WHEN DID INFLATION BECOME MORE VOLATILE AND WHY?

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ABSTRACT

This paper investigates the behavior of inflation over the recent past with primary focus on volatility, not the level of inflation. Over the past 60 years, the inflation rate has shown periods of tranquility as well as periods of volatility. Recent evidence suggests that inflation, after a period tranquility during the 1990s, became more volatile early in the new century (perhaps even as early as 1999)—prior to the current runup in the energy and food sectors. Evidence of the increased volatility is presented and the volatility is modeled with a relatively simple autoregressive conditional heteroskedasticity (ARCH) model. We also attempt to offer some explanation for the recent volatility.

INTRODUCTION

The autoregressive conditional heteroskedasticity (ARCH) model was developed by Robert Engle to explain volatility "clustering," that is, periods in which the variance of a time series is tranquil and other periods in which the variance of the series is more volatile. The ARCH model and its extension, generalized ARCH (GARCH), have been applied to numerous economic and financial series. These models are important in identifying periods of volatility and they also aid in producing more realistic interval forecasts.

DATA, METHOD, PRELIMINARY RESULTS

We collected the monthly measure of the Consumer Price Index (CPI) for the period January 1947 to April 2008. The measure of inflation is the monthly log difference in the CPI at annual rates. That series is shown in Figure 1.

Casual observation of Figure 1 suggests that inflation was quite volatile in the late 1940s and early 1950s, again in the 1970s, and yet again starting around the turn of the century. Periods of tranquility were evident in the late 1950s through most of the 1960s and again in the 1990s. Of course, it is well known that simple inspection of the variance of a series can be misleading when the series is autocorrelated. To correct for this, we fit an autoregressive model to the inflation rate. The lags are chosen using standard penalized likelihood model selection criteria. The form of the autoregressive model can be represented as follows:

$$INFL_t = a_0 + \sum_{i=1}^p b_i INFL_{t-i} + e_t \tag{1}$$

where *INFL* is annualized monthly inflation, *t* indexes time, e_t is a white noise disturbance term and the b_i (i = 1,..., p) are the lag coefficients, and *p* indicates the order of the lags. The two standard penalized likelihood selection criteria are the Akaike information criterion (*AIC*) and the Schwarz information criterion (*SIC*) represented as follows:

$$AIC = (2k/T) + \log(\sigma)$$
⁽²⁾

$$SIC = [k \log(T)/T] + \log(\sigma), \qquad (3)$$

where k is the total number of estimated coefficients in the VAR, T is the number of usable observations, and σ is the scalar estimate of the variance of the equation's disturbance term. If the *AIC* and the *SIC* differ on the number of lags, each indicated model was estimated, with evidence presented here for the most parsimonious model. The *SIC* chooses p = 12, and we present additional evidence based on that model.



FIGURE 1: MONTHLY INFLATION AT ANNUALIZED RATES

Figure 2 depicts the residuals from the autoregressive model for inflation, with the same periods of volatility and tranquility evident.

Testing for volatility is usually accomplished by analysis of the squared residuals from an autoregressive model, such as depicted in Figure 3. The reasoning for testing the squared residuals is simple. The residuals from the autoregressive model (see Figure 2) will be serially uncorrelated as a result of the autoregressive lag fit. Those residuals are, however, not independent. Small (in absolute value) residuals are likely to be followed by additional small residuals, and large residuals are likely followed by other large residuals—that is the meaning of volatility clustering.



FIGURE 3: SQUARED RESIDUALS FROM THE AR MODEL

Figure 3 shows the same clustering effect for the squared residuals. To test for ARCH errors, a second regression is run:

$$e_t^2 = c_0 + \sum_{i=1}^p d_i e_{t-i}^2 + v_t \tag{4}$$

Where e_t^2 represents the squared residuals from equation 1, and the d_i (i = 1,..., p) are lag coefficients and p again indicates the order of the lags. If there are no ARCH effects, then equation 4 will have little explanatory power, i.e., R^2 will be very low. The existence of ARCH effects can be tested in two ways. First with a sample of T residuals, TR^2 is distributed as χ^2 with p degrees of freedom. Alternatively, an Ftest that all d_i coefficients are jointly zero will also indicate whether or not ARCH effects are present. The SIC chooses 2 lags for equation 4. The estimated equation for (4) is:

$$\hat{e}_{t}^{2} = 5.77 + 0.20 \,\hat{e}_{t-1}^{2} + 0.16 \,\hat{e}_{t-2}^{2}$$

$$R^{2} = 0.0891$$

$$T = 695$$
(4)

The null hypothesis of no ARCH effects can be written:

H₀: $d_1 = d_2 = 0$ (there are no ARCH effects) H₁: some $d_i \neq 0$ (there are ARCH effects)

As expected, the null hypothesis is rejected resoundingly for either the χ^2 test ($\chi^2 = 61.95$, p-value = 0.0000), or the *F*-test ($F_{(df = 2,692)} = 33.86$, p-value = 0.0000). We conclude that the process of inflation is subject to *ARCH* effects. Thus we have confirming statistical and visual evidence that small squared residuals tend to be followed by small squared residuals, and large squared residuals are more often followed by other large squared residuals.

OTHER RESULTS

The *ARCH* errors model is typically estimated simultaneously with the autoregressive model of inflation by maximum likelihood methods. That estimation also yields an estimate of the variance of the series, typically known as the *h* series. Again choosing p = 12 for the autoregressive presentation for inflation, and p = 2, for the variance of the series, we present the portion of the equation that represents the variance (here, *h*) of the inflation series (here we are less interested in the autoregressive parameters of the estimate of inflation, since many, many, alternative inflation forecasting models are possible):

$$h_{t} = 4.29 + 0.36 \hat{e}_{t-1}^{2} + 0.20 \hat{e}_{t-2}^{2}$$
(5)
(5.80) (3.93)

Where h is the estimated conditional variance in inflation and the numbers in parentheses are t-statistics. The reader will note the striking similarity between equations 4' and 5. Either of those equations would produce similar estimates of the conditional variance in the rate of inflation.

Figure 4 represents the conditional variance of inflation based on *ARCH* model estimated by maximum likelihood methods. Two things from Figure 4 are striking for recent inflation. First, consistent with prior results, there was a marked period of tranquility, beginning near 1991 and lasting through 1998. Second, the beginnings of recent increased volatility began earlier than we would have anticipated, even as early as 1999. As a final visual for the effects on forecasting of the increase in volatility, we offer Figure 5, an estimate of 95% error bands for inflation forecasts. In the graph, we limit the time period to the 1990s until the end of the dataset and, for simplicity, we assume a 2.5% forecast of inflation.

In the graph, it is once again clear that the variance in inflation, and hence the 95% confidence interval around inflation forecasts was relatively narrow for most on the 1990s and began to widen in 1999, and continues on a wider path through the most recent data.



FIGURE 5: NINETY-FIVE PERCENT ERROR BANDS FOR INFLATION FORECASTS



To summarize the results of this section, we find in favor of *ARCH* effects for the inflation series. The statistical and visual evidence are (we think) very clear. That result is interesting, but not particularly surprising. We do not find surprising the extremely tranquil period through most of the 1990s. That inflation in the middle to late 2000s is also more volatile is also unsurprising. That the genesis of that increased volatility seems to have begun as early as 1999 is (at least to us) a surprise.

ECONOMIC EVENTS AND INFLATION

Why would inflation have been less volatile in the 1990s and more so in the 2000s? Here we present some economic events that may be associated with those effects.

The tranquil period of the 1990s can be considered a part of *The Great Moderation*. This term, coined by Stock and Watson (2003), refers to the simultaneous reduction in the volatility of inflation and real output that began in 1984. Bernanke (2004) popularized this moniker and explained that economists attribute its occurrence to structural changes in the economy, improved monetary policy, and good luck. Structural changes include the smaller share of output attributed to durable goods production, improvements in inventory management, and increased openness in international trade and capital flows. The change in monetary policy refers to the increased emphasis on fighting inflation that began in 1979. Good luck took the form of fewer exogenous shocks, such as oil and other commodity price increases and financial crises. The empirical evidence on the relative importance of these three classes of causes of decreased economic volatility is decidedly mixed and it remains an important area of research.

As noted above, the increased volatility of inflation over the past few years is not surprising. Perhaps the good luck of the 1990s simply ran out. The terrorist attacks on New York and Washington, wars in Afghanistan and Iraq, oil and food price shocks, and the bursting of two speculative bubbles can all be classified as exogenous shocks. The fact that the earliest of these shocks, namely the precipitous decline in stock prices in 2000, occurred in the year *after* the current period of inflation volatility began is surprising and interesting to us. It may be the case that The Great Moderation has ended. Additional research on changes in the volatility of inflation and real output growth, along with a better understanding of their determinants, will surely be forthcoming.

CONCLUSIONS

This research finds in favor of modeling inflation as an *ARCH* process, consistent with much other research on inflation. Our primary findings in this paper include the following three conclusions. First, for much of the 1990s, the variance in inflation was very low in comparison with prior and succeeding periods. Second, the increased variance in inflation that followed the period of tranquility began earlier than expected—as early as 1999. Third, the increased variance in inflation continues through the current period. We provide several explanations for both the period of tranquility and the more volatile path of inflation in the post 1999 era.

Since the measure of inflation we use in this paper includes food and energy prices, a future paper based on core inflation (excluding the more volatile food and energy sectors) is an obvious extension. Such an investigation could determine whether the results of this paper are driven by the more volatile CPI components.

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