Supplementary file

For article:

Quantitative Analysis of Stock Market Resilience during Oil Price Shocks: Evidence from seven Middle East Countries

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Authors:

Hojat Rezaei Soufi

PhD in Industrial Engineering, Central Bank of Iran and Amirkabir University of Technology, Tehran, Iran 1591634311.

Akbar Esfahanipour*

Associate Professor of Industrial Engineering, Department of Industrial Engineering & Management Systems, Amirkabir University of Technology, Tehran, Iran.

* Corresponding author: Address: No. 350, Hafez Ave, Valiasr Square, Tehran, Iran 1591634311, Tel: +98(21)64545300, +98-912-347-9906, Fax: +98(21)6695-4569, Email address: <u>esfahaa@aut.ac.ir</u>

Mohsen Akbarpour Shirazi

Associate Professor of Industrial Engineering, Department of Industrial Engineering & Management Systems, Amirkabir University of Technology, Tehran, Iran 1591634311.

Sepideh Aghajani

PhD in Department of Industrial Engineering, Alzahra University, Tehran, Iran.

A. The algorithm for detecting the turning points

There are complex approaches to identifying turning points in the literature. Given that the purpose of this paper is to calculate resilience, in the case of turning points, the applied method of Rezaei Soufi et al. (2021) is used. Here, the algorithm is presented.

Let's define t_i as the turning point when:

the market index ends an increasing trend at t_i and starts a decreasing period, or

the market index ends a decreasing trend at t_i and starts an increasing period

According to the basic models described in Section 3-3, the turning points should be designed to identify simultaneously increasing or decreasing phases of the SMI trend. In this paper, the following algorithm is used to calculate these points.

According to this algorithm, the period of checking the onset of shock begins when a negative market return occurs. Set this time as t^1 and the time of local minimum in SMI as t^0 . The object of this algorithm is to define the t^- (the negative turning point as the start of decreasing phase). The algorithm works by testing the relationship between the new return of each period and the average returns and standard deviation. To identify the beginning of the disaster period, the index's return value of this time must be higher than the threshold obtained from the mean and standard deviation of the return. It is noteworthy that by observing more negative consecutive returns, satisfying the threshold is increased. Similarly, the algorithm can be used for identifying a positive turning point (t^+).

Algorithm1: identifying the negative turning point (t ⁻)
<i>t_i</i> = the <i>i</i> th step of time
$r_t = ln \frac{I_t}{I_{t-1}}$
$ar{r}$ = the average of negative r_t from t ¹ to t ^o
σ_{r} = the standard deviation of negative r_t from t ¹ to t ^o
Compute the <i>t</i> ⁻ turning point
for <i>t=i</i>
if $r_{ti} < 0$ and $r_{ti} < \bar{r} - 2\sigma_{r}$ then $t_{turning point} = t_i$
else for <i>t=i</i> to <i>T</i>
if $\sum_{t=i}^{Lag+i} r_{ti} < \bar{r} - \frac{2}{Lag} \sigma_{r}$ then t turning point= t_{i+Lag}
find the relevant SMI in t ⁻ turning point
else
There is no negative turning point in the data.

Algorithm2: Identifying positive turning point (t*)

 $t_{i} = \text{the } i \text{ th step of time}$ $r_{t} = ln \frac{I_{t}}{I_{t-1}}$ $\bar{r}^{+} = \text{th eaverage of positive } r_{t} \text{ from } t^{o} \text{ to } t^{2}$ $\sigma_{r+} = \text{th estandard deviation of positive } r_{t} \text{ from } t^{o} \text{ to } t^{2}$ $\sigma_{r+} = \text{th estandard deviation of positive } r_{t} \text{ from } t^{o} \text{ to } t^{2}$ $Compute \text{ the } t^{+}turning \text{ point}$ for t=iif $r_{t} < 0$ and $r_{t} > \bar{r}^{+} + 2\sigma_{r+}$ then $t^{+}turning \text{ point} = t_{i}$ else for t=i to Tif $\sum_{t=i}^{Lag+i} r_{ti} > \bar{r}^{+} + \frac{2}{Lag}\sigma_{r+}$ then $t^{+}turning \text{ point} = t_{i+Lag}$ find the relevant SMI in $t^{+}turning \text{ point}$ else
There is no positive turning point in the data.

B. EGARCH noise recognition algorithm

Using the EGARCH(1,1)-M method proposed by Feng et al. (2014), we calculate the noise of data. According to the method using equation (A-1) and (A-2).

$$\ln i_t = \mu_t + \varphi \ln i_{t-1} + \rho \ln \sigma_t^2 + \varepsilon_t \tag{A-1}$$

$$\ln \sigma_t^2 = \omega + \beta \ln \sigma_{t-1}^2 + \alpha \left| \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \right| + \gamma \frac{\varepsilon_{t-1}}{\sigma_{t-1}}$$
(A-2)

Where i_t is the market index in time t, μ_t , α , β , γ , ω are constant values, and ε_t is the residual value.

Considering the $\overline{\varepsilon_k}$ as the mean of residual in *K* days, the offset of residual at day *t* in the regression model can be calculated using equation (A-3). Here, we use the duration of risk based on the market segmentation process as the K value.

$$\Delta_t = \varepsilon_t - \overline{\varepsilon_k} \tag{A-3}$$

To calculate the noise component index, first, the relationship between index rates of days should be calculated using equations (A-4) and (A-5).

$$r_t = \mu + \varphi_1 r_{t-1} + \rho \ln \sigma_t^2 + \varepsilon_t \tag{A-4}$$

$$\ln \sigma_t^2 = \omega + \beta \ln \sigma_{t-1}^2 + \alpha \left| \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \right| + \gamma \frac{\varepsilon_{t-1}}{\sigma_{t-1}}$$
(A-5)

Accordingly, the noise component index (NCI) can be calculated using equation (A-6).

$$NCI_{t} = \frac{\varepsilon_{t} - \varepsilon_{k}}{r_{t}}$$
(A-6)

Then the denoised value of $r_t(r_t^{new})$ can be calculated using equation (A-7).

$$r_t^{new} = r_{t-1}(1 - NCI_t)$$
(A-7)

It is notable that the NCI can be positive or negative.

C. Statistical analysi	S
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	Oil	Saudi	Kuwait	ait Qatar	United	Oman	Bahrain	Iran
		Arabia			Arab			
					Emirates			
Mean								
μ	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(1.432)	(1.213)	(1.007)	(0.456)	(0.682)	(0.725)	(0.403)	(0.658)
Dummy	-0.011*	-0.009^{*}	-0.004	0.002	-0.003	0.000	0.000	0.001
	(-3.387)	(-3.345)	(-1.618)	(1.112)	(-0.913)	(-0.564)	(-0.292)	(-0.718)
Variance								
Sigma	2.358	1.227	0.646	1.121	0.930	0.744	0.450	0.811
	(2.647)	(2.395)	(2.113)	(1.358)	(1.246)	(1.894)	(1.075)	(2.044)
Dummy	0.007^{*}	0.003*	0.004^{*}	0.000	0.000	0.000	0.000	0.003^{*}
	(6.234)	(8.645)	(3.645)	(1.701)	(2.138)	(1.935)	(1.472)	(3.829)
α_1	0.082	0.093	0.013	-0.052	0.033	0.008	-0.004	0.019
	(1.812)	(2.132)	(0.994)	(-3.145)	(1.546)	(1.011)	(0.755)	(1.503)
β_1	0.834	0.818	0.923	0.753	0.808	0.794	0.788	0.811
	(21.123)	(17.231)	(14.732)	(8.462)	(7.352)	(10.268)	(8.889)	(13.333)
Λ	0.217	0.114	0.0904	-0.0632	0.0619	0.0543	-0.0117	0.0787
	(1.523)	(2.142)	(1.678)	(-0.755)	(0.832)	(0.722)	(-0.256)	(1.125)
Asymmetry	-0.512^{*}	-0.265^{*}	-0.193*	-0.182^{*}	0.073^{*}	-0.213*	-0.165*	0.188^*
	(-2.932)	(-2.321)	(-2.024)	(-1.993)	(1.024)	(-2.149)	(-1.187)	(-2.009)
Tail	12.986^{*}	11.435^{*}	10.267^{*}	9.124^{*}	8.342^{*}	9.797^{*}	10.542^{*}	10.932^{*}
	(99.476)	(65.312)	(77.236)	(53.231)	(47.978)	(50.067)	(44.324)	(52.242)
LJ	23.242	21.429	19.892	20.120	19.993	18.801	19.890	20.003
	[0.532]	[0.503]	[0.614]	[0.293]	[0.371]	[0.305]	[0.480]	[0.415]
LJ2	24.182	23.873	21.138	22.734	20.984	20.045	21.368	22.351
	[0.248]	[0.194]	[0.136]	[0.108]	[0.114]	[0.095]	[0.0988]	[0.121]
ARCH	1.425	1.245	1.313	1.109	0.942	1.083	0.931	1.197
	[0.358]	[0.491]	[0.403]	[0.178]	[0.278]	[0.204]	[0.182]	[0.312]
K-S	[0.821]	[0.722]	[0.632]	[0.562]	[0.432]	[0.401]	[0.505]	[0.593]
C-Vm	[0.739]	[0.812]	[0.345]	[0.598]	[0.329]	[0.691]	[0.931]	[0.769]
A-D	[0.935]	[0.821]	[0.524]	[0.677]	[0.421]	[0.699]	[0.893]	[0.788]

Table C-1. Parameters of marginal distribution model for oil price and capital markets

Note: The numbers inside parentheses are the maximum likelihood values and the test statistics. The values inside brackets in 6 last rows show the P-values. All significant levels have been considered as %95.

D. The index of stock markets and oil price

In this section, first the monthly average of crude oil price graph is presented in figure D-1 and next the logarithm of monthly average of Stock Market Indexes (SMIs) for seven understudied countries are presented in figures D-2 to D-8.



Figure D-1. Monthly average of crude oil price graph



Figure D-2. Monthly average of Saudi Arabia's log of stock market index



Figure D-3. Monthly average of Qatar's log of stock market index



Figure D-4. Monthly average of UAE log of stock market index



Figure D-5. Monthly average of Iran's log of stock market index



Figure D-6. Monthly average of Oman's log of stock market index



Figure D-7. Monthly average of Bahrain's log of stock market index



Figure D-8. Monthly average of Kuwait's log of stock market index

References:

Feng, J., Lin, D. P., & Yan, X. B. (2014). "Research on measure of noise trading in stock market based on EGARCH-M model". In 2014 International Conference on Management Science & Engineering 21th Annual Conference Proceedings (pp. 1183-1189). DOI: 10.1109/ICMSE.2014.6930363 (2014).

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