Economics Bulletin

Volume 32, Issue 2

Informational roles of commodity prices for monetary policy: evidence from the Euro area

Go Tamakoshi
Kobe University

Shigeyuki Hamori
Kobe University

Abstract

This paper examines the linear and nonlinear causal relationships between commodity price indices and macroeconomic variables such as the consumer price index (CPI) and the industrial production index (IP) in the Euro zone. We use monthly time series data from January 1999 to December 2011 and employ a solid nonparametric, nonlinear causality test by Diks and Panchenko (2006) as well as the linear Granger causality test using Lag Augmented Vector Autoregression (LA-VAR) approach. Main findings of the study include: (i) Oil price only linearly Granger-causes the CPI and hence can be seen as a better information variable for the general price level than non-energy commodity price. (ii) There is a significant one-way linear causality from commodity price to IP. (iii) A significant nonlinear relationship between CPI and IP is identified by the nonparametric causality test. Such results are relevant for monetary policy makers who wish to mitigate the possible future inflation by using commodity or oil price indices as information variables.

We are grateful for helpful comments of the editor and an anonymous reviewer.
Citation: Go Tamakoshi and Shigeyuki Hamori, (2012) "Informational roles of commodity prices for monetary policy: evidence from the Euro area", *Economics Bulletin*, Vol. 32 No. 2 pp. 1282-1290.
Contact: Go Tamakoshi - tamakosh@stu.kobe-u.ac.jp, Shigeyuki Hamori - hamori@econ.kobe-u.ac.jp.
Submitted: April 07, 2012. **Published:** April 25, 2012.

1. Introduction

Commodity prices tend to move closely with general inflation, and the former often leads the latter. Contemplating such interdependence between commodity prices and inflation, Garner (1989) contends that commodity price indices (COMs) can be perceived as useful information variables in formulating monetary policy. When policy makers observe increases in COMs and regard them as a portent of future inflation, they can respond to mitigate the possibility of future inflation.

Commodity price movements are regarded as an example of supply-side shocks, and their implications for central banks are less obvious than demand-side pressures. For instance, a positive demand-side shock that increases output and inflation may require a tightening of monetary policy to stabilize both. In contrast, central banks may become hesitant about reacting quickly to commodity price movements if their increases are transitory, and thus, the second round effects on demand are considered minimal. Nonetheless, since the mid 2000s, both oil prices and non-energy commodity prices have experienced unprecedented sharp and persistent increases despite a temporary drop right after the collapse of Lehman Brothers in September 2008. Therefore, it is becoming more worthwhile for central banks to investigate the interrelationship between commodity prices and inflation and its implications on monetary policy.

Recent empirical studies such as Awokuse and Yang (2003) and Bhar and Hamori (2008) that use US data, identified a one-way linear causality from COMs to both the consumer price index (CPI) and the industrial production index (IP). In contrast, using the nonparametric causality test by Hiemstra and Jones (1994), Kyrtsou and Labys (2006) found a bidirectional nonlinear causality between COMs and CPI in the US.

While the above studies focused on analyzing US data, this article is among the first to examine informational roles of commodity prices for monetary policy in the Euro area, using monthly data over the period 1999 to 2011. According to the European Central Bank (ECB), in addition to being a money-growth indicator, an inflation forecast—referred to as a "broadly based assessment of the outlook for future price developments"—is one of the two pillars that determine the appropriate level of interest rates (ECB, 1999). As Fourcans and Vranceanu (2007) noted in their observations on the ECB monetary policy, commodity market developments seem to be one of several variables affecting the central bank's forward-looking inflation expectations, and thus, the ECB closely monitors uncertainties in the markets over long periods.

In our view, the main contributions of this article are threefold. First, our study analyzes informational roles of oil prices (OIL) and non-energy commodity prices and identifies which can be a better proxy for the general price level in the Eurozone. Second, this study examines not only linear, but also nonlinear causality between the commodity (or oil) price and macroeconomic variables such as CPI and IP. Data from the Eurozone, where new members have been accessed, may be impacted by regime shifts; therefore, it was considered worthwhile to employ nonlinear approaches for capturing the potentially complex interdependence among the variables along with the linear Granger causality tests. Third, among various other nonlinear causality tests, we used a new nonparametric methodology by Diks and Panchenko (2006), which overcame the potential over-rejection issue that marred the previously popular method by Hiemstra and Jones (1994).

Our empirical results led to the following main conclusions: (i) In the Eurozone, OIL only linearly Granger-causes CPI and can be viewed as a better information variable for the general price level than non-energy commodity price. (ii) There is significant one-way linear causality from commodity price to IP. (iii) A significant nonlinear relationship between CPI and IP is identified by the nonparametric causality test.

2. Methodology

The Toda and Yamamoto LA-VAR linear causality test

We first conducted the linear Granger causality test using the lag-augmented vector autoregression (LA-VAR) method proposed by Toda and Yamamoto (1995). This method can be used to test coefficients in a level VAR regardless of the results from prior tests of integration order or the existence of cointegration.

While the standard Granger causality test deals with a VAR (*k*) model, where *k* is the true (optimal) lag length, the LA-VAR method requires estimating the following VAR (*p*) model, where *p* is equal to $k + d$ and *d* represents a maximum integration order. That is,

$$y_t = a_0 + a_1 t + A_1 y_{t-1} + ... + A_k y_{t-k} + ... + A_p y_{t-p} + \varepsilon_t, \quad t = 1, 2, \ldots, T \tag{1}$$

where the vector time series $\{y_t\}$ consists of the level of the variables; $a_0, a_1, A_1, ..., A_k$ are the vectors or matrices of coefficients; *t* is the time trend, and ε_t is a vector of error terms. The null hypothesis of Granger non-causality was tested by imposing a zero restriction on the first *p* parameters. Here, *d* must not exceed the true lag length *k*. Toda and Yamamoto (1995) demonstrate that the Wald test statistic has an asymptotic chi-square distribution with degrees of freedom equal to the number of restrictions.

The Diks and Panchenko nonparametric nonlinear causality test

We used the nonparametric test developed by Diks and Panchenko (2006, hereafter DP test) for testing nonlinear Granger causality. This test is an important contribution because it overcame the over-rejection issue observed in the previously popular test advocated by

Hiemstra and Jones (1994, hereafter HJ test).[1]

The general setting for this approach is summarized as follows. The null hypothesis for the Granger test for non-causality from one series (X) to another series (Y) is that $X_t^{\ell_X}$ does not contain additional information about Y_{t+1}, that is,

$$H_0: \; Y_{t+1} \mid (X_t^{\ell_X}; Y_t^{\ell_Y}) \sim Y_{t+1} \mid Y_t^{\ell_Y} \tag{2}$$

where ℓ_X and ℓ_Y are the lag lengths of X and Y, the strictly stationary bivariate time series. To keep notations compact, we only consider the case where $\ell_X = \ell_Y = 1$, drop the time index, and assume that $Z_t = Y_{t+1}$. Then, the null hypothesis can be restated so that the conditional distribution of Z given $(X,Y) = (x, y)$ is the same as that of Z given $Y = y$. Hence, the joint and marginal probability density functions must satisfy the following condition:

$$\frac{f_{X,Y,Z}(x,y,z)}{f_Y(y)} = \frac{f_{X,Y}(x,y)}{f_Y(y)} \cdot \frac{f_{Y,Z}(y,z)}{f_Y(y)} \tag{3}$$

Equation (3) implies that X and Z are independent conditional upon $Y = y$ for each fixed value of y. It is shown that the null hypothesis is specified as

$$E[f_{X,Y,Z}(X,Y,Z) f_Y(Y) - f_{X,Y}(X,Y) f_{Y,Z}(Y,Z)] = 0 \tag{4}$$

This results in the following test statistic:

$$T_n(\varepsilon) = \frac{n-1}{n(n-2)} \sum_i (\hat{f}_{X,Z,Y}(X_i, Z_i, Y_i) \hat{f}_Y(Y_i) - \hat{f}_{X,Y}(X_i, Y_i) \hat{f}_{Y,Z}(Y_i, Z_i)) \tag{5}$$

The local density estimator $\hat{f}_W(W_i)$ for a d_W-variate random vector W at W_i is defined by $\hat{f}_W(W_i) = (2\varepsilon)^{-d_W}(n-1)^{-1} \sum_{j, j \neq i} I_{ij}^W$ where $I_{ij}^W = I(\| W_i - W_j \| < \varepsilon)$ with the indicator function $I(\cdot)$ and the bandwidth ε, depending on the sample size *n*. If $\varepsilon = Cn^{-\beta}(C > 0, 1/4 < \beta < 1/3)$, the test statistic in Equation (5) satisfies the following:

$$\sqrt{n}\frac{(T_n(\varepsilon) - q)}{S_n} \xrightarrow{D} N(0,1) \tag{6}$$

where $\xrightarrow{D}$ denotes convergence in the distribution and S_n is an estimator of the asymptotic variance of T_n.

3. Data

Following a similar study based on US data by Bhar and Hamori (2008), we used monthly

[1] DP demonstrate that the HJ test may over-reject the null hypothesis of non-causality in case of increasing sample sizes, because it ignores the possible variations in conditional distributions.

data for the Euro area on three variables: CPI, IP, and COM.[2] Our approach is unique since we not only consider a vector autoregression (VAR) system including the above three variables, but also another VAR system including OIL instead of COM to compare their informational roles.

Table 1
Description of the dataset

Variable	Description	Unit	Data Source
CPI	Harmonised Index of Consumer Prices (HICP) for the Euro area Seasonally adjusted	Index number (2005 = 100)	Eurostat
IP	Industrial Production Index for the Euro area Seasonally adjusted	Index number (2005 = 100)	Eurostat
COM	ECB Commodity Price Index, Total non-energy commodity, Euro area 17 (fixed composition) Data adjusted for seasonality where required	Euro denominated; Index number (2000 = 100)	European Central Bank (ECB)
OIL	Brent crude oil 1-month forward—fob (free on board) euro per barrel Data adjusted for seasonality where required	euro per barrel	European Central Bank (ECB)

Table 1 describes our data. The data covers a relatively recent period ranging from January 1999 (that is, when the euro was introduced) to December 2011. All data are expressed in natural logarithms. Two points should be highlighted in terms of our data selection. First, for COM, we used the euro-denominated non-energy COM calculated by the ECB rather than the conventionally used Commodity Research Bureau's (CRB) price index for all commodities. Second, in case of OIL, we selected the Brent blend price for one month forward delivery (euro per barrel), not the widely used West Texas Intermediate (WTI) spot price (dollar per barrel). We selected these two variables because they are listed in the statistical database of the ECB, implying that they could be useful in analyzing informational roles because the central bank may be monitoring them for monetary policy making on a regular basis.

4. Empirical Results

Causality relationships using LA-VAR approach

We used the augmented Dickey–Fuller (ADF) and the Phillip–Perron (PP) tests to check for the existence of unit roots. The results indicate that all variables are I(1) variables.[3] Hence, we assume that the maximum integration order (d) is one. Then, we determine the optimum lag length (k) based on the Akaike Information Criterion (AIC).[4]

[2] For the variable IP, we used the industrial production index as a proxy variable for output, because monthly data is available for the index. Such use of the industrial production index is seen in similar existing studies such as Awokuse and Yang (2003), Hamori (2007), and Bhar and Hamori (2008).
[3] The results of the unit root tests will be available upon request.
[4] We confirm that the results from causality tests are qualitatively similar, even if we use the Schwarz Information Criterion (BIC) instead of AIC.

Table 2
Linear causality test: informational roles of the commodity price index

Explained variables	Explanatory variables					
	COM		CPI		IP	
	Test statistics	*p* -value	Test statistics	*p* -value	Test statistics	*p* -value
COM	-	-	4.3499	[0.3607]	6.7432	[0.1501]
CPI	1.6539	[0.7991]	-	-	4.9225	[0.2943]
IP	10.5080	[0.0327]*	9.5496	[0.0487]*	-	-

Note 1 : The three-variable LA-VAR($k+d$) model is estimated
Note 2 : Lag length selection of $k = 4$ is based on Akaike Information Criterion (AIC). The maximum integration degree (d) for the variables is assumed to be one.
Note 3 : Reported test statistics are asymptotic Wald statistics.
Note 4 : * represents statistical significance at the 5% level.

Table 3
Linear causality test: informational roles of the oil price index

Explained variables	Explanatory variables					
	OIL		CPI		IP	
	Test statistics	*p* -value	Test statistics	*p* -value	Test statistics	*p* -value
OIL	-	-	1.0302	[0.5974]	1.1386	[0.5659]
CPI	14.2447	[0.0008]**	-	-	2.6084	[0.2714]
IP	2.4840	[0.2888]	3.4990	[0.1739]	-	-

Note 1 : The three-variable LA-VAR($k+d$) model is estimated
Note 2 : Lag length selection of $k = 2$ is based on Akaike Information Criterion (AIC). The maximum integration degree (d) for the variables is assumed to be one.
Note 3 : Reported test statistics are asymptotic Wald statistics.
Note 4 : ** represents statistical significance at the 1% level.

Table 2 and Table 3 report the results of the linear Granger causality tests for each VAR system including COM and OIL, respectively. Table 2 indicates that there is no significant causality identified between COM and CPI, whilst the commodity price linearly Granger-causes IP at the 5% significance level. Interestingly, Table 3 shows that the oil price linearly Granger-causes CPI, but not IP at the 1% significance level, while neither CPI nor IP affects the oil price. In contrast to Awokuse and Yang (2003) and Bhar and Hamori (2008) which identified the causality from commodity prices to the US CPI and IP, our results using the recent Eurozone data suggest that there exists linear causality from commodity price to IP. Moreover, it is demonstrated that OIL is a more useful information variable than the non-energy commodity price for CPI in the area.

Causality relationships using the DP nonparametric causality test

The above linear, parametric causality test can detect linear relationships among the variables; however, it may overlook complex nonlinear dynamics. Thus, the nonparametric DP test was also employed. In the subsequent analysis, we deal with only the cases where $\ell_X = \ell_Y = 1$. Considering the relatively small sample size of our data (156 observations), we set the value of the bandwidth equal to 1.5, based on the suggestion of Diks and Panchenko (2006). Given these assumptions, we first applied the DP test to the data series in first logarithmic differences, which were found to be stationary. Next, following Bekiros and Diks (2008), we reapplied the nonparametric DP test to the residuals obtained from the VAR systems to show that the detected causality was strictly nonlinear in nature.[5]

Table 4
Nonlinear DP causality test: informational roles of the commodity price index

Pair	Raw data		VAR residuals	
	Test statistics	*p* -value	Test statistics	*p* -value
COM → CPI	0.6210	[0.2672]	0.6870	[0.2459]
CPI → COM	0.7830	[0.2168]	0.1930	[0.4236]
COM → IP	0.1510	[0.4401]	0.6120	[0.2703]
IP → COM	-1.2820	[0.9000]	-0.5990	[0.7253]
CPI → IP	1.7190	[0.0428]*	0.6860	[0.2462]
IP → CPI	-0.1120	[0.5445]	0.0190	[0.4826]

Note 1 : Reported test statistics are *T* -statistics by Diks and Panchenko (2006).
Note 2 : *p* -values are reported in parenthesis. * represents statistical significance at the 5% levels.
Note 3 : Raw data used for nonlinear DP causality tests are the series in first logarithmic difference which are found to be stationary.
Note 4 : VAR residuals for nonlinear DP causality tests are the residuals of the three-variable LA-VAR models.

Table 5
Nonlinear DP causality test: informational roles of the oil price index

Pair	Raw data		VAR residuals	
	Test statistics	*p* -value	Test statistics	*p* -value
OIL→ CPI	0.6170	[0.2686]	-0.3590	[0.6400]
CPI → OIL	-0.7020	[0.7586]	-0.1580	[0.5627]
OIL → IP	1.0650	[0.1434]	0.8320	[0.2027]
IP → OIL	-1.5690	[0.9417]	0.4470	[0.6727]
CPI → IP	1.7190	[0.0428]*	1.7500	[0.0400]*
IP → CPI	-0.1120	[0.5445]	-1.2790	[0.8996]

Note 1 : Reported test statistics are *T* -statistics by Diks and Panchenko (2006).
Note 2 : *p* -values are reported in parenthesis. * represents statistical significance at the 5% level.
Note 3 : Raw data used for nonlinear DP causality tests are the series in first logarithmic difference which are found to be stationary.
Note 4 : VAR residuals for nonlinear DP causality tests are the residuals of the three-variable LA-VAR models.

Table 4 and Table 5 exhibit results of the nonlinear DP causality tests applied to both the raw data and the VAR residuals. We derive two interesting observations from these tables. First, despite the detected linear causality from COM to IP and from OIL to CPI as discussed in the previous sub-section, we find no evidence of significant nonlinear Granger causality among those variables. The lack of such nonlinear relationships suggests that policy makers in the Eurozone can reasonably rely on the linear causality in order to use COM and OIL as information variables for IP and CPI, respectively. Second, there seems to be significant nonlinear unidirectional causality from CPI to IP at the 5% significance level. This is interesting because the New Keynesian literature usually contends that the causality runs from output to inflation. However, our empirical result above is generally considered in line with that of Hasanov et al. (2010). Using a time-varying smooth transition regression model, they found that the inflation-output relationship in Turkey was highly nonlinear and that the causality was regime dependent, varying across time. The nonlinear dependence between Eurozone CPI and IP identified in our analysis implies that a shock to CPI does not necessarily affect IP in expected manners, and hence, policy makers should carefully take into account the complex structure of the variables in forming monetary policies.

[5] Our approach differs from that of Bekiros and Diks (2008) since we took the residuals from the trivariate LA-VAR models applied to the level data, not from the standard VAR systems using first-differenced data.

5. Conclusion

This study adopts both linear and nonlinear Granger causality tests to examine the possibility of using COM and oil prices as information variables for CPI and IP, respectively. We employed a new nonparametric nonlinear technique as well as the LA-VAR approach. Overall, our empirical results show that in the Euro area, oil prices seem to be more useful than the commodity price as a proxy for the general consumer price level, while it is found that commodity price linearly Granger-causes IP. Furthermore, we find that there is significant nonlinear causality from consumer price index to industrial production. Deriving policy implications may require further assessment of the sources of such nonlinear causal linkages; however, monetary authorities should at least be aware of such chaotic interdependence in their policy decisions.

References

Awokuse, T. O. and Yang, J. (2003) The Information Role of Commodity Prices in Formulating Monetary Policy: A Re-examination, *Economics Letters*, **79**, 219–224.

Bekiros, S. D. and Diks, C. G. H. (2008) The Relationship Between Crude Oil Spot and Future Prices: Cointegration, Linear and Nonlinear Causality, *Energy Economics*, **30**, 2673–2685.

Bhar, R. and Hamori, S. (2008) Information Content of Commodity Futures Prices for Monetary Policy, *Economic Modeling*, **25**, 274–283.

Diks, C. G. H. and Panchenko, V. (2006) A New Statistic and Practical Guidelines for Nonparametric Granger Causality Testing, *Journal of Economic Dynamics and Control*, **30**, 1647–1669.

European Central Bank (1999) The Stability-oriented Monetary Policy Strategy of the Eurosystem, ECB Monthly Bulletin, January, 39–50.

Fourcans, A. and Vranceanu, R. (2007) The ECB Monetary Policy: Choices and Challenges, *Journal of Policy Modeling*, **29**, 191–194.

Garner, A. C. (1989) Commodity Prices: Price Target or Information Variables?, *Journal of Money, Credit and Banking*, **21**, 508–514.

Hamori, S. (2007) The Information Role of Commodity Prices in Formulating Monetary Policy: Some Evidence from Japan, *Economics Bulletin*, **5** (13), 1-7.

Hasanov, M., Arac, A., and Telatar, F. (2010) Nonlinearity and Structural Stability in the Phillips Curve: Evidence from Turkey, *Economic Modeling*, **27**, 1103–1115.

Hiemstra, C. and Jones, J. D. (1994) Testing for Linear and Nonlinear Granger Causality in the Stock Price-volume Relation, *The Journal of Finance*, **49**, 1639–1664.

Kyrtsou, C. and Labys, W. C. (2006) Evidence for Chaotic Dependence between US Inflation and Commodity Prices, *Journal of Macroeconomics*, **28**, 256–266.

Toda, H. Y. and Yamamoto, T. (1995) Statistical Inference in Vector Autoregressions with Possibly Near Integrated Processes, *Journal of Econometrics*, **66**, 225–250.