

Discussion of Gondo and Vega "The Dynamics of Investment Projects: Evidence from Peru"

Apostolos Serletis

Bank for International Settlements CCA Research Network on
Commodities (Mexico City, August 18-19, 2016)

This Paper

- The paper uses logit and duration analysis to investigate the effects of commodity prices and uncertainty about commodity prices on firm investment decisions at the project level in the Peruvian economy (a major commodity exporter)
- It uses a dataset of 1109 investment project announcements between 2009 and 2015, obtained from media and public press releases from private firms and from the mining experts surveys and interviews conducted by the central bank
- The information covers different sectors of the economy (mining, hydrocarbons, electricity, industrial, agroindustry, telecommunications, and others)

- In the mining sector (which is closely linked to commodity prices), both commodity prices and commodity price volatility affect investment
- Only commodity price volatility is relevant for other sectors

Some Observations on the Methodology

$$delay_{it} = \alpha_{oi} + \alpha_1 growth_{it} + \alpha_2 volat_{it} + \alpha_3 \mathbf{X}_{it}$$

where

$$delay_{it} = \begin{cases} 1 & \text{if project } i \text{ has been announced to be delayed} \\ 0 & \text{otherwise} \end{cases}$$

$growth_{it}$ = the year on year percentage change in the commodity price

$volat_{it}$ = volatility (the standard deviation of the last 12 months)

\mathbf{X}_{it} = ($conflict_{it}$, $financ_{it}$, fdi_{it} , $volatn_{it}$)

$conflict_{it}$ = number of social conflicts

$financ_{it}$ = a proxy of the size of the investment project

fdi_{it} = the amount of funding from foreign investors

$volatn_{it}$ = the volatility of commodity prices in periods of a downward trend.

Volatility is a very important concept in economics and finance. There are different approaches to measuring volatility. For example:

- 1 Historical volatility
- 2 Implied volatility — see Black-Scholes (1983, *JPE*) option pricing model
- 3 ARCH-type volatility models — see Engle (1982, *Econometrica*)

Why ARCH-Type Models?

$$y_t = \phi_0 + \phi_1 y_{t-1} + \varepsilon_t$$

	Forecasts	
	Unconditional	Conditional
Mean	$\frac{\phi_0}{1-\phi_1}$	$\phi_0 + \phi_1 y_{t-1}$
Variance	$\frac{\sigma^2}{1-\phi_1^2}$	σ^2

The ARCH Model

The autoregressive conditional heteroscedasticity (ARCH) model, developed by Engle (1982), is

$$y_t = \phi_0 + \phi_1 y_{t-1} + \dots + \phi_r y_{t-r} + \varepsilon_t \quad (1)$$

$$\varepsilon_t | \Omega_t \sim D(0, \sigma_t^2)$$

$$\sigma_t^2 = w + \sum_{i=1}^p \alpha_i \varepsilon_{t-i}^2 \quad (2)$$

Equation (1) is the conditional mean equation (referred to as the **mean model**) and describes how the dependent variable, y_t , changes over time. Equation (2) is the conditional variance equation (referred to as the **variance model**). According to (2), σ_t^2 is an autoregressive process of the squared residuals.

The GARCH Model

An extension of the ARCH model is the generalized ARCH, or GARCH, model proposed by Bollerslev (1986).

$$y_t = \phi_0 + \phi_1 y_{t-1} + \dots + \phi_r y_{t-r} + \varepsilon_t$$

$$\varepsilon_t | \Omega_t \sim D(0, \sigma_t^2)$$

$$\sigma_t^2 = w + \sum_{j=1}^q \beta_j \sigma_{t-j}^2 + \sum_{i=1}^p \alpha_i \varepsilon_{t-i}^2$$

and $w > 0, \alpha_1, \dots, \alpha_p, \beta_1, \dots, \beta_q \geq 0$ are unknown coefficients — they are non-negative in order to avoid the possibility of negative conditional variances. Hence, σ_t^2 looks like an ARMA(p, q) process in the $\{\varepsilon_t^2\}$ sequence. It is usually assumed that $p = q = 1$.

The GARCH-in-Mean Model

In this model, the conditional mean and conditional variance equations are

$$y_t = \phi_0 + \phi_1 y_{t-1} + \dots + \phi_r y_{t-r} + \psi \sigma_t^2 + \varepsilon_t$$

$$\varepsilon_t | \Omega_t \sim D(0, \sigma_t^2)$$

$$\sigma_t^2 = w + \sum_{j=1}^q \beta_j \sigma_{t-j}^2 + \sum_{i=1}^p \alpha_i \varepsilon_{t-i}^2.$$

That is, the conditional mean of y_t is a linear function of the conditional variance, σ_t^2 , which in turn is a linear function of past squared innovations and past conditional variances. Thus, the model allows the conditional mean, y_t , to depend on the conditional variance, σ_t^2 . It is usually assumed that $p = q = 1$.

Multivariate Volatility Models

These models are similar to the univariate ones, except that they also specify equations of how the conditional covariances and correlations move over time.

Multivariate volatility models can be used to investigate a large number of issues in economics and finance. For example, as Bauwens *et al.* (2006, p. 79) put it,

“is the volatility of a market leading the volatility of other markets? Is the volatility of an asset transmitted to another asset directly (through its conditional variance) or indirectly (through its conditional covariances)? Does a shock on a market increase the volatility on another market, and by how much? Is the impact the same for negative and positive shocks of the same amplitude?”

Modeling Commodity Price Shocks and Uncertainty

$$\mathbf{B}z_t = \mathbf{C} + \mathbf{\Gamma}_1 z_{t-1} + \dots + \mathbf{\Gamma}_p z_{t-p} + \mathbf{\Lambda} \sqrt{\mathbf{h}_t} + \mathbf{e}_t$$

$$\mathbf{h}_t = \text{diag}(\mathbf{H}_t) = \mathbf{C}_v + \mathbf{F} \text{diag}(\mathbf{e}_{t-1} \mathbf{e}'_{t-1}) + \mathbf{G} \text{diag}(\mathbf{H}_{t-1})$$

- Our measure of commodity price uncertainty is the conditional standard deviation of the change in the (real or nominal) price of the commodity, denoted $\sqrt{\mathbf{h}_{xx,t}}$, and our primary interest is the effect of $\sqrt{\mathbf{h}_{xx,t}}$ on y_t
- Investigate the effects of positive and negative price shocks (of different sizes) and test for nonlinearities and asymmetries
- Investigate robustness using alternative measures of y , data frequencies, and model specifications

See Elder and Serletis (*Journal of Money, Credit and Banking*, 2010).

Mean and Volatility Spillovers in Commodity Markets

VARMA, GARCH-in-Mean, BEKK (1,1,1) Model

$$\mathbf{z}_t = \mathbf{a} + \Gamma \mathbf{z}_{t-1} + \Psi \sqrt{\mathbf{h}_t} + \Theta \mathbf{e}_{t-1} + \boldsymbol{\epsilon}_t$$

$$\boldsymbol{\epsilon}_t | \Omega_{t-1} \sim (\mathbf{0}, \mathbf{H}_t)$$

$$\mathbf{H}_t = \mathbf{C}'\mathbf{C} + \mathbf{B}'\mathbf{H}_{t-1}\mathbf{B} + \mathbf{A}'\boldsymbol{\epsilon}_{t-1}\boldsymbol{\epsilon}_{t-1}'\mathbf{A}$$

This specification allows past volatilities, \mathbf{H}_{t-1} , and lagged values of $\boldsymbol{\epsilon}\boldsymbol{\epsilon}'$ to show up in estimating current volatilities.

See Serletis and Xu (*Energy Economics*, 2016).

Mean and Volatility Spillovers and Structural Breaks

VARMA, GARCH-in-Mean, BEKK (1,1,1) Model with a Structural Break

$$\mathbf{z}_t = \Phi + (\Gamma + \tilde{\Gamma} \times D)\mathbf{z}_{t-1} + (\Psi + \tilde{\Psi} \times D)\epsilon_{t-1} + \epsilon_t$$

where

$$\epsilon_t | \Omega_{t-1} \sim (\mathbf{0}, \mathbf{H}_t)$$

$$\begin{aligned} \mathbf{H}_t = & \mathbf{C}'\mathbf{C} + (\mathbf{B} + \tilde{\mathbf{B}} \times D)' \mathbf{H}_{t-1} (\mathbf{B} + \tilde{\mathbf{B}} \times D) \\ & + (\mathbf{A} + \tilde{\mathbf{A}} \times D)' \epsilon_{t-1} \epsilon_{t-1}' (\mathbf{A} + \tilde{\mathbf{A}} \times D) \end{aligned}$$

where

$$D = \begin{cases} 0 & \text{before 2012} \\ 1 & \text{since 2012 (inflation targeting)} \end{cases}$$

See Serletis and Xu (*Macroeconomic Dynamics*, forthcoming).

Conclusion

- This is an interesting paper
- Measurement matters could be addressed
- The robustness of the results could be investigated using recent advances in macroeconometrics and financial econometrics
- I look forward to seeing the authors' responses.