MODELLING INFLATION, OUTPUT GROWTH AND THEIR UNCERTAINTIES

A thesis submitted for the degree of Doctor of Philosophy

By

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Abstract

This thesis consists of three studies that cover topics in inflation and output growth, and their uncertainties in G7 and developing countries. We utilise the Consumer Price Index (CPI) and Industrial Price Index (IPI) as proxies for the inflation rate (price level) and the growth rate (output), respectively.

Chapter 2 considers the case of three developing countries Turkey, Egypt and Syria. We analyse the inflation and growth using asymmetric PGARCH model. In accordance with this, we estimate all the models using two alternative distributions the normal and Student's *t*. Moreover, dummy variables are chosen in the inflation data according to some economic events in Turkey, Egypt and Syria. Even more, the mean equation is adjusted to include these dummy variables on the intercept.

To summarize, the results show an evidence of the Cukierman–Meltzer (1986) hypothesis, which is labelled as the 'opportunistic Fed' by Grier and Perry (1998), in Egypt and Syria. On the other hand, an evidence of the Holland (1995) hypothesis is obtained in Turkey, this result suggests that the 'stabilizing Fed' notion is plausible.

Moreover, an evidence for the first leg of Friedman (1977) hypothesis is obtained in Egypt and Turkey.

Chapter 3 examines the causal relationship between inflation and output growth, and their variabilities for G7 countries by applying the bivariate constant conditional correlation CCC – GARCH (1,1)-ML models. Moreover, we employ the models including dummy variables in the mean equations to investigate the impact of economic events on inflation and output.

Briefly, there are evidences of the second leg of Friedman (1977) hypothesis in the US, UK, Germany, Italy, France and Canada while there is an evidence of Dotsey and Sarte (2000) in Japan. In addition, there are evidences for positive effect of inflation uncertainty on inflation in the US, Germany, Japan and France in line of Cukierman and Meltzer (1986) hypothesis.

Moreover, the results of estimation CCC-GARCH (1,1) in mean models including dummy variables highlight a strong support for the two legs of Friedman (1977) hypothesis and Cukierman and Meltzer (1986).

Lastly, Chapter 4 is based on examining the inflation rates for three developing countries Turkey, Syria and Egypt by applying the Bai and Perron (2003) breakpoint specification

technique in the monthly inflation data of our sample. As a result, three possible break points for each of the inflation rates in the conditional variance have been determined.

In addition, we employ GARCH model to control the breaks in the conditional mean and variance equations.

To conclude, the autoregressive coefficients seem to cause a statistically significant impact on the breaks only in the case of Turkey, also, the parameters of the mean equation show time varying characteristics across three breaks. As far as the conditional variance is concerned the ARCH parameter (α) shows no time varying behaviour while for the GARCH parameter only one significant break seems to impact the inflation rate in Syria

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Chapter One

Introduction

In the history of development economics, inflation has been thought as a key factor of many studies in developing and developed countries. In addition, one of the most important objectives for any economy is to sustain high output growth.

Considerable uncertainty that surrounds the impact of the inflation rate on the rate of economic growth is one of the most researched topics in macroeconomics on both theoretical and empirical fronts.

The famous hypothesis of Friedman (1977) about the effects of inflation on unemployment consists of two legs: the first one explains that higher inflation rate leads to higher nominal uncertainty, then inflation uncertainty results in lowering the output growth which consider as the second leg of the hypothesis. Therefore, the inflation effects on output growth exist via inflation uncertainty. In addition, Ball (1992) supports the issue of the first leg of Friedman (1977) hypothesis by concluding that the rise in inflation increases uncertainty of inflation rate in future. While Dotsey and Sorte (2000) show that output growth rate can be affected positively by inflation uncertainty in contrast to second Leg of Friedman (1977).

In contrast, Pourgerami and Maskus (1987) develop the argument that in the presence of rising inflation agents may invest more resources in forecasting inflation, thus reducing uncertainty about inflation. This argument is supported by Ungar and Zilberfarb (1993).

The Impact of Inflation Uncertainty on Inflation is positive according to Cukierman and Meltzer (1986) hypothesis and negative according to Holland (1995). Furthermore, output uncertainty has positive effect on the rate of inflation as predicted by Devereux (1989) and Cukierman and Gerlach (2003) and negative effects according to Taylor effect and Cukierman and Meltzer (1986).

Pindyck (1991) shows a negative impact of Output Uncertainty on Output Growth in contrast to the findings of Mirman (1971), Black (1987) and Blackburn (1999).

This study will analyse inflation and growth using asymmetric Power GARCH in mean model for three developing countries named Turkey, Egypt and Syria. We have chosen these countries as an example of developing economies and on the basis that three of them are affected by economic and political problems. In addition, according to the history of Turkey, Egypt and Syria we can detect that the economic policies in these countries are mostly affected by political problems and therefore economic conditions were uncertain and changeable from time to time.

In this chapter, our study contributes to the literate review on the effect of inflation on its uncertainty. such as Berument et al (2001) who examined the effect of inflation on its uncertainty in Turkey using monthly CPI and employing EGARCH model with the including of seasonal dummy variables and the 1994 financial crisis dummy variable. While in our essay, we develop Berument et al‘s work by using long- time series (1969:02 to 2011:02) and employing APARCH-M model and considering more economic and political events. In order investigate the effect of those events on inflation and output rates by applying more dummy variables. In addition, an update in our study contributes to Viorica et al (2014) study who use CPI data and employ PARCH model to investigate the causal relationship between inflation and its uncertainty for the newest EU countries by using the same method PARCH for three developing countries in the Middle East taking in our account the effect economic and political events in these three countries.

Also, we use Karanasos and Schurer (2005), Karanasos and Schurer (2008) study by applying the APGARCH in three Mediterranean countries using dummy variables in the conditional mean equation due to the economic and political events in Turkey, Egypt and Syria. Since the authors in the mentioned studies empirically examine the relationship between inflation and its uncertainty, output growth and its uncertainty. Using monthly CPI and IPI data, APARCH models are estimated for three EU countries to investigate the causal effects between inflation and its uncertainty and for Italy to investigate the relationship between output growth rate and real output.

In accordance with this, we estimate all the models using two alternative distributions the normal and Student’s *t*. Dummies are chosen in the inflation data according to some economic events in Turkey, Egypt and Syria. For this essay, the mean equation is adjusted to include two dummy variables on the intercept.

Despite different GARCH specifications that are used in this field of studies, it seems to be no obvious reason why the conditional variance should assume as a linear function of lagged squared errors since most of previous studies focus on standard Bollerslev-type model which assumes that the conditional variance is a linear function of lagged squared errors (Karanasos and Schurer 2008). However, there is no economic reason to endorse such a strong assumption.

Moreover, the squared term that is common use in this role and most likely to be a reflection of the normality assumption traditionally invoked working with inflation and growth data. However, if we accept that both inflation and output growth data are very likely to have a non-normal error distribution, the superiority of a squared term is lost and other power transformations may be more suitable.

In our sample, we use the Consumer Price Index (CPI) and Industrial Price Index (IPI) as proxies for the inflation rate (price level) and growth rate (output), respectively.

Actually, for non-normal data; by squaring the inflation or output rates one effectively imposes a structure on the data that may furnishes sub-optimal modelling and forecasting performance relative to other power terms (Karanasos and Schurer 2005). To clarify this argument, let π_t and y_t represent inflation and output growth in period *t*, the temporal properties of the functions of $|\pi_t|^d$ and $|y_t|^d$ for positive values of *d* will be considered in this paper. The estimation results show the empirical fact that both autocorrelation functions of $|\pi_t|^d$ and $|y_t|^d$ are curving inward functions of *d* and reach their maximum points when *d* is less than 1. However, the findings of the current study do not support the Bollerslev-type model.

Briefly, the results show an evidence of the Cukierman–Meltzer (1986) hypothesis, which is labelled as the 'opportunistic Fed' by Grier and Perry (1998), in Egypt and Syria. On the other hand, an evidence for the Holland (1995) hypothesis is obtained in Turkey, this result suggests that the 'stabilizing Fed' notion is plausible.

Moreover, an evidence for the first leg of Friedman (1977) hypothesis is obtained in Egypt and Turkey. Also, the results about Turkish output growth indicate that there is support for Pindyck (1991) where more raising in growth will lead to less uncertainty.

Chapter 3 contributes to the literature on inflation by applying the bivariate constant conditional correlation CCC – GARCH (1,1)-ML to examine the causal relationship between inflation and output growth, and their variabilities.

In this essay, our study is contributing new knowledge to what is already known from previous studies of Grier, et al, (2004), Fountac et al (2006) Bhar and Mallik (2013). Grier, et al, (2004) which measured the inflation Producer Price Index (PPI), and the output growth from Industrial

Production Index (IPI), and they used the Vector Autoregressive Matrix Average (VARMA) and GARCH in-mean models.

For example, Fountac et al (2006) employ a bivariate CCC-GARCH model of inflation and output growth to examine the causality relationship among nominal uncertainty, real uncertainty and macroeconomic performance in the G7. The authors used different types of data among seven countries to measure of price and IPI to measure of output growth. In addition, Bhar and Mallik (2013), used PPI and IPI data to investigate the transmission and response of inflation uncertainty and output uncertainty on inflation and output growth in the UK. They applied bivariate EGARCH model with considering two dummy variables due to inflation targeting in 1992 and 1970s oil crises. Thus, we update the previous studies by using CPI as proxy of inflation rate and employing CCC-GARCH model for G7 countries. Also, we consider the monthly CPI and IPI data for all G7 countries and employing CCC-GACH(1,1)-ML with investigating the effect of economic and political events to capture any effect to inflation and output rates in the G7.

Moreover, employing bivariate CCC – GARCH (1,1)-ML models including dummy variables in the mean equations in group of G7 namely the US, UK, Germany, Japan, Italy, France and Canada. The Dummies are chosen from the inflation and growth data according to some economic and political events in G7 countries.

In this investigation, the mean equations are adjusted to include dummy variables on the intercept to capture any possible effects of the Great Recession in 1980 and post terrorist attacks of 9/11 in the US, the inflation targeting in 1992 in the UK, the unification of Germany 1990, the post-Plaza Accord in 1985 in Japan, the all oil crises 1970s in the UK, Italy France and Canada and finally, the financial crisis in 2007 for all G7 countries.

The findings show that there are evidences of the second leg of Friedman (1977) hypothesis in the US, UK, Germany, Italy, France and Canada while there is an evidence of Dotsey and Sarte (2000) in Japan. In addition, there are evidences for positive effect of inflation uncertainty on inflation in the US, Germany, Japan and France in line of Cukierman and Meltzer (1986) hypothesis.

Moreover, the results of estimation CCC-GARCH (1,1) in mean models including dummy variables in the mean highlight a strong support for the two legs of Friedman (1977) hypothesis and Cukierman and Meltzer (1986). The effect of inflation uncertainty on output growth becomes lower in the US, UK, Germany, Italy and France while it becomes higher in Canada and changes from positive effect in Japan to negative one due to the economic and political events.

Finally, Chapter 4 is based on examining the inflation rates for three developing countries Turkey, Syria and Egypt by applying the Bai and Perron (2003) breakpoint specification technique in the monthly inflation data of our sample.

We have chosen these countries as an example of developing economies and on the basis that three of them are affected by economic and political problems. In addition, according to the history of Turkey, Egypt and Syria we can detect that the economic policies in these countries are mostly affected by political problems and therefore economic conditions were uncertain and changeable from time to time.

In this essay, our study is introducing a new aspect to what is examined by previous studies of GöktaG and DiGbudak (2014) and Li and Wei (2015).

GöktaG and DiGbudak (2014) have used the CPI data for the period of 1994:01–2013:12. Both TGARCH) and EGARCH models were employed to investigate the inflation in Turkey. Moreover, using Bai-Perron (2003) breakpoints specification technique structural breaks. Li and Wei (2015) have studied statistically a number of structural breaks in China's inflation persistence based on the monthly retail price index (MRPI) and the quarterly retail price index (QRPI) inflation series from 1983 to 2011.

Thus, we improve these previous studies by examining the inflation rates for three developing countries Turkey, Syria and Egypt by applying the Bai and Perron (2003) breakpoint specification technique in our monthly inflation data of our sample. In order to study the inflation rates, we employ GARCH model to control the breaks in the conditional mean and the conditional variance equations. In particular, the consumer price index (CPI) has been used as the proxy for the inflation rates (price level).

In order to study the inflation rates, we employ GARCH model to control the breaks in the conditional mean and variance equations. In particular, the consumer price index (CPI) has been used as the proxy for the inflation rates (price level).

Inflation rates have become crucial determinants in driving the economy for a number of countries especially for developing countries such as Syria, Turkey and Egypt. Hence, it is important to study the effects of inflation rates in these countries.

Particularly, political uncertainty has effects on economic activities like stock prices that mostly respond to political news (Ľuboš and Veronesi 2013), especially when the economy is weak as it is in the most of developing countries. In addition, political risk affects employment, foreign direct investment (FDI), capital flow, exports and imports (see Gourinchas and Jeanne (2013), Hayakawa et al (2013), Ahmed and Greenleaf (2013) and Liargovas and Skandalis (2012)).

Although several studies have been conducted for these three developing countries, this study attempts to be the first one that uses the breakpoints specification in the conditional mean and variance in the GARCH models.

Since there are many factors that may cause structural changes in the economy of those three developed countries, structural breaks have been detected by applying Bai and perron (2003). Three different break points in the conditional mean have been identified in each country.

Furthermore, three possible break points for each of the inflation rates in the conditional variance have been determined by applying Bai and peroon (2003) technique as well.

Hence, we obtained three significant breakpoints in the conditional mean, whereas only one of three structural breaks is significant in the conditional variance.

As a result, the autoregressive coefficients seem to cause a statistically significant impact on the breaks only in the case of Turkey.

In addition, the parameters of the mean equation show time varying characteristics across three breaks. As far as the conditional variance is concerned the ARCH parameter (α) shows no time varying behaviour while for the GARCH parameter only one significant break seems to impact the inflation rate in Syria..

The effects of Political and Economic Events in Developing Economies: The case of Turkey, Egypt and Syria

2.1. Introduction:

One of the most researched topics in macroeconomics is the issue of welfare costs of inflation on both theoretical and empirical fronts. Friedman (1977) predicted that a rise in inflation leads to more nominal uncertainty. The opposite direction of causation has also been analysed by Cukierman and Meltzer (1986) who argue that central banks (CBs) tend to create inflation surprises in the presence of more inflation uncertainty. Also, there are some theoretical issues about the impact of output uncertainty on output growth. Pindyck (1991) predicted a negative effect of real uncertainty on growth. On the contrary, Mirman (1971), Black (1987), Blackburn (1999) predicted a positive effect of real uncertainty on output growth.

This study will analyse inflation and growth using asymmetric Power GARCH in mean model for three developing countries named Turkey, Egypt and Syria. We have chosen these countries as an example of developing economies and on the basis that three of them are affected by economic and political problems. In addition, according to the history of Turkey, Egypt and Syria we can detect that the economic policies in these countries are mostly affected by political problems and therefore economic conditions were uncertain and changeable from time to time.

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In accordance with this, we estimate all the models using two alternative distributions (the normal and Student's *t*). Dummies are chosen in the inflation data according to some economic events in Turkey, Egypt and Syria. The mean equation is adjusted to include two dummy variables on the intercept.

Despite different GARCH specifications that are used in this field of studies, it seems to be unobvious reason why one should assume that the conditional variance is a linear function of lagged squared errors as most previous studies focus on standard Bollerslev-type model, which assumes that the conditional variance is a linear function of lagged squared errors (Karanasos and Schurer 2008). However, there is no economic reason why one should make such a strong assumption.

The squared term that is commonly used in this rule is most likely to be a reflection of the normality assumption traditionally invoked working with inflation and growth data. However, if we accept that both inflation and output growth data are very likely to have a non-normal error distribution, the superiority of a squared term is lost and other power transformations may be more suitable.

In particular, for non-normal data, by squaring the inflation or output rates one effectively imposes a structure on the data that may possibly furnish sub-optimal modelling and forecasting performance relative to other power terms (Karanasos and Schurer 2005). To clarify this argument, let π_t and y_t represent inflation and output growth in period *t*, respectively. The temporal properties of the functions of $|\pi_t|^d$ and $|y_t|^d$ for positive values of *d* will be considered in this paper. We find, as an empirical fact, that both autocorrelation functions of $|\pi_t|^d$ and $|y_t|^d$ are curving inward functions of d and reach their maximum points when d is less than 1. This result serves as an argument against a Bollerslev-type model.

This study is outlined as follows: in Section 2 we consider in more details the hypotheses about the causality between inflation and its uncertainty as well as the causality between output growth and its uncertainty. Section 3 summarizes the empirical literature to date. In Section 4, we present our econometric model. Section 5 reports and discusses our results. Finally, we conclude our study in Section 6.

2.2. Theoretical Evidence:

Many theories have presented the relationship between inflation and output growth on one hand, and inflation uncertainty and output uncertainty on the other.

2.2.1. The Impact of Inflation on Inflation Uncertainty:

The most theory that described this effect came from Friedman (1977) where he viewed the effect of inflation on unemployment (inflation effects on output growth via inflation uncertainty). The first part of Friedman's hypothesis concentrates on the impact of inflation on nominal uncertainty explaining that an increase in inflation may induce an erratic policy response by monetary authority, and therefore, leads to more uncertainty about the future rate of inflation (see Fountas and Karanasos (2007)).

Moreover, the above issue is supported by Ball (1992) where he presented a model of monetary policy in which a rise in inflation increases uncertainty about the future rate of inflation. In explaining this result, he analyzes an asymmetric information game in which the public faces uncertainty with relation to two types of policymakers that are considered: a weak type that is unwilling disinflation and a tough type that bears the cost of disinflation. The policymakers alternate stochastically in office.

When current inflation is high, the public faces increasing uncertainty about future inflation since it is unknown which policymaker will be in office next period. Consequently, the response to the high-inflation rate will be unknown. Such an uncertainty does not arise in the presence of a low inflation rate. It is also possible that more inflation will lead to a lower level of inflation uncertainty. On the contrary, Pourgerami and Maskus (1987) advance this argument where in the presence of rising inflation agents may invest more resources in forecasting inflation, thus reducing uncertainty about inflation. The same is supported by Ungar and Zilberfarb (1993).

2.2.2. The Impact of Inflation Uncertainty on Inflation:

Cukierman and Meltzer (1986) use a Barro and Gordon (1983) set up, where agents face uncertainty about the rate of monetary growth, and thus inflation. In the presence of this uncertainty, they believe that the policymakers apply an expansionary monetary policy in order to surprise the agents and enjoy output gains.

As a result, there is a positive impact of inflation uncertainty on inflation. Holland (1995) has viewed opposite results about the effect of nominal uncertainty on inflation itself where he presented that greater uncertainty is a part of the cost of inflation. In other words, as inflation uncertainty increases when the inflation rate rises, the policymakers respond by contracting growth of money supply in order to eliminate inflation uncertainty and the associated negative welfare effects. Hence, Holland's argument supports the negative causal impact of inflation variability on inflation.

2.2.3. The impact of Output Uncertainty on Output Growth:

The impact of output uncertainty on output growth rate has been also analysed theoretically. The macro-economic theory where it offered three possibilities to clarify the effect of real uncertainty on output growth. Firstly, according to some business cycle models, there is no correlation between the growth rate and its variability because, in business cycle models, the output uncertainty is determined by price misperceptions in response to monetary shocks. On the other hand, change of the output growth is affected by real factors such as technology (Friedman, 1968). Secondly, as some theories point out, is the positive effect of output uncertainty on the economic growth rate. Mirman (1971) advanced the argument that more income uncertainty would lead to higher savings rate for precautionary reasons which would result in a higher equilibrium rate of economic growth according to the neoclassical growth theory. In addition, Black (1987) argued the positive impact of output variability on the growth rate. His emphasis was based on the hypothesis that investments in riskier technologies will be available only if the average rate of output growth (predicted return on the investments) is large enough to reimburse the cost of extra risk that is supported by Blackburn (1999). Finally, the negative effect of output uncertainty on growth is predicted mainly by Pindyck (1991).

2.3. Empirical Literature:

Recent time-series studies have focused particularly on the GARCH conditional variance of inflation as a statistical measure of nominal uncertainty.

According to our case study, Berument, et al. (2001) modelled inflation uncertainty in Turkey using an EGARCH framework that is based on monthly CPI data between 1986 and 2001. Berument, et al. (2001) use seasonal dummies and dummy due to financial crises in 1994 in both mean and variance equations. The main findings show that monthly seasonality has a significant effect of inflation uncertainty.

In addition, the effects of inflation uncertainty of positive shocks to inflation are greater than that of negative shocks to inflation. Also, there is no significant effect of inflation on its uncertainty when a dummy of financial crises in 1994 is included in mean equation. In a similar manner, Neyapti and Kaya (2001) used an autoregressive conditional heteroskedasticity (ARCH) model to measure inflation variability and to test the relationship between the level and variability of the inflation rate using the monthly wholesale price between 1982 and 1999. Moreover, a significant positive correlation resulted between inflation and its uncertainty.

Using different framework, Berument, et al. (2011) investigated the interaction between inflation and inflation uncertainty in Turkey using monthly data for the time period 1984–2009. The stochastic volatility in mean (SVM) model that they used allows for gathering innovations to inflation uncertainty and assesses the effect of inflation volatility shocks on inflation over time. Berument, et al (2011) indicated that response of inflation to inflation volatility is positive and statistically significant. On the contrary, the response of inflation volatility to inflation is negative but not statistically significant.

However, Ozdemir and Saygili (2009) using P-stare model to explain inflation dynamics in Turkey where money plays an important role in P-stare model by determining the price gap which is postulated to measure the pressure on prices in the economy. The results showed that the price gap does indeed contain considerable information for explaining inflation dynamics in Turkey. Also, money is efficacious in predicting risk to price stability.

At an earlier time, Ozcan, et al (2004) proposed that there is inflation inertia in Turkey during 1988-2004 using model-free techniques model. An evidence supports that there are correlations between the housing rent, US dollar and German mark exchange rate on one side, and Turkish CPI on the other side.

Güney (2016) examined the role of inflation and output uncertainties on monetary policy rules in Turkey using monthly data for the period 2002:01e2014:02. In accordance with that, Güney (2016) used a forward-looking version of the Taylor rule. Then, used 'Enriched Taylor-Type' rule. Where Taylor rule includes inflation and growth uncertainty. The author directly concentrated on the parameters of output and inflation uncertainties. These uncertainties were included into the Taylor-type monetary policy rule. In the same paper, the author applied Generalized Methods of Moments (GMM) for estimating monetary policy reaction function of the Central Bank of the Republic of Turkey (CBRT). Also, he used two lags of interest rate in the monetary policy rule to allow for interest rate smoothing. He found that the CBRT concerns mainly with price stability after the adoption of the inflation targeting programme. In addition, he demonstrated that the CBRT considers inflation and output growth uncertainties in setting the policy rate. This implies that monetary authorities consider economic stability to achieve their objectives. Moreover, he concluded that inflation uncertainty causes a decrease in output further through interest rate channel as a result of CBRT resorting to apply robust monetary policy to reduce both inflation and inflation uncertainty; this implies that inflation uncertainty causes a decline in output further through interest rate channel.

Applying simple models, Helmy (2010) studied inflation dynamics in Egypt using annual data and Granger causality tests, simple VAR, impulse response functions (IRF) and variance error decomposition (VDC) analyses to test for the sources and dynamics of inflation in Egypt. The result of interest is that the inflation in Egypt is affected mainly by growth of money supply, interest rates and exchange rates. In addition, Ghalwash (2010) addressed whether a scientific support of the inflation targeting regime for Egypt is existing or not in theoretical manner that is extracted by a simple VAR model. The result implies that the Central Bank of Egypt and the Egyptian economy is not yet ready for the implementation of an inflation targeting regime.

However, many empirical studies used PARCH model to investigate the correlation between inflation and its uncertainty as well as output growth and output uncertainty in developing countries. For example, Karanasos and Schurer (2005) examined the relationship between growth and real uncertainty in Italy by using asymmetric power ARCH models of the conditional volatility of average output growth with monthly data for the period 1962-2004. According to their results, there is strong negative bidirectional feedback between the two variables. The evidence of causality running from uncertainty to growth is robust to the three alternative forms of "risk premium" used and to the various estimated power transformations of the conditional variance. However, the results for the reverse type of causality are qualitatively altered by changes in the formulation of the power ARCH model. In a parallel manner, Karanasos and Schurer (2008) used the power ARCH models of the conditional variance of inflation to model the relationship between inflation and its uncertainty in three European countries. For all three countries inflation significantly raises inflation uncertainty. Moreover, increased uncertainty affects inflation in all countries but not in the same manner. For Sweden, there is a negative impact in accordance with the Holland hypothesis, whereas for Germany and the Netherlands, the opposite is found in support of the Cukierman–Meltzer hypothesis.

2.4. Power GARCH in Mean Model:

Taylor (1986) and Schwert (1989) introduced the standard deviation GARCH model, where the standard deviation is modelled rather than the variance. This model, along with several other models, is generalized in Ding, Granger and Engle (1993) with the Power ARCH specification. In the Power ARCH model, the power parameter of the standard deviation can be estimated rather than imposed, and the optional parameters are added to capture asymmetry effect.

Let x_t follow an autoregressive (AR) process that enhanced by a 'risk premium' defined in terms of volatility:

$$\Phi(L)x_t = c + kg(h_t) + \varepsilon_t \qquad (2.1)$$

$$\varepsilon_t = e_t\, h_t \qquad (2.2)$$

$$e_t \overset{i.i.d}{\equiv} f(0,1) \qquad (2.3)$$

$$h_t^{\delta} = \omega + \alpha(|e_{t-1}| - \varsigma e_{t-1})^{\delta} + \beta h_{t-1}^{\delta} \qquad (2.4)$$

Where by assumption the finite order polynomial $\Phi(L)x_t \equiv \sum_{i=1}^{p} \emptyset_i L^i$ has zeros outside the unit circle. *c* is a constant parameter, ε_t is the innovation process, h_t is the conditional standard deviation, and e_t is an independently and identically distributed *(i.i.d.)* process.

$\omega > 0, \alpha \geq 0, \beta \geq 0, \delta > 0\ and\ |\varsigma| \leq 1$. Here α and β are the standard ARCH and GARCH parameters, ς is the leverage parameter, and δ is the parameter for the power term. A positive (respect negative) value of the ς means that past negative (respect positive) shocks have a deeper impact on current conditional volatility than past positive (respect negative) shocks.

The model imposes a Box and Cox (1964) transformation in the conditional standard deviation process and the asymmetric absolute innovations. In the APGARCH model, good news ($\varsigma_{t-i} > 0$) and bad news ($\varsigma_{t-i} < 0$) have different predictability for future volatility, because the conditional variance depends not only on the magnitude but also on the sign of ς.

The APARCH(1.1) included the lagged (inflation or output growth) into the variance equation can be written as:

$$h_t^{\delta} = \omega + \alpha(|e_{t-1}| - \varsigma e_{t-1})^{\delta} + \beta h_{t-1}^{\delta} + \gamma x_{t-l} \qquad (2.5)$$

Where ω, α, ς, β, and δ are additional parameters to be estimated, γ is the 'level' term for the *l*th lag of inflation or output growth.

In the influential paper of Engle (1982), the density function of e_t was the standard normal distribution. Bollerslev (1987) tried to capture the high degree of leptokurtosis that is presented in high frequency data and proposed the Student-*t* distribution in order to produce an unconditional distribution with fat tails. Lambert and Laurent (2001) suggested that not only the conditional distribution of innovations may be leptokurtic, but also asymmetric and proposed the Skewed Student-*t* densities function.

The expected value of $f(e_{t-1})$ is given by:

$$E[f(e_{t-1})] = \begin{cases} \frac{1}{\sqrt{x}}\left[(1-\varsigma)^{\delta} + (1+\varsigma)^{\delta}\right]2^{\left(\frac{\delta}{2}-1\right)}\Gamma\left(\frac{\delta+1}{2}\right),,,,,,,,,,\text{if } e_{t-1} \xrightarrow{(i.d.)} N(0,1) \\ \frac{(r-2)^{\frac{\delta}{2}}\left(\frac{r-\delta}{2}\right)\Gamma\left(\frac{\delta+1}{2}\right)}{\Gamma\left(r/2\right)2\sqrt{x}}\left[(1-\varsigma)^{\delta} + (1+\varsigma)^{\delta}\right],,,,,,,,,,\text{if } e_{t-1} \xrightarrow{(i.d.)} t_r(0,1) \end{cases} \qquad (2.6)$$

Where *N* and *t* denote the Normal and Student's *t* distributions, respectively, *r* are the degrees of freedom of Student's *t* distribution and Γ(.) is the gamma function. The *δth* moment of the conditional variance is a function of the above expression (see Karanasos and Schurer 2008).

Within the APARCH model, by specifying permissible values for *α, β, ς, δ* and γ in equation 2.5, it is possible to nest a number of the more standard ARCH and GARCH specifications (see Brooks et al., 2000; Ding et al 1993) for instance in equation 2.5, let *δ*=2 and ς=γ=0 to get the GARCH model.

2.5. Empirical Analysis:

2.5.1. The Case of Turkey:

2.5.1.1. **The Data:**

Monthly data is used on the consumer price index (CPI) as proxies for the price level in Turkey. The data range from February 1969 to February 2011. In addition, monthly data is used on the industrial price index (IPI) as proxies for the output growth. The data range from February 1985 to December 2010. This data is collected from International Financial Statistic (IFS) website.

Both Inflation and output growth are measured by the difference between two months of the natural logarithm of CPI and IPI, i.e. $[\pi_t = \ln(CPI_t/CPI_{t-1}) \times 100]$, $y_t = \ln(IPI_t/IPI_{t-1}) \times 100$, which leaves us with 505 and 311 usable observations for inflation and output growth respectively.

The summary statistics in (Table 2.1) imply that inflation rates are positively skewed whereas output growth rates are skewed negatively. Moreover, displaying significant amounts of excess kurtosis with both series is failing to satisfy the null hypothesis of the Jarque-Bera test for normality. In other words, the large values of the Jarque–Bera statistics imply a deviation from normality. In addition, the results of augmented Dickey–Fuller (1979) and Phillips-Perron (1988) unit root tests imply that we can treat the two rates as stationary processes.

The CPI and inflation rates are plotted in Figure 2.1 and Figure 2.2 respectively. Figure 2.1 clearly shows the economic shock in 1979 as a result of foreign exchange crisis in the Turkish economy, with negative growth, the inflation into triple-digit levels, and wide spread shortages (Rodrik (1990)). In addition, the Turkish economy has experienced two major currency crises in 1994 and 2000 – 2001, as a result of the liberalization of the capital account that has caused an increase in the Turkish lira by 22% complaining the prices level by the end of 1989. (Kibritçioğlu, et al (1999) and Feridun (2008)).

Table 2. 1 Summary statistic for Turkey:

	Inflation - CPI	**Output Growth - IPI**
Mean	2.751742	0.360856
Median	2.290054	0.365145
Maximum	22.07831	15.43024
Minimum	-6.442225	-25.63760
Std. Dev.	2.673235	5.750635
Skewness	1.645259	-0.518888
Kurtosis	11.05003	5.184241
Jarque-Bera	1591.393 (0.000)	75.77886 (0.000)
Sum	1389.630	112.2262
Sum Sq. Dev.	3601.676	10251.64
ADF test	-10.29817{<0.01}	-19.03881{<0.01}
PP test	-19.00086{<0.01}	-42.93710{<0.01}

All data series are International Financial Statistic (IFS). Sample period is monthly, from 1960:01 to 2011:01. Monthly inflation rates are calculated from the Consumer Price Index and output growth rates are calculated from the Industrial Price Index at an annual rates. The numbers in parenthesis are robust P – value.

Figure 2.2 indicates many outlier values in inflation rates, many of them might be attributed to some crisis. Also, Figure 2.1 shows that average inflation has fallen between late 1977 to mid-1980 and mid-1994 as well, which might be considered as a result of the crisis (Berument, Yalcin and Yildirim (2011)). In addition, considering the sample after the end of 2000, we can see the effect of adopting an 'exchange-rate-based stabilization program'

Figure 2. 1CPI in Turkey:

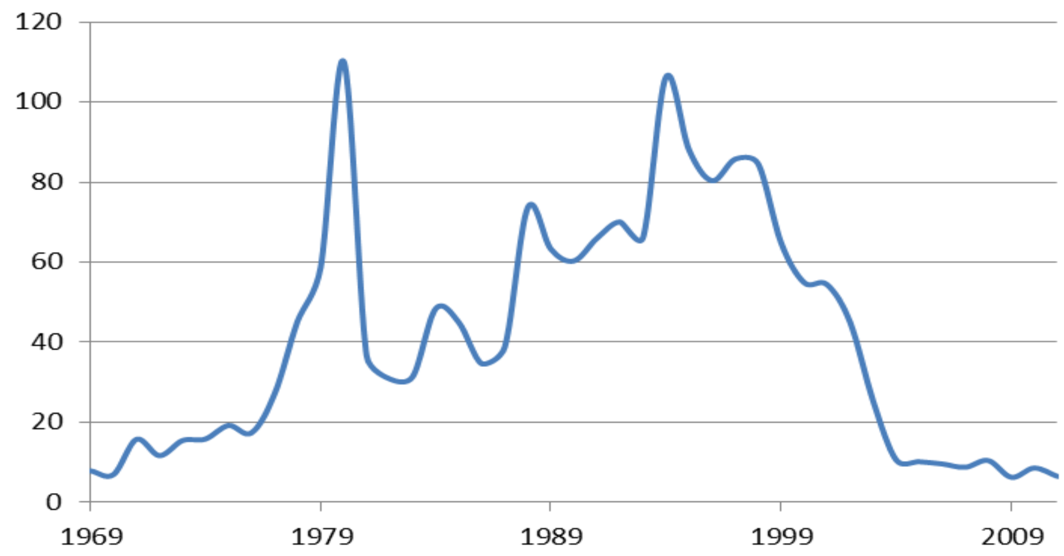
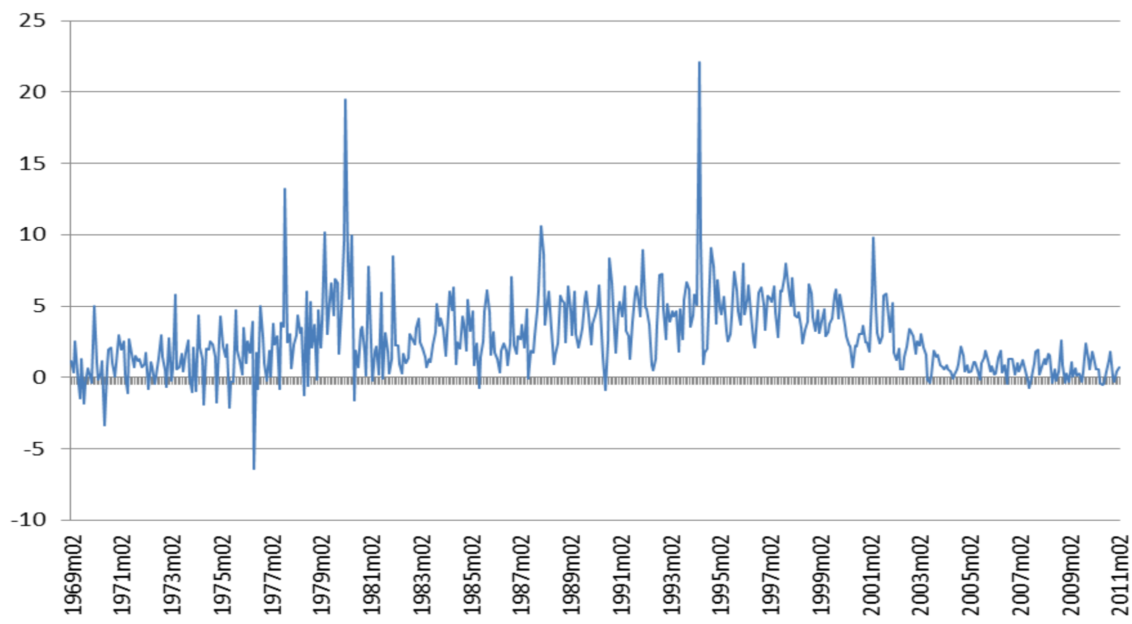


Figure 2. 2 Inflation rates of Turkey:



as well as a quick-fix policy to lower inflation based on the crawling-peg exchange-rate regime in Turkey (Berument, Yalcin and Yildirim (2011)). Moreover, the output growth rate series are plotted in Figure 2.3 and figure 2.4 as we can consider that Turkey has relatively a stable output growth rate.

Figure 2. 3 IPI in Turkey:

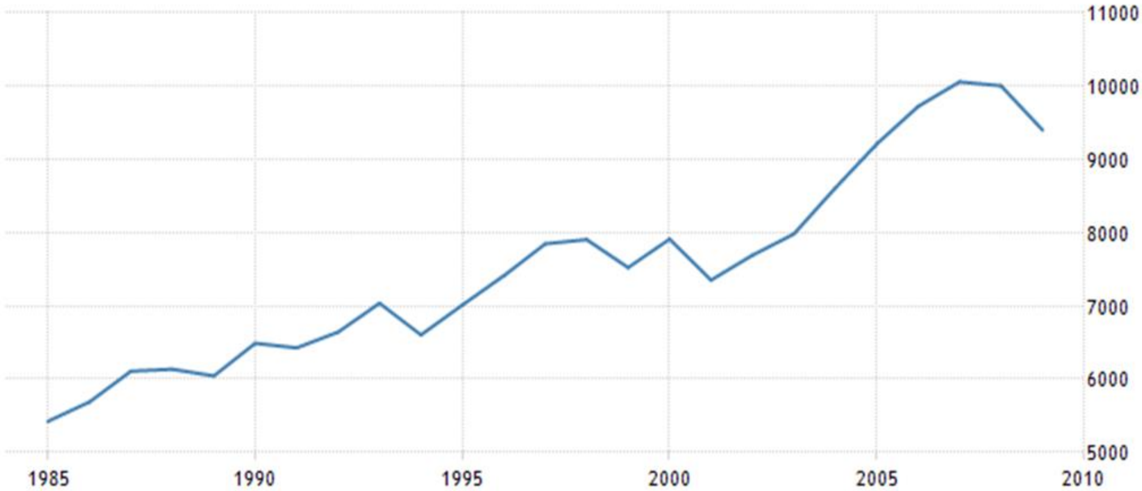
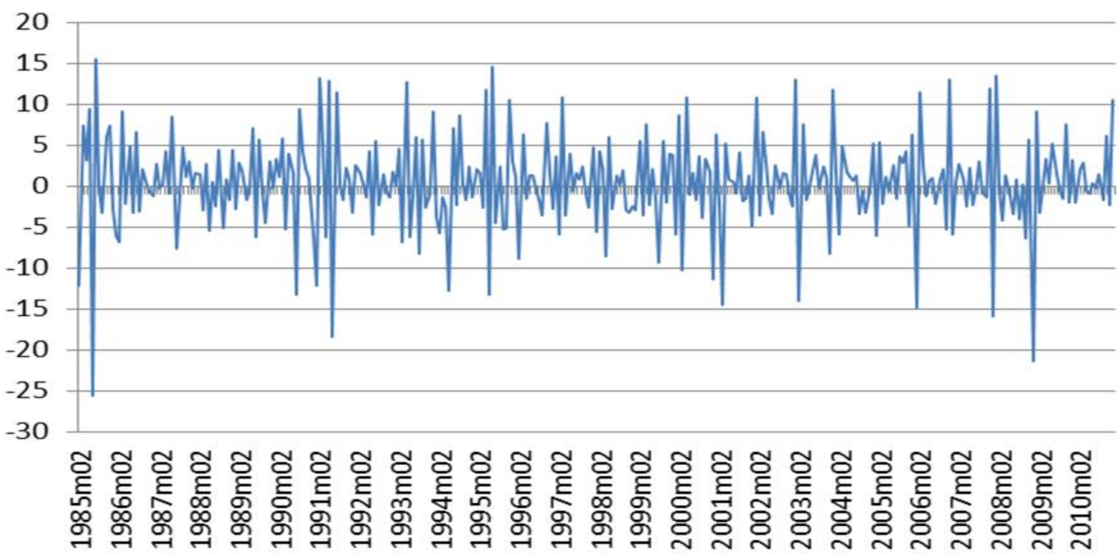


Figure 2. 4 Output growth rates of Turkey



Next, we examine the sample autocorrelations of the power transformed absolute inflation $|\pi_t|^d$ and the power transformed absolute output growth $|y_t|^d$ for various positive values of d. Figure 2.5 shows the autocorrelogram of $|\pi_t|^d$ from lag 1 to 100 for d=0.5, 0.75, 1, 1.5, 2 and 2.5. The horizontal lines show the $\pm 1.96/\sqrt{T}$ confidence interval (CI) for the estimated sample autocorrelations if the process π_t is *i.i.d*. In our case T=505, so CI= ±0.0872.

The sample autocorrelations for $|\pi_t|^{0.5}$ are greater than the sample autocorrelations of $|\pi_t|^d$ for *d=0.75, 1, 1.5, 2 and 2.5* at every lag up to 72 lags. In other words, the most interesting finding from the autocorrelogram is that $|\pi_t|^d$ has the strongest and slowest decaying autocorrelation when $d = 0.5$.

The power transformations of absolute inflation when *d* is less than or equal to 1 have significant positive autocorrelations at least up to lag 75.

Similarly, Figure 2.6 shows the autocorrelogram of $|y_t|^d$ from lag 1 to 20 for *d* =1, 1.5, 1.75, 2, 2.5 and 3. The horizontal lines show the $\pm 1.96/\sqrt{T}$ confidence interval (CI) for the estimated sample autocorrelations if the process y_t is $i.i.d$. In our case T=311, so CI = ±0.1111. The sample autocorrelations for $|y_t|^d$ for $d \leq 2$ are greater than the sample autocorrelations of $|y_t|^d$ for $d > 2$ at lags (1-2) and lags (9-14).

Figure 2. 5 Autocorrelation of $|\pi|^d$ high to low for Turkey

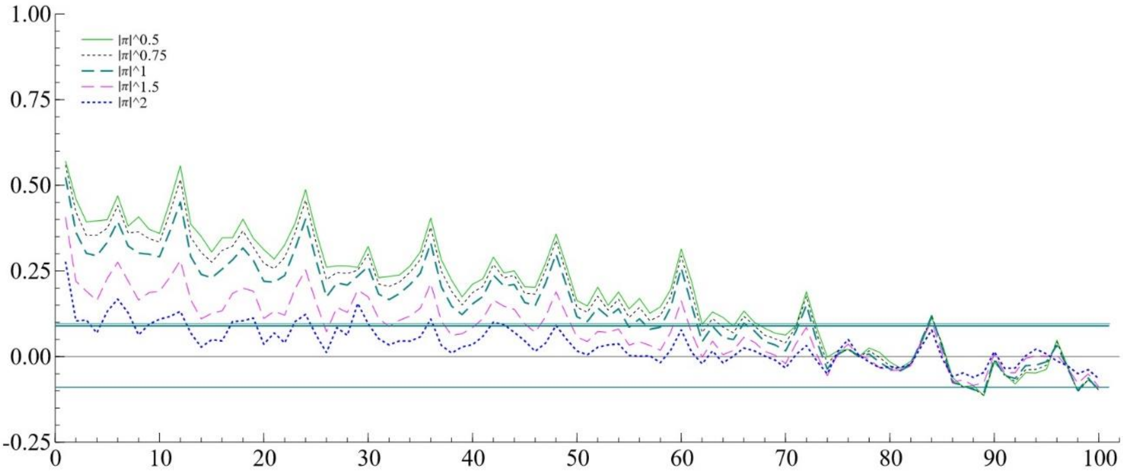
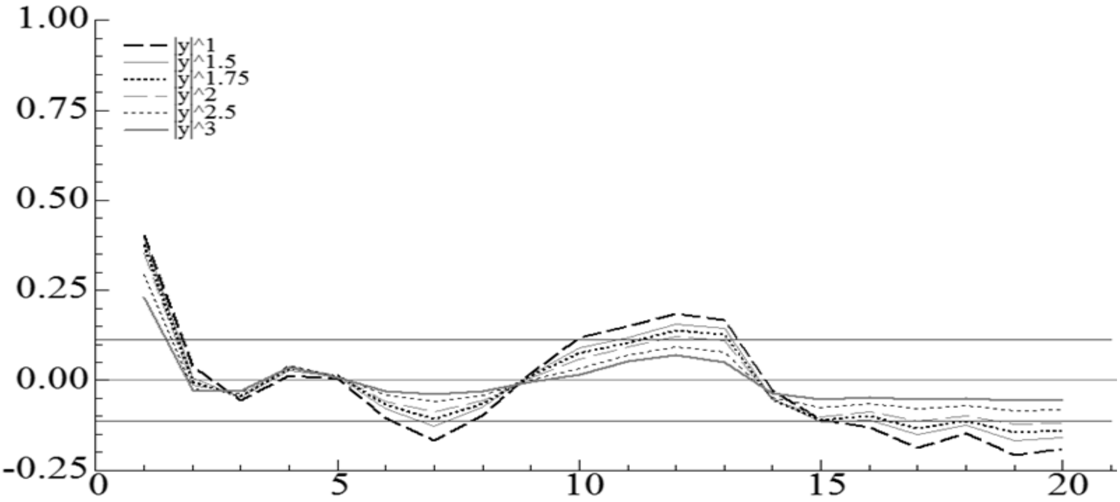


Figure 2. 6Autocorrelation of $|y|^d$ high to low for Turkey



Next, we calculate the sample autocorrelations of the absolute value of inflation $\rho_\tau(d)$ as a function of d for lags τ = 1, 5, 12, 60 and 96. Also, we calculate the sample autocorrelations of the absolute value of output growth $\rho_\tau(d)$ as a function of d for lags τ = 2, 3 and 4 as they are displayed in Figure 2.7 and Figure 2.8 respectively. We can notice from Figure 2.7, for lag 12, the sample autocorrelation function reaches its maximum point at $d^* = 0.25$ where $\rho_\tau(d^*) > \rho_\tau(d)$ for $d^* \neq d$. Furthermore, the sample autocorrelation of the absolute value of output growth as it's indicated in Figure 2.8, there is a unique point $d*$ equal to 0.825, such that $\rho_\tau(d)$ reaches its maximum value at this point that means $\rho_\tau(d^*) > \rho_\tau(d)$ for $d^* \neq d$.

Figure 2. 7 Autocorrelation of $|\boldsymbol{\pi}|^{d}$ at lags 1, 5, 12, 60 and 96 for Turkey

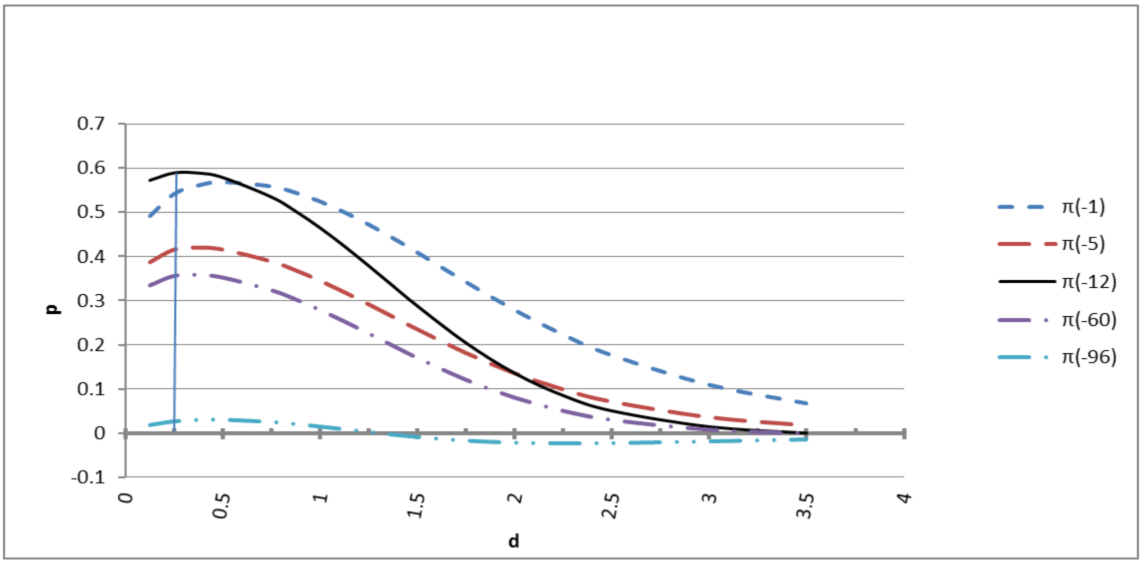
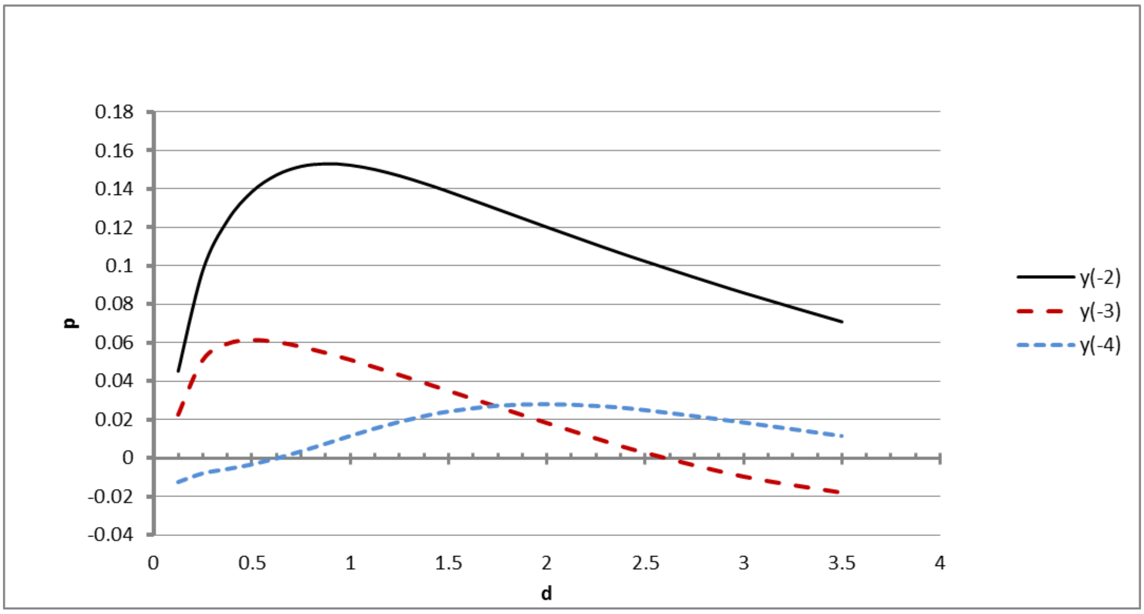


Figure 2. 8 Autocorrelation of $|\boldsymbol{y}|^{d}$ at lags 2, 3 and 4 for Turkey



2.5.1.2. **Estimated models of inflation:**

Using Eviews, the APGARCH(1,1) model is estimated in order to take into consideration the serial correlation observed in the levels and power transformations of our time-series data. Table (2.2) points out the estimated parameters for the period 1969:02–2011:02 that obtained by quasi-maximum likelihood estimation. The best-fitting specification is chosen according to the likelihood ratio results and the minimum value of the information criteria. A number of lags are chosen to capture the serial correlation in Turkish inflation series.

An excess kurtosis in the distribution of inflation and output is exhibited because of the existence of outliers. To accommodate the presence of such leptokurtosis, one should estimate the PGARCH models using non-normal distributions (see Palm (1996) and Karanasos and Schurer (2008)).

In accordance with this, we estimate all the models using two alternative distributions (the normal and Student's *t*). Dummies are chosen in the inflation data according to some economic events in Turkey. The mean equation is adjusted to include two dummy variables on the intercept. In the first one, a dummy variable is selected in the model in order to capture any possible outliers. So, a dummy variable is created (D1) where D1=1 for outlier values (1977:09, 1980:(01 to 05) and 1994:(04 and 05)) and D1=0 otherwise. In addition, we define another dummy variable series (D2) due to the gradualist policies in Turkey by the end of 2000. The definition of this dummy variable is (D2=0 till 2000:12 and D2=1 otherwise).

The results demonstrate that the leverage term ς is highly significant in estimated APGARCH(1,1) with the normal distribution, but with student *t* and when include dummy variables, it becomes insignificant. In our three cases of estimation, the estimated α and β parameters are highly significant.

The estimated power term δ is statistically significant at 1% and 5% when the innovations e_t are Normal and Student's t distributed respectively. The power δ is 0.50 when the innovations e_t is Normal distributed, but the power becomes higher when the innovations e_t are Student's distributed where $\delta = 0.68$. However, due to an insignificant power term when dummies variables are added to model estimation, the power is fixed to a specific value ($\delta = 0.7$) on the basis of the minimum value of Akaike info criterion (AIC) as this model will be referred as PGARCH.

Table 2. 2 APGARCH Models of inflation for Turkey:

	Normal distribution	Normal distribution (Dummies)	Student t distribution
α	0.14 (0.05)***	0.16 (0.03)***	0.11 (0.03)***
β	0.87 (0.06)***	0.87 (0.020)***	0.90 (0.02)***
ς	-0.83 (0.36)***	-	-
δ	0.50 (0.28)*	0.70 -	0.68 (0.34)**
r	-	-	3.70 (0.56)***

Notes: This table reports parameter estimates for the following model:
Variance Equation: $h_t^{\delta} = \omega + \alpha(|e_{t-1}| - \varsigma e_{t-1})^{\delta} + \beta h_{t-1}^{\delta}$
*The numbers in parentheses are robust standard errors. (r) are the degrees of freedom of Student's t distribution. ***, ** and * are significance levels of 1%, 5% and 10%, respectively.*

Next, the estimation results of an APGARCH-M model of inflation with $g(h) = h$ are reported alongside the estimation results of an APGARCH(1,1)-L and APGARCH(1,1)-ML models of inflation with lagged inflation in conditional variance as the "level" effect. Moreover, we include the dummy variables into the mean equation only with the in-mean and mean-level models.

Table 2.3 reports only the estimated parameters of interest. The ARCH and GARCH parameters are highly significant at 1% when we estimate the APGARCH(1,1) in mean and in level separately. The estimates for the 'in-mean' parameter *k* are statistically significant where the in-mean effect is significant at the 1% (*k* = -0.28) for APGARCH(1.1)-M model. Thus, there is a strong evidence in favour of Holland (1995) hypothesis that inflation uncertainty affects inflation negatively. Finally, the power term δ=0.56 is significant for APGARCH(1,1)-M (see column .1).

This means, that if the decline in the inflation uncertainty is 1.00, then the increased corresponding in the inflation is 0.28

Furthermore, the APGARCH(1,1)-L model of inflation with lagged inflation added in the conditional variance equation as "level effect" is estimated. Various lags were considered and

Table 2. 3 APGARCH-ML Models of inflation for Turkey:

	Mean (Dummies) $g(h) = h$	Level	Mean-Level (Dummies) $g(h) = h$
α	0.41 (0.12)***	0.32 (0.09)***	0.56 (0.33)*
β	0.48 (0.10)***	0.51 (0.081)***	0.21 (0.10)**
k	-0.28 (0.08)***	-	-0.24 (0.11)**
γ	-	0.10 (0.05)* {lag 5}	0.28 (0.08)*** {lag 7}
δ	0.56 (0.26)**	0.94 (0.31)***	2.57 (0.63)***

Notes: This table reports parameter estimates for the following model:
Mean Equatin: $\Phi(L)x_t = c + kg(h_t) + \varepsilon_t$
Variance Equation: $h_t^{\delta} = \omega + \alpha(|e_{t-1}| - \varsigma e_{t-1})^{\delta} + \beta h_{t-1}^{\delta} + \gamma \pi_{t-i}$
*The numbers in parentheses are robust standard errors. ***, ** and * are significance levels of 1%, 5% and 10%, respectively.*

we have chosen the significant level term $\gamma = 0.10$ at lag (5) on the basis of the minimum value of Akaike info criterion (AIC). There is strong evidence that inflation affects its uncertainty positively as predicted by Ball (1992) and Friedman (1977). Finally, in the level model (see column 2) the power term (δ=0.94) looks higher than it is in the mean model.

According to this finding, a 100% increase in the inflation rate leads to 10% increasing in the Turkish inflation uncertainty.

Table 2.3 also shows the estimation results of the APGARCH-ML model. When $g(h) = h$ for the in mean effect, and we allow lagged inflation to affect the conditional variance, the level effect at lag (7) $\gamma = 0.28$ is highly significant. Again, the positive and significant level parameter leads to strong evidence for Friedman (1977) and Ball (1992) hypothesis. Moreover, the negative and significant in mean effect (k = -0.24) shows an evidence for Holand (1995) where Turkish inflation uncertainty affects inflation negatively. Finally, the power goes up considerably when we estimate APGARCH(1.1)-ML model.

In other words, a 100% increase in the inflation rate and its uncertainty leads to the corresponding increase in the inflation uncertainty and inflation rate with 28% and 24% respectively.

2.5.1.3. **Estimated models of output growth:**

We proceed with the estimation of the APGARCH(1,1) model in order to take into consideration the serial correlation observed in the levels and power transformations of our time-series data. Table 2.4 reports the estimated parameters of interest for the period 1985:02–2010:12 that were obtained by quasi-maximum likelihood estimation. The best-fitting specification is chosen according to the likelihood ratio results and the minimum value of the information criteria. A number of lags is chosen to capture the serial correlation in Turkish output growth series.

We estimate all the models using two alternative distributions (the Normal and Student's *t*). Moreover, we include dummies for the output growth data according to some economic events in Turkey. The mean equation is adjusted to include two dummy variables on the intercept. In the first one, we use a dummy variable in the model in order to capture any possible outliers. So, we create a dummy variable (D1) where D1 = 1 for outlier values and D1 = 0 otherwise. In addition, we define another dummy variable series (D2) due to the gradualist policies in Turkey by the end of 2000. This dummy variable D2 = 0 till 2000:12 and D2 = 1 otherwise.

For all cases, we find the leverage term ς to be insignificant and thus we re-estimate the model in all cases excluding asymmetric effect. At first, we estimate APGARCH (1,1) when the innovations e_t are normally distributed. The parameters α and β are highly significant but the power term $\delta = 0.63$ is significant weakly. In addition, we estimate the power ARCH model when the error is student's distributed. The ARCH parameter α is highly significant. However, because of insignificant power term δ when innovations e_t are student's t distributed, we fix the power to a specific value (δ = 1.60) according to the Akaike Information Criterion (AIC) and maximum log-likelihood value.

Also, Table 2.4 reports the parameters of interest of the APGARCH model with dummy variables into mean equation (see column 2), α and β are highly significant but the power term (δ = 0.61) is weakly significant.

Table 2. 4 APGARCH Models of output growth for Turkey:

	Normal distribution	Normal distribution (Dummies)	Student distribution
α	0.25 (0.07)***	0.25 (0.08)***	0.43 (0.18)**
β	0.50 (0.18)***	0.44 (0.19)**	-
δ	0.63 (0.36)*	0.61 (0.32)*	1.60 -
r	-	-	3.55 (0.95)***

Notes: This table reports parameter estimates for the following model:
Variance Equation: $h_t^{\delta} = \omega + \alpha(|e_{t-1}| - \varsigma e_{t-1})^{\delta} + \beta h_{t-1}^{\delta}$
*The numbers in parentheses are robust standard errors. (r) are the degrees of freedom of Student's t distribution. ***, ** and * are significance levels of 1%, 5% and 10%, respectively.*

Next, Table (2.5) reports the estimation results of APGARCH-M model of output growth with $g(h) = h$, as well as the estimation results of APGARCH(1,1)-L and APGARCH(1,1)-ML models of output growth.

Table 2.5 reports only the estimated parameters of interest. ARCH and GARCH parameters (α and β) are highly significant at 1% when we estimate the APARCH-M as well as APGARCH(1,1) in level and in mean-level. The estimates for the 'in-mean' parameter (k) are statistically significant where the in-mean effect is significant at the 1% (k = -0.44) for the

APARCH-M model. Thus, there is strong evidence in support of Pindyck (1991) hypothesis that output uncertainty reduces output growth rate by 44%. However, given an insignificant power term and according to the Akaike Information Criterion (AIC) and maximum log-likelihood value, we fix the power at δ = 0.50.

Table 2. 5 APGARCH-ML Models of output growth for Turkey:

	Mean $g(h) = h$	level	Mean-level $g(h) = h$
α	0.39 (0.04)***	0.23 (0.06)***	0.14 (0.05)***
β	-	0.30 (0.04)***	0.50 (0.03)***
k	-0.44 (0.13)***	-	-0.32 (0.08)***
γ	-	-1.13 (0.63)* {lag 5}; -1.31 (0.60)** {lag 6}; +0.60 (0.33)* {lag 13}	-1.77 (0.77)** {lag 5}; -2.57 (1.13)** {lag 6}
δ	0.50 -	2.04 (0.33)***	2.33 (0.292)***

Notes: This table reports parameter estimates for the following model:
Mean Equatin: $\Phi(L)x_t = c + kg(h_t) + \varepsilon_t$
Variance Equation: $h_t^{\delta} = \omega + \alpha(|e_{t-1}| - \varsigma e_{t-1})^{\delta} + \beta h_{t-1}^{\delta} + \gamma \pi_{t-i}$
*The numbers in parentheses are robust standard errors. ***, ** and * are significance levels of 1%, 5% and 10%, respectively.*

Furthermore, we estimate the APGARCH(1,1)-L model of output growth with lagged output added in the conditional variance equation as "level effect". Various lags were considered and we have chosen the significant level terms at lags (5), (6) and (13) respectively (see 'mean-level' column of Table 2.5). On the bases of the minimum value of Akaike info criterion (AIC) there is evidence that output affects its uncertainty negatively ($h_{yt} \overset{-}{\rightarrow} y_t$). This implies that an increase in the employment rate by 1.00 leads to reducing uncertainty of output growth rate with 1.80.

Finally, Table 2.5 also shows the estimation results of an APGARCH-ML model. Where $g(h) = h$ for the in mean effect, and we allow lagged output to affect the conditional variance, the level effect at lag (5 and 6) is significant at 5%. Moreover, the negative and significant in mean effect (k = -0.32) shows a strong evidence for Pindyck (1991) where Turkish output uncertainty affects output growth negatively ($y_t \xrightarrow{-} h_{yt}$). Finally, the power goes up hugely when we estimate APGARCH(1,1) model with mean and mean-level.

2.5.2. The case of Egypt:

2.5.2.1. <u>The Data:</u>

For Egypt, monthly data is used on the CPI as proxies for the price level. The data range from February 1957 to February 2011. These data are collected from IFS website.

The inflation is measured by the difference between two months of the natural logarithm of CPI, i.e. [$\pi_t = \ln(CPI_t/CPI_{t-1}) \times 100$], which leaves us with 649 usable observations for inflation.

The summary statistics in (Table 2.6) imply that inflation rates are positively skewed. Moreover, displaying significant amounts of excess kurtosis with inflation series are failing to satisfy the null hypothesis of the Jarque-Bera test for normality. In other words, the large values of the Jarque–Bera statistics imply a deviation from normality. In addition, the results of augmented Dickey–Fuller (1979) and Phillips-Perron (1988) unit root tests imply that we can treat the inflation rate in Egypt as stationary processes.

The CPI and inflation rates in Egypt are plotted in Figure 2.9 and Figure 2.10 respectively. By taking a look into plotted series, we can relise three subsamples. The first one is from 1970 to 1990 where Egypt turned away from the Soviet Union and initiated an economics open-door policy (see Lofgren (1993)). Since then, the International Monetary Fund (IMF) and the World Bank encouraged comprehensive reform that would make Egypt an outward looking market-oriented capitalist economy in which the privet sector plays a command role.

Secondly, the inflation rate has relatively stayed stable over the period 1990 to 2004. In 1991 the Egyptian government has begun to perform IMF recommendation to improve the area of pricing, the foreign exchange system, interest rates, the money supply and the budget deficit (Lofgren (1993)). Since 2004, the volatility of inflation rates has increased after implementing series of reforms such as tariff reduction, tax administration and public expenditure management.

Table 2. 6 Summary statistic for Egypt:

	Inflation - CPI
Mean	0.691341
Median	0.406516
Maximum	9.464108
Minimum	-7.254355
Std. Dev.	1.650596
Skewness	1.083889
Kurtosis	10.32943
Jarque-Bera	1579.768 (0.000)
Sum	448.6802
Sum Sq. Dev.	1765.454
ADF test	-28.10768{<0.01}
PP test	-28.41991{<0.01}

All data series are International Financial Statistic (IFS). Sample period is monthly, from 1957:02 to 2011:02. Monthly inflation rates are calculated from the Consumer Price Index at an annual rates. The numbers in parenthesis are robust *P – value.*

Figure 2. 9 CPI in Egypt:

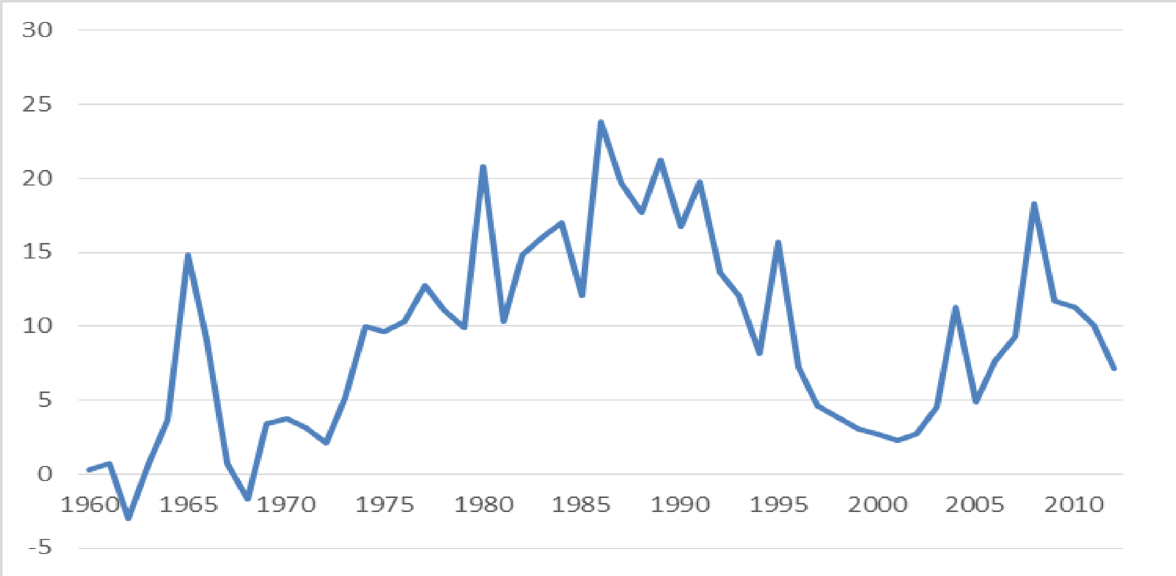
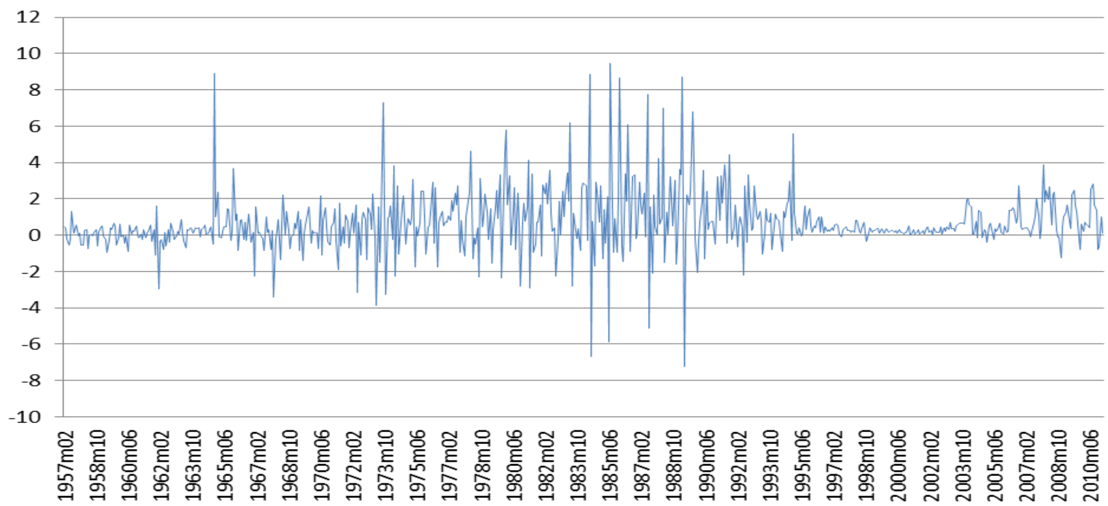


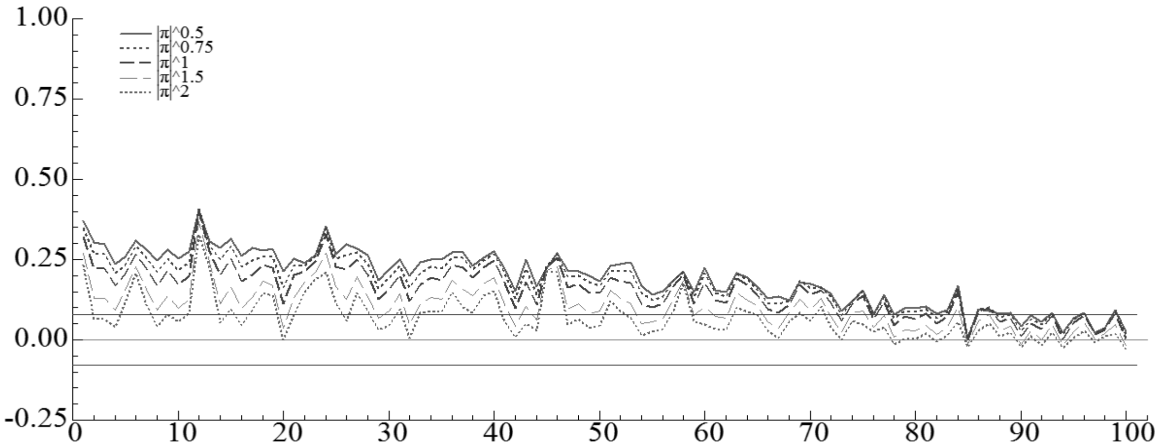
Figure 2. 10 Inflation rates of Egypt over time:



Next, the sample autocorrelations of the power transformed absolute inflation $|\pi_t|^d$ for various positive values of d are examined. Figure (2.11) shows the autocorrelogram of $|\pi_t|^d$ from lag 1 to 100 for d = 0.5, 0.75, 1, 1.5 and 2. The horizontal lines show the $\pm 1.96/\sqrt{T}$ confidence interval (CI) for the estimated sample autocorrelations if the process π_t is *i.i.d*. In our case T = 649, so CI = ±0.0769.

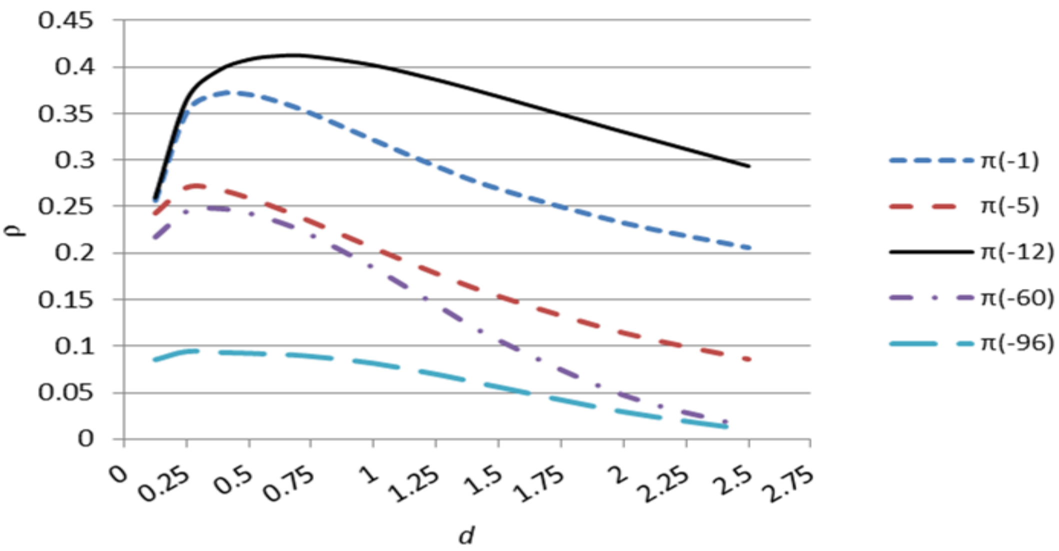
The sample autocorrelations for $|\pi_t|^{0.5}$ are greater than the sample autocorrelations of $|\pi_t|^d$ for *d=0.75, 1, 1.5 and 2* at every lag at least up to 82 lags. In other words, the most interesting finding from the autocorrelogram is that $|\pi_t|^d$ has the strongest and slowest decaying autocorrelation when$d = 0.5$. Furthermore, the power transformations of absolute inflation when d is less than or equal to 1.5 have significant positive autocorrelations at least up to lag 83.

Figure 2. 11 Autocorrelation of $|\pi|^d$ from high to low for Egypt:



Afterwards, we calculate the sample autocorrelations of the absolute value of inflation $\rho_\tau(d)$ as a function of d for lags τ = 1, 5, 12, 60 and 96 as they are displayed in Figure 2.12. It can be noticed that for lag 12, the sample autocorrelation function reaches its maximum point at d*=0.625 where $\rho_\tau(d^*) > \rho_\tau(d)$ for $d^* \neq d$.

Figure 2. 12 Autocorrelation of $|\pi|^d$ at lags 1, 5, 12, 60 and 96 for for Egypt:



2.5.2.2. ***Estimated models of inflation:***

We proceed with the estimation of the APGARCH(1,1) model in order to take into consideration the serial correlation observed in the levels and power transformations of our time-series data. Table 2.7 reports the estimated parameters of interest for the period 1957:02–2011:02 that obtained by quasi-maximum likelihood estimation. The best-fitting specification is chosen according to the likelihood ratio results and the minimum value of the information criteria. Number of lags is chosen to capture the serial correlation in Egyptian inflation series.

First of all, we estimate all APGARCH(1,1) models using two alternative distributions (the Normal and Student's *t*). Moreover, we choose dummies for the inflation data according to some economic and political events in Egypt. We include two dummy variables on the intercept to adjust the mean equation. In the first one, we use a dummy variable in the model in order to capture any possible outliers. So, we create a dummy variable (D1) where D1 = 1 for outlier values (1964:12, 1973:09, 1983:06, 1984:(06 and 07), 1985:07, 1986:(01 and 06), 1987:09, 1988:04 and 1989:(04,05 and 10), and D1 = 0 otherwise. In addition, we define another dummy variable series (D2). This dummy variable D2 = 0 till 1994:10 and D2 = 1 otherwise.

According to the results, Table 2.7 shows that the leverage term ς is highly significant in all cases when we estimate the APGACH(1,1) with the student's *t* and normal distribution and when dummy variables are included into the mean equation. In these three cases of estimation, the estimated APGARCH(1,1) parameters α and β are highly significant.

The estimated power term δ is statistically significant at 1% and 5% when the innovations e_t are Normal and Student's t distributed respectively, where δ is 0.59 when the innovations e_t are Normal distributed, but the power becomes lower when the innovations e_t are Student's distributed (δ = 0.51). However, according to insignificant power term when we add dummies variables to the model estimation, we fix the power to a specific value (δ = 0.6) according to the Akaike Information Criterion (AIC) and maximum log-likelihood value.

Table 2. 7 APGARCH Models of inflation for Egypt:

	Normal distribution	Normal distribution (Dummies)	Student t distribution
α	0.53 (0.17)***	0.16 (0.03)***	0.14 (0.03)***
B	0.55 (0.12)***	0.86 (0.02)***	0.88 (0.02)***
ς	0.27 (0.11)**	-0.65 (0.15)***	-0.59 (0.17)***
δ	0.59 (0.14)***	0.60 -	0.51 (0.26)**
r	-	-	3.70 (0.56)***

Notes: This table reports parameter estimates for the following model:
Variance Equation: $h_t^{\delta} = \omega + \alpha(|e_{t-1}| - \varsigma e_{t-1})^{\delta} + \beta h_{t-1}^{\delta}$
*The numbers in parentheses are robust standard errors. (r) are the degrees of freedom of Student's t distribution. ***, ** and * are significance levels of 1%, 5% and 10%, respectively.*

Next, we report the estimation results of an APGARCH-M model of inflation with $g(h) = h$. In addition, we report the estimation results of an APGARCH(1,1)-L and APGARCH(1,1)-ML models. Moreover, in each case the model estimating run when the innovations e_t are Normal and Student's t distributed respectively.

Table 2.8 reports the estimated parameters of interest. The ARCH and GARCH parameters are highly significant at 1% when we estimate the APGARCH(1,1) in mean, in level and in mean-level for both error distributions (Normal and Student). The leverage term ς is highly significant when the innovations e_t are student distributed. But we take it out where the error distribution is normal as it is insignificant.

Afterwards, we discuss the other APGARCH parameters when innovations e_t are Normal distribution in comparison with the case when error distribution is Student *t*. The in-mean effect (*k*) is positive and significant at 10% with normal distribution. So there is weak evidence of Cukierman and Meltzer (1986) hypothesis where inflation uncertainty affects inflation positively. This means, that if the increase in the inflation uncertainty is 1.00, then the increased corresponding in the inflation is 0.05.

Table 2. 8 APGARCH-ML Models of inflation for Egypt:

	Normal distribution Mean $g(h) = h$	Student distribution Mean $g(h) = h$	Normal distribution level	Student distribution level	Normal distribution Mean-level $g(h) = h$	Student distribution Mean-level $g(h) = h$
α	0.33 (0.04)***	0.15 (0.03)***	0.63 (0.30)**	0.13 (0.02)***	0.15 (0.03)***	0.14 (0.02)***
β	0.70 (0.11)***	0.88 (0.02)***	0.55 (0.15)***	0.91 (0.01)***	0.88 (0.02)***	0.93 (0.02)***
ς	-	-0.57 (0.16)***	-	-0.89 (0.17)***	-	-0.97 (0.11)***
k	0.05 (0.02)*	0.13 (0.04)**	-	-	0.10 (0.05)**	0.15 (0.04)***
γ	-	-	0.10 (0.04)** {3}	-0.03 (0.02)* {3}	0.17 (0.03)*** {3}	-0.05 (0.02)** {2}
δ	0.50 -	0.58 (0.24)**	0.97 (0.19)***	0.69 (0.17)***	1.62 (0.23)***	0.66 (0.14)***
r	-	3.49 (0.41)***	-	3.37 (0.42)***	-	3.41 (0.41)***

Notes: This table reports parameter estimates for the following model:
Mean Equatin: $\Phi(L)x_t = c + kg(h_t) + \varepsilon_t$
Variance Equation: $h_t^{\delta} = \omega + \alpha(|e_{t-1}| - \varsigma e_{t-1})^{\delta} + \beta h_{t-1}^{\delta} + \gamma\pi_{t-i}$
*The numbers in parentheses are robust standard errors. ***, ** and * are significance levels of 1%, 5% and 10%, respectively.*

Also, there is an evidence support Cukierman and Meltzer (1986) when the error distribution is student's t where (*k*) is positive and significant at 5%. The same finding can be considered for APGARCH(1,1) in mean-level model. When the error distribution is student *t*, the mean effect (*k = 0.15*) is positive and highly significant that means a strong evidence support Cukierman and Meltzer (1986) hypothesis as well as when the error is Normal distributed.

Furthermore, we include lagged inflation in variance equation. The level effects for estimated models APGARCH(1,1)-L and APGARCH(1.1)-ML show a contrary results. When the error is Normal distributed, the level effects at lag (3) (γ=0.10 and γ=0.17) of APGARCH(1,1)-L and APGARCH(1.1)-ML respectively are positive and significant. Thus, there is strong evidence supports Ball (1992) and Friedman (1977) hypothesis that inflation affects positively its uncertainty. On the other hand, when we run the model with student error distribution we find

that inflation affects inflation uncertainty negatively that means a weak evidence of Pourgerami and Maskus (1987), Ungar and Zilberfarb (1993) hypothesis as (γ = -0.03 and γ=-0.05) are significant at 10% and 5% respectively.

In summary, for both APGARCH(1,1)-L and APGARCH(1,1)-L, a 100% increase in the inflation rate leads to the positive corresponding change in the inflation uncertainty with 10% and 17% when innovations e_t are Normal. However, a 100% increase in the inflation rate leads to the negative corresponding change in the inflation uncertainty with 3% and 5% when innovations e_t are Student t.

2.5.3. Syria case study:

2.5.3.1. <u>The Data:</u>

For Syria inflation case study, monthly data is used on the CPI as proxies for the price level. The data range from February 1957 to July 2012. This data is collected from IFS website**.**

The inflation is measured by the difference between two months of the natural logarithm of CPI, i.e. $[\pi_t = \ln(CPI_t / CPI_{t-1}) \times 100]$, which leaves us with 666 usable observations for inflation.

The summary statistics in (Table 2.9) imply that inflation rates are negatively skewed. Moreover, displaying significant amounts of excess kurtosis with inflation series are failing to satisfy the null hypothesis of the Jarque-Bera test for normality. In other words, the large values of the Jarque–Bera statistics imply a deviation from normality. In addition, the results of augmented Dickey–Fuller (1979) and Phillips-Perron (1988) unit root tests imply that we might consider the inflation rate in Syria as stationary processes.

The CPI and inflation rates are plotted in Figure 2.13 and Figure 2.14. We can notice that many outlier points could be considered as a result of the crisis. The outlier samples show that average inflation has fallen between 1964 to mid-1977 that might due to political crises. Also, between 1979 and late 1982 due to civil war as well as the same position after med-2011. In addition, a new economic policy has reformed new exchange rates system which allowed privet sector to invest in 1991. Moreover, Syria has faced variety of US sanctions since 1979 and European sanctions between 1985 and 1990. These sanctions had been reflected on price levels as showed in Figure 2.13 between 1985 and 1990.

Table 2. 9 Summary statistic for Syria:

	Inflation - CPI
Mean	0.686196
Median	0.654961
Maximum	12.69319
Minimum	-13.90898
Std. Dev.	2.726204
Skewness	-0.000599
Kurtosis	5.613953
Jarque-Bera	189.6088 (0.000)
Sum	457.0067
Sum Sq. Dev.	4942.407
ADF test	-4.210868{<0.01}
PP test	-23.60727{<0.01}

All data series are International Financial Statistic (IFS). Sample period is monthly, from 1957:02 to 2012:07. Monthly inflation rates are calculated from the Consumer Price Index at an annual rates. The numbers in parenthesis are robust *P – value.*

Figure 2. 13 CPI in Syria:

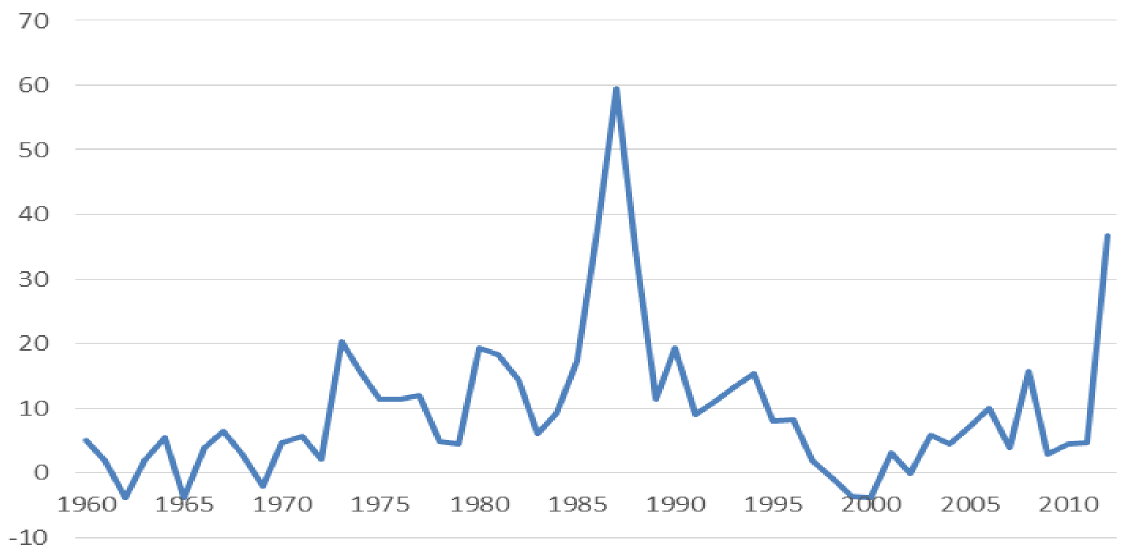
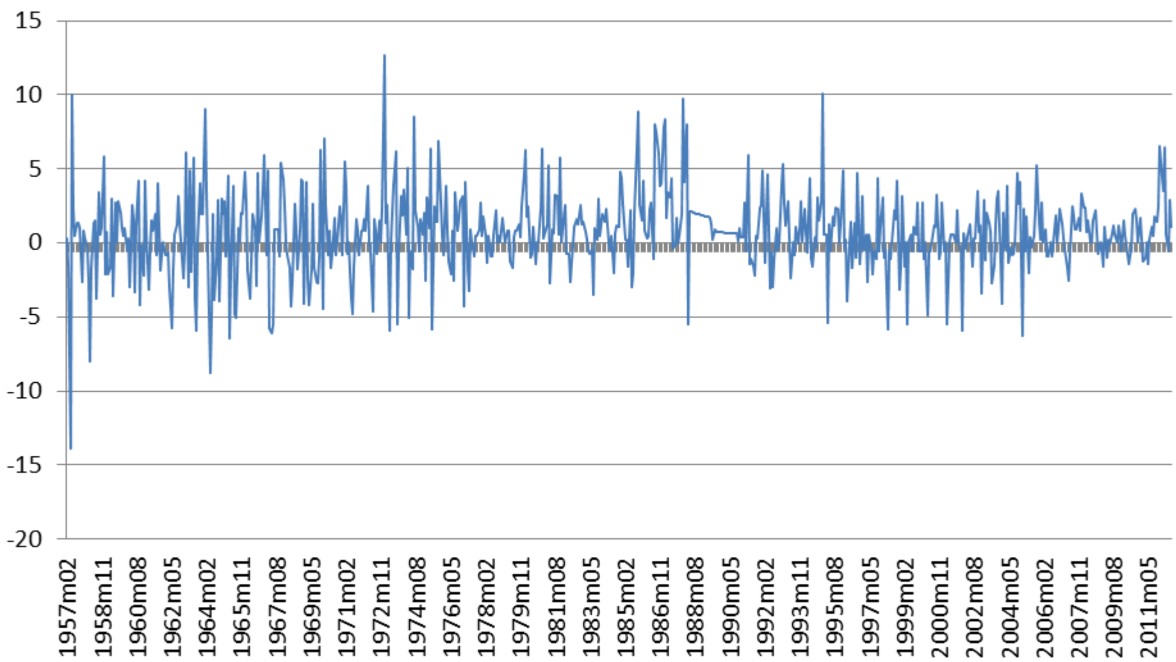


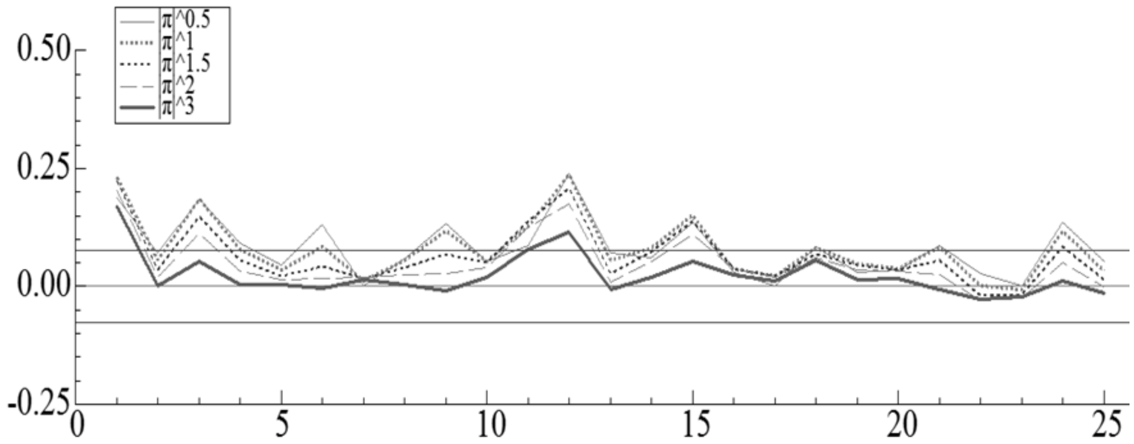
Figure 2. 14 Inflation of Syria over time:



Next, we examine the sample autocorrelations of the power transformed absolute inflation $|\pi_t|^d$ for various positive values of d. (Figure 2.15) shows the autocorrelogram of $|\pi_t|^d$ from lag 1 to 25 for d = 0.5, 1, 1.5, 2 and 3. The horizontal lines show the $\pm 1.96/\sqrt{T}$ confidence interval (CI) for the estimated sample autocorrelations if the process π_t is *i.i.d*. In our case T=666, so CI= ±0.0759.

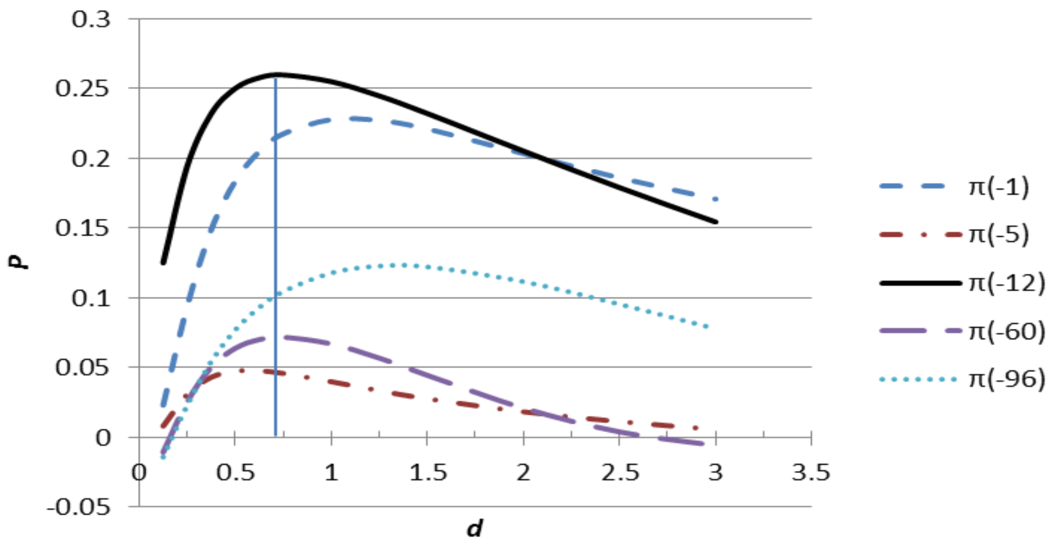
The sample autocorrelations for $|\pi|^1$ are greater than the sample autocorrelations of $|\pi_t|^d$ for *d = 0.5, 1.5, 2 and 3* at lags (1-2) then $|\pi_t|^{0.5}$ becomes greater at lags (3 - 7). Furthermore, the power transformations of absolute inflation when *d* is less than or equal to 2 have significant positive autocorrelations at least up to lag 22.

Figure 2. 15 Autocorrelation of $|\pi|^d$ from high to low for Syria:



Furthermore, the sample autocorrelations of the absolute value of inflation $\rho_\tau(d)$ as a function of *d* for lags τ = 1, 5, 12, 60 and 96 are calculated. Figure 2.16 shows that for lag 12, the sample autocorrelation function reaches its maximum point at *d*=0.75 where $\rho_\tau(d^*) > \rho_\tau(d)$ for $d^* \neq d$.

Figure 2. 16 Autocorrelation of $|\pi|^d$ at lags 1, 5, 12, 60 and 96 Syria:



2.5.3.2. **Estimated models of inflation:**

We proceed with the estimation of the APGARCH(1,1) model in order to take into consideration the serial correlation observed in the levels and power transformations of our time-series data. Table 2.10 reports the estimated parameters for the period 1957:02–2012:07 that obtained by quasi-maximum likelihood estimation. The best-fitting specification is chosen according to the likelihood ratio results and the minimum value of the information criteria. A number of lags are chosen to capture the serial correlation in Syrian inflation series.

Firstly, we estimate the model APGARCH(1.1) using two alternative error distributions (the Normal and Student's *t*). Moreover, we choose dummies for the inflation data according to some economic events in Syria. The mean equation is adjusted by including four dummy variables on the intercept. Firstly, we define dummy variables series due to some events that might affect Syrian economy where D1 = 1 for periods (1958M04 to 1961M09), D2 = 1 for period (1988M04 to 1990M08) and D3 = 1 for period (2011M08 to 2012M07), and D1=D2=D3=0 otherwise. Secondly, we define another dummy variable in the model in order to capture any possible outliers. Thus, we create a dummy variable (D4) where D4 = 1 for outlier values (1957:04, 1973:01 and 1995:01) and D4 = 0 otherwise.

In the concluding results, as it's indicated in Table 2.10, the leverage term ς is highly significant in estimated APGARCH(1,1) with the Normal and Student *t* distribution, but when dummy variables are included and innovations e_t are Normal distributed, it becomes insignificant, so we re-estimate the model excluding the leverage term. In examined three cases of estimation, the GARCH parameters α and β are highly significant.

The estimated power term δ is statistically significant at 5% in all three estimated models when the errors are Normal distributed (with and without including dummy variables in the mean equation) and Student *t* distributed as well. The power δ is 0.80 when the error is Normal distributed is greater than the power when the innovations e_t are Student's *t* distributed.

Table 2. 10 APGARCH Models of inflation for Syria:

	Normal distribution	Normal distribution (Dummies)	Student t distribution
α	0.14 (0.03)***	0.14 (0.04)***	0.18 (0.04)***
β	0.78 (0.05)***	0.78 (0.06)***	0.78 (0.45)***
ς	-0.72 (0.23)***	-	-0.49 (0.11)***
δ	0.80 (0.36)**	1.42 (0.55)***	0.62 (0.25)**
r	-	-	4.20 (0.80)***

Notes: This table reports parameter estimates for the following model:
Variance Equation: $h_t^\delta = \omega + \alpha(|e_{t-1}| - \varsigma e_{t-1})^\delta + \beta h_{t-1}^\delta$
*The numbers in parentheses are robust standard errors. (r) are the degrees of freedom of Student's t distribution. ***, ** and * are significance levels of 1%, 5% and 10%, respectively.*

Next, we report the estimation results of an APGARCH-M model of inflation with $g(h) = h$ as well as the estimation results of an APGARCH(1.1)-L and APGARCH(1,1)-ML models of inflation with lagged inflation in conditional variance. Moreover, we include the dummy variables into mean equation of estimation APGARCH(1.1)-M model.

Table 2. 11 APGARCH Model-ML of inflation for Syria:

	Mean (dummies) $g(h) = h$	Level		Mean-level $g(h) = h$	
α	0.14 (0.04)***	0.11 (0.03)***		0.11 (0.02)***	
β	0.79 (0.06)***	0.84 (0.03)***		0.84 (0.03)***	
k	0.32 (0.19)*	-		0.12 (0.06)*	
γ_i	-	-0.78 (0.34)** {lag 7}	0.60 (0.25)** {lag 8}	-1.00 (0.15)*** {lag 7}	0.77 (0.15)*** {lag 8}
δ	0.74 (0.29)**	2.29 (0.44)***		2.46 (0.233)***	

Notes: This table reports parameter estimates for the following model:
Mean Equatin: $\Phi(L)x_t = c + kg(h_t) + \varepsilon_t$
Variance Equation: $h_t^{\delta} = \omega + \alpha(|e_{t-1}| - \varsigma e_{t-1})^{\delta} + \beta h_{t-1}^{\delta} + \gamma\pi_{t-i}$
*The numbers in parentheses are robust standard errors. ***, ** and * are significance levels of 1%, 5% and 10%, respectively.*

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Table 2.11 reports the estimated parameters of interest. The ARCH and GARCH parameters are highly significant at 1% for all three cases of estimation. The estimates for the 'in-mean' effect parameters (k) are positive and statistically significant at 10% for APGARCH(1.1)-M and APGARCH(1.1)-ML models. So, there is weak evidence in favour of Cukierman and Meltzer (1986) hypothesis which supports that inflation uncertainty affects inflation positively.

This implies the if the increase in the inflation uncertainty is 1.00, then the increased corresponding in the inflation is 0.32 when we applied APGARCH(1.1)-M, and 0.12 when we applied APGARCH(1.1)-ML models.

In addition, the obtained results of APGARCH (1,1)-L show that inflation rate affects its uncertainty negatively. To illustrate, the sum of γ_7=-0.78 and γ_8=+0.60 equal to -0.18

Furthermore, we estimate the APGARCH(1,1)-L model of inflation with lagged inflation added in the conditional variance equation as "level effect". Various lags were considered and we have chosen the significant level terms at lags (7 and 8) on the bases of the minimum value of Akaike info criterion (AIC). There is evidence that inflation affects its uncertainty negatively as supported by Pourgerami and Maskus (1987), Ungar and Zilberfarb (1993). Similarly, we find a strong evidence in favour of Pourgerami and Maskus (1987) hypothesis that inflation affects its uncertainty negatively when we estimate as APGARCH(1,1)-ML model. Finally, the power terms are highly significant in all three cases.

According to this finding, a 100% increase in the inflation rate leads to 18% and 23% decreasing in the Syrian inflation uncertainty.

2.6. Conclusion

In this chapter, we have used monthly data on inflation in three Mediterranean countries to investigate the possible relationship between inflation and its uncertainty. We also have used monthly data on output growth in Turkey to investigate the possible relationship between output and its uncertainty. Following our empirical investigation and testing a number of economic hypotheses, we achieved the following result.

The overall evidences for the economic hypotheses we tested were mixed. There was evidence for the Cukierman–Meltzer hypothesis, which was labelled as the 'opportunistic Fed' by Grier and Perry (1998), in the two Arabic countries (Egypt and Syria). Therefore, increases in nominal uncertainty raised the optimal average inflation by increasing the stimulus for the policy-maker to create inflation surprises. In contrast, evidence for the Holland (1995) hypothesis was obtained in Turkey. This result suggested that the 'stabilizing Fed' notion is plausible.

Moreover, we obtained support in favour of Friedman (1977) and Ball (1992) in Egypt and Turkey where inflation raises its uncertainty, which creates real welfare losses and then leads to monetary tightening to lower inflation and thus also uncertainty. The results about Turkish output growth showed that there is support for Pindyck (1991) where more raising in growth will lead to less uncertainty.

In addition, there was a significant effect of the economic shock in 1979 as a result of foreign exchange crisis in the Turkish economy, the negative growth, the inflation into triple-digit levels, wide spread shortages and the two major currency crises in 1994 and 2000 – 2001. More precisely, the effect of inflation on its uncertainty had increased 18% after considering the effect of failed economic policies in Tukey. Again, the same finding was obtained for inflation in Syria.

Appendix 2

2.6.1. Appendix 2.A for Table 2.2

Dependent Variable: CPI
Method: ML - ARCH (Marquardt) - Normal distribution
Sample (adjusted): 1969M02 2011M02
Bollerslev-Wooldridge robust standard errors & covariance
Presample variance: backcast (parameter = 0.7)

@SQRT(GARCH)^C(12) = C(8) + C(9)*(ABS(RESID(-1)) - C(10)*RESID(-1))^C(12) + C(11)*@SQRT(GARCH(-1))^C(12)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
CPI(-1)	0.399678	0.062335	6.411776	0.0000
CPI(-2)	0.110997	0.021203	5.234892	0.0000
CPI(-6)	0.151841	0.026312	5.770839	0.0000
CPI(-11)	0.123995	0.028761	4.311281	0.0000
CPI(-12)	0.332769	0.042928	7.751876	0.0000
CPI(-13)	-0.189159	0.062406	-3.031078	0.0024
C	0.256952	0.097107	2.646080	0.0081
Variance Equation				
C(8)	0.051042	0.021297	2.396667	0.0165
C(9)	0.142403	0.056621	2.515019	0.0119
C(10)	-0.836881	0.362077	-2.311334	0.0208
C(11)	0.871551	0.061190	14.24342	0.0000
C(12)	0.504082	0.281178	1.792751	0.0730

R-squared	0.398275	Mean dependent var	2.808137
Adjusted R-squared	0.390831	S.D. dependent var	2.671539
S.E. of regression	2.085116	Akaike info criterion	3.956510
Sum squared resid	2108.639	Schwarz criterion	4.058912
Log likelihood	-961.3015	Hannan-Quinn criter.	3.996720
Durbin-Watson stat	2.152755		

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Appendix 2.A (Continued)

Dependent Variable: CPI

Method: ML - ARCH (Marquardt) - Normal distribution
Sample (adjusted): 1969M02 2011M02
Bollerslev-Wooldridge robust standard errors & covariance

Presample variance: backcast (parameter = 0.7)

@SQRT(GARCH)^0.7 = C(9) + C(10)*ABS(RESID(-1))^0.7 + C(11)
*@SQRT(GARCH(-1))^0.7

Variable	Coefficient	Std. Error	z-Statistic	Prob.
CPI(-1)	0.289618	0.032351	8.952440	0.0000
CPI(-4)	0.068525	0.033375	2.053218	0.0401
CPI(-6)	0.159057	0.034600	4.597094	0.0000
CPI(-11)	0.153223	0.040183	3.813113	0.0001
CPI(-12)	0.218005	0.053682	4.061049	0.0000
C	0.148074	0.058214	2.543590	0.0110
D1	6.703749	0.335486	19.98220	0.0000
D2	0.532528	0.142531	3.736235	0.0002
		Variance Equation		
C(9)	0.001758	0.012208	0.144009	0.8855
C(10)	0.169142	0.031863	5.308338	0.0000
C(11)	0.877517	0.020515	42.77415	0.0000

R-squared	0.441988	Mean dependent var	2.804406
Adjusted R-squared	0.433934	S.D. dependent var	2.670108
S.E. of regression	2.008919	Akaike info criterion	3.955464
Sum squared resid	1957.341	Schwarz criterion	4.049188
Log likelihood	-964.0220	Hannan-Quinn criter.	3.992263
Durbin-Watson stat	2.152755		

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Appendix 2.A (Continued)

Dependent Variable: CPI
Method: ML - ARCH (Marquardt) - Student's t distribution
Sample (adjusted): 1969M02 2011M02
Presample variance: backcast (parameter = 0.7)

@SQRT(GARCH)^C(10) = C(7) + C(8)*ABS(RESID(-1))^C(10) + C(9)
*@SQRT(GARCH(-1))^C(10)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
CPI(-1)	0.284503	0.035548	8.003319	0.0000
CPI(-2)	0.067863	0.032050	2.117407	0.0342
CPI(-6)	0.182742	0.030676	5.957193	0.0000
CPI(-11)	0.113067	0.028853	3.918726	0.0001
CPI(-12)	0.271607	0.030502	8.904572	0.0000
C	0.031246	0.075632	0.413130	0.6795
Variance Equation				
C(7)	0.020606	0.020079	1.026212	0.3048
C(8)	0.115333	0.034885	3.306064	0.0009
C(9)	0.903879	0.029131	31.02796	0.0000
C(10)	0.686975	0.348857	1.969216	0.0489
T-DIST. DOF	3.706725	0.561468	6.601841	0.0000

R-squared	0.391839	Mean dependent var	2.804406
Adjusted R-squared	0.385595	S.D. dependent var	2.670108
S.E. of regression	2.092937	Akaike info criterion	3.785111
Sum squared resid	2133.248	Schwarz criterion	3.878835
Log likelihood	-922.0299	Hannan-Quinn criter.	3.821910
Durbin-Watson stat	1.909421		

2.6.2. Appendix 2.B for Table 2.3

Dependent Variable: CPI
Method: ML - ARCH (Marquardt) - Normal distribution
Sample (adjusted): 1969M02 2011M02
Bollerslev-Wooldridge robust standard errors & covariance
Presample variance: backcast (parameter = 0.7)

@SQRT(GARCH)^C(14) = C(11) + C(12)*ABS(RESID(-1))^C(14) + C(13)
*@SQRT(GARCH(-1))^C(14)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
@SQRT(GARCH)	-0.285923	0.081165	-3.522750	0.0004
CPI(-1)	0.153730	0.040909	3.757846	0.0002
CPI(-6)	0.188241	0.026618	7.071796	0.0000
CPI(-7)	0.112294	0.032148	3.493040	0.0005
CPI(-8)	0.079591	0.029744	2.675834	0.0075
CPI(-11)	0.195628	0.040766	4.798776	0.0000
CPI(-12)	0.271067	0.026296	10.30818	0.0000
C	0.416733	0.097569	4.271178	0.0000
D1	8.534918	3.447247	2.475865	0.0133
D2	0.503209	0.100051	5.029544	0.0000

Variance Equation

C(11)	0.289321	0.087250	3.315980	0.0009
C(12)	0.412372	0.129362	3.187733	0.0014
C(13)	0.486100	0.105159	4.622528	0.0000
C(14)	0.567854	0.269813	2.104623	0.0353

R-squared	0.429741	Mean dependent var	2.804406
Adjusted R-squared	0.419115	S.D. dependent var	2.670108
S.E. of regression	2.035044	Akaike info criterion	4.001376
Sum squared resid	2000.299	Schwarz criterion	4.120660
Log likelihood	-972.3391	Hannan-Quinn criter.	4.048211
Durbin-Watson stat	1.837764		

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Appendix 2.B (continued)

Dependent Variable: CPI
Method: ML - ARCH (Marquardt) - Normal distribution
Sample (adjusted): 1969M02 2011M02
Bollerslev-Wooldridge robust standard errors & covariance
Presample variance: backcast (parameter = 0.7)

@SQRT(GARCH)^C(9) = C(5) + C(6)*ABS(RESID(-1))^C(9) + C(7)
*@SQRT(GARCH(-1))^C(9) + C(8)*CPI(-5)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
CPI(-1)	0.266355	0.053537	4.975136	0.0000
CPI(-6)	0.164869	0.043561	3.784761	0.0002
CPI(-12)	0.398907	0.055087	7.241420	0.0000
C	0.201786	0.094004	2.146571	0.0318
Variance Equation				
C(5)	0.216807	0.061400	3.531063	0.0004
C(6)	0.324505	0.091415	3.549783	0.0004
C(7)	0.513864	0.081001	6.343884	0.0000
C(8)	0.106491	0.054696	1.946973	0.0515
C(9)	0.944262	0.313205	3.014840	0.0026

R-squared	0.364734	Mean dependent var	2.804406
Adjusted R-squared	0.360837	S.D. dependent var	2.670108
S.E. of regression	2.134689	Akaike info criterion	4.050942
Sum squared resid	2228.322	Schwarz criterion	4.127624
Log likelihood	-989.5571	Hannan-Quinn criter.	4.081050
Durbin-Watson stat	1.836387		

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Appendix 2.B (continued)

Dependent Variable: CPI
Method: ML - ARCH (Marquardt) - Normal distribution
Sample (adjusted): 1969M02 2011M02
Bollerslev-Wooldridge robust standard errors & covariance
Presample variance: backcast (parameter = 0.7)

@SQRT(GARCH)^C(13) = C(9) + C(10)*ABS(RESID(-1))^C(13) + C(11)
*@SQRT(GARCH(-1))^C(13) + C(12)*CPI(-7)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
@SQRT(GARCH)	-0.243653	0.115223	-2.114627	0.0345
CPI(-1)	0.254551	0.046922	5.425014	0.0000
CPI(-6)	0.237155	0.042914	5.526348	0.0000
CPI(-11)	0.167367	0.064342	2.601205	0.0093
CPI(-12)	0.261776	0.049271	5.313028	0.0000
C	0.326562	0.162456	2.010150	0.0444
D1	7.912666	3.226698	2.452248	0.0142
D2	0.259208	0.185750	1.395468	0.1629
Variance Equation				
C(9)	0.964491	0.377357	2.555907	0.0106
C(10)	0.564914	0.332026	1.701412	0.0889
C(11)	0.214896	0.107468	1.999628	0.0455
C(12)	0.289740	0.087313	3.318427	0.0009
C(13)	2.570501	0.632215	4.065862	0.0000

R-squared	0.443364	Mean dependent var	2.804406
Adjusted R-squared	0.435331	S.D. dependent var	2.670108
S.E. of regression	2.006439	Akaike info criterion	4.020659
Sum squared resid	1952.512	Schwarz criterion	4.131423
Log likelihood	-978.0925	Hannan-Quinn criter.	4.064149
Durbin-Watson stat	1.992636		

2.6.3. Appendix 2.C for Table 2.4

Dependent Variable: IPI
Method: ML - ARCH (Marquardt) - Normal distribution
Sample (adjusted): 1985M04 2010M12
Bollerslev-Wooldridge robust standard errors & covariance
Presample variance: backcast (parameter = 0.7)

@SQRT(GARCH)^C(7) = C(4) + C(5)*ABS(RESID(-1))^C(7) + C(6)
*@SQRT(GARCH(-1))^C(7)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
IPI(-1)	-0.675269	0.062444	-10.81408	0.0000
IPI(-2)	-0.211605	0.045945	-4.605594	0.0000
C	0.759487	0.177622	4.275866	0.0000
		Variance Equation		
C(4)	0.804095	0.529784	1.517779	0.1291
C(5)	0.253381	0.072445	3.497551	0.0005
C(6)	0.500392	0.189692	2.637920	0.0083
C(7)	0.639847	0.368910	1.734424	0.0828

R-squared	0.339687	Mean dependent var	0.378891
Adjusted R-squared	0.335372	S.D. dependent var	5.711384
S.E. of regression	4.656191	Akaike info criterion	5.849347
Sum squared resid	6634.116	Schwarz criterion	5.933921
Log likelihood	-896.7241	Hannan-Quinn criter.	5.883160
Durbin-Watson stat	1.988631		

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Appendix 2.C (continued

Dependent Variable: IPI
Method: ML - ARCH (Marquardt) - Normal distribution
Sample (adjusted): 1985M04 2010M12
Bollerslev-Wooldridge robust standard errors & covariance
Presample variance: backcast (parameter = 0.7)

@SQRT(GARCH)^C(9) = C(6) + C(7)*ABS(RESID(-1))^C(9) + C(8)
*@SQRT(GARCH(-1))^C(9)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
IPI(-1)	-0.642044	0.044196	-14.52713	0.0000
IPI(-2)	-0.177740	0.050387	-3.527481	0.0004
C	0.795256	0.181056	4.392311	0.0000
D1	-1.055196	1.793680	-0.588286	0.5563
D2	-0.059477	0.288082	-0.206460	0.8364
Variance Equation				
C(6)	0.916590	0.591700	1.549080	0.1214
C(7)	0.254990	0.081548	3.126865	0.0018
C(8)	0.440904	0.193550	2.277983	0.0227
C(9)	0.613848	0.328674	1.867647	0.0618

R-squared	0.343526	Mean dependent var	0.378891
Adjusted R-squared	0.334888	S.D. dependent var	5.711384
S.E. of regression	4.657883	Akaike info criterion	5.857006
Sum squared resid	6595.547	Schwarz criterion	5.965744
Log likelihood	-895.9075	Hannan-Quinn criter.	5.900480
Durbin-Watson stat	2.078993		

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Appendix 2.C (continued)

Dependent Variable: IPI
Method: ML - ARCH (Marquardt) - Student's t distribution
Sample (adjusted): 1985M04 2010M12
Bollerslev-Wooldridge robust standard errors & covariance
Presample variance: backcast (parameter = 0.7)
@SQRT(GARCH)^1.6 = C(4) + C(5)*ABS(RESID(-1))^1.6

Variable	Coefficient	Std. Error	z-Statistic	Prob.
@SQRT(GARCH)	-0.243653	0.115223	-2.114627	0.0345
IPI(-1)	-0.627578	0.060616	-10.35333	0.0000
IPI(-2)	-0.197789	0.047760	-4.141314	0.0000
C	0.956056	0.212981	4.488923	0.0000
		Variance Equation		
C(4)	9.163407	2.033095	4.507123	0.0000
C(5)	0.439912	0.184188	2.388390	0.0169
T-DIST. DOF	3.550094	0.950909	3.733368	0.0002

R-squared	0.335584	Mean dependent var	0.378891
Adjusted R-squared	0.331242	S.D. dependent var	5.711384
S.E. of regression	4.670636	Akaike info criterion	5.785760
Sum squared resid	6675.341	Schwarz criterion	5.858252
Log likelihood	-887.8999	Hannan-Quinn criter.	5.814743
F-statistic	30.91098	Durbin-Watson stat	2.078066
Prob(F-statistic)	0.000000		

2.6.4. Appendix 2.D for Table 2.5

Dependent Variable: IPI
Method: ML - ARCH (Marquardt) - Normal distribution
Sample (adjusted): 1985M04 2010M12
Bollerslev-Wooldridge robust standard errors & covariance
Presample variance: backcast (parameter = 0.7)

@SQRT(GARCH)^0.5 = C(5) + C(6)*ABS(RESID(-1))^0.5

Variable	Coefficient	Std. Error	z-Statistic	Prob.
@SQRT(GARCH)	-0.449807	0.136098	-3.305036	0.0009
IPI(-1)	-0.652719	0.031673	-20.60826	0.0000
IPI(-2)	-0.207015	0.031552	-6.561020	0.0000
C	2.469741	0.598967	4.123336	0.0000
Variance Equation				
C(5)	1.467489	0.093043	15.77207	0.0000
C(6)	0.390564	0.048209	8.101555	0.0000

R-squared	0.335864	Mean dependent var	0.378891
Adjusted R-squared	0.329331	S.D. dependent var	5.711384
S.E. of regression	4.677302	Akaike info criterion	5.832439
Sum squared resid	6672.532	Schwarz criterion	5.904931
Log likelihood	-895.1119	Hannan-Quinn criter.	5.861422
F-statistic	30.84862	Durbin-Watson stat	2.041939

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Dependent Variable: IPI
Method: ML - ARCH (Marquardt) - Normal distribution
Sample (adjusted): 1985M04 2010M12
Bollerslev-Wooldridge robust standard errors & covariance
Presample variance: backcast (parameter = 0.7)

@SQRT(GARCH)^C(10) = C(4) + C(5)*ABS(RESID(-1))^C(10) + C(6)
*@SQRT(GARCH(-1))^C(10) + C(7)*IPI(-5) + C(8)*IPI(-6) + C(9)IPI(-13)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
IPI(-1)	-0.672745	0.049840	-13.49814	0.0000
IPI(-2)	-0.259089	0.045427	-5.703423	0.0000
C	1.312978	0.163327	8.038937	0.0000
		Variance Equation		
C(4)	10.99978	6.024948	1.825705	0.0679
C(5)	0.236468	0.062938	3.757143	0.0002
C(6)	0.302090	0.048681	6.205466	0.0000
C(7)	-1.139933	0.633835	-1.798470	0.0721
C(8)	-1.310382	0.605601	-2.163773	0.0305
C(9)	0.604942	0.336729	1.796524	0.0724
C(10)	2.041081	0.334424	6.103268	0.0000

R-squared	0.334568	Mean dependent var	0.404129
Adjusted R-squared	0.330057	S.D. dependent var	5.460072
S.E. of regression	4.469072	Akaike info criterion	5.743617
Sum squared resid	5891.919	Schwarz criterion	5.867681
Log likelihood	-845.7989	Hannan-Quinn criter.	5.793278
Durbin-Watson stat	1.935776		

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Appendix 2.D (continued)

Dependent Variable: IPI
Method: ML - ARCH (Marquardt) - Student's t distribution
Sample (adjusted): 1985M04 2010M12
Presample variance: backcast (parameter = 0.7)

@SQRT(GARCH)^C(10) = C(5) + C(6)*ABS(RESID(-1))^C(10) + C(7)
*@SQRT(GARCH(-1))^C(10) + C(8)*IPI(-5) + C(9)*IPI(-6)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
@SQRT(GARCH)	-0.325471	0.088247	-3.688204	0.0002
IPI(-1)	-0.703983	0.059584	-11.81498	0.0000
IPI(-2)	-0.212356	0.043960	-4.830686	0.0000
C	2.131598	0.276563	7.707450	0.0000
		Variance Equation		
C(5)	13.39277	5.787898	2.313926	0.0207
C(6)	0.144152	0.051231	2.813770	0.0049
C(7)	0.501542	0.037445	13.39415	0.0000
C(8)	-1.775129	0.777783	-2.282294	0.0225
C(9)	-2.578008	1.133310	-2.274759	0.0229

R-squared	0.329973	Mean dependent var	0.376323
Adjusted R-squared	0.323295	S.D. dependent var	5.457710
S.E. of regression	4.489627	Akaike info criterion	5.806846
Sum squared resid	6067.182	Schwarz criterion	5.928823
Log likelihood	-875.5440	Hannan-Quinn criter.	5.855634
Durbin-Watson stat	1.894319		

2.6.5. Appendix 2.E for Table 2.7

Dependent Variable: ECPI
Method: ML - ARCH (Marquardt) - Normal distribution
Sample (adjusted): 1958M03 2011M02
Bollerslev-Wooldridge robust standard errors & covariance
Presample variance: backcast (parameter = 0.7)

@SQRT(GARCH)^C(15) = C(11) + C(12)*(ABS(RESID(-1)) - C(13)*RESID(-1))^C(15) + C(14)*@SQRT(GARCH(-1))^C(15)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
ECPI(-2)	0.204273	0.027864	7.330946	0.0000
ECPI(-3)	0.078625	0.018143	4.333531	0.0000
ECPI(-4)	-0.054779	0.017233	-3.178618	0.0015
ECPI(-6)	0.158501	0.022983	6.896417	0.0000
ECPI(-7)	0.054652	0.019660	2.779824	0.0054
ECPI(-8)	-0.101187	0.028131	-3.596971	0.0003
ECPI(-10)	0.095399	0.026158	3.647008	0.0003
ECPI(-12)	0.293197	0.022460	13.05396	0.0000
ECPI(-13)	0.165601	0.019484	8.499347	0.0000
C	-0.001055	0.020740	-0.050886	0.9594
		Variance Equation		
C(11)	0.098114	0.049533	1.980773	0.0476
C(12)	0.530447	0.172184	3.080704	0.0021
C(13)	0.274195	0.118399	2.315860	0.0206
C(14)	0.550705	0.129348	4.257531	0.0000
C(15)	0.590425	0.145450	4.059309	0.0000

R-squared	0.016770	Mean dependent var	0.703692
Adjusted R-squared	0.002634	S.D. dependent var	1.663460
S.E. of regression	1.661267	Akaike info criterion	3.230659
Sum squared resid	1727.640	Schwarz criterion	3.335734
Log likelihood	-1012.349	Hannan-Quinn criter.	3.271455
Durbin-Watson stat	2.178504		

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Appendix 2.E (continued)

Dependent Variable: ECPI
Method: ML - ARCH (Marquardt) - Normal distribution
Sample (adjusted): 1958M03 2011M02
Bollerslev-Wooldridge robust standard errors & covariance
Presample variance: backcast (parameter = 0.7)

@SQRT(GARCH)^0.6 = C(8) + C(9)*(ABS(RESID(-1)) - C(10)*RESID(-1))^0.6 + C(11)*@SQRT(GARCH(-1))^0.6

Variable	Coefficient	Std. Error	z-Statistic	Prob.
ECPI(-2)	0.085141	0.026133	3.257953	0.0011
ECPI(-6)	0.160916	0.034435	4.673082	0.0000
ECPI(-7)	0.135825	0.035270	3.851010	0.0001
ECPI(-12)	0.215602	0.039856	5.409561	0.0000
C	0.148233	0.019384	7.647132	0.0000
D1	5.619859	1.625829	3.456612	0.0005
D2	-0.102565	0.051534	-1.990236	0.0466
		Variance Equation		
C(8)	0.015367	0.005420	2.835412	0.0046
C(9)	0.161472	0.030570	5.281996	0.0000
C(10)	-0.659505	0.155619	-4.237939	0.0000
C(11)	0.867439	0.025025	34.66315	0.0000

R-squared	0.206726	Mean dependent var	0.701707
Adjusted R-squared	0.199171	S.D. dependent var	1.662906
S.E. of regression	1.488119	Akaike info criterion	2.898912
Sum squared resid	1395.134	Schwarz criterion	2.975874
Log likelihood	-912.3035	Hannan-Quinn criter.	2.928791
Durbin-Watson stat	2.013862		

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Dependent Variable: ECPI
Method: ML - ARCH (Marquardt) - Normal distribution
Sample (adjusted): 1958M03 2011M02
Bollerslev-Wooldridge robust standard errors & covariance
Presample variance: backcast (parameter = 0.7)

@SQRT(GARCH)^C(10) = C(6) + C(7)*(ABS(RESID(-1)) - C(8)*RESID(
-1))^C(10) + C(9)*@SQRT(GARCH(-1))^C(10)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
ECPI(-2)	0.104337	0.030817	3.385648	0.0007
ECPI(-6)	0.116213	0.028427	4.088103	0.0000
ECPI(-7)	0.106351	0.027041	3.932900	0.0001
ECPI(-12)	0.232476	0.025364	9.165526	0.0000
C	0.135650	0.017076	7.943973	0.0000
Variance Equation				
C(6)	0.016820	0.006985	2.407926	0.0160
C(7)	0.143610	0.030583	4.695739	0.0000
C(8)	-0.591199	0.175390	-3.370771	0.0007
C(9)	0.881283	0.021103	41.76093	0.0000
C(10)	0.518968	0.263165	1.972025	0.0486
T-DIST. DOF	3.656427	0.448868	8.145875	0.0000

R-squared	0.058215	Mean dependent var	0.701707
Adjusted R-squared	0.052254	S.D. dependent var	1.662906
S.E. of regression	1.618877	Akaike info criterion	2.875895
Sum squared resid	1656.322	Schwarz criterion	2.952857
Log likelihood	-904.9727	Hannan-Quinn criter.	2.905774
Durbin-Watson stat	2.215657		

2.6.6. *Appendix 2.F for Table 2.8*

Dependent Variable: ECPI
Method: ML - ARCH (Marquardt) - Normal distribution
Sample (adjusted): 1958M03 2011M02
Bollerslev-Wooldridge robust standard errors & covariance
Presample variance: backcast (parameter = 0.7)
@SQRT(GARCH)^0.5 = C(10) + C(11)*ABS(RESID(-1))^0.5 + C(12)
*@SQRT(GARCH(-1))^0.5

Variable	Coefficient	Std. Error	z-Statistic	Prob.
@SQRT(GARCH)	0.051887	0.027333	1.898314	0.0577
ECPI(-1)	0.077664	0.025735	3.017902	0.0025
ECPI(-2)	0.212225	0.037014	5.733587	0.0000
ECPI(-4)	-0.111166	0.024218	-4.590287	0.0000
ECPI(-6)	0.172411	0.031913	5.402527	0.0000
ECPI(-7)	0.147646	0.014679	10.05833	0.0000
ECPI(-10)	0.053370	0.018713	2.852034	0.0043
ECPI(-12)	0.199712	0.028232	7.074007	0.0000
C	0.023832	0.013744	1.733970	0.0829
Variance Equation				
C(10)	0.061807	0.047074	1.312988	0.1892
C(11)	0.336621	0.115974	2.902565	0.0037
C(12)	0.703187	0.115289	6.099314	0.0000

R-squared	0.020121	Mean dependent var	0.701707
Adjusted R-squared	0.007638	S.D. dependent var	1.662906
S.E. of regression	1.656544	Akaike info criterion	3.216296
Sum squared resid	1723.318	Schwarz criterion	3.300254
Log likelihood	-1012.390	Hannan-Quinn criter.	3.248892
Durbin-Watson stat	2.324024		

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Appendix 2.F (continued)

Dependent Variable: ECPI
Method: ML - ARCH (Marquardt) - Student's t distribution
Sample (adjusted): 1958M03 2011M02
Presample variance: backcast (parameter = 0.7)
@SQRT(GARCH)^C(11) = C(7) + C(8)*(ABS(RESID(-1)) - C(9)*RESID(-1))^C(11) + C(10)*@SQRT(GARCH(-1))^C(11)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
@SQRT(GARCH)	0.138539	0.043757	3.166092	0.0015
ECPI(-2)	0.093656	0.033187	2.822082	0.0048
ECPI(-6)	0.095835	0.028701	3.339100	0.0008
ECPI(-7)	0.065708	0.027956	2.350460	0.0188
ECPI(-12)	0.204790	0.026051	7.860978	0.0000
C	0.101727	0.023366	4.353590	0.0000
Variance Equation				
C(7)	0.011501	0.006087	1.889312	0.0589
C(8)	0.150473	0.032408	4.643071	0.0000
C(9)	-0.574959	0.165598	-3.472020	0.0005
C(10)	0.886866	0.020685	42.87458	0.0000
C(11)	0.585270	0.240366	2.434907	0.0149

R-squared	0.060328	Mean dependent var	0.701707
Adjusted R-squared	0.052882	S.D. dependent var	1.662906
S.E. of regression	1.618340	Akaike info criterion	2.863176
Sum squared resid	1652.605	Schwarz criterion	2.954130
Log likelihood	-898.9214	Hannan-Quinn criter.	2.898487
F-statistic	3.375897	Durbin-Watson stat	2.218519
Prob(F-statistic)	0.000085		

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Appendix 2.F (continued)

Dependent Variable: ECPI
Method: ML - ARCH (Marquardt) - Normal distribution
Sample (adjusted): 1958M03 2011M02
Bollerslev-Wooldridge robust standard errors & covariance
Presample variance: backcast (parameter = 0.7)
@SQRT(GARCH)^C(12) = C(8) + C(9)*ABS(RESID(-1))^C(12) + C(10)
*@SQRT(GARCH(-1))^C(12) + C(11)*ECPI(-3)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
ECPI(-2)	0.159163	0.063026	2.525356	0.0116
ECPI(-3)	0.119417	0.044151	2.704746	0.0068
ECPI(-6)	0.240727	0.033764	7.129662	0.0000
ECPI(-7)	0.116456	0.045686	2.549069	0.0108
ECPI(-8)	-0.131968	0.038430	-3.434024	0.0006
ECPI(-12)	0.212493	0.031733	6.696372	0.0000
C	0.085714	0.026412	3.245316	0.0012
Variance Equation				
C(8)	0.033376	0.027985	1.192617	0.2330
C(9)	0.634921	0.308279	2.059563	0.0394
C(10)	0.549215	0.153581	3.576064	0.0003
C(11)	0.101363	0.042713	2.373100	0.0176
C(12)	0.978810	0.196373	4.984438	0.0000

R-squared	0.008685	Mean dependent var	0.701707
Adjusted R-squared	-0.000756	S.D. dependent var	1.662906
S.E. of regression	1.663535	Akaike info criterion	3.232385
Sum squared resid	1743.430	Schwarz criterion	3.316343
Log likelihood	-1017.515	Hannan-Quinn criter.	3.264980
Durbin-Watson stat	2.182160		

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Appendix 2.F (continued)

Dependent Variable: ECPI
Method: ML - ARCH (Marquardt) - Student's t distribution
Sample (adjusted): 1958M03 2011M02
Presample variance: backcast (parameter = 0.7)
@SQRT(GARCH)^C(12) = C(7) + C(8)*(ABS(RESID(-1)) - C(9)*RESID(
-1))^C(12) + C(10)*@SQRT(GARCH(-1))^C(12) + C(11)*ECPI(-3)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
ECPI(-2)	0.082168	0.034974	2.349388	0.0188
ECPI(-6)	0.114019	0.028440	4.009158	0.0001
ECPI(-7)	0.079812	0.029717	2.685728	0.0072
ECPI(-9)	0.061404	0.031225	1.966501	0.0492
ECPI(-12)	0.190205	0.026591	7.152906	0.0000
C	0.134717	0.022389	6.017045	0.0000
Variance Equation				
C(7)	0.015094	0.006296	2.397569	0.0165
C(8)	0.135611	0.023576	5.752133	0.0000
C(9)	-0.894346	0.178742	-5.003552	0.0000
C(10)	0.917278	0.019337	47.43542	0.0000
C(11)	-0.038513	0.021009	-1.833177	0.0668
T-DIST. DOF	3.379522	0.422205	8.004464	0.0000

R-squared	0.008685	Mean dependent var	0.701707
Adjusted R-squared	-0.000756	S.D. dependent var	1.662906
S.E. of regression	1.663535	Akaike info criterion	2.863176
Sum squared resid	1743.430	Schwarz criterion	2.954130
Log likelihood	-1017.515	Hannan-Quinn criter.	2.898487
		Durbin-Watson stat	2.218519

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Appendix 2.F (continued)

Dependent Variable: ECPI

Method: ML - ARCH (Marquardt) - Student's t distribution

Sample (adjusted): 1958M03 2011M02

Presample variance: backcast (parameter = 0.7)

@SQRT(GARCH)^C(12) = C(7) + C(8)*(ABS(RESID(-1)) - C(9)*RESID(
-1))^C(12) + C(10)*@SQRT(GARCH(-1))^C(12) + C(11)*ECPI(-3)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
ECPI(-2)	0.082168	0.034974	2.349388	0.0188
ECPI(-6)	0.114019	0.028440	4.009158	0.0001
ECPI(-7)	0.079812	0.029717	2.685728	0.0072
ECPI(-9)	0.061404	0.031225	1.966501	0.0492
ECPI(-12)	0.190205	0.026591	7.152906	0.0000
C	0.134717	0.022389	6.017045	0.0000
		Variance Equation		
C(7)	0.015094	0.006296	2.397569	0.0165
C(8)	0.135611	0.023576	5.752133	0.0000
C(9)	-0.894346	0.178742	-5.003552	0.0000
C(10)	0.917278	0.019337	47.43542	0.0000
C(11)	-0.038513	0.021009	-1.833177	0.0668
C(12)	0.693908	0.173019	4.010590	0.0001
T-DIST. DOF	3.379522	0.422205	8.004464	0.0000

R-squared	0.060328	Mean dependent var	0.701707
Adjusted R-squared	0.052882	S.D. dependent var	1.662906
S.E. of regression	1.618340	Akaike info criterion	2.863176
Sum squared resid	1652.605	Schwarz criterion	2.954130
Log likelihood	-898.9214	Hannan-Quinn criter.	2.898487
F-statistic	3.375897	Durbin-Watson stat	2.218519
Prob(F-statistic)	0.000085		

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Appendix 2.F (continued)

Dependent Variable: ECPI
Method: ML - ARCH (Marquardt) - Normal distribution
Sample (adjusted): 1958M03 2011M02
Bollerslev-Wooldridge robust standard errors & covariance
Presample variance: backcast (parameter = 0.7)
@SQRT(GARCH)^C(15) = C(11) + C(12)*ABS(RESID(-1))^C(15) + C(13)
*@SQRT(GARCH(-1))^C(15) + C(14)*ECPI(-3)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
@SQRT(GARCH)	0.210994	0.053537	3.941089	0.0001
ECPI(-2)	0.164088	0.068500	2.395460	0.0166
ECPI(-4)	-0.094418	0.049419	-1.910559	0.0561
ECPI(-5)	-0.070790	0.040400	-1.752223	0.0797
ECPI(-6)	0.134926	0.057018	2.366360	0.0180
ECPI(-7)	0.082674	0.049001	1.687174	0.0916
ECPI(-8)	-0.088089	0.040901	-2.153745	0.0313
ECPI(-12)	0.255289	0.038675	6.600917	0.0000
ECPI(-13)	0.080802	0.030655	2.635902	0.0084
C	0.066918	0.038156	1.753833	0.0795
Variance Equation				
C(11)	0.019244	0.030624	0.628386	0.5298
C(12)	0.682868	0.398644	1.712979	0.0867
C(13)	0.547096	0.172399	3.173429	0.0015
C(14)	0.121228	0.065870	1.840400	0.0657
C(15)	1.195721	0.339643	3.520525	0.0004

R-squared	0.036061	Mean dependent var	0.703692
Adjusted R-squared	0.022203	S.D. dependent var	1.663460
S.E. of regression	1.644889	Akaike info criterion	3.231108
Sum squared resid	1693.743	Schwarz criterion	3.336183
Log likelihood	-1012.492	Hannan-Quinn criter.	3.271904
Durbin-Watson stat	2.235185		

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Appendix 2.F (continued)

Dependent Variable: ECPI

Method: ML - ARCH (Marquardt) - Student's t distribution

Sample (adjusted): 1958M03 2011M02

Presample variance: backcast (parameter = 0.7)

@SQRT(GARCH)^C(12) = C(7) + C(8)*(ABS(RESID(-1)) - C(9)*RESID(
-1))^C(12) + C(10)*@SQRT(GARCH(-1))^C(12) + C(11)*ECPI(-2)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
@SQRT(GARCH)	0.155367	0.047879	3.245000	0.0012
ECPI(-2)	0.057819	0.031184	1.854136	0.0637
ECPI(-6)	0.081994	0.029344	2.794178	0.0052
ECPI(-7)	0.055388	0.028597	1.936860	0.0528
ECPI(-12)	0.179159	0.026734	6.701502	0.0000
C	0.115913	0.026354	4.398391	0.0000
Variance Equation				
C(7)	0.010525	0.006524	1.613173	0.1067
C(8)	0.147294	0.023337	6.311616	0.0000
C(9)	-0.974994	0.116037	-8.402419	0.0000
C(10)	0.933366	0.020957	44.53798	0.0000
C(11)	-0.054483	0.026649	-2.044498	0.0409
C(12)	0.664564	0.142382	4.667470	0.0000
T-DIST. DOF	3.416070	0.419027	8.152380	0.0000

R-squared	0.071664	Mean dependent var	0.701707
Adjusted R-squared	0.064308	S.D. dependent var	1.662906
S.E. of regression	1.608549	Akaike info criterion	2.853394
Sum squared resid	1632.668	Schwarz criterion	2.944348
Log likelihood	-895.8059	Hannan-Quinn criter.	2.888705
Durbin-Watson stat	2.316552		

2.6.7. *Appendix 2.G for Table 2.10*

Dependent Variable: SCPI
Method: ML - ARCH (Marquardt) - Normal distribution
Sample (adjusted): 1958M02 2012M07
Bollerslev-Wooldridge robust standard errors & covariance
Presample variance: backcast (parameter = 0.7)
@SQRT(GARCH)^C(10) = C(6) + C(7)*(ABS(RESID(-1)) - C(8)*RESID(
-1))^C(10) + C(9)*@SQRT(GARCH(-1))^C(10)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
SCPI(-1)	0.076031	0.039625	1.918744	0.0550
SCPI(-2)	0.109038	0.032596	3.345095	0.0008
SCPI(-11)	0.088302	0.036567	2.414773	0.0157
SCPI(-12)	0.327860	0.040964	8.003642	0.0000
C	0.367337	0.081304	4.518057	0.0000
Variance Equation				
C(6)	0.232813	0.096609	2.409845	0.0160
C(7)	0.142493	0.031202	4.566817	0.0000
C(8)	-0.729293	0.238212	-3.061525	0.0022
C(9)	0.785201	0.054017	14.53632	0.0000
C(10)	0.804535	0.367982	2.186343	0.0288

R-squared	0.152706	Mean dependent var	0.699042
Adjusted R-squared	0.147483	S.D. dependent var	2.660937
S.E. of regression	2.456892	Akaike info criterion	4.529046
Sum squared resid	3917.571	Schwarz criterion	4.597595
Log likelihood	-1470.998	Hannan-Quinn criter.	4.555627
Durbin-Watson stat	2.052761		

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Appendix 2.G (continued)

Dependent Variable: SCPI
Method: ML - ARCH (Marquardt) - Normal distribution
Sample (adjusted): 1958M02 2012M07
Bollerslev-Wooldridge robust standard errors & covariance
Presample variance: backcast (parameter = 0.7)
@SQRT(GARCH)^C(13) = C(10) + C(11)*ABS(RESID(-1))^C(13) +
C(12)*@SQRT(GARCH(-1))^C(13)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
SCPI(-3)	-0.092794	0.045823	-2.025040	0.0429
SCPI(-6)	-0.114435	0.035903	-3.187380	0.0014
SCPI(-11)	0.096234	0.036305	2.650746	0.0080
SCPI(-12)	0.325155	0.038634	8.416366	0.0000
C	0.401827	0.088323	4.549516	0.0000
D1	-0.163477	0.377827	-0.432677	0.6652
D2	0.041471	0.228372	0.181596	0.8559
D3	2.131898	0.691322	3.083799	0.0020
D4	10.51565	1.184589	8.877045	0.0000
Variance Equation				
C(10)	0.286627	0.199116	1.439494	0.1500
C(11)	0.157290	0.040873	3.848300	0.0001
C(12)	0.786312	0.065582	11.98977	0.0000
C(13)	1.429262	0.554067	2.579581	0.0099

R-squared	0.206444	Mean dependent var	0.699042
Adjusted R-squared	0.196601	S.D. dependent var	2.660937
S.E. of regression	2.385065	Akaike info criterion	4.476556
Sum squared resid	3669.107	Schwarz criterion	4.565670
Log likelihood	-1450.834	Hannan-Quinn criter.	4.511111
F-statistic	13.98305	Durbin-Watson stat	1.919896
Prob(F-statistic)	0.000000		

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Appendix 2.G (continued)

Dependent Variable: SCPI
Method: ML - ARCH (Marquardt) - Student's t distribution
Sample (adjusted): 1958M02 2012M07
Presample variance: backcast (parameter = 0.7)
@SQRT(GARCH)^C(10) = C(6) + C(7)*(ABS(RESID(-1)) - C(8)*RESID(
-1))^C(10) + C(9)*@SQRT(GARCH(-1))^C(10)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
SCPI(-2)	0.058596	0.030815	1.901519	0.0572
SCPI(-6)	-0.110303	0.029031	-3.799514	0.0001
SCPI(-11)	0.093729	0.025899	3.619083	0.0003
SCPI(-12)	0.318155	0.026457	12.02544	0.0000
C	0.354040	0.070279	5.037616	0.0000
		Variance Equation		
C(6)	0.149073	0.049433	3.015683	0.0026
C(7)	0.188422	0.045498	4.141363	0.0000
C(8)	-0.492572	0.177146	-2.780604	0.0054
C(9)	0.780537	0.045295	17.23230	0.0000
C(10)	0.628232	0.255855	2.455425	0.0141
T-DIST. DOF	4.202420		0.809974	5.188336

R-squared	0.150875	Mean dependent var	0.699042
Adjusted R-squared	0.145642	S.D. dependent var	2.660937
S.E. of regression	2.459544	Akaike info criterion	4.443306
Sum squared resid	3926.033	Schwarz criterion	4.518710
Log likelihood	-1441.961	Hannan-Quinn criter.	4.472545
Durbin-Watson stat	1.905548		

2.6.8. Appendix 2.H for Table 2.11

Dependent Variable: SCPI
Method: ML - ARCH (Marquardt) - Normal distribution
Sample (adjusted): 1958M02 2012M07
Bollerslev-Wooldridge robust standard errors & covariance
Presample variance: backcast (parameter = 0.7)
@SQRT(GARCH)^C(14) = C(11) + C(12)*ABS(RESID(-1))^C(14) +
C(13)*@SQRT(GARCH(-1))^C(14)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
@SQRT(GARCH)	0.321753	0.195470	1.646046	0.0998
SCPI(-6)	-0.110005	0.038775	-2.837030	0.0046
SCPI(-10)	-0.080899	0.047517	-1.702521	0.0887
SCPI(-11)	0.108588	0.037172	2.921263	0.0035
SCPI(-12)	0.316111	0.037138	8.511704	0.0000
C	-0.330583	0.418408	-0.790096	0.4295
D1	-0.295010	0.391475	-0.753587	0.4511
D2	-0.072827	0.209701	-0.347293	0.7284
D3	2.070809	0.707491	2.926977	0.0034
D4	10.65292	1.449985	7.346918	0.0000
Variance Equation				
C(11)	0.179620	0.098228	1.828596	0.0675
C(12)	0.146234	0.040822	3.582262	0.0003
C(13)	0.793700	0.067495	11.75931	0.0000
C(14)	0.747139	0.295478	2.528579	0.0115

R-squared	0.202113	Mean dependent var	0.699042
Adjusted R-squared	0.190962	S.D. dependent var	2.660937
S.E. of regression	2.393421	Akaike info criterion	4.483919
Sum squared resid	3689.130	Schwarz criterion	4.579888
Log likelihood	-1452.242	Hannan-Quinn criter.	4.521133
F-statistic	12.54859	Durbin-Watson stat	1.945802
Prob(F-statistic)	0.000000		

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Appendix 2.H (continued)

Dependent Variable: SCPI
Method: ML - ARCH (Marquardt) - Normal distribution
Sample (adjusted): 1958M02 2012M07
Bollerslev-Wooldridge robust standard errors & covariance
Presample variance: backcast (parameter = 0.7)
@SQRT(GARCH)^C(11) = C(6) + C(7)*ABS(RESID(-1))^C(11) + C(8)
*@SQRT(GARCH(-1))^C(11) + C(9)*CPI(-7) + C(10)*CPI(-8)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
SCPI(-2)	0.113617	0.039733	2.859558	0.0042
SCPI(-6)	-0.119591	0.034908	-3.425877	0.0006
SCPI(-11)	0.103583	0.037481	2.763635	0.0057
SCPI(-12)	0.336292	0.038202	8.803076	0.0000
C	0.295090	0.084557	3.489849	0.0005
Variance Equation				
C(6)	0.386044	0.267264	1.444430	0.1486
C(7)	0.115270	0.035341	3.261632	0.0011
C(8)	0.845448	0.037448	22.57635	0.0000
C(9)	-0.786410	0.342075	-2.298937	0.0215
C(10)	0.601544	0.255396	2.355340	0.0185
C(11)	2.291357	0.445197	5.146838	0.0000

R-squared	0.149872	Mean dependent var	0.699042
Adjusted R-squared	0.144633	S.D. dependent var	2.660937
S.E. of regression	2.460997	Akaike info criterion	4.537066
Sum squared resid	3930.671	Schwarz criterion	4.612470
Log likelihood	-1472.621	Hannan-Quinn criter.	4.566305
Durbin-Watson stat	1.908447		

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Appendix 2.H (continued)

Dependent Variable: SCPI
Method: ML - ARCH (Marquardt) - Normal distribution
Sample (adjusted): 1958M02 2012M07
Bollerslev-Wooldridge robust standard errors & covariance
Presample variance: backcast (parameter = 0.7)
@SQRT(GARCH)^C(12) = C(7) + C(8)*ABS(RESID(-1))^C(12) + C(9)
*@SQRT(GARCH(-1))^C(12) + C(10)*CPI(-7) + C(11)*CPI(-8)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
@SQRT(GARCH)	0.127863	0.067706	1.888513	0.0590
CPI(-2)	0.103785	0.035897	2.891164	0.0038
CPI(-6)	-0.133581	0.032967	-4.051948	0.0001
CPI(-11)	0.098133	0.037552	2.613259	0.0090
CPI(-12)	0.338566	0.038758	8.735338	0.0000
C	0.068709	0.113507	0.605325	0.5450
Variance Equation				
C(7)	0.430396	0.236322	1.821228	0.0686
C(8)	0.111248	0.023856	4.663400	0.0000
C(9)	0.842848	0.032956	25.57489	0.0000
C(10)	-1.003140	0.159974	-6.270630	0.0000
C(11)	0.779499	0.150100	5.193203	0.0000
C(12)	2.463204	0.233979	10.52748	0.0000
T-DIST. DOF	4.202420		0.809974	5.188336

R-squared	0.149316	Mean dependent var	0.699042
Adjusted R-squared	0.142752	S.D. dependent var	2.660937
S.E. of regression	2.463701	Akaike info criterion	4.534155
Sum squared resid	3933.244	Schwarz criterion	4.616414
Log likelihood	-1470.669	Hannan-Quinn criter.	4.566053
Durbin-Watson stat	1.912120		

Chapter Three

Inflation, Output Growth and Their Uncertainties for the G7 Countries

3.1. Introduction:

The relationship between inflation and output growth is one of the most researched topics in macroeconomics on both theoretical and empirical fronts. Much of the debate in this field has focused on the levels of the two series.

The famous hypothesis of Friedman (1977) about the effects of inflation on unemployment consists two legs: The first one concentrates on the higher impact of inflation on nominal uncertainty, which then decreases the output growth in the second leg. Therefore, the inflation effects on output growth exist via inflation uncertainty.

Cukierman and Meltzer (1986) argue that central banks (CBs) tend to create inflation surprises in the presence of more inflation uncertainty. However, Holland (1995) has viewed opposite results about the effect of nominal uncertainty on inflation itself.

Pourgerami and Maskus (1987) found negative effect of inflation on its variability as related to the first part of Friedman's hypothesis. Also, Dotsey and Sarte (2000) discovered a positive effect of inflation uncertainty on output growth rate.

Furthermore, theoretical impact of output uncertainty on output growth is shown differently, where it is negative (as Pindyck 1991 indicated), positive (according to (Mirman 1971 and Black 1987). Additionally, Devereux (1989) supports positive effect of output volatility on inflation.

Moreover, there are some theoretical issues about the impact of output uncertainty on output growth. Pindyck (1991) predicted a negative effect of real uncertainty on growth. On the contrary, Mirman (1971), Black (1987), Blackburn (1999) predicted a positive effect of real uncertainty on output growth.

In addition, in this essay, our study is contributing new knowledge to what is already known from previous studies of Grier, et al, (2004), Fountac et al (2006) Bhar and Mallik (2013). Grier, et al, (2004) which measured the inflation Producer Price Index (PPI), and the output growth from Industrial Production Index (IPI), and they used the Vector Autoregressive Matrix Average (VARMA) and GARCH in-mean models.

For example, Fountac et al (2006) employ a bivariate CCC-GARCH model of inflation and output growth to examine the causality relationship among nominal uncertainty, real uncertainty and macroeconomic performance in the G7. The authors used different types of data among seven countries to measure of price and IPI to measure of output growth. In addition, Bhar and Mallik (2013), used PPI and IPI data to investigate the transmission and response of inflation uncertainty and output uncertainty on inflation and output growth in the UK. They applied bivariate EGARCH model with considering two dummy variables due to inflation targeting in 1992 and 1970s oil crises. Thus, we update the previous studies by using CPI as proxy of inflation rate and employing CCC-GARCH model for G7 countries. Also, we consider the monthly CPI and IPI data for all G7 countries and employing CCC-GACH(1,1)-ML with investigating the effect of economic and political events to capture any effect to inflation and output rates in the G7.

This study will be based on the group of G7 namely (the US, the UK, Germany, Japan, Italy, France and Canada). We employ a bivariate constant conditional correlation CCC – GARCH (1,1)-ML to examine the causal relationship between inflation and output growth, and their variabilities. Then, we employ a bivariate CCC – GARCH (1,1)-ML model including dummy variables in the mean equations. Dummies are chosen in the inflation and growth data according to some economic and political events in the G7 countries.

The mean equations are adjusted to include dummy variables on the intercept to capture any possible effects of the Great Recession in 1980 and post terrorist attacks of 9/11 in the US, the inflation targeting in 1992 in the UK, the unification of Germany 1990, the post-Plaza Accord in 1985 in Japan, the all oil crises 1970s in the UK, Italy France and Canada and finally, the financial crisis in 2007 for all G7 countries.

This essay is outlined as follows: in Section 2 we consider in more details the hypotheses about the causality between inflation and its uncertainty as well as the causality between output growth and its uncertainty. Section 3 summarizes the empirical literature up to date. Section 4 outlines the methodology. Section 5 describes the data and variables. Section 6 evaluates the empirical findings. Finally we conclude our study in Section 7.

3.2. Theoretical Evidence:

Many theories have presented the relationship between inflation and output growth on one hand, and inflation uncertainty and output uncertainty on the other.

3.2.1. The Impact of Inflation on Inflation Uncertainty:

Friedman (1977) viewed the effect of inflation on the growth (inflation effects on output growth via inflation uncertainty). The first part of Friedman's hypothesis concentrates on the impact of inflation on its uncertainty explaining that an increase in inflation may induce an erratic policy response by monetary authority, and therefore, lead to more uncertainty about the future rate of inflation (see Fountas and Karanasos (2007)).

Moreover, the above issue is supported by Ball (1992) where he presented a model of monetary policy in which a rise in inflation increases uncertainty about the future rate of inflation. In explaining this result, he analyzes an asymmetric information game in which the public faces uncertainty with relation to two types of policymakers that are considered: a weak type that is unwilling disinflation and a tough type that bears the cost of disinflation. The policymakers alternate stochastically in office. When current inflation is high, the public faces increasing uncertainty about future inflation, as it is unknown which policymaker will be in office next period and consequently what the response to the high-inflation rate will be! Such an uncertainty does not arise in the presence of a low inflation rate. It is also possible that more inflation will lead to a lower level of inflation uncertainty.

On the contrary, Pourgerami and Maskus (1987) advance the argument that in the presence of rising inflation agents may invest more resources in forecasting inflation, thus reducing uncertainty about inflation. This argument is supported by Ungar and Zilberfarb (1993).

3.2.2. The Impact of Inflation Uncertainty on Inflation:

Cukierman and Meltzer (1986) use a Barro and Gordon (1983) set up, where agents face uncertainty about the rate of monetary growth, and thus inflation. In the presence of this uncertainty, they believe that the policymakers apply an expansionary monetary policy in order to surprise the agents and enjoy output gains. As a result, there is a positive impact of inflation uncertainty on inflation.

Holland (1995) has viewed opposite results about the effect of nominal uncertainty on inflation itself where he presented that greater uncertainty is a part of the cost of inflation. In other words, as inflation uncertainty increases when the inflation rate rises, the policymakers respond by contracting growth of money supply in order to eliminate inflation uncertainty and the associated negative welfare effects. Hence, Holland's argument supports the negative causal impact of inflation variability on inflation.

3.2.3. The impact of inflation uncertainty on output growth:

The second part of Friedman's hypothesis supports the idea that raised inflation uncertainty would leads to a negative output growth rate. In other words, Friedman expected that an increase in inflation uncertainty results increased rates of unanticipated inflation, and therefore, will be associated with the costs of unanticipated inflation. Such costs arise from the effect of nominal uncertainty on both the intertemporal and intratemporal allocation of resources (see Fountas and Karanasos (2007)). Inflation uncertainty affects interest rates, and then all decisions relating to the intertemporal allocation of resources. Also, inflation uncertainty impacts the real cost of the production factors and price of the final commodities, and hence, the intratemporal allocation (see Bredin and Fountas (2005)).

In contrast, Dotsey and Sorte (2000) analyzed the effect of inflation uncertainty on economic growth. A cash-in-advance model that allows for precautionary savings and risk aversion, they show that output growth rate can be affected positively by inflation uncertainty. Particularly, their argument based on that an increase in the variability of monetary growth, and then inflation, conduces more uncertain in the return to money balances and leads to a fall in the demand for real money balances and consumption. Hence, agents increase precautionary savings and the pool of funds available to finance investment increases (see Fountas and Karanasos (2007).

3.2.4. The effect of output uncertainty on inflation and output growth:

The effect of output uncertainty on inflation was investigated theoretically by Devereux (1989) where he extended the Barro and Gordon (1983) model by introducing wage indexation endogenously (see Bredin and Fountas (2005)). Devereux (1989) considers the effect of an exogenous increase in output uncertainty on the degree of wage indexation and the optimal rate of inflation. Then, he indicates that an increase in output uncertainty will decrease the optimal amount of wage indexation that leads the policymaker to adopt more inflation surprises for obtaining desirable real effects. In summary, the output uncertainty has positive effect on the rate of inflation, a point which has been supported by Cukierman and Gerlach (2003) (see Fountas and Karanasos (2007)).

The effect in the opposite direction of this issue can be obtained by returning to Cukierman and Meltzer (1986) where they found positive effect of nominal uncertainty on inflation. By taking into account that output uncertainty decreases nominal uncertainty (Taylor effect), the Cukierman and Meltzer (1986) theory implies a negative effect of output variability on inflation.

In addition, the impact of output uncertainty on output growth rate has been analysed theoretically. The macro-economic theory offered three possibilities to clarify the effect of real uncertainty on output growth: Firstly, according to some business cycle models, there is no correlation between the growth rate and its uncertainty, because in business cycle models the output uncertainty is determined by price misperceptions in response to monetary shocks. Change of the output growth is affected by real factors such as technology.

The second possibility, as some theories point out, is the positive effect of output uncertainty on the economic growth rate. Mirman (1971) advanced the argument that more income uncertainty would lead to higher savings rate for precautionary reasons which would result in a higher equilibrium rate of economic growth according to the neoclassical growth theory.

In addition, Black (1987) argued that the impact of output variability on the growth rate is positive. His emphasis was based on the hypothesis that investments in riskier technologies will be available only if the average rate of output growth (predicted return on the investments) is large enough to reimburse the cost of extra risk; this positive impact is supported by Blackburn (1999). Finally, the negative effect of output uncertainty on growth is predicted mainly by Pindyck (1991). (see Fountas and Karanasos 2007)

Table 2. 12 Summary of Theories:

Theories, the effect of:	sign
Inflation on inflation uncertainty:	
Friedman (1977), Ball (1992)	+
Pourgerami and Maskus (1987), Ungar and Zilberfarb (1993)	-
Inflation uncertainty on inflation:	
Cukierman and Meltzer (1986)	+
Holland (1995)	-
Inflation uncertainty on output growth:	
Friedman (1977)	-
Dotsey and Sarte (2000)	+
Output uncertainty on inflation:	
Devereux (1989), Cukierman and Gerlach (2003)	+
Taylor effect and Cukierman and Meltzer (1986)	-
Output uncertainty on output growth:	
Pindyck (1991)	-
Mirman (1971), Black (1987), Blackburn (1999)	+

3.3. The Empirical Evidence

There are many early empirical studies on the relationship between inflation and its uncertainty on the one hand and the effect of nominal uncertainty on output growth rates on the other hand. Moreover, many studies have investigated the volatility feedback between nominal and real uncertainties. Some of these studies highlighted the relationship between output growth and real uncertainty while others measured uncertainty using the conditional variance of inflation and output rates that is obtained by the GARCH approach. Those studies can be summarised as following:

Elder (2003) examined the effects of inflation uncertainty on real economic activity. He investigated the different ways about that nominal uncertainty impacts output growth rates inside economic sectors. Furthermore, he presented some advantages of the approach that examines the above relationship by employing a parameterised and flexible multivariate framework. This approach is less ad hoc than single equation reduced forms and it shows the effects of simultaneity and generated regressors that it is common in low-order dynamic models and two-step estimation methodology that could emerge in efficient estimates of parameters. Also, it utilised a relatively large set of conditioning information that can control the effect of supply shocks and level of inflation (see page 2).

Under these benefits, the author took this approach and examined how the nominal uncertainty affects the real economic activity. . In order to do that, the author formed a framework which integrates the identified Vector Auto Regression (VAR) methodology with a multivariate generalised autoregressive conditional heteroskedastic (MGARCH) model. After that, Elder (2003) adopted the general VAR specification to obtain the MGARCH in-mean (MGARCH-M) VAR model and supported it by deriving the impulse function. Then, he re-evaluated the effects of inflation uncertainty on real economic activity.

Moreover, he followed some methods in the literature using the conditional variance of the inflation forecast errors as a measure of inflation uncertainty. The author used the Consumer Price Index (CPI) data (the CPI without shelter, the CPI research series, the CPI with shelter and interpolated GDP deflator) (see page (3) Elder (2003)) to measure the inflation rates. Also, he used Industrial Production and interpolated (GDP) data as a base to measure output rates. The data examined was monthly obtained and covered the period between October 1982 and March 2000. However, to ensure that the results are not sensitive to the sample period, another model was estimated over the period from August 1966 to March 2000. The estimation of the

VAR and MGARCH-M VAR model was given by (2-2) - (2-5) with lag length of (7) by performing the tests for these models, it was found that the MGARCH-M VAR model is preferred over the homo-skedasticity VAR, because it could capture the dynamic normally associated with such as VARs.

Finally, Elder (2003) concluded his study by finding an empirical evidence stating that inflation uncertainty has significantly tended to reduce the real economic activity during the period after 1982. Similarly, an average shock to nominal uncertainty has led to reduce output growth over three months about 22 points (according to particular finding in Elder (2003)) and the same was found in the period before 1982 (from 1966 to 1978). This effect of inflation uncertainty is strong to particular measure of output and inflation, the sample period and the lag length of the VAR. Lastly, the paper concluded that the findings are particularly persuaded because the formed empirical model controls for the potentially confounding effects like the effect of the level of inflation, supply shocks and lagged monetary policy (the lower inflation the higher output growth via inflation uncertainty)

Grier, et al, (2004) studied the asymmetric effect of growth volatility and inflation volatility on the rates of output growth and inflation. They analysed the asymmetric response of inflation and output growth to positive and negative of equal quantity. The authors depended on monthly data for the US. Their data covered the period from April 1947 to October 2000. They measured the inflation Producer Price Index (PPI), and in the same step, the output growth from Industrial Production Index (IPI). Grier, et al (2004) used the Vector Autoregressive Matrix Average (VARMA) and GARCH in-mean models.

In addition, they used the Generalised Impulse Response Functions (GIRFs) to analyse the time profile of the effects of shocks on the growth and inflation rates in the future. Finally, the author concluded by finding strong evidence supporting that an increase in output uncertainty is connected by higher average growth rates. In contrast, they found that increased inflation uncertainty is associated with a lower average rate of growth. However, they did not find any evidence to support the propositions that higher nominal uncertainty makes policy makers raise the average inflation rate according to the discovery that the higher inflation uncertainty is associated with lower average rate of inflation.

Similarly, there is no evidence that an increase of average inflation rate can be a result of rising growth uncertainty. On the other hand, the paper implied that all existing ARCH or GARCH models of inflation and output growth are not properly specified. Hence, those models are suspected regarding their specifications according to the significant non-diagonally innovation that is shown by conditional volatility of inflation and output growth. Finally, the economically significant effects of asymmetric response of inflation and growth to their uncertainty are confirmed by generalised impulse response experiments which showed the effect and persistence of shocks to inflation and growth on future inflation and output growth.

Using a general multivariate GARCH-M model instead of a bivariate VAR model; Bredin and Fountas (2005) investigated the probable relationship between macroeconomic uncertainty (both nominal and real) and macro-economic performance, where their study was based on the group of seven (G7). They adopted the simultaneous approach of VARMA (Vector Auto-regressive Moving Average) GARCH-M model for both inflation and output growth taking into account the conditional variance as a measure of inflation uncertainty and output growth uncertainty; in this investigation they used monthly data for the countries of G7 in the period from 1957 to 2003. The data was on Consumer Price Index (CPI) or Producer Price Index (PPI) as proxies for inflation. Also, for determining the output growth rates, the data on Industrial Production Index (IPI) was used.

The multivariate GARCH-M model had led to the following results Firstly, there are mixed effects of uncertainty associated with the rate of inflation on output growth. Thus, the belief of Friedman that the nominal uncertainty may have negative effect on economy's real sector got little support by this study. Secondly, there is mixed evidence in favour of Cukierman-Meltzer's (1986) hypothesis. So, the countries are expected to react differently to the change in the nominal uncertainty. Thirdly, there is evidence that in Canada, Germany and the UK the output growth uncertainty positively affects output growth rate which is fitted with Black (1987). In contrary, this effect is negative in the other countries of the G7. With these findings, authors emphasised the importance of the development of macroeconomic theories as it provides the motivation for the simultaneous analysis of economic growth and business cycle variability in macroeconomic modelling. Finally, the positive effect of real uncertainty on inflation got some support as it agrees with Devereux (1989) hypothesis.

Considering the ambiguity surrounds the link between nominal uncertainty and real uncertainty, Karanasos and Kim (2005) investigated the relationship between inflation uncertainty and output uncertainty. They use a bivariate GARCH model to estimate the conditional mean of inflation rate and output rate. A Granger causality test (Wald test) was employed to choose the model that is performed on the assumptions that the conditional variance matrix follows the BEKK model. Moreover, the authors used monthly data for the US, Japan and Germany where the inflation rate is measured by producer price index (PPI), while, output rate is based on industrial price index (IPI). The data covered the period from February – 1957 to August – 2000. The findings of this study shows that, in the US and Japan, inflation volatility affects positively on output growth volatility. However, it does not provide clearly evidence in Germany that higher nominal uncertainty decreases real uncertainty. Nonetheless, in Japan and Germany, a positive effect began to exist in the eighties and nineties.

Caporale and Kontonikas (2009) investigated the relationship between inflation and its uncertainty in twelve EMU countries namely: Germany, France, Italy, Spain, Portugal, Greece, Ireland, Finland, Belgium, the Netherlands, Luxembourg and Austria. The introduction to the Euro area in 1999 could have affected both inflation expectation and inflation uncertainty by new policy regime which followed the European Central Bank (ECB) (*see page (2)*). In other words, the authors analysed empirically how the policy regime with the common interest rate that was set by (ECM) has effects on inflation uncertainty and inflation itself. They used a GARCH in-mean model and considered it more efficient than a tow-step approach. However, the GARCH-M model is employed in two-step approach by estimating conditional variance using GARCH specification firstly and then is contained in the conditional mean equation to carry out the causality test.

The GARCH-M model allows the test of possible lagged effect of nominal uncertainty on inflation itself that is determined by monthly or quarterly frequency. Therefore the authors employed the GARCH-M model using this approach to distinguish between short-run and steady-state inflation uncertainty.

Furthermore, they used monthly consumer price index data (CPI) for the twelve EMU countries mentioned earlier. The data covered the period from January 1980 to November 2004. Here, they measured inflation by taking the first difference of the logarithm of seasonally adjusted CPI. All in all, they used the adopted framework to make a difference between various types of nominal uncertainty that can affect the inflation process. In addition, they focused on the new policy regime shift that happened in 1999 (the year of entering EU) which means that in this study there are six years of Euro were included. Thus, they modelled the introduction of the Euro period with dummy step corresponding the adoption of the Euro, and then they investigated four issues: steady-state inflation; steady-state inflation uncertainty; inflation persistence; and the relationship between inflation and its uncertainty.

The overall conclusion shows that in term of both actual and steady-state inflation, the inflation performance had been very different over the whole study period. There is a clear evidence that adopting the Euro has had a significant impact on the relationship between inflation and nominal uncertainty and this is what has occurred well before the beginning of 1999. Furthermore, in many cases the inflation of the Euro age has not had advantages from the viewpoint of inflation uncertainty. For instance, in Austria and Italy, there has been a step increased in the steady-state uncertainty following the adoption of the Euro.

Moreover, in Austria, Italy, Germany, Greece, France, Spain, Belgium and Luxembourg, it would seem that the pursuit of anti-inflationary policies by the ECB is counterproductive, in the sense that lower inflation might lead to higher steady-state uncertainty. On the other hand, the same approach was applied to short-run uncertainty in Germany, Greece and Ireland where Friedman and Ball connection between inflation and nominal uncertainty is not found during the Euro period. In summary, the higher steady-state inflation uncertainty, and the break-down in the relationship between inflation and inflation uncertainty follow the introduction of the Euro.

Fountas and Karanasos (2007) analysed the casual effect between inflation and output growth on one side and inflation and output growth uncertainty (nominal and real) on the other side.

This study is based on the G7 countries. The paper presented the past theories which examined the relationship between the inflation and output growth and their uncertainty where contrary results were found about the casual effect of the above variables. The methodology that was used in this paper followed the univariate CARCH-type model, taking into account, that inflation and output growth uncertainty are measured by estimated conditional variance of inflation and output growth rates, respectively.

The authors performed the Granger-Causality test to examine the casual effect between the above four variables (inflation, output growth, nominal and real uncertainty). Also, they performed the causality test by taking three different lag lengths (4, 8 and 12). The main study focused on the US case and then extended to the other six countries in the G7 (Canada, France, Germany, Italy, Japan, and the UK). As for the US, the annual inflation and output growth rates are determined by the Consumer Price Index (CPI) and the Industrial Production Index (IPI), respectively.

The CPI and IPI are monthly data in the period between February-1957 and August-2000. The study is extended to approach the other G7 countries and used the same type of data (CPI and IPI) for these countries covered the same period as in the US case. The authors chose a 2C-AGARCH (1,1) model for the UK and an AGARCH (1,1) model for the other five countries to estimate conditional variance as a measure of inflation uncertainty. However, for measuring output growth uncertainty, they used a GARCH (1,1) model for Canada, France and Italy on one hand, and 2C-GARCH (1,1) for the others on the other hand.

However, the analysis was re-performed by using the Producer Price Index PPI data instead of CPI to determine the inflation rate and then measured the inflation uncertainty using GARCH (1,1) for Canada, Germany, Japan and the UK.

Fountas and Karanasos (2007) concluded that firstly inflation is a primary positively determining factor of inflation uncertainty either using CPI or PPI data, except for the case of Germany, where it was a negative determinant. Secondly, there are mixed effects of nominal uncertainty on output growth, so the negative impact of inflation uncertainty economy's real sector (as Friedman believed) is limited. Thirdly, countries are anticipated to react differently to a change in the degree of uncertainty surrounding the inflation rate, according to a mixed evidence by Cukierman and Meltzer's hypothesis. Fourthly, in most countries there is a positive relationship between real uncertainty and output growth rate. Finally, real uncertainty does not seem to cause more inflation.

Karanasos and Schurer (2007) investigated the linearity of relationship between inflation and its uncertainty in three European countries (Germany, Netherlands and Sweden). The authors focused on optimal strategy that the monetary authorities have to follow if a greater inflation led to an increase in nominal uncertainty which has a negative correlation with economic activity (according to what many researchers have found). The authors used the parametric power ARCH model (PARCH model).

This model increases the elasticity of the conditional variance specification by allowing the data to determine the power of inflation for which the predictable structure in the volatility pattern is the strongest. This has major implications for an inflation uncertainty hypothesis. Then, they tested the relationship between inflation and its uncertainty by estimating the

PARCH in-mean model with the conditional variance equation incorporating lags of the series of inflation (the ‘level’ effect).

The estimated values of the “in mean” and the “level” effects are weak in comparison to the changes in the heteroscedasticity (the ‘power’ term). Furthermore, the data which was used in this study was on CPI as a determining of price level. The data covered the period from January 1962 to January 2004 in the three European countries Germany, Netherlands and Sweden. Then the authors estimated the equation of AR-PGARCH (1,1).

In conclusion, they presented two results. First, the overall evidence is mixed for the tested economic hypothesis, where the authors found that in Germany and Netherlands case, an increase in inflation uncertainty gives encouragement to policy makers to great inflation causing a rise in optimal average inflation. This supports the Cukierman and Meltzer hypothesis. On the other hand, in Sweden where the Holland hypothesis was applied a higher nominal uncertainty leads to lower inflation via monetary tightening. However, the effect of inflation on its uncertainty was positive for all three countries (as it was predicted by first leg of Friedman hypothesis). Secondly, in sensitivity analysis they found that an arbitrary choice of the Heteroscedasticity parameter impacts significantly in the relationship between inflation a nominal uncertainty.

Conrad and Karanasos (2008) examined the intertemporal relationship between the volatilities of inflation and output growth in the US using monthly data of CPI and IPI as proxies of inflation and output growth respectively. It is the first time that the bivariate unrestricted extended constant conditional correlation UECCC – GARCH (1, 1) was applied in such field of study. This approach allows for volatility feedback to be either positive or negative. Their examination indicates that greater output volatility causes lower inflation uncertainty. However, strong evidence supports that higher nominal uncertainty leads to decrease real uncertainty.

Fountas and Karanasos (2008**)** investigated the relationship between the economic and the variability of the Real Business Cycle (RBC). They employed a long span of annual output data for five industrial European countries namely France, Germany, Italy, Sweden and the UK.

These data start in the 1800s and span over 100 years. The long period enabled the authors to include the periods of significant variations in output growth like the two World Wars, the Great Depression and the Volatile in 1970 in their analyses. Moreover, the anual data allowed them to perform the test of Black (1987) hypothesis which is better to be done in a study that uses a low frequency data. In addition the data was proxy by the index of industrial production (IP) where the output growth is measured by the change of the lag (IP).

Furthermore, it used the conditional variance of the output rates to determine the real uncertainty. The authors depended on the AR(p)-GARCH (1,1) model in their methodology to test the Black hypothesis and the relationship between output growth and real uncertainty. They had chosen an AR(0) model for Sweden, an AR(1) model for Germany, an AR(3) model for the UK and France and AR(4) model for Italy.

In addition, the GARCH (1,1) model was chosen for Germany, France and Sweden, while the ARCH (1,1) was chosen for Italy and UK. Fountas and Karanasos (2008) found two main conclusions: First, more real output uncertainty leads to higher growth rate in three out of the five studied countries (in Germany, Italy and the UK). This evidence supports the Black (1987) hypothesis and Blackburn (1999) hypothesis. Secondly, there is a strong evidence in favour of the relationship between growth and real output uncertainty, where it was a negative casual effect in four out of the five studied countries (Germany, Italy, France and UK).

Bredin, Elder and Fountas (2009) tested empirically for the impact of nominal macroeconomic uncertainty on inflation and output growth for five Asian countries namely India, South Korea, Malaysia, Philippines and Singapore. The development of GARCH model techniques enabled the measurement of inflation uncertainty by the conditional variance of shocks of the inflation series. The authors showed that the effect of the nominal and real uncertainty on macroeconomic performance has several ways to be examined. If the conditional variance of inflation and output growth are estimated independently from each other, a univariate GARCH framework can be employed and, subsequently a Granger causality test can be used to examine their relationship.

On the other hand, a bivariate GARCH in-mean (GARCH-M) model can be estimated and at the same time the effect of uncertainty on macroeconomic performance can be tested. However, the authors modelled the inflation and output growth simultaneously in a Vector Autoregressive Moving Average (VARMA) GARCH-M model, where equations for both inflation and output growth were estimated and enriched by the conditional standard deviation of inflation and growth that was presented in VARMA model.

Also, the conditional variance covariance matrix for the shocks to inflation and growth was displayed by GARCH in-mean model. Moreover, in this paper, an impulse response functions from a VAR-GARCH-M model that has a structural interpretation was estimated. However, Bredin, et al (2009) used quarterly data referring to the five Asian countries. These data were the IPI to determine the output growth rates and CPI as a proxy for inflation rates.

The range of data period was different for each country. It began in the first quarter of 1963 for India, the first quarter of 1966, for Singapore, the first quarter of 1970 for South Korea and Malaysia, and the first quarter of 1981, for Philippines.

However, it ends in the first quarter of 2005 for Singapore, South Korea and Malaysia, and in the last quarter of 2005 for the other two countries. Finally, the simultaneous approach that was adopted by authors was proxy uncertainty by the conditional variance of unanticipated shocks to the inflation and output growth time series led to many results: First, there was not enough support to the second part of Friedman hypothesis that inflation uncertainty can be detrimental to the economy's sectors. Secondly, the changes in the degree of uncertainty surrounding the inflation rate lead to different reactions in the economies of those countries. This means mixed evidence in favour of Cukierman and Meltzer (1986) hypothesis.

Thirdly, the effect of output growth uncertainty on output growth was negative in all countries of study which supports what was found in macroeconomic modelling on the simultaneous analysis of economic growth and business cycle variability. Finally, the positive impact of real uncertainty on inflation according to Devereux (1989) hypothesis gained some support. All in all, the results that were obtained in this study indicated that macroeconomic uncertainty may even improve macroeconomic performance as it is associated with large average rate output growth and average rate of inflation.

Conrad et al (2010) investigated the link between inflation, output growth and their variabilities in the UK. Monthly data of CPI and IPI are used to determine the price level and growth rate. The data cover the period from January – 1962 to January – 2004. In their paper, the authors employed a bivariate UECCC – GARCH (1, 1) model that incorporates mean and level effects.

This approach allows using several lags of conditional variances as regresses in the mean equation. The empirical result shows that the choice of lags impacts the sign effect between variables. At lag one, the impact of real variability on growth is positive as predicted by Blackburn, but at lag three, it turns to be negative as predicted by Pindyck. Besides that, positive or negative feedbacks can be shown between the variabilities.

Bhar and Mallik (2010) discussed the effects of inflation uncertainty and growth uncertainty on inflation and output growth in the United States over the period 1957:04 to 2007:04 by studying a multivariate EGARCH-M model and using the producer price index (PPI) and industrial price index (IPI) as the proxy for the inflation rates and output growth rate. In addition, the 1970s oil has been included as a dummy in the inflation equation. Their results showed a positive effect of inflation uncertainty on inflation rate, but nominal uncertainty reduces output growth. While, there is no effect of output uncertainty on inflation or output growth rates. On the other hand, the oil price has significant effects inflation. In summary, Bhar and Mallik (2010) results have important implications for inflation-targeting monetary policy, and the aim of stabilization policy in general.

Moreover, (Bhar and Mallik ,2013) used different methodology and different data to investigate the transmission and response of inflation uncertainty and output uncertainty on inflation and output growth in the UK. They have applied the bi-variate EGARCH model. The obtained results proposed that inflation uncertainty impacts on inflation before the inflation–studied period positively and significantly, while the effect becomes significantly negative after the inflation-studied period. Whilst the output uncertainty impacts negatively and significantly on inflation, it has a positive impact on growth. Furthermore, the results also stated that the inflation uncertainty decreases the output growth before and after the inflation-studied period significantly. Their results support the generalised impulse response methods.

Conrad and Karanasos (2015) extended the UECCC GARCH technique, which was considered in their study (2010), by allowing the lagged in mean and level effects besides the asymmetries in the conditional variances. For this study, they used the US data to investigate the twelve potential intertemporal relationships among inflation, growth and their uncertainties.

Their findings were as follows. First, the high rate of inflation is a key determinant of output growth in bidirectional Nexis through the nominal uncertainty. Secondly, output growth enhances inflation indirectly via the reduction in real uncertainty channel.

On the other side, Caporale et al (2012) examined the relationship between inflation and inflation uncertainty in the Euro area by applying AR-GARCH model. Moreover, the authors attempted to account for mentioned linkage in VAR structure taking in their consideration the possible impact when the policy regime change at the beginning of EMU in 1999.

They found that since the start point of EMU, the steady-state inflation and inflation uncertainty have reduced steadily, while a short run relationship has been achieved. Moreover, the logical order of dummy procedure showed that a structural break occurs when the inception of euro and providing lower long–term uncertainty. Consequently, they indicated the reversed relationship of causality in the euro period which the Friedman –Ball supported empirically. This finding supports the concept of ECB which states that less inflation uncertainty can be provided by reducing the inflation rate.

Baharumshaha and Woharc (2016) used a system generalized method of moments (SGMM) that controls for instrument proliferation to demonstrate the relationship between inflation, inflation uncertainty, and economic growth in a panel of 94 emerging and developing countries over the period 1976-2010. I

n this study, the authors obtained the following findings; Firstly, when both the proliferation of instruments problem and the biased standard error in SGMM are accounted for, the results imply that only in non-inflation crisis countries, inflation and growth are negatively correlated, however, inflation uncertainty increases growth. The three-regime model results confirm the negative effect of high inflation rates on growth rates and vice versa. Secondly, the negative-level effect of not keeping inflation in check out weighs the positive effect from uncertainty in non-inflation crisis countries in all three regimes.

Finally, the positive effect of inflation uncertainty on growth through a precautionary motive is confirmed when inflation reaches moderate ranges (5.6–15.9%). Briefly, the results of this research are robust to a battery of diagnostic tests, including the issue of weak and the proliferation of instruments and biased standard error.

3.4. Methodology:

Some of the former studies have examined the causal relationship between inflation and output growth by applying the autoregressive conditional heteroscedasticity (ARCH) models which introduced by Engle (1982). However, most previous literatures have applied the generalized autoregressive conditional heteroscedasticity (GARCH) models which introduced by Bollerslev (1986) in order to measure both the inflation uncertainty and output uncertainty.

The two most commonly used specifications are the diagonal constant conditional correlation (DCCC) model (such as Grier and Perry, 2000, and Fountas and Karanasos, 2007,) and the BEKK representation (for example Grier and Grier, 2006,). Moreover, these two specifications are characterized by rather restrictive assumptions regarding potential volatility spillovers.

In this study, we employ a bivariate constant conditional correlation GARCH (1,1) in-mean-level (CCC-GARCH (1,1)-ML) to examine the causal relationship between inflation and output growth on one side, and their variabilities from the other side.

Moreover, we include dummy variables in the mean equation for each country to capture any possible effects with regards to political and economic events.

Let π_t denote the inflation rate and y_t denote the output growth rate, respectively:

$$\Phi_{\pi\pi}(L)\pi_t = c_\pi + \Phi_{\pi y}(L)y_t + \delta_{\pi\pi}\sqrt{h_{\pi,t-l_{\pi\pi}}} + \delta_{\pi y}\sqrt{h_{y,t-l_{\pi y}}} + \varepsilon_{\pi,t}. \quad 3.1$$

$$\Phi_{yy}(L)y_t = c_y + \Phi_{y\pi}(L)\pi_t + \delta_{yy}\sqrt{h_{y,t-l_{yy}}} + \delta_{y\pi}\sqrt{h_{\pi,t-l_{y\pi}}} + \varepsilon_{y,t}. \quad 3.2$$

$$h_{\pi t} = \omega_\pi + \beta_\pi h_{\pi,t-1} + \alpha_\pi \varepsilon^2_{\pi,t-1} + \gamma_\pi \pi_{t-i}. \quad 3.3$$

$$h_{yt} = \omega_y + \beta_y h_{y,t-1} + \alpha_y \varepsilon^2_{y,t-1} + \gamma_y \pi_{t-i}. \quad 3.4$$

$$h_{\pi y,t} = \rho\sqrt{h_{\pi,t}}\sqrt{h_{y,t}}\ . \quad 3.5$$

We assume that the roots of $\Phi_{\pi\pi}(L) = \sum_{j=1}^{p_{\pi\pi}} \varphi_{\pi\pi}^{j} L^{j}$, $\Phi_{\pi y}(L) = \sum_{j=1}^{p_{\pi y}} \varphi_{\pi y}^{j} L^{j}$, $\Phi_{y\pi}(L) = \sum_{j=1}^{p_{y\pi}} \varphi_{y\pi}^{j} L^{j}$, and $\Phi_{yy}(L) = 1 - \sum_{j=1}^{p_{yy}} \varphi_{yy}^{j} L^{j}$ have zeros outside the unit circle. In addition, *c* is a constant parameter, L is the lag operator, $h_{\pi t}$ and h_{yt} are the conditional variance. The residuals are conditionally distributed $\varepsilon_{\pi t} \,/\, F_{t-1} \sim N(0, h_{\pi t})$, $\varepsilon_{yt} \,/\, F_{t-1} \sim N\left(0, h_{yt}\right)$. In other words $h_{\pi t} = \mathbb{E}(\varepsilon_{\pi t}^{2}/F_{t-1})$, $h_{yt} = \mathbb{E}\left(\varepsilon_{yt}^{2}/F_{t-1}\right)$, ω, α, β, and γ are parameters to be estimated.

3.5. Data and Variables:

In this study, we use the data for the G7 countries, namely the US, the UK, Germany, Japan, Italy, France and Canada (Balcilar and Ozdemir (2013)). In our empirical analysis, we use the Consumer Price Index (CPI) and Industrial Price Index (IPI) as the proxies for the inflation rate (price level) and growth rate (output) respectively as common in previous studies such as (Elder (2004), Grier, et al (2004), Bredin and Fountas (2004), Mladenovic (2009) and Fountas and Karanasos (2007)).

We employ seasonalized monthly data, obtained from the International Financial Statistic (IFS) covering the period from 1960:01 to January 2011:01 for (the US, the UK, Germany, Japan, Italy and France), while the data for Canada are available from 1965:10 January 2011:01. Allowing for differencing and lags of dependent variables leaves 612 usable observations for the US, the UK, Germany, Japan, Italy and France, while leaves 543 Canada. In addition, the annualized inflation and output growth series are calculated as 1200 times the monthly difference in the natural logarithm of the Consumer Price Index and the Industrial Production Index respectively. See equation 3.1 (for inflation) and equation 3.2 (for growth):

$$\pi_t = [ln(CPI_t) - ln(CPI_{t-1})] \times 1200 \qquad (1)$$

Where:

π_t : Inflation rate.

CPI : Consumer Price Index.

t : time.

$$y_t = [ln(IPI_t) - ln(IPI_{t-1})] \times 1200 \qquad (2)$$

Where:

y_t : Output growth.

IPI : Industrial Price Index.

t : time.

Next, the summary statistics in (Table 3.2) imply that inflation rates are positively skewed in the The UK, Germany, Japan, Italy, France and Canada. Whereas, inflation rate in the US is skewed negatively. Moreover, display significant amounts of excess kurtosis with inflation series failing to satisfy the null hypothesis of the Jarque-Bera test for normality. In other words, the large values of the Jarque–Bera statistics imply a deviation from normality. In addition, the results of augmented Dickey–Fuller (1979) and Phillips-Perron (1988) unit root tests imply that we can treat the inflation rates in the G7 countries as stationary processes.

Table 3.2 Summary statistic for inflation in G7 countries:

	The US	**The UK**	**Germany**	**Japan**	**Italy**	**France**	**Canada**
Mean	1.717637	5.774300	2.767369	1.423291	0.229953	4.477204	4.309625
Median	1.551760	4.859263	2.503879	0.771900	0.161740	3.690601	3.921578
Maximum	9.327295	51.69918	20.66472	22.08123	1.344556	23.24567	31.53950
Minimum	-10.07840	-17.22440	-8.463510	-7.223965	-0.374740	-10.66662	-12.44535
Std. Dev.	1.848393	7.662232	4.002023	3.555421	0.237770	4.588046	5.144286
Skewness	-0.024441	1.831931	0.669420	1.333803	1.472049	0.660161	0.586320
Kurtosis	6.725149	10.36771	4.092789	6.404284	5.765512	3.762011	4.653529
Jarque-Bera	353.9177 (0.000)	1692.675 (0.000)	76.16027 (0.000)	476.9844 (0.000)	407.8943 (0.000)	59.25970 (0.000)	92.97166 (0.000)
Sum	1051.194	3464.580	1693.630	871.0543	137.9719	2740.049	2340.126
Sum Sq. Dev.	2087.517	35167.17	9785.890	7723.663	33.86423	12861.65	14343.32
ADF test	-12.3977 {<0.01}	-15.9916 {<0.01}	-15.8561 {<0.01}	-20.2833 {<0.01}	-10.5849 {<0.01}	-12.1739 {<0.01}	-10.5411 {<0.01}
PP test	-13.2348 {<0.01}	-16.4153 {<0.01}	-15.9042 {<0.01}	-20.4793 {<0.01}	-10.1913 {<0.01}	-12.2953 {<0.01}	-10.6059 {<0.01}

All data series are International Financial Statistic (IFS). Sample period is monthly, from 1960:01 to 2011:01 (with the exception of Canada which data are available from 1965:10). Monthly inflation rates are calculated from the Consumer Price Index at an annual rates. The numbers in parenthesis are robust *P – value.*

In addition, the summary statistics in (Table 3.4) imply that output growth rates are negatively skewed in the The US, Germany, Japan, France and Canada. However, output growth rate in the UK and Italy are skewed positively. Moreover, display significant amounts of excess kurtosis with output growth rate series failing to satisfy the null hypothesis of the Jarque-Bera test for normality. In other words, the large values of the Jarque–Bera statistics imply a deviation from normality. In addition, the results of augmented Dickey–Fuller (1979) and Phillips-Perron (1988) unit root tests imply that we can treat the output growth rates in the G7 countries as stationary processes.

Table 3.3 Summary statistic for output growth in G7 countries:

	The US	The UK	Germany	Japan	Italy	France	Canada
Mean	1.148141	1.192075	2.418191	1.833244	0.079106	2.396386	2.335293
Median	1.406109	1.347601	2.716997	2.023399	0.258604	1.349073	2.233852
Maximum	15.85814	116.7787	139.3247	24.73724	40.42907	309.1525	42.19795
Minimum	-22.02450	-94.59050	-119.3030	-48.81867	-38.28700	-378.6544	-48.45001
Std. Dev.	4.048421	16.14516	21.14801	8.064796	11.82502	28.52734	13.23498
Skewness	-0.893094	0.032076	-0.172702	-1.115104	0.032162	-0.553332	-0.259263
Kurtosis	6.914434	13.43579	9.041281	8.473807	7.003914	86.82946	3.667566
Jarque-Bera	472.0883 (0.000)	2777.200 (0.000)	933.7176 (0.000)	890.8778 (0.000)	400.8865 (0.000)	179229.4 (0.000)	16.16587 (0.000)
Sum	702.6621	729.5498	1479.933	1121.945	47.46370	1466.588	1268.064
Sum Sq. Dev.	10014.11	159267.1	273262.5	39740.01	83758.87	497237.3	94939.31
ADF test	-32.5311 {<0.01}	-29.7971 {<0.01}	-17.0639 {<0.01}	-39.6233 {<0.01}	-29.7289 {<0.01}	-30.3692 {<0.01}	-15.7627 {<0.01}
PP test	-36.2648 {<0.01}	-47.1846 {<0.01}	-32.5054 {<0.01}	-37.5282 {<0.01}	-97.8505 {<0.01}	-62.1181 {<0.01}	-30.5462 {<0.01}

All data series are International Financial Statistic (IFS). Sample period is monthly, from 1960:01 to 2011:01 (with the exception of Canada which data are available from 1965:10). Monthly output growth rates are calculated from the Industrial Price Index at an annual rates. The numbers in parenthesis are robust *P – value.*

Finally, we plotted both inflation rate and output rate for all G7 countries:

Figure 3. 1 Inflation and output growth of the US over time:

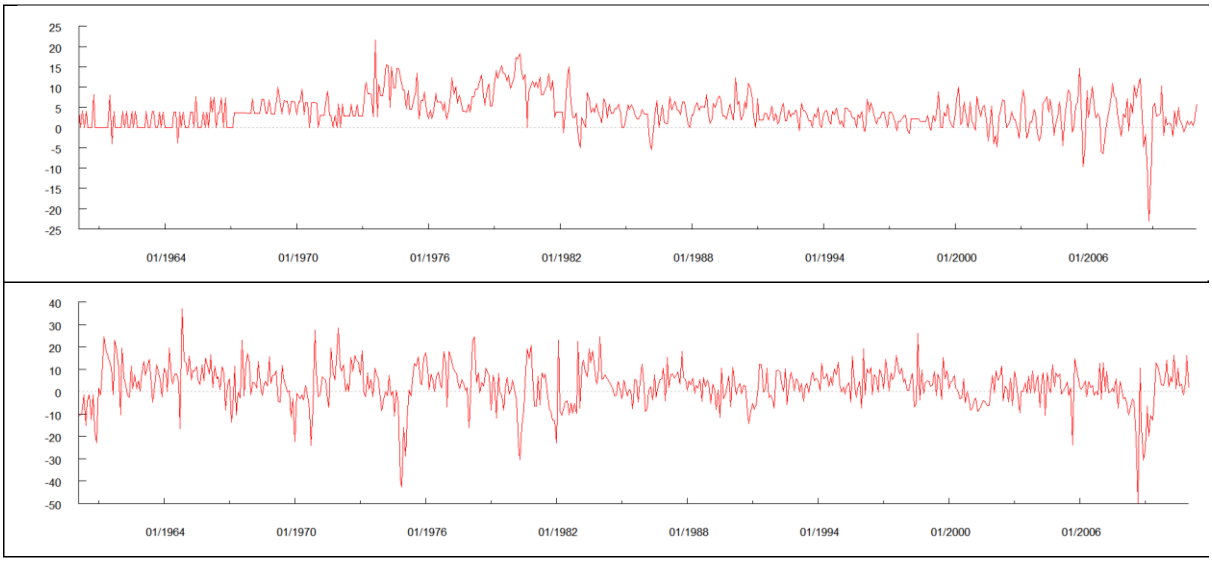


Figure 3.2 Inflation and output growth of the UK over time:

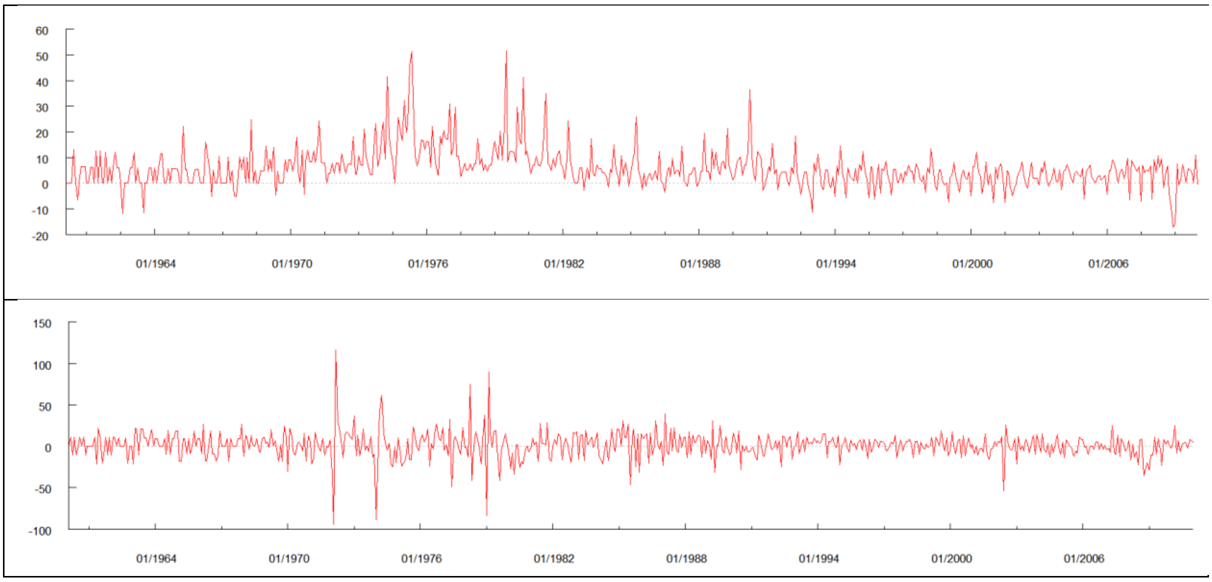


Figure 3.3 Inflation and output growth of Germany over time:

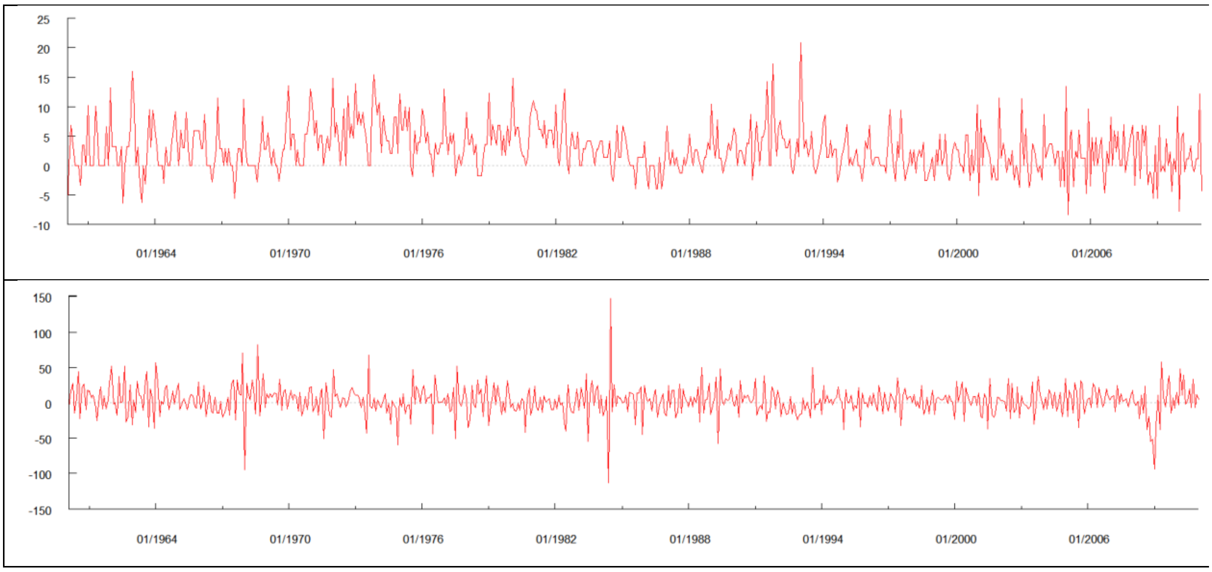


Figure 3.4 Inflation and output growth of Japan over time:

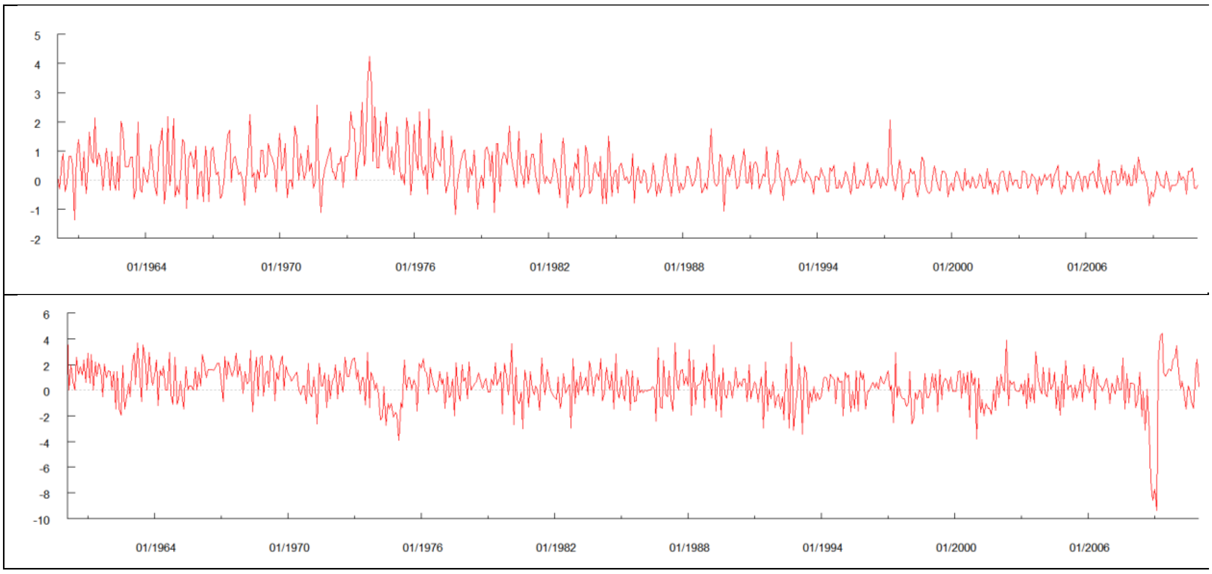


Figure 3.5 Inflation and output growth of Italy over time:

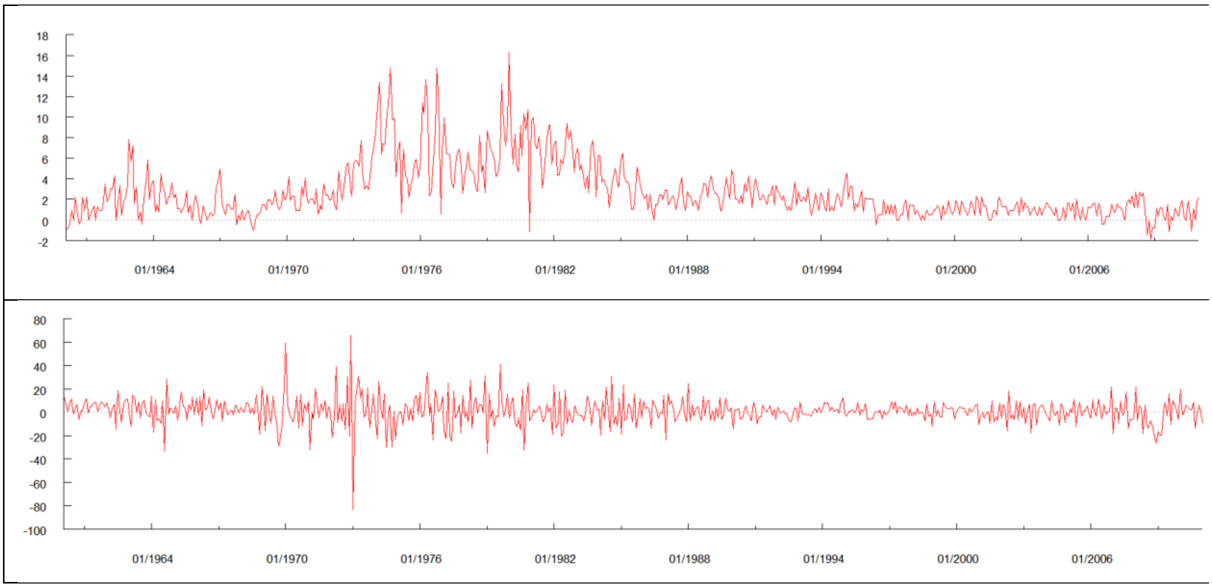


Figure 3.6 Inflation and output growth of France over time:

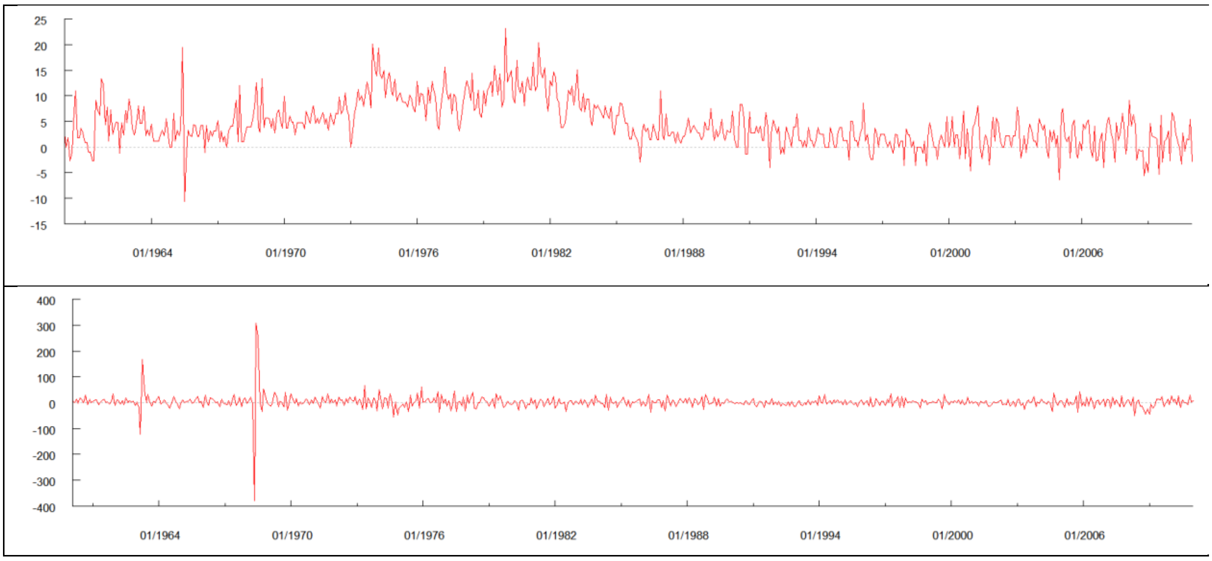
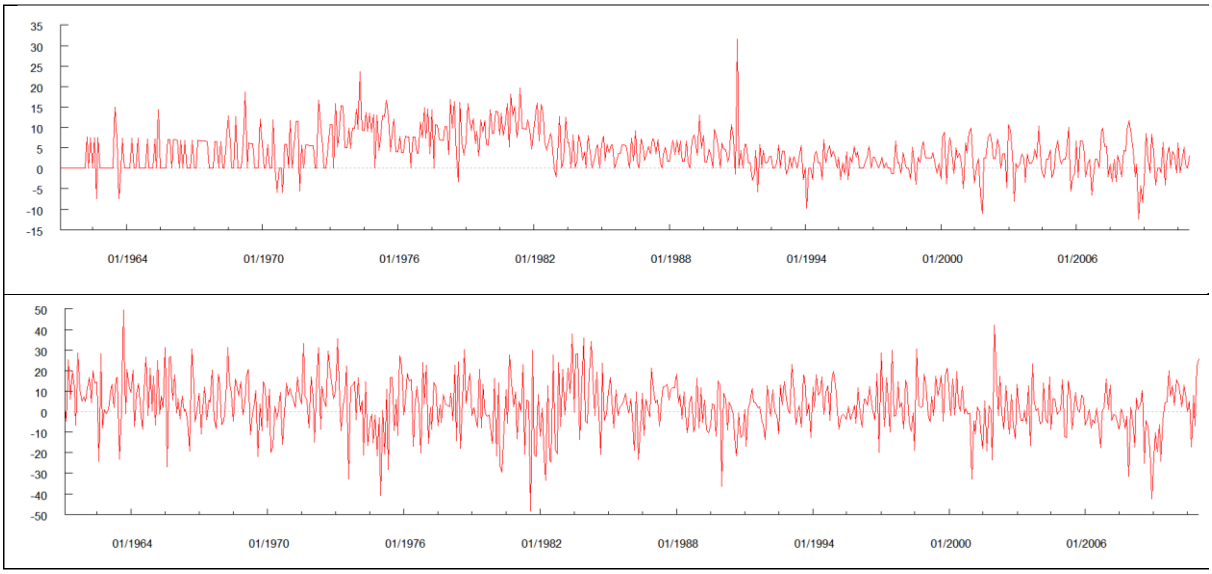


Figure 3.7 Inflation and output growth of Canada over time:



3.6. Empirical analysis:

We begin with the US case and then extend our analysis to the other G7 countries:

3.6.1. The case of the US:

The estimation of the various formulations was obtained by MLE (maximum likelihood estimation) as carried out in the Time series modelling.

Firstly, we estimate CCC-GARCH (1, 1)-ML without dummy variables in mean equations. (Table 3.4) shows the estimated parameters of equation 3.3 for inflation uncertainty and the parameters of equation 3.4 for output uncertainty. The best AR (GARCH) specification has been chosen upon the Likelihood Ratio (LR) and three alternative information criteria (Schwarz, Hannan-Quinn and Akaike criterion). We choose AR(12) and AR(2) for conditional variance of inflation and output growth respectively . We first consider and discuss the implications of the results of Table 3.4.

Table 3.4 CCC-GARCH (1, 1)-ML model for the US:

In-mean and level effects:	
$\delta_{\pi\pi}(t-2)$	0.51 (0.25)**
$\delta_{\pi y,t}(t)$	−0.05 (0.07)
$\delta_{y\pi}(t-2)$	−1.14 (0.45)**
$\delta_{yy}(t-2)$	0.29 (0.14)**
$\gamma_{\pi\pi}(t-1)$	0.18 (0.09)**
$\gamma_{y\pi}(t-1)$	1.47 (0.81)*
GARCH(1,1) coefficients:	
α_{π}	0.19 (0.06)***
β_{π}	0.69 (0.07)***
α_{y}	0.35 (0.10)***
β_{y}	0.25 (0.11)**

Notes: *Notes: This table reports parameter estimates for the following model:*

Mean Equations: $\Phi_{\pi\pi}(L)\pi_t = c_\pi + \Phi_{\pi y}(L)y_t + \delta_{\pi\pi}\sqrt{h_{\pi,t-l_{\pi\pi}}} + \delta_{\pi y}\sqrt{h_{y,t-l_{\pi y}}} + \varepsilon_{\pi,t}$

$$\Phi_{yy}(L)y_t = c_y + \Phi_{y\pi}(L)\pi_t + \delta_{yy}\sqrt{h_{y,t-l_{yy}}} + \delta_{y\pi}\sqrt{h_{\pi,t-l_{y\pi}}} + \varepsilon_{y,t}$$

Variance Equations: $h_{\pi t} = \omega_\pi + \beta_\pi h_{\pi,t-1} + \alpha_\pi \varepsilon^2_{\pi,t-1} + \gamma_\pi \pi_{t-i}$

$$h_{yt} = \omega_y + \beta_y h_{y,t-1} + \alpha_y \varepsilon^2_{y,t-1} + \gamma_y \pi_{t-i}$$

*The numbers in parentheses are robust standard errors. ***, ** and * are significance levels of 1%, 5% and 10%, respectively.*

First, all coefficients (α_π, α_y, β_π and β_y) of the conditional variances are statistically significant.

Second, to check the effect of inflation rate on inflation uncertainty, we insert the inflation variable in the conditional variance equation of inflation. Since, the coefficient of inflation rate ($\gamma_{\pi\pi-1} = 0.18$) is positive and significant, hence, there is overwhelming evidence for the first leg of the Friedman (1977) hypothesis (also as predicted by Ball (1992)), where higher inflation rate will lead to higher nominal uncertainty (after one month), this result supports the previous evidences that they are found by Fountas and Karanasos (2007) and Fountas, Karanasos and Karanassou (2000).

Third, a higher nominal uncertainty will increase inflation rate in two months' time as indicated by the positive and significant coefficient ($\delta_{\pi\pi} = 0.51$), this finding is concurrent with the

Cukierman and Meltzer (1986) theory. However, the insignificant $\delta_{\pi y}$ coefficient shows that there isn't any effect of output uncertainty on inflation.

Fourth, the positive and significant effect of output uncertainty on growth rate indicates evidence of Black (1987) hypothesis; $h_{yt} \overset{+}{\rightarrow} y_t$ as predicted by Mirman (1971), Blackburn (1999) and found empirically by Conrad and Karanasos (2008).

Finally, the significant and negative coefficient ($\delta_{y\pi} = -1.14$) is an evidence that inflation uncertainty affects output growth rate in a negative manner $h_{\pi t} \overset{-}{\rightarrow} y_t$ (the known as second leg of Friedman (1977) hypothesis), as found empirically by Elder (2003), Grier, et al (2004), Fountas and Karanasos (2007) and Conrad and Karanasos (2008).

More precisely, a 100% increase in the inflation uncertainty and output uncertainty leads to corresponding increase in the inflation rate by 51% and 29% respectively. Moreover, a 100% decline in the inflation uncertainty leads to an increase in the output growth rate by 114%.

Lastly, a 100% increase in inflation rate leads to 18% rise in the inflation uncertainty.

Briefly, Inflation causes uncertainty about future prices, interest rates, and exchange rates. This in turn increases the risks among potential trade partners and discouraging trade. The uncertainty that associated with inflation increases the risk while associated with the investment and production activity of firms and markets.

Secondly, we estimate CCC-GARCH (1, 1)-ML models including dummy variables in the mean equations. Dummies are chosen in the inflation and growth data according to some economic and political events in the US. The mean equation is adjusted to include three dummy variables on the intercept.

In the first one, a dummy variable is selected due to the Great Recession in 1980 (Palley 2011, Ireland 2000), this dummy variable is D1=1 for the time between 03/1980 and 01/1998 and D1=0 otherwise. In the second one, the dummy variable is D2=1 after the terrorist attacks of 9/11 to 01/2011 (Kosova and Enz 2012) and D2=0 otherwise. The last dummy variable is D3=1 for the time 08/2007 to 01/2011 and D3=0 otherwise, due to the financial crisis (Cassola and Morana 2012, Gray 2014).

Table 3.5 shows the estimated parameters of equation 3.3 for inflation uncertainty and the parameters of equation 3.4 for output uncertainty. The best AR (GARCH) specification has been chosen upon the Likelihood Ratio (LR) and three alternative information criteria (Schwarz, Hannan-Quinn and Akaike criterion). We choose AR(12) and AR(2) for conditional variance of inflation and output growth respectively.

We consider and discuss the implications of Table (3.4).

First, all coefficients (α_π, α_y, β_π and β_y) of the conditional variances are statistically significant.

Table 3.5 CCC-GARCH (1, 1)-ML model for the US with Dummy variables in mean equation:

In-mean and level effects:	
$\delta_{\pi\pi}\ (t-2)$	0.56 (0.29)*
$\delta_{\pi y}\ (t)$	−0.06 (0.07)
$\delta_{y\pi}\ (t-2)$	−1.16 (0.51)**
$\delta_{yy}\ (t-2)$	0.35 (0.15)**
$\gamma_{\pi\pi}\ (t-1)$	0.20 (0.09)**
$\gamma_{y\pi}\ (t-1)$	1.45 (0.83)*
GARCH(1,1) coefficients:	
α_π	0.19 (0.09)**
β_π	0.68 (0.07)***
α_y	0.35 (0.11)***
β_y	0.24 (0.12)*

Notes: *Notes: This table reports parameter estimates for the following model:*

Mean Equations: $\Phi_{\pi\pi}(L)\pi_t = c_\pi + \Phi_{\pi y}(L)y_t + \delta_{\pi\pi}\sqrt{h_{\pi,t-l_{\pi\pi}}} + \delta_{\pi y}\sqrt{h_{y,t-l_{\pi y}}} + \varepsilon_{\pi,t}$

$$\Phi_{yy}(L)y_t = c_y + \Phi_{y\pi}(L)\pi_t + \delta_{yy}\sqrt{h_{y,t-l_{yy}}} + \delta_{y\pi}\sqrt{h_{\pi,t-l_{y\pi}}} + \varepsilon_{y,t}$$

Variance Equations: $h_{\pi t} = \omega_\pi + \beta_\pi h_{\pi,t-1} + \alpha_\pi \varepsilon^2_{\pi,t-1} + \gamma_\pi \pi_{t-i}$

$$h_{yt} = \omega_y + \beta_y h_{y,t-1} + \alpha_y \varepsilon^2_{y,t-1} + \gamma_y \pi_{t-i}$$

*The numbers in parentheses are robust standard errors. ***, ** and * are significance levels of 1%, 5% and 10%, respectively.*

Second, to check the effect of inflation rate on inflation uncertainty, we insert the inflation variable in the conditional variance equation of inflation. Since, the coefficient of inflation rate

($\gamma_{\pi\pi} = 0.20$) is positive and significant, there is overwhelming evidence for the first leg of the Friedman (1977) hypothesis (as predicted by Ball 1992 as well), where higher inflation rate will lead to higher nominal uncertainty (after one month).

Third, there is a weak evidence for Cukierman and Meltzer (1986) hypothesis that a higher inflation uncertainty will increase inflation rate in two months time as indicated by the positive and significant coefficient ($\delta_{\pi\pi} = 0.56$). However, the insignificant $\delta_{\pi y}$ coefficient shows that there isn't any effect of output uncertainty on inflation.

Fourth, the positive and significant effect of output uncertainty on growth rate ($\delta_{yy} = 0.35$) indicates evidence in support of Black (1987) hypothesis; $h_{yt} \overset{+}{\rightarrow} y_t$ as predicted by Mirman (1971), Blackburn (1999) as well.

Finally, the significant and negative coefficient ($\delta_{y\pi} = -1.16$) is an evidence that inflation uncertainty affects output growth rate in a negative manner $h_{\pi t} \overset{-}{\rightarrow} y_t$ (the known as second leg of Friedman (1977) hypothesis).

In details, a 100% increase in the inflation uncertainty and output uncertainty leads to a corresponding increase in the inflation rate by 56% and 35% respectively. Moreover, a 100% decline in the inflation uncertainty leads to an increase in the output growth rate by 116%.

Lastly, a 100% increase in inflation rate causes a 20% rise in the inflation uncertainty.

In comparison with Table 3.4, we can confirm that the effect of economic and political comes into existence in the US. The effect of inflation uncertainty on inflation, the effect of output uncertainty on growth rate and the effect of inflation on inflation uncertainty increase by the effect of economic and political events. In addition, absolute $\delta_{\pi y}$ coefficient shows an increasing in the effect of inflation uncertainty on output growth rate by the effect of economic and political events.

More precisely, the Great Recession in 1980, 9/11 accident and the financial crisis in 2007 have leaded to the corresponding changes in the effect of inflation uncertainty on inflation rate, the effect of output uncertainty on growth rate, the effect of inflation rate on inflation uncertainty and the negative effect of inflation variability on output growth rate with 5%, 6%, 2% and 1.7% respectively.

3.6.2. Extension to the other G7 countries without considering dummies:

Next, we extend our study and apply the above empirical approach to the rest of the G7 countries, namely the UK, Germany, Japan, Italy, France and Canada. As previously, we have two series of inflation rate (as determined by CPI) and output growth rate (as determined by IPI) for each country. The ADF and PP tests of the unit root null hypothesis for each country are reported in Table 3.2. The null hypothesis of unit root is rejected by ADF and PP tests for all six countries.

The estimation of the various formulations is obtained by maximum likelihood estimation (MLE). The best fitting VAR [GARCH] models are chosen under the Likelihood Ratio (LR) and three alternatives criteria, for estimating the conditional variance of inflation, we choose AR(13) for the UK, AR(12) for Germany, AR(13) for Japan, AR(13) for Italy, AR(12) France and AR(13) for Canada.

Also, for estimating the conditional variance of output growth, we choose AR(4) for the UK, AR(2) for Germany, AR(2) for Japan, AR(4) for Italy, AR(4) for France and AR(5) for Canada. As we have done in the US case, we estimate AR-CCC-GARCH (1, 1) of inflation and output growth in all six countries. This process is for investigating the effect of both nominal uncertainty and real uncertainty on inflation and output growth.

The estimation of AR-CCC GARCH (1,1) without including any dummy variable:

3.6.2.1. The case of the UK:

Table 3.6 doesn't show any evidence of Holland (1995) because the $\delta_{\pi\pi}$ coefficient is in significant. Also, the insignificant $\delta_{\pi y}$ coefficient doesn't confirm the Cukierman and Meltzer (2003) and Devereux (1989) hypothesis.

However, the effect of inflation on inflation uncertainty $\gamma_{\pi\pi} = 0.45$ is positive and significant, this means evidence for the first leg of the Friedman (1977) hypothesis (as predicted by Ball 1992 as well).

Table 3.6 CCC-GARCH (1, 1)-ML model for the UK:

In-mean and level effects:	
$\delta_{\pi\pi}(t-2)$	-0.02 (0.13)
$\delta_{\pi y}(t-3)$	0.02 (0.05)
$\delta_{y\pi}\ (t-2)$	-0.87 (0.45)*
$\delta_{yy}\ (t-2)$	0.20 (0.11)*
$\gamma_{\pi\pi}(t-1)$	0.45 (0.25)*
$\gamma_{y\pi}(t-1)$	5.20 (1.18)***
GARCH(1,1) coefficients:	
α_π	0.12 (0.00)***
β_π	0.86 (0.06)***
α_y	0.24 (0.08)***
β_y	0.36 (0.10)***

Notes: *Notes: This table reports parameter estimates for the following model:*

Mean Equations: $\Phi_{\pi\pi}(L)\pi_t = c_\pi + \Phi_{\pi y}(L)y_t + \delta_{\pi\pi}\sqrt{h_{\pi,t-l_{\pi\pi}}} + \delta_{\pi y}\sqrt{h_{y,t-l_{\pi y}}} + \varepsilon_{\pi,t}$

$$\Phi_{yy}(L)y_t = c_y + \Phi_{y\pi}(L)\pi_t + \delta_{yy}\sqrt{h_{y,t-l_{yy}}} + \delta_{y\pi}\sqrt{h_{\pi,t-l_{y\pi}}} + \varepsilon_{y,t}$$

Variance Equations: $h_{\pi t} = \omega_\pi + \beta_\pi h_{\pi,t-1} + \alpha_\pi \varepsilon^2_{\pi,t-1} + \gamma_\pi \pi_{t-i}$

$$h_{yt} = \omega_y + \beta_y h_{y,t-1} + \alpha_y \varepsilon^2_{y,t-1} + \gamma_y \pi_{t-i}$$

*The numbers in parentheses are robust standard errors. ***, ** and * are significance levels of 1%, 5% and 10%, respectively.*

Also, the negative and significant $\delta_{y\pi} = -0.87$ coefficient is evidence that inflation uncertainty affects output growth rate in a negative manner $h_{\pi t} \overset{-}{\rightarrow} y_t$ as predicted in the known second leg of Friedman (1977) hypothesis.

In addition, the positive and significant effect of output uncertainty on growth rate indicates evidence of Black (1987) hypothesis; $h_{yt} \overset{+}{\rightarrow} y_t$ as predicted by Mirman (1971), Blackburn (1999).

Finally, all coefficients (α_π, α_y, β_π and β_y) of the conditional variances are statistically significant.

Briefly, Inflation causes uncertainty about future prices, interest rates, and exchange rates, and this in turn increases. The risks among potential trade partners and discouraging trade. The uncertainty with associated with inflation increases the risk that associated with the investment and production activity of firms and markets.

3.6.2.2. <u>**The case of Germany:**</u>

Table 3.7 indicates evidence of Cukierman and Meltzer (1986). So, the inflation uncertainty affects positively on inflation, the $\delta_{\pi\pi} = 0.79$ coefficient is positive and significant. However, the insignificant $\delta_{\pi y}$ coefficient doesn't confirm the Cukierman and Meltzer (2003) and Devereux (1989) hypothesis. Therefore, there is no evidence for the effect of output uncertainty on inflation.

Furthermore, the effect of inflation on inflation uncertainty is negative and significant ($\gamma_{\pi\pi} = 0.36 - 0.38 = -0.02$), this means evidence for Pourgerami and Maskus (1987), Ungar and Zilberfarb (1993) arguments.

Table 3.7 CCC-GARCH (1, 1)-ML model for Germany:

In-mean and level effects:	
$\delta_{\pi\pi}(t-2)$	0.79 (0.18)***
$\delta_{\pi y}(t)$	−0.04 (0.02)
$\delta_{y\pi}(t)$	− 1.92 (0.45)***
$\delta_{yy}(t)$	0.58 (0.12)***
$\gamma_{\pi\pi}(t-2, t-3)$	0.36−0.38 (0.20)* (0.17)**
$\gamma_{y\pi}(t-1)$	−1.60 (0.48)***
GARCH(1,1) coefficients:	
α_{π}	0.15 (0.05)***
β_{π}	0.46 (0.06)***
α_{y}	0.24 (0.06)***
β_{y}	0.35 (0.08)***

Notes: *Notes: This table reports parameter estimates for the following model:*

Mean Equations: $\Phi_{\pi\pi}(L)\pi_t = c_\pi + \Phi_{\pi y}(L)y_t + \delta_{\pi\pi}\sqrt{h_{\pi,t-l_{\pi\pi}}} + \delta_{\pi y}\sqrt{h_{y,t-l_{\pi y}}} + \varepsilon_{\pi,t}$

$$\Phi_{yy}(L)y_t = c_y + \Phi_{y\pi}(L)\pi_t + \delta_{yy}\sqrt{h_{y,t-l_{yy}}} + \delta_{y\pi}\sqrt{h_{\pi,t-l_{y\pi}}} + \varepsilon_{y,t}$$

Variance Equations: $h_{\pi t} = \omega_\pi + \beta_\pi h_{\pi,t-1} + \alpha_\pi \varepsilon^2_{\pi,t-1} + \gamma_\pi \pi_{t-i}$

$$h_{yt} = \omega_y + \beta_y h_{y,t-1} + \alpha_y \varepsilon^2_{y,t-1} + \gamma_y \pi_{t-i}$$

*The numbers in parentheses are robust standard errors. ***, ** and * are significance levels of 1%, 5% and 10%, respectively.*

Also, the negative and significant $\delta_{y\pi} = -1.92$ coefficient is evidence that inflation uncertainty affects output growth rate in a negative manner $h_{\pi t} \overset{-}{\rightarrow} y_t$ as predicted in the known second leg of Friedman (1977) hypothesis.

In addition, the positive and significant effect of output uncertainty on growth rate indicates evidence of Black (1987) hypothesis; $h_{yt} \overset{+}{\rightarrow} y_t$ as predicted by Mirman (1971), Blackburn (1999).

Finally, all coefficients (α_π, α_y, β_π and β_y) of the conditional variance are statistically significant.

More precisely, a 100% increase in the inflation uncertainty and output uncertainty leads to corresponding increase in the inflation rate by 79% and 58% respectively. Moreover, a 100% decline in the inflation uncertainty leads to an increase in the output growth rate by 192%.

Lastly, a 100% increase in inflation rate causes 2% decline in the inflation uncertainty.

3.6.2.3. The case of Japan:

Table 3.8 shows the positive and significant effect of inflation uncertainty on inflation ($\delta_{\pi\pi} = 0.49$). This is a strong evidence for Cukierman and Meltzer (1986). However, the insignificant $\delta_{\pi y}$ coefficient doesn't confirm the Cukierman and Meltzer (2003) and Devereux (1989) hypothesis. So, there is no evidence for the effect of output uncertainty on inflation.

Moreover, the positive and significant $\delta_{y\pi} = 0.95$ coefficient is evidence that inflation uncertainty affects output growth rate in a positive manner $h_{\pi t} \overset{+}{\rightarrow} y_t$ as predicted Dotsey and Sarte (2000) argument.

The insignificant positive δ_{yy} coefficient doesn't support any evidence neither of Black (1987) hypothesis nor Mirman (1971) and Blackburn (1999) arguments.

However, there is a strong evidence for the first leg of Friedman (1977) hypothesis and Ball (1992) theory. There is effect of inflation on inflation uncertainty is positive and significant ($\gamma_{\pi\pi} = 0.08$).

Finally, all coefficients (α_{π}, α_{y}, β_{π} and β_{y}) of the conditional variance are statistically significant.

Table 3.8 CCC-GARCH (1, 1)-ML model for Japan:

In-mean and level effects:	
$\delta_{\pi\pi}(t)$	0.49 (0.15)***
$\delta_{\pi y}(t)$	−0.01 (0.04)
$\delta_{y\pi}(t)$	0.95 (0.56)*
$\delta_{yy}(t)$	0.07 (0.24)
$\gamma_{\pi\pi}(t-1)$	0.08 (0.02)***
$\gamma_{y\pi}(t-1)$	0.25 (0.13)*
GARCH(1,1) coefficients:	
α_{π}	0.11 (0.03)***
β_{π}	0.86 (0.12)***
α_{y}	0.13 (0.02)***
β_{y}	0.21 (0.07)***

Notes: *Notes: This table reports parameter estimates for the following model:*

Mean Equations : $\Phi_{\pi\pi}(L)\pi_t = c_\pi + \Phi_{\pi y}(L)y_t + \delta_{\pi\pi}\sqrt{h_{\pi,t-l_{\pi\pi}}} + \delta_{\pi y}\sqrt{h_{y,t-l_{\pi y}}} + \varepsilon_{\pi,t}$

$$\Phi_{yy}(L)y_t = c_y + \Phi_{y\pi}(L)\pi_t + \delta_{yy}\sqrt{h_{y,t-l_{yy}}} + \delta_{y\pi}\sqrt{h_{\pi,t-l_{y\pi}}} + \varepsilon_{y,t}$$

Variance Equations: $h_{\pi t} = \omega_\pi + \beta_\pi h_{\pi,t-1} + \alpha_\pi \varepsilon^2_{\pi,t-1} + \gamma_\pi \pi_{t-i}$

$$h_{yt} = \omega_y + \beta_y h_{y,t-1} + \alpha_y \varepsilon^2_{y,t-1} + \gamma_y \pi_{t-i}$$

*The numbers in parentheses are robust standard errors. ***, ** and * are significance levels of 1%, 5% and 10%, respectively.*

In details, a 100% increase in the inflation uncertainty leads to corresponding increase in the inflation rate by 49%. In addition, a 100% increase in the inflation uncertainty leads to an increase in the output growth rate by 95%.

Lastly, a 100% increase in inflation rate causes 8% rise in the inflation uncertainty and 25% increase in the output uncertainty.

3.6.2.4. **The case of Italy:**

Table 3.9 shows a positive insignificant $\delta_{\pi\pi}$. This implies that is no effect of inflation uncertainty on inflation; so, there isn't any evidence for Cukierman and Meltzer (1986). However, the negative and significant $\delta_{\pi y}$ coefficient confirms Taylor effect and Cukierman and Meltzer (1986) theories. So, there is evidence for the effect of output uncertainty on inflation.

In addition, the negative and significant $\delta_{y\pi} = -1.34$ coefficient is evidence that inflation uncertainty affects output growth rate in a negative manner $h_{\pi t} \overset{-}{\rightarrow} y_t$ (the known as second leg of Friedman (1977) hypothesis). But the insignificant positive δ_{yy} coefficient doesn't support any evidence neither of Black (1987) hypothesis nor Mirman (1971) and Blackburn (1999) arguments.

However, there is evidence for the first leg of the Friedman (1977) hypothesis and Ball (1992) theory according to the positive and significant ($\gamma_{\pi\pi} = 0.19$).

Finally, all coefficients (α_{π}, α_{y}, β_{π} and β_{y}) of the conditional variances are statistically significant.

Table 3.9 CCC-GARCH (1, 1)-ML model for Italy:

In-mean and level effects:	
$\delta_{\pi\pi}(t-2)$	0.12 (0.24)
$\delta_{\pi y,t}(t-2)$	-0.02 (0.01)*
$\delta_{y\pi}(t-4)$	-1.34 (0.71)*
$\delta_{yy}(t-4)$	0.12 (0.14)
$\gamma_{\pi\pi}(t-1)$	0.19 (0.07)**
$\gamma_{y\pi}(t-1)$	--
GARCH(1,1) coefficients:	
α_{π}	0.11 (0.03)***
β_{π}	0.85 (0.07)***
α_{y}	0.15 (0.06)***
β_{y}	0.83 (0.07)***

Notes: *Notes: This table reports parameter estimates for the following model:*

Mean Equations: $\Phi_{\pi\pi}(L)\pi_t = c_\pi + \Phi_{\pi y}(L)y_t + \delta_{\pi\pi}\sqrt{h_{\pi,t-l_{\pi\pi}}} + \delta_{\pi y}\sqrt{h_{y,t-l_{\pi y}}} + \varepsilon_{\pi,t}$

$$\Phi_{yy}(L)y_t = c_y + \Phi_{y\pi}(L)\pi_t + \delta_{yy}\sqrt{h_{y,t-l_{yy}}} + \delta_{y\pi}\sqrt{h_{\pi,t-l_{y\pi}}} + \varepsilon_{y,t}$$

Variance Equations: $h_{\pi t} = \omega_\pi + \beta_\pi h_{\pi,t-1} + \alpha_\pi \varepsilon^2_{\pi,t-1} + \gamma_\pi \pi_{t-i}$

$$h_{yt} = \omega_y + \beta_y h_{y,t-1} + \alpha_y \varepsilon^2_{y,t-1} + \gamma_y \pi_{t-i}$$

*The numbers in parentheses are robust standard errors. ***, ** and * are significance levels of 1%, 5% and 10%, respectively.*

More precisely, a 100% increase in inflation rate causes 19% rise in the inflation uncertainty. Also, a 100% decline in the inflation uncertainty leads to an increase in the output growth rate by 134%.

3.6.2.5. The case of France:

Table 3.10 indicates the positive and significant effect of inflation uncertainty on inflation ($\delta_{\pi\pi} = 5.81$). This is a strong evidence for Cukierman and Meltzer (1986). Also, the significant and positive $\delta_{\pi y}$ coefficient confirms the Cukierman and Meltzer (2003) and Devereux (1989) hypothesis. So, there is evidence for the effect of output uncertainty on inflation.

Table 3.10 CCC-GARCH (1, 1)-ML model for France:

In-mean and level effects:	
$\delta_{\pi\pi}(t-4)$	5.81 (2.67)**
$\delta_{\pi y}(t-1)$	– 0.02 (0.01)**
$\delta_{y\pi}(t-3)$	– 6.69 (1.58)***
$\delta_{yy}(t-2)$	– 0.22 (0.09)**
$\gamma_{\pi\pi}(t-2)$	0.12 (0.05)**
$\gamma_{y\pi}(t-1)$	--
GARCH(1,1) coefficients:	
α_{π}	0.19 (0.06)***
β_{π}	0.69 (0.07)***
α_{y}	0.35 (0.10)***
β_{y}	0.25 (0.11)**

Notes: *Notes: This table reports parameter estimates for the following model:*

Mean Equations: $\Phi_{\pi\pi}(L)\pi_t = c_\pi + \Phi_{\pi y}(L)y_t + \delta_{\pi\pi}\sqrt{h_{\pi,t-l_{\pi\pi}}} + \delta_{\pi y}\sqrt{h_{y,t-l_{\pi y}}} + \varepsilon_{\pi,t}$

$$\Phi_{yy}(L)y_t = c_y + \Phi_{y\pi}(L)\pi_t + \delta_{yy}\sqrt{h_{y,t-l_{yy}}} + \delta_{y\pi}\sqrt{h_{\pi,t-l_{y\pi}}} + \varepsilon_{y,t}$$

Variance Equations: $h_{\pi t} = \omega_\pi + \beta_\pi h_{\pi,t-1} + \alpha_\pi \varepsilon^2_{\pi,t-1} + \gamma_\pi \pi_{t-i}$

$$h_{yt} = \omega_y + \beta_y h_{y,t-1} + \alpha_y \varepsilon^2_{y,t-1} + \gamma_y \pi_{t-i}$$

*The numbers in parentheses are robust standard errors. ***, ** and * are significance levels of 1%, 5% and 10%, respectively.*

Moreover, the negative and significant $\delta_{y\pi} = -6.69$ coefficient is evidence that inflation uncertainty affects output growth rate in a negative manner. So, there is evidence for the second leg of the Friedman (1977) hypothesis.

The significant and negative $\delta_{yy} = -0.22$ coefficient supports evidence for Pindyck (1991) arguments.

In addition, there is evidence for first leg of Friedman (1977) hypothesis and Ball (1992) theory. Where the effect of inflation on inflation uncertainty is positive and significant ($\gamma_{\pi\pi} = 0.12$).

Finally, all coefficients (α_{π}, α_{y}, β_{π} and β_{y}) of the conditional variance are statistically significant.

In details, a 100% increase in the inflation uncertainty and output uncertainty leads to a massive corresponding increase in the inflation rate by 581% and 58% respectively. Moreover, a 100% decline in the inflation uncertainty leads to huge increase the output growth rate by 669%.

Lastly, a 100% increase in inflation rate causes a 12% decline in the inflation uncertainty.

3.6.2.6. <u>The case of Canada:</u>

Table 3.11 doesn't support any evidence of Cukierman and Meltzer (1986) because of the insignificant $\delta_{\pi\pi}$ coefficient. So, the effect inflation uncertainty on inflation doesn't exist. However, the significant and nigative $\delta_{\pi y} = -0.12$ coefficient confirms the Taylor effect and Cukierman and Meltzer (1986) hypothesis. Therefore, there is evidence for the effect of output uncertainty on inflation.

Furthermore, the effect of inflation on inflation uncertainty is positive and significant ($\gamma_{\pi\pi} = -0.76 + 0.90 = +0.14$), this means evidence for the first leg of the Friedman (1977) hypothesis (as predicted by Ball 1992 as well).

Also, the negative and significant $\delta_{y\pi} = -0.20$ coefficient is evidence that inflation uncertainty affects output growth rate in a negative manner as predicted in the known second leg of Friedman (1977) hypothesis.

Table 3.11 CCC-GARCH (1, 1)-ML model for Canada:

In-mean and level effects:	
$\delta_{\pi\pi}(t-2)$	0.10 (0.24)
$\delta_{\pi y}(t-1)$	− 0.12 (0.04)**
$\delta_{y\pi}(t)$	− 0.20 (0.01)**
$\delta_{yy}(t)$	1.61 (1.14)
$\gamma_{\pi\pi}(t-1/t-2)$	−0.76+0.90 (0.44)* (0.40)**
$\gamma_{y\pi}(t-1)$	--
GARCH(1,1) coefficients:	
α_{π}	0.16 (0.06)***
β_{π}	0.74 (0.12)***
α_{y}	0.32 (0.10)***
β_{y}	0.29 (0.11)***

Notes: *Notes: This table reports parameter estimates for the following model:*

Mean Equations: $\Phi_{\pi\pi}(L)\pi_t = c_\pi + \Phi_{\pi y}(L)y_t + \delta_{\pi\pi}\sqrt{h_{\pi,t-l_{\pi\pi}}} + \delta_{\pi y}\sqrt{h_{y,t-l_{\pi y}}} + \varepsilon_{\pi,t}$

$$\Phi_{yy}(L)y_t = c_y + \Phi_{y\pi}(L)\pi_t + \delta_{yy}\sqrt{h_{y,t-l_{yy}}} + \delta_{y\pi}\sqrt{h_{\pi,t-l_{y\pi}}} + \varepsilon_{y,t}$$

Variance Equations: $h_{\pi t} = \omega_\pi + \beta_\pi h_{\pi,t-1} + \alpha_\pi \varepsilon^2_{\pi,t-1} + \gamma_\pi \pi_{t-i}$

$$h_{yt} = \omega_y + \beta_y h_{y,t-1} + \alpha_y \varepsilon^2_{y,t-1} + \gamma_y \pi_{t-i}$$

*The numbers in parentheses are robust standard errors. ***, ** and * are significance levels of 1%, 5% and 10%, respectively.*

In addition, Table 3.11 doesn't support any evidence of Black (1987) hypothesis, Mirman (1971) and Blackburn (1999) argument as well; according to the insignificant δ_{yy}.

Finally, all coefficients (α_π, α_y, β_π and β_y) of the conditional variance are statistically significant.

More precisely, a 100% decline in the inflation uncertainty leads to an increase in the output growth rate by 20%. Moreover, a 100% increase in inflation rate causes an increase with 14% in the inflation uncertainty.

3.6.3. Extension to the other G7 countries by considering dummies:

We estimate the CCC-GARCH (1, 1)-ML models including dummy variables in the mean equations. Dummies are chosen in the inflation and growth data according to some economic and political events in the UK, Germany, Japan, Italy, France and Canada. The mean equations in growth and inflation are adjusted to include dummy variables on the intercept as follows;

For the UK: The first dummy variable is selected due to the inflation targeting (Kontonikas 2004); this dummy variable is D1=0 before October 1992 and D1=1 onwards. In the second one, the dummy variable is D2=1 for the time 06/1970 to 01/1992 due to the all oil crises from the 1970s energy crisis, 1973 oil crisis , 1979 oil crisis and The Persian Gulf War of the Early 1990s (Ostrander and Lowry 2012. Rodríguez and Sánchez 2005). The last dummy variable is D3=1 for the time 08/2007 to 01/2011 and D3=0 otherwise, due to the financial crisis (Cassola and Morana 2012, Gray 2014).

For Germany: The first dummy variable is selected due to the unification of Germany. So, this dummy variable is D1=0 before October 1990 and D1=1 onwards (Harris 1991). In addition, the dummy variable is D2=1 for the time 08/2007 to 01/2011 and D2=0 otherwise, due to the financial crisis (Cassola and Morana 2012, Gray 2014, Cherniaev 1998 and Chauncy 1991).

For Japan: The first dummy variable is selected by considering the post-Plaza Accord in 1985. So, this dummy variable is D1=0 before October 1985 and D1=1 onwards (Kano and Morita 2015). In addition, the dummy variable is D2=1 for the time 08/2007 to 01/2011 and D2=0 otherwise, due to the financial crisis (Cassola and Morana 2012, Gray 2014).

For Italy, France and Canada: The first dummy variable is D1=1 for the time 06/1970 to 01/1992 due to the all oil crises from the 1970s energy crisis, 1973 oil crisis , 1979 oil crisis and The Persian Gulf War of the Early 1990s (Ostrander and Lowry 2012. Rodríguez and Sánchez 2005). The last dummy variable is D2=1 for the time 08/2007 to 01/2011 and D3=0 otherwise, due to the financial crisis (Cassola and Morana 2012, Gray 2014).

The estimation of the CCC-GARCH (1, 1)-ML models including dummy variables in the mean equations as follows,

3.6.3.1. <u>The case of the UK:</u>

Table 3.12 shows the estimated parameters of equation 3.3 for inflation uncertainty and the parameters of equation 3.4 for output uncertainty.

We consider and discuss the implications of Table (3.12).

First, all coefficients (α_{π}, α_{y}, β_{π} and β_{y}) of the conditional variances are statistically significant.

Second, to check the effect of inflation rate on inflation uncertainty, we insert the inflation variable in the conditional variance equation of inflation. Since, the coefficient of inflation rate ($\gamma_{\pi\,\pi} = 0.50$) is positive and significant, there is evidence for the first leg of the Friedman (1977) and Ball (1992) hypothesis, where higher inflation rate will lead to higher nominal uncertainty (after one month).

Third, there is no evidence for Holand (1995) or Cukierman and Gerlach (2003) hypothesis because of the insignificant coefficients $\delta_{\pi\pi}$ and $\delta_{\pi y}$.

In addition, the insignificant δ_{yy} coefficient means that there isn't any effect of output uncertainty on output growth.

Finally, the significant and negative coefficient ($\delta_{y\pi} = -0.82$) is an evidence that inflation uncertainty affects output growth rate in a negative manner (the known as second leg of Friedman (1977) hypothesis).

More precisely, a 100% increase in the inflation rate leads to a corresponding increase in inflation uncertainty and output uncertainty by 50% and 503% respectively. Moreover, a 100% decline in the inflation uncertainty leads to an increase in the output growth rate by 82%.

Table 3.12 CCC-GARCH (1, 1)-ML model for the UK with Dummy variables in mean equation:

In-mean and level effects:	
$\delta_{\pi\pi}(t-1)$	-0.11 (0.41)
$\delta_{\pi y}(t-3)$	0.02 (0.04)
$\delta_{y\pi}(t-3)$	-0.82 (0.45)*
$\delta_{yy}(t-3)$	0.14 (0.11)
$\gamma_{\pi\pi}(t-1)$	0.50 (0.26)*
$\gamma_{y\pi}(t-1)$	5.03 (1.07)***
GARCH(1,1) coefficients:	
α_{π}	0.15 (0.01)***
β_{π}	0.84 (0.07)***
α_{y}	0.23 (0.09)***
β_{y}	0.35 (0.10)***

Notes: *Notes: This table reports parameter estimates for the following model:*

Mean Equations: $\Phi_{\pi\pi}(L)\pi_t = c_\pi + \Phi_{\pi y}(L)y_t + \delta_{\pi\pi}\sqrt{h_{\pi,t-l_{\pi\pi}}} + \delta_{\pi y}\sqrt{h_{y,t-l_{\pi y}}} + \varepsilon_{\pi,t}$

$$\Phi_{yy}(L)y_t = c_y + \Phi_{y\pi}(L)\pi_t + \delta_{yy}\sqrt{h_{y,t-l_{yy}}} + \delta_{y\pi}\sqrt{h_{\pi,t-l_{y\pi}}} + \varepsilon_{y,t}$$

Variance Equations: $h_{\pi t} = \omega_\pi + \beta_\pi h_{\pi,t-1} + \alpha_\pi \varepsilon^2_{\pi,t-1} + \gamma_\pi \pi_{t-i}$

$$h_{yt} = \omega_y + \beta_y h_{y,t-1} + \alpha_y \varepsilon^2_{y,t-1} + \gamma_y \pi_{t-i}$$

*The numbers in parentheses are robust standard errors. ***, ** and * are significance levels of 1%, 5% and 10%, respectively.*

In comparison with table 3.6, we can confirm that the effect of economic and political events comes into existence in the UK. Considering the absolute $\delta_{y\pi}$; the effect of inflation uncertainty on output growth decreased about 5%. However, the effect of inflation on inflation uncertainty increased about 5%. In other words, economic and political events achieve less effect of inflation uncertainty on growth and more effect of inflation on its uncertainty.

Moreover, the 1970s energy crisis, the inflation targeting policy in 1992 and the financial crisis in 2007 have leaded to the corresponding changes in the effect of the inflation uncertainty on output growth and the effect of inflation rate on its uncertainty with 5% decreasing and 5% increasing respectively.

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3.6.3.2. **The case of Germany:**

By considering the implications of Table 3.13, we notice the following:

First, all coefficients (α_π, α_y, β_π and β_y) of the conditional variances are statistically significant.

Second, to check the effect of inflation rate on inflation uncertainty, we insert the inflation variable in the conditional variance equation of inflation. Since, the coefficient of inflation rate ($\gamma_{\pi\pi} = 0.34 - 0.38 = -0.04$) is negative and significant, there is overwhelming evidence for the Pourgerami and Maskus (1987), Ungar and Zilberfarb (1993) where higher inflation rate will lead to lower nominal uncertainty.

Third, there is a strong evidence for Cukierman and Meltzer (1986) hypothesis that a higher Inflation uncertainty will lead to greater inflation rate in one month time as indicated by the positive and significant coefficient ($\delta_{\pi\pi} = 0.83$). However, the negative and significant $\delta_{\pi y} = -0.05$ coefficient shows that there is a strong effect of output uncertainty on inflation.

Fourth, the positive and significant effect of output uncertainty on growth rate ($\delta_{yy} = 0.51$) indicates a strong evidence in support of Black (1987) hypothesis and as prediction of Mirman (1971), Blackburn (1999) as well.

Finally, the significant and negative coefficient ($\delta_{y\pi} = -1.83$) is an evidence that inflation uncertainty affects output growth rate in a negative manner $h_{\pi t} \overset{-}{\rightarrow} y_t$ as considered by second leg of Friedman (1977) hypothesis.

More precisely, a 100% increase in the inflation uncertainty and output uncertainty leads to corresponding increase in the inflation rate by 83% and 51% respectively. Moreover, a 100% decline in the inflation uncertainty leads to an increase in the output growth rate by 183%.

Lastly, a 100% increase in inflation rate causes a 4% decline in the inflation uncertainty.

In comparison with table 3.7, we notice that the effect of economic and political events comes into existence in the Germany. Considering the absolute $\delta_{y\pi}$; the effect of inflation uncertainty on output growth decreased from 1.92 to 1.83. In addition, the effect of inflation uncertainty on inflation and inflation on its uncertainty increased. In other words, economic and political events achieve less effect of inflation uncertainty on growth and more effect of inflation uncertainty on inflation and inflation on its uncertainty.

Table 3.13 CCC-GARCH (1, 1)-ML model for Germany with Dummy variables in mean equation:

In-mean and level effects:	
$\delta_{\pi\pi}(t-1)$	0.83 (0.18)***
$\delta_{\pi y}(t)$	− 0.05 (0.02)***
$\delta_{y\pi}(t)$	− 1.83 (0.52)***
$\delta_{yy}(t)$	0.51 (0.13)***
$\gamma_{\pi\pi}(t-2, t-3)$	0.34 (0.20)* −0.38 (0.17)**
$\gamma_{y\pi}(t-1)$	−1.53 (0.54)***
GARCH(1,1) coefficients:	
α_{π}	0.15 (0.05)***
β_{π}	0.48 (0.06)***
α_{y}	0.26 (0.07)***
β_{y}	0.31 (0.10)***

Notes: *Notes: This table reports parameter estimates for the following model:*

Mean Equations: $\Phi_{\pi\pi}(L)\pi_t = c_\pi + \Phi_{\pi y}(L)y_t + \delta_{\pi\pi}\sqrt{h_{\pi,t-l_{\pi\pi}}} + \delta_{\pi y}\sqrt{h_{y,t-l_{\pi y}}} + \varepsilon_{\pi,t}$

$$\Phi_{yy}(L)y_t = c_y + \Phi_{y\pi}(L)\pi_t + \delta_{yy}\sqrt{h_{y,t-l_{yy}}} + \delta_{y\pi}\sqrt{h_{\pi,t-l_{y\pi}}} + \varepsilon_{y,t}$$

Variance Equations: $h_{\pi t} = \omega_\pi + \beta_\pi h_{\pi,t-1} + \alpha_\pi \varepsilon^2_{\pi,t-1} + \gamma_\pi \pi_{t-i}$

$$h_{yt} = \omega_y + \beta_y h_{y,t-1} + \alpha_y \varepsilon^2_{y,t-1} + \gamma_y \pi_{t-i}$$

*The numbers in parentheses are robust standard errors. ***, ** and * are significance levels of 1%, 5% and 10%, respectively.*

In other words, the unification of Germany in 1990 and the 2007s financial crisis have leaded to the corresponding change in the induced effect of the inflation uncertainty on output rate with 5%. However, the corresponding changes in the induced effect of the inflation on inflation uncertainty and vice versa are 2% and 5% increasing respectively.

3.6.3.3. **The case of Japan:**

Table 3.14 shows the positive and significant effect of inflation uncertainty on inflation ($\delta_{\pi\pi} = 0.40$). This is a strong evidence for Cukierman and Meltzer (1986). However, the insignificant $\delta_{\pi y}$ coefficient doesn't confirm the Cukierman and Meltzer (2003) and Devereux (1989) hypothesis. So, there is no evidence for the effect of output uncertainty on inflation.

The insignificant positive δ_{yy} coefficient doesn't support any evidence neither of Black (1987) hypothesis nor Mirman (1971) and Blackburn (1999) arguments.

On the other hand, the negative and significant $\delta_{y\pi} = -0.63$ coefficient is evidence that inflation uncertainty affects output growth rate in a negative manner (the known as second leg of Friedman (1977) hypothesis).

Table 3.14 CCC-GARCH (1, 1)-ML model for Japan with Dummy variables in mean equation:

In-mean and level effects:	
$\delta_{\pi\pi}(t)$	0.40 (0.17)***
$\delta_{\pi y}(t)$	−0.02 (0.04)
$\delta_{y\pi}(t-3)$	−0.63 (0.33)*
$\delta_{yy}(t-3)$	0.05 (0.16)
$\gamma_{\pi\pi}(t-1)$	0.09 (0.03)***
$\gamma_{y\pi}(t-2)$	0.18 (0.04)***
GARCH(1,1) coefficients:	
α_π	0.13 (0.03)***
β_π	0.84 (0.08)***
α_y	0.11 (0.04)***
β_y	0.26 (0.07)***

Notes: *Notes: This table reports parameter estimates for the following model:*

Mean Equations: $\Phi_{\pi\pi}(L)\pi_t = c_\pi + \Phi_{\pi y}(L)y_t + \delta_{\pi\pi}\sqrt{h_{\pi,t-l_{\pi\pi}}} + \delta_{\pi y}\sqrt{h_{y,t-l_{\pi y}}} + \varepsilon_{\pi,t}$

$$\Phi_{yy}(L)y_t = c_y + \Phi_{y\pi}(L)\pi_t + \delta_{yy}\sqrt{h_{y,t-l_{yy}}} + \delta_{y\pi}\sqrt{h_{\pi,t-l_{y\pi}}} + \varepsilon_{y,t}$$

Variance Equations: $h_{\pi t} = \omega_\pi + \beta_\pi h_{\pi,t-1} + \alpha_\pi \varepsilon^2_{\pi,t-1} + \gamma_\pi \pi_{t-i}$

$$h_{yt} = \omega_y + \beta_y h_{y,t-1} + \alpha_y \varepsilon^2_{y,t-1} + \gamma_y \pi_{t-i}$$

*The numbers in parentheses are robust standard errors. ***, ** and * are significance levels of 1%, 5% and 10%, respectively.*

Furthermore, there is a strong evidence for the first leg of Friedman (1977) hypothesis and Ball (1992) theory. Where the effect of inflation on inflation uncertainty is positive and significant $(\gamma_{\pi\pi} = 0.09)$.

Finally, all coefficients (α_{π}, α_{y}, β_{π} and β_{y}) of the conditional variances are statistically significant.

In details, a 100% increase in the inflation uncertainty leads to a corresponding increase in the inflation rate by 40%. In addition, a 100% increase in the inflation uncertainty leads to a decrease in the output growth rate by 63%.

Lastly, a 100% increase in inflation rate causes a 9% rise in the inflation uncertainty and an 18% increase in the output uncertainty.

In comparison with table 3.8, we notice that the effect of economic and political events comes into existence in Japan. Considering the $\delta_{y\pi}$ coefficient the effect of inflation uncertainty on output growth shifted from positive $\delta_{y\pi} = 0.95$ to negative $\delta_{y\pi} = -0.63$ in three months. In addition, the effect of inflation uncertainty on inflation has decreased. Whereas, the effect of inflation rate on its uncertainty has raised.

In other words, economic and political events achieve contrasted effect of inflation uncertainty on growth, and higher effect of inflation on its uncertainty.

More precisely, the post-Plaza Accord in 1985 and the 2007s financial crisis have leaded to the corresponding change in the effect of the inflation on inflation uncertainty and vice versa with 10% decreasing and 12% increasing respectively. However, the effect of inflation uncertainty on output growth rate decreased 50% and then shifted from positive to negative as well.

3.6.3.4. The case of Italy:

Table 3.15 indicates a negative and significant $\delta_{\pi y}$ coefficient confirms Taylor effect and Cukierman and Meltzer (1986) theory. So, there is evidence for negative effect of output uncertainty on inflation. In addition, the negative and significant $\delta_{y\pi} = -0.72$ coefficient is evidence that inflation uncertainty affects output growth rate in a negative manner (the known as second leg of Friedman (1977) hypothesis).

However, the positive and insignificant $\delta_{\pi\pi}$ and the positive and insignificant δ_{yy} imply that there are no effect of inflation uncertainty on inflation and output uncertainty on growth rate. So, there isn't any evidence for Cukierman and Meltzer (1986) and Devereux (1989), Cukierman and Gerlach (2003) as well.

However, there is evidence for the first leg of Friedman (1977) hypothesis and Ball (1992) theory. The effect of inflation on inflation uncertainty is positive and significant ($\gamma_{\pi\pi} = 0.09 - 0.07 = 0.02$) at the one and fifth month lags.

Finally, all coefficients (α_{π}, α_{y}, β_{π} and β_{y}) of the conditional variances are statistically significant.

In details, a 100% increase in inflation rate causes a 2% rise in the inflation uncertainty. Also, a 100% decline in the inflation uncertainty leads to an increase the output growth rate by 72%.

In comparison with Table 3.9, we notice that the effect of economic and political events comes into existence in Italy. Considering the absolute $\delta_{y\pi}$ coefficient, the effect of inflation uncertainty on output growth decreased from $\delta_{y\pi} = -1.34$ to $\delta_{y\pi} = -0.72$ at the third month lag.

Table 3.15 CCC-GARCH (1, 1)-ML model for Italy with Dummy variables in mean equation:

In-mean and level effects:	$\underset{(0.02)^{***}}{0.09}$ $\underset{(0.02)^{***}}{-0.07}$
$\delta_{\pi\pi}(t-2)$	$\underset{(0.18)}{0.12}$
$\delta_{\pi y,t}(t-2)$	$\underset{(0.01)^{*}}{-0.02}$
$\delta_{y\pi}(t-3)$	$\underset{(0.40)^{*}}{-0.72}$
$\delta_{yy}(t-4)$	$\underset{(0.16)}{0.11}$
$\gamma_{\pi\pi}(t-1,t-5)$	$\underset{(0.02)^{***}}{0.09}$ $\underset{(0.02)^{***}}{-0.07}$
$\gamma_{y\pi}(t-1)$	--
GARCH(1,1) coefficients:	
α_{π}	$\underset{(0.03)^{***}}{0.08}$
β_{π}	$\underset{(0.05)^{***}}{0.88}$
α_{y}	$\underset{(0.06)^{***}}{0.14}$
β_{y}	$\underset{(0.06)^{***}}{0.85}$

Notes: *Notes: This table reports parameter estimates for the following model:*

Mean Equations: $\Phi_{\pi\pi}(L)\pi_t = c_\pi + \Phi_{\pi y}(L)y_t + \delta_{\pi\pi}\sqrt{h_{\pi,t-l_{\pi\pi}}} + \delta_{\pi y}\sqrt{h_{y,t-l_{\pi y}}} + \varepsilon_{\pi,t}$

$$\Phi_{yy}(L)y_t = c_y + \Phi_{y\pi}(L)\pi_t + \delta_{yy}\sqrt{h_{y,t-l_{yy}}} + \delta_{y\pi}\sqrt{h_{\pi,t-l_{y\pi}}} + \varepsilon_{y,t}$$

Variance Equations: $h_{\pi t} = \omega_\pi + \beta_\pi h_{\pi,t-1} + \alpha_\pi \varepsilon^2_{\pi,t-1} + \gamma_\pi \pi_{t-i}$

$$h_{yt} = \omega_y + \beta_y h_{y,t-1} + \alpha_y \varepsilon^2_{y,t-1} + \gamma_y \pi_{t-i}$$

*The numbers in parentheses are robust standard errors. ***, ** and * are significance levels of 1%, 5% and 10%, respectively.*

Also, the effect of inflation on its uncertainty has decreased from $\gamma_{\pi\pi} = 0.19$ to $\gamma_{\pi\pi} = 0.02$,

More precisely, the 1970s energy crisis and the 2007s financial crisis have leaded to the corresponding change in the induced effect of the inflation uncertainty on output growth rate with 85%. Also, the corresponding change in the effect of the inflation rate on inflation uncertainty has been eight times reduced as a result of the 1970s energy crisis and the 2007s financial crisis.

3.6.3.5. The case of France:

` By considering the implications of Table 3.16, we notice the following:

First, all coefficients (α_π, α_y, β_π and β_y) of the conditional variances are statistically significant.

Second, the coefficient of inflation rate ($\gamma_{\pi\pi} = 0.10$) is positive and significant. So, there is evidence for the first leg of Friedman (1977) hypothesis and Ball (1992) theory, where higher inflation rate will lead to higher nominal uncertainty.

Third, there is evidence for Cukierman and Meltzer (1986) hypothesis that a higher Inflation uncertainty will lead to greater inflation rate at the third month lag as indicated by the positive and significant coefficient ($\delta_{\pi\pi} = 4.92$). However, the negative and significant $\delta_{\pi y} = -0.03$ coefficient shows that there is an effect of output uncertainty on inflation as predicted by the Cukierman and Meltzer (2003) and Devereux (1989) hypothesis.

Fourth, the negative and significant effect of output uncertainty on growth rate ($\delta_{yy} = -0.30$) indicates evidence in support of Pindyck (1991) theory.

Finally, the significant and negative coefficient ($\delta_{y\pi} = -5.60$) is an evidence that inflation uncertainty affects output growth rate in a negative manner $h_{\pi t} \overset{-}{\rightarrow} y_t$ as considered by second leg of Friedman (1977) hypothesis.

In details, a 100% increase in the inflation uncertainty and output uncertainty leads to corresponding high increase in the inflation rate by 581% and 58% respectively. Moreover, a 100% decline in the inflation uncertainty leads to a high increase in the output growth rate by 669%.

Lastly, a 100% increase in inflation rate causes a 12% decline in the inflation uncertainty.

Table 3.16 CCC-GARCH (1, 1)-ML model for France with Dummy variables in mean equation:

In-mean and level effects:	
$\delta_{\pi\pi}(t-3)$	4.92 (2.80)**
$\delta_{\pi y}(t-1)$	− 0.03 (0.01)**
$\delta_{y\pi}(t-3)$	− 5.60 (1.49)***
$\delta_{yy}(t-2)$	− 0.30 (0.13)**
$\gamma_{\pi\pi}(t-1)$	0.10 (0.04)**
$\gamma_{y\pi}(t-1)$	--
GARCH(1,1) coefficients:	
α_{π}	0.16 (0.06)***
β_{π}	0.70 (0.08)***
α_{y}	0.34 (0.10)***
β_{y}	0.25 (0.11)**

Notes: *Notes: This table reports parameter estimates for the following model:*

Mean Equations: $\Phi_{\pi\pi}(L)\pi_t = c_\pi + \Phi_{\pi y}(L)y_t + \delta_{\pi\pi}\sqrt{h_{\pi,t-l_{\pi\pi}}} + \delta_{\pi y}\sqrt{h_{y,t-l_{\pi y}}} + \varepsilon_{\pi,t}$

$$\Phi_{yy}(L)y_t = c_y + \Phi_{y\pi}(L)\pi_t + \delta_{yy}\sqrt{h_{y,t-l_{yy}}} + \delta_{y\pi}\sqrt{h_{\pi,t-l_{y\pi}}} + \varepsilon_{y,t}$$

Variance Equations: $h_{\pi t} = \omega_\pi + \beta_\pi h_{\pi,t-1} + \alpha_\pi \varepsilon^2_{\pi,t-1} + \gamma_\pi \pi_{t-i}$

$$h_{yt} = \omega_y + \beta_y h_{y,t-1} + \alpha_y \varepsilon^2_{y,t-1} + \gamma_y \pi_{t-i}$$

*The numbers in parentheses are robust standard errors. ***, ** and * are significance levels of 1%, 5% and 10%, respectively.*

In comparison with Table 3.10, we notice that the effect of economic and political events comes into existence in France. Considering the absolute $\delta_{y\pi}$; the effect of inflation uncertainty on output growth decreased from 6.69 to 5.60. The effect of inflation uncertainty on inflation and inflation on its uncertainty decreased.

In other words, economic and political events achieve less effect of inflation uncertainty on growth and less effect of inflation uncertainty on inflation and inflation on its uncertainty as well.

In other words, the 1970s energy crisis and the 2007s financial crisis have leaded to the corresponding changes in the reduced effect of the inflation uncertainty on output growth rate, the inflation rate on its uncertainty and vice versa was with 19%, 20% and 18% respectively.

3.6.3.6. <u>The case of Canada:</u>

Table 3.17 shows the following indications:

First, the coefficient of inflation rate ($\gamma_{\pi\pi} = -0.74 + 0.91 = 0.17$) is positive and significant, then, there is evidence for the first leg of the Friedman (1977) hypothesis (as predicted by Ball 1992 as well), therefore a higher inflation rate will lead to higher nominal uncertainty.

Second, the evidence of Taylor effect and Cukierman and Meltzer (1986) theories is existence by the negative and significant $\delta_{\pi y} = -0.13$. Therefore, higher output uncertainty leads to low inflation rate.

Finally, the significant and negative coefficient ($\delta_{y\pi} = -0.19$) is an evidence that inflation uncertainty affects output growth rate in a negative manner $h_{\pi t} \overset{-}{\rightarrow} y_t$ (the known as second leg of Friedman (1977) hypothesis).

Table 3.17 CCC-GARCH (1, 1)-ML model for Canada with Dummy variables in mean equation:

In-mean and level effects:	
$\delta_{\pi\pi}(t-2)$	0.09 (0.20)
$\delta_{\pi y}(t-1)$	− 0.13 (0.04)**
$\delta_{y\pi}(t)$	− 0.19 (0.03)***
$\delta_{yy}(t)$	1.65 (1.14)
$\gamma_{\pi\pi}(t-1/t-2)$	−0.74+0.91 (0.40)* (0.43)**
$\gamma_{y\pi}(t-1)$	--
GARCH(1,1) coefficients:	
α_π	0.15 (0.06)***
β_π	0.74 (0.12)***
α_y	0.30 (0.10)***
β_y	0.32 (0.12)***

Notes: *Notes: This table reports parameter estimates for the following model:*

Mean Equations: $\Phi_{\pi\pi}(L)\pi_t = c_\pi + \Phi_{\pi y}(L)y_t + \delta_{\pi\pi}\sqrt{h_{\pi,t-l_{\pi\pi}}} + \delta_{\pi y}\sqrt{h_{y,t-l_{\pi y}}} + \varepsilon_{\pi,t}$

$$\Phi_{yy}(L)y_t = c_y + \Phi_{y\pi}(L)\pi_t + \delta_{yy}\sqrt{h_{y,t-l_{yy}}} + \delta_{y\pi}\sqrt{h_{\pi,t-l_{y\pi}}} + \varepsilon_{y,t}$$

Variance Equations: $h_{\pi t} = \omega_\pi + \beta_\pi h_{\pi,t-1} + \alpha_\pi \varepsilon^2_{\pi,t-1} + \gamma_\pi \pi_{t-i}$

$$h_{yt} = \omega_y + \beta_y h_{y,t-1} + \alpha_y \varepsilon^2_{y,t-1} + \gamma_y \pi_{t-i}$$

*The numbers in parentheses are robust standard errors. ***, ** and * are significance levels of 1%, 5% and 10%, respectively.*

As an illustration, a 100% decline in the inflation uncertainty leads to an increase in the output growth rate by 20%. Moreover, a 100% increase in inflation rate causes an increase by 14% in the inflation uncertainty.

In comparison with table 3.11, we can confirm that the effect of economic and political comes into existence in Canada. The negative effect of output uncertainty on inflation and the positive effect of inflation on its uncertainty increased,

Furthermore, absolute $\delta_{\pi y}$ coefficient shows decreasing in the effect of inflation uncertainty on output growth rate by the effect of economic and political events.

In other words, the 1970s energy crisis and the 2007s financial crisis have leaded to the corresponding changes in the induced effect of inflation on its uncertainty and the induced effect of inflation uncertainty on output growth rate with 19% and 21% respectively.

Finally, we summarize the results that are obtained for the US inflation and output uncertainty in both cases, before considering the effect of economic and political events and considering them. (see Table 3.18)

More precisely, a 100% increase in the inflation uncertainty and output uncertainty leads to corresponding increase in the inflation rate by 51% and 29% respectively. Moreover, a 100% decline in the inflation uncertainty leads to an increase in the output growth rate by 114%.

Lastly, a 100% increase in inflation rate leads to 18% rise in the inflation uncertainty.

Table 2. 13 Summary of the US results:

The effect of:	The US results before including dummy effects	The US results before including dummy effects
Inflation uncertainty on inflation	0.51 (0.25)**	0.56 (0.29)*
Output uncertainty on inflation	−0.05 (0.07)	−0.06 (0.07)
Inflation uncertainty on output	−1.14 (0.45)**	−1.16 (0.51)**
Output uncertainty on inflation	0.29 (0.14)**	0.35 (0.15)**
Inflation on its uncertainty	0.18 (0.09)**	0.20 (0.09)**
Inflation on output uncertainty	1.47 (0.81)*	1.45 (0.83)*

On the second hand, the Great Recession in 1980, 9/11 accident and the financial crisis in 2007 have leaded to the corresponding changes in the effect of inflation uncertainty on inflation rate, the effect of output uncertainty on growth rate, the effect of inflation rate on inflation uncertainty and the negative effect of inflation variability on output growth rate with 5%, 6%, 2% and 1.7% respectively.

3.7. Conclusion:

In this chapter we have used monthly data contained the CPI and IPI as proxies of inflation and output growth rate for the G& countries. We have employed CCC-GARCH (1,1)-ML models to investigate the relationship among inflation, inflation uncertainty, output growth and real uncertainty.

The estimations of our model showed the evidences of the second leg of Friedman (1977) hypothesis. So, inflation uncertainty affected output growth in a negative manor ($h_\pi \overset{-}{\rightarrow} y$) in the US, the UK, Germany, Italy, France and Canada. While inflation uncertainty affected output growth positively ($h_\pi \overset{+}{\rightarrow} y$) in Japan as predicted by Dotsey and Sarte (2000).

In addition, we found evidences for positive effect of inflation uncertainty on inflation ($h_\pi \overset{+}{\rightarrow} \pi$) in the US, Germany, Japan and France as a support of Cukierman and Meltzer (1986) hypothesis.

The negative effect of output uncertainty on inflation ($h_y \overset{+}{\rightarrow} \pi$ was detected in the case of Italy, France and Canada. So, there was an evidence of Taylor effect and Cukierman and Meltzer (1986).

Evidences of Mirman (1971), Black (1987) and Blackburn (1999) hypotheses were obtained in the case the US, the UK and Germany.

Finally, the effect of inflation on its uncertainty $\pi \overset{+}{\rightarrow} h$ was obtained in the case of the US, the UK and Japan. So, we had evidences of the first leg of Friedman (1977) and Ball (1992).

Then, we re-estimate CCC-GARCH (1,1) models including dummy variables in the mean equation according to some economic and political events in the G7 countries.

Our results highlight the importance of taking into consideration the economic and political events in our study.

In particular, we find strong support for the two legs of Friedman (1977) hypothesis that is higher inflation increases its uncertainty, and then affects output growth negatively. In addition, we find support for Cukierman and Meltzer (1986).

Moreover, we find that the economic and political events come into existence. For instance, the effect of inflation uncertainty on output growth becomes lower in the US, the UK, Germany, Italy and France, while becomes higher in Canada and changes from positive effect in Japan to negative one.

In details, the financial crisis in 2007 has affected all the G7 countries for both their inflation rate and output growth rate. In details, the effect of inflation rate on its uncertainty has been increased in the US, the UK, Germany and Canada. Whereas, it has been decreased in other countries. The effect of inflation uncertainty on output growth rate has been decreased in all the G7 countries with the exception of the US. Lastly, the impact of inflation uncertainty on inflation rate has been increased in the US and Germany. On the contrary, this effect has been decreased in Japan, France and Canada.

Appendix 3

3.7.1. Appendix 3.1.A for Table 3.3

```
System of Equations for
1: US CPI
2: US IPI
600 observations  (13-612) used for estimation
with 12 pre-sample observations.
Estimation Method: Conditional ML (Time Domain)
Gaussian Likelihood
Vector-ARIMA(12,0,0) with GARCH-M(1,1)

Strong convergence
                       Log Likelihood = -3034.94
                    Schwarz Criterion = -3111.71
               Hannan-Quinn Criterion = -3079.48
                     Akaike Criterion = -3058.94
                              Estimate  Std. Err.   t Ratio  p-Value
                             |---------|----------|--------|--------|
Error Correlation Matrix
                Equation 1   Equation 2
Equation 1          1.0000
Equation 2       0.0015259       1.0000

Error Correlations = C(i,j) / (1 + |C(i,j)|):
C(2,1)                         0.00154    0.04502     0.034    0.973

Equation 1, for US CPI:
[2]Intercept                   0.30605    0.29379     1.042    0.298
Garch-M SD Eq. 1(-2)           0.51026    0.25846     1.974    0.049
Garch-M SD Eq. 2              -0.05509    0.07096    -0.776    0.438
AR1(1,1)                       0.30976    0.05382     5.756        0
AR2(1,2)                       0.04168     0.0147     2.835    0.005
AR7(1,1)                       0.15763    0.03652     4.316        0
AR11(1,1)                      0.14261    0.03876     3.679        0
AR12(1,1)                      0.16533    0.04144      3.99        0
[2]GARCH Intercept^(1/2)       0.74691      0.251    ------   ------
GARCH Alpha1(1,1)              0.19155    0.06635     2.887    0.004
GARCH Beta1(1,1)               0.69001    0.07307     9.443        0
[G2]US CPId(-1)                0.18868    0.09004     2.096    0.037
              Residual Sum of Squares = 6443.02
                            R-Squared =  0.4187
                        R-Bar-Squared =  0.4078
                          Residual SD =  3.3101
                    Residual Skewness =  0.2322
                    Residual Kurtosis =  4.6347
                     Jarque-Bera Test =  72.202     {0}

Equation 2, for US IPI:
[2]Intercept                   6.08973    1.06918     5.696        0
Garch-M SD Eq. 1(-2)          -1.14248    0.45191    -2.528    0.012
Garch-M SD Eq. 2(-2)           0.29234    0.14424     2.027    0.043
AR2(2,2)                       0.12795    0.04549     2.813    0.005
AR3(2,2)                       0.17405    0.03929      4.43        0
AR4(2,2)                       0.09286    0.03864     2.403    0.017
AR10(2,1)                     -0.22687    0.08105    -2.799    0.005
[2]GARCH Intercept^(1/2)       4.68788     0.7799    ------   ------
GARCH Alpha1(2,2)              0.35443    0.10554     3.358    0.001
GARCH Beta1(2,2)               0.25731    0.11647     2.209    0.028
[G2]US CPId(-1)                1.47277    0.81908     1.798    0.073
              Residual Sum of Squares = 42081.5
                            R-Squared =  0.1709
                        R-Bar-Squared =  0.1554
                          Residual SD =  8.4595
                    Residual Skewness = -0.3899
                    Residual Kurtosis =  4.8394
                     Jarque-Bera Test = 99.7879     {0}
```

3.7.2. Appendix 3.1.B for Table 3.4

```
System of Equations for
1: US CPId
2: US IPId
600 observations  (13-612, dates 1961, Mth 2 to 2011, Mth 1) used for estimation
with 12 pre-sample observations.
Estimation Method: Conditional ML (Time Domain)
Gaussian Likelihood
Vector-ARIMA(12,0,0) with GARCH-M(1,1)

Strong convergence
                       Log Likelihood = -3029.48
                    Schwarz Criterion = -3125.43
               Hannan-Quinn Criterion = -3085.15
                     Akaike Criterion = -3059.48
                              Estimate  Std. Err.   t Ratio  p-Value
                             |---------|----------|--------|--------|
Error Correlation Matrix
                Equation 1   Equation 2
Equation 1          1.0000
Equation 2      -0.0037650       1.0000

Error Correlations = C(i,j) / (1 + |C(i,j)|):
C(2,1)                        -0.00382    0.04628    -0.082    0.934

Equation 1, for US CPId:
[2]Intercept                    0.4267    0.88529     0.482     0.63
[1]Garch-M SD Eq. 1(-2)        0.56634    0.29499      1.92    0.055
[1]Garch-M SD Eq. 2            -0.0635    0.07506    -0.846    0.398
[2]D1                         -0.05132    0.56946     -0.09    0.928
[2]D2                          0.55629     0.8703     0.639    0.523
[2]D3                          -0.2213    0.41734     -0.53    0.596
AR1(1,1)                       0.30592    0.05975      5.12        0
AR2(1,2)                       0.03962    0.02303      1.72    0.086
AR7(1,1)                       0.15666    0.03715     4.217        0
AR11(1,1)                      0.14166     0.0414     3.422    0.001
AR12(1,1)                      0.16515    0.04138     3.991        0
[2]GARCH Intercept^(1/2)         0.731     0.2643    ------   ------
GARCH Alpha1(1,1)              0.19795    0.09316     2.125    0.034
GARCH Beta1(1,1)               0.68137    0.07991     8.527        0
[G2]US CPId(-1)                0.20221    0.09882     2.046    0.041
              Residual Sum of Squares = 6472.42
                            R-Squared =  0.4154
                        R-Bar-Squared =  0.4015
                          Residual SD =  3.3255
                    Residual Skewness =  0.2031
                    Residual Kurtosis =  4.5842
                     Jarque-Bera Test =  66.864     {0}

Equation 2, for US IPId:
[2]Intercept                    8.1533    1.77308     4.598        0
[1]Garch-M SD Eq. 1(-2)       -1.16692    1.48413    -0.786    0.432
[1]Garch-M SD Eq. 2(-2)        0.35203    0.15391     2.287    0.023
[2]D1                         -0.11784    1.52087    -0.077    0.938
[2]D2                         -0.84895    3.43767    -0.247    0.805
[2]D3                         -1.78354    0.77281    -2.308    0.021
AR2(2,2)                       0.12117    0.04568     2.653    0.008
AR3(2,2)                       0.15663    0.03997     3.919        0
AR4(2,2)                       0.07159    0.04898     1.462    0.144
AR10(2,1)                     -0.27065    0.14081    -1.922    0.055
[2]GARCH Intercept^(1/2)       4.68898      0.855    ------   ------
GARCH Alpha1(2,2)              0.35894    0.11442     3.137    0.002
GARCH Beta1(2,2)               0.24804    0.12936     1.917    0.056
[G2]US CPId(-1)                1.45802    0.83767     1.740    0.082
              Residual Sum of Squares = 41524.2
                            R-Squared =  0.1828
                        R-Bar-Squared =  0.1632
                          Residual SD =  8.4226
                    Residual Skewness =  -0.492
                    Residual Kurtosis =  4.8234
                     Jarque-Bera Test = 107.327     {0}
```

3.7.3. Appendix 3.2.A for Table 3.5

```
System of Equations for
1: uk inf
2: uk out
584 observations  (17-600, dates 1961, Mth 6 to 2010, Mth 1) used for estimation
with 16 pre-sample observations.
Estimation Method: Conditional ML (Time Domain)
Gaussian Likelihood
Vector-ARIMA(16,0,0) with GARCH-M(1,1)

Strong convergence

                       Log Likelihood = -3572.08
                    Schwarz Criterion = -3651.7
               Hannan-Quinn Criterion = -3618.37
                     Akaike Criterion = -3597.08
                              Estimate  Std. Err.   t Ratio  p-Value
                             |---------|----------|--------|--------|
Error Correlation Matrix
                Equation 1   Equation 2
Equation 1          1.0000
Equation 2        0.042822       1.0000

Error Correlations = C(i,j) / (1 + |C(i,j)|):
C(2,1)                         0.04521    0.05256      0.86     0.39

Equation 1, for uk inf:
[2]Intercept                   0.45406     0.6662     0.682    0.496
[3]Garch-M SD Eq. 1(-2)       -0.02819    0.13199    -0.214    0.831
[3]Garch-M SD Eq. 2(-3)        0.02635    0.05231     0.504    0.615
AR1(1,1)                       0.21155    0.04658     4.542        0
AR2(1,1)                       0.19503    0.04229     4.612        0
AR5(1,2)                       0.04149    0.02014      2.06     0.04
AR6(1,1)                       0.12954    0.03485     3.717        0
AR12(1,1)                      0.61757    0.04232    14.593        0
GARCH Intercept^(1/4)          1.16657     0.2633    ------   ------
GARCH Alpha1(1,1)              0.12762    0.01998     6.387        0
GARCH Beta1(1,1)               0.69001    0.07307     9.443        0
[G2]uk inf(-1)                 0.45709    0.25992     1.759    0.079
              Residual Sum of Squares = 18179.6
                            R-Squared =  0.4779
                        R-Bar-Squared =  0.4674
                          Residual SD =  5.6338
                    Residual Skewness =  0.5434
                    Residual Kurtosis =  5.4635
                     Jarque-Bera Test = 176.414     {0}
Box-Pierce (residuals):          Q(4)  = 40.9301     {0}
Box-Pierce (squared residuals): Q(20) = 17.6153  {0.605}

Equation 2, for uk out:
[2]Intercept                   1.35634    1.89922     0.714    0.475
[3]Garch-M SD Eq. 1(-3)       -0.87196    0.45985     1.896    0.058
[3]Garch-M SD Eq. 2(-3)        0.20277    0.11963    -1.695    0.091
AR1(2,2)                       0.23921    0.05132     4.661        0
AR3(2,2)                       0.10488    0.05224     2.008    0.045
AR5(2,2)                       0.13482      0.041     3.288    0.001
AR7(2,1)                      -0.19015    0.07548    -2.519    0.012
GARCH Intercept^(1/4)          3.03784     0.1212    ------   ------
GARCH Alpha1(1,1)              0.24355    0.08722     2.792    0.002
GARCH Beta1(2,2)               0.36231     0.1047     3.460    0.008
[G2]uk inf(-1)                 5.20177    1.18236     4.399        0
              Residual Sum of Squares =  153443
                            R-Squared =  0.0391
                        R-Bar-Squared =  0.0198
                          Residual SD = 16.3589
                    Residual Skewness = -0.5974
                    Residual Kurtosis =  6.3045
                     Jarque-Bera Test = 300.456     {0}
```

3.7.4. Appendix 3.2.B for Table 3.11

```
System of Equations for
1: uk inf
2: uk out
584 observations  (17-600, dates 1961, Mth 6 to 2010, Mth 1) used for estimation
with 16 pre-sample observations.
Estimation Method: Conditional ML (Time Domain)
Gaussian Likelihood
Vector-ARIMA(16,0,0) with GARCH-M(1,1)

Strong convergence

                       Log Likelihood = -3572.08
                    Schwarz Criterion = -3651.7
               Hannan-Quinn Criterion = -3618.37
                     Akaike Criterion = -3597.08
                             Estimate  Std. Err.   t Ratio  p-Value
                            |---------|----------|--------|--------|
Error Correlation Matrix
                Equation 1   Equation 2
Equation 1          1.0000
Equation 2        0.042822       1.0000

Error Correlations = C(i,j) / (1 + |C(i,j)|):
C(2,1)                        0.04521    0.05256      0.86     0.39

Equation 1, for uk inf:
[2]Intercept                  0.45406     0.6662     0.682    0.496
[3]Garch-M SD Eq. 1(-2)      -0.02819    0.13199    -0.214    0.831
[3]Garch-M SD Eq. 2(-3)       0.02635    0.05231     0.504    0.615
[2]D1                        -0.07132    0.56946    -0.125    0.828
[2]D2                         0.62629     0.8703     0.719    0.581
[2]D3                         -0.3213    0.41734     -0.76    0.526
AR1(1,1)                      0.21155    0.04658     4.542        0
AR2(1,1)                      0.19503    0.04229     4.612        0
AR5(1,2)                      0.04149    0.02014      2.06     0.04
AR6(1,1)                      0.12954    0.03485     3.717        0
AR12(1,1)                     0.61757    0.04232    14.593        0
GARCH Intercept^(1/4)         1.16657     0.2633    ------   ------
GARCH Alpha1(1,1)             0.15762    0.01998     7.888        0
GARCH Beta1(1,1)              0.84001    0.07307    11.495        0
[G2]uk inf(-1)                0.50309    0.26292     1.906    0.079
              Residual Sum of Squares = 18179.6
                            R-Squared =  0.4779
                        R-Bar-Squared =  0.4674
                          Residual SD =  5.6338
                    Residual Skewness =  0.5434
                    Residual Kurtosis =  5.4635
                     Jarque-Bera Test = 176.414     {0}
Equation 2, for uk out:
[2]Intercept                  1.35634    1.89922     0.714    0.475
[3]Garch-M SD Eq. 1(-3)      -0.87196    0.45985     1.896    0.058
[3]Garch-M SD Eq. 2(-3)       0.20277    0.11963    -1.695    0.091
[2]D1                        -0.11784    1.52087    -0.077    0.938
[2]D2                         -3.2412    1.88039    -1.724    0.085
[2]D3                        -1.72354    0.77281    -2.230    0.031
AR1(2,2)                      0.23921    0.05132     4.661        0
AR3(2,2)                      0.10488    0.05224     2.008    0.045
AR5(2,2)                      0.13482      0.041     3.288    0.001
AR7(2,1)                     -0.19015    0.07548    -2.519    0.012
GARCH Intercept^(1/4)         3.03784     0.1212    ------   ------
GARCH Alpha1(1,1)             0.23355    0.08722     2.677    0.002
GARCH Beta1(2,2)              0.35231     0.1047     3.364    0.008
[G2]uk inf(-1)                5.03177    1.07236     4.692    0.005
              Residual Sum of Squares =  153443
                            R-Squared =  0.0391
                        R-Bar-Squared =  0.0198
                          Residual SD = 16.3589
                    Residual Skewness = -0.5974
                    Residual Kurtosis =  6.3045
                     Jarque-Bera Test = 300.456     {0}
```

3.7.5. Appendix 3.3.A for Table 3.6

```
System of Equations for
1: Ger inf
2: Ger out
600 observations  (13-612, dates 1961, Mth 2 to 2011, Mth 1) used for estimation
with 12 pre-sample observations.
Estimation Method: Conditional ML (Time Domain)
Gaussian Likelihood
Vector-ARIMA(12,0,0) with GARCH-M(1,1)

Strong convergence
                      Log Likelihood = -3603.92
                   Schwarz Criterion = -3690.28
              Hannan-Quinn Criterion = -3654.03
                    Akaike Criterion = -3630.92
                             Estimate  Std. Err.   t Ratio  p-Value
                            |---------|----------|--------|--------|
Error Correlation Matrix
                Equation 1   Equation 2
Equation 1         1.0000
Equation 2       -0.050979      1.0000

Error Correlations = C(i,j) / (1 + |C(i,j)|):
C(2,1)                       -0.05429    0.05208    -1.042    0.298

Equation 1, for Ger inf:
[2]Intercept                 -1.03598    0.22794    -4.545        0
[3]Garch-M SD Eq. 1(-1)       0.79873    0.18247     4.377        0
[3]Garch-M SD Eq. 2          -0.04865    0.02923    -1.664    0.097
AR1(1,1)                      0.09742    0.03874     2.515    0.012
AR2(1,2)                       0.0162    0.00581     2.788    0.005
AR3(1,2)                       0.0187    0.00703     2.659    0.008
AR4(1,2)                      0.01125    0.00653     1.723    0.085
AR10(1,1)                       0.121    0.03245     3.729        0
AR12(1,1)                     0.50303      0.044    11.432        0
[2]GARCH Intercept^(1/2)       2.0524     0.1551    ------   ------
GARCH Alpha1(1,1)             0.15892    0.05879     2.703    0.007
GARCH Beta1(1,1)              0.46814    0.06316     7.412        0
[G2]Ger inf(-2)               0.36083    0.20245     1.782    0.075
[G2]Ger inf(-3)              -0.38512    0.17771    -2.167    0.031
              Residual Sum of Squares =  6504.6
                            R-Squared =  0.3237
                        R-Bar-Squared =  0.3093
                          Residual SD =  3.3302
                    Residual Skewness =  0.6114
                    Residual Kurtosis =  4.3155
                     Jarque-Bera Test = 80.6511     {0}

Equation 2, for Ger out:
[2]Intercept                  0.71142    1.23594     0.576    0.565
[3]Garch-M SD Eq. 1          -1.92971    0.45783    -4.215        0
[3]Garch-M SD Eq. 2           0.58428    0.12056     4.846        0
AR1(2,2)                      0.32533    0.04181     7.781        0
AR3(2,2)                       0.1927    0.04442     4.338        0
AR4(2,2)                      0.07184    0.04202      1.71    0.088
AR5(2,1)                      -0.3077    0.16514    -1.863    0.063
AR10(2,1)                    -0.39607    0.18037    -2.196    0.028
[2]GARCH Intercept^(1/2)      12.4734     0.5004    ------   ------
GARCH Alpha1(2,2)             0.24283    0.06823     3.559        0
GARCH Beta1(2,2)              0.35307    0.08968     3.937        0
[G2]Ger inf(-1)              -1.60811    0.48998    -3.282    0.001
              Residual Sum of Squares =  235724
                            R-Squared =  0.1259
                        R-Bar-Squared =  0.1073
                          Residual SD = 20.0339
                    Residual Skewness = -0.5407
                    Residual Kurtosis =  6.5102
                     Jarque-Bera Test = 337.269     {0}
```

3.7.6. Appendix 3.3.B for Table 3.12

```
System of Equations for
1: Ger inf
2: Ger out
600 observations  (13-612, dates 1961, Mth 2 to 2011, Mth 1) used for estimation
with 12 pre-sample observations.
Estimation Method: Conditional ML (Time Domain)
Gaussian Likelihood
Vector-ARIMA(12,0,0) with GARCH-M(1,1)

Strong convergence
                      Log Likelihood = -3603.92
                   Schwarz Criterion = -3690.28
              Hannan-Quinn Criterion = -3654.03
                    Akaike Criterion = -3630.92
                             Estimate  Std. Err.   t Ratio  p-Value
                            |---------|----------|--------|--------|
Error Correlation Matrix
                Equation 1   Equation 2
Equation 1          1.0000
Equation 2       -0.056341       1.0000

Error Correlations = C(i,j) / (1 + |C(i,j)|):
C(2,1)                       -0.05429    0.05208    -1.042    0.298
Equation 1, for Ger inf:
[2]Intercept                 -1.71596    0.22926    -3.123    0.002
[3]Garch-M SD Eq. 1(-1)       0.83647    0.18957     4.412        0
[3]Garch-M SD Eq. 2          -0.05645    0.02868    -1.968     0.05
[2]D1                        -0.50412    0.31236    -1.614    0.107
[2]D2                        -0.00456    0.55935    -0.008    0.993
AR1(1,1)                      0.09742    0.03874     2.515    0.012
AR2(1,2)                       0.0162    0.00581     2.788    0.005
AR3(1,2)                       0.0187    0.00703     2.659    0.008
AR10(1,2)                     0.11250    0.03253     3.506        0
AR12(1,1)                     0.49303    0.04499    11.004        0
[2]GARCH Intercept^(1/2)       2.0324     0.1521    ------   ------
GARCH Alpha1(1,1)             0.15354    0.05918     2.594     0.01
GARCH Beta1(1,1)              0.48067    0.06114     7.862        0
[G2]Ger inf(-2)               0.34411     0.2051     1.678    0.094
[G2]Ger inf(-3)              -0.38862    0.17579    -2.211    0.027
              Residual Sum of Squares =  6504.6
                            R-Squared =  0.3237
                        R-Bar-Squared =  0.3093
                          Residual SD =  3.3302
                    Residual Skewness =  0.6114
                    Residual Kurtosis =  4.3155
                     Jarque-Bera Test = 80.6511      {0}
Equation 2, for Ger out:
[2]Intercept                  1.63142    2.80594     0.583    0.559
[3]Garch-M SD Eq. 1          -1.83575    0.52837    -3.472    0.001
[3]Garch-M SD Eq. 2           0.51766    0.13074     3.959        0
[2]D1                        -1.21372    1.46432    -0.289    0.408
[2]D2                          4.9004    3.13255     1.564    0.118
AR1(2,2)                      0.32533    0.04181     7.781        0
AR2(2,2)                       0.1927    0.04442     4.338        0
AR3(2,2)                      0.07184    0.04202      1.71    0.088
AR5(2,1)                     -0.37685    0.17074    -2.207    0.028
AR10(2,1)                    -0.41607    0.18037    -2.324    0.028
[2]GARCH Intercept^(1/2)      12.4734     0.5004    ------   ------
GARCH Alpha1(2,2)             0.26054    0.07771     3.353    0.001
GARCH Beta1(2,2)              0.31638    0.10057     3.146    0.002
[G2]Ger inf(-1)              -1.53812    0.54075    -2.844    0.005
              Residual Sum of Squares =  235724
                            R-Squared =  0.1259
                        R-Bar-Squared =  0.1073
                          Residual SD = 20.0339
                    Residual Skewness = -0.5407
```

3.7.7. Appendix 3.4.A for Table 3.7

```
System of Equations for
1: Jap inf
2: Jap out
599 observations  (14-612, dates 1961, Mth 3 to 2011, Mth 1) used for estimation
with 13 pre-sample observations.
Estimation Method: Conditional ML (Time Domain)
Gaussian Likelihood
Vector-ARIMA(13,0,0) with GARCH-M(1,1)

Strong convergence

                       Log Likelihood = -808.604
                    Schwarz Criterion = -898.137
               Hannan-Quinn Criterion = -860.559
                     Akaike Criterion = -836.604
                              Estimate  Std. Err.   t Ratio  p-Value
                              |---------|----------|--------|--------|
Error Correlation Matrix
                Equation 1   Equation 2
Equation 1         1.0000
Equation 2       -0.022958       1.0000

Error Correlations = C(i,j) / (1 + |C(i,j)|):
C(2,1)                        -0.02374   0.04901    -0.484    0.628

Equation 1, for Jap inf:
[1]Intercept                  -0.28819   0.14432    -1.997    0.046
[3]Garch-M SD Eq. 1            0.49285   0.15984     3.083    0.002
[3]Garch-M SD Eq. 2           -0.01448   0.04368    -0.332     0.74
AR2(1,1)                       0.14308    0.0405     3.533        0
AR2(1,2)                       0.01851   0.00972     1.905    0.057
AR5(1,2)                       0.02793   0.00887     3.149    0.002
AR6(1,2)                        0.0202   0.00838     2.411    0.016
AR7(1,1)                       0.06223   0.03568     1.744    0.082
AR11(1,1)                      0.08519   0.03617     2.355    0.019
AR12(1,1)                      0.49148   0.04009    12.259        0
GARCH Intercept^(1/2)          0.20608    0.0475    ------   ------
GARCH Alpha1(1,1)              0.11916   0.03144     3.790        0
GARCH Beta1(1,1)                 0.864     0.123     7.024        0
[G2]Jap inf(-1)                0.08469   0.02968     2.853    0.004
              Residual Sum of Squares = 184.247
                            R-Squared =  0.3401
                        R-Bar-Squared =  0.3255
                          Residual SD =  0.5611
                    Residual Skewness =  0.6291
                    Residual Kurtosis =  5.1995
                     Jarque-Bera Test = 160.252     {0}



Equation 2, for Jap out:
[1]Intercept                  -0.27316   0.47336    -0.577    0.564
[3]Garch-M SD Eq. 1            0.95188   0.56417     1.687    0.092
[3]Garch-M SD Eq. 2            0.07899   0.24193     0.326    0.744
AR1(2,2)                       0.18257   0.05289     3.452    0.001
AR2(2,2)                       0.20018   0.04824      4.15        0
AR3(2,2)                       0.36053   0.05122     7.039        0
AR4(2,1)                      -0.16578   0.08012    -2.069    0.039
AR4(2,2)                       0.15608   0.04739     3.294    0.001
AR13(2,1)                     -0.25253   0.08846    -2.855    0.004
GARCH Intercept^(1/2)          1.02526    0.0473    ------   ------
GARCH Alpha1(1,1)              0.13419    0.0271     4.503        0
GARCH Beta1(2,2)               0.21129    0.0725     2.914
[G2]Jap inf(-1)                 0.2531    0.1308     1.935    0.053
              Residual Sum of Squares = 1276.32
                            R-Squared =  0.1207
                        R-Bar-Squared =  0.1011
                          Residual SD =   1.477
                    Residual Skewness = -0.1733
                    Residual Kurtosis =  3.6065
                     Jarque-Bera Test = 12.1808 {0.002}
```

3.7.8. Appendix 3.4.B for Table 3.13

```
System of Equations for
1: Jap infl
2: Jap output
599 observations  (14-612, dates 1961, Mth 3 to 2011, Mth 1) used for estimation
with 13 pre-sample observations.
Estimation Method: Conditional ML (Time Domain)
Gaussian Likelihood
Vector-ARIMA(13,0,0) with GARCH-M(1,1)

Strong convergence
iteration time:   1:37.74
                   Log Likelihood = -804.932
                 Schwarz Criterion = -904.058
            Hannan-Quinn Criterion = -862.454
                  Akaike Criterion = -835.932
                        Estimate  Std. Err.   t Ratio  p-Value
                       |---------|----------|--------|--------|
Error Correlation Matrix
              Equation 1   Equation 2
Equation 1       1.0000
Equation 2    -0.022484       1.0000

Error Correlations = C(i,j) / (1 + |C(i,j)|):
C(2,1)                  -0.02324    0.04898    -0.474    0.635

Equation 1, for Jap infl:
[2]Intercept            -0.02302    0.11117    -0.207    0.836
[1]D1                   -0.21991    0.09681    -2.272    0.023
[1]D2                    0.04698    0.09139     0.514    0.607
[3]Garch-M SD Eq. 1      0.40565    0.17104     2.372    0.018
[3]Garch-M SD Eq. 2     -0.02767    0.04051    -0.683    0.495
AR2(1,1)                -0.15921    0.03994    -3.986        0
AR2(1,2)                 0.01609    0.00963     1.671    0.095
AR5(1,2)                 0.02558     0.0091     2.811    0.005
AR6(1,2)                 0.01953    0.00847     2.306    0.021
AR11(1,1)                0.08289     0.0362      2.29    0.022
AR12(1,1)                0.48555     0.0402    12.078        0
GARCH Intercept^(1/2)    0.21911     0.0477    ------   ------
GARCH Alpha1(1,1)        0.13209    0.03257     2.523    0.002
GARCH Beta1(1,1)         0.84482    0.08439    26.601        0
[G2]Jap infl(-1)         0.09285      0.033     2.814    0.005
            Residual Sum of Squares = 183.167
                          R-Squared =  0.3434
                      R-Bar-Squared =  0.3271
                        Residual SD =  0.5601
                  Residual Skewness =  0.5834
                  Residual Kurtosis =  5.1515
                   Jarque-Bera Test = 149.512       {0}
Equation 2, for Jap output:
[2]Intercept             0.82447    0.25731     3.204    0.001
[1]D1                   -0.91098     0.2206     -4.13        0
[1]D2                   -0.11659    0.62996    -0.185    0.853
[3]Garch-M SD Eq. 1(-3) -0.63769    0.33458    -1.906    0.057
[3]Garch-M SD Eq. 2(-3)  0.00075    0.16788     0.004    0.996
AR1(2,2)                 -0.2129    0.05074    -4.196        0
AR2(2,2)                 0.18646    0.04277      4.36        0
AR3(2,2)                 0.34946    0.04336      8.06        0
AR4(2,2)                 0.14114     0.0459     3.075    0.002
AR13(2,1)               -0.25918    0.08656    -2.994    0.003
GARCH Intercept^(1/2)    1.03476     0.0514    ------   ------
GARCH Alpha1(2,2)        0.11604    0.04221     4.277        0
GARCH Beta1(2,2)         0.26934    0.07189     1.159    0.247
[G2]Jap infl(-2)         0.18425    0.04918     1.235        0
            Residual Sum of Squares = 1286.64
                          R-Squared =  0.1189
                      R-Bar-Squared =   0.097
                        Residual SD =  1.4847
                  Residual Skewness = -0.1365
                  Residual Kurtosis =  3.6957
                   Jarque-Bera Test = 13.9426 {0.001}
```

3.7.9. Appendix 3.5.A for Table 3.8

```
System of Equations for
1: Ita inf
2: Ita out
599 observations  (14-612, dates 1961, Mth 3 to 2011, Mth 1) used for estimatior
with 13 pre-sample observations.
Estimation Method: Conditional ML (Time Domain)
Gaussian Likelihood
Vector-ARIMA(13,0,0) with GARCH-M(1,1)

Strong convergence

                       Log Likelihood = -2585.98
                    Schwarz Criterion = -2669.12
               Hannan-Quinn Criterion = -2634.22
                     Akaike Criterion = -2611.98
                              Estimate  Std. Err.   t Ratio  p-Value
                              |---------|----------|--------|--------|
Error Correlation Matrix
                Equation 1    Equation 2
Equation 1          1.0000
Equation 2       -0.016887        1.0000

Error Correlations = C(i,j) / (1 + |C(i,j)|):
C(2,1)                        -0.01735    0.04213    -0.412    0.681

Equation 1, for Ita inf:
[1]Intercept                  -0.06045    1.00625     -0.06    0.952
[3]Garch-M SD Eq. 1(-2)        0.12808    0.24362     0.526    0.599
[3]Garch-M SD Eq. 2(-2)       -0.02524    0.01437     1.757     0.08
AR1(1,1)                       0.44345    0.04665     9.506        0
AR4(1,1)                       0.08005    0.04233     1.891    0.059
AR5(1,2)                        0.0693    0.01532     1.302    0.003
AR7(1,1)                       0.09614    0.03568     2.695    0.007
AR12(1,1)                      0.34089    0.04348      7.84        0
AR13(1,1)                      0.13212    0.03917     3.373    0.001
GARCH Intercept^(1/2)          0.19967     0.1725    ------   ------
GARCH Alpha1(2,2)              0.11345    0.03702     3.064        0
GARCH Beta1(2,2)               0.85989    0.07611    11.297        0
[G2]Ita inf(-1)                0.19226    0.07645     2.515    0.012
              Residual Sum of Squares =  1492.1
                            R-Squared =  0.6649
                        R-Bar-Squared =   0.658
                          Residual SD =  1.5948
                    Residual Skewness =   0.434
                    Residual Kurtosis =  3.8075
                     Jarque-Bera Test = 35.0758      {0}

Equation 2, for Ita out:
[1]Intercept                  -0.01676    1.10977    -0.015    0.988
[3]Garch-M SD Eq. 1(-4)       -1.34473    0.71239    -1.851    0.065
[3]Garch-M SD Eq. 2(-4)        0.12749    0.15126     0.843      0.4
AR1(2,2)                       0.26557    0.04433     5.991        0
AR5(2,1)                      -0.67705    0.31006    -2.184    0.029
AR5(2,2)                       0.08236    0.04072     2.023    0.044
AR6(2,2)                       0.14371    0.04474     3.212    0.001
GARCH Intercept^(1/2)          3.83671     0.8419    ------   ------
GARCH Alpha1(2,2)               0.1554     0.0675     2.302        0
GARCH Beta1(2,2)               0.83809    0.07181    11.671        0

              Residual Sum of Squares = 71289.5
                            R-Squared =  0.1119
                        R-Bar-Squared =  0.0937
                          Residual SD = 11.0277
                    Residual Skewness = -0.0002
                    Residual Kurtosis =  4.2273
                     Jarque-Bera Test = 37.5933      {0}
```

3.7.10. Appendix 3.5.B for Table 3.14

```
System of Equations for
1: Ita inf
2: Ita out
599 observations  (14-612, dates 1961, Mth 3 to 2011, Mth 1) used for estimation
with 13 pre-sample observations.
Estimation Method: Conditional ML (Time Domain)
Gaussian Likelihood
Vector-ARIMA(13,0,0) with GARCH-M(1,1)


Strong convergence

                        Log Likelihood = -3603.92
                    Schwarz Criterion = -3690.28
               Hannan-Quinn Criterion = -3654.03
                      Akaike Criterion = -3630.92
                              Estimate  Std. Err.   t Ratio  p-Value
                             |---------|----------|--------|--------|
Error Correlation Matrix
                Equation 1   Equation 2
Equation 1        1.0000
Equation 2      -0.016887       1.0000

Error Correlations = C(i,j) / (1 + |C(i,j)|):
C(2,1)                        -0.01735    0.04213    -0.412    0.681

Equation 1, for Ita inf:
[1]Intercept                  -0.15007    0.83619    -0.179    0.858
[3]Garch-M SD Eq. 1(-2)        0.12808    0.24362     0.526    0.599
[3]Garch-M SD Eq. 2(-2)       -0.02524    0.01437     1.757     0.08
[2]D1                          0.20867    0.17312     1.205    0.229
[2]D2                          0.06988    0.26229     0.266     0.79
AR1(1,1)                       0.44345    0.04665     9.506        0
AR4(1,1)                       0.21155    0.04658     4.542        0
AR2(1,1)                       0.19503    0.04229     4.612        0
AR5(1,2)                       0.04149    0.02014      2.06     0.04
AR6(1,1)                       0.12954    0.03485     3.717        0
AR13(1,1)                      0.61757    0.04232    14.593        0
GARCH Intercept^(1/2)           2.0524     0.1551    ------   ------
GARCH Alpha1(2,2)              0.08871    0.03628     2.445    0.015
GARCH Beta1(2,2)               0.88397    0.05003    17.669        0
[G2]Ita inf(-1)                0.09592    0.02634     3.642        0
[G2]Ita inf(-5)               -0.07293    0.02746    -2.656    0.008
                Residual Sum of Squares =  153443
                              R-Squared =  0.0391
                          R-Bar-Squared =  0.0198
                            Residual SD = 16.3589
                      Residual Skewness = -0.5974
                      Residual Kurtosis =  6.3045
                        Jarque-Bera Test = 300.456       {0}

Equation 2, for Ita out:
[1]Intercept                   3.03784     0.1212    ------   ------
[3]Garch-M SD Eq. 1(-3)       -0.72783    0.41046    -1.775    0.091
[3]Garch-M SD Eq. 2(-4)        0.11085     0.1669     0.664    0.507
[2]D1                          0.19037    1.44221     0.132    0.895
[2]D2                         -2.61313    1.77152    -1.475    0.141
AR1(2,2)                       0.12117    0.04568     2.653    0.008
AR5(2,1)                       -0.3077    0.16514    -1.863    0.063
AR5(2,2)                       0.10488    0.05224     2.008    0.045
AR6(2,2)                       0.14371    0.04474     3.212    0.001
GARCH Intercept^(1/2)          12.0524     0.5251    ------   ------
GARCH Alpha1(2,2)                0.149    0.06508     2.289    0.022
GARCH Beta1(2,2)               0.85037    0.06243    13.621        0

              Residual Sum of Squares = 77289.5
                            R-Squared =  0.0319
                        R-Bar-Squared =  0.0137
                          Residual SD =   11.49
                    Residual Skewness =  0.0043
                    Residual Kurtosis =  4.1673
                      Jarque-Bera Test = 33.5933       {0}
```

3.7.11. Appendix 3.6.A for Table 3.9

```
System of Equations for
1: fr inf
2: fr out
601 observations  (12-612, dates 1961, Mth 1 to 2011, Mth 1) used for estimation
with 11 pre-sample observations.
Estimation Method: Conditional ML (Time Domain)
Gaussian Likelihood
Vector-ARIMA(12,0,0) with GARCH-M(1,1)

Weak convergence (no improvement in line search)

                    Log Likelihood = -2604.17
                Schwarz Criterion = -2690.55
           Hannan-Quinn Criterion = -2654.28
                 Akaike Criterion = -2631.17
                          Estimate  Std. Err.   t Ratio  p-Value
                         |---------|----------|--------|--------|
Error Correlation Matrix
                Equation 1   Equation 2
Equation 1        1.0000
Equation 2      0.044247       1.0000

Error Correlations = C(i,j) / (1 + |C(i,j)|):
C(2,1)                     0.04678    0.04773      0.98     0.327

Equation 1, for fr inf:
[2]Intercept               0.51849    0.42498      1.22     0.223
Garch-M SD Eq. 1(-4)      -5.81884    2.67581    -2.175      0.03
Garch-M SD Eq. 2(-1)      -0.02657    0.01251    -2.124     0.034
AR1(1,1)                   0.29864    0.07314     4.083         0
AR2(1,2)                   0.00964    0.00264      3.65         0
AR6(1,1)                   0.58464    0.10668      5.48         0
AR9(1,1)                   0.07547    0.04118     1.833     0.067
[2]GARCH Intercept^(1/2)   1.04228     0.2194    ------    ------
GARCH Alpha1(1,1)          0.19155    0.06635     2.887     0.004
GARCH Beta1(1,1)           0.69001    0.07307     9.443         0
[G2]fr inf(-2)             0.12634     0.0511     2.472     0.014
              Residual Sum of Squares = 991.736
                            R-Squared =  0.5815
                        R-Bar-Squared =  0.5726
                          Residual SD =  1.2992
                    Residual Skewness =  0.2761
                    Residual Kurtosis =  7.5186
                     Jarque-Bera Test = 518.935     {0}


Equation 2, fr out:
[2]Intercept               9.94032    1.35455     7.338         0
Garch-M SD Eq. 1(-3)      -6.69063    1.58313    -4.226         0
Garch-M SD Eq. 2(-2)      -0.22077    0.09751    -2.264     0.024
AR2(2,2)                   0.20018    0.04824      4.15         0
AR6(2,1)                  -0.56295    0.26663    -2.111     0.035
AR10(2,1)                 -0.50019     0.2736    -1.828     0.068
[2]GARCH Intercept^(1/2)   4.88612      0.251    ------    ------
GARCH Alpha1(2,2)          0.35443    0.10554     3.358         0
GARCH Beta1(2,2)           0.25731    0.11647     2.209     0.017
              Residual Sum of Squares =  100624
                            R-Squared =  0.0107
                        R-Bar-Squared = -0.0103
                          Residual SD = 13.0832
                    Residual Skewness = -2.5811
                    Residual Kurtosis = 28.8493
                     Jarque-Bera Test = 17399.9     {0}
```

3.7.12. Appendix 3.6.B for Table 3.15

```
System of Equations for
1: fr inf
2: fr out
601 observations  (12-612, dates 1961, Mth 1 to 2011, Mth 1) used for estimation
with 11 pre-sample observations.
Estimation Method: Conditional ML (Time Domain)
Gaussian Likelihood
Vector-ARIMA(12,0,0) with GARCH-M(1,1)

Weak convergence (no improvement in line search)

                       Log Likelihood = -3034.94
                    Schwarz Criterion = -3111.71
               Hannan-Quinn Criterion = -3079.48
                     Akaike Criterion = -3058.94
                            Estimate  Std. Err.   t Ratio  p-Value
                           |---------|----------|--------|--------|
Error Correlation Matrix
                Equation 1   Equation 2
Equation 1        1.0000
Equation 2      0.041247       1.0000

Error Correlations = C(i,j) / (1 + |C(i,j)|):
C(2,1)                       0.01735    0.04213     0.412    0.681


Equation 1, for fr inf:
[2]Intercept                 0.51849    0.42498      1.22    0.223
Garch-M SD Eq. 1(-3)         4.42884    2.80581     1.578     0.03
Garch-M SD Eq. 2(-1)        -0.03657    0.01251    -2.923    0.034
[2]D1                       -0.05132    0.56946     -0.09    0.928
[2]D2                        0.55629     0.8703     0.639    0.523
AR2(1,1)                     0.19503    0.04229     4.612        0
AR5(1,2)                     0.04149    0.02014      2.06     0.04
AR6(1,1)                     0.12954    0.03485     3.717        0
AR12(1,1)                    0.61757    0.04232    14.593        0
[2]GARCH Intercept^(1/2)     1.04228     0.2194    ------   ------
GARCH Alpha1(1,1)             0.1614    0.01505    10.724    0.009
GARCH Beta1(1,1)             0.70915    0.08855     8.008    0.005
[G2]fr inf(-1)               0.10634     0.0411     2.587    0.015
              Residual Sum of Squares = 1072.42
                            R-Squared =  0.4154
                        R-Bar-Squared =  0.4015
                          Residual SD =  3.3255
                    Residual Skewness =  0.2031
                    Residual Kurtosis =  4.5842
                     Jarque-Bera Test =  66.864     {0}

Equation 2, for out:
[2]Intercept                 9.94032    1.35455     7.338        0
Garch-M SD Eq. 1(-3)        -5.60363    1.49313    -3.752        0
Garch-M SD Eq. 2(-2)         -0.3027    0.13751    -2.201    0.024
[2]D1                       -0.05132    0.56946     -0.09    0.928
[2]D2                        0.55629     0.8703     0.639    0.523
AR10(2,2)                    0.50019     0.2736     1.828    0.068
AR5(2,2)                     0.12117    0.04568     2.653    0.008
AR3(2,1)                    -1.44503    0.76855     -1.88    0.061
[2]GARCH Intercept^(1/2)     4.88612      0.251    ------   ------
GARCH Alpha1(2,2)            0.34709    0.10417     3.331        0
GARCH Beta1(2,2)             0.25028    0.11427     2.190    0.017
              Residual Sum of Squares = 101524.2
                            R-Squared =  0.1828
                        R-Bar-Squared =  0.1632
                          Residual SD =  8.4226
                    Residual Skewness =  -0.492
                    Residual Kurtosis =  4.8234
                     Jarque-Bera Test = 107.327     {0}
```

Appendix 3.7.A for Table 3.10

```
System of Equations for
1: Can inf
2: Can out
600 observations  (13-543) used for estimation
with 12 pre-sample observations.
Estimation Method: Conditional ML (Time Domain)
Gaussian Likelihood
Vector-ARIMA(12,0,0) with GARCH-M(1,1)

Strong convergence
                      Log Likelihood = -3106.33
                   Schwarz Criterion = -3225.71
              Hannan-Quinn Criterion = -3176.48
                    Akaike Criterion = -3144.94
                               Estimate  Std. Err.   t Ratio  p-Value
                              |---------|----------|--------|--------|
Error Correlation Matrix
                Equation 1   Equation 2
Equation 1        1.0000
Equation 2      0.015062       1.0000

Error Correlations = C(i,j) / (1 + |C(i,j)|):
C(2,1)                          0.01545    0.04734     0.326    0.744

Equation 1, for Can inf:
[2]Intercept                    0.14748    1.13224      0.13    0.896
Garch-M SD Eq. 1(-2)            0.10854    0.24677      0.44     0.66
Garch-M SD Eq. 2(-1)           -0.12892    0.67109    -0.192    0.015
AR1(1,1)                        0.09471    0.04642      2.05    0.042
AR2(1,2)                        0.04168     0.0147     2.835    0.005
AR3(1,1)                        0.15763    0.03652     4.316        0
AR9(1,1)                        0.09742    0.03874     2.515    0.012
AAR12(1,1)                      0.49303    0.04499    11.004        0
[2]GARCH Intercept^(1/2)        0.74691      0.251    ------   ------
GARCH Alpha1(1,1)               0.19155    0.06635     2.887    0.004
GARCH Beta1(1,1)                0.69001    0.07307     9.443        0
[G2]Can inf(-1)                -0.76511    0.44816    -1.707    0.067
[G2]Can inf(-2)                 0.90362    0.41646     2.169     0.57
              Residual Sum of Squares = 6443.02
                            R-Squared =  0.4187
                        R-Bar-Squared =  0.4078
                          Residual SD =  3.3101
                    Residual Skewness =  0.2322
                    Residual Kurtosis =  4.6347
                     Jarque-Bera Test =  72.202     {0}

Equation 2, for Can out:
[2]Intercept                    6.08973    1.06918     5.696        0
Garch-M SD Eq. 1(-2)           -0.20557    0.08433     2.437    0.032
Garch-M SD Eq. 2(-2)            1.63142    2.80594     0.583    0.559
AR2(2,2)                        0.12795    0.04549     2.813    0.005
AR3(2,2)                        0.07184    0.04202      1.71    0.088
AR4(2,2)                        0.08236    0.04072     2.023    0.044
AR10(2,1)                      -0.67705    0.31006    -2.184    0.029
[2]GARCH Intercept^(1/2)        4.68788     0.7799    ------   ------
GARCH Alpha1(2,2)               0.32443    0.10054     3.226    0.001
GARCH Beta1(2,2)                0.29731    0.11647     2.552    0.008
              Residual Sum of Squares = 42081.5
                            R-Squared =  0.1709
                        R-Bar-Squared =  0.1554
                          Residual SD =  8.4595
                    Residual Skewness = -0.3899
                    Residual Kurtosis =  4.8394
                     Jarque-Bera Test = 99.7879     {0}
```

Appendix 3.7.B for Table 3.16

```
System of Equations for
1: Can inf
2: Can out
600 observations  (13-543) used for estimation
with 12 pre-sample observations.
Estimation Method: Conditional ML (Time Domain)
Gaussian Likelihood
Vector-ARIMA(12,0,0) with GARCH-M(1,1)
Strong convergence
                       Log Likelihood = -3603.92
                    Schwarz Criterion = -3690.28
               Hannan-Quinn Criterion = -3654.03
                     Akaike Criterion = -3630.92
                              Estimate  Std. Err.   t Ratio  p-Value
                             |---------|----------|--------|--------|
Error Correlation Matrix
               Equation 1   Equation 2
Equation 1        1.0000
Equation 2      0.015062       1.0000

Error Correlations = C(i,j) / (1 + |C(i,j)|):
C(2,1)                         0.01545    0.04734     0.326    0.744
Equation 1, for Can inf:
[2]Intercept                  -1.71596    0.22926    -3.123    0.002
[3]Garch-M SD Eq. 1(-2)        0.09647    0.20957     0.459    0.744
[3]Garch-M SD Eq. 2(-1)       -0.13645    0.0405      3.369    0.061
[2]D1                         -0.50412    0.31236    -1.614    0.107
[2]D2                         -0.00456    0.55935    -0.008    0.993
AR1(1,1)                       0.09742    0.03874     2.515    0.012
AR2(1,2)                        0.0162    0.00581     2.788    0.005
AR3(1,2)                        0.0187    0.00703     2.659    0.008
AR10(1,2)                      0.11250    0.03253     3.506        0
AR12(1,1)                      0.49303    0.04499    11.004        0
[2]GARCH Intercept^(1/2)        2.0324     0.1521    ------   ------
GARCH Alpha1(1,1)              0.15354    0.06918     2.219     0.01
GARCH Beta1(1,1)               0.74067    0.12114     6.114        0
[G2]Can inf(-1)               -0.74411    0.4051     -1.836    0.092
[G2]Can inf(-3)                0.91862    0.43579      2.21    0.027
              Residual Sum of Squares =  6504.6
                            R-Squared =  0.3237
                        R-Bar-Squared =  0.3093
                          Residual SD =  3.3302
                    Residual Skewness =  0.6114
                    Residual Kurtosis =  4.3155
                     Jarque-Bera Test = 80.6511       {0}
Equation 2, for Can out:
[2]Intercept                   1.63142    2.80594     0.583    0.559
[3]Garch-M SD Eq. 1           -0.19575    0.03289    -5.951    0.001
[3]Garch-M SD Eq. 2            1.65766    0.14074     1.453    0.326
[2]D1                         -1.21372    1.46432    -0.289    0.408
[2]D2                           4.9004    3.13255     1.564    0.118
AR1(2,2)                       0.32533    0.04181     7.781        0
AR2(2,2)                        0.1927    0.04442     4.338        0
AR4(2,2)                       0.07184    0.04202      1.71    0.088
AR10(2,1)                     -0.41607    0.18037    -2.324    0.028
[2]GARCH Intercept^(1/2)       12.4734     0.5004    ------   ------
GARCH Alpha1(2,2)              0.30154    0.10771     2.799    0.001
GARCH Beta1(2,2)               0.32638    0.12057     2.706    0.002
              Residual Sum of Squares =  235724
                            R-Squared =  0.1259
                        R-Bar-Squared =  0.1073
                          Residual SD = 20.0339
                    Residual Skewness = -0.5407
```

Modelling Inflation with Structural Breaks
The case of Turkey, Syria and Egypt

4.1. Introduction

Inflation rates have become crucial determinants in driving the economy for a number of countries especially for developing countries such as Syria, Turkey and Egypt. Hence, it is important to study the effects of inflation rates in these countries.

We have chosen these countries as an example of developing economies and on the basis that three of them are affected by economic and political problems. In addition, according to the history of Turkey, Egypt and Syria we can detect that the economic policies in these countries are mostly affected by political problems and therefore economic conditions were uncertain and changeable from time to time.

Particularly, political uncertainty has effects on economic activities like stock prices that mostly respond to political news (Ľuboš and Veronesi 2013), especially when the economy is weak as it is in the most of developing countries. In addition, political risk affects employment, foreign direct investment (FDI), capital flow, exports and imports (see Gourinchas and Jeanne (2013), Hayakawa et al (2013), Ahmed and Greenleaf (2013) and Liargovas and Skandalis (2012)).

In this essay, our study is contributing new knowledge to what is already known from previous studies GöktaG and DiGbudak (2014) and Li and Wei (2015).

GöktaG and DiGbudak (2014) used the CPI data for the period of 1994:01–2013:12. Both TGARCH) and EGARCH models were employed to investigate inflation in Turkey. Moreover, Using Bai-Perron (2003) breakpoints specification technique structural breaks. Li and Wei (2015) studied statistically the number of structural breaks in China's inflation persistence based on the monthly retail price index (MRPI) and the quarterly retail price index (QRPI) inflation series from 1983 to 2011.

Thus, we update these previous studies to examine the inflation rates for three developing countries Turkey, Syria and Egypt by applying the Bai and Perron (2003) breakpoint specification technique in the monthly inflation data of our sample. In order to study the inflation rates, we employ GARCH model to control the breaks in the conditional mean and variance equations. In particular, the consumer price index (CPI) has been used as the proxy for the inflation rates (price level).

In this study, we examine the inflation rates for three developing countries Turkey, Syria and Egypt by applying the Bai and Perron (2003) breakpoint specification technique in the monthly inflation data of our sample. In order to study the inflation rates, we employ GARCH model to control the breaks in the conditional mean and variance equations. In particular, the consumer price index (CPI) has been used as the proxy for the inflation rates (price level).

Although several studies have been conducted for these three developing countries, this study attempts to be the first study that uses the breakpoints specification in the conditional mean and variance in the GARCH models.

Since there are many factors that may cause structural changes in the economy of the aforementioned countries, structural breaks have been detected by applying Bai and perron (2003). Three different break points in the conditional mean have been identified in each country. Furthermore, three possible break points for each of the inflation rates in the conditional variance have been determined by applying Bai and peroon (2003) technique as well.

Hence, we obtain significant impact of the three breaks in conditional mean, whereas only one breakpoint in the conditional variance has significant effect.

This study is organized as follows. Section 2 reviews the empirical literature to date. Section 3 describes the model specifications and the econometric methodology. Section 4 presents the data and variables used in the analysis. Section 5 reports results discussion. Finally, the conclusions are presented in Section 6.

4.2. Empirical Literature:

Recent time-series studies have focused particularly on the GARCH conditional variance of inflation as a statistical measure of nominal uncertainty.

According to our case study, Berument, et al. (2001) modelled inflation uncertainty in Turkey using an EGARCH framework that is based on monthly CPI data between 1986 and 2001. Berument, et al. (2001) use seasonal dummies due to financial crises in 1994 in the mean and variance equations. The main findings show that monthly seasonality has a significant effect of inflation uncertainty.

In addition, the effects of inflation uncertainty of positive shocks to inflation are greater than that of negative shocks to inflation. Also, there is no significant effect of inflation on its uncertainty when a dummy of financial crises in 1994 is included in mean equation. In a similar manner, Neyapti and Kaya (2001) used an autoregressive conditional heteroskedasticity (ARCH) model to measure inflation variability and to test the relationship between the level and variability of the inflation rate using the monthly wholesale price between 1982 and 1999. Moreover, a significant positive correlation resulted between inflation and its uncertainty.

Using different framework, Berument, et al. (2011) investigated the interaction between inflation and inflation uncertainty in Turkey using monthly data for the time period 1984 – 2009. The stochastic volatility in mean (SVM) model that they used allows for gathering innovations to inflation uncertainty and assesses the effect of inflation volatility shocks on inflation over time. Berument, et al. (2011) indicated that response of inflation to inflation volatility is positive and statistically significant. However, the response of inflation volatility to inflation is negative but not statistically significant.

Ozdemir and Saygili (2009) used P-stare model to explain inflation dynamics in Turkey where money plays an important role in P-stare model by determining the price gap, which is postulated to measure the pressure on prices in the economy. The results showed that the price gap does indeed contain considerable information for explaining inflation dynamics in Turkey. Also, money is efficacious in predicting risk to price stability.

Earlier, Ozcan, et al. (2004) proposed that there is inflation inertia in Turkey during 1988 -2004 using model-free techniques model. The found evidence supports that there are correlations between the housing rent, US dollar and German mark exchange rate on one side, and Turkish CPI on the other side.

Applying simple models, Helmy (2010) studied inflation dynamics in Egypt by using annual data and Granger causality tests, simple VAR, impulse response functions (IRF) and variance error decomposition (VDC) analyses to test the sources and dynamics of inflation in Egypt. The result of interest is that the inflation in Egypt is affected mainly by growth of money supply, interest rates and exchange rates.

In addition, Ghalwash (2010) addressed whether a scientific support of the inflation targeting regime for Egypt is existing or not in theoretical manner that is extracted by a simple VAR model. The result implies that the Central Bank of Egypt and the Egyptian economy is not yet ready for the implementation of an inflation targeting regime.

Although the welfare cost of inflation and inflation uncertainty are considered well by Helmy (2010), the mentioned relational is still insignificant in the case of Egypt. Therefore, Sharf (2015) studied the casual relationship between inflation and inflation uncertainty in Egypt by applying time series and using monthly data over period January 1974 - April 2015. In addition, Sharf (2015) followed Ziovt and Andrew (2002) and clemente et al (1998) to control endogenous related to any potential structural breaks in the time series methods of inflation. In his study, GARCH_M model has employed to consider any feedback impacts. In addition, he accounted for (ERSAP) which considered by the Egyptian government in early 1990s. his findings was in line with Friedman –Ball and Cukierman –Meltzer hypotheses. Moreover, his results agree of adopting inflation targeting policy in Egypt. So, the reliability of monetary policy and reducing the inflation uncertainty should prompt by monetary authorities.

Using similar methods but different sample, Karahan(2012) examined the link between inflation and inflation uncertainty in Turkey during 2002 to 2011 by applying two step technique. For first step, monthly inflation data and ARMA-GARCH are tested. Then, the calculated conditional variance from these tests is considered as monthly inflation uncertainly series. In the second step, he applied the causality tests between original inflation and the series of generated inflation uncertainty. His study corroborates the ideas of Friedman’s hypothesis, who demonstrated that when there is inflationary times cause high inflation uncertainty in

Turkey. In addition, his findings imply that the inflation targeting monetary policy is credible after 2002 in Turkey.

The inflation uncertainty in the Turkey was modelled by GöktaG and DiGbudak (2014). In this study, the authors used monthly CPI data as proxy of Turkish inflation rates. The CPI index was obtained for the period of 1994:01–2013:12. Both symmetric and asymmetric GARCH-type models were employed. Moreover, a structural break in the series had been investigated since there are many factors that may lead to structural change within the economic course of Turkey. Using Bai-Perron (2003) breakpoints specification technique, two different break points in mean and variance had been detected to be in the mean in February 2002 and the break occurring in the variance in June 2001.

Among the most widely used GARCH-type symmetric models, we examined ARCH and GARCH while, among the asymmetric models, GJR-GARCH (TGARCH) and EGARCH were examined to find the most appropriate one. ARCH and EGARCH models were determined to be the most appropriate models

The inclusion of those break points in the related equations led to the projection of appropriate forecasting models. Moreover, it was found that while in the periods prior to the break in both variance and mean, the inflation itself was the reason for inflation uncertainty. However, following the dates of the break, the relationship changed bidirectionally. In the meantime, when the series was taken as a whole without considering the break, bidirectional causality relationship was also detected.

In a forthcoming study by Khan (2016) tested directly the effect of inflation on output growth variability using a large panel of 25 developed and emerging European economies. In the empirical estimation, the author mainly followed Lucas (1973), signal extraction model. The data that were used in this paper to measure the output variability based on both monthly (IPI) over the period (2000:01 to 2012:12), quarterly (IPI) over the period (1998:Q1 to 2012:Q4) as well. In addition, CPI data is used as a proxy of inflation rate. His results support the argument of nonlinear relationship between the two variables and advance certain inflation thresholds below, whereas the inflation appeases the sectoral output growth variability and above this level it aggravates the later.

4.3. Methodology:

In this Section, for the three inflation rates, we have applied GARCH models with structural breaks (for applications of GARCH-in-mean models to inflation see, among others, Baillie et al, 1996, Conrad and Karanasos, 2010, Conrad and Karanasos 2015 and the references therein).

Let y_t denote the inflation rate at time *t* and define its mean equation as:

$$y_t = \varphi_0 + \sum_{\tau=1}^{3} \varphi_0^{\tau} D_t^{\tau} + (\varphi_1 + \sum_{\tau=1}^{3} \varphi_1^{\tau} D_t) y_{t-1} + \varepsilon_t \qquad (4.1)$$

Where $\varepsilon_t \,/\, \Omega_{t-1} \sim N(0, \sigma_t^2)$ is the innovation, which is conditionally (as of time $t-1$) normally distributed with zero mean and conditional variance σ_t^2. D_t^{τ} are dummy variables defined as 0 in the period before each break and 1 after the break. The breakpoints τ = 1; 2; 3 are given in Tables 4.2 and 4.3. In addition, σ_t^2 is specified as a GARCH(1; 1) process:

$$h_t = \omega + \alpha \varepsilon_{t-1}^2 + (\beta + \sum_{\tau=1}^{3} \beta^{\tau} D_t^{\tau}) h_{t-1} \qquad (4.2)$$

where α and β denote the ARCH and GARCH parameters.

4.4. Data and Variables:

Monthly data is used on the monthly CPI as proxy for the price level in Turkey, Syria and Egypt. The data available from 1957:01 to 2011:02 (with the exception of Turkey which data are available from 1969:02)

Then Let y_t denote the inflation rate at time t, where [$y_t = \log(CPI_t/CPI_{t-1}) \times 100$].

Table 4. 1 Summary statistic for inflation in Turkey, Syria and Egypt:

	Turkey	Syria	Egypt
Mean	2.751742	0.686196	0.686196
Median	2.290054	0.654961	0.654961
Maximum	22.07831	12.69319	12.69319
Minimum	-6.442225	-13.90898	-13.90898
Std. Dev.	2.673235	2.726204	2.726204
Skewness	1.645259	-0.000599	-0.000599
Kurtosis	11.05003	5.613953	5.613953
Jarque-Bera	1591.393 (0.000)	189.6088 (0.000)	189.6088 (0.000)
Sum	1389.630	457.0067	457.0067
Sum Sq. Dev.	3601.676	4942.407	4942.407
ADF test	-10.29817{<0.01}	-4.210868{<0.01}	-4.210868{<0.01}
PP test	-19.00086{<0.01}	-23.60727{<0.01}	-23.60727{<0.01}

All data are International Financial Statistic (IFS). Sample period is monthly, from 1960:01 to 2011:01 (with the exception of Canada which data are available from 1965:10). Monthly inflation rates are calculated from the Consumer Price Index at an annual rates. The numbers in parenthesis are robust *P – value.*

The summary statistics in (Table 4.1) imply that inflation rates in Turkey are positively skewed whereas inflation rate in Egypt and Syria are skewed negatively. Moreover, displaying significant amounts of excess kurtosis with both series is failing to satisfy the null hypothesis of the Jarque-Bera test for normality. In other words, the large values of the Jarque–Bera statistics imply a deviation from normality. In addition, the results of augmented Dickey–Fuller (1979) and Phillips-Perron (1988) unit root tests imply that we can treat the two rates as stationary processes

In addition, the results of augmented Dickey–Fuller (1979) and Phillips-Perron (1988) unit root tests imply that we can treat the two rates as stationary processes

The inflation rates for the Turkey are plotted in Figure 4.1, however, the graphs reveal that Turkish economy was suffered by the effect of the sharp increase in the world oil prices in 1973 – 1974; the government had failed to take sufficient measure to adopt to the effect of 1973s oil crisis. These government's efforts had finished the resulting deficits with short-term loans from foreign lenders (see Onder (1990) and Rodrik (1990)).

By 1979, Turkish economy stood in a foreign exchange crisis, with negative growth, the inflation into triple-digit levels, and wide spread shortages (Rodrik (1990)).

After unsuccessful efforts in 1978-1979 and the two failed IMF program in the early 1980s where the purpose of this program was to liberalize the economy to create a market based system, to reduce inflation, and to increase the efficiency of the banking sector (Feridun (2008)); the Turkish government has announced new strategy called for imports-substitution policy that designed to encourage exports that could finance imports.

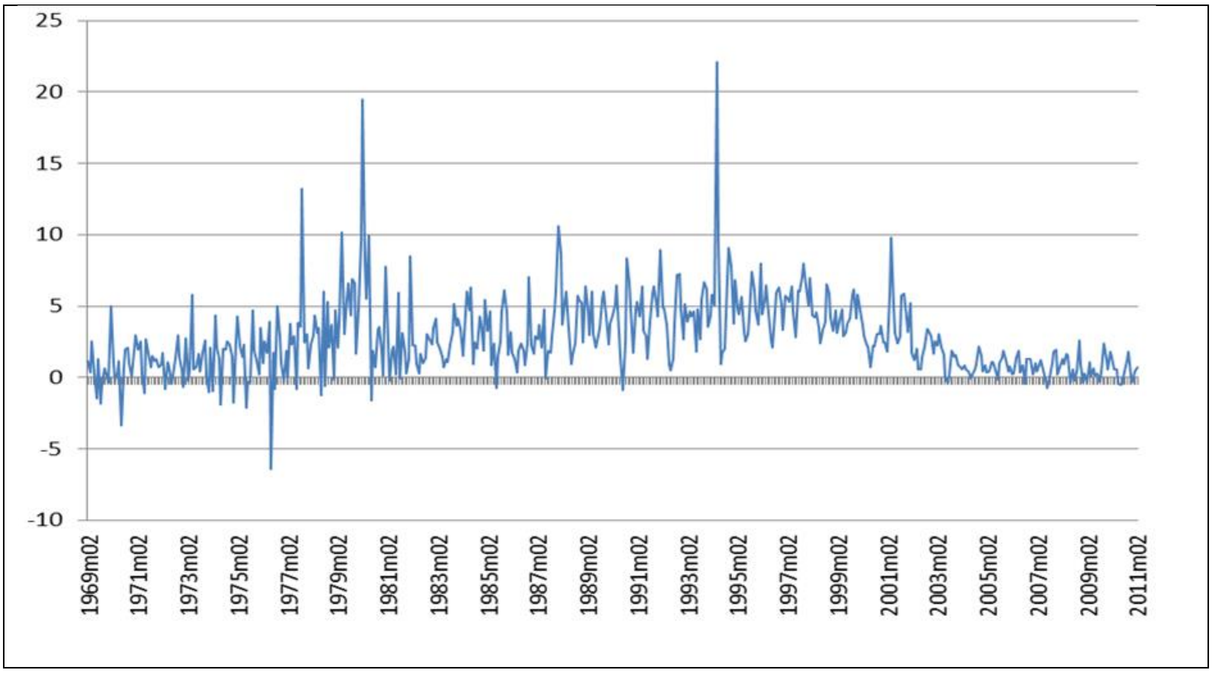
Thus, Turkish economy after the reforms in 1980 became on an outwardly oriented course (Aricanli and Rodrik (1990)). However, the far reaching stabilization package yield was not as planed and expected where imports increased more than exports. Moreover, in 1985, housing and tourism had been the only sectors experiencing a noticeable increase in private investment (Aricanli and Rodrik (1990)). Hence, there was an increasing in investment in 1986 and 1987.

In addition, because of the liberalization of the capital account in August 1989; the Turkish economy experienced a massive inflow of short-term capital and the he threat of capital reversals became an important motive in policymaking, which required a firm commitment to high interest rates (Feridun (2008)).

After that, the economy attended two major currency crises in 1994 and 2000 – 2001, because of the liberalization of the capital account that caused increasing of the Turkish lira by 22% by the end of 1989. Thereafter (Kibritçioğlu, et al (1999) and Feridun (2008)).

Regarding to the sample after the end of 2000, we notice that the effect of adopting an 'exchange-rate-based stabilization program', a quick-fix policy to lower inflation based on the crawling-peg exchange-rate regime in Turkey (Berument, Yalcin and Yildirim (2011)).

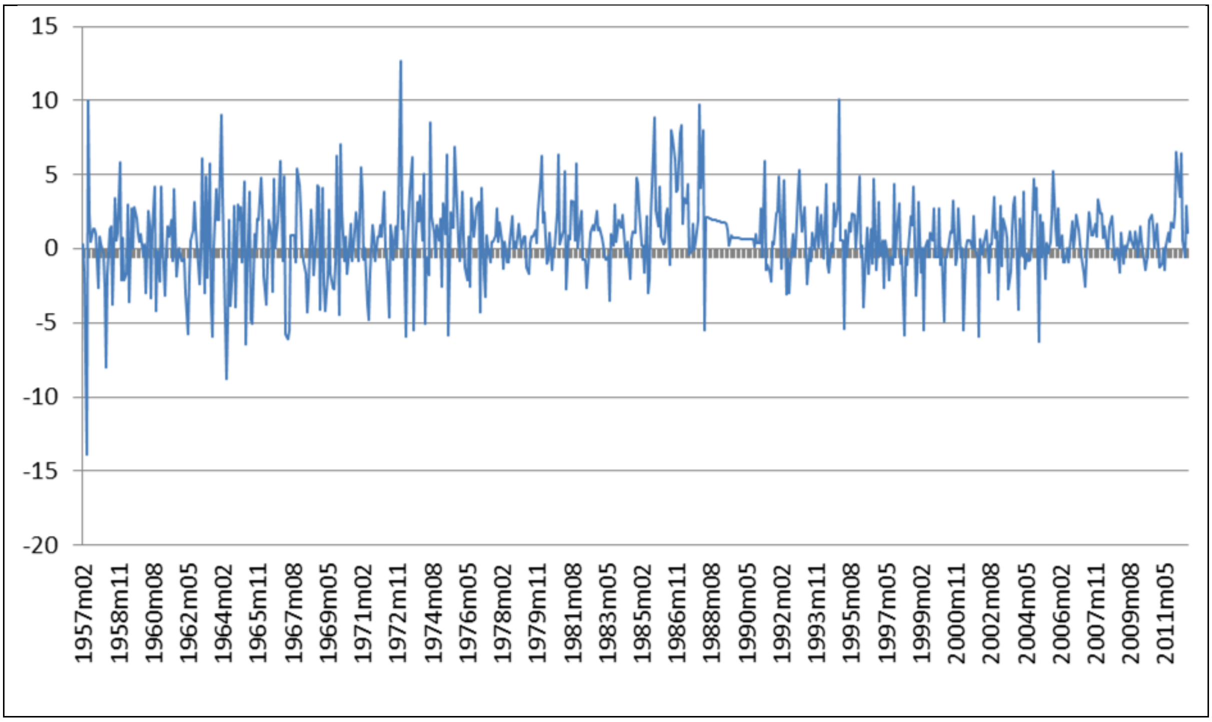
Figure 4.1 Inflation of Turkey over time:



In Syria, Figure 4.2 indicates many outlier points and breaks that might be due to the crisis. The outlier samples show that average inflation fell between 1963 to mid-1977 that might due to politic crisis and events. In 1963, a new strategy was performed in the early 1963 by the law of nationalization.

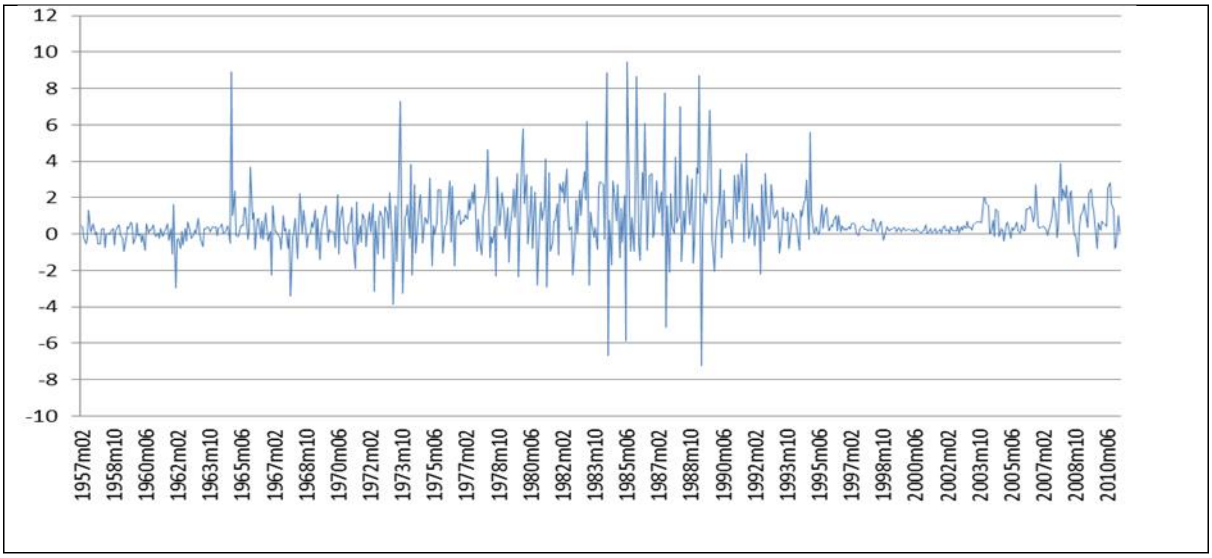
The conflict with Israel, which caused wars in June 1967 and October 1973, was ended partly by disengagement agreements. In other words, this period affected the Syrian economy by the high cost of state of war with Israel.

Figure 4.2 Inflation of Syria over time:



Also, between 1979 to late 1982 due to civil war as well as the same position after med-2011. In addition, in 1991 a new economic policy reformed new exchange rates system allowed privet sector to invest. Moreover, Syria faced variety of sanctions; US since 1979 and European sanctions from 1985 to 1990.

Figure 4.3 Inflation of Egypt over time:



For Egyptian inflation rates in Figure 4.3, we consider three subsamples. The first one is from 1970 to 1990 where Egypt turned away from the Soviet Union and initiated an economics open-door policy (see Lofgren (1993)). Since then, the IMF and the World Bank encouraged comprehensive reform that would make Egypt an outward looking market-oriented capitalist economy in which the privet sector plays a command role.

Secondly, the inflation rate reminded relatively stable over the period from 1990 to 2004. In 1991 the Egyptian government began to perform IMF recommendation for improving the area of pricing, the foreign exchange system, interest rates, the money supply and the budget deficit (Lofgren (1993)). Finally, since 2004, the volatility of inflation rates increased after implementing series of reforms including tariff reduction, tax administration and public expenditure management.

4.5. Empirical Analysis:

4.5.1. Estimated Breaks:

Factors such as political changes and wars, economic crisis, technological innovations influence macroeconomic time series developments. Therefore, it is essential that these elements are considered in research otherwise models can suffer from making mistakes at the very early stage of forecasting process to wrong model determination. Hence, it is very important to identify possibility of any structural break of the variables considered. One of the widely used methods to test the existence of a structural break is Bai-Perron test which allows internal and multiple breaks. This method was introduced by Bai (1997), Bai and Perron (1998) and Bai and Perron (2006).

Forecasting the number and the location of breaks with their autoregressive coefficients is one of the most important attributes of Bai-Perron method. Additionally, allowing heteroskedasticity and autocorrelation in error is another advantage of Bai-Perron procedure. Using Newey-West procedure or including the variables' lags in the model is suggested in order to deal with the nonparametric autocorrelation problem Antoshin, et al (2008) which allows the independent and error term have different distribution for sub-periods.

Below equation represents the model of the Bai and Perron (2003) multiple structural break test and constructed by considering *m* break (m+1 regime).

$$y_t = x_t'\beta + z_t'\delta_j + u_t \qquad (4.3)$$

For j=1, …, m+1, t=T_{j-1}+1,….,T_j and T_0=0 and T_{m+1}=T, y_t depended variable, β and δ_j *(j=1,…,m+1)* corresponding coefficient vectors and (T_1, . . . ,T_m) indexes point out unknow break points.

As the equation 4.3 indicates, vector of independent variables $x_t'\beta$ and $z_t'\delta_j$ on the right hand side of the model are split between two groups of regime specific coefficients and unchanged parameters across sub-periods.

The first break occurs in T_1 in such a way that the first break starts from T=1 and ends in T=T_1 and in T=T_2 in such a way that the second starts from T_1+1 and ends in T_2 Finally, the last break follows the same manner up to *m*th break, the duration begin from T_m+1 and continues until end of the data Bai and Perron (2006).

Before the introduction of Bai-Perron test, SupWald statistics was used by the existing models to identify a break only against null break. However, Bai and Perron test made it possible to examine the alternative hypothesis stating fewer structural breaks against many number of breaks.

While both techniques produce the same results when there is only one structural break, Bai-Perron method is more appropriate as it simultaneously forecasts the breaks and the break points Zhang and Clovise (2009).

Three different tests were introduced by Bai and Perron (2003) for multiple breaks. These alternatives are i) binary maximum test dealing with unknown number of breaks versus null hypothesis, ii) sup-type test of fixed number of breaks versus no break, and iii) sequentially testing break null hypothesis versus single change.

The last proposed method considers a single break in a null hypothesis $l=1$ against alternative hypothesis $l+1=2$ break and continues until the null hypothesis is rejected. In more details, critical values of the operations given by Bai and Perron (2003) starts with l number of breaks and break points are continued to be forecasted until the next test statistic $F(l+1 \mid l)$ becomes insignificant.

The procedure is useful by determining whether additional structural breaks significantly lead to a reduction in the sum of residuals squares.

By applying the Bai and Perron (2003) breakpoint specification technique in the data for three inflation rates in three countries (Turkey, Syria and Egypt). we identify three possible breakpoints for each of the inflation rates (see Tables 4.2 and 4.3 below). The results successfully captured events of great significance, such as the late 1970 soil crises, the global economic crises of the early 1980s (1980 – 1982) and the external debt crises of Egypt during the period covering 1985 – 1990

Table 4. 2 The break points in the conditional mean:

Break	Turkey	Syria	Egypt
1	**1977:06**	**1972:09**	**1973:07**
2	**1987:09**	**1985:08**	**1985:06**
3	**2002:01**	**1988:03**	**1991:10**

Notes: The dates in bold indicate break dates
For which, in Table 4.4 at least one dummy variable is significant.

Table 4. 3 The break points in the conditional variance:

Break	Turkey	Syria	Egypt
1	1979:02	1958:04	**1973:04**
2	1980:05	**1986:07**	1984:05
3	**2002:01**	1988:04	**1989:01**

Notes: The dates in bold indicate break dates
For which, in Table 4.4 at least one dummy variable is significant.

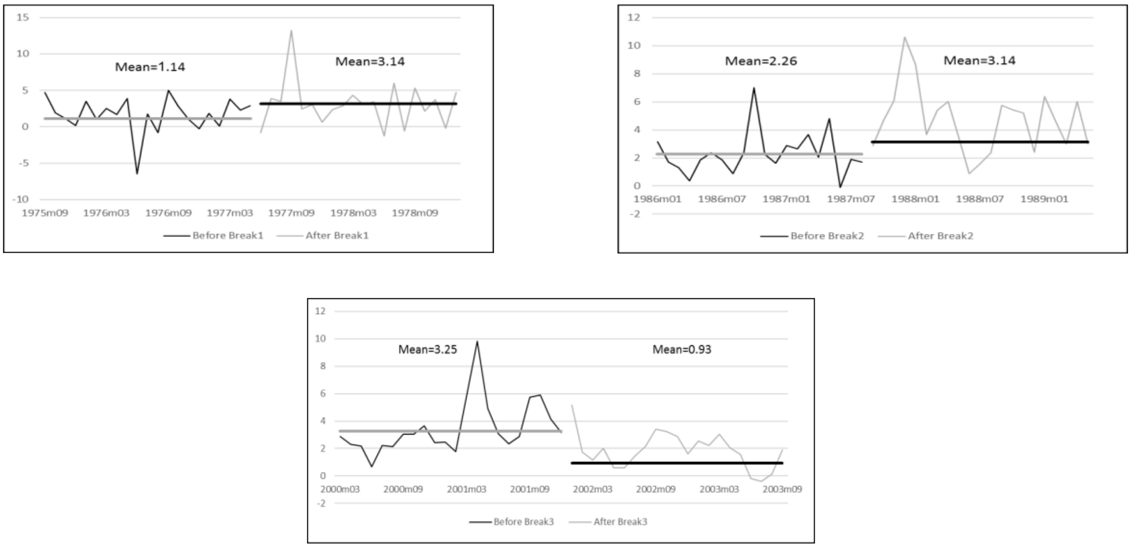
Graphical displays of these significant break points in the conditional mean are given in Figure 4.4, Figuar 4.5 and Figuar 4.6 in Turkey, Syria and Egypt respectively.

Figure 4.4 indicates the structural breaks in Turkey. It shows clearly that Bai perron (2003) breakpoints specification capture many economic events Such as the effect of the sharp increase in the world oil prices in 1973 – 1974. Also the reflection of failing by the Turkish government to take sufficient measure to adopt to the effect of 1973s oil crisis. As a result, deficits with short-term loans from foreign lenders (see Onder (1990) and Rodrik (1990)).

Moreover, there was an increasing in investment in 1986 and 1987 as a result of growing in the housing and tourism sectors experiencing (Aricanli and Rodrik (1990)).

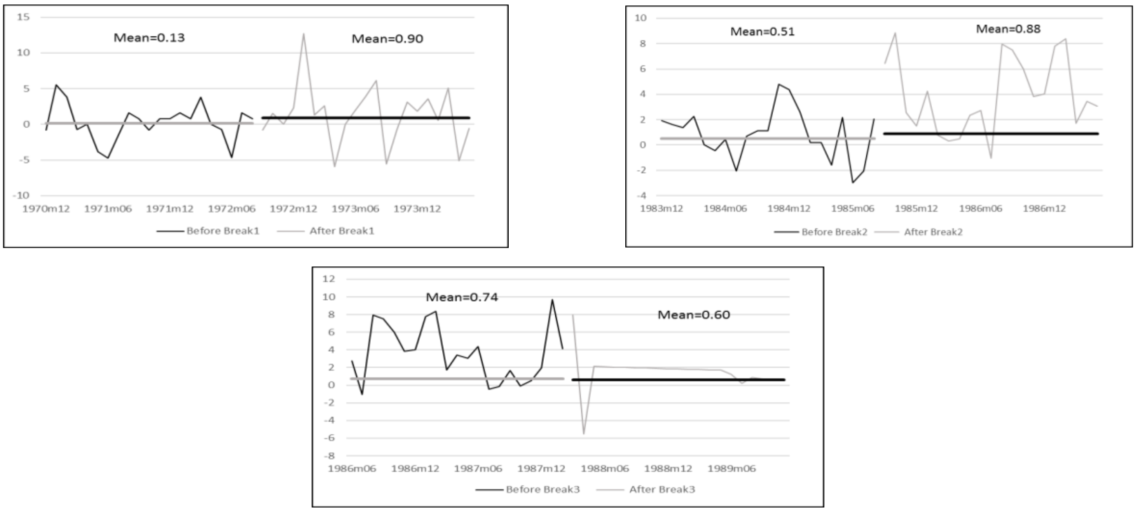
In addition, the effect of adopting an 'exchange-rate-based stabilization program', a quick-fix policy to lower inflation in 2000 based on the crawling-peg exchange-rate regime had a sharp impact in Turkish economy by the beginning of 2002. (Berument, Yalcin and Yildirim (2011)).

Figure 4.4 The break points in the conditional mean for Turkey:



Further, Figure 4.5 below shows the break points in the conditional mean in Syria. The first breakpoint captured the post new political situation period that happened in 1970 and during the period of getting financial grants from other countries.

Figure 4.5 The break points in the conditional mean for Syria:

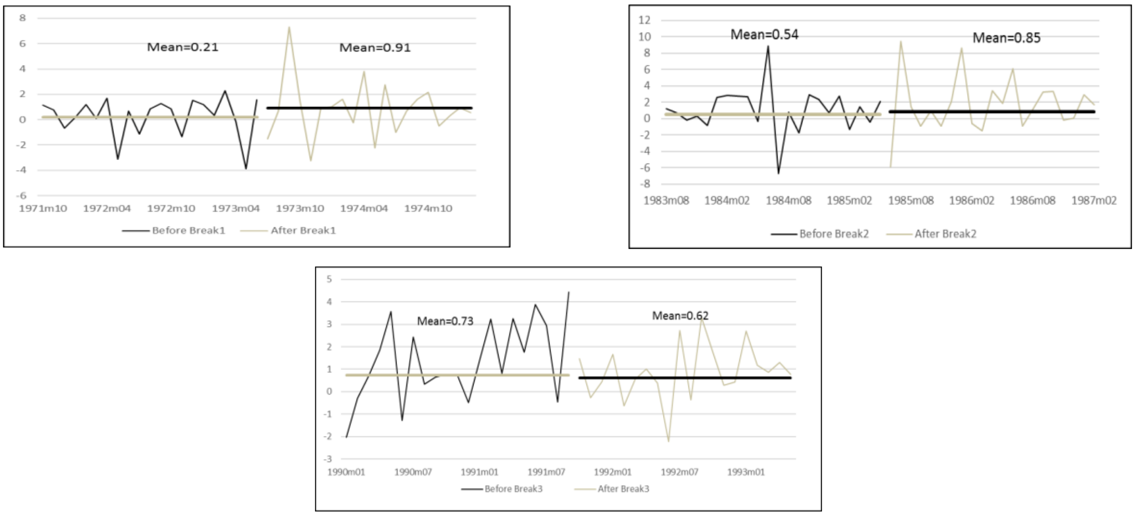


The global economic crises of early 1980s (1980-1982) had light effect on Syrian inflation rate.

As a final point, Figure 4.5 indicates light effect of structural breaks on inflation especially the break at the beginning 1988.

In the end, the structural breaks for Egypt are shown in Figure 4.6. the base point we obtain from Figure 4.6 is the light impact of economic and political events on Egyptian inflation rate.

Figure 4.6 The break points in the conditional mean for Egypt:



4.5.2. Estimated models:

We estimate the GARCH (1,1) model for three inflation rates in Turkey, Syria and Egypt allowing the conditional means and variances to switch across the breakpoints (see equation 4.1 and 4.2) identified by the Bai and Perron (2003) producer.

We use the obtained and significant breakpoints that are indicated in Table 4.2 to create dummy variables (D_t^{τ} and D_t) in the conditional mean that is defined as 0 in the period before each break and 1 in the period after the break.

In addition, we use the significant breakpoints in Table 4.3 to create dummy variables (D_t^{τ}) in the conditional variance that is defined as 0 in the period before each break and 1 in the period after the break.

Table 4.4 points out the estimated parameters for the inflation rates that obtained by quasi-maximum likelihood estimation. Moreover, the best-fitting specification is chosen according to the likelihood ratio results and the minimum value of the information criteria (AIC). Furthermore, the tests for the remaining serial correlation suggested that all the three models seem to be well-specified since there is no autocorrelation in either the standardized residuals or squared standardized residuals at 5% statistical significance level.

The case of two constants (φ,ω) the effects of breaks are significant in all cases, with the exception of the conditional mean equation of Syria and Egypt inflation rates. Whereas, the autoregressive coefficients (φ_1^{τ}) seem to cause a statistically significant impact on the breaks only in the case of Turkey.

Table 4. 4 The estimated GARCH models for Turkey, Syria and Egypt inflation rates allowing for breaks in the conditional mean and variance:

Coefficient	Turkey	Syria	Egypt
Mean Equation			
φ_0	9.23 (7.75)***	1.23 (0.48)	1.54 (1.28)
φ_1	-	0.09 (2.27)**	-
φ_0^1	-	8.18 (2.33)**	10.21 (4.78)***
φ_0^2	-	30.44 (4.77)***	8.04 (2.42)***
φ_0^3	-	-33.47 (-5.46)***	-14.69 (-5.46)***
φ_1^1	0.56 (9.08)***	-	-
φ_1^2	0.21 (3.22)***	-	-
φ_1^3	-0.47 (-5.59)***	-	-
Variance Equation			
ω	49.87 (3.07)***	53.87 (2.84)***	16.21 (2.48)***
α	0.06 (2.87)***	0.07 (2.95)***	0.16 (3.24)***
β	0.88 (30.65)***	0.87 (25.79)***	0.82 (13.07)***
β^1	-	-	0.02 (0.60)
β^2	-	-0.04 (-1.76)*	-
β^3	0.0359 (0.005)	-	-0.19 (-3.38)***
$LB(1)$	0.0359 (0.005)	0.27 (0.60)	0.34 (0.56)
$MCL(1)$	0.0359 (0.005)	0.63 (0.43)	0.04 (0.84)

Notes: Table 4.4 reports parameter estimates for the following model:

Mean Equation: $y_t = \varphi_0 + \sum_{\tau=1}^{3} \varphi_0^{\tau} D_t^{\tau} + (\varphi_1 + \sum_{\tau=1}^{3} \varphi_1^{\tau} D_t) y_{t-1} + \varepsilon_t$

Variance Equation: $h_t = \omega + \alpha \varepsilon_{t-1}^2 + (\beta + \sum_{\tau=1}^{3} \beta^{\tau} D_t^{\tau}) h_{t-1}$

*The number in parentheses represent t-statistics. LB and MCL denote Ljung-Box and McLeod-Li tests for serial correlation of one lag on the standardized and squared standardized residuals, respectively (p-values reported in brackets). ***,**,*, indicates significance at the 1%, 5%; 10% , level respectively.*

In particular, the parameters of the mean equation show time varying characteristics across three breaks. As far as the conditional variance is concerned, the ARCH parameter (α) shows no time varying behaviour while for the GARCH parameter only one significant break seems to impact each of the three inflation rates.

In other words, there is a weak significant break ($\beta^2 = -0.04$) for inflation rate in Syria. Whilst, the structural breaks for inflation in Turkey and Egypt have no significant impact in conditional variance.

Next, we report the persistence of the volatility process in Turkey, Syria and Egypt. Table 4.5 reports the time varying persistence in both the mean and the variance equations. Moreover, we have only considered the significant coefficients that have previously reported in Table 4.4 above.

Table 4.5 Time varying coefficients in GARCH(1,1) processes for Turkey, Syria and Egypt:

	Turkey	Syria	Egypt
$\varphi_1 + \varphi_0^\tau + \varphi_1^\tau$	0.30	5.24	3.56
$\alpha + \beta + \beta^\tau$	0.94	0.90	0.98

Notes: Table 4.4 reports parameter estimates for the following model:
Mean Equation: $y_t = \varphi_0 + \sum_{\tau=1}^{3} \varphi_0^\tau D_t^\tau + (\varphi_1 + \sum_{\tau=1}^{3} \varphi_1^\tau D_t) y_{t-1} + \varepsilon_t$
Variance Equation: $h_t = \omega + \alpha\varepsilon_{t-1}^2 + (\beta + \sum_{\tau=1}^{3} \beta^\tau D_t^\tau) h_{t-1}$

The parameters of the mean equation show time varying characteristics across three breaks. In addition, the sum ($\alpha + \beta$) measures the persistence of the volatility process. A common finding in the literature is that estimates of this sum tend to be close to one, indicating that the volatility is highly persistent. However, it has been argued that this high persistence may be due to structural breaks in the volatility process, (Elyasiani and Mansur 1998), According to the results in Table 4.5, we can notice that volatility is persistent in Egypt higher than the other two countries. This means that it might take a longer time for the variance to return to its long-run level, as shocks should push it away from its long-run level (see Wessam et al 2013).

4.6. Conclusion:

In this study, we examined the inflation rates for three developing countries Turkey, Syria and Egypt by applying the Bai and Perron (2003) breakpoint specification technique in the monthly inflation CPI data of our sample. In order to study the inflation rates, we employed GARCH model to control the breaks in the conditional mean and variance equations.

We applied the Bai and Perron (2003) breakpoint specification technique in our data. We identified three possible breakpoints for each of the inflation rates. The obtained results have successfully captured events of great significance, such as the late 1970 soil crises, the global economic crises of the early 1980s (1980 – 1982) and the external debt crises of Egypt during the period covering 1985 – 1990.

In our finding, the case of two constants (φ, ω) the effects of breaks are significant in all cases, with the exception of the conditional mean equation of Syria and Egypt inflation rates. Whereas, the autoregressive coefficients seem to cause a statistically significant impact on the breaks only in the case of Turkey.

In addition, the parameters of the mean equation show time varying characteristics across three breaks. As far as the conditional variance is concerned the ARCH parameter (α) shows no time varying behaviour while for the GARCH parameter only one significant break seems to impact each of the three inflation rates.

Chapter Five

Conclusion Remarks

In this section, we provide a summary of our results in this thesis. In Chapter 2, we have employed monthly data of inflation in three Mediterranean countries to investigate the potential relationship between inflation and its uncertainty. Moreover, we have used monthly data of output growth in Turkey to capture any possible relationship between output and its uncertainty. By applying a variety of economic hypotheses, the investigation in this chapter showed the following results. Firstly, the overall evidence of the examined economic hypotheses report shows that the Cukierman–Meltzer hypothesis is supported here, which was labelled as the ‘opportunistic Fed’ by Grier and Perry (1998), in bpth Egypt and Syria. Accordingly, the increase in nominal uncertainty could raise the optimal average inflation by increasing the stimulus for the policy-maker to create inflation surprises. In contrast, evidence for the Holland (1995) hypothesis is obtained in Turkey. This result suggested that the ‘stabilizing Fed’ notion is plausible.

Also, the estimation result in Egypt and Turkey is in favour of Friedman (1977) and Ball (1992) where inflation raises its uncertainty, the later creates real welfare losses and then leads to monetary tightening to lower inflation and thus also uncertainty.

In addition, the results about the Turkish output growth showed that there is a support for Pindyck (1991) theory where more raising in growth will lead to less uncertainty.

In addition, there was a significant effect of the economic shock in 1979 as a result of foreign exchange crisis in the Turkish economy, the negative growth, the inflation into triple-digit levels, wide spread shortages and the two major currency crises in 1994 and 2000 – 2001. More precisely, the effect of inflation on its uncertainty had increased 18% after considering the effect of failed economic policies in Tukey. Again, the same finding was obtained for inflation in Syria.

In Chapter 3, monthly data included the CPI and IPI as proxies of inflation and output growth rate for the G7 countries were examined by employing bivariate CCC-GARCH (1,1)-ML models to investigate the relationship among inflation, inflation uncertainty, output growth and real uncertainty.

The findings of this chapter showed that there are evidences of the second leg of Friedman (1977) hypothesis. As the result, inflation uncertainty affects output growth in a negative manner $(h_\pi \overset{-}{\rightarrow} y)$ in the US, the UK, Germany, Italy, France and Canada. While inflation uncertainty affects output growth positively $(h_\pi \overset{+}{\rightarrow} y)$ in Japan as predicted by Dotsey and Sarte (2000). In addition, we provided evidences for positive effect of inflation uncertainty on inflation $(h_\pi \overset{+}{\rightarrow} \pi)$ in the US, Germany, Japan and France which are in line of Cukierman and Meltzer (1986) hypothesis.

Our analysis revealed the negative effect of output uncertainty on inflation $(h_y \overset{-}{\rightarrow} \pi)$ in the case of Italy, France and Canada. Therefore, there was an evidence of Taylor effect and Cukierman and Meltzer (1986). The results in the case of the US, the UK and Germany showed that the evidences of Mirman (1971), Black (1987) and Blackburn (1999) hypotheses were obtained. Finally, the effect of inflation on its uncertainty $\pi \overset{+}{\rightarrow} h_\pi$ was obtained in the case of the US, the UK and Japan. As a result, we had evidences of the first leg of Friedman (1977) and Ball (1992).

Afterward, we re-estimated the bivariate CCC-GARCH (1,1) models including dummy variables in the mean equation, taking into consideration according to some economic and political events in G7 countries. Our results highlight the importance of taking into account the economic and political events in our study. In particular, we found strong support for the two legs of Friedman (1977) hypothesis that is higher inflation increases its uncertainty, and then affects output growth negatively. In addition, our findings support the Cukierman and Meltzer (1986) hypothesis.

In other words, the financial crisis in 2007 has affected all the G7 countries for both their inflation rate and output growth rate. In details, the effect of inflation rate on its uncertainty has been increased in the US, the UK, Germany and Canada. Whereas, it has been decreased in other countries. The effect of inflation uncertainty on output growth rate has been decreased in all the G7 countries with the exception of the US. Lastly, the impact of inflation uncertainty on inflation rate has been increased in the US and Germany. On the contrary, this effect has been decreased in Japan, France and Canada.

Since, Inflation causes uncertainty about future prices, interest rates and exchange rates. This in turn increases the risks among potential trade partners and discouraging trade. The uncertainty that associated with inflation increases the risk associated with the investment and production activity of firms and markets. Our analysis suggests many implications. One policy implication is that reducing inflation rate will reduce the uncertainty about future prices, interest rates, and exchange rates. Then, will lead to an increasing in economic output growth.

Another policy implication from these research is that the effects of economic and political events have to be considered by economic and monetary authority in any future reforms in our sample countries. For example, these economic events changed the effect of inflation uncertainty on output growth rate from positive to negative impact.

Finally, in Chapter 4, we examined the inflation rates for three developing countries that are Turkey, Syria and Egypt by applying the Bai and Perron (2003) breakpoint specification technique in the monthly inflation of our CPI data sample. In order to study the inflation rates, we employed GARCH model to control the breaks in the conditional mean and the conditional variance equations.

In the way of applying breakpoint specification technique, we identified three possible breakpoints for each of the inflation rates. The obtained results have successfully captured great significante events, such as the late 1970 soil crises, the global economic crises of the early 1980s (1980 – 1982) and the external debt crises of Egypt during the period covering 1985 – 1990.

Accordingly, the coefficients of two constants (φ, ω) which represent the effects of breaks are significant in all cases, with the exception of the conditional mean equation of Syria and Egypt inflation rates. Whereas, the autoregressive coefficients seem to cause a statistically significant impact on the breaks in the case of Turkey only.

Moreover, the parameters of the mean equation show time varying characteristics across the three breaks. As far as the conditional variance is concerned the ARCH parameter (α), it shows no time varying behaviour while for the GARCH parameter only one significant break seems to impact each of the three inflation rates.

Our future research could focus on investigating the impact of inflation uncertainty on output growth in developing countries. In addition, it might focus on the causal relationships between inflation rate, output growth and interest rate using trivariate constant conditional correlation GARCH mode. This would be of a particular help in order to the issues about the causal effects between inflation rate, output growths and interest rate.

Although the author believes that this thesis covers quite a lot of background, it also has several limitations. One of the main limitations of this research is the data related to output growth in developing countries, in addition to the multiple sources of consumer price index and industrial price index for the G7 countries. In spite of these limitations, all the essays in this thesis will make a fairly significant contribution to the literature on inflation and output growth studies.

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