Environmental Research ∎ (∎∎∎∎) ∎∎∎–∎∎∎

Contents lists available at ScienceDirect

Environmental Research

journal homepage: www.elsevier.com/locate/envres

Time-varying coefficient vector autoregressions model based on dynamic correlation with an application to crude oil and stock markets

Fengbin Lu [a], Han Qiao [b,*], Shouyang Wang [b], Kin Keung Lai [c], Yuze Li [d]

[a] Academy of Mathematics and Systems Science, Chinese Academy of Sciences, Beijing 100190, China
[b] School of Economics and Management, University of Chinese Academy of Sciences, Beijing 100190, China
[c] Department of Management Sciences, City University of Hong Kong, Hong Kong
[d] Department of Industrial Engineering, University of Toronto, Canada

ARTICLE INFO

Article history:
Received 8 July 2015
Received in revised form
2 March 2016
Accepted 12 July 2016

Keywords:
Time-varying coefficient VAR
Dynamic lagged correlation
Granger causality
Crude oil
Stock market

ABSTRACT

This paper proposes a new time-varying coefficient vector autoregressions (VAR) model, in which the coefficient is a linear function of dynamic lagged correlation. The proposed model allows for flexibility in choices of dynamic correlation models (e.g. dynamic conditional correlation generalized autoregressive conditional heteroskedasticity (GARCH) models, Markov-switching GARCH models and multivariate stochastic volatility models), which indicates that it can describe many types of time-varying causal effects. Time-varying causal relations between West Texas Intermediate (WTI) crude oil and the US Standard and Poor's 500 (S&P 500) stock markets are examined by the proposed model. The empirical results show that their causal relations evolve with time and display complex characters. Both positive and negative causal effects of the WTI on the S&P 500 in the subperiods have been found and confirmed by the traditional VAR models. Similar results have been obtained in the causal effects of S&P 500 on WTI. In addition, the proposed model outperforms the traditional VAR model.

1. Introduction

Major economic and political events have important influences on financial markets and lead to market structure changes, so the causal relations among financial markets usually evolve with time. Many empirical studies have provided the evidence that the causal relations among financial or economic variables were not constant (e.g., Hamilton, 1988; Hamilton, 1989; Kim, 1994; Krolzig, 1997; Primiceri, 2005; Cogley and Sargent, 2005; Granger, 2008; Christopoulos and León-Ledesma, 2008; Hong et al., 2009; Lu et al., 2014). Time-varying causality has many implications for policy making, forecasting and risk management. Therefore, ignoring time-varying causality may lead to misleading conclusions. As a result, many researchers have done comprehensive studies and have proposed some methods for empirical studies.

Time-varying parameter vector autoregression (VAR) models are the most popular methods to examine the evolving causal relations among financial markets or economic systems. The most popular method may be the time-varying parameter VAR (TVP VAR), in which the parameters follow random walk processes. For instance, Cogley and Sargent (2002) built a random coefficient VAR for inflation, unemployment, and interest rate. It used Bayesian methods to estimate the parameters. Cogley and Sargent (2005) extended the model of Cogley and Sargent (2002) to incorporate time-varying variances. Primiceri (2005) proposed a time-varying structural vector autoregression model, in which the time variation were derived from both the coefficients and the variance covariance matrix of the model's innovations. As discussed by Granger (2008), the most used and successful TVP models are based on a Kalman filter specification which has both an interpretation in terms of an underlying “states pace” factor and a sophisticated estimation procedure. Another is the regime-switching VAR models (e.g., Krolzig, 1997; Krolzig and Sensier, 2000; Krolzig et al., 2002). In the regime-switching VAR model, the parameters shift from one regime to another. For example, Krolzig (1997) developed the Markov-switching vector autoregressive (MS VAR) to the economic modeling of dynamic systems subject to shifts in regime and researched the empirical business cycle. Krolzig and Sensier (2000) applied MS VAR to predict multiple time series and found that MS VAR yielded some improvements when compared to the constant-parameter, linear

* Correspondence to: School of Economics and Management, University of Chinese Academy of Sciences, No. 80, Zhongguancun East Road, Haidian District Beijing 100190, China.
E-mail addresses: fblu@amss.ac.cn (F. Lu), qiaohan@ucas.ac.cn (H. Qiao), sywang@amss.ac.cn (S. Wang), mskklai@cityu.edu.hk (K.K. Lai), richardyz.li@mail.utoronto.ca (Y. Li).

http://dx.doi.org/10.1016/j.envres.2016.07.015
0013-9351/

time-series models. Finally, Christopoulos and León-Ledesma (2008) proposed another regime-switching VAR, where the coefficients follow the logistic smooth transition autoregressive (LSTAR) function of time t, and applied the model to examine the causal relationship between US money and output.

The causality between crude oil and stock markets has been examined by a large number of papers. The empirical studies have revealed the complex and sometimes contrary findings. However, few papers have examined the time-varying causal relations between the two variables. After applying the VAR model, Huang et al. (1996) found no evidence of a relationship between daily oil prices and market returns such as the S&P 500. However, Sadorsky (1999) showed that positive oil price shocks depressed real stock returns by building the VAR model with GARCH effects for US monthly data. Ciner (2001) found some evidence of nonlinear Granger causality between crude oil futures returns and stock index returns. Using a multivariate threshold regression model, Huang et al. (2005) found that oil price changes could negatively impact stock returns only when the price increase in previous period exceeded a threshold value. Kilian (2009) decomposed the real price of crude oil into three components and estimated the dynamic effects of the shocks on the real price of oil. The result showed that not all the oil shocks were alike. Kilian and Park (2009) reported that the reaction of U. S. real stock returns to an oil price shock differed greatly depending on whether the change in the price of oil was driven by demand or supply shocks in the oil market. Based on a two regime Markov-switching exponential generalized autoregressive conditional heteroskedasticity (EGARCH) model, Aloui and Jammazi (2009) showed that there were two episodes of the behavior and an increase in oil price played a significant role in determining both the volatility of stock returns and the probability of transition across regimes. Jammazi and Aloui (2010) combined wavelet analysis with the Markov switching vector autoregressive (MS-VAR) approach to explore the impact of the crude oil shocks on the stock market returns for UK, France and Japan over the period of January 1989 to December 2007. They found that crude oil shocks did not affect the recession stock market phases (except for in Japan), but the shocks significantly reduced moderate and/or expansion stock market phases temporarily. Using the capital asset pricing model (CAPM) based on the state-space model, Zhang and Wei (2011) proved the time-varying influence of advanced stock market risk on the oil market and showed more linearity. Applying VEC and VAR models, Lee et al. (2012) showed that oil price shocks did not have a significant impact on the composite index of the G7 countries, but exerted significant influences on some sector indexes for some countries; besides, their results also showed that the stock price changes in Germany, the UK and the US Granger-caused oil price changes. Using the generalized autoregressive conditional heteroskedasticity (GARCH) and Dynamic conditional Correlation Multivariate GARCH models, Mollick and Assefa (2013) examined the contemporary causality between the two variables and found that oil prices had a slightly negative effect on the stock returns before the financial crisis of 2008–2009, but had a positive effect on the stock returns in the subsample of mid-2009 due to the worldwide expectations of recovery.

This paper takes a new route. It proposes a new time-varying coefficient VAR model based on dynamic correlations (i.e., DCTV VAR), and examines the time-varying causal relations between crude oil and US stock markets. It is known that the correlation is a measure of relationship. In general, the stronger the correlation, the stronger the degree of the causal relation. This is the motivation behind defining the coefficients in the DCTV VAR model as linear functions of dynamic lagged correlations. This paper attempts to show that the DCTV VAR model can describe time-varying causal relations. To build the DCTV VAR model, a proper dynamic correlation model is firstly used to estimate the dynamic lagged correlations. Then, the time-varying coefficients in the VAR model are defined as the linear functions of dynamic lagged correlations. The least squares (LS) estimation or maximum likelihood estimation (MLE) can be applied. When all of the dynamic lagged correlations are constant, the DCTV VAR model becomes the traditional VAR model. Furthermore, when two stationary time series are mutually independent, their dynamic conditional (lagged) correlation is close to 0, which means that time-varying coefficients in DCTV VAR model will be limited.

The reminder of the paper is structured as follows: In Section 2, the paper presents the time-varying coefficient VAR model based on dynamic correlation. In Section 3, the proposed models are applied to examine time-varying causal relations between WTI crude oil futures price and S&P 500 stock index. In Section 4, the paper presents the findings and conclusions.

2. Time-varying coefficient VAR model based on dynamic correlation

In this section, the paper introduces a new time-varying coefficient VAR model based on dynamic lagged correlation.

Suppose $y_t=(y_{1,t}, y_{2,t}, \dots, y_{n,t})'$, $t=1, 2, \dots, T$ is a n-dimension vector process. The VAR model with lag order p is:

$$y_t=c+B_1y_{t-1} + B_2y_{t-2}+\dots+B_py_{t-p} + u_t \tag{1}$$

where, c is a n-dimension constant vector, $B_i, i = 1,\dots,p$ are the coefficient matrices, and u_t is the error vector. u_t is usually assumed to be i.i.d. (independent and identically distributed) normal with mean zero and covariance matrix Ω, i.e., $u_t \sim N(0,\Omega)$.

The time-varying coefficient VAR model is the extension of VAR, in which the coefficients are allowed to change over time,

$$y_t = c_t + B_{1,t}y_{t-1} + B_{2,t}y_{t-2}+\dots+B_{p,t}y_{t-p} + u_t \tag{2}$$

Here, $B_{k,t} = \begin{pmatrix} b_{11,k,t} & b_{12,k,t} & & b_{1n,k,t} \\ b_{21,k,t} & b_{22,k,t} & \dots & b_{2n,k,t} \\ \cdots & \cdots & & \cdots \\ b_{n1,k,t} & b_{n2,k,t} & & b_{nn,k,t} \end{pmatrix}$ is the matrix of time-varying coefficients. In the MS VAR, TVP VAR and LSTAR VAR models shown above, time-varying coefficient changes over time in certain patterns. In the TVP VAR model, the coefficients usually follow random walk processes as shown below:

$$c_t = c_{t-1} + \epsilon_{0,t}; B_{i,t} = B_{i,t-1} + \epsilon_{i,t},\ i = 1, \dots, p \tag{3}$$

The MCMC method is usually used to estimate TVP VAR models. In regime-switching VAR models with K regimes, the coefficient is constant in each regime and shifts from one regime to another with certain probability,

$$c_t = c_{S(t)}; B_{i,t} = B_{i,S(t)},\ i = 1, \dots, p \tag{4}$$

In which $S(t)=1,\dots,K$ is a latent state variable driving the matrices of parameters. Finally, the coefficients in LSTAR VAR model (Christopoulos and León-Ledesma, 2008) follow the LSTAR functions of time t. Take a bivariate VAR(p) model for an example:

$$\begin{pmatrix} y_{1,t} \\ y_{2,t} \end{pmatrix} = \begin{pmatrix} c_1 \\ c_2 \end{pmatrix} + \begin{pmatrix} b_{11,1} & b_{12,1} \\ b_{21,1} & b_{22,1} \end{pmatrix}\begin{pmatrix} y_{1,t-1} \\ y_{2,t-1} \end{pmatrix} + \dots + \begin{pmatrix} b_{11,p} & b_{12,p} \\ b_{21,p} & b_{22,p} \end{pmatrix}\begin{pmatrix} y_{1,t-p} \\ y_{2,t-p} \end{pmatrix} + \begin{pmatrix} u_{1,t} \\ u_{2,t} \end{pmatrix} \tag{5}$$

Christopoulos and León-Ledesma (2008) let $b_{k,12}$ and $b_{k,21}$ follow a LSTR functional form:

$$\begin{aligned} b_{12,k} &= \omega_{12,k} + \lambda_{12,k}(1 + e^{-\lambda_{1k}(\tau - c_{1k}T)})^{-1} b_{21,k} \\ &= \omega_{21,k} + \lambda_{21,k}(1 + e^{-\lambda_{2k}(\tau - c_{2k}T)})^{-1} \end{aligned} \tag{6}$$

Please cite this article as: Lu, F., et al., Time-varying coefficient vector autoregressions model based on dynamic correlation with an application to crude oil and stock markets. Environ. Res. (2016), http://dx.doi.org/10.1016/j.envres.2016.07.015