STOCK RETURNS AND INFLATION: THE IMPACT OF INFLATION TARGETING

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Abstract

This paper investigates the dynamic interaction between inflation and stock returns in four inflation targeting countries. We find that following the introduction of formal targets, inflation persistence and the magnitude of volatility spillovers between inflation and stock returns have been reduced.

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1 Introduction

Ever since the early 1990s, some countries adopted inflation targeting as a new monetary policy strategy. So far, these regimes are claimed to be a success since inflation persistence declined, inflation rates became lower and less volatile, and inflation expectations were anchored at low levels[1].

Furthermore, it is expected that a regime consistent with low and stable inflation tends, as a by-product, to promote financial market stability (Bordo and Wheelock, 1998). Given that stock returns measure nominal payoffs, "when inflation of goods' prices is uncertain, the volatility of nominal asset returns should reflect inflation volatility" (Schwert, 1989, p.1124), hence lower inflation variability should exert a calming effect on stock market volatility. This view draws support from a theoretical literature that emphasizes the importance of informational asymmetries in credit markets and shows how higher inflation adversely affects credit market frictions with negative consequences for financial sector performance (see e.g. Huybens and Smith, 1999)[2].

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[1]See Kontonikas (2004) for UK evidence.

[2]Moreover, a number of empirical studies finds a significant relationship between high, sustained rates of inflation and financial crises; see among others, Boyd et al. (2001).

Despite the success in controlling inflation, during the late 1990s-early 2000 international capital markets witnessed large swings in stock prices generating concern among academics and policy-makers about the impact of stock price movements on the real economy and the broader consequences of inflation targeting. Kontonikas and Ioannidis (2005) show that an inflation targeting regime with strong interest rate reaction to inflation should lead to lower stock market volatility. On the other hand, the New Environment Hypothesis (NEH, see e.g. Borio and Lowe, 2002) claims that in an economic environment characterised by low inflation, unsustainable financial imbalances may build up since investors, exhibiting money illusion, consider that the real cost of capital has been significantly reduced. Exponents of the NEH argue that price stability is not a sufficient condition for stock market stabilisation and, in fact, the absence of obvious inflationary pressures adds to the sustainability of the stock market booms, by removing the threat of interest rate increases.

The novelty of this paper consists in jointly modelling the dynamic interaction between inflation and stock returns using a VAR-GARCH specification that allows for the impact of inflation targeting to be explicitly taken into account. In the debate between the standard view that emphasizes the stabilising effects of inflation targeting and the NEH, important answers lie in the statistical identification of the volatility spillovers between inflation and stock returns. A decrease in the magnitude of volatility spillovers from inflation to stock returns, following the introduction of inflation targeting, would imply further support for the benefits of this monetary policy framework.

2 Data

Our data comprises of four OECD countries (Australia, Canada, Sweden, United Kingdom) that have announced an inflation target[3]. We measure nominal stock returns , r_t, and inflation, π_t, as the first difference of the natural logarithm of the stock price index (SPI) and the consumer price index (CPI), respectively: $r_t = 100 * (\ln SPI_t - \ln SPI_{t-1})$, $\pi_t = 100 * (\ln CPI_t - \ln CPI_{t-1})$[4].

3 Econometric model and results

Engle and Kroner (1995) propose a class of multivariate GARCH models, the BEKK, with the special property of ensuring a positive definite conditional variance matrix. Following Engle and Kroner (1995), we model the joint processes governing stock returns, r_t, and inflation, π_t, using the following bivariate VAR-GARCH(1,1) specification:

$$\mathbf{x}_t = \boldsymbol{\gamma} + \boldsymbol{\beta}\mathbf{x}_{t-1} + \mathbf{u}_t \tag{1}$$

where $\mathbf{x}_t = (\pi_t, r_t)'$, and the residual vector $\mathbf{u}_t = (e_{1,t}, e_{2,t})'$ follows a bivariate Normal distribution, with its corresponding conditional variance covariance matrix given by:

[3] Inflation targeting commenced on the following dates: Australia 1994-Q3; Canada 1991-M2; Sweden 1995-M1; United Kingdom 1992-M10.

[4] For Canada, Sweden, and the United Kingdom we use monthly data over the period 1980:12-2004:4. For Australia, where only quarterly data are available, the sample is 1980:Q4-2004:Q4.

$$H_t = \begin{bmatrix} h_{1t} & h_{12t} \\ h_{12t} & h_{2t} \end{bmatrix} \tag{2}$$

The parameter vector of the mean equation (1) is defined by the constant $\boldsymbol{\gamma} = (\boldsymbol{\gamma}_1, \boldsymbol{\gamma}_2)'$ and the matrix of coefficients $\boldsymbol{\beta} = (\beta_{11}, \beta_{12} \mid \beta_{21}, \beta_{22})$, while the parameter matrices for the variance equation (2) are defined as C, which is restricted to be upper triangular, and two unrestricted matrices A and G. In order to account for the effects of inflation targeting on the time series structure of inflation and stock returns and the volatility transmission mechanism, we include a dummy variable (denoted by a star) for the autoregressive and cross-effects parameters in the conditional mean as well as the cross-effects in the conditional variance[5]. The dummy is equal to zero prior to the adoption of inflation targeting and one thereafter. Hence, the first and second moments will take the forms given by Eq. (3) and (4) respectively:

$$\begin{bmatrix} \pi_t \\ r_t \end{bmatrix} = \begin{bmatrix} \boldsymbol{\gamma}_1 \\ \boldsymbol{\gamma}_2 \end{bmatrix} + \begin{bmatrix} (\boldsymbol{\beta}_{11} + \boldsymbol{\beta}_{11}^*) & (\boldsymbol{\beta}_{12} + \boldsymbol{\beta}_{12}^*) \\ (\boldsymbol{\beta}_{21} + \boldsymbol{\beta}_{21}^*) & (\boldsymbol{\beta}_{22} + \boldsymbol{\beta}_{22}^*) \end{bmatrix} \begin{bmatrix} \pi_{t-1} \\ r_{t-1} \end{bmatrix} + \begin{bmatrix} e_{1,t} \\ e_{2,t} \end{bmatrix} \tag{3}$$

$$H_t = C'C + \begin{bmatrix} g_{11} & (g_{12} + g_{12}^*) \\ (g_{21} + g_{21}^*) & g_{22} \end{bmatrix}' H_{t-1} \begin{bmatrix} g_{11} & (g_{12} + g_{12}^*) \\ (g_{21} + g_{21}^*) & g_{22} \end{bmatrix}$$

$$+ \begin{bmatrix} a_{11} & (a_{12} + a_{12}^*) \\ (a_{21} + a_{21}^*) & a_{22} \end{bmatrix}' \begin{bmatrix} e_{1,t-1}^2 & e_{1,t-1}e_{2,t-1}' \\ e_{1,t-1}e_{2,t-1}' & e_{2,t-1}^2 \end{bmatrix} \begin{bmatrix} a_{11} & (a_{12} + a_{12}^*) \\ (a_{21} + a_{21}^*) & a_{22} \end{bmatrix} \tag{4}$$

Equation (4) models the dynamic process of H_t as a linear function of its own past values H_{t-1} and past values of the squared innovations $\left(e_{1,t-1}^2, e_{2,t-1}^2\right)$, in both cases allowing for own and cross influences in the conditional variance. This specification (with the unrestricted matrices A and G) allows the conditional variances and covariances of inflation and stock returns to affect each other, thereby enabling one to test the null hypothesis of no volatility spillover effects in one or even both directions.

[Table 1]

The estimated VAR-GARCH(1,1) model with associated robust standard errors (see Bollerslev and Wooldridge, 1992) and likelihood function values are presented in Table 1. Tests for causality-in-variance are carried out for each model, alternatively constraining the matrices A and/or G to be upper triangular or lower triangular, thereby allowing for causality only in one direction at a one time. Hypothesis testing is performed using a likelihood ratio test (LR). Appropriate empirical critical values are computed by means of bootstrapping[6]. The null hypothesis of unidirectional cross-market spillovers is rejected for all sample countries. Therefore, an unrestricted specification that allows for bi-directional spillovers is

[5] Caporale and Spagnolo (2003) employ a similar VAR-GARCH specification to investigate the real effects of financial crises.

[6] We find that the LR test has finite-sample Type-I error probabilities that do not differ significantly from the nominal value of 0.05, with empirical rejection frequencies reasonably close to the corresponding asymptotic ones.

preferred. Furthermore, Ljung-Box statistics show no sign of remaining serial correlation and heteroskedasticity in the standardized and the squared standardized residuals of inflation and stock returns.

Estimates of the conditional mean indicate that over the full sample, the inflation persistence coefficient ($\boldsymbol{\beta}_{11}$) is positive and statistically significant in all cases. Canada exhibits the greatest degree of inflation persistence, followed by Australia, UK, and Sweden. The coefficient of the dummy variable that is associated with inflation persistence ($\boldsymbol{\beta}_{11}^{*}$) is negative and statistically significant in all cases indicating that during the targeting period inflation is less persistent ($\boldsymbol{\beta}_{11} + \boldsymbol{\beta}_{11}^{*} < \boldsymbol{\beta}_{11}$).

Contrary to the Efficient Markets Hypothesis prediction of no time-series dependence in stock returns, the full sample estimate for the autoregressive component of stock returns ($\boldsymbol{\beta}_{22}$) is statistically significant for Sweden. The estimated $\boldsymbol{\beta}_{22}$ coefficient is positive, supporting 'momentum' type of strategies since positive returns are likely to be followed by further price increases. It appears that the underlying stock market dynamics do not change over the two sub-periods (before and after targeting) since $\boldsymbol{\beta}_{22}^{*}$ is statistically insignificant in all cases.

Considering the conditional mean cross-effects running from past inflation on current stock returns, the estimated coefficient (β_{21}) is statistically significant, only for Australia with its value (2.6) indicating that equity market investment in Australia more than compensates for increases in consumer prices. However, the estimated value of $\boldsymbol{\beta}_{21}^{*}$ suggests that during the targeting period the inflation premium is almost eliminated. Finally, only in the case of Sweden, post-targeting, there appears to be a statistically significant conditional mean cross-effect running from lagged stock returns to current inflation ($\boldsymbol{\beta}_{12}^{*} = -0.02$)[7].

Moving on to the conditional variance estimates, the parameters in A reveal whether the conditional variances of inflation and stock returns are correlated with past squared deviations from their respective means. Focusing upon the parameters a_{21} and a_{12}, that depict how the past squared errors of one variable affects the current conditional volatility of the other variable, they are significantly different from zero only in the case of Sweden. The magnitude of cross-series spillovers of shocks onto volatility is substantially greater from inflation to stock returns, since: $|a_{12}| > |a_{21}|$. The parameters in G describe how the current levels of conditional volatilities are correlated with past conditional volatilities. The estimates of the off-diagonal elements (g_{12} and g_{21}) show that in all sample countries there are statistically significant bi-directional spillovers between stock market and inflation volatility. Again, the magnitude of spillovers is substantially greater from inflation to stock returns, than vice versa, since: $|g_{12}| > |g_{21}|$. Our results differ from earlier findings of Schwert (1989) for the US market in showing that the causality link is stronger from macroeconomic to stock market volatility.

[Table 2]

In order to evaluate the impact of inflation targeting on the volatility transmission between inflation and stock returns we employ the following rule: if the absolute value of the relevant coefficient ($a_{12}, a_{21}, g_{12}, g_{21}$) is greater (smaller) for the full sample than for the targeting period, it implies that there has been a decrease (increase) in the magnitude of volatility

[7] Filardo (2000) uses US data and reports a negative correlation between lagged stock returns and current inflation.

spillovers during targeting. If instead, the absolute value is the same across the two periods then 'no change' is suggested. The summary of the results in Table 2 suggests that while there have been no changes in the magnitude of cross-series spillovers from past shocks onto current volatilities, major shifts are observed in the magnitude of spillovers from past onto current volatilities. In particular, following the introduction of targeting there has been a decrease in the magnitude of volatility spillovers from inflation to stock returns in three out of the four countries (Australia, Canada, and United Kingdom): $|g_{12}| > |g_{12} + g_{12}^*|$. This is in line with the traditional view that a monetary policy framework that focuses on price stability exerts a calming effect on stock market volatility. Only in Sweden the introduction of targeting appears to have increased the magnitude of volatility spillovers from inflation to stock returns thereby providing some support for the NEH. Considering whether the magnitude of volatility spillovers from stock returns to inflation has been affected by targeting, we can see that in all cases there has been a decrease: $|g_{21}| > |g_{21} + g_{21}^*|$. Thus, inflation targeting seems to have generated a self-reinforcing volatility calming mechanism. That is, lower inflation volatility translates to smaller spillover to stock market volatility, which in turn produces smaller spillover to inflation variance.

4 Conclusions

This paper investigates how the introduction of inflation targeting affected the dynamic interaction between inflation and stock returns within a sample of four countries which have adopted an inflation targeting policy. The effect of targeting has been modelled by including a dummy variable in the conditional mean and variance specification of inflation and stock returns within a bivariate VAR-GARCH framework. This extension and the focus on the second moments differentiate this study from other contributions to the literature on linkages between stock returns and inflation. Our empirical results shed some further light in the debate about the relative benefits of inflation targeting. Focusing on the second moments, we identify major changes in the spillovers from past onto current volatilities following the introduction of inflation targeting. Specifically, the magnitude of volatility spillovers between inflation and stock returns has been lower thereby supporting the idea that a monetary policy regime that aims for price stabilization exerts a self-reinforcing calming effect on stock market volatility. Hence, higher financial stability may be classified among the benefits of explicit inflation targeting. However, whether monetary authorities might be able to achieve financial stability via inflation targeting is an issue which can only be addressed in the context of a structural model. This is beyond the scope of the present article, but constitutes an interesting topic for future research.

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TABLE 1

Stock Market Returns and Inflation Causality-in-Mean and Volatility Spillovers								
Param.	Australia		Canada		Sweden		United Kingdom	
γ_1	0.522	(0.101)	0.141	(0.017)	0.186	(0.029)	0.236	(0.024)
γ_2	1.387	(0.629)	0.518	(0.249)	0.991	(0.319)	1.117	(0.375)
β_{11}	0.612	(0.079)	0.658	(0.061)	0.341	(0.061)	0.423	(0.073)
β_{11}^*	-0.339	(0.121)	-0.646	(0.076)	-0.251	(0.081)	-0.386	(0.078)
β_{12}	0.003	(0.011)	0.003	(0.003)	0.008	(0.006)	-0.005	(0.006)
β_{12}^*	-0.018	(0.021)	0.001	(0.005)	-0.021	(0.009)	0.006	(0.009)
β_{21}	2.597	(1.176)	-0.216	(0.596)	0.027	(0.526)	-0.261	(0.607)
β_{21}^*	-2.410	(1.198)	0.911	(0.902)	-1.491	(1.169)	-1.032	(0.884)
β_{22}	-0.188	(0.191)	0.138	(0.102)	0.272	(0.079)	-0.084	(0.057)
β_{22}^*	0.163	(0.212)	-0.029	(0.105)	0.067	(0.103)	0.032	(0.113)
c_{11}	0.001	(0.909)	0.001	(0.866)	0.007	(0.076)	0.003	(0.817)
c_{12}	1.108	(0.563)	1.716	(0.891)	3.789	(7.001)	2.889	(0.441)
c_{22}	0.552	(0.176)	0.171	(0.045)	1.255	(9.954)	0.115	(0.033)
a_{11}	-0.229	(0.112)	-0.761	(0.124)	0.056	(0.150)	-0.804	(0.094)
a_{12}	-1.381	(1.392)	-1.757	(1.455)	2.203	(1.003)	0.246	(2.334)
a_{12}^*	0.114	(1.588)	3.121	(2.361)	0.739	(1.842)	0.614	(3.322)
a_{21}	-0.014	(0.018)	-0.005	(0.009)	-0.031	(0.014)	-0.006	(0.005)
a_{21}^*	-0.017	(0.023)	0.015	(0.009)	0.031	(0.019)	0.005	(0.011)
a_{22}	0.772	(0.274)	-0.346	(0.106)	0.443	(0.096)	0.593	(0.104)
g_{11}	0.426	(0.215)	0.529	(0.172)	-0.508	(0.189)	0.021	(0.059)
g_{12}	5.112	(1.748)	-5.223	(0.375)	-3.288	(1.276)	5.147	(1.543)
g_{12}^*	-7.975	(3.190)	1.508	(0.252)	9.229	(2.006)	-5.943	(3.036)
g_{21}	-0.036	(0.032)	0.018	(0.001)	0.101	(0.017)	0.055	(0.017)
g_{21}^*	0.036	(0.041)	-0.014	(0.001)	-0.166	(0.024)	-0.101	(0.037)
g_{22}	0.544	(0.181)	-0.821	(0.156)	-0.121	(0.109)	0.324	(0.114)
Log-Lik		-251.82		-398.47		-575.07		-503.81
LR test		[0.039]		[0.045]		[0.042]		[0.043]
C. V.		(0.047)		(0.052)		(0.048)		(0.049)
LB_π		2.45		1.17		2.81		3.87
LB_π^2		4.15		3.98		4.16		3.05
LB_r		1.09		3.16		2.22		4.11
LB_r^2		4.23		2.34		3.12		3.21

Note: Quasi-maximum likelihood standard errors based on Bollerslev and Wooldridge (1992) are reported in brackets. LB and LB^2 are respectively the Ljung-Box (1978) test on the significance of autocorrelations of 5 lags in the standardized and squared standardized residuals. The covariance stationary condition is satisfied by all the estimated models, all the eigenvalues of $A \otimes A + G \otimes G$ being less than one in modulus. LR tests [p-value] and corresponding bootstrapped critical values (C.V.) are respectively reported in square and round brackets.

Table 2

Impact of Inflation Targeting on Volatility Spillovers				
Parameter	Australia	Canada	Sweden	United Kingdom
$\boldsymbol{a}_{12}$	Insignificant	Insignificant	no-change	Insignificant
$\boldsymbol{a}_{21}$	Insignificant	Insignificant	no-change	Insignificant
$\boldsymbol{g}_{12}$	Decrease	Decrease	Increase	Decrease
$\boldsymbol{g}_{21}$	Insignificant	Decrease	Decrease	Decrease

Note: If $|\theta_{ij}| < |\theta_{ij} + \theta^*_{ij}| \Rightarrow$ increase; if $|\theta_{ij}| > |\theta_{ij} + \theta^*_{ij}| \Rightarrow$ decrease; if $|\theta_{ij}| = |\theta_{ij} + \theta^*_{ij}| \Rightarrow$ no change, where $\theta = (\alpha,\ g)$. If the estimated coefficient is statistically insignificant at the 5% level, its value is taken as zero.