Dynamic Linkages between Output Growth and Macroeconomic Volatility: Evidence using Greek Data

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Abstract

This paper provides empirical evidence regarding the causal links between macroeconomic uncertainty and output growth using Greek data. Uncertainty is considered in distinct components, namely the inflation uncertainty and the output growth uncertainty. The results reveal significant negative causal effects on output growth running from output growth uncertainty as well as from inflation uncertainty indirectly via the inflation rate.

JEL Codes: C33, C53, O52, E32

Key Words: Growth, Uncertainty, Cointegration, GARCH, Granger-causality

I. Introduction

It is widely accepted that the macroeconomic environment is characterized by uncertainty sourced from various types of macroeconomic activities which may lead agents to mistaken decisions and large transaction costs. This could decrease the rate of capital formation and consequently the economic growth. The direct or indirect impacts of macroeconomic uncertainty on growth is a topic of major importance and attracts the interest of the international theoretical and empirical literature.

Macroeconomic uncertainty is usually proxied by inflation and/or output volatility. Actually, both real uncertainty (arising from output volatility) and nominal (or inflation) uncertainty may affect the rate of output growth. However, there is no consensus among macroeconomists on the direction of these effects.

In this context, the present paper attempts to explore the existence of all possible causal effects among output growth, inflation and their respective volatilities using Greek data. Moreover, the analysis employs time series techniques in conjunction with GARCH modeling to quantify uncertainty and to investigate for the existence and direction of possible causal links. To our knowledge, there is no empirical evidence from Greece regarding the causal links between macroeconomic uncertainty and output growth. Besides, the entire set of all possible twelve relationships among the considered variables has been explored only for the case of Japan by Fountas *et al*. (2002).

The structure of the paper is organized as follows. Section 2, presents some theoretical issues regarding the relationships explored and the respective empirical literature. Section 3, provides a brief description of the methodological tools used in the context of the empirical analysis. Section 4, reports the empirical findings while last section provides some concluding remarks.

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II. Theoretical issues

The relationship between inflation and economic growth has been a matter of considerable ambiguity. Friedman (1977) suggests that inflation is the result of transforming resources to the government through seniorage. Bruno (1995), based on empirical results from a sample of 127 countries, reports evidence of a positive relationship between inflation and growth which turns to negative in country cases where inflation exeeds the 30%. Feldstein (1997) argues in favour of negative effect from inflation to capital accumulation which further justifies a negative relationship between inflation and growth.

In this direction, a brief exposition of the main approaches on this matter follows.

Inflation and inflation uncertainty

The impact of inflation on output growth may take place indirectly, via the inflation uncertainty channel. According to Friedman (1977), changes in inflation may induce erratic policy actions by the monetary authorities, a fact that may result in increased uncertainty regarding inflation in the future. Also, Ungar and Zilberfarb (1993), provide the necessary conditions for positive effects of inflation on its volatility.

Friedman's hypothesis finds empirical support in a number of studies i.e. Fountas (2001), Fountas *et al*. (2004a), Karanasos *et al*. (2004), Apergis (2004), Conrad and Karanasos (2005), Thornton (2008) and Conrad *et al.* (2010).

Possible effects from uncertainty on inflation have also been investigated with Cukierman and Meltzer (1986), to argue in favour of positive causal effects and Holland (1995) to support the existence of negative ones.

The empirical evidence regarding the impact of inflation uncertainty on inflation is rather mixed. Grier and Perry (1998), in their G7 study find evidence in favour of the Cukierman-Meltzer hypothesis for some countries and in favour of the Holland hypothesis for the rest. Moreover, Grier and Perry (2000) and Hwang (2001) find no empirical evidence for the impact of inflation uncertainty on inflation for the U.S. Finally, Grier *et al*. (2004) and Narayan *et al*. (2009), report evidence for a negative effect of inflation uncertainty on inflation for the US and China respectively.

Inflation uncertainty and output growth

According to Friedman's hypothesis, the increasing uncertainty about inflation distorts the effectiveness of the price mechanism in allocating resources efficiently, and leads to negative effects on output. Dotsey and Sarte (2000), in a model that allows for precautionary savings and risk aversion, show that increased inflation uncertainty can have a positive effect.

The empirical evidence on the impact of inflation uncertainty on output growth is rather mixed. Tommassi (1994), Grier and Perry (2000), Fountas (2001), Grier *et al*. (2004), Fountas *et al* (2006), Andreou *et al* (2008), Annicchiarico *et al* (2008) and Narayan *et al* (2009), find evidence of a negative effect. Lensink *et al* (1999) find only some evidence for a significant negative effect of inflation uncertainty on economic growth. In contrast, Coulson and Robins (1985), find evidence of a positive effect while Jansen (1989), reports no evidence. Fountas *et al*. (2004a) and Fountas and Karanasos (2007), also find mixed evidence by means of a two-step approach that combines the estimation of a GARCH model with the implementation of Granger-causality tests.

Considering the impact of output growth on inflation uncertainty, the existance of a short-run Phillips curve indicates that output growth affects inflation uncertainty positively. Bruner (1993), supports a negative association between them while Ungar and Zilberfarb (1993), argue that increased output growth may lead to higher inflation and to lower inflation uncertainty.

Output volatility and inflation

The effect of output growth uncertainty on inflation is addressed by Devereux (1989). Devereux's theory suggesting positive causal effects from output uncertainty towards inflation rate, has also been examined by Cukierman and Gerlach (2003). Theoretically, the opposite sign in causality is also possible. Actually, Taylor effect predicts a negative association between inflation uncertainty and output variability, which in combination with Cukierman-Meltzer hypothesis of a positive causal effect from inflation uncertainty on inflation implies that a negative causal impact from output uncertainty on inflation can be expected.

The available empirical evidence on the Devereux hypothesis is rather limited. Grier and Perry (2000) and Grier *et al*. (2004), find no evidence for US while Fountas and Karanasos (2007), using GARCH models for the G7, find evidence of positive causal effects of the output uncetainty on inflation only for Italy and the UK.

Output volatility and output growth

Regarding the relation between ouput volatility and output growth, the literature considers the following three approaches. The first, is traced back to Keynes (1936) and predicts a negative association between output variability and average growth. Keynes argued that entrepreneurs take into consideration the fluctuations in economic activity, *w*hen they estimate the return on their investment. The larger the output fluctuations, the higher the perceived riskiness of investment projects and, hence, the lower the demand for investment and output growth. Bernanke (1983), Pindyck (1991) and Ramey and Ramey (1991), also suggest the existence of a negative relationship between output volatility and growth.

The second approach predicts a positive effect of real uncertainty on output growth which is justified by Solow's (1956) neoclassical growth theory, according to which, more income variability (uncertainty) would lead to a higher savings rate for precautionary reasons, and hence to a higher equilibrium rate of economic growth. This argument has been advanced by Mirman (1971), while Black (1987) and Blackburn (1999), argue that high output volatility and high growth coexist. Furthermore, Blackburn and Pelloni (2004), predict that real shocks generate a positive correlation between output volatility and growth while nominal shocks produce a negative one.

According to the third approach, the determinants of the two variables may be different. Friedman (1968), Phelps (1968), and Lucas (1972), support the hypothesis of independence between output volatility and its growth rate.

The empirical evidence on the relation between output volatility and output growth is mixed. In their seminal paper Ramey and Ramey (1995), find evidence of a negative effect. Henry and Olekalns (2002), discover a negative link between volatility and real GDP growth for the U.S. Moreover, Asteriou and Price (2005), using panel data for a sample of 59 indusrial and developing countries find that output uncertainty reduces both investment and growth; also, Badinger (2010), for a sample of 128 countries, present evidence of a negative effect from volatility on growth . In contrast, Caporale and McKiernan (1996, 1998), using a GARCH-in-mean and an ARCH-M model for the UK and the US respectively, obtain evidence of a positive causal relationship. Based on cross-country data Kornendi and

Meguire (1985) or on pooled data (Grier and Tullock, 1989), support evidence of a positive association. Using multivariate GARCH models, Grier *et al*. (2004), Fountas and Karanasos (2007), Andreou *et al* (2008), Narayan *et al* (2009) and Lee (2010), find evidence in favour of a positive effect from uncertainty on growth for the US, G7 and China respectively.

In contrast with the previous findings, Speight (1999), Fountas *et al*. (2004b), and Fang and Miller (2008) find no link between output volatility and growth for the UK the Japan, and the US respectively. Annicchiarico *et al* (2008), found a rather ambiguous relationship between output growth and real variability.

More recently, Fountas and Karanasos (2006), Fountas et al. (2006), Fang and Miller (2009) and Fang et al (2008), consider the possibility of a two-way relationship between output growth and its volatility. In the first two studies, for the G3 and G7 cases, the authors find that that bi-directional causality between output growth and its volatility exists in two out of three and in two out of seven countries, respectively. Fang and Miller (2009), using an ARCH in mean model, find no effects running from output volatility on output growth or from output growth on its volatility for Japan. Fang et al (2008), focus on the appropriate specifications of the conditional volatility of real GDP growth rates for the G7 (excluding France) and considering the existence of possible structural shifts by means of the ICSS algorithm find that the conditional standard deviation has no statistical significance in all countries except Japan. The lagged growth rate of output produces significant negative and positive effects on the conditional variances in German and Japan respectively. No significant effects exist in Canada, Italy, the United Kingdom and the United States.

III. Methodological issues

Cointegration

The long-run relationship between a number of series can be looked at from the viewpoint of cointegration (Engle and Granger, 1987). Cointegration is a time series modelling technique developed to deal with non-stationary time series in a way that does not waste the valuable long-run information contained in the data. Moreover, the need to evaluate models which combine both short-run and long-run properties and which at the same time maintain stationarity in all of the variables, has prompted a reconsideration of the problem of regression using variables measured at their levels.

Let x(t) be a vector of n-component time series each integrated of order one. Then x(t) is said to be cointegrated CI(1, 1) if there exists a vector ϕ such that

$$s(t) = \phi' x(t)$$

is I(0). Stationarity of s(t) implies that the n variables of x(t) do not drift away from one another over the long-run, obeying thus an equilibrium relationship. If ϕ exists, it will not be unique, unless x(t) has only two elements. The Engle and Granger (1987) approach can deal with the possibility of only one linear combination of variables that is stationary. Advances in cointegration theory (Johansen and Juselius, 1990) have developed a maximum likelihood (ML) testing procedure on the number of cointegrating vectors, which also allows inferences on parameter restrictions. The ML method uses a vector autoregressive (VAR) model

$$\Delta x(t) = \sum_{i=1}^{q-1} \Pi_i \Delta x(t-i) + \Pi x(t-q) + \mu + v(t) \qquad (1)$$

where x(t) is a $n\times1$ vector of variables, $\prod$ is a $n\times n$ matrix of rank $r\leq n$, μ is a $n\times1$ vector of constant terms, v(t) is a $n\times1$ vector of residuals and Δ is the first difference operator. The testing procedure involves the hypothesis $H_2 : \Pi = \alpha \cdot \beta'$, where α and β are $n\times r$ matrices of loadings and eigenvectors respectively, that there are r cointegrating vectors β_1, β_2, … , β_r

which provide r stationary linear combinations $\beta' x(t-q)$. The likelihood ratio (LR) statistic for testing the above hypothesis

$$\lambda_{trace}(r) = -T \cdot \sum_{i=r+1}^{n} \ln(1-\lambda_i) \quad (2)$$

is a test that there are at most r cointegrating vectors versus the general alternative (trace), where λ_i corresponds to the n-r smaller eigenvalues. The n×r matrix of cointegrating vectors β can be obtained as the r, n-element eigenvectors corresponding to λ_i.

The LR test statistic for testing r against r+1 cointegrating vectors is given by

$$\lambda_{max}(r) = -T \cdot \ln(1-\lambda_{r+1}) \quad (3)$$

The above tests (2) and (3) are used to determine the significant eigenvalues and the corresponding number of eigenvectors. Moreover, the above tests are known as ‘cointegration test based on the trace of the stochastic matrix’ and ‘cointegration test based on maximal eigenvalue of the stochastic matrix’, respectively.

Modelling uncertainty -the GARCH methodology

Recent studies measure uncertainty as proposed in the work of Cukierman and Meltzer(1986) and Devereux(1989), where uncertainty is the variance of the stochastic or unpredictable component of a variable. In this direction, GARCH modelling has been adopted by the majority of the relevant empirical efforts. Actually, GARCH techniques estimate a model of the variance of unpredictable innovations in a variable, rather than simply calculating a variability. That is, GARCH models estimate a time-varying residual variance that corresponds well to the notion of uncertainty in Cukierman and Meltzer and Devereux.

The empirical analysis employs the GARCH technique to model the uncertainty variables. Chou (1988) 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) suggest that:

$$h^2(t) = \omega + \sum_{i=1}^{q} \alpha(i)\varepsilon^2(t-i) + \sum_{i=1}^{p} \beta(i)h^2(t-i) = \omega + \alpha(L)\varepsilon^2(t) + \beta(L)h^2(t) \quad (4)$$

with

$$0 < \alpha(L) + \beta(L) < 1 \quad (5)$$

Condition (5) ensures stationarity of the conditional volatility. Iterative maximum likelihood techniques are used to estimate the parameters of the GARCH model.

IV. Empirical analysis

Data

Quarterly data on industrial production (IP) and prices, measured by the consumer price index (CP), were obtained from the OECD Main Economic Indicators CD-ROM over the period 1966Q1-2007Q3. Both variables are used in natural logarithms and are denoted by LIP and LCP, respectively.

Integration analysis

Unit root nonstationarity of the involved variables is tested by using the methodology proposed by Dickey-Fuller (1981). Table 1 reports the unit root test results. The hypothesis of a unit root is rejected for all the series in first differences at the 5% significance level. Therefore, the above variables should be used in first difference form. Further, 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 has only a transitory effect, and the series returns to the path it would have 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.

Cointegration analysis

Since LIP and LCP are found I(1), the existence of a cointegration relationship between them is investigated by means of the Johansen ML cointegration technique. We present evidence (Table 2) in favour of a long-run equilibrium relationship between LIP and LCP.

In the context of our analysis the appropriate mean growth and inflation processes are identified through the Error Correction Vector Autoregressive (ECVAR) system presented below:

$$\Delta LIP_t = \delta_1 + \sum_{i=1}^{p} \alpha_{1i} \Delta LIP_{t-i} + \sum_{i=1}^{p} \beta_{1i} \Delta LCP_{t-i} + \gamma_{11} DUMIP + \gamma_{12} DUMCP + \lambda_1 ECT_{t-1} + u_{\Delta LIP} \quad (6)$$

$$\Delta LCP_t = \delta_2 + \sum_{i=1}^{p} \alpha_{2i} \Delta LIP_{t-i} + \sum_{i=1}^{p} \beta_{2i} \Delta LCP_{t-i} + \gamma_{21} DUMIP + \gamma_{22} DUMCP + \lambda_2 ECT_{t-1} + u_{\Delta LCP} \quad (7)$$

where $u_{\Delta LIP}$ and $u_{\Delta LCP}$ are the output and inflation shocks, respectively and ECT is the Error Correction Term. DUMIP and DUMCP are dummy variables to account for outliers in the LIP and LCP series respectively.

The associated error correction estimates are reported in Table 3, while in Table 4 we present the distributional properties of the obtained residuals series, with regard to the skewness and kurtosis measures. As shown in the last table the normality hypothesis is rejected in both cases. Besides, the diagnostics suggest that both the growth and inflation equations suffer from ARCH effects (Table 4) and hence the hypothesis of a time-varying conditional variance is applied.

GARCH estimates for growth and inflation

A GARCH(1, 1) model, as determined by the Akaike and Schwarz criteria, is estimated to proxy the output growth volatility. The same GARCH specification is chosen to model the volatility of inflation. The estimates of both GARCH equations are presented in Table 5. It should be noted that in both specifications the sum of the estimated GARCH parameters is 0.921 and 0.948, respectively, implying that current information remains very important for the forecasts of the conditional variances for long horizons. The estimated volatilities for output growth and inflation are denoted by UIP and UCP, respectively.

Causality effects

Having estimated the uncertainty variables we next proceed with the estimation of a VAR specification which involves output growth, inflation as well as the estimated volatilities for output growth and inflation. Besides, two dummy variables DIP and DCP were also included to account for outliers. Actually, DIP takes the value 1 in 2002, 2nd quarter while DCP in

2002, 2nd and 3rd quarter. The selection of the lag-length for the estimated VAR was based on Sims (1980) Likelihood Ratio (LR) tests and was determined equal to 2. Next, we continued with testing for Granger-causality effects among the involved variables. The results are reported in Table 6 and, for the shake of saving space, we report only the block exogeneity Wald tests and the respective probability values along with the signs of the net effect. More particularly, the results suggest that:

- Growth is negatively Granger-caused primarily by its volatility (*p*-value<0.01), while a negative though weaker effect runs from the inflation rate (*p*-value ≈ 0.1). Our finding is in line with Bernanke's and Pindyck's hypotheses. Similar empirical findings are reported by Apergis (2004).
- Inflation rate is found to be negatively Granger-caused by output growth (*p*-value<0.05) as well as by both measures of volatility, i.e. the volatility of output growth reports a p-value of less than 0.05, while inflation volatility reports a p-value less than 0.01. The negative effect of output volatility on inflation supports the Cukierman-Meltzer hypothesis. Moreover, the negative effect of inflation uncertainty on inflation provides evidence in favour of Holland's hypothesis.
- Inflation volatility is found to be negatively Granger-caused only by the inflation rate (p-value < 0.01).
- Finally, the output growth volatility is found to be positively affected only by output growth (*p*-value<0.01). Fountas (2006), reports mixed results from the G3.

V. Concluding remarks

This paper attempted to investigate any causal linkages among output growth, inflation and the volatility of output growth and inflation using Greek data.

The empirical analysis used ECVAR modeling in conjunction with GARCH technique to quantify the volatility series of output growth and inflation. Next, the analysis applied Granger-type tests to detect significant causal effects running among the examined variables.

The main conclusion drawn from the above findings, briefly suggest that:

- Inflation significantly causes its volatility measure and to a weaker degree output growth.
- Inflation volatility Granger-causes inflation.
- Output growth volatility exhibits strong causal impacts running towards output growth and inflation.
- Growth is found to significantly Granger-cause its volatility and the inflation rate.

In sum, the results highlight the negative effects of macroeconomic uncertainty on growth and argue for stronger efforts from the economic authorities, towards a stable macroeconomic environment if aiming at higher rates of economic growth.

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Appendix

Table 1. Augmented Dickey-Fuller (ADF) Unit Root Tests

Variables	Levels	
	Without Trend	With Trend
LIP (2)	-2.858	-2.827
LCP (2)	-1.484	0.558
Variables	First Differences	
	Without Trend	With Trend
ΔLIP (1)	-13.278	-13.483
ΔLCP (1)	-11.677	-11.877

Notes:

1) The number of lags (indicating in the parentheses in the first column), used for the calculation of the ADF statistics, is based on the Schwarz Bayesian Criterion (SBC) provided by Microfit.
2) The critical values from Fuller (1976), for the respective degrees of freedom and the 5% level of significance, are -2.880 and -3.439 for the non-trended and trended case, respectively.

Table 2. Cointegration Tests

List of variables included in the cointegrating vector: LIP, LCP List of I(0) variables included in the VAR: DUMIP, DUMCP				
Cointegration LR Test Based on Maximal Eigenvalue of the Stochastic Matrix				
Null	Alternative	Statistic	95% Crit. Value	90% Crit. Value
r = 0	r = 1	88.162	11.030	9.280
r ≤ 1	r = 2	2.580	4.160	3.040
Cointegration LR Test Based on Trace of the Stochastic Matrix				
Null	Alternative	Statistic	95% Crit. Value	90% Crit. Value
r = 0	r ≥ 1	90.742	12.360	10.250
r ≤ 1	r = 2	2.580	4.160	3.040

Table 3. Error Correction Models

Dependent variable: ΔLIP

Regressor	Coefficient	St. Error	T-Ratio	Prob.
ΔLIP(-1)	-0.82621	0.056225	-14.6948	0.000
ΔLIP(-2)	-0.61410	0.059537	10.3146	0.000
ΔLIP(-3)	-0.43185	0.061419	-7.0313	0.000
ΔLIP(-4)	-0.28807	0.058508	-4.9236	0.000
ΔLIP(-5)	-0.13722	0.052469	-2.6152	0.010
ΔLCP(-1)	-0.11406	0.071221	-1.6015	0.111
ΔLCP(-2)	-0.08994	0.064150	-1.4020	0.163
ΔLCP(-3)	-0.18138	0.065489	-2.7697	0.006
ΔLCP(-4)	-0.10050	0.063940	-1.5717	0.118
ΔLCP(-5)	-0.12880	0.064625	-1.9931	0.048
ECT(-1)	-0.38407	0.049230	-7.8015	0.000
DUMIP	0.44624	0.030361	14.6981	0.000
DUMCP	0.02646	0.038760	0.68269	0.496

ECT = -0.060216·LIP + 0.059022·LCP

$R^2 = 0.695$ $\bar{R}^2 = 0.670$ $F\text{-stat} = 28.122\,[0.000]$

Dependent variable: ΔLCP

Regressor	Coefficient	St. Error	T-Ratio	Prob.
ΔLIP(-1)	-0.080261	0.058923	-1.3621	0.175
ΔLIP(-2)	-0.072351	0.062394	-1.1596	0.248
ΔLIP(-3)	0.024720	0.064366	0.3841	0.701
ΔLIP(-4)	-0.051219	0.061316	-0.8353	0.405
ΔLIP(-5)	-0.029162	0.054987	-0.5304	0.597
ΔLCP(-1)	-0.20986	0.074638	-2.8118	0.006
ΔLCP(-2)	-0.21603	0.067228	-3.2134	0.002
ΔLCP(-3)	-0.009388	0.068631	-0.1368	0.891
ΔLCP(-4)	0.092147	0.067008	1.3752	0.171
ΔLCP(-5)	0.051409	0.067726	0.7591	0.449
ECT(-1)	-0.28491	0.051592	-5.5224	0.000
DUMIP	0.024396	0.031817	0.7668	0.444
DUMCP	0.32895	0.040620	8.0982	0.000

ECT = -0.060216·LIP + 0.059022·LCP

$R^2 = 0.362$ $\bar{R}^2 = 0.311$ $F\text{-stat} = 7.011\,[0.000]$

Table 4. Distributional Properties of the Residuals from the Error Correction Models and ARCH test

Variables	Skewness	Kurtosis-3	ARCH test: Lag length (q)	ARCH test: Test statistic LM=TR^2	ARCH test: p-value
$\hat{u}_{\Delta LIP}$	-1.277	6.778	2	33.262	0.000
			4	32.929	0.000
$\hat{u}_{\Delta LCP}$	-3.963	29.827	2	7.590	0.022
			4	7.970	0.093

Note: The general form of the tested model is

$$\hat{u}_t^2 = a_0 + a_1\hat{u}_{t-1}^2 + a_2\hat{u}_{t-2}^2 + \ldots + a_q\hat{u}_{t-q}^2 + v_t .$$

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 5. GARCH Models

Variable	Order (p, q)	$h_t^2 = \alpha_0 + \sum_{i=1}^{q}\alpha_i u_{t-i}^2 + \sum_{j=1}^{p}\beta_j h_{t-j}^2$
UIP	(1, 1)	$h_t^2 = \underset{(0.000078)}{0.000441} + \underset{(0.263017)}{0.818630}\,u_{t-1}^2 + \underset{(0.050397)}{0.101920}\,h_{t-1}^2$
UCP	(1, 1)	$h_t^2 = \underset{(0.000017)}{0.000041} + \underset{(0.287041)}{0.855135}\,u_{t-1}^2 + \underset{(0.040724)}{0.092598}\,h_{t-1}^2$

Note: The numbers in parentheses indicate the asymptotic standard errors.

Table 6. VAR Granger Causality/Block Exogeneity Wald Tests

Dependent variable ΔLIP					
Excluded	Hypotheses tested	Chi-sq	df	Prob.	Sign of the effect
ΔLCP(t-i)	Lagged ΔLCP do not Granger-cause ΔLIP	4.561	2	0.102	–
UCP(t-i)	Lagged UCP do not Granger-cause ΔLIP	3.946	2	0.139	–
UIP(t-i)	Lagged UIP do not Granger-cause ΔLIP	109.7	2	0.000	–
$R^2 = 0.734$ $\bar{R}^2 = 0.716$ F - stat = 40.492 [0.000]					

Dependent variable ΔLCP					
Excluded	Hypotheses tested	Chi-sq	df	Prob.	Sign of the effect
ΔLIP(t-i)	Lagged ΔLIP do not Granger-cause ΔLCP	6.079	2	0.048	–
UCP(t-i)	Lagged UCP do not Granger-cause ΔLCP	45.08	2	0.000	–
UIP(t-i)	Lagged UIP do not Granger-cause ΔLCP	7.533	2	0.023	–
$R^2 = 0.484$ $\overline{R}^2 = 0.449$ F - stat = 13.799 [0.000]					
Dependent variable UCP					
Excluded	Hypotheses tested	Chi-sq	df	Prob.	Sign of the effect
ΔLIP(t-i)	Lagged ΔLIP do not Granger-cause UCP	0.474	2	0.789	–
ΔLCP(t-i)	Lagged ΔLCP do not Granger-cause UCP	180.7	2	0.000	–
UIP(t-i)	Lagged UIP do not Granger-cause UCP	0.152	2	0.927	–
$R^2 = 0.617$ $\overline{R}^2 = 0.591$ F - stat = 23.674 [0.000]					
Dependent variable UIP					
Excluded	Hypotheses tested	Chi-sq	df	Prob.	Sign of the effect
ΔLIP(t-i)	Lagged ΔLIP do not Granger-cause UIP	433.6	2	0.000	+
ΔLCP(t-i)	Lagged ΔLCP do not Granger-cause UIP	0.347	2	0.841	+
UCP(t-i)	Lagged UCP do not Granger-cause UIP	0.487	2	0.784	+
$R^2 = 0.785$ $\overline{R}^2 = 0.770$ F - stat = 53.683 [0.000]					