Volatility spillovers pre and post inflation targeting period in Spain: a VAR-DBEKK-MGARCH approach

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Abstract. In this research project we theoretically characterize a diagon al DBEEK within a VAR-MGARCH setting to estimate the dynamic causal effects on volatility between the inflation rate, the unemployment rate, consumer confidence and the policy rate before and after the Spain's entry into the Euroarea. Inflation volatility has decreased once an inflation target has become entrenched, becoming past volatility more restrictive. Moreover, after January 2002, the long-term effect of inflation on the volatility of unemployment, consumer confidence and the policy rate has been reduced. Now there is a more restrictive influence of past volatility on the variables studied. Spain's loss of monetary power has led to lower levels of volatility spillovers between variables, but to a greater effect of the past on present volatility in the short-run.

Keywords: Diagonal BEKK · Inflation targeting · GARCH model · Volatility spillovers.

1 Introduction

Volatility is a key element in the operation and predictability of any variable or natural process occurring around us. Regarding the area that concerns us-monetary policy-, volatility arouses interest not only within the investment, academic or political community, but also among the general public. As it is well known, in 1990, a large number of countries adopted an explicit policy of determining an inflation target (IT), in order to try to anchor economic agents' expectations around acceptable ranges of inflation levels, based on their confidence in central banks. This may have been a turning point in the variability rates seen so far. That is, over the same period, there seems to be evidence that volatility fell across the board in those countries that explicitly adopted targets relative to those that did not. According to Cecchetti and Ehrmann (2000), over the last decade (1990-2000), aversion to inflation variability increased in all major world economies, regardless of whether they operated with inflation targets or not. It is obvious, and furthermore demonstrated both theoretically and empirically, for example in Kontonikas (2004), that high unpredictable volatility increases inflation uncertainty and induces large economic costs that distort intra- and inter-temporal decisions, redistributing wealth from those who are debtors to those who are creditors, and reducing the effectiveness of relative prices in adjusting economic actions. Following the ideas of Kontonikas (2004) and referring to arguments of economists on this subject, Friedman (1977) established that there was a positive correlation between the level of inflation and the uncertainty around it, showing that high levels of inflation are associated with high levels of uncertainty and lower GDP growth. On the other hand, and following Kontonikas' (2004) line of argument, Ball (1992) took Friedman's assertion into account and brought it into the realm of an asymmetric information game between the public and the policymaker. This led to what is known as the Friedman-Ball prediction, and states that policies aimed at reducing average inflation will lead to a reduction in inflation uncertainty. Inflation targeting is therefore supposed to try to reduce uncertainty by trying to anchor expectations, but according to Johnson (2002), inflation targeting reduces expected inflation but no positive economic effects in the form of lower inflation uncertainty.

In this paper we are going to analyze the dependence and volatility spillovers on inflation, unemployment, policy rate and a proxy for potential growth, namely, consumer confidence, prior to the adoption of an european inflation target in Spain (January 1^{st} 2002), and post IT. To do this, we are going to utilize a quadrivariate GARCH DBEKK model proposed by Engle and Kroner in 1990, that estimates the conditional mean function and the conditional volatility function of high-dimensional relationships, which has been widely used to study volatility spillovers between multi-markets. We will take 429 months as the analysis period, from June 1986 to February 2022. For the modeling of the VAR equations, we will consider the optimal lag length criteria, basing the decisions on all the information criteria we have, and the p-values of each lag.

The rest of the paper is organized as follows. The next section briefly continues a literature review on inflationary volatility (uncertainty) and how it can be modelled, but from a theoretical point of view, in order to provide a common thread to the paper and try to respond to these statements by taking the Spanish price level as a reference. Section 3 describes the data used for this purpose and the methodology to conduct the analysis. Section 4 delves into the empirical model used for inflation and uncertainty, and finally, section 5 provides conclusions and policy implications.

2 Literature review

As already mentioned, the central idea of Friedman's 1977 paper was the positive relationship between the price level and the uncertainty around it. In addition, as has also been mentioned, in the asymmetric information game proposed by Ball (1992), there are always two policymakers who alternate stochastically in power, and the public knows that one of them is a "tough" type and that is willing to bear the costs of disinflation. Ball proposed that when inflation was low, both types of policymakers would try to keep it at that level, but when inflation was high, it was known by the public that not only was it high and the economic costs of high inflation had to be borne, but also the uncertainty around it increased, and the future of monetary policy became vague, largely because the period of time that these high levels would last was unknown. This is mitigated when a reliable central bank sets an inflation target, which anchors expectations and thus the public will know, or at least believe, that in the medium term, the mean price level will return to the target. Roughly speaking, temporal uncertainty disappears.

As pointed out in Kontonikas (2004) and Cukierman and Meltzer (1986), high levels of inflationary uncertainty increases the optimal level of inflation, reversing the causation established by Friedman and Ball. Policymakers maximize their own welfare, motivated by political interests, which are positively correlated with monetary surprises and negatively correlated with monetary growth, that is, lighting the fuse of inflation. This induces the public to not know how to discern between movements motivated by objectives or by transitory monetary errors. In other words, and according to Kontonikas (2004), an increase in uncertainty around monetary growth and inflation prompts the policymaker to create inflation surprises and stimulate the real economy, which leads to the acceptance that uncertainty and optimal average inflation are positively related. Sometimes the problem arises from the most primitive part of the analysis, and it is how uncertainty is measured. Fischer (1981) uses the moving standard deviation of inflation as a measure, but which has the drawback that greater volatility does not necessarily carry greater explicit or implicit uncertainty. This would only be true when the agents do not have all the information necessary to predict the increase in variability, and that which could jeopardize the rational expectations argument. Other economists make use of surveys at the population-individual level in which the key answers are to questions related to expected inflation. Johnson (2002) therefore measures uncertainty as the standard deviation of these answers, of these ”forecasts”, and found great similarities with the arguments put forward by Friedman-Ball.

But, since Engle presented his seminal paper in 1982 in which he explained in detail the innovative ARCH model, and later Bollerslev (1986) its extension, called GARCH, economists began to use this type of model to characterize movements of inflation according to its temporal variability, that is, to predict the volatility of those variables whose variance was not stationary. Thus, the researchers used these mathematical specifications to explain periods in which the uncertainty was not deterministic. Kontonikas (2004) used different types of GARCH specifications to analyze the relationship between inflation uncertainty-volatility and the role of inflation targeting in this marriage in the United Kingdom. Moreover, Broto (2011), analyzed the impact of IT in Latin America using a quadratic structural ARCH, finding that IT supported lower inflation levels as well as lower uncertainty levels, which confirms the Friedman-Ball view.

Notwithstanding, it must be discerned that when it comes to information, almost all situations lead to not all information being distributed equally among all economic agents. This leads to frictions in information regarding inflation expectations, where price shocks cause disagreement between households and companies, and little disagreement between policymakers, professional forecasters and participants in experiments, according to Cornand *et al.* (2021). Therefore, different economic agents react differently to price shocks, and despite anchored expectations, this can lead to unaccounted-for price variations, changing in some instances central banks' operations.

When it comes to study the volatility of various variables simultaneously, and in particular intra- and inter-market dependency as well as the subsequent spillovers, other models have also been used for this purposes, but not so much between macroeconomic variables. With respect to oil price and equity returns, linear models such as vector autorregresive (VARs) have been applied to study the dynamic relationship of both, taking their dependencies into account (Arouri *et al.* (2010); Wang *et al.* (2013)). However, these models have not been able to capture the non-linear aspects of the complex relationships that plague markets and macroeconomic variables. Other models, such as time-varying copula models, have been applied in order to eliminate the dynamic nonlinearity gap. As for instance in Yu *et al.* (2020) and Christoffersen *et al.* (2012), they employed these type of models to bear the high tail dependence of international stocks in mind; Avdulaj and Baruník (2015) to capture dynamic tail dependence in crude oil prices, and in Aloui *et al.* (2013) to try to better understand the contagion risk and the strong tail dependence of economies in transition. Notwithstanding, time-varying copula models have been able to determine the dependence between two markets, but they were not able to rigorously study that dependence when multi-market interactions are the object of study. To solve this, vine copula models arose.

These models do now allow us to capture this more complex multi-market dependencies. These are noted in Kraus and Czado (2017), Allen *et al.* (2013), Dißmann *et al.* (2013). But, unsurprisingly, these mathematical specifications lack extreme accuracy, and err on the side of not being able to clarify the direction of these dependencies. To ameliorate these flaws, authors such as Awartani and Maghyereh (2013), Du and He (2015), Zhang and Wang (2014), Chuang *et al.* (2007) and Salisu and Mobolaji (2013) make use of VAR-BEKK-MGARCH models, arguing that they allow obtaining more accurate results, being able to model extreme situations of risk spillovers, which GED-GARCH models are not able to fulfill, or need fewer parameters to estimate than DCC-MECGARCH models. Also, many studies using this VAR-DBEKK-MGARCH models do not take into account the potential for structural breaks and regime changes, which is an important element to consider when analyzing volatility spillovers across time. Therefore, to correct for imprecision, while saving distances, and taking Yu *et al.* (2020) as a reference, we will consider, as the only turning point the entry of Spain into the euro.

3 Data and methodology

3.1 Data

This study analyzes volatility spillovers in unemployment, inflation rate, policy rate and consumer confidence in Spain. The empirical project will also identify whether the inter- intradependence between these variables was different prior and post the inflation targeting period, where the prior period in this sample is 1986M6 – 2001M12 and the post IT period is 2002M1 – 2022M2. For the inflation rate, we have obtained the series of the consumer price index (CPI) for Spain (100 = 2015), for all items, from the OECD, as well as the consumer confidence index, the total unemployment rate and the policy rate. The extracted CPI is not seasonally adjusted, so it has been processed using the TRAMO-SEATS [1] method developed by Gómez and Maravall (1992).

These variables have been selected because of their relationship in economic terms. With respect to the relationship between inflation and growth [2], instructed by Andrés and Hernando (1997), that the effects of inflation on per capita income are unequivocally negative in the long run. However, other views still persist, such as those put forward by Tobin (1965) and Mundell (1965), who argue that there is a positive relationship between inflation and output. On the other hand, the early rational expectations models of Lucas (1972, 1973), Barro (1976, 1980) and Sidrauski (1967), do not predict any relationship between anticipated money and output growth. More recent models show that high money growth can have a negative effect on economic growth. In Villarreal *et al.* (2014), it is concluded that there is no evidence of a significant tradeoff between inflation and growth for the sample and period considered, except if national experiences with average annual inflation above 65% year-on-year are included. That is, outside regimes with persistently very high inflation rates, there is no systematic or significant inverse relationship between inflation and the growth rate of productive activity.

With respect to the unemployment and inflation rates, A. Okun characterized the negative effects of unemployment and inflation by the misery index—the sum of the unemployment and inflation rates, estimating happiness equations in which an individual subjective measure of life satisfaction is regressed against unemployment and inflation rate, and controlling for personal characteristics, country, and year fixed effects. Moreover, in Blanchflower *et al.* (2014), is found that both higher unemployment and higher inflation lower well-being and that unemployment depresses well-being more than inflation. Following this literature, Fitzgerald *et al.* (2020) found that both the reduced form and the structural parameters of the Phillips curve are quite stable over time, consistent with the findings in Álvarez *et al.* (2018). However, what is common knowledge is that policies that are effective at boosting economic output and bringing down unemployment tend to exacerbate inflation, while policies that rein in inflation

[1] Could have also been used X13 ARIMA – CENSUS for good approximations.

[2] Regarding the comparisons from now on between inflation and growth are done using the consumer confidence index, as clarified, proxy for potential economic growth.

frequently constrain the economy and worsen unemployment. Therefore, an in-depth analysis of the volatility spillovers between these aggregates would be very useful.

3.2 Unit root test and descriptive statistics

In order to make the data time consistent and less skewed, we will first take the logarithm of each observation except for the interest rate and inflation rate [3]. However, to perform a correct temporal analysis, it is necessary that the variables behave in a stationary manner. Thus, both the Augmented Dickey-Fuller test (ADF) and the Phillips-Perron test (PP) will be applied for the sake of robustness. In Table A1 are presented the results of the tests for the variables in levels and first differenced, where the t-statistics are specified [4] and in brackets the p-values. It is concluded that the unemployment rate, the interest rate and the consumer confidence index are stationary with an order of integration of one, I(1), and that the inflation rate, with the help of the KPSS test, is I(0). This is because for both tests, the null hypothesis states that the variable under study has a unit root, that is, stationary, and is rejected for the three cases at the 5% level of significance.

Moreover, in Table A2 we can find the most important descriptive statistics to study how each of the variables behave, and also to understand the distribution each one follows. To be more precise, we clearly see that for each variable, the p-value of the Jarque-Bera test is 0 (below 0.05), which means that can be rejected the hypothesis that the errors of the variables are normally distributed, so for the model should be reasonable to use a t'student distribution.

3.3 VAR-DBEKK-MGARCH model

In order to estimate the volatility spillovers between variables before and after Spain's entry into the euro, we will use a VAR-DBEEK-MGARCH model for each period to be considered. A structural break analysis could have been used for the whole period to find the dynamic turning points in the dependence between variables when the date of the structural change is known, using the Chow test (Chow, 1960), or the Bai-Perron test (Bai and Perron, 1998) for multiple unknown structural changes. In our case, since the objective is to know the change in volatility that occurred after Spain's entry into the euro, we will take January 1^{st}, 2002 as the structural change, and from the results we will consider whether it really meant a structural change or not.

[3] The consumer price index is transformed as follows to derive the inflation rate:

$$\pi_t = \ln CPI_t - \ln CPI_{t-1} \tag{1}$$

[4] Adjusted t-statistics for the PP test.

As explained before, this model seems to offset the flaws of other methods, such as vine copula models, GED-GARCH or DCC-MECGARCH models, so it seems reasonable to adjust the purpose of the project to this methodology. For the period from June 1986 to December 2001, the optimal lag, according to the Akaike, Schwartz and Hannah-Quinn information criteria is 2, so the model will use a VAR(2), while for the period after IT, the model will consider a VAR(3). On the other hand, for the sake of consistency we have to make sure that the residuals of the models behave as white noise and are not serially correlated, and also if the variables, in levels, are cointegrated [5]. Table A3 presents the results of the residual autocorrelation LM test for the two periods, concluding that for both VARs, the residuals are white noise and are not serially correlated. Table 1 presents the results of the Johansen test, from which it is extracted that for both periods, there is one cointegrating equation (with no linear trend and a constant). Thus, and taking into account the values obtained from the stability analysis of the VARs, where for both models no root lies outside the unit circle, we can confirm that the levels-VAR approximation fits the data correctly. Together with the results of the White heteroskedasticity test of the two VARs, plots of the monthly variables display volatility clustering and leverage effects, making ARCH models applicable.

Table 1: Johansen test.

No. of CEs	p-value (pre-IT)	p-value (post-IT)
None*	0.0019	0.0026
At most 1	0.3880	0.5199
At most 2	0.7477	0.2938

Note: the * signals the trace test indicates 1 cointegrating equation at the 5% level, and denotes rejection of the null hypothesis of no cointegration. The p-values are the ones of Mackinnon-Haug-Michelis.

Because of the results obtained from the cointegration test, we should follow a VECM approach if the aim were to study the long-term effect of shocks, but as the objective of the paper is to analyze the volatility spillovers pre and post IT period between variables, we will compute the VARs in levels [6]. Next, the diagonal BEKK model is a multivariate GARCH model developed by Baba, Engle Kraft and Kroner in 1990, that permits the explicit and dynamic parametrization of conditional covariances. It reduces the number of coefficients to be estimated by restricting the parameter matrices to be diagonal, and also addresses the difficulty with VECH by ensuring that the conditional covariance matrix is always positive definite (Erten *et al.* (2012)). As stated in the literature, it is common to observe GARCH (1,1) models when studying, among others, inflation, since especially higher orders correspond to data with much higher

[5] For this analysis we need to take variables that are I(1) in levels. Thus, we have only studied the cointegration between consumer confidence, policy rate and the unemployment rate because the inflation rate was determined to be I(0).

[6] Notwithstanding, see appendix for the post-IT IRFs, where for both periods the unemploymente, policy rate and consumer confidence conintegrated with inflation.

frequencies, such as daily or weekly, with a large number of observations. That is why the GARCH to be considered will be of order (1,1). Therefore, the general quadrivariate diagonal BEKK model is given as:

$$H_t = C'C + A'(\varepsilon_t \varepsilon'_{t-1})A + B'(H_{t-1})B \tag{2}$$

where H_t is an nxn conditional variance covariance matrix, C is an upper triangular matrix of parameters, ε is a $nx1$ disturbance vector and A and B are nxn diagonal parameter matrices. Diagonal elements provide with own market shocks and volatility, whereas off diagonal elements suggest the impact of shocks of one variable to another. In general, and according to Antonakakis *et al.* (2017), the coefficients of matrices A and B indicate the innovations in each specific variable/market and the persistence or the rate of the decay of news in each specific variable/market, respectively.

Let be Ω a 3x3 matrix and equal to $C'C$. Therefore, we have:

$$\begin{pmatrix} c_{11} & 0 & 0 \\ c_{12} & c_{22} & 0 \\ c_{13} & c_{23} & c_{33} \end{pmatrix} \times \begin{pmatrix} c_{11} & c_{12} & c_{13} \\ 0 & c_{22} & c_{23} \\ 0 & 0 & c_{33} \end{pmatrix} = \begin{pmatrix} c_{11}^2 & c_{11}c_{12} & c_{11}c_{13} \\ c_{11}c_{12} & c_{12}^2 c_{22}^2 & c_{12}c_{13} + c_{22}c_{23} \\ c_{11}c_{13} & c_{12}c_{13} + c_{22}c_{23} & c_{13}^2 c_{23}^2 c_{33} \end{pmatrix} \tag{3}$$

and thus the equation will follow:

$$\begin{aligned} \begin{pmatrix} h_{11,t} & h_{12,t} & h_{13,t} \\ h_{21,t} & h_{22,t} & h_{23,t} \\ h_{31,t} & h_{32,t} & h_{33,t} \end{pmatrix} &= \begin{pmatrix} \omega_{11,t} & \omega_{12,t} & \omega_{13,t} \\ \omega_{21,t} & \omega_{22,t} & \omega_{23,t} \\ \omega_{31,t} & \omega_{32,t} & \omega_{33,t} \end{pmatrix} \\ &+ \begin{pmatrix} a_{11} & 0 & 0 \\ 0 & a_{22} & 0 \\ 0 & 0 & a_{33} \end{pmatrix}' \begin{pmatrix} \varepsilon_{1,t-1} \\ \varepsilon_{2,t-1} \\ \varepsilon_{3,t-1} \end{pmatrix} \begin{pmatrix} \varepsilon_{1,t-1} \\ \varepsilon_{2,t-1} \\ \varepsilon_{3,t-1} \end{pmatrix}' \begin{pmatrix} a_{11} & 0 & 0 \\ 0 & a_{22} & 0 \\ 0 & 0 & a_{33} \end{pmatrix}' \\ &+ \begin{pmatrix} b_{11} & 0 & 0 \\ 0 & b_{22} & 0 \\ 0 & 0 & b_{33} \end{pmatrix}' \begin{pmatrix} h_{11,t-1} & h_{12,t-1} & h_{13,t-1} \\ h_{21,t-1} & h_{22,t-1} & h_{23,t-1} \\ h_{31,t-1} & h_{32,t-1} & h_{33,t-1} \end{pmatrix} \begin{pmatrix} b_{11} & 0 & 0 \\ 0 & b_{22} & 0 \\ 0 & 0 & b_{33} \end{pmatrix} \end{aligned} \tag{4}$$

For the sake of clarity, matrix B is related to GARCH effects, and shows the persistence in conditional volatility between variable i and j, whereas matrix A is related to ARCH effects, and shows the degree of innovation from variable i to j.

From Table 2 and the equations from 15-34 [7] can be clearly seen how after Spain's entry into the euro zone, the persistence of inflation volatility has been reduced, going from an effect of 0.985755 to 0.819505. Furthermore, the long-term effect of inflation on unemployment, the interest rate and consumer confidence has also been reduced, although to a lesser extent on the policy rate. These conclusions are drawn by analyzing the pre and post coefficients of the GARCH terms in equations 5-8, i.e., h_{1j} indicates the effect of inflation on j=2 unemployment, j=3 policy rate and j=4 consumer confidence. Also using Table

[7] See appendix for a thoroughly clarification of the results obtained.

2 and taking into account the significance of the coefficients, we see that before the adoption of the euro, Spanish inflation was not affected by its previous innovations, so that its future volatility up to that moment was not affected by previous values. However, post IT the coefficient is significant and therefore now it does have an influence. This conclusion makes economic sense because if there is now a believed and sustained inflation target in the medium to long term, the previous price level, and therefore its variability, matters. The central bank then takes the relevant decisions to redirect the course of prices and maintain its credibility.

On the other hand, and regarding unemployment, the influence of its past (ARCH effects) was positive, i.e., it increased its volatility, while post IT, this relationship became negative. Something similar occurs between unemployment and the policy rate and consumer confidence, where now past innovations in unemployment positively affect these variables by increasing their short-term volatilities. Before the adoption of European inflation target, Spanish inflation was an "instrument" that could be altered through interest rates at any time the economic situation required it, but now that monetary policy is out of the Bank of Spain's control, unemployment volatility spillovers fall on the policy rate and consumer confidence, generating a chain effect.

Table 2: Estimation results of the VAR-DBEKK-MGARCH.

Coefficients	pre-IT	post-IT
C(1,1)	9.92E-09	3.23E-06
C(1,2)	5.05E-08	-1.62E-07
C(1,3)	2.82E-06	2.53E-06**
C(1,4)	-2.39E-08	-2.08E-07
C(2,2)	-5.23E-07	1.20E-06***
C(2,3)	-1.20E-05	1.26E-07
C(2,4)	5.91E-08	-7.31E-08
C(3,3)	0.01176***	9.31E-07
C(3,4)	4.15E-06	3.71E-07
C(4,4)	3.74E-08	5.97E-07
A(1,1)	0.000907	-0.142121*
A(2,2)	-0.040097	0.106329***
A(3,3)	0.595336***	0.658690***
A(4,4)	0.347742***	0.179626**
B(1,1)	0.992852***	0.905265***
B(2,2)	1.011445***	0.977947***
B(3,3)	0.769895***	0.838021***
B(4,4)	0.942844***	0.878525***

Note: 1, 2, 3 and 4 between brackets represent the inflation rate, unemployment, policy rate and the consumer confidence, respectively. B, A and C are the parameter matrix of residual, conditional and constant as specified in Eq. (2), respectively. ***, ** and * indicate confidence levels at 1%, 5% and 10%, respectively.

As past values and past volatility of inflation now matter, one of the instruments used to stabilize the price level is the interest rate, so now not only the past of prices but also the past of the policy rate is taken into account to make decisions, i.e., the past now has a potential effect of increasing its volatility, passing from 0.3544 to 0.4339. Once the inflation expectations are (almost) anchored, both the persistence (long-term) volatility of consumer confidence is lower, and prior the IT period volatility mattered less.

4 Conclusions and further extensions

This study concludes one of the facts recited in the inflationary literature, which is that inflation volatility decreases once an inflation target becomes entrenched and therefore past volatility becomes more restrictive. No matter how, directly or indirectly through the IT, Laubach and Posen (1997) established that inflation expectations have come down, in most cases, only as inflation-targeting central banks have demonstrated that they can deliver low inflation levels, arguing that there is no evidence that the introduction of inflation targets materially affects private-sector expectations of inflation. However, inflation targets offer transparency of policy; they make explicit the central bank's policy intentions in a way that should improve private-sector planning, enhance the possibility of public debate about the direction of monetary policy, and increases central bank's accountability (Bernanke and Mishkin (1997)). This shows that there is a direct relationship between short-run and long-run volatility when an IT exists because under it, the central bank would be forced to publicize the implications of its short-run actions for expected inflation in the long-run.

Some economists argue, and as was also observed in the first years after the adoption of the IT by Switzerland, that maintaining low levels of inflation, and therefore complying with the IT, is achieved at the cost of sacrificing GDP and increasing unemployment. However, this study shows that both before and after the IT, the volatility spillover of short-term inflation on unemployment is negative (the volatility of inflation decreases the variability of unemployment), although it increases in the post-IT period, whereas for consumer confidence (a country's growth proxy), it goes from positively affecting its variability to negatively affecting it, that is, reducing its variability in the short term. In general, there is a greater effect of past innovations on the volatility of innovations, and also a lower long-term persistence of variability, except in inflation.

Much remains to be investigated in this regard. Together with this model, it could be investigated whether these inter-market considerations analyzed here are bidirectional (boomerang effect), by conducting a Wald test. A synthetic control for Spain in order to study what would have happened to inflation volatility if it would not have adopted the IT would represent an important robustness exam for the model presented. This further research will constitute a paramount step if we want to understand the weight of IT on uncertainty and volatility in an economy. Being able to do the same in developing countries and compare it to developed ones will give us a sign on whether uncertainty is due to the quality of institutions or due to their dependence on capital markets.

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5 Appendix

Here we present the resultant conditional and covariance equations derived from the formulation of the DBEKK-MGARCH procedure from the VARs estimated presented in (4), but for the four-variable case:

$$h_{11,t} = \omega_{11}^2 + a_{11}^2\varepsilon_{1,t-1}^2 + b_{11}^2 h_{11,t-1} \tag{5}$$

$$h_{12,t} = \omega_{11}\omega_{12} + a_{11}a_{22}\varepsilon_{1,t-1}\varepsilon_{2,t-1} + b_{11}b_{22}h_{12,t-1} \tag{6}$$

$$h_{13,t} = \omega_{11}\omega_{13} + a_{11}a_{33}\varepsilon_{1,t-1}\varepsilon_{3,t-1} + b_{11}b_{33}h_{13,t-1} \tag{7}$$

$$h_{14,t} = \omega_{11}\omega_{14} + a_{11}a_{44}\varepsilon_{1,t-1}\varepsilon_{4,t-1} + b_{11}b_{44}h_{14,t-1} \tag{8}$$

$$h_{22,t} = \omega_{12}^2\omega_{22}^2 + a_{22}^2\varepsilon_{2,t-1}^2 + b_{22}^2 h_{22,t-1} \tag{9}$$

$$h_{23,t} = \omega_{12}\omega_{13} + \omega_{22}\omega_{23} + a_{22}a_{33}\varepsilon_{2,t-1}\varepsilon_{3,t-1} + b_{22}b_{33}h_{23,t-1} \tag{10}$$

$$h_{24,t} = \omega_{12}\omega_{14} + \omega_{22}\omega_{24} + a_{22}a_{44}\varepsilon_{2,t-1}\varepsilon_{4,t-1} + b_{22}b_{44}h_{24,t-1} \tag{11}$$

$$h_{33,t} = \omega_{13}^2\omega_{33}^2 + a_{33}^2\varepsilon_{3,t-1}^2 + b_{33}^2 h_{33,t-1} \tag{12}$$

$$h_{34,t} = \omega_{13}\omega_{14} + \omega_{33}\omega_{34} + a_{33}a_{44}\varepsilon_{3,t-1}\varepsilon_{4,t-1} + b_{33}b_{44}h_{34,t-1} \tag{13}$$

$$h_{44,t} = \omega_{14}^2\omega_{44}^2 + a_{44}^2\varepsilon_{4,t-1}^2 + b_{44}^2 h_{44,t-1} \tag{14}$$

In our case, we have four variables to study, so the resultant conditional and covariance equations for the pre-IT period can be represented as follows using a t'student distribution for the model, and plugging in the results presented in Table 2:

$$h_{11,t} = 9.92E-09 + 8.23E-07\varepsilon_{1,t-1}^2 + 0.985755h_{11,t-1} \tag{15}$$

$$h_{12,t} = 5.05E-08 - 3.64E-05\varepsilon_{1,t-1}\varepsilon_{2,t-1} + 1.00422h_{12,t-1} \tag{16}$$

$$h_{13,t} = 2.82E-06 - 5.41E-04\varepsilon_{1,t-1}\varepsilon_{3,t-1} + 0.76439h_{13,t-1} \tag{17}$$

$$h_{14,t} = -2.39E-08 + 3.15E-04\varepsilon_{1,t-1}\varepsilon_{4,t-1} + 0.9361h_{14,t-1} \tag{18}$$

$$h_{22,t} = -5.32E-07 - 1.61E-03\varepsilon_{2,t-1}^2 + 1.02302h_{22,t-1} \tag{19}$$

$$h_{23,t} = -1.20E-05 - 0.02387\varepsilon_{2,t-1}\varepsilon_{3,t-1} + 0.77871h_{23,t-1} \tag{20}$$

$$h_{24,t} = 5.91E-08 - 0.01394\varepsilon_{2,t-1}\varepsilon_{4,t-1} + 0.956468h_{24,t-1} \tag{21}$$

$$h_{33,t} = 0.011760 + 0.354425\varepsilon_{3,t-1}^2 + 0.592738h_{33,t-1} \tag{22}$$

$$h_{34,t} = 4.15E-06 + 0.207023\varepsilon_{3,t-1}\varepsilon_{4,t-1} + 0.725891h_{34,t-1} \tag{23}$$

$$h_{44,t} = 3.74E-08 + 0.120924\varepsilon_{4,t-1}^2 + 0.888955h_{44,t-1} \tag{24}$$

And for the post-IT period:

$$h_{11,t} = 3.23E-06 + 0.020198\varepsilon_{1,t-1}^2 + 0.819505h_{11,t-1} \tag{25}$$

$$h_{12,t} = -1.62E-07 - 0.015112\varepsilon_{1,t-1}\varepsilon_{2,t-1} + 0.885301h_{12,t-1} \tag{26}$$

$$h_{13,t} = 2.53E - 06 - 0.093614\varepsilon_{1,t-1}\varepsilon_{3,t-1} + 0.758631h_{13,t-1} \tag{27}$$

$$h_{14,t} = -2.08E - 07 - 0.025529\varepsilon_{1,t-1}\varepsilon_{4,t-1} + 0.795298h_{14,t-1} \tag{28}$$

$$h_{22,t} = 1.20E - 06 + 0.011306\varepsilon_{2,t-1}^2 + 0.95638h_{22,t-1} \tag{29}$$

$$h_{23,t} = 1.26E - 07 + 0.070038\varepsilon_{2,t-1}\varepsilon_{3,t-1} + 0.81954h_{23,t-1} \tag{30}$$

$$h_{24,t} = -7.31E - 08 + 0.019099\varepsilon_{2,t-1}\varepsilon_{4,t-1} + 0.859151h_{24,t-1} \tag{31}$$

$$h_{33,t} = 9.31E - 07 + 0.433873\varepsilon_{3,t-1}^2 + 0.702279h_{33,t-1} \tag{32}$$

$$h_{34,t} = 3.71E - 07 + 0.118318\varepsilon_{3,t-1}\varepsilon_{4,t-1} + 0.73622h_{34,t-1} \tag{33}$$

$$h_{44,t} = 5.97E - 07 + 0.032265\varepsilon_{4,t-1}^2 + 0.771806h_{44,t-1} \tag{34}$$

Moreover, a sensitivity analysis have been conducted using quarterly data from the REMS database to test whether monthly data is good or not to study volatility spillovers. For this case, we used instead of the growth of the consumer confidence index (proxy of growth), the seasonally and calendar adjusted GDP in millions of euros at constant prices (100=2015).

The following analysis of the long-run IRFs is not related to the aim of this research, but it is slightly mentioned because its results may be of interest. As series are cointegrated, we can analyze the short and long-run effects. From the first set of IRFs (pre IT), the long-run (accumulated) effect of one standard deviation shocks onto the variables under study are insignificant (like a placebo analysis). For most of them the shock produces no remarkable effect except the impact of inflation rate on the interest rate (positive impact) and the negative effect of the inflation rate on the consumer confidence. Not only due to the negligible effect of intra-variable shocks, but also to reasons of space, we will avoid showing the IRFs for the pre inflation targeting period.

For the post IT period (see Figure 1 here in the Appendix), things change, and reactions are a bit higher. In general, as imposed by Choleski, inflation rate does not react in the first period to shocks on unemployment, consumer confidence and interest rate, but for the confidence and the unemployment rate, the accumulated responses are negative and significant as of the second month. The same happens with consumer confidence after a shock in unemployment, but now the negative response occurs in the first month and quickly the effect of the shock becomes more damaging. Moreover, a positive shock in inflation makes the interest rate to react positively and after the 4 month, it reverses a little bit (due to the parsimonious actions of central banks) and then the effect continous increasing. Notwithstanding, there are some IRFs, such as the one that represents the shock of the inflation rate on the unemployment rate, that are not significant, causing no effect on the other after an innovation. This could be due to the fact that in spite of being seasonally adjusted, since the series are monthly, traces may remain, or because inflation, which is I(0), is being analyzed together with three I(1) variables (in the VECM approach). Perhaps other methods of identification of the SVAR model are more appropriate.

Table A1 3: Unit root tests

Variables	ADF pre-IT	PP pre-IT	ADF post-IT	PP post-IT
lcc	-1.8235 (0.3683)	-1.5172 (0.5229)	-2.8418 (0.0540)	-2.1997 (0.2070)
int	-0.8411 (0.8045)	0.9103 (0.7833)	-1.6082 (0.4769)	-1.3837 (0.5901)
lunemp	-0.4473 (0.8971)	0.4007 (0.9826)	-1.3463 (0.6082)	-1.2091 (0.6710)
dlcpi	-0.2645 (0.1123)	-12.1048 (0.0000)	-2.5000 (0.1000)	-12.0121 (0.0000)
Δlcc	-5.1417 (0.0000)	-4.5613 (0.0002)	-4.8784 (0.0001)	-3.9930 (0.0017)
Δint	-5.5241 (0.0000)	-9.0982 (0.0000)	-6.4387 (0.0000)	-6.4326 (0.0000)
$\Delta lunemp$	-4.1462 (0.0011)	-5.6156 (0.0000)	-4.2846 (0.0006)	-5.1495 (0.0000)
$\Delta dlcpi$	-12.3977 (0.0000)	-75.7913 (0.0001)	-11.0932 (0.0000)	-6.15293 (0.0001)

Table A2 4: Descriptive statistics

Statistics	dlcpi	int	unempl	cc
Mean	0.2486	4.8374	2.7688	4.6047
Median	0.2513	3.2926	2.8094	4.6137
Maximum	1.8226	19.8030	3.2734	4.6489
Minimum	-1.9263	-0.5820	2.0669	4.5153
Std. dev.	0.5152	5.2226	0.3068	0.0311
Skewness	-0.4394	0.8865	-0.5232	-0.9953
Kurtosis	4.5685	2.5103	2.4154	3.2256
Jarque-Bera	57.6451	60.4812	25.6798	71.7393
Probability	0.0000	0.0000	0.0000	0.0000
Observations	428	428	428	428

Table A3 5: Autocorrelation LM test

Lag	Rao F-stat (pre IT)	df (pre IT)	p-value (pre IT)	Rao F-stat (post IT)	df (post IT)	p-value (post IT)
1	1.1402	(16, 513.9)	0.3141	1.4857	(16, 568.9)	0.0993
2	0.9829	(16, 513.9)	0.4740	1.1967	(16, 568.9)	0.2655
3	0.8545	(16, 513.9)	0.6228	1.1036	(16. 568.9)	0.3478
4	NA	NA	NA	1.1355	(16, 568.9)	0.3180
5	NA	NA	NA	0.7620	(16, 568.9)	0.7293
6	NA	NA	NA	1.5000	(16, 568.9)	0.1000
7	NA	NA	NA	0.9284	(16, 568.9)	0.5361
8	NA	NA	NA	0.7819	(16, 568.9)	0.7070
9	NA	NA	NA	1.5525	(16, 568.9)	0.0770
10	NA	NA	NA	1.2014	(16, 568.9)	0.2617
11	NA	NA	NA	1.2565	(16, 568.9)	0.2203
12	NA	NA	NA	1.3315	(16, 568.9)	0.1720
13	NA	NA	NA	1.1719	(16, 568.9)	0.2860

Note: the null hypothesis states that there is no serial correlation at lag h. For the pre-IT period, the VAR computed has 2 lags, whereas for the post-IT period, VAR(12). No lag significant at the 5% level, so no serial correlation concluded.

Fig. 1: Impulse response functions post IT