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Oil shocks and stock return volatility☆

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ABSTRACT

Asset return volatility is important to the macroeconomy. This paper asks whether oil price volatility can be used as a predictor of stock return volatility. In contrast with previous research, we focus on the out-of-sample predictive power of oil price volatility rather than on in-sample inference. Formal tests of out-of-sample predictive ability find no evidence supporting the use of oil price volatility as a predictor of future stock return volatility. Further analysis using rolling window estimation and structural break tests shows that the coefficients of this relationship are very unstable. The coefficients can be positive, negative, or close to zero depending on the sample that is chosen. We discuss the implications of this finding for monetary policy.

1. Introduction

The volatility of asset prices is believed by many to have important effects on the macroeconomy (see e.g. Phelps, 1999). This suggests that monetary and fiscal policy should be made taking into account the volatility of asset prices, and in particular, the volatility of stock prices. Farmer (2012) has advocated a policy of direct government intervention to reduce the volatility of the stock prices. If these views are correct, and the government should be offsetting or even preventing volatility of stock prices, it is important to find good predictors of stock price volatility. An obvious candidate is oil price volatility. There are many published estimates of the effect of oil shocks on macroeconomic variables.[1] A growing literature has found evidence that oil price shocks have an effect on stock prices,[2] with most authors finding that higher oil prices have a negative effect on stock returns.

A natural question is whether oil price volatility is a useful predictor of stock market volatility. Several papers have considered this question and concluded that oil price volatility can be used to improve upon forecasts of stock return volatility. Elyasiani, Mansur, and Odusami (2011) estimated GARCH(1,1) models of industry stock returns that allowed the variance of the error term to depend on the previous day's oil price volatility. For the period from December 1998 to December 2006, they were able to reject the null hypothesis of a zero coefficient in the variance equation for five of thirteen industries. Sadorsky (1999) reported impulse response functions and forecast error variance decompositions for real stock returns following shocks to the price of oil and oil price volatility. Papers with a more specialized focus include Sadorsky (2003), which investigated the effect of oil price volatility on the volatility of technology stocks, and Hammoudeh, Dibooglu, and Aleisa (2004), which estimated the effect of oil price volatility on the volatility of oil industry stock prices. The conclusion of all of these papers is that there is a useful forecasting relationship between lagged oil price volatility and stock return volatility.

This paper differs from the others by focusing on the *out-of-sample* forecast power of oil price volatility.[3] As emphasized by Clark and McCracken (2013), "Forecasts need to be good to be

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[1] Some recent papers include Atems, Kapper, and Lam (2015), Edelstein and Kilian (2009), Hamilton (2011), Herrera and Pesavento (2009), Herrera, Lagalo, and Wada (2011), Kilian (2009), Kilian and Lewis (2010), Kilian and Vigfusson (2011), and Melichar (2016).

[2] See e.g. Alsalman and Herrera (2015), Apergis and Miller (2009), Basher, Haug, and Sadorsky (2012), Chen (2010), Cunado and De Gracia (2014), Jones and Kaul (1996), and Kilian and Park (2009).

[3] It is important to stress that the goal of this paper is not to estimate a model of stock return volatility. That has been done in many previous papers, and it would

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useful for decision making. Determining if forecasts are good involves formal evaluation of the forecasts." One reason in particular that a correlation identified in the full sample might not translate into good forecasts is parameter instability (Pettenuzzo & Timmerman, 2011). We build on the work done in the papers cited above by evaluating the out-of-sample forecast accuracy of stock return volatility models with and without oil price volatility. We investigate the stability of the parameters of the relationship through time. Full-sample Granger causality test results, along with the other in-sample evaluation techniques applied in the previous literature, can be misleading in the presence of parameter instability, and we find that to be the case.

The most important result to emerge from our analysis is that the relationship between oil price volatility and stock return volatility is unstable. Rolling window regression estimates show that the coefficients vary substantially over time. The variation in the parameter estimates is so substantial that it is possible to find any desired correlation between the variables – positive, negative, or zero – simply by choosing an appropriate subsample of the data. Structural break tests reject the null hypothesis of parameter stability for the S&P 500, the CRSP value-weighted index, and industry-level returns for 49 sectors that cover nearly all of the economy. Formal tests of out-of-sample predictive ability that exclude the 2008–2009 financial crisis period find no support for the use of oil price volatility as a predictor of stock return volatility. On the basis of our findings of parameter instability and the failure of models with oil price volatility to consistently improve out-of-sample forecasts of stock return volatility in the past, and in contrast to the existing literature, we conclude that there is no basis for using oil price volatility as a predictor of stock return volatility.

2. Data

Daily data on West Texas Intermediate (WTI) spot prices were downloaded from the Federal Reserve Economic Database (FRED) provided by the Federal Reserve Bank of St. Louis. We use two stock indexes. Data on the S&P 500 closing price were downloaded from Yahoo! Finance. The CRSP value-weighted index and industry-level value-weighted returns for 49 sectors were downloaded from the website of professor Kenneth French.[4] In Table 1 are the complete names of all industry sectors and their shortened names that are used in the text. All data cover the period January 2, 1986 (the earliest available date for daily oil prices) to April 30, 2015. We use the natural log return of all variables.

Volatility of the oil price and stock return data are measured as the realized volatility of those series. The realized volatility of each series was calculated as the sample standard deviation for each month. Fig. 1 plots the realized volatility series of WTI price change as well as the S&P 500 and the CRSP returns for the period January 1986 to April 2015. Realized volatility has been used as a measure of volatility in the existing literature (see e.g. Andersen, Bollerslev, Diebold, & Labys, 2003; Schwert, 1989).

One might question the decision to use realized volatility measures rather than the popular GARCH family of volatility models. There is no obvious reason to prefer a GARCH model. The advantage of using a realized volatility measure is that it is consistent with the real-time nature of an actual forecasting exercise. That can be done with GARCH models, but only if one sacrifices efficiency, and it is unclear what would be gained from doing so. Second, even if one were willing to estimate a GARCH model using small subsamples of the data, the realized volatility measures would be able to take full advantage of the rich information available in the daily data, while the GARCH model would discard all intramonthly data. This was one of the motivations for introducing realized volatility (Andersen et al., 2003). If the goal of our paper were instead to estimate a volatility model using the full sample of data, a GARCH model would be a natural starting point.

Table 1
List of industry sectors.

Name used in the text	Complete name
Agriculture	Agriculture
Food Prod	Food Products
Candy Soda	Candy &Soda
Beer	Beer &Liquor
Tobacco	Tobacco Products
Recreation	Recreation
Entertain	Entertainment
Printing	Printing and Publishing
Cons Goods	Consumer Goods
Apparel	Apparel
Healthcare	Healthcare
Med Equip	Medical Equipment
Pharma Prod	Pharmaceutical Products
Chemicals	Chemicals
Rubber Plas	Rubber and Plastic Products
Textiles	Textiles
Constr Mat	Construction Materials
Construct	Construction
Steel Works	Steel Works Etc
Fabric Prod	Fabricated Products
Machinery	Machinery
Electric Equip	Electrical Equipment
Autos	Automobiles and Trucks
Aircraft	Aircraft
Shipbuild	Shipbuilding, Railroad Equipment
Defense	Defense
Prec Metals	Precious Metals
Mining	Non-Metallic and Industrial Metal Mining
Coal	Coal
Petroleum	Petroleum and Natural Gas
Utilities	Utilities
Communic	Communication
Pers Serv	Personal Services
Bus Serv	Business Services
Computers	Computers
Comp Soft	Computer Software
Electro Equip	Electronic Equipment
Meas Control	Measuring and Control Equipment
Bus Suppl	Business Supplies
Ship Cont	Shipping Containers
Transport	Transportation
Wholesale	Wholesale
Retail	Retail
Rest Hotels	Restaurants, Hotels, Motels
Banking	Banking
Insurance	Insurance
Real Estate	Real Estate
Trading	Trading
Others	Others

3. Full-sample results

3.1. Contemporaneous relationship

Following Den Haan (2000), we measure the comovement between stock return volatility and oil price volatility as the correlation of the residuals of a vector autoregressive (VAR) model[5]:

$$s_t = \alpha_0 + \alpha_1 s_{t-1} + \alpha_2 w_{t-1} + \varepsilon_{st} \tag{1}$$

be straightforward to do so using a GARCH model or one of its many variants, but that would not by itself provide any information about out-of-sample stock return volatility prediction. Hypothesis testing and characterizing the dynamics of the process are important but distinct from forecast evaluation.

[4] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

[5] The results presented here are robust to the use of longer lag lengths.