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Asymmetric causality tests with an application

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Abstract This article argues that there are several logical reasons for the existence of asymmetric causal effects that need to be taken into account but usually are neglected in the literature. It suggests allowing for asymmetry in the causality testing by using the cumulative sums of positive and negative shocks. A bootstrap simulation approach with leverage adjustment is used to generate critical values that are robust to non-normality and time-varying volatility. An application to the efficient market hypothesis in the UAE is provided. The results show that the equity market is informationally efficient with regard to the oil shocks regardless if these shocks are positive or negative.

Keywords Asymmetric causality · Positive shocks · Negative shocks · Efficient market hypothesis · Bootstrap · The UAE

JEL Classification C32 · E17

1 Introduction

The issue of testing whether or not a variable precedes another variable is increasingly gaining attention in empirical research. This is basically testing for causality in the Granger (1969) sense. There is a massive literature on Granger causality both theoretically and empirically. The vector autoregressive (VAR) model,[1] or some form of its transformation, is usually used for finding empirical evidence on the existence or absence of causality.

[1] The VAR model was introduced by Sims (1980).

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However, in previously published papers on causality, to the best knowledge, it is assumed that the impact of a positive shock is the same as the impact of a negative shock in the absolute terms. In the existing literature, there is no separation between the causal impact of positive and negative shocks. This might be a too restrictive assumption because in many cases there is potentially an asymmetric structure regarding the causal impacts. For example, it is widely agreed that people react differently to a positive shock compared to a negative one of the same absolute magnitude in the financial markets. The asymmetric character of returns and the underlying correlations in financial markets are investigated by among others Longin and Solnik (2001); Ang and Chen (2002); Hong and Zhou (2008) as well as Alvarez-Ramirez et al. (2009). Investors tend to react more to negative news than the positive ones.

Another reason for the potential existence of asymmetric causal effects could be due to the existence of the asymmetric information phenomenon. Since the pioneer work of Akerlof (1970); Spence (1973); and Stiglitz (1974) it is widely agreed that markets with asymmetric information exist. Based on this fact, we maintain that it is important to allow for an asymmetric structure in the causality testing. We suggest taking into account this asymmetric behavior in causality testing by constructing the cumulative sums of positive and negative shocks. A bootstrap simulation approach with leverage adjustments can be utilized to produce more precise critical values. The advantage of the bootstrap simulation technique is that it relies on the empirical distribution of the underlying data set, which does not necessarily have to follow a normal distribution. This is an important advantage because many financial variables are not normally distributed and their volatility is time-varying. In fact, the probability of extreme events in the financial markets is quite often much higher than what the normal distribution would indicate.[2] This asymmetric causality test method combined with bootstrap simulations that is suggested in this paper is applied to the efficient market hypothesis (EMH) in the UAE stock market with regard to both positive and negative oil shocks.

The organization of the rest of the article is as follows. Next section develops the econometric methodology pertinent to the asymmetric causality inference. Section 3 presents an application to the financial market hypothesis with regard to positive as well as negative oil shocks. The last section concludes the article.

2 Asymmetric causality inference

The idea of transforming data into both cumulative positive and negative changes originates from Granger and Yoon (2002). The authors, however, used this approach to test for cointegration, which they entitled as hidden cointegration. In this article, we extend their work to causality analysis and refer to it as asymmetric causality testing. It is asymmetric in the sense that positive and negative shocks may have different causal impacts. Assume that we are interested in investigating the causal relationship

[2] Oil prices are also characterized by high volatility according to Meyler (2009).

between two integrated variables y_{1t} and y_{2t} defined as the following random walk processes[3]:

$$y_{1t} = y_{1t-1} + \varepsilon_{1t} = y_{10} + \sum_{i=1}^{t} \varepsilon_{1i}, \tag{1}$$

and

$$y_{2t} = y_{2t-1} + \varepsilon_{2t} = y_{20} + \sum_{i=1}^{t} \varepsilon_{2i}, \tag{2}$$

where $t = 1,2,\ldots T$, the constants $y_{1,0}$ and $y_{2,0}$ are the initial values, and the variables ε_{1i} and ε_{2i} signify white noise disturbance terms. Positive and negative shocks are defined as the following: $\varepsilon_{1i}^{+} = \max\left(\varepsilon_{1i}, 0\right)$, $\varepsilon_{2i}^{+} = \max\left(\varepsilon_{2i}, 0\right)$, $\varepsilon_{1i}^{-} = \min\left(\varepsilon_{1i}, 0\right)$, and $\varepsilon_{2i}^{-} = \min\left(\varepsilon_{2i}, 0\right)$, respectively. Therefore, one can express $\varepsilon_{1i} = \varepsilon_{1i}^{+} + \varepsilon_{1i}^{-}$ and $\varepsilon_{2i} = \varepsilon_{2i}^{+} + \varepsilon_{2i}^{-}$. It follows that

$$y_{1t} = y_{1t-1} + \varepsilon_{1t} = y_{1,0} + \sum_{i=1}^{t} \varepsilon_{1i}^{+} + \sum_{i=1}^{t} \varepsilon_{1i}^{-},$$

and similarly

$$y_{2t} = y_{2t-1} + \varepsilon_{2t} = y_{2,0} + \sum_{i=1}^{t} \varepsilon_{2i}^{+} + \sum_{i=1}^{t} \varepsilon_{2i}^{-}.$$

Finally, the positive and negative shocks of each variable can be defined in a cumulative form as $y_{1t}^{+} = \sum_{i=1}^{t} \varepsilon_{1i}^{+}$, $y_{1t}^{-} = \sum_{i=1}^{t} \varepsilon_{1i}^{-}$, $y_{2t}^{+} = \sum_{i=1}^{t} \varepsilon_{2i}^{+}$, and $y_{2t}^{-} = \sum_{i=1}^{t} \varepsilon_{2i}^{-}$. Note that, by construction, each positive as well as negative shock has a permanent impact on the underlying variable. The next step is to test the causal relationship between these components. In the following, we will focus only on the case of testing for causal relationship between positive cumulative shocks.[4] Assuming that $y_t^{+} = (y_{1t}^{+}, y_{2t}^{+})$, the test for causality can be implemented by using the following vector autoregressive model of order p, VAR (p):

$$y_t^{+} = v + A_1 y_{t-1}^{+} + \cdots + A_p y_{t-1}^{+} + u_t^{+}, \tag{3}$$

where y_t^{+} is the 2×1 vector of the variables, v is the 2×1 vector of intercepts, and u_t^{+} is a 2×1 vector of error terms (corresponding to each of the variables representing the cumulative sum of positive shocks). The matrix A_r is a 2×2 matrix of parameters

[3] Asymmetric causality testing can also be implemented for stationary variables. In that case, positive or negative changes can be used instead of the cumulative sums.

[4] To conduct tests for causality between negative cumulative shocks, the vector $y_t^{-} = (y_{1t}^{-}, y_{2t}^{-})$ is used. Other combinations are also possible.

for lag order $r\,(r = 1, \ldots, p)$. The following information criterion is used to select the optimal lag order (p):

$$\mathrm{HJC} = \ln(|\widehat{\Omega}_j|) + j\left(\frac{n^2 \ln T + 2n^2 \ln(\ln T)}{2T}\right), \qquad j = 0, \ldots, p. \tag{4}$$

where $|\widehat{\Omega}_j|$ is the determinant of the estimated variance–covariance matrix of the error terms in the VAR model based on lag order j, n is the number of equations in the VAR model and T is the number of observations.[5] After selecting the optimal lag order, we test the null hypothesis that kth element of y_t^+ does not Granger-cause the ωth element of y_t^+.[6] That is, the following hypothesis is tested:

$$H_0: \text{the row } \omega,\ \ \text{column } k\ \ \text{element in } A_r \text{ equals zero for } r = 1, \ldots, p. \tag{5}$$

In order to define a Wald test in a compact form, we make use of the following denotations[7]:

$$\begin{aligned}
Y &:= (y_1^+, \ldots, y_T^+) \quad (n \times T)\text{matrix},\\
D &:= (v, A_1, \ldots, A_p) \quad (n \times (1 + np))\text{ matrix},\\
Z_t &:= \begin{bmatrix} 1 \\ y_t^+ \\ y_{t-1}^+ \\ \vdots \\ y_{t-p+1}^+ \end{bmatrix} \quad ((1 + np) \times 1)\text{ matrix, for } t = 1, \ldots, T,\\
Z &:= (Z_0, \ldots, Z_{T-1}) \quad ((1 + np) \times T)\text{ matrix, and}\\
\delta &:= (u_1^+, \ldots, u_T^+) \quad (n \times T)\text{ matrix.}
\end{aligned}$$

Now, we can define the VAR(p) model compactly as the following:

$$Y = DZ + \delta \tag{6}$$

The null hypothesis of non-Granger causality, $H_0: C\beta = 0$, is tested by the following test method:

$$\mathrm{Wald} = (C\beta)'[C((Z'Z)^{-1} \otimes S_{\mathrm{U}})C']^{-1}(C\beta), \tag{7}$$

[5] This information criterion is suggested by Hatemi-J (2003). The simulation experiments in Hatemi-J (2008) indicate that this information criterion is robust to ARCH and it also performs well when the VAR model is used to forecast.

[6] It should be mentioned that an additional unrestricted lag was included in the VAR model in order to take into account the effect of one unit root as suggested by Toda and Yamamoto (1995).

[7] Note that we assume the p initial values for each variable are available. For details on this assumption see Lutkepohl (2005).

where $\beta = \text{vec}(D)$ and vec indicates the column-stacking operator; $\otimes$ represents the Kronecker product, and C is a $p \times n(1 + np)$ indicator matrix with elements ones for restricted parameters and zeros for the rest of the parameters. S_{U} is the variance–covariance matrix of the unrestricted VAR model estimated as $\text{S}_{\text{U}} = \frac{\hat{\delta}'_{\text{U}}\hat{\delta}_{\text{U}}}{T-q}$, where q is the number of parameters in each equation of the VAR model. When the assumption of normality is fulfilled, the Wald test statistic above has an asymptotic χ^2 distribution with the number of degrees of freedom equal to the number of restrictions to be tested (in this case equal to p).

However, financial data does not usually follow a normal distribution and the existence of autoregressive conditional heteroskedasticity (ARCH) effects is more the rule than an exception. To remedy this problem, we make use of the bootstrapping simulation technique. This approach is implemented as the following.

We first estimate the regression Eq. 6 with restrictions implied by the null hypothesis of Granger non-causality imposed. Next is producing the bootstrap data, Y_t^*, by using the estimated coefficients from the regression, the original data and the bootstrapped residuals. That is, generate $Y^* = \hat{D}Z + \delta^*$. The bootstrapped residuals (δ^*) are created by T random draws with replacement from the regression's modified residuals, each with equal probability of $1/T$. These bootstrapped residuals are mean-adjusted to make sure that the mean value of the residuals is zero in each bootstrap sample. This is achieved by subtracting the mean value of the resulting set of drawn modified residuals from each of the modified residuals in that particular set. The modified residuals are the regression's original residuals that are adjusted via *leverages* to have constant variance.[8] The bootstrap simulations are repeated ten thousand times and each time the Wald test is estimated. In this way, the distribution of the test is generated. The bootstrap critical value at the α-level of significance (c_α^*) is obtained by taking the (α)th upper quantile of the distribution of the bootstrapped Wald test. The final step in the procedure is to calculate the Wald test using the original data and compared it to the bootstrap critical value. The null hypothesis of non-Granger causality is rejected at the α level of significance if the Wald test generated in the final step is greater than the bootstrap critical value (c_α^*). The bootstrap critical values are produced for three different significant significance levels. The bootstrap simulations are implemented by using statistical software components written in GAUSS.[9]

The conducted simulation experiments indicate clearly that tests for causality based on the bootstrap distribution have better size and power properties compared to tests based on asymptotic distributions, especially in the cases in which the desirable statistical assumptions are violated.

[8] For more details on leverage adjustment, see Davison and Hinkley (1999) for univariate cases and Hacker and Hatemi-J (2006) for multivariate cases.

[9] Program procedures written in GAUSS to calculate the cumulative sums and to run leveraged bootstrap simulations for the causality test are available upon request.

3 An application

3.1 The efficient market hypothesis

One of the fundamental issues in financial markets is the so-called EMH. According to this hypothesis, a financial market is informationally efficient if it is not possible to predict the future prices of the financial assets in that market. Thus, the best guess of the asset price for the next period is the current price because the likelihood of a price increase is as high as the likelihood of a price decrease in the next period. Only unexpected and sudden news will cause price changes. If the market is efficient the financial assets will be neither overpriced nor underpriced but correctly priced and as a result the price will be a genuine measure of value. Thus, the issue of whether financial markets are informationally efficient or not has import repercussions at both micro and macro levels (i.e., for both the individual investor as well as the entire financial system).

The unpredictability of the stock prices was pioneered by Bachelier (1900) and Cowles (1933, 1944). However, the efficient market literature was established only in the mid-1960s via the seminal work of Fama (1965); Samuelson (1965) and Mandelbrot (1966).[10] Fama (1970) promoted the EMH and described three forms of this hypothesis. In the weak form, the market is taken to be efficient if prices reflect all relevant information and it is not possible to predict prices based on the information contained in the past values of the prices. In the semi-strong form, the market is efficient if it is not likely to predict the price even if all publically available information is utilized in addition to the past prices. In the strong form of the efficient market hypothesis, it is not possible to predict the price even if insider (private information) is also used. We test for the EMH in the UAE stock market with regard to the oil shocks because oil is the most important source of income in the country. Any fluctuation of the oil prices has a major impact on the economy including the financial markets.

3.2 The data

The sample period covers the period of May 2006 through March 2008 on daily basis. The number of observation is 488. The S&P Emerging Market Index for the UAE is used as the stock price index. The ALS Price index for Petrol is used for the oil price index.[11] The data source is the Reuters' database. Prior to asymmetric causality testing we conducted tests for unit roots by using the Ng and Perron (2001) procedures. The results, not reported, showed that each variable contains one unit root. This is also evident from the time plots presented in Fig. 1.[12]

[10] For some applied papers on the EMH see among others, Lo and MacKinlay (1988); Lo (1997); Fama (1998); Ojah and Karemera (1999); Henry and Olekalns (2002); Abraham et al. (2002); Buguk and Brorsen (2003); Malkiel (2003); Al-Khazali et al. (2007); Cajueiro et al. (2009); Ibrahim and Aziz (2003); Hatemi-J (2004a,b) as well as Lim and Kim (2008).

[11] The abbreviation ALS stands for the Arab Light, Saudi, which is the main Saudi crude blend.

[12] In addition, we tested for cointegration between the underlying variables using the Johansen–Juselius approach. The results, not reported, revealed that the null hypothesis of no cointegration could be rejected

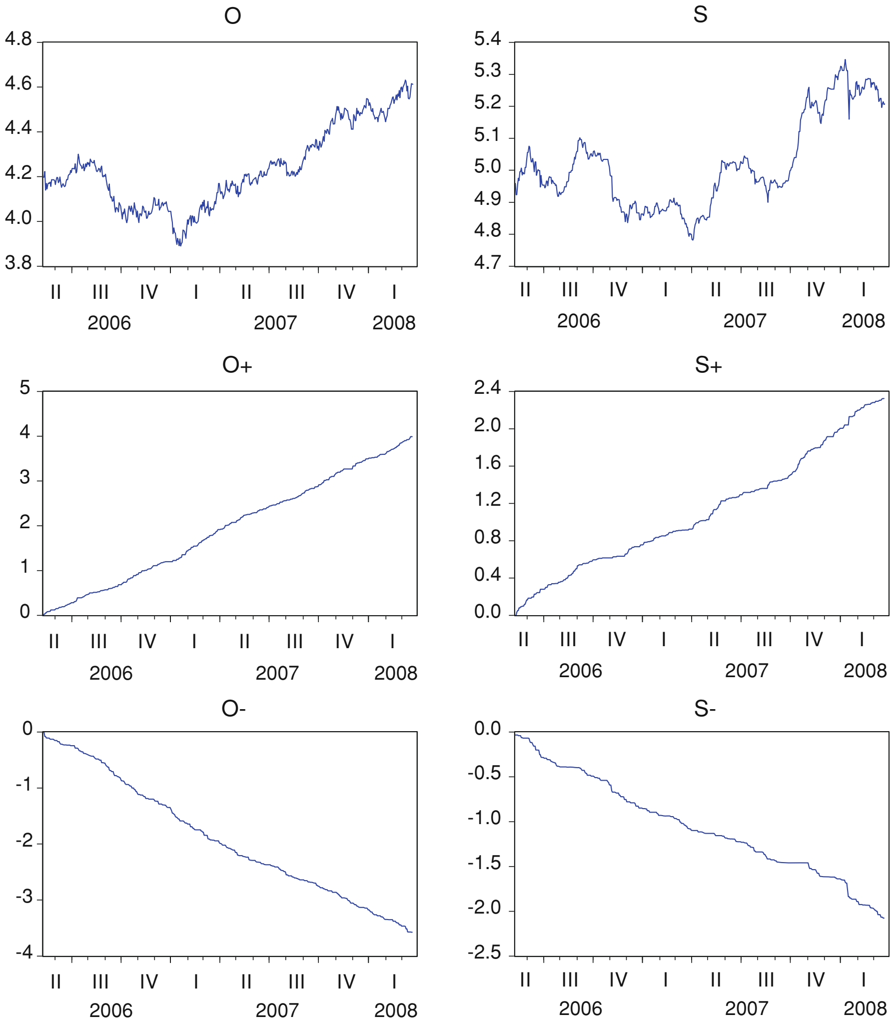

Fig. 1 The time plots of the variables as well as their positive and negative cumulative sums, during April 2006 to March 2008, on daily basis. O is the logarithmic value of the oil price index, S is the logarithmic value of the stock price index. The cumulative positive sum of each variable is indicated by $+$ and the cumulative negative sum is indicated by $-$

3.3 The empirical findings

As pointed out earlier, it is important to allow for an asymmetric structure in the causality testing. We make use of a bootstrap method with leverage adjustments as presented

Footnote 12 continued
for all five combinations. Note that no trend was included in the VAR model when tests for cointegration were conducted. It should be mentioned that cointegration is not a prerequisite for testing for causality between integrated variables within the VAR framework as long as additional unrestricted lags are included in the model, according to Toda and Yamamoto (1995).

Table 1 Tests for multivariate normality and ARCH in the VAR model

Variables in the VAR model	Multivariate normality	Multivariate ARCH	VAR order (max lag = 10)
(O, S)	<0.0001	<0.0001	1
(O^+, S^+)	<0.0001	0.8880	1
(O^-, S^-)	<0.0001	0.0060	1
(O^+, S^-)	<0.0001	0.0020	2
(O^-, S^+)	<0.0001	0.4120	1

O stands for the oil price and S is the stock price. Cumulative positive and negative shocks are used
The optimal lag order in the VAR model was selected based on the minimization of the information criterion expressed by Eq. 4
The test suggested by Doornik and Hansen (2008) was used for testing the null hypothesis of multivariate normality
A bootstrap multivariate LM test developed by Hacker and Hatemi-J (2005) was used to test for ARCH effects. The bootstrap simulations of this ARCH test was implemented by a statistical software component produced by Hacker and Hatemi-J (2009)
The p values for the diagnostic tests are presented

in the previous section. This method provides valid inference even if the underlying variables are non-normally distributed with potential ARCH volatility. These properties characterize the data to a large extent based on the results presented in Table 1. The null hypothesis of multivariate normality is strongly rejected regardless whether the VAR model is estimated for positive, negative, or a combination of the cumulative shocks. The null hypothesis of no multivariate ARCH is also strongly rejected for three out of five cases. Therefore, it is important to utilize the bootstrap test in this case because the standard methods that are based on normality and constant variance are likely to not perform accurately.

The results of these asymmetric causality tests are presented in Table 2. Based on these results, the null hypothesis that the oil shocks do not Granger-cause the stock prices cannot be rejected at any conventional significance level. This is also the case for positive and negative cumulative oil shocks as well as the combinations of these

Table 2 The results of tests for causality using the bootstrap simulations

Null hypothesis	Test value	Bootstrap CV at 1%	Bootstrap CV at 5%	Bootstrap CV at 10%
$O \neq> S$	0.352	7.094	3.511	2.376
$O^+ \neq> S^+$	1.891	6.841	3.961	2.730
$O^- \neq> S^-$	1.131	7.191	3.916	2.676
$O^+ \neq> S^-$	0.455	9.475	5.931	4.585
$O^- \neq> S^+$	0.136	7.305	3.714	2.593

The denotation $A \neq> B$ means that variable A does not cause variable B
CV stands for critical value
It should be mentioned that the χ^2 critical values for one degree of freedom are 6.64, 3.84, and 2.71 at the 1, 5, and 10% significance levels. For two degrees of freedom the χ^2 critical values are 9.21, 5.99, and 4.60 at the 1, 5, and 10% significance levels

shocks. We interpret these results as empirical evidence for the support of the efficient market hypothesis in the semi-strong form, assuming that the public information consists of only oil shocks. Hence, the likelihood of achieving systematic opportunities for abnormal returns based on the information from oil shocks in the UAE stock market is ruled out. That is, any attempt for arbitrage via creating a strategy based on fluctuations in the oil prices will not be successful.

4 Conclusions

This article argues that it is important to allow for an asymmetric structure in the causality testing because of the asymmetric information phenomenon. It is also possible that economic agents would react differently to the new information depending on whether it is a good news or a bad news. We suggest achieving this by constructing the cumulative positive and negative shocks of the underlying variables in the model. The bootstrap simulation approach with leverage adjustment can be utilized to generate critical values that are robust to non-normality and time-varying volatility that characterize the financial data. User friendly Gauss codes are produced to implement the tests.

An application to the efficient market hypothesis of the stock market in the UAE with regard to both permanent positive and negative shocks as well as the combinations of these shocks is provided. The results show that the null hypotheses of no causality of the oil shocks on the stock market cannot be rejected at any conventional significance level. This indicates that the stock market in the UAE is informationally efficient with regard to the oil shocks regardless if these shocks are positive or negative. It should be pointed out that in this particular application the same causal inference was obtained regardless of whether asymmetric structure in causality testing is accounted for or not. This can be interpreted as the robustness of the empirical findings. Future applications of the asymmetric causality test may, however, reveal cases in which it will matter whether the asymmetric property is taken into account or not.

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