

Inflation-Gap Persistence in the U.S.

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Abstract

We estimate vector autoregressions with drifting coefficients and stochastic volatility for post WWII U.S. inflation. To make contact with the concept of inflation incorporated in recent DSGE models, we focus on the inflation gap, defined as the deviation of inflation from a pure random-walk component of inflation. We measure the persistence of the inflation gap in terms of short- to medium-term predictability. We present evidence that inflation-gap persistence increased until Volcker brought mean inflation down in the early 1980s and that it then fell during the chairmanships of Volcker and Greenspan. We interpret these changes in terms of estimates of a dynamic new Keynesian model that highlight the importance of changes in the central bank's inflation target.

This paper studies whether inflation persistence changed after the Great Inflation. The literature reports mixed evidence on this question, with some authors contending that inflation persistence has declined (e.g. Timothy Cogley and Thomas J. Sargent 2001 and 2005a) and others maintaining that it is unchanged (e.g., Christopher A. Sims 2001, James H. Stock 2001, and Frederick Pivetta and Ricardo A. Reis 2007). One reason for the disagreement is that the literature looks at diverse features of

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the inflation process. Some papers focus on inflation itself, while others examine the inflation gap,¹ which we define as the difference between inflation and the Federal Reserve’s long-run target for inflation. We agree that inflation remains persistent, principally because of drift in target inflation. But we argue below that the inflation gap has become less persistent since the Volcker disinflation.

Distinguishing between inflation and the inflation gap resolves some elements of the controversy but not all. Another source of disagreement is that previous evidence on inflation-gap persistence is itself inconclusive. For instance, estimates reported by Cogley and Sargent (2001 and 2005a) suggest a decline, but the estimates are imprecise and statistically insignificant, leaving open the possibility that inflation-gap persistence remains unchanged. Here we report new evidence of a statistically significant decrease in persistence after the Volcker disinflation. The main reason we obtain stronger results is that we introduce a new measure of persistence based on short- and medium-term predictability. Our new measures are estimated more precisely, so we can now say that it is very likely that inflation-gap persistence declined after the Great Inflation.

We organize the discussion as follows. We begin by explaining why we focus on the inflation gap. Then we describe a vector autoregressions with drifting parameters and stochastic volatility similar to those of Cogley and Sargent (2005a) and Giorgio E. Primiceri (2005). We use these statistical models to define trend inflation and to focus attention on the inflation gap.

Next we define a measure of persistence in terms of inflation-gap predictability, in particular, as the fraction of total inflation-gap variation j quarters ahead that is due to past shocks.² We say that the inflation gap is *weakly persistent* when the effects of shocks decay quickly and that it is *strongly persistent* when they decay slowly. When the effects of past shocks die quickly, future shocks account for most of the variation in the inflation gap, pushing our measure close to zero. But when the effects of past shocks decay slowly, they account for a higher proportion of near-term movements, pushing our measure of persistence closer to one. Thus, a large fraction of variation over short to medium horizons that is due to past shocks signifies strong persistence

¹Some of our own earlier work is vague about the feature of interest. For instance, calculations in Cogley and Sargent (2001 and 2005a) pertain to the inflation gap, but the text refers misleadingly to inflation persistence. One goal of this paper is to clarify this issue.

²This measure is inspired by Robert B. Barsky (1987) and Francis X. Diebold and Lutz Kilian (2001).

and a small fraction indicates weak persistence. Under a convenient approximation, our measure is the R^2 statistic for j -step ahead inflation-gap forecasts.³ Heuristically, a connection between predictability and persistence arises because past shocks give rise to forecastable movements, while future shocks contribute to forecast errors. Hence, the continuing influence of past shocks can be measured by the proportion of predictable variation in the inflation gap.

We deduce persistence measures from the posterior distribution of a drifting-parameter VAR, then study how they have changed since the Great Inflation. A key finding is that inflation gaps were highly predictable circa 1980, but are much less so now. Furthermore, the evidence of declining persistence is statistically significant at conventional levels.

After reviewing the purely descriptive statistical evidence, we use a simple dynamic new Keynesian model to examine what caused changes in the law of motion for inflation. We find that both monetary policy and non-policy factors contributed to the decline in persistence. With respect to monetary policy, the chief improvement is not a more aggressive reaction to inflation a la Richard H. Clarida, Jordi Gali, and Mark Gertler (2000) or Thomas A. Lubik and Frank Schorfheide (2004), but rather that the Fed's long-run inflation target was better anchored after the Volcker disinflation. This is because changes in the inflation target induce very persistent inflation-gap dynamics. The post-Volcker improved stability of the long-run inflation objective reduces the relative importance of this persistent component. Among non-policy factors, we find that mark-up shocks became less volatile and persistent after the mid-1980s, and this also contributed to changes in the law of motion for inflation.

Finally, the paper concludes by relating our work to the broader literature and suggesting directions for further research.

1 Why we focus on the inflation gap

We decompose inflation π_t into two parts, a stochastic trend τ_t that (to a first-order approximation) evolves as a driftless random walk, and an inflation gap $g_t = \pi_t - \tau_t$ that represents temporary differences between actual and trend inflation. In general

³Strictly speaking, we should say 'pseudo forecasts' because we neglect complications associated with real-time forecasting. This is not a shortcut; it is intentional. Our goal is to make retrospective statements about inflation persistence. To attain as much precision as possible, we use ex post revised data and estimate parameters using data through the end of the sample.

equilibrium models, trend inflation is typically pinned down by a central bank's long-run target. Accordingly, we associate movements in trend inflation with shifts in the Federal Reserve's target. Because trend inflation is a driftless random walk, actual inflation has a unit autoregressive root and is highly persistent. In our view, target inflation has not stopped drifting, though its conditional variance has declined.⁴

The inflation gap measures the difference between actual inflation and the central bank's long-run target. Many papers on optimal monetary policy assume that the central bank minimizes a quadratic loss function that, among other things, penalizes variation in the inflation gap.⁵ In those settings, an optimal policy rule renders the inflation gap stationary, for otherwise the central bank's loss would be unbounded. An optimal policy eventually brings inflation back to the bank's long-run target. Inflation-gap persistence measures the rate at which convergence to the long-run target can be expected to occur, a rate that depends on interactions between the monetary policy rule and private sector behavior. Our objective is to measure inflation-gap persistence, to assess evidence for its changes over time, and to interpret those changes in light of a dynamic new Keynesian model.

Whether persistence in raw inflation or in the inflation gap is more interesting depends on the context. On the one hand, for pricing long-term nominal bonds, persistence in raw inflation is more relevant. A number of authors explain the volatility of long-term bond yields by pointing to shifts in the Fed's long-term target (e.g., see Sharon Kozicki and Peter A. Tinsley 2001 and Andrew Ang, Jean Boivin, and Sen Dong 2007). On the other hand, for understanding the speed and effectiveness with which a Central Bank brings inflation in proximity to its target, inflation-gap persistence is more salient.⁶

⁴For evidence that the innovation variance for τ_t has declined, see Stock and Mark W. Watson (2007).

⁵Frequently this assumption is tacit, as the inflation target is often assumed to be constant.

⁶Cogley and Argia M. Sbordone (2008) exploit the distinction between inflation and inflation-gap persistence to resolve a puzzle involving the new Keynesian Phillips curve (NKPC). A number of studies that base estimation on raw inflation data conclude that purely forward-looking versions of the NKPC generate too little inflation persistence. To repair that shortcoming, various researchers have tacked on ad hoc backward-looking elements. But the NKPC is typically derived using a log-linear approximation around an inflation target of zero, so that what is called inflation in that model is better thought of as the inflation gap. When Cogley and Sbordone fit their model to measures of the inflation gap, backward-looking elements drop out, and a purely forward-looking version fit well.

2 A VAR

As in Cogley and Sargent (2005a) and Primiceri (2005), we estimate VARs with drifting parameters and stochastic volatility. Our model can be cast as follows,

$$y_t = X'_{t-1}\theta_{t-1} + \varepsilon_{yt}, \quad (1)$$

$$\theta_t = \theta_{t-1} + \varepsilon_{st}. \quad (2)$$

Equation (1) is the measurement equation for a state-space representation, and equation (2) is the state equation. The vector y_t contains current observations on inflation, unemployment, and a short-term nominal interest rate, and X_{t-1} includes constants plus two lags of y_t . The parameter vector θ_t evolves as a driftless random walk subject to a reflecting barrier that guarantees nonexplosive VAR roots at every date. The state and measurement innovations ε_{st} and ε_{yt} are conditionally normal with mean zero and variances Q_t and R_t , respectively. We assume that ε_{st} and ε_{yt} are distributed independently.⁷

The matrices Q_t and R_t have the form

$$\text{var}(\varepsilon_{st}) = Q_t = B_s^{-1}H_{st}B_s^{-1'}, \quad (3)$$

$$\text{var}(\varepsilon_{yt}) = R_t = B_y^{-1}H_{yt}B_y^{-1'}, \quad (4)$$

where H_{st} and H_{yt} are diagonal and B_s and B_y are lower triangular. The diagonal elements of H_{st} and H_{yt} are independent, univariate stochastic-volatility processes that evolve as driftless, geometric random walks:

$$\ln h_{j,t} = \ln h_{j,t-1} + \sigma_j \eta_{jt}, \quad (5)$$

$j = 1, \dots, \dim(\varepsilon_{it}), i = s, y$. The volatility innovations η_{jt} are standard normal variates, and the variance of $\Delta \ln h_{jt}$ depends on the free parameter σ_j . For tractability and

⁷This assumption is problematic because it implies that shifts in target inflation are unrelated to news about inflation and other macroeconomic variables. Our preferred theory is that the Fed chooses its inflation target and revises it in response to changes in its beliefs about the structure of the economy (e.g., see Sargent 1999, Cogley and Sargent 2005b, Primiceri 2006, and Sargent, Noah M. Williams, and Tao Zha 2006). The learning models developed in those papers imply that state and measurement innovations should be correlated. For that reason, Cogley and Sargent (2001) estimated a time-varying VAR with correlated state and measurement innovations, but with constant innovation variances. We have experimented with models incorporating both time-varying volatility and correlated state and measurement innovations, but we have not succeeded in estimating them because our simulations fail to converge. We leave this important problem for future research.

parsimony, we assume that the volatility innovations are mutually independent and also independent of the normalized state and measurement innovations. The lower-triangular matrices B_s and B_y have 1's along the main diagonal and free parameters below. For example, if $\dim(\varepsilon_{it}) = n$,

$$B_i = \begin{bmatrix} 1 & 0 & 0 & 0 \\ \beta_{21} & 1 & 0 & 0 \\ \dots & \dots & \dots & \dots \\ \beta_{n1} & \dots & \beta_{n,n-1} & 1 \end{bmatrix}. \quad (6)$$

Specification (3)-(6) is convenient for modeling recurrent persistent changes in variances. Among other things, it ensures that Q_t and R_t are positive definite and allows for time-varying correlations between vectors of innovations.

This model extends those of Cogley and Sargent (2005a) and Primiceri (2005) by allowing stochastic volatility in the parameter innovations. Our earlier papers allowed for stochastic volatility in the VAR innovations but assumed a constant state-innovation variance, $Q_t = Q$. This extension is motivated by one of Stock and Watson's (2007) results. In a univariate unobserved-components model for inflation, they found evidence of a decline in the innovation variance for trend inflation after the Volcker disinflation. This feature of the data will be important later when we use a DSGE model to interpret the causes of changes in the law of motion for inflation.

In what follows, we make frequent use of the companion form of a VAR,

$$z_{t+1} = \mu_t + A_t z_t + \varepsilon_{zt+1}. \quad (7)$$

The vector z_t includes current and lagged values of y_t , the vector μ_t contains the VAR intercepts, and the companion matrix A_t contains the autoregressive parameters. We use the companion form for multi-step forecasting. When we do that, we approximate multi-step forecasts by assuming that VAR parameters will remain constant at their current values going forward in time. This approximation is common in the literature on bounded rationality and learning, being a key element of an 'anticipated-utility' model (David M. Kreps 1998). In other papers, we have found that it does a good job of approximating the mean of Bayesian predictive densities (e.g., see Cogley, Sergei Morozov, and Sargent 2005 and Cogley and Sargent 2008).

With this assumption, we can form local-to-date t approximations to the moments of z_t . For the unconditional mean, we follow Stephen Beveridge and Charles R. Nelson (1981) by defining the stochastic trend in z_t as the value to which the series is expected

to converge in the long run, $\bar{z}_t = \lim_{h \rightarrow \infty} E_t z_{t+h}$. With θ_t held constant at its current value, we approximate this as

$$\bar{z}_t \approx (I - A_t)^{-1} \mu_t. \quad (8)$$

To a first-order approximation, \bar{z}_t evolves as a driftless random walk,⁸ implying that inflation and the other variables in y_t have a unit root. We interpret the stochastic trend in inflation as an estimate of target inflation. Thus, $\tau_t = e_\pi \bar{z}_t$, where e_π is a selector vector.

Having assumed that \bar{z}_t is a driftless random walk, the stability constraint on A_t just rules out a second unit or explosive root. There is an emerging consensus that the price level is best modeled as an $I(2)$ process; few observers think that it is $I(3)$. The stability constraint rules out an $I(3)$ representation. Similarly, although the natural rate of unemployment and real interest might drift, their first differences probably do not.

After subtracting \bar{z}_t from both sides of (7) and invoking the anticipated-utility approximation, we get a forecasting model for gap variables,

$$(z_{t+1} - \bar{z}_t) = A_t(z_t - \bar{z}_t) + \varepsilon_{z,t+1}. \quad (9)$$

We approximate j -period-ahead forecasts of gap variables as $A_t^j \hat{z}_t$, where $\hat{z}_t = z_t - \bar{z}_t$,⁹ and we approximate the forecast-error variance by

$$\text{var}_t(\hat{z}_{t+j}) \approx \sum_{h=0}^{j-1} (A_t^h) \text{var}(\varepsilon_{z,t+1}) (A_t^h)'. \quad (10)$$

To approximate the unconditional variance of \hat{z}_{t+1} , we take the limit of the conditional variance as the forecast horizon j increases,¹⁰

$$\text{var}(\hat{z}_{t+1}) \approx \sum_{h=0}^{\infty} (A_t^h) \text{var}(\varepsilon_{z,t+1}) (A_t^h)'. \quad (11)$$

Under the anticipated-utility approximation, this is also the unconditional variance of \hat{z}_{t+s} for $s > 1$.

⁸A first-order Taylor series approximation makes \bar{z}_t a linear function of θ_t , which evolves as a driftless random walk.

⁹By the anticipated-utility approximation, $E_t \bar{z}_{t+j} = \bar{z}_t$. This is a good approximation because \bar{z}_t is a driftless random walk to a first-order approximation.

¹⁰This is a second-moment counterpart of the Beveridge-Nelson trend.

3 Persistence and predictability

A second difference relative to our earlier papers concerns how we measure persistence. Our earlier work characterizes inflation-gap persistence in terms of the normalized spectrum at frequency zero. Here we introduce statistics that measure short- and medium-term predictability. These are estimated more precisely, making it possible to obtain sharper results.

To measure persistence at a given date t , we calculate the fraction of the total variation in g_{t+j} that is due to shocks inherited from the past relative to those that will occur in the future. This is equivalent to 1 minus the fraction of the total variation due to future shocks. Since future shocks account for the forecast error, that fraction can be expressed as the ratio of the conditional variance to the unconditional variance,

$$R_{jt}^2 = 1 - \frac{\text{var}_t(e_\pi \hat{z}_{t+j})}{\text{var}(e_\pi \hat{z}_{t+j})} \approx 1 - \frac{e_\pi \left[\sum_{h=0}^{j-1} (A_t^h) \text{var}(\varepsilon_{zt+1}) (A_t^h)' \right] e_\pi'}{e_\pi \left[\sum_{h=0}^{\infty} (A_t^h) \text{var}(\varepsilon_{zt+1}) (A_t^h)' \right] e_\pi'}. \quad (12)$$

We label this R_{jt}^2 because it is analogous to the R^2 statistic for j -step ahead forecasts. This fraction must lie between zero and one, and it converges to zero as the forecast horizon j lengthens.¹¹ Whether it converges rapidly or slowly reflects the degree of persistence. If past shocks die out quickly, the fraction converges rapidly to zero. But if one or more shocks decay slowly, the fraction may converge only gradually to zero, possibly remaining close to one for some time. Thus, for small or medium $j \geq 1$, a small fraction signifies weak persistence and a large fraction strong persistence.

This ratio depends on all of the parameters of the companion matrix A_t . Sometimes economists summarize persistence in a VAR by focusing on the largest autoregressive root in A_t . This is problematic for two reasons. One is that the largest root could be associated not with inflation but with another variable in the VAR. Hence the largest root of A_t might exaggerate persistence in the inflation gap. Another problem is that two large roots could matter for inflation, in which case the largest root of A_t would understate the degree of persistence. We think it is important to retain all the information in A_t .

Nevertheless, (12) is not entirely satisfactory because it depends on the conditional variance V_{t+1} in addition to the conditional mean parameters A_t . Changes in V_{t+1}

¹¹This follows from the stability constraint on A_t .

that take the form of a scalar multiplication are not a problem because the scalar cancels in numerator and denominator. But R_{jt}^2 is not invariant to other changes in V_{t+1} . For instance, our measure of persistence would be reduced by a change in the composition of structural shocks away from those whose impulse response functions decay slowly and toward those whose impulse response functions vanish quickly.

This problem relates to questions about why inflation persistence has changed, not whether it has changed. For the moment, we want to focus on the latter. We think that assembling descriptive statistical evidence about inflation persistence is a useful first step. We prefer to use a structural model for causal interpretation, as for example in section 5.

In what follows, we focus on horizons of 1, 4, and 8 quarters, those being the most relevant for monetary policy. We calculate values of R_{jt}^2 implied by drifting-parameter VARs and study how they have changed over time.

4 Properties of inflation

We study two measures of inflation, namely, the log-differences of the GDP and PCE chain-weighted price indices. Stock and Watson (2007) examine GDP inflation. Colleagues in the Federal Reserve system encouraged us to look at PCE inflation as well, saying that the Fed pays more attention to the PCE for policy purposes.¹²

The VAR also conditions on unemployment and a short-term nominal interest rate. Unemployment is measured by the civilian unemployment rate. The original monthly series was converted to a quarterly basis by sampling the middle month of each quarter. To guarantee that expectations of the unemployment rate always lie between 0 and 1, we specify the VAR in terms of the logit of the unemployment rate. The secondary market rate on three-month Treasury bills measures the nominal interest rate. The nominal interest data are also sampled monthly, and we converted to a quarterly series by selecting the first month of each quarter in order to align the interest rate as well as possible with inflation.

The inflation and unemployment data are seasonally adjusted, and the sample spans the period 1948.Q1 to 2006.Q4. The data are available from the Federal Reserve

¹²Fed officials prefer the PCE because it measures the cost of consumption goods and hence is more closely related to the cost of living. Being a chain-weighted index, the PCE is subject to less substitution bias than the CPI.

Economic Database (FRED) and have FRED mnemonics GDPCTPI, PCECTPI, UNRATE, and TB3MS, respectively.

Our priors are described in the appendices. For the most part, they follow our earlier papers. Our guiding principle was to use proper priors to ensure that the posterior is proper, but to make the priors as weakly informative as possible, so that the posterior is dominated by information in the data.¹³ The posteriors were simulated using Markov Chain Monte Carlo algorithms, details of which can also be found in the appendices.

4.1 Trend inflation and inflation volatility

A number of our findings resemble those reported elsewhere (e.g. Cogley and Sargent 2005a, Stock and Watson 2007). We briefly touch on them before moving on to novel results.

Figure 1 portrays the posterior median and interquartile range for trend inflation, with estimates for GDP inflation shown in the left panel and those for PCE inflation in the right. The estimates are conditioned on data through 2006.Q4. Hence, the figure presents a retrospective interpretation of the data.

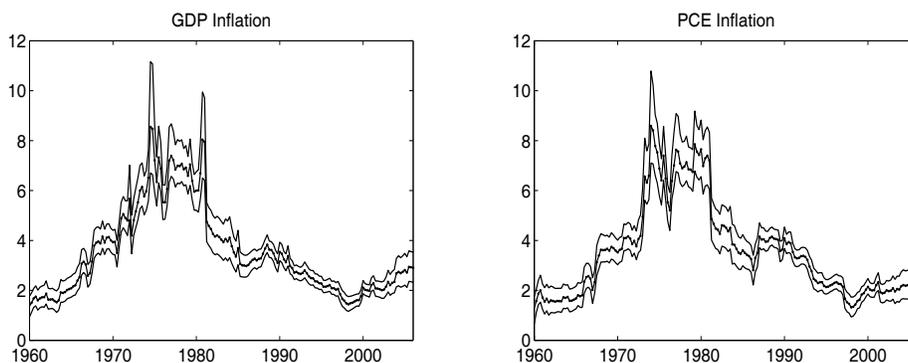


Figure 1: Trend Inflation

The estimates differ in some details from those reported elsewhere, but the broad contour is the same. Trend inflation was low and steady in the early 1960s, began rising in the mid-1960s, and attained twin peaks near the times of the 1970s oil

¹³We think this is appropriate for exploratory data analysis. However it means that we cannot compare models via Bayes factors for reasons having to do with the Lindley paradox. E.g., see Alan E. Gelfand (1996).

shocks. It fell sharply during the Volcker disinflation and then settled down to the neighborhood of 2 percent after the mid-1990s.

Figure 2 summarizes changes in inflation volatility. Once again, we plot the posterior median and interquartile range at each date. The top row shows the standard deviation for the inflation innovation, and the bottom plots a local-to-date- t approximation to the unconditional standard deviation of the inflation gap.¹⁴

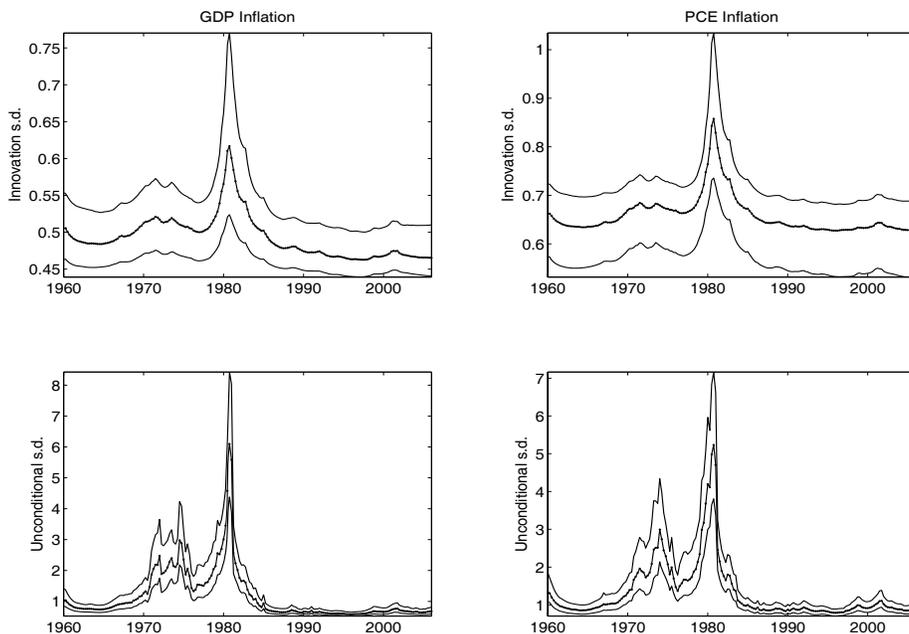


Figure 2: Inflation Volatility

The innovation variance remains roughly constant for most of the sample, except for a spike in the late 1970s and early 1980s when the Fed was targeting monetary aggregates. The unconditional variance for the inflation gap also spikes around that time, but the magnitude of the spike is much greater. In the early 1980s, the standard deviation of inflation innovations rose by about 10 basis points, an increase of roughly 20 percent. At the same time, the unconditional standard deviation of the inflation gap increased by roughly 4 percentage points, or about 200 percent. Hence changes in the innovation variance account for a relatively small proportion of changes in the unconditional variance.

¹⁴This approximation is defined in eq. (11)

Stock and Watson (2007) assume that the transitory component of inflation is a martingale difference, and they find that its variance is roughly constant throughout the sample. For a martingale difference, the two measures of volatility shown in figure 2 coincide. Apart from the spike around 1980, we find that the innovation variance for inflation is roughly constant, and in that respect our estimates agree with theirs. However, we also find a substantial decline in the unconditional variance of the inflation gap after the Volcker disinflation. Our model differs from theirs by allowing for serial dependence in the inflation gap, possibly with time-varying persistence. In principle, a decline in persistence could account for the patterns shown in figure 2. In what follows, we look more closely into this question.

4.2 Has the inflation gap become less persistent?

To focus more clearly on changes in persistence, we turn to evidence on inflation-gap predictability. For each draw in the posterior distribution, we calculate R_{jt}^2 statistics as in equation (12) and then study how they change during and after the Great Inflation. Figure 3 portrays the posterior median and interquartile range for R_{jt}^2 at each date for $j = 1, 4$, and 8 quarters.

The top row refers to 1-quarter ahead forecasts. In the mid 1960s, VAR pseudo forecasts accounted for approximately 50 to 55 percent of the variation of the inflation gap (see footnote 3 for why we say ‘pseudo’). During the Great Inflation, this increased to more than 90 percent and at times approached 99 percent. The inflation gap became less predictable during the Volcker disinflation, and after that R_{1t}^2 settled to the neighborhood of 50 percent.

The second and third rows refer to 4 and 8 quarter forecasting horizons. As expected, R_{jt}^2 statistics are lower for longer horizons. For $j = 4$, VAR pseudo forecasts accounted for roughly a quarter of the inflation-gap variation in the mid 1960s, for approximately 50 to 75 percent during the Great Inflation, and for about 15 percent after the Volcker disinflation. For $j = 8$, the numbers follow a similar pattern but are lower. VAR pseudo forecasts accounted for about 10 percent of inflation-gap variation in the mid-1960s, for 20 to 35 percent during the mid 1970s and early 1980s, and for 10 percent or less after the Volcker disinflation. Taken at face value, the figure suggests the inflation gap was more persistent during the Great Inflation and less persistent after the mid-1980s.

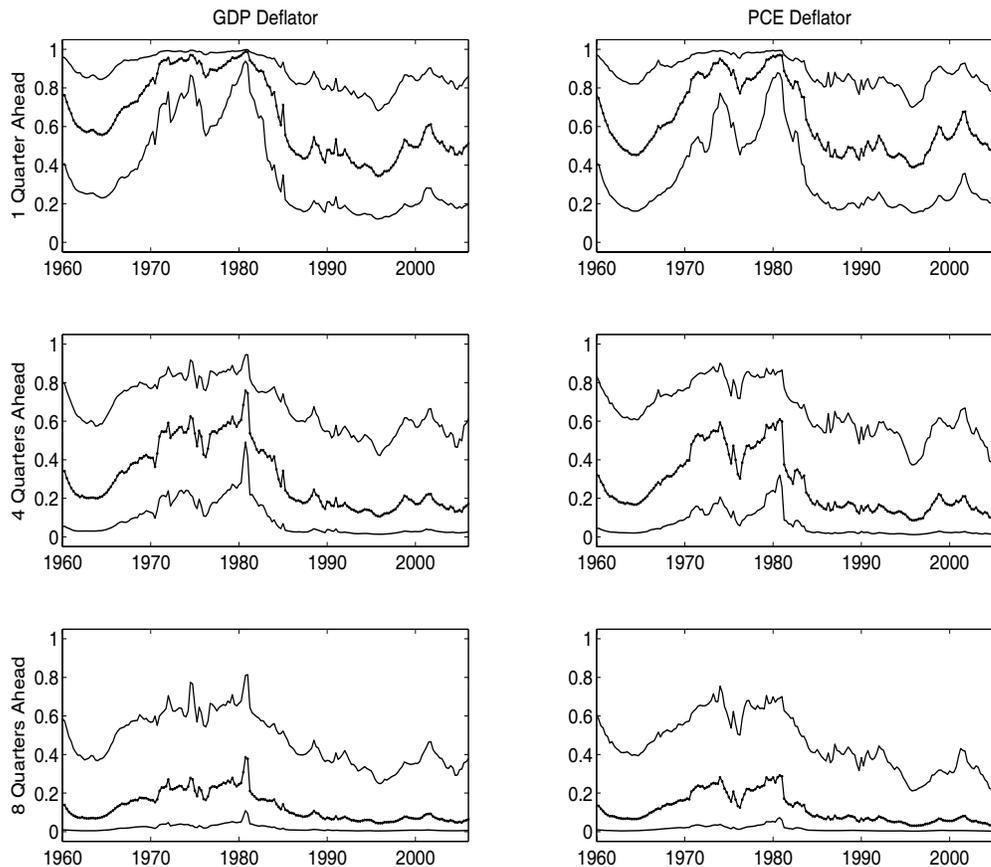


Figure 3: $R^2_{t,j}$ Statistics

The controversy about inflation-gap persistence hinges not on the evolution of the posterior median or mean, however, but rather on whether *changes* in R^2_{jt} are statistically significant. To assess this, we examine the joint posterior distribution for $(R^2_{jt}, R^2_{j\tau})$ across pairs of time periods (t, τ) . There are many possible pairs, of course, and to make the problem manageable we concentrate on two pairs, 1960-1980 and 1980-2004. The years 1960 and 2006 are the beginning and end of our sample, respectively. We chose 1980.Q4 because it was the eve of the Volcker disinflation and because it splits the sample roughly in half. However, the results reported below are not particularly sensitive to this choice. Dates adjacent to 1980.Q4 tell much the same story.

Figure 4 depicts a number of pairwise comparisons for R^2_{1t} . The top row plots the joint distribution for the years 1980 and 2006, with values of $R^2_{1,1980}$ plotted on the

x -axis and the associated value of $R_{1,2006}^2$ shown on the y -axis. Similarly, the bottom row portrays the joint distribution for the years 1960 and 1980, with values for 1960 on the x -axis and those for 1980 on the y -axis.¹⁵

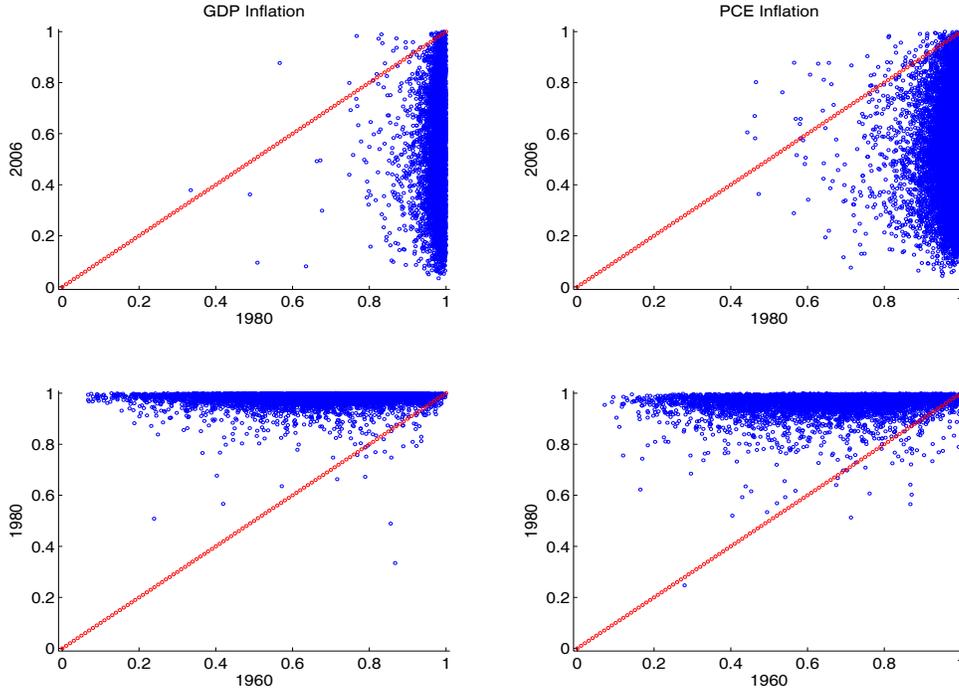


Figure 4: Joint Distribution for R_1^2 Statistics, 1960-80 and 1980-2006

Each point in the respective panels represents a draw from the joint distribution for years x and y . Thus, combinations clustered near the 45 degree line represent pairs for which there was little or no change between years x and y . Those below the 45 degree line represent a decrease in predictability ($R_{1,y}^2 < R_{1,x}^2$), while those above the 45 degree line represent increasing persistence ($R_{1,y}^2 > R_{1,x}^2$). Very few points lie close to the 45 degree line. On the contrary, in the top row, virtually the entire distribution lies below the 45 degree line, signifying that $R_{1,1980}^2 > R_{1,2004}^2$ with high probability. Similarly, in the bottom row, most of the point lie above the 45 degree line, signifying that $R_{1,1960}^2 < R_{1,1980}^2$ with high probability.

¹⁵Our MCMC algorithm generates draws of sequences of R_{1t}^2 for $t = 1, \dots, T$, thus capturing dependence across t . We discard most of those time periods, retaining only 1960.Q4, 1980.Q4, and 2006.Q4. Each panel is a scatterplot of joint outcomes for a pair of those years.

Table 1 records the fraction of posterior draws for which R_{jt}^2 declined between 1980 and 2006. For 1-step ahead pseudo forecasts, the probability of a decline is 99.5 and 98.5 percent, respectively, for GDP and PCE inflation, thus confirming the visual impression conveyed by the figure. For 4- and 8-quarter ahead forecasts, the joint distributions are less tightly concentrated than those shown above, and the probabilities are a bit lower. Nevertheless, at the 4-quarter horizon, the probability of a decline in R_{jt}^2 is 96.5 percent for GDP inflation and 94.3 percent for PCE inflation. At the 8-quarter horizon, the probabilities are and 90.1 and 89.6 percent, respectively, for the two inflation measures.

Table 1: Probability of Changing R_{jt}^2

GDP Inflation			
pair	1 Quarter Ahead	4 Quarters Ahead	8 Quarters Ahead
1980, 2006	0.995	0.965	0.909
1960, 1980	0.992	0.944	0.868
PCE Inflation			
pair	1 Quarter Ahead	4 Quarters Ahead	8 Quarters Ahead
1980, 2006	0.985	0.943	0.896
1960, 1980	0.969	0.845	0.773

Table 1 also reports the probability of an increase in $R_{j,t}^2$ between 1960 and 1980. For GDP inflation, this probability is 99.2 percent for 1-quarter ahead pseudo forecasts, 94.4 percent for 1-year ahead forecasts, and 86.8 percent for 2-year ahead forecasts. The probabilities are lower for PCE inflation, but the results still point to a significant change in predictability at the 1-quarter horizon.

Thus, statistically significant evidence for changes in inflation-gap persistence emerges from VARs. Estimates of R_{jt}^2 put posterior probabilities above 96 percent on an increase in persistence during the Great Inflation and a decline in persistence after the Volcker disinflation. The results for 4-quarter ahead forecasts also point in this direction, standing at the 94 or 96 percent levels for a fall in persistence in the second half of the sample and straddling the 90 percent level for a rise in the first half. The results for 2-year ahead forecasts hint at a change in persistence, but fall short of statistical significance.

The main reason we obtain stronger results than in our earlier papers is that we examine a different measure of persistence. Our earlier papers characterized inflation-gap persistence in terms of the normalized spectrum at frequency zero. That statistic is estimated less precisely than R_{jt}^2 , and had we used it here the results would still be statistically insignificant. Measure of short- and medium-term predictability are estimated more precisely, producing sharper results.

One aspect of the results that might be a cause for concern is that the distribution of R_{1t}^2 clusters near its upper bound of unity during much of the Great Inflation. Taken at face value, that means the inflation gap had a near unit root at that time. One possible explanation involves the Fed’s attitude toward disinflation. According to Cogley and Sargent (2005b) and Primiceri (2006), the Fed sought lower inflation throughout this period but wanted to disinflate very slowly. A policy of very gradual disinflation could make the inflation gap highly persistent and account for the pileup near unity.

Alternatively, the pileup might reflect model misspecification. For instance, suppose there were a spike in the trend innovation variance at some date, associated with a big jump in the true value of τ_t . If for some reason the model underestimated the trend innovation variance at that date, estimates of τ_t would not be able to jump by as much of the true value and would instead approach the true value in a sequence of smaller steps. The model’s autoregressive parameters would compensate by adding persistence, moving at least one of the VAR roots toward unity. Our stochastic volatility specification allows jumps in τ_t , but the model is complicated and high dimensional and might not fully capture this feature of the data. More research directed toward estimating models with jumps would be helpful for addressing this concern.

5 A More Structural Analysis

In this section we offer a structural explanation of the statistical findings presented above. We estimate a New-Keynesian model along the lines of Julio J. Rotemberg and Michael Woodford (1997) and Jean Boivin and Marc P. Giannoni (2006). However, differently from these studies, we allow for the Central Bank’s inflation target to change over time. Our goal is to construct and estimate a simple model to help us understand the causes of the declines observed in the volatility and predictability of

inflation.

5.1 The model

The model economy is populated by a representative household, a continuum of monopolistically competitive firms, and a government. The representative household maximizes

$$E_t \sum_{s=0}^{\infty} \delta^s b_{t+s} \left[\log (C_{t+s} - hC_{t+s-1}) - \varphi \int_0^1 \frac{L_{t+s}(i)^{1+\nu}}{1+\nu} di \right], \quad (13)$$

subject to a sequence of budget constraints

$$\int_0^1 P_t(i) C_t(i) di + B_t + T_t \leq R_{t-1} B_{t-1} + \Pi_t + \int_0^1 W_t(i) L_t(i) di. \quad (14)$$

B_t represents government bonds, T_t denotes lump-sum taxes and transfers, R_t is the gross nominal interest rate, and Π_t the profits that firms pay to the household. C_t is a Dixit-Stiglitz aggregator of differentiated consumption goods,

$$C_t = \left[\int_0^1 C_t(i)^{\frac{1}{1+\theta_t}} di \right]^{1+\theta_t}. \quad (15)$$

P_t is the associated price index, $L_t(i)$ denotes labor of type i that is used to produce differentiated good i , and $W_t(i)$ is the corresponding nominal wage. The coefficients h and ν set the degree of internal habit formation and the inverse Frisch elasticity of labor supply, respectively. Finally, b_t and θ_t are exogenous shocks that follow the stochastic processes

$$\begin{aligned} \log b_t &= \rho_b \log b_{t-1} + \varepsilon_{b,t} \\ \log \theta_t &= (1 - \rho_\theta) \log \theta + \rho_\theta \log \theta_{t-1} + \varepsilon_{\theta,t}. \end{aligned} \quad (16)$$

The random variable b_t is an intertemporal preference shock perturbing the discount factor, and θ_t can be interpreted as a shock to the firms' desired mark-up.

Each differentiated consumption good is produced by a monopolistically competitive firm using a linear production function,

$$Y_t(i) = A_t L_t(i), \quad (17)$$

where $Y_t(i)$ denotes the production of good i , and A_t represents aggregate labor productivity. We model A_t as a unit root process with a growth rate $z_t \equiv \log(A_t/A_{t-1})$ that follows the exogenous process

$$z_t = (1 - \rho_z)\gamma + \rho_z z_{t-1} + \varepsilon_{z,t}. \quad (18)$$

As in Guillermo A. Calvo (1983), at each point in time a fraction ξ of firms cannot re-optimize their prices and simply indexes them to the steady-state value of inflation. Subject to the usual cost-minimization condition, a re-optimizing firm chooses its price ($\tilde{P}_t(i)$) by maximizing the present value of future profits,

$$E_t \sum_{s=0}^{\infty} \xi^s \delta^s \lambda_{t+s} \left\{ \tilde{P}_t(i) \pi^s Y_{t+s}(i) - W_{t+s}(i) L_{t+s}(i) \right\}, \quad (19)$$

where π is the gross rate of inflation in steady state and λ_{t+s} is the marginal utility of consumption.

The monetary authority sets short-term nominal interest rates according to a Taylor rule,

$$\frac{R_t}{R} = \left(\frac{R_{t-1}}{R} \right)^{\rho_R} \left[\left(\frac{\bar{\pi}_{4,t}}{(\pi_t^*)^4} \right)^{\frac{\phi_\pi}{4}} \left(\frac{Y_t}{Y_t^*} \right)^{\phi_Y} \right]^{1-\rho_R} e^{\varepsilon_{R,t}}. \quad (20)$$

The central bank smooths interest rates and responds to two gaps, the deviation of annual inflation ($\bar{\pi}_{4,t}$) from a time-varying inflation target and the difference between output and its flexible price level. R is the steady-state value for the gross nominal interest rate and $\varepsilon_{R,t}$ is a monetary policy shock that we assume to be *i.i.d.*

Following Peter N. Ireland (2007), we model the inflation target π_t^* as an exogenous random process,

$$\log \pi_t^* = (1 - \rho_*) \log \pi + \rho_* \log \pi_t^* + \varepsilon_{*,t}. \quad (21)$$

There are many reasons that the Central Bank's inflation target might vary over time. Our favorite one is that the central bank adjusts its target as it learns about the structure of the economy. For instance, Sargent (1999), Cogley and Sargent (2005b), Primiceri (2006), and Sargent, Williams, and Zha (2006) hypothesize that changing beliefs about the output-inflation tradeoff generated a pronounced low-frequency, hump-shaped pattern in inflation. We approximate outcomes of this learning process by an exogenous random variable like (21).¹⁶

¹⁶As in Ireland (2007), we also experimented with a model in which target inflation evolves

5.2 Model solution and observation equation

Since the technology process A_t is assumed to have a unit root, consumption, real wages, and output evolve along a stochastic growth path. To solve the model, we first rewrite it in terms of deviations of these variables from the technology process. Then we solve the log-linear approximation of the model around the non-stochastic steady state. We specify the vector of observable variables as $[\log Y_t - \log Y_{t-1}, \pi_t, R_t]$. For estimation, we use data on per-capita GDP growth, the quarterly growth rate of the GDP deflator, and the Federal funds rate.¹⁷

5.3 Bayesian inference and priors

We use Bayesian methods to characterize the posterior distribution of the model's structural parameters. Table 2 reports our priors. These priors are relatively disperse and are broadly in line with those adopted in previous studies (see, for instance, Marco Del Negro, Frank Schorfheide, Frank Smets and Rafael Wouters 2007 or Alejandro Justiniano and Giorgio Primiceri 2008). But a few items deserve discussion.

- We set the Frisch elasticity of labor supply ($1/\nu$) to 0.5 and the steady-state price mark-up (θ) to 10%. These parameters only enter the slope of the Phillips curve and are not identified separately from the degree of price stickiness ξ . Since we treat ξ as a free parameter, we must calibrate ν and θ .
- For all but two persistence parameters, we use a Beta prior with mean 0.6 and standard deviation 0.2. One exception concerns labor productivity, which already includes a unit root. For this reason, we center the prior for the autocorrelation of its growth rate (ρ_z) at 0.4. The other exception is the autocorrelation of the inflation target shock, which we calibrate to 0.995. In other words, we restrict π_t^* so that it captures low-frequency movements in inflation.¹⁸
- Because it governs the rate at which π_t^* drifts, the standard deviation of the innovation to the inflation target is a crucial parameter in our analysis. We

partly endogenously in response to innovations in technology and the mark-up. However, with uninformative priors on these new coefficients, we found that variation in π_t^* is still driven primarily by the exogenous shock $\varepsilon_{*,t}$. The results for that version of the model are almost identical to those presented below.

¹⁷These variables are standard for estimating small-scale DSGE models (see, for instance, Boivin and Giannoni 2006).

¹⁸Section 5.6 describes the results of an alternative specification of the model where we set $\rho_* = 1$.

want a weakly informative prior in order to let the data dominate the posterior. Accordingly, we adopt a uniform prior on $(0,0.15)$. For the standard deviations of the other shocks, we follow Del Negro et al. (2007) by choosing priors that are fairly disperse and that generate realistic volatilities for the endogenous variables.

- In light of the results of Clarida et al. (2000) and Lubik and Schorfheide (2004), we experimented with a model with indeterminate equilibrium outcomes. However, identification was very weak. Moreover, such a model increased the value of the likelihood and posterior at the mode only slightly, while introducing several additional free parameters. As a consequence, we decided to truncate the prior at the boundary of the determinacy region.

Table 2: Priors for Structural Parameters

COEFFICIENT	PRIOR		
	Density	Mean	Standard Deviation
ν	<i>Calibrated</i>	2	—
θ	<i>Calibrated</i>	0.1	—
100γ	<i>Normal</i>	0.475	0.025
$100(\pi - 1)$	<i>Normal</i>	0.5	0.1
$100(\delta^{-1} - 1)$	<i>Gamma</i>	0.25	0.1
h	<i>Beta</i>	0.5	0.1
ξ	<i>Beta</i>	0.66	0.1
ϕ_π	<i>Normal</i>	1.7	0.3
ϕ_y	<i>Gamma</i>	0.3	0.2
ρ_R	<i>Beta</i>	0.6	0.2
ρ_z	<i>Beta</i>	0.4	0.2
ρ_θ	<i>Beta</i>	0.6	0.2
ρ_*	<i>Calibrated</i>	0.995	—
ρ_b	<i>Beta</i>	0.6	0.2
$100\sigma_R$	<i>Inverse Gamma</i>	0.15	1
$100\sigma_z$	<i>Inverse Gamma</i>	1	1
$100\sigma_\theta$	<i>Inverse Gamma</i>	0.15	1
$100\sigma_*$	<i>Uniform</i>	0.075	0.0433
$100\sigma_b$	<i>Inverse Gamma</i>	1	1

5.4 Estimation Results

We estimate the model separately on two subsamples.¹⁹ The first, 1960:I - 1979:III, corresponds approximately to the period of rising inflation before the Volcker chairmanship. The second period, 1982:IV - 2006:IV, corresponds to the Volcker and Greenspan chairmanships, excluding the years of monetary targeting, for which the Taylor rule might not represent an appropriate description of systematic monetary policy (see, for instance, Sims and Zha 2006 or Michael S. Hanson 2006). Figure 5 presents the model-implied evolution of the Central Bank inflation objective. Notice that it resembles quite closely the VAR-based estimate of the permanent component of inflation plotted in figure 1.

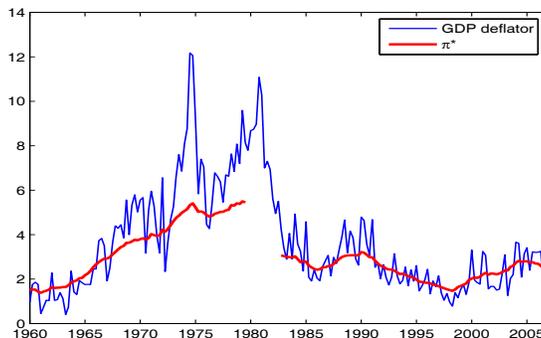


Figure 5: The Central Bank's Inflation Target

Table 3 reports estimates of the structural parameters. While many coefficients are similar across subsamples, there are some important differences. For example, we find that the Taylor-rule coefficient for inflation (ϕ_π) increased from 1.55 in the first subsample to 1.78 in the second. While an increase is consistent with findings of Clarida, et al. (2000) and Lubik and Schorfheide (2004), we do not find values of ϕ_π in the pre-1980 period as low as they do. This might be due to the fact that, for simplicity, we have ruled out indeterminacy a priori. Another possibility is that the presence of a time-varying inflation target reduces the difference between reactions to inflation in the two subsamples.

¹⁹The literature on estimation of DSGE models with drifting parameters and stochastic volatility is progressing (see, for instance, Jesus Fernandez-Villaverde and Juan Rubio-Ramirez 2008), but a number of computational challenges remain before these techniques can be applied to a model like ours. In particular, Fernandez-Villaverde and Rubio-Ramirez restrict attention to models with a single drifting parameter, while Cogley (2008) emphasizes the importance of allowing several parameters to drift jointly. Since that is currently beyond the computational frontier, we opt for a simpler approach based on split-sample estimation.

A second notable change in monetary policy concerns the innovation variances for the two shocks, $\varepsilon_{*,t}$ and $\varepsilon_{R,t}$. According to our estimates, both declined substantially after the Volcker disinflation. The innovation variance for the shock to target inflation fell by almost 50 percent, from 0.081 to 0.049, while the variance for the funds-rate shock declined even more, from 0.16 to 0.07. The decline in σ_* should not be surprising, given the findings of Stock and Watson (2007) and our VAR results. It contributes directly to the decline in inflation volatility after 1980.

Table 3: Posteriors for Structural Parameters

COEFFICIENT	1960-1979			1982-2006		
	Median	25th pct	75th pct	Median	25th pct	75th pct
100γ	0.468	0.452	0.484	0.484	0.467	0.500
$100(\pi - 1)$	0.501	0.435	0.566	0.516	0.452	0.581
$100(\delta^{-1} - 1)$	0.159	0.121	0.204	0.255	0.199	0.319
h	0.445	0.390	0.502	0.526	0.482	0.568
ξ	0.782	0.741	0.818	0.800	0.762	0.835
ϕ_π	1.557	1.372	1.746	1.784	1.598	1.974
ϕ_y	0.643	0.541	0.772	0.66	0.562	0.784
ρ_R	0.704	0.630	0.759	0.633	0.576	0.686
ρ_z	0.264	0.156	0.390	0.297	0.191	0.415
ρ_θ	0.598	0.515	0.676	0.255	0.182	0.344
ρ_b	0.699	0.632	0.758	0.876	0.850	0.898
$100\sigma_R$	0.160	0.147	0.174	0.069	0.063	0.076
$100\sigma_z$	0.641	0.527	0.797	0.493	0.426	0.562
$100\sigma_\theta$	0.118	0.097	0.139	0.126	0.114	0.137
$100\sigma_*$	0.081	0.062	0.104	0.049	0.037	0.065
$100\sigma_b$	2.533	2.226	2.889	2.429	2.146	2.785

Among the nonpolicy parameters, most change only slightly across the two samples. This is comforting because these parameters are supposed to be invariant to changes in monetary policy. One exception is the persistence parameter ρ_θ for the cost-push shock, which declines from 0.6 to 0.25. Thus, the cost-push shock is less persistent and has smaller unconditional variance after 1982. This decline might reflect the reduced incidence of oil-price shocks in the second half of the period.

Table 4 summarizes the model's implications for inflation volatility and predictability at the posterior median of the model parameters. Column 1 reports the unconditional standard deviation of inflation, while columns 2–4 report R^2 statistics

for inflation-gap predictability for forecasting horizons of 1, 4 and 8 quarters.²⁰ The inflation gap here is defined as the difference between inflation and the central bank inflation objective that, in the DSGE model, captures the permanent component of inflation. Notice that, in line with our statistical VAR findings, the model reproduces well the substantial decline in inflation volatility and predictability. All decrease by roughly 50 to 70 percent.

Table 4: Implications of the DSGE Model for Inflation Volatility and Predictability

	$100 \cdot std(\hat{\pi}_t)$	R_1^2	R_4^2	R_8^2
1960:I - 1979:III	4.702	0.631	0.433	0.409
1982:IV - 2006:IV	2.354	0.206	0.136	0.124
Percent Change	-50	-67	-69	-70

5.5 Counterfactuals

We are sufficiently encouraged by the performance of the DSGE model to conduct some counterfactual exercises in order to understand the causes of the decline in inflation volatility and predictability. In the first experiment, we combine the Taylor-rule coefficients ($[\phi_\pi, \phi_y, \rho_R, \sigma_R, \sigma_*]$) of the second subsample with the private-sector parameters of the first. In this way, we assess the extent to which better monetary policy would have reduced inflation volatility and persistence during the Great Inflation. In the second experiment, we combine the private-sector parameters of the second subsample with the policy parameters of the first. This scenario illustrates the contribution of nonpolicy factors to the improvement in inflation outcomes.

Table 5 reports the results. The numbers recorded there represent the proportion of the total change across subsamples accounted for by the hypothetical structural shift,

$$100 \times \frac{\text{counterfactual change}}{\text{total change}}.$$

Positive numbers signify that the counterfactual goes in the same direction as the total change, and negative numbers mean that it goes in the opposite direction.

²⁰Since we estimate the model on two separate subsamples, the joint posterior distribution of the coefficients of the first and second subsample is not available. Therefore, we cannot report standard errors.

Table 5: Counterfactual Exercises Based on the DSGE Model

COEFFICIENTS	VOLATILITY	PERSISTENCE		
		R_1^2	R_4^2	R_8^2
Policy 2, Private 1	75	43	90	91
σ_*	69	32	68	69
ϕ_π	9	13	28	28
Private 2, Policy 1	36	43	15	14
ρ_θ	7	-39	-109	-111

Monetary policy seems to be the most important factor behind the fall in inflation volatility, with the change in policy rule accounting for 75 percent of the decline. In contrast, nonpolicy parameters – primarily in the form of a less volatile and persistent cost-push shock – accounts for 36 percent of the decline. This is a substantial contribution, but only about half the magnitude of the effect of monetary policy.²¹

The results for predictability are similar, especially at the 4 and 8 quarter horizons. At those horizons, better monetary policy accounts for approximately 90 percent of the decline, while changes in private-sector behavior account for around 15 percent. At the 1-quarter horizon, however, the two factors contribute equally to the decline in predictability, each accounting for 43 percent of the total change. Thus, for a complete picture, both private and policy factors are needed.

The second and third rows of the table 5 look more closely at particular aspects of monetary policy. Here we change a single Taylor-rule parameter, holding all other coefficients equal to the estimated value from subsample 1. Otherwise the experiments are the same as before.

Among monetary-policy coefficients, changes in the variability of the inflation objective (σ_*) and in the reaction to inflation (ϕ_π) have the largest impact on inflation outcomes. The more stable inflation objective is responsible for the largest portion of the decline in inflation volatility and persistence, accounting for roughly two-thirds of the total change.

That a decline in σ_* reduces overall inflation volatility is obvious. Why it reduces inflation-gap persistence is less transparent. This is best understood as a composition effect. The inflation gap is driven by a number of shocks, some whose effects are short-lived and others whose effects are longer lasting. It turns out that inflation-target

²¹The two numbers need not sum to 100 because the model is nonlinear in the coefficients and, therefore, the total change is not the sum of the effects of the policy and nonpolicy coefficients shift.

shocks induce persistent responses in the inflation gap. A decline in their innovation variance therefore reduces overall inflation-gap persistence by diminishing the relative importance of this persistent component.

To illustrate this point, figure 6 plots the impulse response of the inflation gap and real interest rate to a one percentage point increase in the central bank’s inflation target. The blue line depicts the response in the first subsample. Because the model is linear, a reduction in σ_* with everything else held constant just scales the impulse responses toward zero. As in Ireland (2007), inflation overshoots the increase in the target, producing a positive inflation gap. The overshooting is due to the fact that the nominal interest rate initially responds little, leading to a substantial fall in the real interest rate (figure 6b), an increase in the output gap and marginal cost, and a positive jump in expected inflation. The weak initial reaction of nominal interest rates depends on the form of our policy rule (20), according to which R_t responds only to the difference between actual and target inflation. Had we adopted a policy rule in which the inflation target also affects the intercept (e.g., as in Schorfheide 2005), the overshooting would have been less likely.

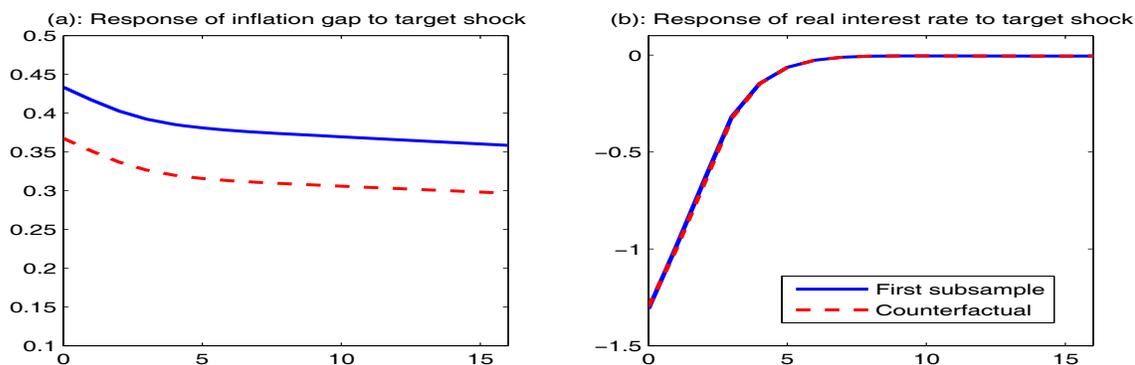


Figure 6: Responses to a One-Percent Increase in the Inflation Target.

After the initial overshooting, the inflation gap decays slowly back to zero. There are two reasons why this is the case. First, the policy response is weak. The central bank raises the nominal interest rate and brings the real interest rate back to its steady state level within a few quarters, but the real interest rate never rises above its steady-state level. Thus, although the central bank reverses the initial decline in the real rate, it stops short of raising the real interest rate to reverse the increase in

inflation gap. The second reason for the slow decay is that the estimated degree of price stickiness makes aggregate price adjustments slow. As a consequence, after the initial jump, the inflation gap moves gradually back to zero.

The other change in policy highlighted in table 5 involves a stronger monetary-policy reaction to inflation. The red lines in figure 6 plot the counterfactual response of the inflation gap and the real rate to a target shock, when we replace the policy reaction to inflation in the first subsample with the corresponding coefficient for the 1983-2006 period. Interestingly, the shape of the inflation gap response is unchanged, while the magnitude is reduced. In our model, however, this is secondary to enhanced stability of the inflation target, accounting for about 10 percent of the decline in volatility and 13-28 percent of the decline in predictability. One reason why we find a smaller contribution than have others (e.g., Lubik and Schorfheide (2004) or Boivin and Giannoni (2006)) is that we truncate our prior on the boundary of the determinacy region. Thus, our feedback parameter rises from 1.56 to 1.78. Enhanced feedback plays a role in our model, but not the primary role.

We also look more closely at the particular aspects of private-sector behavior that have the greatest influence on changing inflation outcomes. Among nonpolicy parameters, the key change is the shift in the persistence of the mark-up shock. The final row of table 6 sheds light on its contribution. Everything else equal, the decline in persistence of the mark-up shock (ρ_θ) would have induced an *increase* in inflation-gap persistence. This might seem surprising but has a simple explanation: a reduction in ρ_θ corresponds to a decrease in the unconditional variability of the mark-up shock, which reduces the volatility of inflation due to this shock. As a consequence, the role of the inflation-target shock for inflation becomes relatively larger, and this increases persistence.²²

5.6 A unit root in the target inflation

In our baseline specification, we set $\rho_* = 0.995$. We did this because the baseline specification does not possess a non-stochastic steady state when $\rho_* = 1$ and cannot be log-linearized. Following Ireland (2007), we can address this problem by modifying the baseline model. In particular, to accommodate a unit root in target inflation, we (i) alter the indexation scheme so that non-optimizing firms are fully indexed to a

²²The autoregressive parameter ρ_b on the discount-factor shock also changes substantially after 1982, but this has a negligible effect on inflation dynamics.

weighted average of target and lagged inflation and (ii) set the policy-inertia coefficient ρ_R in the monetary-policy rule equal to unity. With these changes, the model has a well defined steady state and can be log-linearized in the usual way. However, this version of the model generates extremely low inflation-gap predictability in both subsamples. Upon further investigation, we found that this is due to the arbitrary restriction on ρ_R , the inertia coefficient in the policy rule.

We want our DSGE model to reproduce two features of the VAR statistical description: (i) a highly persistent inflation target and (ii) some degree of inflation-gap predictability, especially in the first subsample. A DSGE model with a unit root in the target inflation is consistent with the first feature of the data but is sharply at odds with second. On the other hand, a model with $\rho_* = 0.995$ approximates both features well. This motivates our specification choice.

6 Relation to the literature

Andrew T. Levin and Jeremy M. Piger (2006) also emphasize the importance of accounting for shifts in target inflation when estimating inflation persistence. They estimate univariate autoregressions with breaks in the intercept at unknown dates. We interpret their shifting intercept as a way to model movements in target inflation. They find that inflation is less persistent after adjusting for shifts in the intercept, and they conclude that findings of high-persistence are artifacts of using empirical methods that neglect shifts in monetary-policy regimes. Earlier versions of their paper also investigated shifts in autoregressive parameters that would induce changes in inflation-gap persistence. For the period 1984-2004, they fail to detect a significant shift in autoregressive parameters. Our findings are consistent with theirs, because the big decline in persistence shown in figures 3 and 4 occurred before the beginning of their sample.

Stock and Watson (2007) also document changes in the predictability of inflation, reporting that inflation has become absolutely easier but relatively harder to forecast in the Volcker-Greenspan era. In an absolute sense, forecasting inflation is easier because inflation is less volatile and its innovation variance is smaller. But in a relative sense, predicting inflation has become more difficult because future inflation is less closely correlated with current inflation and other predictors.

Stock and Watson estimate a univariate unobserved-components model for infla-

tion. Our VAR can be interpreted as a multivariate extension of their model. To recover their representation, set $y_t = \pi_t$, $X_t = 1$, $\theta_t = \tau_t$, and $B_s = B_y = 1$. Their representation makes inflation the sum of a driftless random walk and a martingale-difference error and highlights the importance of drift in trend inflation. Our main focus, however, is on the inflation gap, $g_t \equiv \pi_t - \tau_t$. We want to know how persistent g_t is and whether the degree of persistence in g_t has changed over time. Stock and Watson’s model is not a suitable vehicle for investigating this issue because it imposes that g_t is serially uncorrelated for all t . Our VAR extends their model by allowing for time-varying serial dependence in the inflation gap and by including unemployment and nominal interest as predictors of inflation.

Stock and Watson also interpret a result of Andrew G. Atkeson and Lee E. Ohanian (2001) in terms of the changing time-series properties of inflation. Atkeson and Ohanian studied the predictive power of backward-looking Phillips-curve models during the Volcker-Greenspan era and found that Phillips-curve forecasts were inferior to a naive forecast that equates expected inflation over the next 12 months with the simple average of inflation over the previous year. Stock and Watson show that Phillips-curve models were more helpful during the Great Inflation, and they account for the change by pointing to two features of the data. First, like many macroeconomic variables, unemployment has become less volatile since the mid-1980s. Hence there is less variation in the predictor. Second, the coefficients linking unemployment and other activity variables to future inflation have declined in absolute value, further muting their predictive power.

Our VARs share these characteristics, while our estimated structural model reproduces the declining predictive power of real activity for future inflation.²³ For explaining Atkeson and Ohanian’s results, however, the relative importance of policy and nonpolicy factors is reversed. Changes in private sector parameters go in the right direction and overpredict the total decline in the output coefficient in a Phillips-curve regression, while changes in policy parameters go in the wrong direction and predict an increase in forecastability. Once again, both policy and nonpolicy factors contribute to explaining the outcomes.

Luca Benati (2008) provides perhaps the most comprehensive analysis of inflation persistence in the literature. Across a wide variety of monetary regimes and

²³Our replication and analysis of Atkeson and Ohanian’s findings can be found in an unpublished appendix posted on our web page.

historical periods, he finds strong evidence of changes in inflation persistence. In particular, inflation tends to be weakly persistent in monetary regimes with a clearly defined nominal anchor and highly persistent otherwise. He interprets this finding as reflecting the workings of the cross-equation restrictions emphasized by Lucas (1976).

For the period in which we are interested, however, Benati (2008) fails to detect a change in U.S. inflation persistence, measured either by the GDP or PCE deflator (see Benati's table VIII). He explains that his results differ from ours because he is interested in inflation persistence, while we examine inflation-gap persistence. Since trend inflation continued to drift after the Volcker disinflation, our representation implies that raw inflation still had an autoregressive root equal to unity, explaining Benati's findings. Our results only say that deviations between actual and trend inflation became less persistent.²⁴

A number of other papers also use new Keynesian DSGE models estimated across various subsamples to examine how changes in monetary policy altered equilibrium outcomes. Prominent examples include Lubik and Schorfheide (2004) and Boivin and Gianonni (2006), among others. These papers attribute improvements in inflation outcomes to better monetary policy, but they say that the primary cause was stronger feedback to expected inflation. As in Clarida, et al., their estimates suggest that the Fed violated the Taylor principle during the Great Inflation but satisfied it after the Volcker disinflation. Thus, monetary policy contributed to higher inflation volatility and persistence during the 1970s by failing to determine a unique equilibrium.²⁵

One difference between our model and theirs is that we allow target inflation to vary within each subperiod, while they assume it is constant. This distinction is significant because our results suggest that a reduced innovation variance for the inflation target was the single most important improvement in monetary policy during the Volcker-Greenspan years. We also find a stronger policy reaction to inflation after the mid-1980s, but the change is smaller, and its contribution is secondary.

It is true that we truncate our prior on the boundary of the determinacy region, thus ruling out indeterminacy, but the data led us to this modeling choice. As de-

²⁴Benati also examines univariate inflation persistence while we study predictability based on a multivariate information set. In earlier work, we found that multivariate models produced stronger evidence of changes in predictability than univariate models.

²⁵In a textbook new Keynesian model, Benati and Paolo Surico (2008) demonstrate that a more aggressive policy reaction to inflation reduces inflation persistence and predictability. They do not estimate a policy rule for the Great Inflation, however, thus stopping short of the stance taken by Lubik-Schorfheide and Boivin-Giannoni.

scribed above, preliminary estimates of a specification that allowed for indeterminacy increased the posterior mode only slightly, while introducing several new free parameters. Bayesian model comparisons reward fit and penalize free parameters. In this case, the improvement in fit seemed too slight to compensate for the additional model complexity, and we chose to focus on the simpler representation. That specification points toward better anchoring of the inflation target as the chief improvement of policy.

More work is needed to get to the bottom of this question. Obtaining a decisive resolution empirically might be difficult, however, in light of Andreas Beyer and Roger E.A. Farmer's (2007) analysis of identification.

Finally, Pivetta and Reis (2007), Benati and Surico (2008), Fabio Canova, Luca Gambetti, and Evi Pappa (2008) and Canova and Gambetti (2009) use VAR methods to study changes in inflation persistence. Their papers report mixed results, with Benati and Surico replicating our results, Canova et al. reporting only weakly statistically significant changes in inflation persistence, and Pivetta and Reis finding that changes in persistence are statistically insignificant. One possible explanation for this discrepancy is that Benati and Surico use our new measure of persistence based on short- and medium-term predictability, which is estimated more precisely, while Pivetta and Reis and Canova et al. do not. Moreover, Pivetta and Reis use univariate methods that we have found to weaken the evidence in favor of changes in inflation persistence.

7 Concluding remarks

This paper reports what vector autoregressions with drifting coefficients and stochastic volatility say about inflation-gap persistence, defined as the fraction of variation of future inflation gaps that is due to past shocks. A high proportion means that past shocks retain influence for a long time, while a low proportion signifies that their influence decays quickly. Since past shocks give rise to forecastable variation in future inflation gaps, our concept of persistence is closely related to predictability. VAR estimates point to a statistically significant increase in inflation-gap predictability during the Great Inflation and to a statistically significant decline in predictability after the Volcker disinflation.

We have used a new Keynesian DSGE model to interpret what might have caused

these changes. We find evidence that both better policy and changes in the environment confronting firms – in the form of less volatile and less persistent cost-push shocks – contributed to improved inflation outcomes. In our DSGE model, the enhanced stability of the Fed’s long-run inflation target stands as the single most important factor behind the reductions in inflation volatility and persistence.

The DSGE model treats the inflation target as an exogenous random process. Explaining why it drifts is a priority for future research. We like stories that feature learning and what it implies about changing central bank beliefs about the structure of the economy (Cogley and Sargent 2005b, Primiceri 2006, and Sargent, Williams, and Zha 2006), but more work is needed to understand this source of variations over time in monetary policy.

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