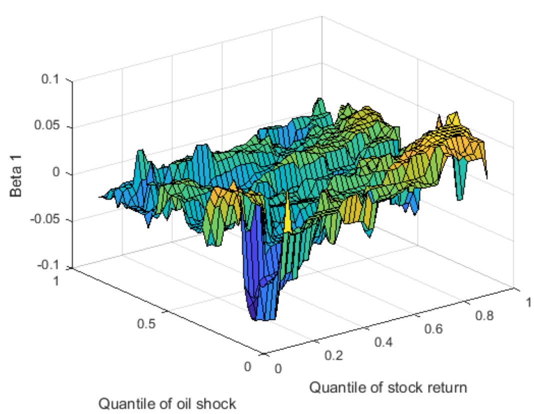
(b) China's β_1: period 1993–2016



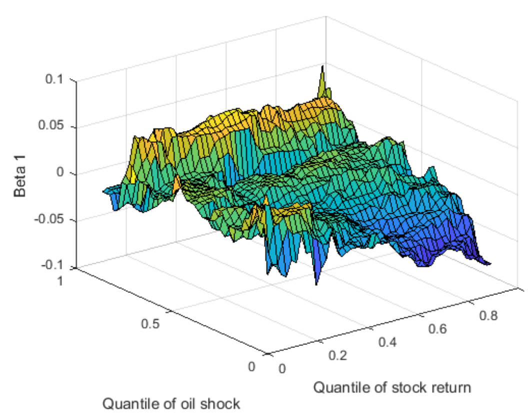
(c) Japan's β_1: period 1988–2007



(d) Japan's β_1: period 1988–2016

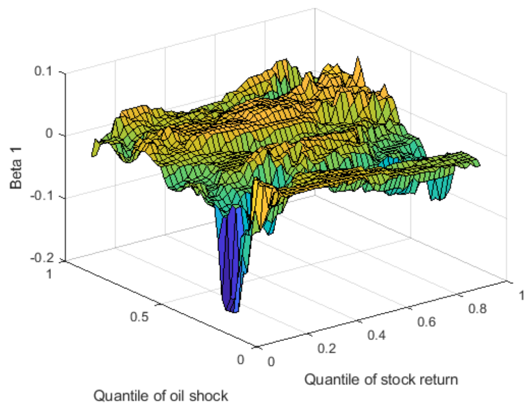


(e) India's β_1: period 1993–2007

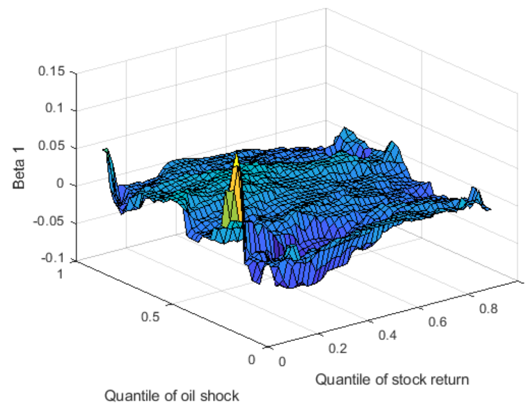


(f) India's β_1: period 1993–2016

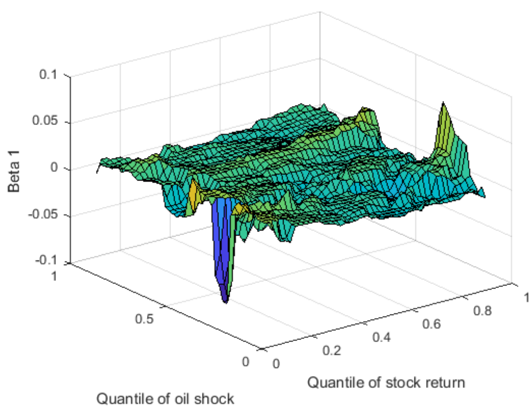
Figure 7: 3D representation of β_1 as a function of θ and τ for largest oil importing countries.



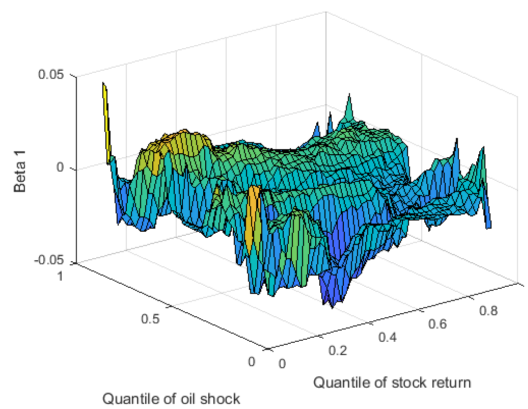
(a) South Korea's β_1: period 1988–2007



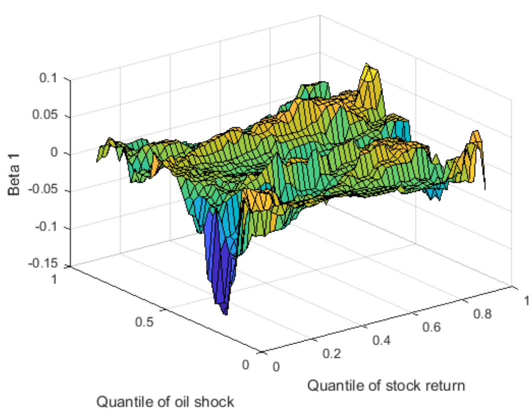
(b) South Korea's β_1: period 1988–2016



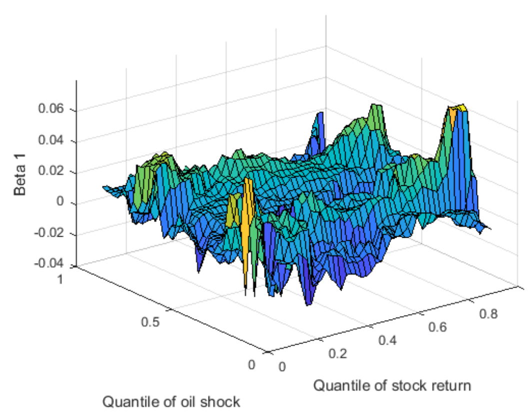
(c) Germany's β_1: period 1988–2007



(d) Germany's β_1: period 1988–2016



(e) Taiwan's β_1: period 1988–2007

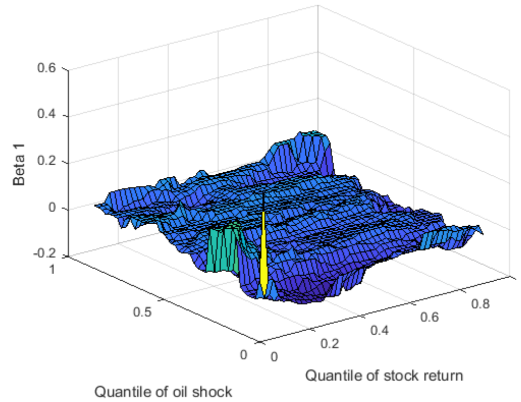


(f) Taiwan's β_1: period 1988–2016

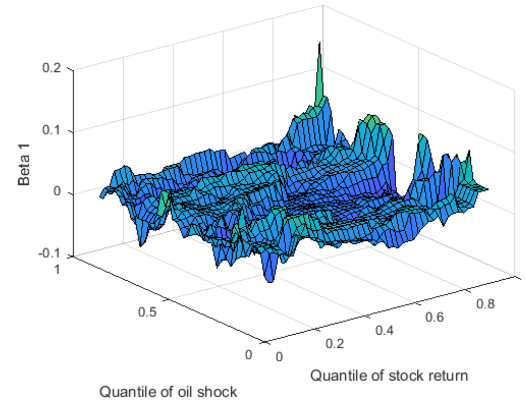
Figure 8: 3D representation of β_1 as a function of θ and τ for medium oil importing countries.

3.2.2 Oil exporting countries

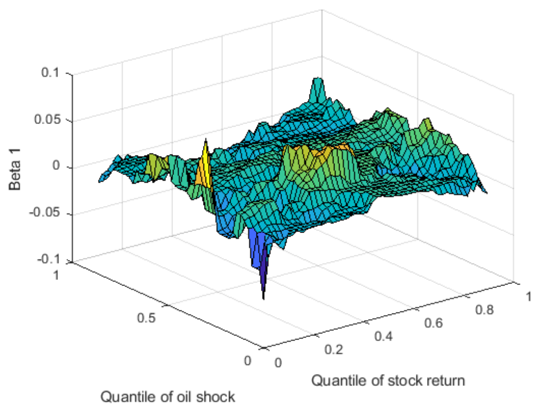
The slope estimates for oil importing countries are presented in Figures 9 & 10 below for both the baseline period 1988:1–2007:12 and the extended period 1988:1–2016:12. Except Venezuela for which data are not available for the extended period 1988:1–2016:12, we see that the slope estimates are different between the two periods for the other countries. This again highlights that the instability of the relationship between the distributions of oil price shocks and stock market returns over time. For the baseline period 1988:1–2007:12, the estimated $\widehat{\beta}_{1j}(\theta, \tau)$ tend to meander around zero in most of the parameter regions, a finding similar to Sim and Zhou (2015, Fig. 4). However, we note that when stock markets are performing well, a large negative oil price shock ($\mathbf{q_1}$) does not have a significant impact on the stock returns in any of the countries, while poor market conditions affects the stock returns of all countries when there is a large negative oil price shock ($\mathbf{q_1}$: Canada) or a small negative oil price shock ($\mathbf{q_2}$: Russia, Norway, Mexico, and Venezuela). The latter results highlight not only the similarities between Russia and Venezuela on one side, and Norway and Mexico on the other, but also how Russia and Venezuela differ from Norway and Mexico (as poor market conditions combining with a small negative oil price shock tend to increase stock returns in the former countries while the opposite effect is observed for the latter). For the extended period 1988:1–2016:12, except Russia, the estimates of $\widehat{\beta}_{1j}(\theta, \tau)$ tend to meander around zero in most of the parameter regions, and we do not observe a significant effects on their stock returns when market are performing well and there is a negative oil price shock ($\mathbf{q_1}$ or $\mathbf{q_2}$), and similarly for Russia.



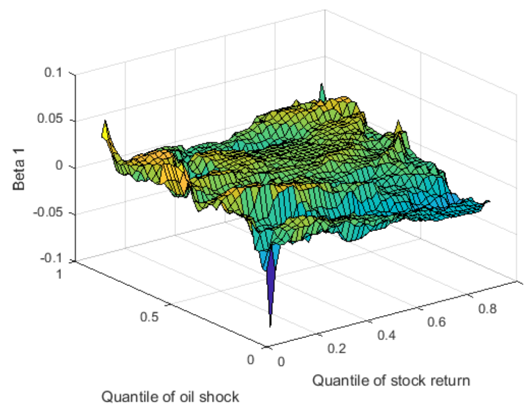
(a) Russia's β_1: period 1995–2007



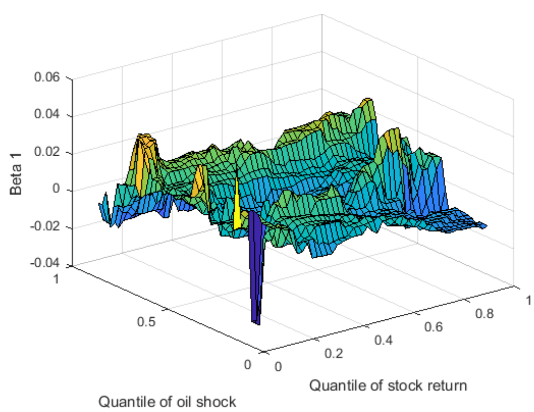
(b) Russia's β_1: period 1995–2016



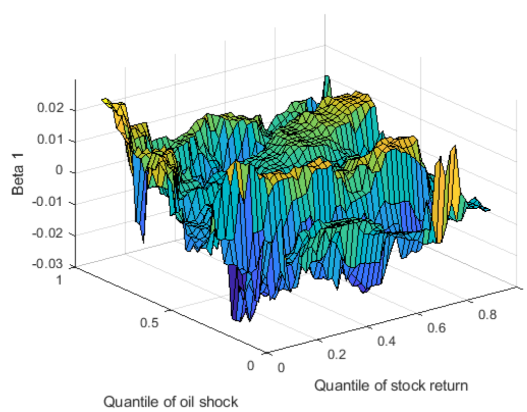
(c) Norway's β_1: period 1988–2007



(d) Norway's β_1: period 1988–2016

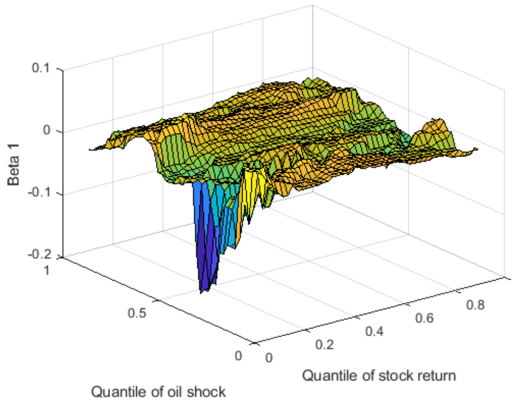


(e) Canada's β_1: period 1988–2007

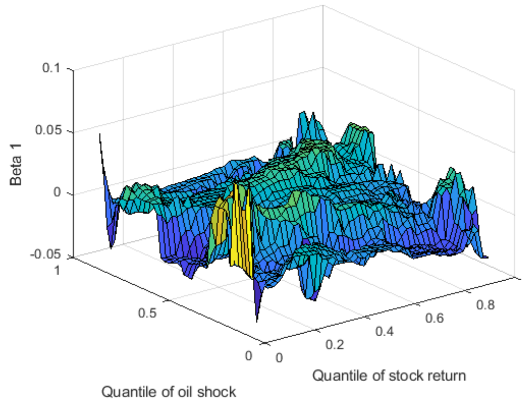


(f) Canada's β_1: period 1988–2016

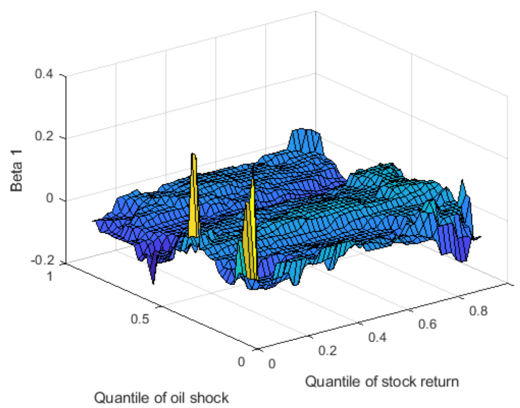
Figure 9: 3D representation of β_1 as a function of θ and τ for oil exporting countries: Russia, Norway, and Canada



(a) Mexico's β_1: period 1988–2007



(b) Mexico's β_1: period 1988–2016

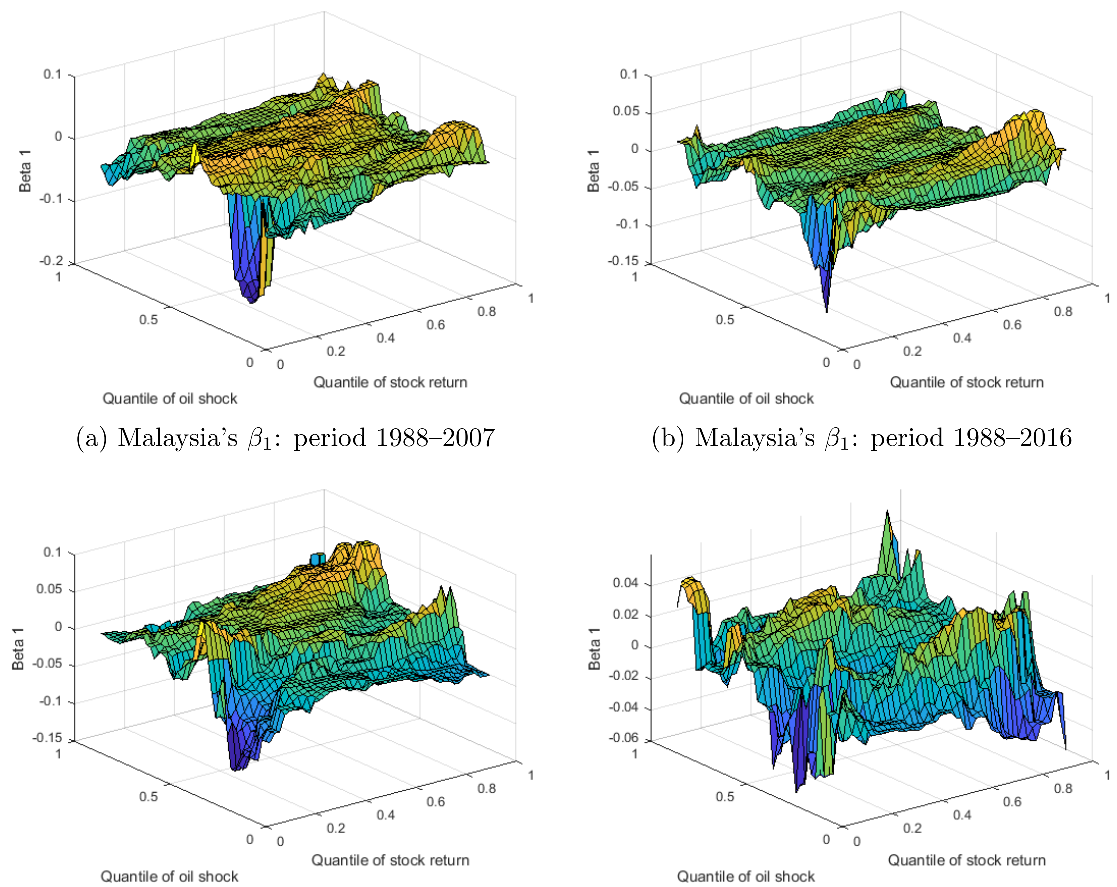


(c) Venezuela's β_1: period 1993–2007

Figure 10: 3D representation of β_1 as a function of θ and τ for oil exporting countries: Mexico and Venezuela.

3.2.3 Moderately oil dependent countries

Figures 11 & 12 below show the 3D representation of the slope estimates for moderately oil dependent countries for both the baseline period 1988:1–2007:12 and the extended period 1988:1–2016:12. While Malaysia shows little differences in the slope estimates for both periods, the form of the shapes differ between periods for Philippines, Thailand, and Colombia. This again indicates that the relationship between the distributions of oil price shocks and stock market returns is not stable over time. More importantly, we see that the results of Thailand are no longer similar to that of China and Japan for both the baseline and extended periods, as was the case of the intercept estimates [see Figure 6]. Furthermore, Malaysia, Philippines, and Thailand share the same results in the sense that when the stock market is performing poorly (θ-quantiles of the stock returns less than 0.25), a small negative oil price shock ($\mathbf{q_2}$) often results in low returns, while Colombia experience lower returns when the market is performing poorly (θ-quantiles of the stock returns less than 0.25) and there is a large negative oil price shock ($\mathbf{q_1}$). Finally, while the estimates of $\widehat{\beta}_{1j}(\theta, \tau)$ tend to meander around zero in most of the parameter regions for the extended period 1988:1–2016:12 [similar to Sim and Zhou (2015, Fig. 4)], we do not observe such a phenomenon for the baseline period 1988:1–2007:12, which is at odds with the main finding by Sim and Zhou (2015) for the US.



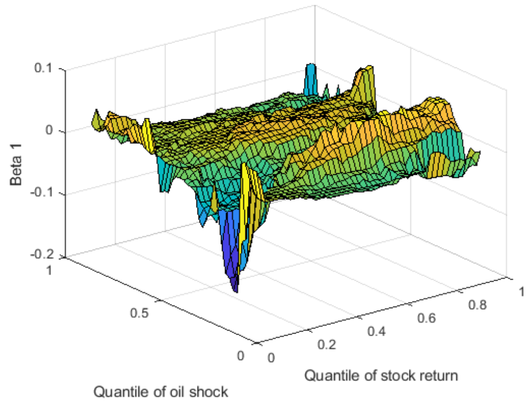
(a) Malaysia's β_1: period 1988–2007

(b) Malaysia's β_1: period 1988–2016

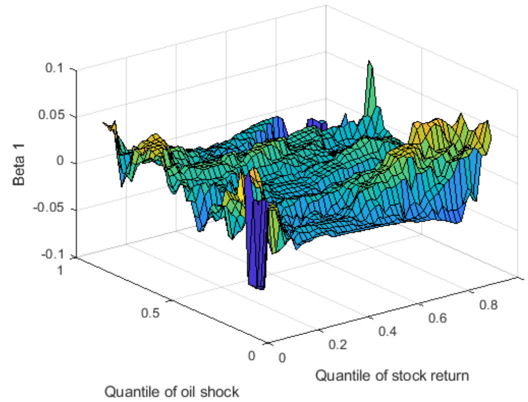
(c) Philippines's β_1: period 1988–2007

(d) Philippines's β_1: period 1988–2016

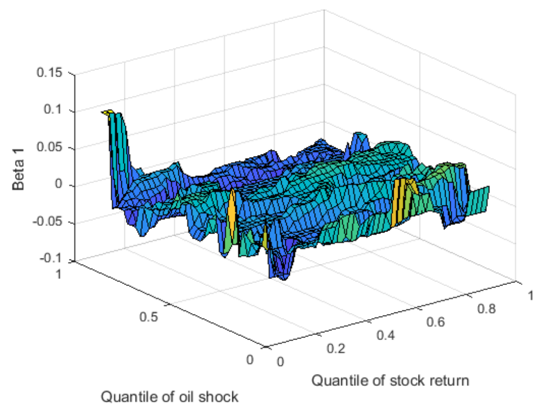
Figure 11: 3D representation of β_1 as a function of θ and τ for moderately oil dependent countries: Malaysia and Philippines



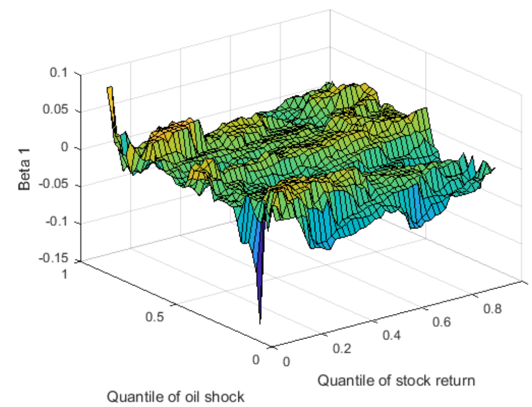
(a) Thailand's β_1: period 1988–2007



(b) Thailand's β_1: period 1988–2016



(c) Colombia's β_1: period 1993–2007



(d) Colombia's β_1: period 1993–2016

Figure 12: 3D representation of β_1 as a function of θ and τ for moderately oil dependent countries: Thailand and Colombia

4 Discussion

Stock markets are often linked with economic performance, e.g. higher stock prices reflect an increase in the discounted expected earnings which provides potentially useful information about future economic growth. The hypothesis that oil prices affect economic growth through their relationship with the stock market returns is now widely accepted. Higher oil prices, for example, contributes to headline inflation that reduces real consumption and economic agents may be willing to accept lower rate of returns on financial assets in order to smooth consumption to future periods. Higher oil prices also lead to higher cost of production, which may constrain the economy and limit investment opportunities. The basic theory of asset pricing says that factors that have plausible systematic influence on consumption or investment opportunities, such as crude oil prices, should affect the pricing of large stock aggregates. However, the empirical evidence on the effects that oil price shocks exert on stocks using mean regression-type analyses has been mitigated or sometimes inconclusive.[11]

Sim and Zhou (2015) show that a quantile-on-quantile (QQ) regression approach can reveal interesting characteristics about the link between the stock markets and oil price shocks that are usually buried under OLS-type regressions. In particular, they find that *large negative oil price shocks* (i.e., low oil price shock quantiles) affect the US stock returns positively when the US market is performing well (i.e., high return quantiles), while positive oil price shocks have no effect on the US stock returns. This asymmetric effect of oil price shocks implies that *only large negative oil price shocks* have an impact on the US economic growth, and that small negative oil price shocks (i.e., middle oil price shock quantiles) and positive oil price shocks (i.e., upper oil price shock quantiles) have no significant effect on the real economic activity.

In this study, we have extended Sim and Zhou's (2015) analysis to 15 countries which include oil importers, exporters, and moderately oil dependent countries. Our results should be viewed as purely descriptive and we are far from identifying causal patterns between the distribution of oil price shocks and that of stock market returns. We found that the results by Sim and Zhou (2015) are not universal and should not be generalized naively to other countries. Unlike the US, there is no asymmetric effect of oil price shocks on stock returns for most countries considered (including the largest oil importers: China, Japan, and India). In particular, positive oil price shocks (i.e., upper oil price quantiles) often tend to have a bigger impact on the stock returns than large negative oil price shocks (i.e., low oil price quantiles) in most countries covered, which is at odds with Sim and Zhou (2015). This suggests that in most of the 15 countries studied, all oil price shock types (from large negative to large positive) can substantially affect economic growth when the stock market performs well. For example, under well performing markets, a *large positive oil price shock* will often boost the stock returns (thus the economy) more than a *large negative oil price shock* in Russia, Canada, China, South Korea, Norway, Malaysia, and Philippines. This finding underscores the complexity of the relationship between oil price shocks and economic growth. In addition, our results indicate that under poor market conditions (quantiles of the stock returns less than 0.25), all types of oil price shocks (from large negative to large positive) decrease stock returns (thus have a negative effect on economic growth) for all countries; see the negative estimated impact in Tables 2-4. Although this result is anticipated, it is interesting to note some similarities across countries which corroborate the findings by Sim and Zhou (2015). In particular, most countries, with the exception of Canada and Norway, experience their deepest decrease in

[11] e.g., see Kling (1985), Jones and Kaul (1996), Chen et al. (1986), Apergis and Miller (2009), Abhyankar et al. (2013), and Lin et al. (2010), among others.

stock returns when the stock market is performing poorly and there is *larger negative oil price shocks* ($\mathbf{q_1}$).

It is possible that the main US results by Sim and Zhou (2015) could not be generalized to the 15 other countries because of the drastic change in the early 2000s that the US oil supply has experienced due to the shale revolution in the oil production; see Bataa and Park (2017). The structural break in Bataa and Park (2017) was estimated to have taken place around June 2002, so we re-estimate our model for the pre-break period 1988:1–2001:12 to further investigate this issue. We consider both the US and the 15 countries in our sample.[12] Table 5 shows the results of the intercept estimates.

First, with the exception of Japan, when the market is performing well, the results of the other 14 countries do not align with that of the US in the pre-structural break period (see Table 5). In particular, China, India, South Korea, Mexico, and Norway all experience higher returns when there is *a large positive oil price shock* and the stock market is performing well, while the US and Japan experience greater returns when there is *a large negative oil price shock* under the same market conditions. This suggests that the drastic change in the early 2000s that the US oil supply has experienced due to the shale revolution in the oil production may not be the only driver of our main findings in Section 3. Second, restricting the analysis to the pre-structural break period 1988:1–2001:12 reinforces our earlier conclusions that the relationship between the distributions of oil price shocks and stock market returns is not stable over time in most countries (Table 5 vs. Tables 2-4). Again, we find the anticipated result that all countries (including the US) experience lower stock returns when the market is performing poorly (quantiles of the stock returns less than 0.25) irrespective of the type of oil price shock (from large negative to large positive). Like the US, most countries experience the largest decrease in stock returns under poor market conditions for large negative oil price shocks, with the exceptions of Mexico and India. While most countries seem to follow this trend at one point in time, the list of exceptions depends on the time period considered, thus highlighting the fragility of the results through time.

[12]Canada and Taiwan are not included in Table 5 due to insufficient data for the QQ estimation.

Market conditions	Oil price shock	Period 1988:–2001:12					
		Max impact of β_0					
		China	Japan	India	S. Korea	Germany	US
Positive	$\mathbf{q_1}$	0.272	0.209*	0.101	0.128	0.096	0.110*
	$\mathbf{q_2}$	0.139	0.199*	0.194	0.185	0.120	0.102*
	$\mathbf{q_3}$	0.196	0.076	0.206	0.159	0.103	0.084
	$\mathbf{q_4}$	0.542*	0.189	0.269*	0.357*	0.093	0.077
Negative	$\mathbf{q_1}$	−0.344*	−0.279*	-0.177	−0.342*	−0.166*	−0.115*
	$\mathbf{q_2}$	-0.154	-0.112	−0.334*	-0.253	-0.078	-0.076
	$\mathbf{q_3}$	-0.147	-0.146	-0.161	-0.122	-0.084	-0.056
	$\mathbf{q_4}$	-0.260	-0.104	−0.106*	-0.181	-0.087	−0.098*

Market conditions	Oil price shock	Period 1988:–2001:12			
		Max impact of β_0			
		Mexico	Russia	Norway	Venezuela
Positive	$\mathbf{q_1}$	0.145	0.281	0.072	0.188
	$\mathbf{q_2}$	0.134	0.461	0.103	0.322*
	$\mathbf{q_3}$	0.157	0.427	0.136	0.216
	$\mathbf{q_4}$	0.262*	0.268	0.191*	0.244
Negative	$\mathbf{q_1}$	−0.225*	−0.824*	−0.195*	−0.522*
	$\mathbf{q_2}$	−0.396*	-0.597	-0.128	-0.342
	$\mathbf{q_3}$	-0.112	-0.258	-0.140	-0.459
	$\mathbf{q_4}$	-0.165	-0.291	-0.094	-0.164

Table 5: Joint effects of market conditions and oil price shocks on the intercept estimate for all countries.

5 Conclusion

In this paper, we replicate the quantile-on-quantile model developed by Sim and Zhou (2015) to measure the dependence between the distribution of the US stock returns and that of oil price shocks, and we extend the model to 15 other countries. These countries are separated into three categories depending on their net trade balance in crude oil: (i) oil importers– China, Germany, India, Japan, South Korea, and Taiwan; (ii) oil exporters– Canada, Mexico, Norway, Russia, and Venezuela; and (iii) moderately oil dependent countries– Malaysia, Philippines, Thailand, and Columbia.

Our findings reveal that the relationship between the distributions of oil price shocks and stock market returns is usually unstable overtime, and varies depending on the countries' classification. In particular, we show that the conclusion by Sim and Zhou (2015) that large negative oil price shocks increase stock returns when markets are performing well is only partially supported by the largest oil importers– China, Japan and India– during the period 1988:1–2007:12. This relationship however does not hold when extending the study to more recent data (period 1988:1–2016:12). In that case, we find that China and India present higher returns when markets perform well and there is a large positive oil price shock. Furthermore, we find that large positive oil price shocks often lead to higher stock returns when markets perform well for both oil exporting countries– Canada, Russia, Norway– and moderately oil dependent countries– such as Malaysia, Philippines and Thailand. In most cases, large oil price shocks depress further already poorly performing markets, as in Sim and Zhou (2015). Finally, the asymmetric effect between positive and negative oil price shocks observed in the US market by Sim and Zhou (2015) is less evident in most countries, whether we consider the baseline period 1988:1–2007:12 or the extended period 1988:1–2016:12.

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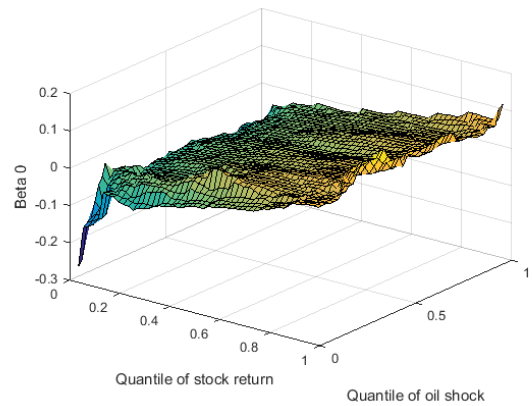
Appendices

Market conditions	Oil price shock	Max β_0 : 1973–2007	Max β_0 : 19738–2016
Positive	$\mathbf{q_1}$	0.127	0.117
	$\mathbf{q_2}$	0.141*	0.139*
	$\mathbf{q_3}$	0.106	0.120
	$\mathbf{q_4}$	0.120	0.095
Negative	$\mathbf{q_1}$	-0.264^*	-0.248^*
	$\mathbf{q_2}$	-0.129	-0.092
	$\mathbf{q_3}$	-0.106	-0.098
	$\mathbf{q_4}$	-0.104	-0.140^*

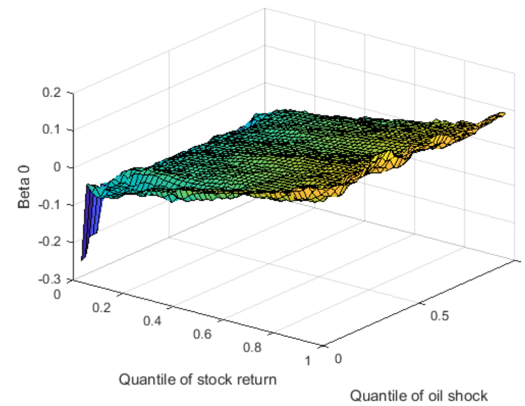
Table 6: Joint market conditions and oil price shocks on the intercept estimate for the US: 1973:1-2007:12 and 1973:1-2016:12

Variable Name	Source
Oil price/production levels	http://www-personal.umich.edu/~lkilian/
Index of cargo ocean shipping freight rates	http://www-personal.umich.edu/~lkilian/
US stock market returns	Center for Research in Security Prices (CRSP)
Standard stock market price index: China, Germany, India, Japan, South Korea, Taiwan Canada, Mexico, Norway, Russia, Venezeuala Colombia, Malaysia, Philippines, Thailand,	MSCHIN$, MSGERM$, MSINDI$, MSJPAN$ MSKORE$, MSTAIW$, MSCNDA$, MSMEXF$ MSNWAY$, MSRUSS$, MSVENF$, MSCOLM$, MSMALF$, MSPHLF$, MSTHAF$: MSCI (Datastream)
Consumer Price Index: China, Germany, India, Japan, South Korea, Taiwan Canada, Mexico, Norway, Russia, Venezeuala Colombia, Malaysia, Philippines, Thailand,	CHCCPI..E, BDCCPI..E, INCCPI..E, JPCCPI..E KOCCPI..E, TWCCPI..E, CNCCPI..E, MXCCPI..E NWCCPI..E, RSCCPI..E, VECONPRCF, CBCCPI..E MYCCPI..E, PHCCPI..E, THCCPI..E, Datastream

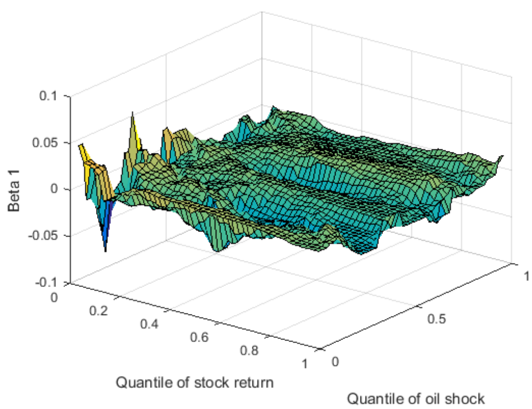
Table 7: Data Source



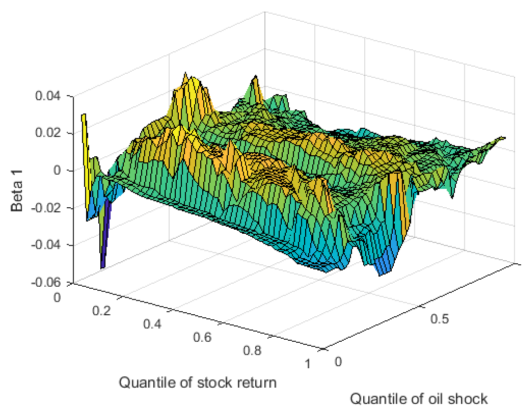
(a) US β_0: period 1973–2007



(b) US β_0: period 1973–2016



(c) US β_1: period 1973–2007



(d) US β_1: period 1973–2016

Figure 13: 3D representation of β_0 and β_1 as a function of θ and τ for the US