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Linear and non-linear causality between price indices and commodity prices ☆

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We apply linear and non-linear Granger causality tests to four U.S. price indices and 31 commodity series, which expand a 54-year period (January 1957–December 2011). We find evidence of linear Granger causality mostly from individual commodities to price indices. The latter, however, seem to Granger-cause individual commodity prices in a non-linear fashion. Overall, our estimation results show that Agricultural raw materials (cotton, hides, rubber, and wool), Beverages (coffee), Food (maize, rice, and wheat), Minerals, ores and metals (copper), and Vegetable oilseeds and oils (groundnut oil and soybean oil) display bidirectional linear and non-linear feedback effects vis-à-vis price indices. These findings suggest that not only shocks on commodity demand and supply may impact aggregate price indices, but also that non-commodity shocks, embodied in aggregate price indices, may impact commodity prices linearly and nonlinearly.

Introduction

A great bulk of literature has concentrated on the role of commodity prices as leading indicators of macroeconomic factors such as inflation, interest rates, and money. Examples are Webb (1988), Marquis and Cunningham (1990), Blomberg and Harris (1995), Furlong and Ingenito (1996), and Browne and Cronin (2007), among others. Most of these studies have relied on linear models and have found mixed evidence about the suitability of commodity prices to forecasting future inflation.

Another strand of the literature has stressed the importance of non-linear dependence between commodity prices and inflation. For instance, Kyrtsou and Labys (2007) study such non-linear linkages between the U.S Consumer Price Index (CPI) and an aggregate metal price index. They conclude that there is a significant and positive non-linear feedback from the CPI to the metal price series, but that the converse non-linear causality is much weaker. Kyrtsou (2008) extends this work by analyzing non-linear feedbacks between the CPI and a set of primary commodities, including aluminum, copper, gold, lead, nickel, petrol, platinum and silver, among others. She finds that most commodities non-linearly cause the CPI, but bidirectional causality is achieved only by lead and crude oil. In particular, Kyrtsou concludes that the absence of non-linear causality from inflation to gold would lend support to Mahdavi and Zhou (1997)'s finding about the limited role of gold to monetary policy guidance.

Related literature has concentrated on linear price linkages between energy and non-energy commodities. In particular, Baffes (2007) analyzed oil spills on 35 primary commodities during the period 1960–2005. He estimated that the price elasticity with respect to oil, or pass-through, was highest for Fertilizers (0.33), followed by Agriculture and Metals (0.17 and 0.11, respectively).

More recent literature has called into question the role of commodity-price shocks as a key driver of business cycles. For instance, Kilian (2009) concludes that much of the oil price increase in the 2000 s could be ascribed to a rising aggregate demand. In turn, Alquist and Coibion (2013) develop a general equilibrium macroeconomic model with a factor structure for real commodity prices, which decomposes each commodity price into three components. The first one captures idiosyncratic price movements. The second one, labeled as the indirect aggregate common (IAC) factor, captures shocks that are not directly related to commodity demand and supply (e.g., aggregate productivity shocks and shocks to labor supply). The third one, labeled as the direct aggregate common factor, represents the shocks that directly affect commodity supply and demand, holding aggregate output constant. Alquist and Coibion find that around 60–70% of the variance in real commodity prices and most of the historical changes in commodity prices since the early 1970's are due to the IAC factor.

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The aim of this article is to explore feed-back effects between price indices and commodity prices from a linear and non-linear perspective. In this regard, our work extends Kyrtsou (2008) by analyzing a comprehensive data base of 31 commodities – belonging to Agricultural raw materials, Beverages, Food, Minerals, ores and metals, and Vegetable oilseeds and oils – and four major U.S. price indices – CPI Urban Consumers All items, CPI Urban Consumer Commodities, PPI Finished Goods, and PPI Crude Materials for Further Processing – over the period of 1957–2011. Our work contributes to the extant literature in three aspects. First, when gauging linear feedbacks, we utilize a modified Granger causality test, which is robust to non-spherical disturbances and whose lag length is chosen optimally. Second, we extend Kyrtsou (2008)'s work by letting all of the parameters involved in non-linear Granger causality testing vary freely, and by selecting their optimal values on the basis of an information criterion. Third, our work shows that the sampled commodity series exhibit more linear and non-linear dependency with respect to the PPI than to the CPI. This finding may suggest that the PPI, rather than the CPI, is a more suitable deflator to computing real commodity prices.

This article is organized as follows. Methodology, The data, and Empirical results sections present the methodology, data description and exploratory testing, and empirical results, respectively. Conclusions and implications section concludes by summarizing the main findings.

Methodology

Robust linear Granger causality test

The testing for linear spillover effects from a price index logarithmic (log) return to a given commodity log return (and vice versa) is based on the concept of Granger causality:

$$r_t^i = \delta_0 + \mathbf{B}_1 \mathbf{x}_t^i + \mathbf{B}_2 \mathbf{y}_t + \xi_t, \quad t = 1, \ldots, T \tag{1}$$

where r_t^i is the log return on commodity i at time t, $\mathbf{x}_t$ is a vector containing lagged values of r_t^i, and $\mathbf{y}_t$ is a vector containing lagged values of the log return on the price index. The number of lags included on the right-hand side of (1) is chosen according to the Hannan–Quinn information criteria (HQIC).[1]

Under the null hypothesis of no feedback or Granger causality from $\mathbf{y}$ to r_t^i, $\mathbf{B}_2 = \mathbf{0}$. The testing of this set of linear constraints is carried out by means of an F-test:

$$F = \frac{(\mathbf{C}\hat{\boldsymbol{\beta}} - \mathbf{q})'(\mathbf{C}\mathrm{Var}(\hat{\boldsymbol{\beta}}|\mathbf{Z})\mathbf{C}')^{-1}(\mathbf{C}\hat{\boldsymbol{\beta}} - \mathbf{q})}{J} \sim F(J \times T - k) \tag{2}$$

where $\mathbf{Z}$ is a matrix containing the observations of $\mathbf{x}_t$ and $\mathbf{y}_t$, J is the number of exclusion constraints, $\hat{\boldsymbol{\beta}}$ is a $k \times 1$ vector containing the unconstrained ordinary least square (OLS) estimates, $\mathbf{C}$ is a $J \times k$ matrix associated to the exclusion constraints, $\mathbf{q}$ is a $J \times 1$ vector of zeros, and T is the sample size.

In order to take into consideration that ξ_t may be serially correlated and heterocedastic, the OLS variance–covariance matrix is based on the Newey–West estimate:

$$\widehat{\mathrm{Var}(\hat{\boldsymbol{\beta}}|\mathbf{Z})} = \frac{1}{T}\left(\frac{\mathbf{Z}'\mathbf{Z}}{T}\right)^{-1} \mathbf{Q} \left(\frac{\mathbf{Z}'\mathbf{Z}}{T}\right)^{-1} \tag{3}$$

where

$$\mathbf{Q} = \frac{1}{T}\sum_{t=1}^{T} \hat{\xi}_t^2 \mathbf{z}_t \mathbf{z}_t' + \frac{1}{T}\sum_{j=1}^{q}\sum_{t=j+1}^{T} \varpi_j \hat{\xi}_t \hat{\xi}_{t-j} (\mathbf{z}_t \mathbf{z}_{t-j}' + \mathbf{z}_{t-j}\mathbf{z}_t'),$$

$$\varpi_j = 1 - \frac{j}{q+1},$$

$q = \mathrm{floor}(4 \times (T/100)^{2/9})$, $\mathbf{z}_t$ is the row vector of $\mathbf{Z}$ at time t.

In order to illustrate numerical differences between the robust linear Granger causality test and its conventional counterpart, we designed the following experiment. Consider the bi-variate VAR: $W_t = \mu_W + a_{11} W_{t-1} + a_{12} Z_{t-1} + u_{Wt}$ (i); $Z_t = \mu_Z + a_{21} W_{t-1} + a_{22} Z_{t-1} + u_{Zt}$ (ii) where u_W and u_Z are both AR (1) processes: $u_{Wt} = \rho_1 u_{Wt-1} + \varepsilon_{1t}$ and $u_{Zt} = \rho_2 u_{Zt-1} + \varepsilon_{2t}$, such that $|\rho_i| < 1$ and ε_{it} is Gaussian white noise. Table A1 in Appendix reports four scenarios for given parameter values $\mu_W = \mu_Z = 0.1$, $a_{11} = 0.8$, $a_{12} = 0.2$, $a_{21} = 0.1$, $a_{22} = 0.7$, $\rho_1 = 0.7$, $\rho_2 = 0.3$.[2]

As can be seen from the table, numerical differences between the two statistics are more apparent for a relatively small sample of $T = 100$ observations. In this case, the average p-value for the conventional test would erroneously lead to the conclusion that Z does not Granger cause W at the 5% significance level (i.e., $a_{21} = 0$ in the population model). As the sample size increases, the numerical discrepancy between the two statistics shortens, but the conventional statistic appears as downward biased as it assumes that both u_W and u_Z are serially uncorrelated.

Non-linear Granger causality test

Hritsu-Varsakelis and Kyrtsou (2010)'s non-linear Granger causality test is based on the following model specification:[3]

$$X_t = \alpha_{11}\left(\frac{X_{t-\tau_1}}{1 + X_{t-\tau_1}^{c_1}}\right) - \delta_{11} X_{t-1} + \alpha_{12}\left(\frac{Y_{t-\tau_2}}{1 + Y_{t-\tau_2}^{c_2}}\right) - \delta_{12} Y_{t-1} + \upsilon_t \tag{4.1}$$

$$Y_t = \alpha_{21}\left(\frac{X_{t-\tau_1}}{1 + X_{t-\tau_1}^{c_1}}\right) - \delta_{21} X_{t-1} + \alpha_{22}\left(\frac{Y_{t-\tau_2}}{1 + Y_{t-\tau_2}^{c_2}}\right) - \delta_{22} Y_{t-1} + \eta_t \tag{4.2}$$

where X and Y are a pair of related time series, α_{ij} and δ_{ij}, $i, j = 1, 2$, are parameters to be estimated for given τ_i (delays) and c_i, $i = 1, 2$, and $\upsilon_t \sim \mathrm{NID}(0, \sigma_\upsilon^2)$ and $\eta_t \sim \mathrm{NID}(0, \sigma_\eta^2)$. Model specification (4.1) and (4.2) represents a non-linear structure, known as the bi-variate noisy Mackey–Glass model. This is an extension of the univariate model discussed by Kyrtsou and Terraza (2003), a discrete version of the Mackey–Glass equation[4] plus white noise.

The aim of the non-linear Granger causality test is to capture whether past values of, say, Y have a significant impact of the form $Y_{t-\tau_2}/\left(1 + Y_{t-\tau_2}^{c_2}\right)$ on X. That is, under the null hypothesis that Y does not cause X non-linearly, $\alpha_{12} = 0$. Similarly, under the null hypothesis that X does not cause Y non-linearly, $\alpha_{21} = 0$. For given values of c_1 and

[1] The marginal cost of adding parameters using Hannan–Quinn information criterion exceeds that of Akaike information criterion (AIC), but it is lower than that of Schwartz information criteria (SIC). In other words, HQIC will choose fewer parameters than AIC but more than SIC. It has been shown that both HQIC and SIC are asymptotically consistent, unlike AIC which is biased towards selecting an over-parameterized model (see, for instance, Hannan and Quinn, 1979, and Enders, 2010, chapter 2).

[2] These parameter values ensure that the error terms are stationary ($|\rho_i| < 1$) and that the VAR model is stable: the roots of $(1 - a_{11}L)(1 - a_{22}L) - a_{12}a_{21}L^2$ lie outside the unit circle, where L is the lag operator (see, Enders, 2010, Chapter 5).

[3] This test has been also discussed by Kyrtsou and Labys (2006, 2007) and by Kyrtsou (2008).

[4] The Mackey–Glass equation is a non-linear time delay differential equation of the form $dX/dt = X_\tau / 1 + X_\tau^n - \gamma X$, where β, γ, τ and n are positive real numbers, and X_τ represents the value of X at time $(t - \tau)$. Depending on the values of the parameters β, γ, τ and n, the Mackey–Glass equation gives rise to a range of periodic and chaotic dynamics. The equation was originally used by Mackey and Glass to illustrate the appearance of complex dynamics in physiological control systems (Glass and Mackey, 2010).