A Multivariate Model for the Relationship Between Agricultural Prices and Inflation Uncertainty: Evidence Using Greek Data

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Abstract

This paper investigates the determinants of agricultural price formation emphasising on the detection of possible impacts caused by inflation uncertainty. The empirical methodology employs the GARCH technique to model the "uncertainty" variable, as well as VAR modelling and variance decomposition analysis to investigate possible causal effects among the involved variables.

Keywords: *agriculture, Greece, inflation uncertainty, GARCH, variance decomposition*

Introduction

It is common sense that macroeconomic instability reflects on macroeconomic policy. Furthermore, macroeconomic policy causes impacts on the agricultural sector reflecting, among others, on the formation of the sector's price indices (Chambers and Just, 1979, 1981, 1982, 1986; Gardner, 1981; Grennes and Lapp, 1986; Groenewegen, 1986; Orden, 1986; Orden and Fackler, 1989; Han *et al.*, 1990; Robertson and Orden, 1990; Moss, 1992; Loizou, Mattas and Pagoulatos, 1997). Consequently, it is argued that the degree of macroeconomic instability is strongly related to the behaviour of the agricultural price indices.

The above considerations primarily stress the need for a method to measure the degree of macroeconomic instability and henceforth to incorporate it explicitly into the econometric models that attempt to investigate the determinants of the agricultural price indices behaviour. More specifically, recent empirical efforts proxy, in most cases, the macroeconomic instability explicitly, either by the inflation uncertainty or by the dispersion of prices (Katsimbris 1985, Bullard and Keating 1995, Davis and Kanago 1996, Ma 1998). This is due to the fact that inflation is often taken as a summary measure of the overall macroeconomic stance, and hence the volatility of its unpredictable component can be viewed as an indicator of the overall macroeconomic uncertainty (Eberly, 1993).

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A widely used method to quantify macroeconomic instability is to approximate it by a measure for the inflation uncertainty (Bajo-Rubiou and Sosvilla-Rivero, 1994; Golob, 1994; Sauer and Bohara, 1995). Actually, inflation uncertainty is defined as the variance of the forecasting error of inflation (Holland, 1995).

Although, the international empirical literature presents a large number of research papers exploring the relationship of agricultural prices and macroeconomic variables, there is rather little empirical evidence, to the best of my knowledge, on the effects of inflation uncertainty to agricultural prices. This gap in literature is even more obvious in the case of Greece.

In the above context, this paper attempts to cover this gap employing Greek data. More specifically, the paper investigates the determinants of agricultural price formation emphasising on the detection of possible impacts caused by inflation uncertainty. The empirical methodology employs the GARCH technique to model the "uncertainty" variable, as well as VAR modelling and variance decomposition analysis to investigate possible causal effects among the involved variables.

The rest of the paper is organised as follows: Next section, presents methodological issues used in the empirical analysis, and follow the results. Concluding remarks are given in the last section.

Methodological issues

The GARCH methodology

The empirical analysis employs the GARCH technique to model the uncertainty variable. GARCH modelling is considered to be superior among time series proxies, since it is possible to simultaneously model the mean and variance of a series. According to Enders (1995), conditional modelling is superior to unconditional modelling. Chou (1988), also argues in favour of GARCH models on the grounds that they are capable of capturing various dynamic structures of conditional variance, of incorporating heteroscedasticity into the estimation procedure, and of allowing simultaneous estimation of several parameters under examination.

If ε denotes the innovations in the mean for a specific stochastic process, y(t), and h a time-varying, positive, and measurable function of the time t-1 information set, then the GARCH(p,q) model proposed by Bollerslev (1986) suggests that:

$$h^2(t)=\omega+\sum_{i=1}^{q}\alpha(i)\varepsilon^2(t-i)+\sum_{i=1}^{p}\beta(i)h^2(t-i)=\omega+\alpha(L)\varepsilon^2(t)+\beta(L)h^2(t) \quad (1)$$

with $$0<\alpha(L)+\beta(L)<1, \quad (2)$$

where $\alpha(L)$ and $\beta(L)$ are polynomials in the lag operator L.

Condition (2) ensures stationarity of the conditional volatility. Expression (1) could be interpreted as an ARMA model for $\varepsilon^2(t)$. Following Bollerslev (1988), the identification of equation (1) is similar to that proposed by Box and Jenkins methodology. Iterative maximum likelihood techniques are used to estimate the parameters of the GARCH model. (The employed algorithm has been developed by Berndt *et al.*, (1974)).

Variance decomposition

The next step of this study considers variance decomposition analysis. This technique involves the transformation of the system into its moving-average representation and then to obtain a vector of orthogonal innovations estimated from the data. Furthermore, the analysis traces the dynamics of an innovation in any of the involved variables over time to account for the total amount of system variation attributable to each innovation.

More specifically, according to the Wold decomposition theorem, any finite linearly regular covariance stationary process y(t), m×1, has a moving average representation

$$y(t) = \sum_{s=0}^{\infty} \Phi(s)u(t-s) \tag{3}$$

with Var[u(t)]=Σ.

Even although u(t) is serially uncorrelated by construction, the components of u(t) may be contemporaneously correlated, so an orthogonalizing transformation to u(t) is done so that (3) can be rewritten as[1]

$$y(t) = \sum_{s=0}^{\infty} \Phi(s)P^{-1}Pu(t-s) = \sum_{s=0}^{\infty} \Theta(s)w(t-s) \tag{4}$$

where $\Theta(s)=\Phi(s)P^{-1}$, w(t-s)=Pu(t-s) and Var[w(t)]=Var[Pu(t)]=I.

When P is taken to be lower triangular matrix, the coefficients of Θ(s) represent "responses to shocks or innovations" in particular variables. More precisely, the jk-th element of Θ(s) is assumed to represent the effect on variable j of a unit innovation in the k-th variable that has occurred s periods ago. Furthermore, we can allocate the variance of each element in y to sources in elements of w, since w is serially and contemporaneously uncorrelated. The orthogonalization provides

$$\sum_{s=0}^{T} \Theta(s)_{ij}^{2} \qquad (5),$$

which is the components-of-error variance in the T+1 step ahead forecast of y_i which is accounted for by innovations in y_j.

Empirical analysis

Data

Following Moss (1992), Orden and Fackler (1989), and Robertson and Orden (1990), the variables employed in the empirical analysis are: The real effective exchange rate (ER), the money supply (M1), the consumer price index (CP), the index of manufacturing production[2] (MP), the index of producer prices of agricultural products (output prices) (PR), and the index of purchase prices of the means of agricultural production (input prices) (PP).

The empirical analysis is carried out using monthly data[3] over the period 1981:1 to 1998:2. All variables are expressed in logarithms, and henceforth are denoted by LER, LM1, LCP, LMP, LPR, and LPP, respectively.

Generating the "inflation uncertainty" variable

In order to generate the "inflation uncertainty" variable, as a first step we estimated a univariate ARIMA model[4] for CP. The optimal specification[5] was found to be of order (2, 1, 0). Next, the distributional properties of the residual series $\hat{\varepsilon}_t$, obtained from the above ARIMA model were tested. The results for skeweness (0.3165; p-value 0.0102), and kurtosis (1.0626; p-value 0.0067), suggested the rejection of the normality hypothesis and thus we further tested the residuals for possible ARCH effects. Based on the results reported in Table 1, we concluded the presence of ARCH effects. Therefore, we proceeded with testing for the appropriate GARCH specification via the Box-Jenkins identification approach. The optimal estimated GARCH model is

$$h_t^2 = \underset{(0.000005)}{0.000044} + \underset{(0.049811)}{0.186736}\varepsilon_{t-1}^2 \qquad (6)$$

We should notice here that, as it is required, the estimated coefficients obey the stationarity rule, i.e., their sum is less than unity. The fitted values from the above estimated GARCH model were then used as a proxy for the inflation uncertainty variable.

The VAR model

Next, a VAR model of the following form was specified

$$\mathbf{z}_t = \mathbf{A}_1\mathbf{z}_{t-1} + \mathbf{A}_2\mathbf{z}_{t-2} + \ldots + \mathbf{A}_{k-1}\mathbf{z}_{t-k+1} + \mathbf{A}_k\mathbf{z}_{t-k} + \boldsymbol{\mu} + \boldsymbol{\varepsilon}_t \qquad (7),$$

where

$$\mathbf{z}_t = \left[\Delta LPR \quad \Delta LER \quad \Delta LM1 \quad \Delta LMP \quad \Delta LCP \quad \Delta LPP \quad HCP\right]_t' \qquad (8)$$

with HCP denoting the proxy for uncertainty, and Δ the first-difference operator.

All the endogenous variables, except HCP, were used in first differences[6], since appropriate unit root tests suggested that the series were integrated of order one, except the uncertainty series which was found integrated of order zero[7] (Tables 2 and 3). The importance of the unit root properties of a series has to do with policy implications as well. If a series is stationary (or I(0); integrated of order zero), then a shock to the series only has a transitory effect, and the series returns to path it would have taken if the shock had not occurred. If a series is non-stationary (or I(1); integrated of order one), then the effect of a shock is permanent. Hence, and according to the results in Table 2, shocks to the examined agricultural price indices would have permanent effects (they are both I(1)), while shocks to the rates of the agricultural price indices would have transitory effects (they are found I(0); Table 3).

Next, in order to specify the optimal number of lagged terms in the VAR, we adopted a strategy based on Sims (1980) likelihood ratio (LR) test. The results indicated that a 14-lag VAR system was the appropriate specification. The adopted lag-structures were further checked for serial correlation, misspecification, normality and heteroscedasticity. Due to space limitations, we report only the diagnostics from the two agricultural price equations:

Dependent variable: ΔLPR

SC=19.043 (0.078), RESET=2.256 (0.133), NO=0.091 (0.956), HE=1.292 (0.256),

Dependent variable: ΔLPP

SC=18.550 (0.100), RESET=0.458 (0.498), NO=0.570 (0.752), HE=0.409 (0.522),

where SC is a serial correlation test, RESET is a functional form test, NO is a normality test, and HE is a heteroscedasticity test. Numbers in parentheses denote p-values.

Furthermore, in order to test for parameter constancy, we applied the CUSUM and CUSUMSQ tests that revealed stability of the parameter estimates.

Variance decomposition

In this section we proceed with the investigation of possible causal impacts of the involved macroeconomic variables on the examined agricultural price indices through variance decompositions. Following the methodology previously described, the moving average representation of the VAR system (7) can be used to depict the responses of all variables to shocks (i.e. innovations) in the residuals. Given the unrestricted VAR system, typical random shocks are positive residuals of one standard deviation unit in each equation.

The variance decomposition of the producer price index is reported in Table 4. More specifically, Table 4 reports the percentage of the variance of the k-month ahead forecast error of the variables that is attributable to each of the shocks for k=2, 6, 12, 24, 36, 48 and 60. We consider a 2-6 months ahead time horizon as short-run, a 12-24 months ahead time horizon as medium-run and a 36-60 months ahead horizon as long-run (Blanchard and Watson, 1986).

According to the results, the producer price index is explained basically by the path of money growth, the GDP growth, the inflation rate and the inflation uncertainty. The explanatory power of the above determinants appears significant in the medium and long-run time horizon. In particular, ΔLM1 explains 9.6-12% of the variation of ΔLPR, ΔLMP explains 7.4-11.5%, ΔLCP explains 9.6-9.9% and HCP explains 6.5-10.2%. ΔLER and ΔLPP contribute with rather insignificant percentages.

As it regards the index of purchase prices of the means of agricultural production, the variance decomposition results, reported in Table 5, indicate the followings: The index of producer prices contributes with significant percentages in all periods varying between 10.5-16.4%. Money growth, inflation and inflation uncertainty contribute significantly only after the sixth month with 13.4-15.6%, 10.4-16.3% and 9.7-15.2%, respectively.

Focusing on the impact of inflation uncertainty on the above examined agricultural price indices, we observed a significant contribution in explaining their variation during the medium and long-run time horizon. Thus, omission of the uncertainty will lead to biased estimation and spurious inferences regarding the explanatory power of the variables used as determinants for the agricultural price indices.

Conclusions

This study has investigated the determinants of agricultural price formation with particular emphasis on the detection of possible impacts caused by inflation uncertainty. The empirical analysis has used the GARCH technique to model the "uncertainty" variable, in conjunction with VAR modelling and variance decompositions to trace out possible causal relationships among the involved variables.

The analysis has been carried out over the period 1981:1 to 1998:2 using monthly data for two agricultural price indices, namely the index of producer prices and the index of purchase prices of the means of production, along with a set of basic macroeconomic variables such as the real effective exchange rate, the money supply, the consumer price index, and the index of manufacturing production.

In sum, the results have provided evidence of significant causal effects running from the macroeconomic environment towards the agricultural price indices. Furthermore, the results revealed a significant contribution of the inflation uncertainty on the formation of the examined price indices. In particular, inflation uncertainty explains near 15% of the variation of the above mentioned price indices, mainly in the medium and long-run time horizon.

Considering the above findings, we should stress the followings: First, it is clear that empirical efforts attempting to investigate the behaviour of agricultural prices, should hereafter consider inflation uncertainty as an additional determinant. The above suggestion is based on the empirical findings of our research which reveal that the uncertainty variable causes significantly the price variables. Second, the results further stress the fact that macroeconomic policy decisions are strongly reflected on the agricultural sector and thus they perform a very important role in any effort towards price stability in this sector.

Notes

1 The representation (4) is obtained by decomposing Σ^{-1} as $\Sigma^{-1}=P'P$.

2 Since monthly observations for Greek GDP are not available, we proxied this variable (as is usual in the empirical literature) with the monthly index of manufacturing production which is strongly correlated with the former variable.

3 Data are obtained from IFS (International Financial Statistics) and Eurostat (various issues). All empirical analysis employs RATS (version 4.20) computer package.

4 The use of ARIMA models, as a first step, in order to estimate the unpredict-

able part of the behaviour of a data series is quite common in the relevant literature. Next, these estimates are used to model the uncertainty variable through GARCH technique.

5 We employed the Akaike information criterion.

6 A common fact in the empirical analysis is that many macroeconomic series are characterised by nonstationarities, implying that the classical t and F-tests are not appropriate (Fuller, 1976), since they may lead to invalid results. Thus, as it is required in standard econometric analysis, the series under consideration are examined, first, for unit root nonstationarity employing the methods developed by Fuller (1976) and Dickey and Fuller (1981).

7 Since the set of endogenous variables consists of series of different order of integration, we use a VAR model. The consideration of an ECVAR model (Error-Correction VAR), in order to capture possible long-run information, is not justified.

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Appendix

Table 1. Test for ARCH effects

Variable	Lag length (q)	Test statistic $LM = TR^2$	p-value
$\hat{\varepsilon}_t$	1	5.2747	0.0216
	2	6.4865	0.0390
	3	6.7568	0.0800

Note:

The general form of the tested model is

$$\hat{\varepsilon}_t^2 = \alpha_0 + \alpha_1 \hat{\varepsilon}_{t-1}^2 + \alpha_2 \hat{\varepsilon}_{t-2}^2 + \ldots + \alpha_q \hat{\varepsilon}_{t-q}^2 + v_t .$$

With a sample of T residuals, under the null hypothesis of no ARCH errors, the test statistic TR^2 converges to a X_q^2 distribution (Enders, 1995).

Table 2. Augmented Dickey-Fuller (ADF) unit root tests (Levels)

Variables	Without trend			With trend		
	k	ADF	Q-statistic (Ljung-Box)	k	ADF	Q-statistic (Ljung-Box)
LER	2	-1.5558 (-2.8782)	24.8629 (0.0518)	3	-1.5932 (-3.4367)	22.6279 (0.0666)
LM1	12	-0.2738 (-2.8792)	46.6398 (0.0902)	12	-2.8773 (-3.4381)	47.2522 (0.0808)
LCP	12	-1.6765 (-2.8792)	19.4493 (0.3646)	12	-0.5774 (-3.4381)	19.5739 (0.3573)
LMP	12	-1.1971 (-2.8792)	20.4511 (0.3080)	12	-1.4598 (-3.4381)	20.3136 (0.3154)
LPR	12	-1.5463 (-2.8792)	10.0346 (0.0742)	12	-1.4484 (-3.4381)	9.3381 (0.0963)
LPP	1	-1.5460 (-2.8781)	26.1532 (0.0519)	1	-1.2906 (-3.4364)	25.9796 (0.0543)
HCP	0	-10.3834 (-2.8794)	19.9454 (0.2770)	0	-10.4003 (-3.4384)	20.2468 (0.2618)

Notes:

1) Dickey-Fuller (DF) and Augmented Dickey-Fuller (ADF) tests are based, respectively, on the following regressions:

$$\Delta y_t = \mu + \alpha t + \delta y_{t-1} + \varepsilon_t, \tag{A.1}$$

and

$$\Delta y_t = \mu + \alpha t + \delta y_{t-1} + \sum_{i=1}^{k} \delta_i \Delta y_{t-i} + \varepsilon_t, \tag{A.2}$$

where Δ is the first-difference operator and ε_t is a stationary random error. The null hypothesis is that y_t is a non-stationary series and it is rejected when δ is significantly negative. Regression (Notes on Table 2: Continued …) (A.2) is estimated only in the case where the errors from (A.1) are found to be serially correlated.

2) The numbers in columns labelled "k" report the lag length in (A.2), while the numbers in parentheses in columns labelled "ADF" are the critical values at 5% significance level (MacKinnon, 1991).

3) The numbers in parentheses in columns labelled "Q-statistic" are p-values for the Ljung-Box Q-statistic

$$Q = T(T+2)\sum_{j=1}^{m} \frac{r_j^2}{T-j}, \tag{A.3}$$

where r_j indicate the value of the autocorrelation function.

Table 3. Augmented Dickey-Fuller (ADF) unit root tests (First-differences)

Variables	Without trend			With trend		
	k	ADF	Q-statistic (Ljung-Box)	k	ADF	Q-statistic (Ljung-Box)
ΔLER	2	-8.4896 (-2.8783)	22.9078 (0.0861)	2	-8.5663 (-3.4367)	24.2393 (0.0611)
ΔLM1	11	-4.9744 (-2.8792)	46.5278 (0.1124)	11	-4.9598 (-3.4381)	46.6185 (0.1106)
ΔLCP	10	-3.1404 (-2.8791)	5.1454 (0.398)	10	-4.4646 (-3.4379)	6.0039 (0.306)
ΔLMP	11	-7.6177 (-2.8792)	20.7964 (0.2898)	11	-7.5905 (-3.4381)	20.6917 (0.2952)
ΔLPR	11	-3.5289 (-2.8792)	9.5455 (0.1451)	11	-3.8197 (-3.4381)	10.0552 (0.1223)
ΔLPP	0	-9.3836 (-2.8781)	25.4907 (0.0842)	0	-9.5217 (-3.4364)	26.1813 (0.0712)

Table 4. Variance decomposition of ΔLPR

Forecast horizon	Standard error	Percentage of variation of ΔLPR due to shocks in						
		ΔLPR	ΔLER	ΔLM1	ΔLMP	ΔLCP	ΔLPP	HCP
2	0.0138	95.179	0.299	1.063	0.003	0.347	2.808	0.297
6	0.0183	70.859	0.876	9.774	2.948	4.356	7.144	4.040
12	0.0207	57.736	2.348	9.587	7.387	9.596	6.862	6.481
24	0.0241	50.435	3.564	10.534	9.705	10.258	7.250	8.251
36	0.0257	46.740	4.540	11.313	10.861	9.993	7.130	9.419
48	0.0265	45.071	4.906	11.811	11.515	9.874	6.994	9.826
60	0.0270	44.158	5.126	12.002	11.542	9.925	7.061	10.183

Table 5. Variance decomposition of ΔLPP

Forecast horizon	Standard error	Percentage of variation of ΔLPP due to shocks in						
		ΔLPR	ΔLER	ΔLM1	ΔLMP	ΔLCP	ΔLPP	HCP
2	0.0053	12.718	6.699	0.181	1.069	8.115	71.215	0.003
6	0.0068	10.510	6.155	13.434	2.634	10.356	47.168	9.740
12	0.0084	12.641	10.346	11.666	2.329	16.257	33.946	12.812
24	0.0096	14.315	8.834	15.546	3.755	14.782	27.813	14.952
36	0.0104	15.777	8.970	15.568	3.942	13.976	26.790	14.975
48	0.0105	16.093	8.864	15.633	4.003	13.760	26.425	15.218
60	0.0106	16.392	8.936	15.570	4.047	13.728	26.205	15.118