

INFLATION IN THE G7: MIND THE GAP(S)?

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We investigate the importance of trend inflation and the real-activity gap in explaining inflation in G7 countries since 1960. Our analysis is based on a bivariate unobserved components model of inflation and unemployment in which inflation is decomposed into a stochastic trend and a transitory component. As in recent implementations of the New Keynesian Phillips Curve, it is the transitory component of inflation, or “inflation gap,” that is driven by the real-activity gap, which we measure as the deviation of unemployment from its natural rate. We find that both trend inflation and the inflation gap have been consistent and substantial determinants of inflation at business cycle horizons for all G7 countries since 1960. Also, the real-activity gap explains a large fraction of the variation in the inflation gap for each country. These results provide empirical support for the New Keynesian Phillips Curve augmented with trend inflation.

Keywords: Inflation Persistence, Natural Rate, New Keynesian Phillips Curve, Trend Inflation

1. INTRODUCTION

The Phillips curve is one of the most recognizable theoretical constructs in macroeconomics. In its modern form, the Phillips curve relates observed inflation to expected inflation and a measure of excess demand, where the latter is most commonly expressed as the gap between the actual and potential levels of real activity. This relationship between inflation and the “real-activity gap” is a primary channel through which monetary policy is assumed to affect the inflation rate in most contemporary macroeconomic models.

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Despite its theoretical appeal, the empirical evidence linking the real-activity gap to inflation is mixed. A large literature, typified by the work of Robert Gordon (1982, 1997, 1998), estimates Phillips curve equations for which the expected inflation term is replaced by lags of inflation. In the “accelerationist” version of this model, the coefficients on lagged inflation are constrained to sum to unity. Such “backward looking” implementations of the Phillips curve typically find that the real-activity gap, whether measured using output or the unemployment rate, is strongly statistically significant as a driver for U.S. inflation. However, if one instead assumes rational expectations, as in the “New Keynesian” version of the Phillips curve (NKPC), the evidence in favor of the real-activity gap as an inflation driver is lessened. A number of studies, including Fuhrer and Moore (1995), Fuhrer (1997), Roberts (2001), and Estrella and Fuhrer (2002), find that the estimated effect of the real-activity gap in NKPC equations for U.S. inflation is insignificant, and in some cases has a counterintuitive sign.¹

Another empirical shortcoming of the NKPC relates to its inability to generate substantial inflation persistence. The NKPC implies that inflation is a discounted present value of expected real-activity gap terms, which, assuming the real-activity gap is covariance-stationary, implies that inflation itself is covariance-stationary. Further, estimates of the discounted present value of expected gap terms display low levels of persistence. This is at odds with the behavior of inflation, as it is difficult to reject the null hypothesis of a unit root in inflation for many countries. Indeed, it is now standard for univariate statistical characterizations of inflation to include a stochastic trend.² In response to this, recent contributions, including Cogley and Sbordone (2008) and Goodfriend and King (2012), augment the NKPC to allow for time-varying trend inflation. In these models, it is the “inflation gap” (i.e., the difference between inflation and its trend) that is influenced by the real-activity gap. Empirical implementations of the NKPC with trend inflation provide more evidence in favor of the real-activity gap as an inflation driver. For example, Lee and Nelson (2007), Harvey (2008), Piger and Rasche (2008), and Kim et al. (in press) find that the real-activity gap is a statistically significant driver of the U.S. inflation gap, whereas Cogley and Sbordone (2008) find that the fit of the NKPC for the inflation gap is improved over that for inflation itself.

In this paper, we provide evidence regarding the importance of trend inflation and the real-activity gap in explaining inflation variation for the G7 economies. We work with a bivariate unobserved components (UC) model of inflation and unemployment that is a reduced form of the NKPC with trend inflation. The real-activity gap is measured using the “unemployment gap,” defined as the deviation of unemployment from its natural rate. As in Staiger et al. (1997) and Laubach (2001), the natural rate is defined as the stochastic trend in unemployment. The unemployment gap is assumed to drive the inflation gap, measured as the deviation of actual and trend inflation. Following a large recent literature, for example Stock and Watson (2007), we measure trend inflation using the stochastic trend in inflation. Importantly, we allow for instability, in the form of multiple discrete structural breaks of unknown timing, in the variance of shocks to this stochastic

trend. The model is estimated using a Bayesian framework, and posterior probabilities are used to formally incorporate uncertainty regarding alternative numbers of structural breaks.

We fit our bivariate UC model to inflation and unemployment rates of G7 countries over sample periods that range from the past 40 to the past 50 years, depending on data availability for a given country. The estimation results suggest that both the inflation trend and the inflation gap have been important drivers of actual inflation at business cycle horizons for all countries throughout these sample periods. In particular, both the inflation trend and the inflation gap have contributed significantly to the variation of inflation at horizons ranging from one quarter to five years, although their relative importance has changed over time.

Turning to the determinants of the inflation gap, the results suggest that, consistent with the NKPC, the unemployment gap has been an important contributor to its variation in G7 countries. The average percentage of inflation gap variance attributed to the unemployment gap over the entire sample exceeds 30% for all G7 countries, and 50% for five countries. For most countries, this percentage has been at or near historic highs in recent years. Further, the level of the variance contributed by the unemployment gap to the variance of the inflation gap is notably quite stable for all countries over this sample period, supporting the idea of the NKPC as a structural concept that provides a useful theory of inflation.

The results also provide new estimates of time-varying trend inflation for the G7 economies, as well as shedding new light on the possible presence of structural changes in the variance of shocks to inflation and unemployment. For most of the countries considered, the level of trend inflation has varied substantially over time in a hump-shaped pattern, with low trend inflation in the 1960s, high trend inflation in the 1970s and early 1980s, and low trend inflation thereafter. Also, for all of the countries, trend inflation is near historical lows by the end of the sample period. For many of the countries, the level of trend inflation has generally been above actual inflation for significant periods in the 1980s and 1990s, which is driven by unemployment rates that are above the estimated natural rate. This result highlights the information that the real-activity gap adds for identification of trend inflation. Finally, model comparisons provide strong evidence of multiple structural breaks in the variance of shocks to inflation and unemployment for France, Italy, the United Kingdom, and the United States, but less evidence of multiple breaks for Canada, Japan, and Germany. For all of the countries, the volatility of shocks to trend inflation is at or near historic lows at the end of the sample period.

Because trend inflation in our model represents permanent variation in inflation, it is closely tied to long-horizon expectations of inflation. Indeed, as in Beveridge and Nelson (1981), the long-run expectation of inflation at time t is equivalent to the expectation of trend inflation formed using time- t information. Thus, our results could alternatively be interpreted as suggesting that long-horizon inflation expectations have played an important, although not dominant, role in explaining inflation variation at business cycle horizons in most G7 countries, and that

long-horizon expectations are currently “anchored” at low levels across the G7. This recent similarity exists despite differences in monetary institutions across G7 countries, primarily the choice of whether or not the monetary authority will formally adopt inflation targeting.

Our paper is most closely related to several recent studies of inflation dynamics that incorporate trend inflation. Lee and Nelson (2007), Harvey (2008), Piger and Rasche (2008), and Kim et al. (in press) estimate similar bivariate UC models of inflation and unemployment and investigate the statistical significance of the real-activity gap.³ However, they do not consider data outside the United States. Cecchetti et al. (2007), estimate a UC model that separates each G7 inflation series into a stochastic trend plus a cycle and allow for time variation in the variance of shocks to the inflation trend. However, these authors focus on univariate analysis in which the cyclical component of inflation is not influenced by the real-activity gap, and so do not provide evidence regarding the relative importance of the real-activity gap for explaining inflation variation in the G7. Further, we find that incorporating information from the real-activity gap for identification of trend inflation makes for significant differences in the estimated pattern of trend inflation in several countries. Finally, most previous studies do not consider formal testing or model comparisons regarding the statistical importance of parameter changes. For several countries, most notably Canada, our results support conclusions regarding structural change different from those reached in Cecchetti et al. (2007), who impose a fairly specific structure on the ongoing time variation in the variance of shocks.

The remainder of this paper is organized as follows. Section 2 motivates and details the bivariate UC model used in our analysis. Section 3 discusses the G7 inflation data and describes the Bayesian techniques we use for estimation and model comparison. Section 4 presents posterior model probabilities comparing models with alternative numbers of structural breaks, whereas Section 5 provides new estimates of trend inflation, the natural rate, and the associated inflation and real-activity gaps. Section 6 presents results regarding the contribution of trend inflation and the inflation gap to the variability of inflation changes, as well as the contribution of the unemployment gap to the variance of the inflation gap. Section 7 concludes.

2. MODEL SPECIFICATION

We assume that the quarterly inflation rate, π_t , is an $I(1)$ process with trend/cycle representation

$$\pi_t = \bar{\pi}_t + \pi_t^s, \quad (1)$$

where the trend component, $\bar{\pi}_t$, represents the stochastic trend in inflation, and π_t^s is a zero-mean, covariance-stationary process that, following Cogley et al. (2010), we label the “inflation gap.” As is standard in the recent literature, trend inflation

is modeled as a driftless random walk,

$$\bar{\pi}_t = \bar{\pi}_{t-1} + v_t, \quad (2)$$

where v_t represents a stochastic shock to trend inflation. Stock and Watson (2007) and Piger and Rasche (2008) find that the variance of shocks to trend inflation in the United States has varied substantially over time, whereas Cecchetti et al. (2007) document similar patterns for some G7 economies. To capture the possibility of changes to the volatility of shocks to trend inflation, we assume that v_t is a Gaussian random variable with time-varying variance,

$$v_t \sim N(0, \sigma_{v,t}^2),$$

where $\sigma_{v,t}^2$ follows a discrete structural break process with m structural changes, so that $\sigma_{v,t}^2 = \sigma_{v,i}^2$, $i = 1, \dots, m + 1$. In the empirical implementation of the model, we treat the dates of the structural changes, $\tau_1, \tau_2, \dots, \tau_m$, as unknown parameters, and the selection of m as a problem of model selection.⁴

The trend inflation component has strong links to the long-horizon forecast of inflation, which is equivalent to “core inflation” as defined by Bryan and Cecchetti (1994). Because π_t^s is covariance-stationary with zero mean, and $\bar{\pi}_t$ follows a random walk, the long-horizon inflation expectation can be written as

$$\lim_{h \rightarrow \infty} \frac{1}{h} E_t(\pi_{t+h}) = E_t(\bar{\pi}_t),$$

where E_t is an expectation formed using information available at time t . Thus, the minimum mean-squared error estimate of trend inflation at time t is equivalent to the long-horizon forecast of inflation arising from the model. Also, as discussed in Bernanke (2007), because trend inflation in the model captures permanent changes to the inflation rate, it is unlikely that trend inflation would display substantial variation that was not mirrored in long-horizon forecasts of inflation. Finally, several studies, including Cecchetti et al. (2007), Clark and Davig (2008), and Piger and Rasche (2008), show that survey measures of long-horizon inflation expectations are closely aligned with estimates of trend inflation in the United States.

The modern Phillips curve posits a short-run tradeoff between inflation and the real-activity gap. In our framework, this suggests that the real-activity gap should be a driver of the inflation gap, which represents the temporary deviation of inflation from its stochastic trend. To capture this, we specify the following linear relationship between the inflation gap and the real-activity gap:

$$\pi_t^g = \sum_{j=0}^{p_x} \delta_j x_{t-j} + z_t. \quad (3)$$

In (3), π_t^g is partially determined by a distributed lag of the real-activity gap, denoted x_t . We augment (3) with a residual component, z_t , meant to capture

variation in the inflation gap not related to the real-activity gap. We assume that this residual component has an autoregressive representation,

$$\psi(L) z_t = \omega_t, \tag{4}$$

where $\psi(L)$ is an invertible lag polynomial and ω_t is a Gaussian stochastic shock with time-varying variance,

$$\omega_t \sim N(0, \sigma_{\omega,t}^2).$$

Consistent with the variance of trend inflation, $\sigma_{\omega,t}^2$ is assumed to follow a discrete structural break process with m structural changes, where the timing of the structural changes is shared with that of changes in the variance of trend inflation.

We measure the real-activity gap as the unemployment gap, or the deviation of the unemployment rate from its natural rate. In particular, and similarly to inflation, we assume that the quarterly unemployment rate is an $I(1)$ process with a trend/cycle representation

$$u_t = \bar{u} + x_t. \tag{5}$$

Following Staiger et al. (1997) and Laubach (2001), we assume that the natural rate, \bar{u}_t , is equivalent to the stochastic trend in the unemployment rate, modeled as a random walk with drift:

$$\begin{aligned} \bar{u}_t &= \mu + \bar{u}_{t-1} + \eta_t, \\ \eta_t &\sim N(0, \sigma_{\eta,t}^2). \end{aligned} \tag{6}$$

Finally, the unemployment gap is modeled as an autoregressive process,

$$\begin{aligned} \phi(L) x_t &= \varepsilon_t, \\ \varepsilon_t &\sim N(0, \sigma_{\varepsilon,t}^2), \end{aligned} \tag{7}$$

where $\phi(L)$ is an invertible lag polynomial. Again, to model time-varying volatility, $\sigma_{\eta,t}^2$ and $\sigma_{\varepsilon,t}^2$ are assumed to follow a discrete structural break process with m structural changes, where the timing of the structural changes is shared with that for the other shocks in the model. We assume that the four shocks in the model are mutually independent of one another, both contemporaneously and at all leads and lags.⁵

Taken together, equations (1)–(7) form a bivariate UC model for inflation and unemployment. As discussed in Harvey (2008) and Kim et al. (in press), this model can be interpreted as the reduced form of the NKPC with trend inflation described in Goodfriend and King (2012). In particular, the NKPC with trend inflation implies that the inflation gap has the following dynamics:

$$\pi_t^g = \kappa \sum_{j=0}^{\infty} \beta^j E_t(x_{t+j}), \tag{8}$$

where β is the discount rate. Assuming that x_t follows an autoregressive process as in (7), the expectations in (8) have a simple, recursive structure that yields a linear expression for π_t^g in terms of current and lagged values of the real-activity gap. For example, if $x_t = \phi x_{t-1} + \varepsilon_t$, then we have the following reduced form for (8) upon substituting expectations:

$$\begin{aligned}\pi_t^g &= \delta x_t, \\ \delta &= \frac{\kappa}{1 - \beta\phi}.\end{aligned}$$

Thus, the inflation gap equation in (3) is a reduced form of (8), augmented to include a role for a serially correlated residual component (z_t).⁶

The model in (1)–(7) also has connections to the accelerationist version of backward-looking Phillips curve models. In these models, inflation dynamics are described by

$$\pi_t = \sum_{j=1}^{p_\pi} \alpha_j \pi_{t-j} + \sum_{j=1}^{p_x} \delta_j x_{t-j} + z_t, \quad (9)$$

where $\sum_{j=1}^{p_\pi} \alpha_j = 1$. As discussed in Harvey (2008) and Piger and Rasche (2008), equations (1)–(3) result from replacing the lags of inflation in (9) with the trend inflation component in (2). However, although related, these models have significant differences in their implications for inflation dynamics. In the accelerationist Phillips curve, inflation persistence is a structural feature of the model, in that all variation in inflation becomes mechanically imbedded in the permanent component of inflation. By contrast, in the model in (1)–(7), only events that influence the shock to trend inflation have permanent effects. Further, Stock and Watson (2007) and Cecchetti et al. (2007) present evidence that the first difference of G7 inflation series contain important moving average dynamics. The additive structure of the trend/cycle decomposition in (1) generates such dynamics, regardless of the influence of the unemployment gap.

3. DATA AND ESTIMATION

We estimate the bivariate UC model in (1)–(7) for each of the G7 countries, which requires data on inflation (π_t) and the unemployment rate (u_t). To measure the inflation rate, we use the log first difference, multiplied by 400, of the quarterly consumer price index, whereas the unemployment rate is a household survey-based measure. All data were obtained from the OECD database. For each country, we use the longest sample for which all necessary variables were available. Data for Canada, Germany, Italy, the United Kingdom, and the United States begin between 1957 and 1963, and for France and Japan in 1968 and 1970, respectively. All data series end in either the first or second quarter of 2010. Table 1 details the exact sample periods used in estimation for each country.

We have identified a few specific cases in which exogenous events, such as shifts in VAT or other sales tax rates, resulted in large transitory fluctuations in the inflation series. The dates of these events are listed in Table 2. In order not to allow

TABLE 1. Data sample periods

| Country | Period |
|----------------|-----------------|
| Canada | 1961:Q2–2010:Q2 |
| France | 1968:Q1–2010:Q2 |
| Germany | 1962:Q2–2010:Q1 |
| Italy | 1960:Q2–2010:Q1 |
| Japan | 1970:Q2–2010:Q2 |
| United Kingdom | 1963:Q2–2010:Q2 |
| United States | 1957:Q2–2010:Q2 |

such outliers to dominate our results regarding the contribution of the transitory component of inflation to the inflation process, we replace these outliers with the centered six-quarter medians of adjacent observations that were not themselves outliers.⁷ Meanwhile, the allowance of a residual component in the inflation gap means that our model can capture other transitory shocks to headline inflation that are not related to a Phillips curve relationship.

The bivariate UC model is based on the assumption that both the inflation and unemployment rate follow a unit root process. To provide some evidence regarding the validity of this assumption, Table 3 shows the results of unit root tests for each series by country. The results of these tests are largely consistent with the assumptions of the model. In particular, we cannot reject the null hypothesis of a unit root at the 5% level for any of the unemployment rates or for six of the seven inflation rates, the exception being Japanese inflation.

We estimate the bivariate UC model using a Bayesian framework, which requires prior specifications for each of the model parameters. Our prior densities are independent across parameters. Turning to individual parameters, our prior density for each shock variance, $\sigma_{\omega,i}^2$, $\sigma_{\eta,i}^2$, $\sigma_{\varepsilon,i}^2$, and $\sigma_{v,i}^2$, $i = 1, \dots, m + 1$, is inverse gamma with shape parameter 2.5 and scale parameter 0.5. For each slope parameter in the inflation gap equation, δ_i , each autoregressive parameter in the residual component of the inflation gap, ψ_i , and the drift in the natural rate, μ , our prior density is standard normal. For each autoregressive parameter in the unemployment gap equation, ϕ_i , our prior density is normal with mean zero and variance $(0.5/i)^2$. This prior shrinks the autoregressive terms toward zero, which reflects our prior

TABLE 2. Dates of inflation outliers due to exogenous events

| Country | Date | Event |
|----------------|---------------|--------------------------|
| Canada | 1991:1 | Cigarette tax change |
| | 1994:1–1994:2 | Cigarette tax change |
| Germany | 1991:1–1991:4 | Reunification |
| | 1993:1 | VAT introduction |
| Japan | 1997:2 | Consumption tax increase |
| United Kingdom | 1990:2 | Poll tax introduction |

TABLE 3. Augmented Dickey–Fuller tests

| Country | Unemployment rate | CPI inflation |
|----------------|-------------------|---------------|
| Canada | 0.45 | 0.27 |
| France | 0.85 | 0.29 |
| Germany | 0.12 | 0.06 |
| Italy | 0.46 | 0.57 |
| Japan | 0.22 | 0.00 |
| United Kingdom | 0.14 | 0.30 |
| United States | 0.18 | 0.06 |

Notes: The table contains the MacKinnon (1996) p -values for the augmented Dickey–Fuller (ADF) test for a unit root in the indicated series. Lag lengths were selected using the Akaike information criterion based on a maximum lag length of 12 quarterly lags. The ADF test regression included an intercept for all series, and included a deterministic trend for French and Japanese inflation and French, German, and Japanese unemployment.

belief that the real-activity gap should be a clearly stationary process, and avoids potential identification issues associated with a UC model in which the transitory component displays near-unit-root behavior. Finally, for the dates of the structural breaks to shock variances, $\tau_1, \tau_2, \dots, \tau_m$, we assume a uniform distribution across all admissible combinations of m break dates. As admissible, we consider all break dates that do not occur in the first or final 10% of the sample and have at least 5% of the sample between breaks. By incorporating structural breaks, we can consider as long a sample period as possible based on data availability, without worrying that we are averaging estimates across major structural changes in the economy.

To simulate samples from the posterior distribution of the model parameters, we use a Metropolis-within-Gibbs sampling algorithm. The model parameters are divided into two blocks, the first holding the m structural break dates, and the second consisting of all other model parameters. To sample from the posterior distribution of the break dates, conditional on the other parameters of the model, we use the Gibbs sampling steps detailed in Wang and Zivot (2000). To sample from the posterior distribution of the other model parameters, conditional on the structural break dates, we use a Metropolis–Hastings step with proposals generated from a random walk chain. The variance–covariance matrix of innovations to the random walk chain is calibrated using a multivariate normal approximation to the posterior distribution of the relevant parameters.⁸ With the variance–covariance matrix of this approximating distribution denoted as \hat{V} , the variance–covariance matrix for the innovations to the random walk chain is then set equal to $c\hat{V}$, where c is a scalar calibrated to yield acceptable proposal acceptance rates.⁹ Conditional on each draw of all model parameters, we also draw a realization of trend inflation, $\bar{\pi}_t$, and the natural rate, \bar{u}_t , from their respective posterior distributions using the multimove sampler of Carter and Kohn (1994). All results are based on 20,000 draws after an initial 5,000 draws are discarded. To check that

the sampler had converged, we ran the algorithm multiple times from dispersed sets of starting values and obtained very similar summary statistics regarding the sampled posterior distributions.

For each country, we estimate alternative versions of the model that differ by the number of structural breaks in the variance of innovations to the model shocks, where we consider from $m = 0$ to 4 breaks. To compare alternative values of m , we use the posterior probability of the model with m breaks, $\Pr(m|Y)$, where Y represents the data used in estimation. From Bayes's rule, this probability is proportional to the marginal likelihood of the model with m structural breaks multiplied by the prior probability of m structural breaks:

$$\Pr(m|Y) \propto f(Y|m) \Pr(m).$$

To calculate the marginal likelihood, we use an asymptotic approximation provided by the Schwarz information criterion (SIC).¹⁰ Under fairly general conditions, the SIC statistic is a consistent estimate of the log of the marginal likelihood and is a popular choice to approximate the marginal likelihood in applied work.¹¹ Using this approximation, we then have the following equation for the posterior model probability:

$$\Pr(m|Y) = \frac{e^{SIC_m} \Pr(m)}{\sum_{m=0}^4 e^{SIC_m} \Pr(m)}.$$

Finally, to set the prior model probability, $\Pr(m)$, we give equal prior weight to the case of constant parameters and changing parameters, so $\Pr(m = 0) = 0.5$ and $\Pr(m > 0) = 0.5$. We then assign equal prior probability to each value of $m > 0$ considered, or $\Pr(m) = \frac{1}{8}$, $m = 1, \dots, 4$.

4. EVIDENCE FOR STRUCTURAL BREAKS IN VOLATILITY

We begin by comparing models with alternative numbers of structural breaks in the volatility of model shocks.¹² For each country, Table 4 presents the posterior model probability for alternative numbers of structural break from 0 to 4, constructed as discussed in Section 3. The probabilities provide strong evidence for structural breaks in the volatility of model shocks to inflation and unemployment over the sample periods considered here. For six of the G7 countries, the posterior probability of at least one break is close to 100%. An interesting exception is Canada, for which the model with no structural breaks is strongly preferred. For the remaining countries, the posterior probability is mixed across different numbers of breaks. For Germany there is strong evidence of a single break, whereas for the United Kingdom and the United States, the evidence favors three and four breaks, respectively. For France, Italy, and Japan, the posterior probability is spread across alternative numbers of breaks. In the results presented in the following, we average posterior distributions for objects of interest from models that assume a specific number of breaks according to the posterior model probabilities in Table 4. This

TABLE 4. Posterior probability for number of breaks in variance of model shocks

| Country | Number of breaks | | | | |
|----------------|------------------|-------|-------|-------|-------|
| | 0 | 1 | 2 | 3 | 4 |
| Canada | 99.2% | 0.8% | 0.0% | 0.0% | 0.0% |
| France | 0.0% | 1.3% | 54.3% | 44.4% | 0.0% |
| Germany | 2.2% | 93.9% | 0.0% | 0.0% | 3.9% |
| Italy | 0.0% | 0.0% | 10.7% | 17.8% | 71.5% |
| Japan | 0.0% | 69.6% | 18.5% | 11.9% | 0.0% |
| United Kingdom | 0.0% | 0.1% | 0.0% | 99.9% | 0.0% |
| United States | 0.0% | 0.0% | 0.0% | 1.8% | 98.2% |

Notes: The table contains the posterior probabilities of alternative numbers of structural breaks in the variances of model shocks. Posterior probabilities are based on the asymptotic approximation given by the SIC, as discussed in Section 3.

Bayesian model averaging (BMA) produces inferences that are not conditioned on a particular number of structural breaks and is the standard Bayesian solution to incorporating model uncertainty.

5. ESTIMATES OF TREND INFLATION AND THE NATURAL RATE

In this section, we first present estimates of trend inflation and estimates of the (potentially) time-varying variance of shocks to trend inflation for the G7 countries. We then turn to estimates of the natural rate and the unemployment gap, as well as providing some initial evidence regarding the relationship between the inflation gap and the unemployment gap.

5.1. Trend Inflation

Figure 1 displays the actual inflation rate, along with the median of the BMA posterior distribution of $\bar{\pi}_t$. There are three similarities across countries that we highlight here. First, there is a general reduction in trend inflation that begins in the late 1970s to early 1980s and continues to near the end of the sample, where trend inflation is at or near its lowest sample level. Second, the estimates of $\bar{\pi}_t$ follow a hump-shaped pattern in which trend inflation is lower in the 1960s, higher in the 1970s, and lower again since the early 1980s. The magnitude of these changes varies across countries, and is least pronounced for Germany. Third, for most countries, there are examples of substantial and persistent deviations of trend inflation from actual inflation, which reflects the influence of the inflation gap. The primary exception is France, for which the estimates of trend inflation follow actual inflation rather closely.

Figure 2 displays the median of the BMA posterior distribution of $\sigma_{v,t}^2$, the variance of shocks to trend inflation. This posterior distribution integrates out uncertainty regarding the number and location of structural breaks, which explains

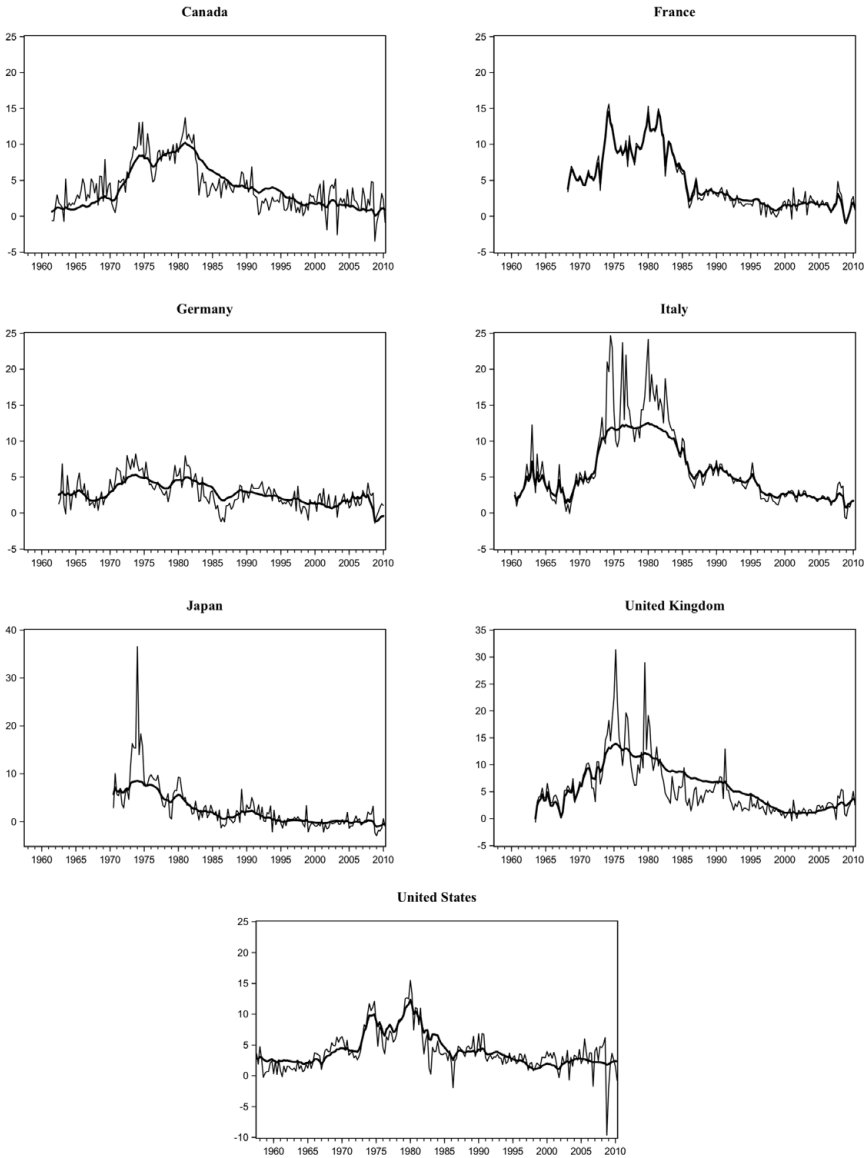


FIGURE 1. Inflation and estimated trend inflation. The graphs plot the quarterly inflation rate (thin line), measured using the CPI, along with the median of the posterior distribution for trend inflation (thick line). Note that the vertical scale is unique for Japan, the United Kingdom, and the United States.

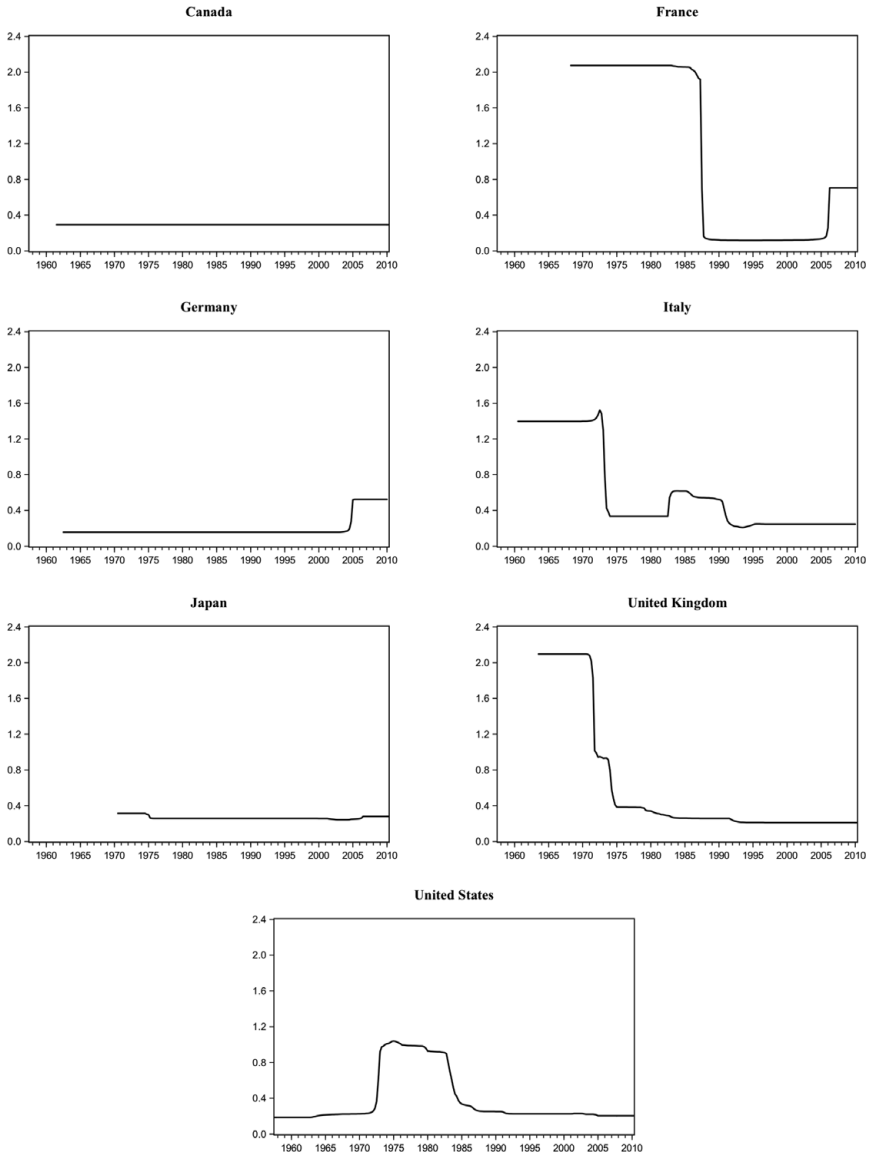


FIGURE 2. Variance of shocks to trend inflation. The graphs plot the median of the posterior distribution of the variance of shocks to trend inflation.

the smoother pattern to the posterior median of $\sigma_{v,t}^2$ in some cases than would be suggested by a model with known number and locations of breaks. The results in Figure 2 can usefully be divided into three groups. First, for the United States, the volatility of shocks to trend inflation display a pattern similar to that observed for the level of trend inflation in Figure 1. In particular, when the level of trend

inflation is high, the volatility of shocks to trend inflation is also high. Second, for France, Italy, and the United Kingdom, the volatility of shocks to trend inflation follows a pattern of being high early in the sample and lower thereafter. For the four countries in these two groups, the decline in the variance of shocks to trend inflation from the peak value to the end of sample value are quantitatively large, with the end of sample variance being less than 40% of the peak variance in all cases. Finally, for Canada, Germany, and Japan, the volatility of shocks to trend inflation is fairly stable at low values throughout the sample. For all countries, the estimated variance of shocks to trend inflation is near a sample period low at the end of the sample. There is remarkable similarity in the estimated variance of trend inflation in the final sample period, with all variances lying in a tight range from 0.2 (United States) to 0.7 (France).

As discussed earlier, trend inflation is likely closely linked to long-horizon inflation expectations, suggesting that the results in Figures 1 and 2 could alternatively be interpreted as results regarding the evolution and uncertainty of long-horizon inflation expectations. Thought of in this way, Figures 1 and 2 suggest that long-horizon inflation expectations have played an important role in the determination of actual inflation paths over the sample periods considered here, and that uncertainty regarding long-horizon expectations of inflation is currently at historically low levels in all G7 countries. Given the important role that the credibility of the monetary authority likely has in the determination of uncertainty regarding long-horizon inflation expectations, it is notable that this recent “anchoring” of inflation expectations exists despite the fact that there are substantial differences in the monetary institutions across these countries, most notably the presence or absence of a formal inflation-targeting framework.

An interesting feature of Figures 1 and 2 is that there are several countries with similar estimated patterns for the level of trend inflation that do not have similar estimated patterns for the volatility of trend inflation, with Canada, the United States, and the United Kingdom providing a leading example. Each of these countries has estimates of trend inflation that follow a hump-shaped pattern over the sample. However, whereas the United States shows strong evidence of a similar hump-shaped pattern for trend inflation volatility, this pattern is not a feature of the preferred model for the United Kingdom and Canada. In other words, Figures 1 and 2 do not provide consistent evidence for a link between the level of trend inflation and its volatility, or, cast in terms of inflation expectations, between the level of trend inflation and the uncertainty associated with long-horizon inflation expectations. Notably, these results are not consistent with the traditional hypothesis, prominently argued for in Okun (1971) and Friedman (1977), that there is a strong positive relationship between inflation levels and uncertainty about future inflation, at least not within the G7 countries for the sample periods considered here.

Our modeling strategy uses unemployment to inform estimates of trend inflation and trend inflation volatility. To see the value added by this bivariate approach, it is useful to compare the results in Figures 1 and 2 with those in Cecchetti

et al. (2007), who estimate trend inflation in the G7 countries using a univariate UC model of inflation. The deviations of inflation from the Cecchetti et al. (2007) estimates of trend inflation, as displayed in Figure 3.1 of their paper, are in many cases smaller and less persistent than is true for the estimates from our model. For example, for Italy and the United States, their estimates of trend inflation track inflation very closely, whereas our estimates of trend inflation are relatively smooth. In Canada, Germany, and the United Kingdom, the deviations of inflation from their measure of trend inflation are much less persistent than the deviations from our estimates displayed in Figure 1. In a number of countries, there are large, persistent deviations of inflation below our measure of trend inflation during periods in the 1980s and 1990s when these economies were in recession, which is not a feature of the Cecchetti et al. (2007) estimates. As we will show later, this result is driven by substantial deviations of unemployment above the estimated natural rate over these periods, and highlights the role the unemployment gap plays in the identification of trend inflation for our model.

Cecchetti et al. (2007) also find that the variance of trend inflation follows a pattern very similar to the level of trend inflation for most countries, whereas, as discussed previously, our results find much less such similarity. In addition to the information provided by the unemployment rate, another reason for this difference is our consideration of model uncertainty regarding the number of structural changes. As a leading example, Cecchetti et al. (2007) document trend inflation volatility in Canada that follows a hump-shaped pattern, undergoing multiple structural breaks. However, the model comparisons presented here suggest that the model with no breaks in Canadian trend inflation volatility is strongly preferred to the model that includes breaks. Thus, consideration of uncertainty regarding the number of structural changes can have very significant effects on the results.

5.2. The Natural Rate and Unemployment Gap

We next present estimates of the natural rate of unemployment and the unemployment gap, which are estimated inside the bivariate UC model and therefore informed by the behavior of inflation and the NKPC. Figure 3 displays the actual unemployment rate along with the median of the BMA posterior distribution of the natural rate, \bar{u}_t , for each country. For all countries, the natural rate evolves relatively smoothly as compared to actual unemployment, taking persistent, substantial deviations from the unemployment rate. In Canada, Italy, the United Kingdom, and the United States, the natural rate follows a hump-shaped pattern, whereas for France, Germany, and Japan, the natural rate drifts upward over the entire sample. In several countries, the natural rate rises noticeably during the late 2000s global recession. This is especially true in the United States, where the natural rate at the end of the sample is at a sample period high of 7.4%. Figure 4 displays the median of the BMA posterior distribution of $\sigma_{\eta,t}^2$, the variance of shocks to the natural rate. There is relatively little time variation in these variances compared with that seen for the variance of shocks to trend inflation in Figure 2.

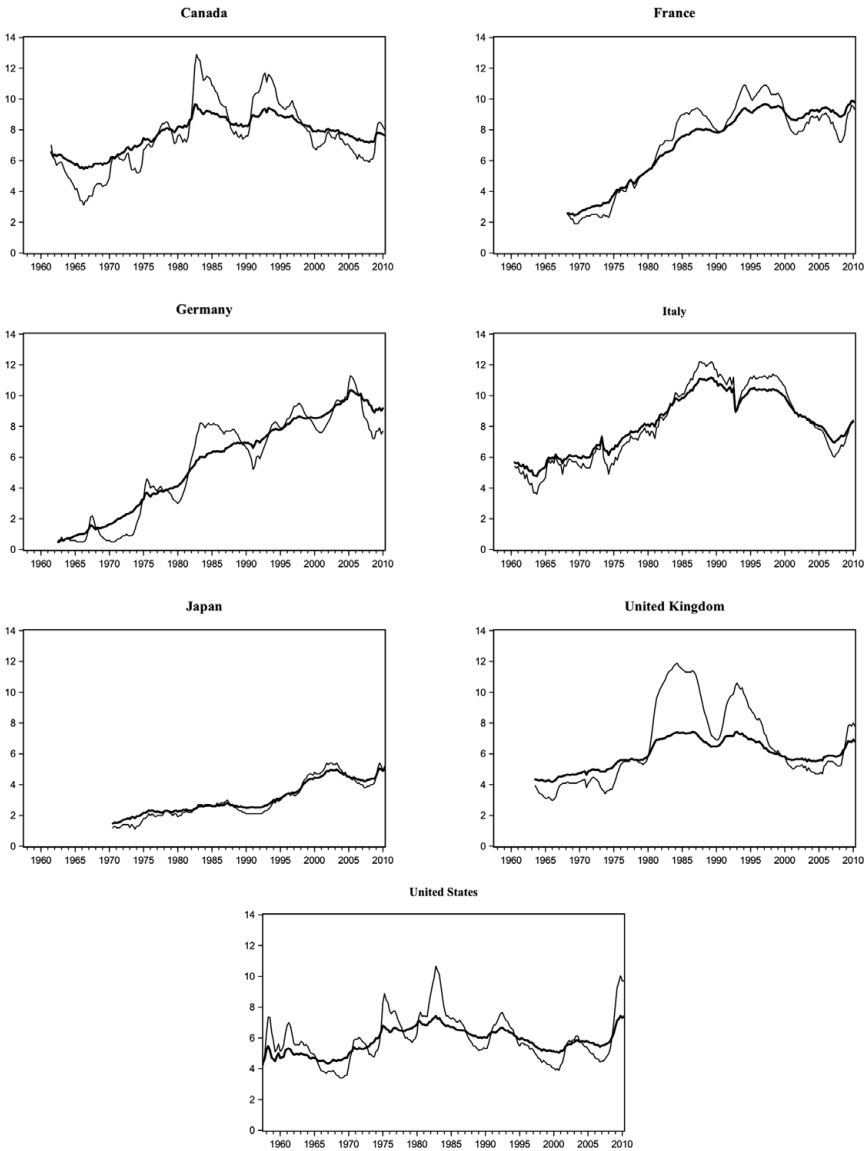


FIGURE 3. Unemployment rate and estimated natural rate. The graphs plot the quarterly unemployment rate (thin line) and the median of the posterior distribution for the natural rate of unemployment (thick line).

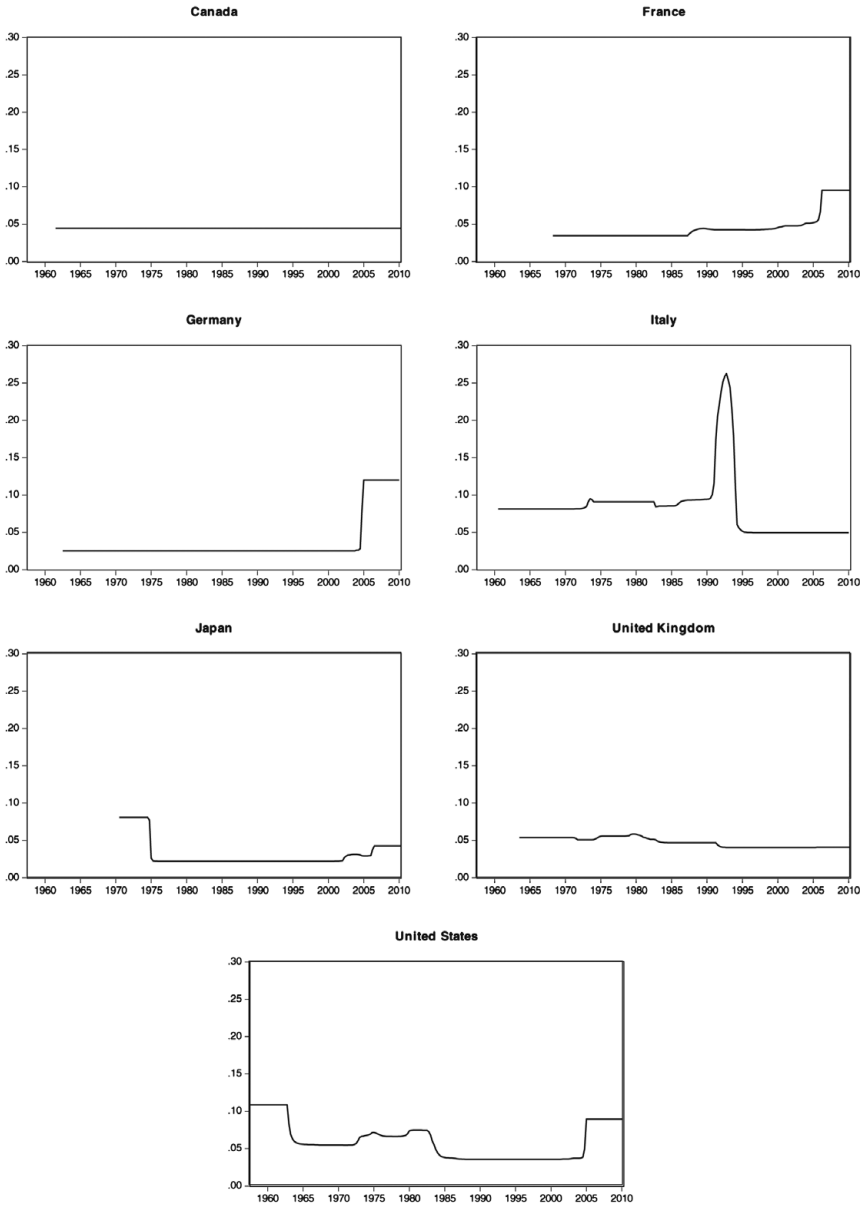


FIGURE 4. Variance of shocks to the natural rate. The graphs plot the median of the posterior distribution of the variance of shocks to the natural rate.

Figure 5 displays the median of the BMA posterior distribution of the unemployment gap, which is a primary theoretical driver of the inflation gap in the NKPC with trend inflation. As a first pass to gauging the empirical relationship between the unemployment gap and the inflation gap, Figure 5 also presents the median of the BMA posterior distribution of the inflation gap. From Figure 5, there is strong visual evidence of such a relationship in many G7 countries. In particular, for most countries, there is a striking pattern of persistent positive unemployment gaps being associated with persistent negative inflation gaps and vice versa. This pattern appears stronger in Canada, France, Germany, the United Kingdom, and the United States, and weaker in Japan and Italy. Overall, this is suggestive evidence of an important role for the unemployment gap in determining the inflation gap in G7 countries. In the next section we expand on this evidence, providing quantitative measures of the importance of this relationship.

6. CONTRIBUTION OF INFLATION COMPONENTS TO INFLATION VARIATION

This section presents results regarding the contributions of the various inflation drivers in the model of (1)–(7) to inflation volatility. We begin by documenting the relative contributions of the inflation trend and inflation gap to the variance of inflation changes. We then turn to the relative contributions of the unemployment gap and the residual component to the variance of the inflation gap.

6.1. Determinants of Inflation Volatility

To measure the relative importance of the inflation trend vs. the inflation gap for inflation volatility, we construct variance decompositions. As the model assumes that inflation contains a unit root, we focus on explaining the volatility of inflation changes at various horizons. To measure the contribution of the inflation trend to variation in j -quarter inflation changes, we construct the following ratio:

$$V_{j,t} = \frac{v(\bar{\pi}_t - \bar{\pi}_{t-j})}{v(\pi_t - \pi_{t-j})},$$

where $v(\cdot)$ denotes a variance. For models with structural changes in the volatility of model shocks, $V_{j,t}$ may vary with t . To obtain draws from the posterior distribution for $V_{j,t}$ based on a model with a particular value of m , we compute $V_{j,t}$ analytically for each draw from the posterior distribution of the model parameters. We then obtain draws from the BMA posterior distribution for $V_{j,t}$ using the model-specific draws and the posterior model probabilities in Table 4. Given that inflation is determined by trend inflation and the inflation gap only, and shocks to these components are independent, the contribution of the inflation gap to the variance of j -quarter inflation changes is simply $1 - V_{j,t}$.

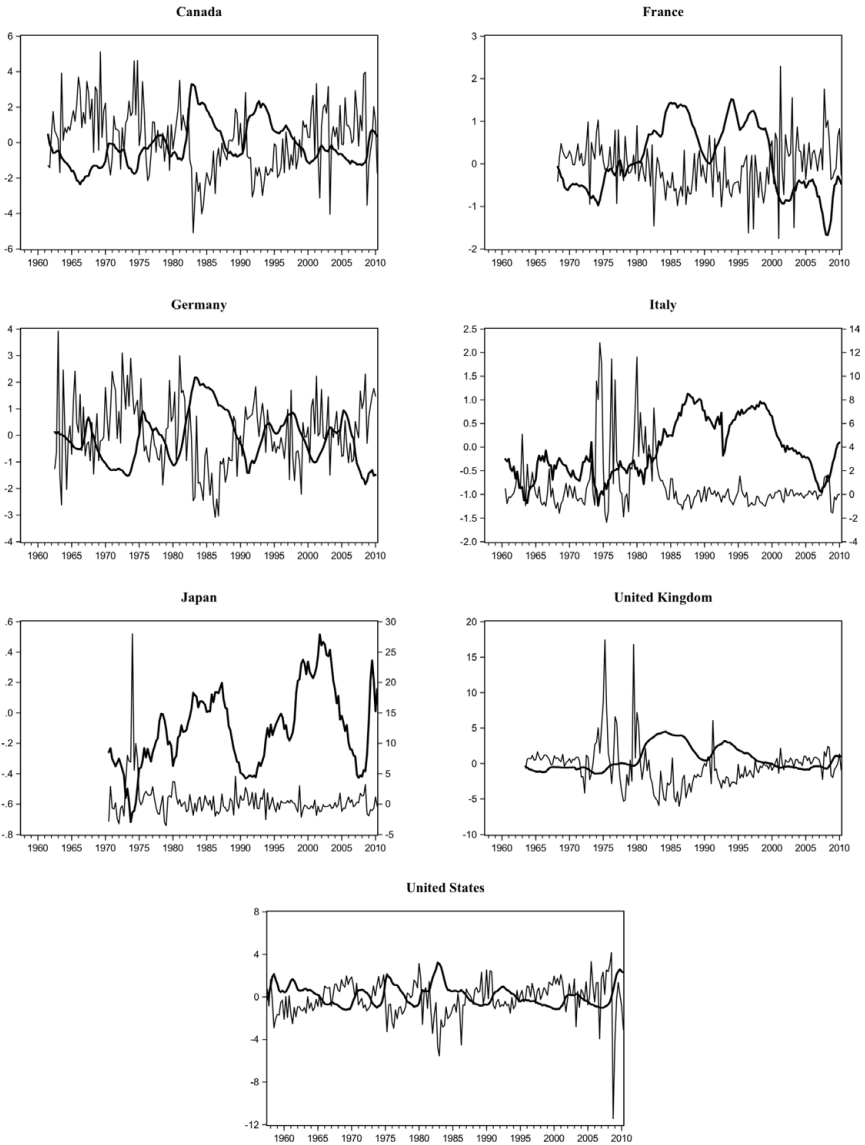


FIGURE 5. Estimated unemployment gap and inflation gap. The graphs plot the median of the posterior distribution for the inflation gap (thin line) and the unemployment gap (thick line). For Italy and Japan, the left vertical axis refers to the unemployment gap, whereas the right vertical axis refers to the inflation gap.

Figure 6 presents the median of the posterior distribution for $V_{j,t}$ at horizons of $j = 1, 4,$ and 20 quarters. There are several points from Figure 6 that we highlight here. First, there is a general increase in $V_{j,t}$ as the horizon increases. This is not surprising, as we would expect the inflation trend, which represents the unit root process in inflation, to eventually dominate the variation of inflation changes as the horizon grows. Second, there is substantial variation in $V_{j,t}$ over time for many countries. This implies that changes in the variance of trend inflation shocks documented in Figure 2 were not mirrored by proportional changes in the variability of the inflation gap. As an example, in some cases, notably Italy and the United Kingdom, $V_{j,t}$ is far from sample period lows at the end of the sample, despite the variance of trend inflation shocks being at sample period lows.

Third, both trend inflation and the inflation gap have played an important role in the variance of inflation changes at business cycle horizons. Focusing on four-quarter inflation changes, the average value of $V_{4,t}$ ranges from a minimum of 0.17 (Japan) to a maximum of 0.61 (France), and is between 0.2 and 0.4 for all other countries. Thus, on the average over the past 50 years, both the inflation trend and the inflation gap have contributed considerable amounts to the variance of four-quarter inflation changes. Looking at only the most recent sample period, $V_{4,t}$ ranges from 0.04 (United States) to 0.69 (France), and lies between 0.2 and 0.5 for all other countries. Thus, for most countries, the United States being the primary exception, both the inflation trend and the inflation gap continue to contribute to the variance of inflation changes in recent years. In the United States, the inflation gap dominates the variance of one- and four-quarter inflation changes at the end of the sample period.

As was discussed in Section 5.1, the univariate inflation analysis of Cecchetti et al. (2007) produced volatile inflation trends and small inflation gaps for several countries for which our bivariate analysis estimates smoother inflation trends and large and persistent inflation gaps. This highlights the importance of including information on the real-activity gap for identifying the relatively large contribution of the inflation gap to overall inflation variance that we document in Figure 6. We now turn to providing formal measures of the determinants of inflation gap volatility, including the role played by the real-activity gap.

6.2. Determinants of Inflation Gap Volatility

The results in Figure 6 suggest that the inflation gap plays an important role in the determination of actual inflation in G7 countries. Given this, we now turn to results regarding the determination of the inflation gap. We are interested in the relative contributions of the drivers of the inflation gap in equation (2), namely the unemployment gap and the residual component, to the variance of the inflation gap. To measure these contributions, we again construct variance decompositions. As the inflation gap is covariance-stationary in our model, we focus on explaining

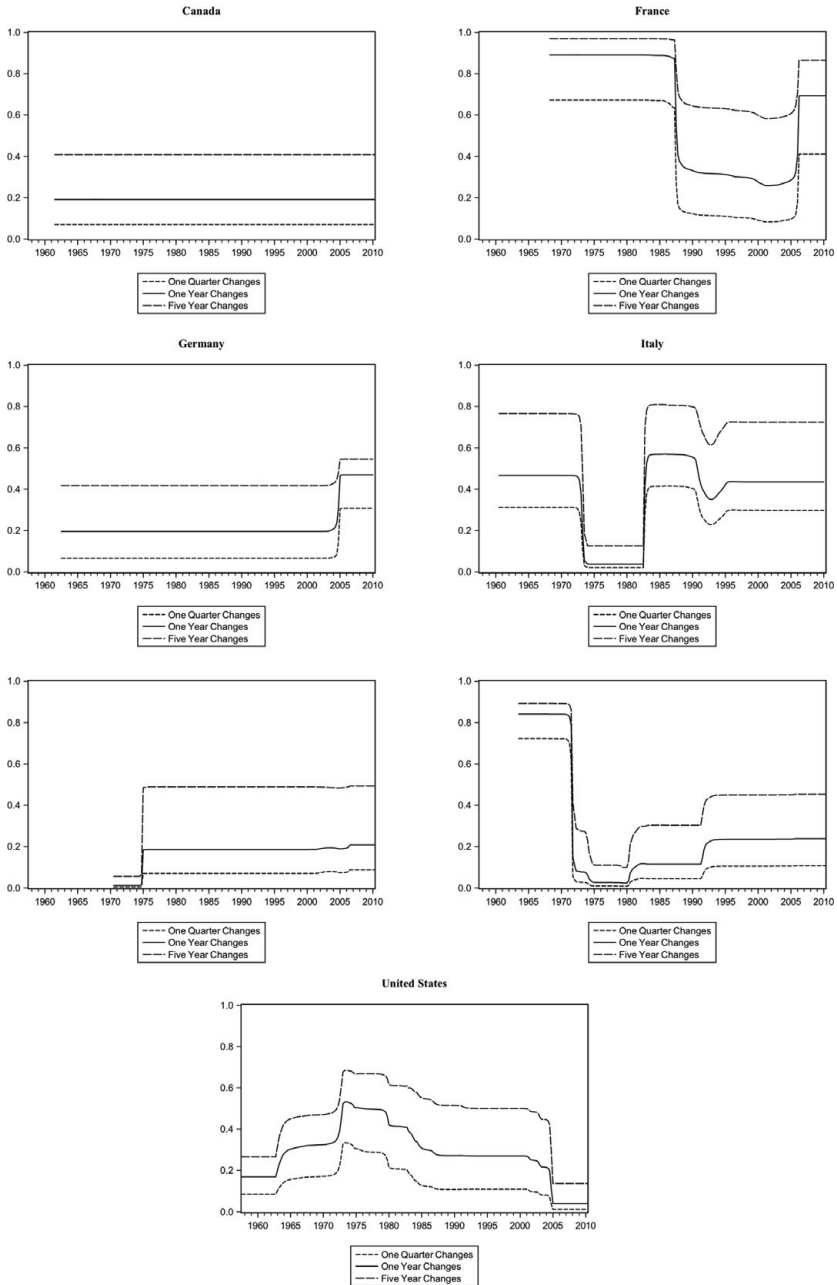


FIGURE 6. Contribution of inflation trend to variance of inflation changes. The graphs plot the median of the posterior distribution of the proportion of the variance of actual inflation changes at alternative horizons accounted for by the variance of changes to trend inflation.

the variance of the level of the inflation gap. In particular, we construct the ratio

$$R_t = \frac{v \left(\sum_{j=0}^{p_x} \delta_j x_{t-j} \right)}{v(\pi_t^g)},$$

which gives the proportion of total inflation gap variance accounted for by the unemployment gap component. Draws from the BMA posterior distribution for R_t are obtained as described for $V_{j,t}$ previously. As the inflation gap is determined by the unemployment gap and residual component only, and shocks to these components are independent, the contribution of the residual component to inflation gap variance is given by $1 - R_t$.

Figure 7 presents the median of the BMA posterior distribution of R_t and provides evidence that the unemployment gap has been an important contributor to inflation gap variance for all G7 countries. The average value of R_t over the entire sample period ranges from a minimum of 0.31 (Japan) to a maximum of 0.73 (United States) and exceeds 0.5 for all countries except Japan and Italy. For most countries, the importance of the unemployment gap is at or near historic highs in recent years. The exception is the United States, for which R_t declines steadily over the sample period and obtains the lowest end-of-sample value in the G7 countries. However, even this minimum value suggests that the unemployment gap provides more than 30% of the variance in the U.S. inflation gap.

To isolate the sources of time variation in the value of R_t , Figure 8 presents the BMA posterior distributions of the variance of the inflation gap, the variance of the unemployment gap component of the inflation gap, and the variance of the residual component of the inflation gap. For most countries, the variance of the unemployment gap component is relatively stable over the sample period as compared with the variance of the residual component, meaning that significant historical variation in R_t in Figure 7 is driven primarily by changes in the variance of the residual component. An exception is the United States, where the variances of both components have displayed significant variation over the sample period. Even here, however, Figure 8 demonstrates that the secular decline in R_t documented for the United States is due primarily to a steady increase in the variance of the residual component, rather than a decline in the variance of the unemployment gap component. Overall, it appears that the unemployment gap makes a stable contribution to the variation of the inflation gap in these countries, supporting the NKPC as a structural concept that provides a useful theory of inflation.

Although the contribution of the real-activity gap to inflation gap variance is substantial, the value of R_t in Figure 7 also reveals a significant role for the residual component. Further, the results in Figure 8 show that the residual component has been an important contributor to time variation in the variance of the inflation gap. A primary candidate for the source of this residual component is supply shocks, which are not directly measured in our bivariate UC model. To investigate this

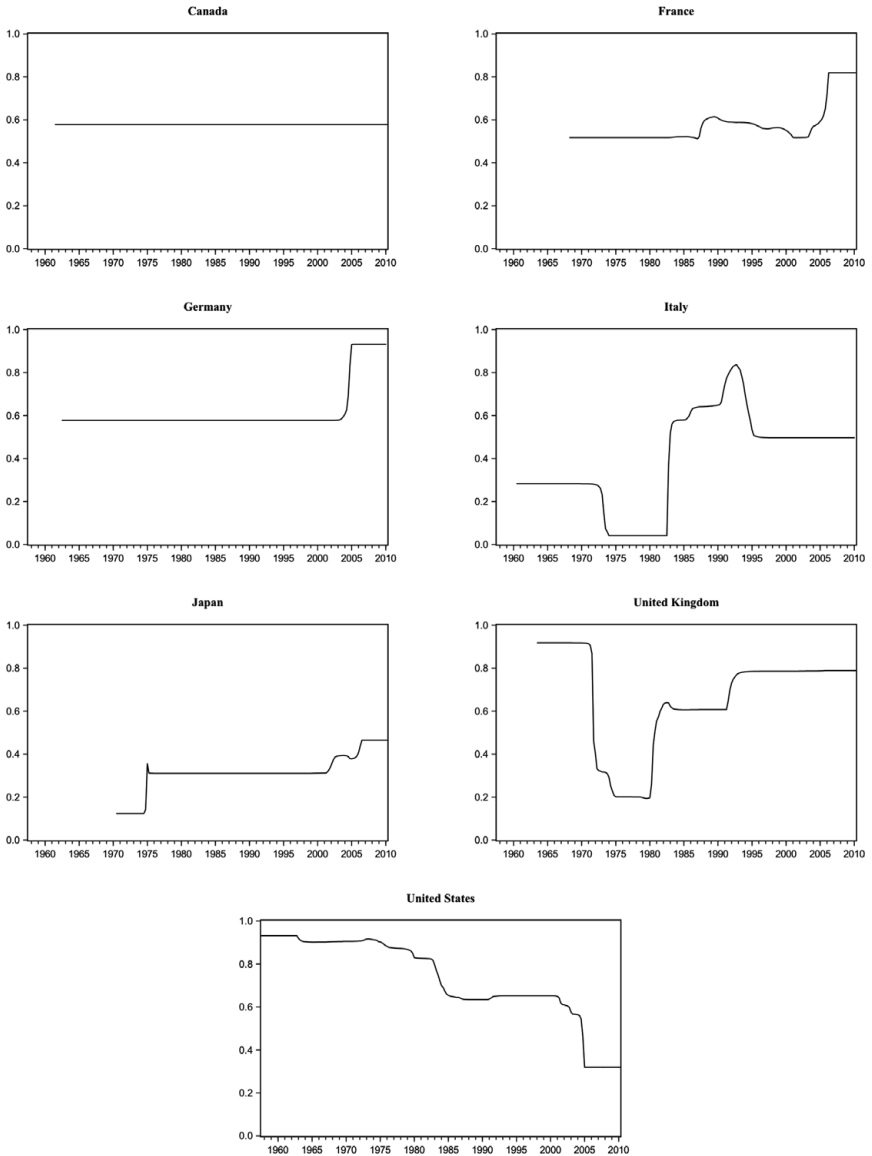


FIGURE 7. Contribution of unemployment gap to variance of inflation gap. The graphs plot the median of the posterior distribution of the proportion of the variance of the inflation gap accounted for by the variance of the unemployment gap.

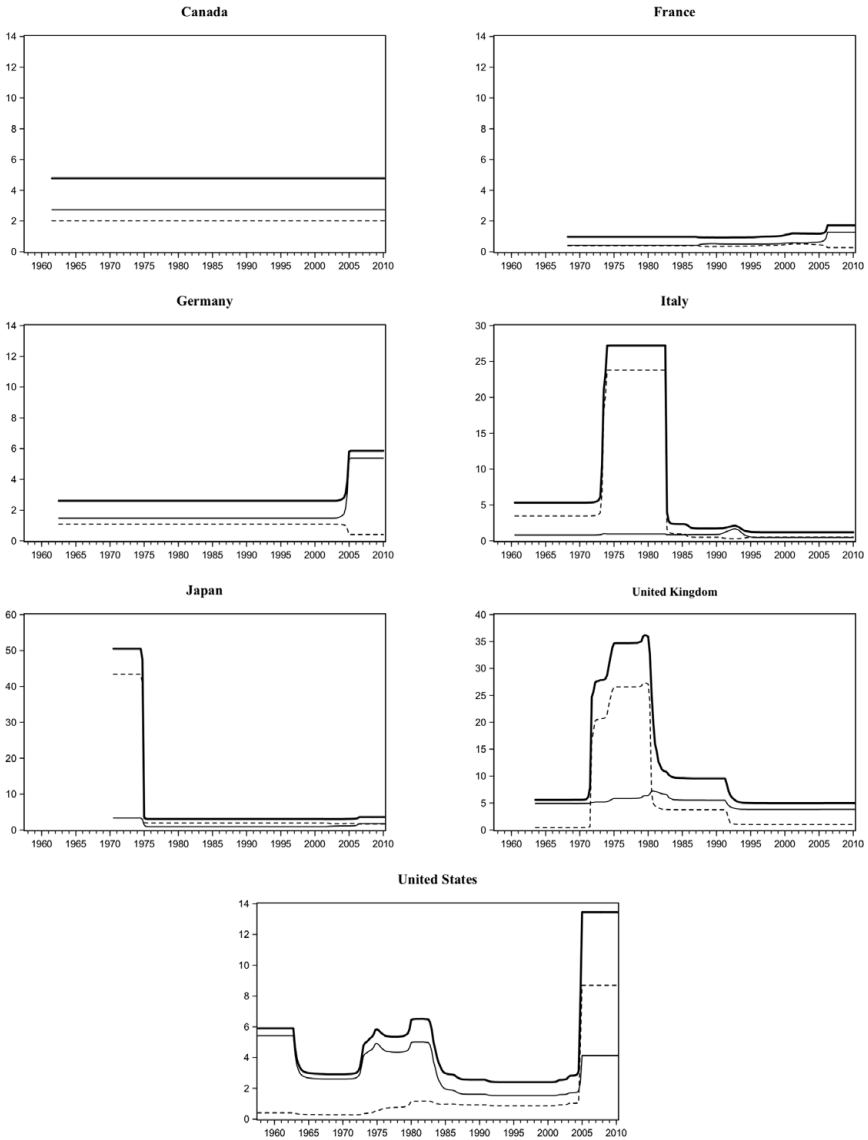


FIGURE 8. Variance of inflation gap and inflation gap components. The graphs plot the median of the posterior distribution of the variance of the inflation gap (thick solid line), the variance of the unemployment gap component of the inflation gap (thin solid line), and the variance of the residual component of the inflation gap (thin dashed line). Note that the vertical scale is unique for Italy, Japan, and the United Kingdom.

possibility, Figure 9 plots the BMA posterior distribution of the residual component of the inflation gap along with the (demeaned) inflation rate of the food and energy price component of the CPI for each country. This “noncore” component of inflation is often singled out as being disproportionately affected by supply shocks. For most countries, there is substantial comovement between the estimated residual component of the inflation gap and the noncore inflation rate. Although there are clear examples where the two series diverge, many of the swings in noncore inflation are mirrored in the residual component of the inflation gap. In recent years this is particularly true; the residual component mirrors the relatively large swings in noncore inflation very closely. The full-sample correlation coefficient for the two series ranges from 0.26 (United Kingdom) to 0.72 (United States), and is between 0.42 and 0.69 for all other countries. The relative volatility of the series is also similar, with a primary exception being France, for which the estimated residual component is substantially smoother than the noncore inflation rate.

Taken together, these results suggest the inflation gap has contributed significantly to the variability of inflation changes in all of the G7 countries over the past 40–50 years, and that the unemployment gap has been a substantial and consistent driver of the inflation gap for these countries. Again, this is supportive of the NKPC, once it is augmented to include a trend inflation component, as an empirically relevant model for the G7 countries. That said, there is also a substantial portion of the inflation gap, measured by the residual component in our model, that is driven by factors external to the NKPC theory. This residual is highly correlated with food and energy price inflation in most countries, suggesting supply shocks as an important additional driver of transitory fluctuations in inflation.

7. CONCLUSION

We have estimated a bivariate unobserved components model of inflation and unemployment in the G7 countries using Bayesian techniques and used it to shed light on the relative importance of trend inflation and the real-activity gap for explaining variability in realized inflation. Our results reveal that both trend inflation and the deviation of inflation from trend inflation, or the so-called inflation gap, have contributed significantly to variation in inflation changes at business cycle horizons in the G7 countries. Further, we find that the real-activity gap, measured as the deviation of the unemployment rate from the natural rate, is an important determinant of the inflation gap for these countries.

We have also provided new estimates of trend inflation in the G7 countries that take into account information on the real-activity gap for identification, as well as formal comparisons of models with and without time variation in the volatility of model shocks. These comparisons reveal important changes in the volatility of trend inflation in some countries but not others. Both the level and the volatility of trend inflation are quite low in all countries near the end of the sample period, which suggests that long-horizon inflation expectations are anchored at low levels across the G7 economies.

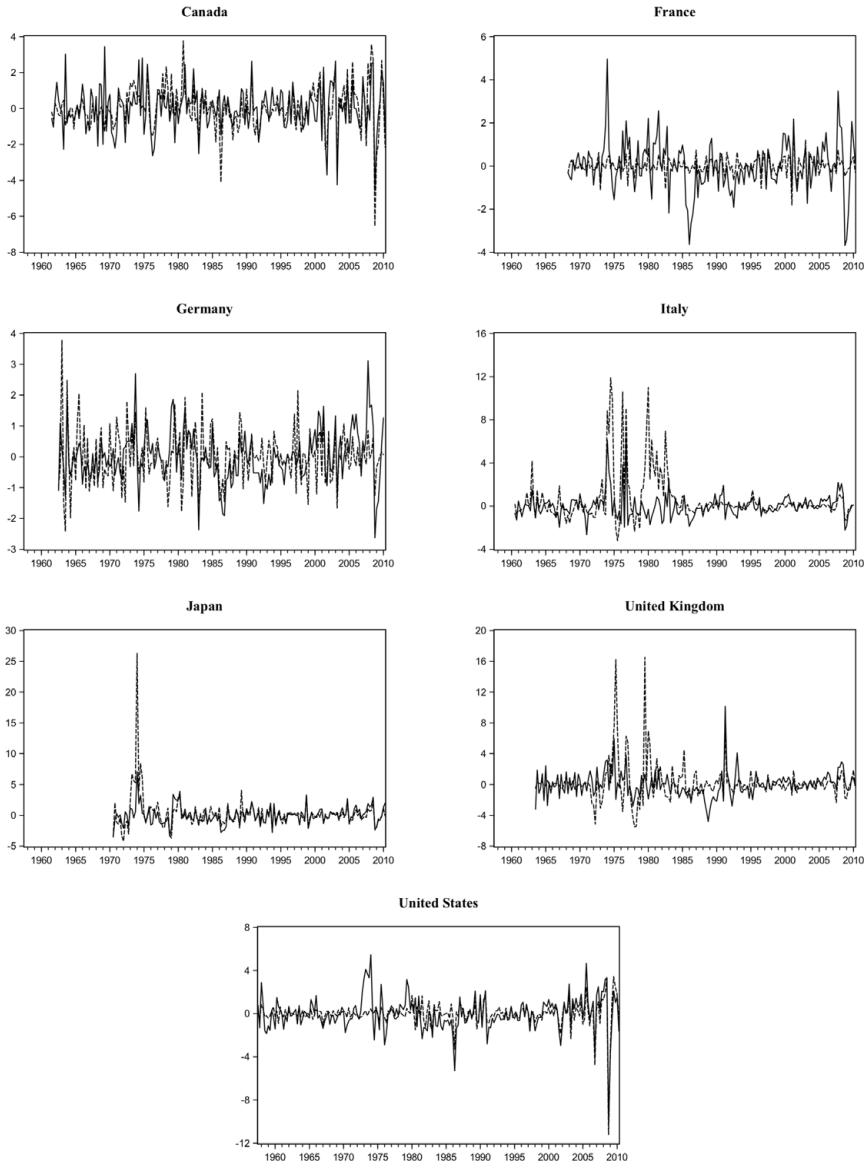


FIGURE 9. Inflation residual component and food and energy price components. The graphs plot the demeaned quarterly rate of CPI food and energy price inflation (solid line), along with the median of the posterior distribution for the residual component of the inflation gap (dotted line). Note that the vertical scale differs across countries.

Our analysis is based on in-sample estimation, and does not address the issue of out-of-sample forecasting, where the performance of traditional Phillips-curve-type models has been disappointing [Stock and Watson (2009)]. Even if the NKPC with trend inflation is a correct characterization of inflation dynamics, producing out-of-sample forecasts from the bivariate UC model is complicated by the need for end-of-sample unemployment gap estimates, which, as is detailed in Orphanides and Van Norden (2002, 2005), can be unreliable. However, there is some encouraging recent evidence in this regard for the United States, as both Stock and Watson (2010) and Kim et al. (in press) find that versions of the NKPC with trend inflation improve out-of-sample forecasts of the U.S. inflation gap over univariate models.

A primary focus of our analysis has been on explaining the determinants of the inflation gap. However, for many countries, trend inflation has also been an important contributor to the variability of observed inflation. This result suggests that it is important to understand the determination of trend inflation in order to adequately explain the historical path of actual inflation in most countries. Given the link between trend inflation and long-horizon inflation expectations, one approach to understanding the evolution of trend inflation is to understand the determinants of long-horizon inflation expectations. To this end, a number of recent studies, including Clark and Davig (2008) and Kiley (2008) for U.S. inflation and Barnett et al. (2010) for U.K. inflation, have investigated the effects of various types of shocks on long-horizon inflation expectations. Further research on this topic is likely to be an important avenue for improved understanding of the inflation process in the G7.

NOTES

1. In the NKPC, the theoretical driving variable for inflation is real marginal cost, which is generally proxied for with the real-activity gap. Gali and Gertler (1999) and Gali et al. (2001) consider an alternative proxy, the average labor share of national income, and report a better fit for modeling U.S. and Euro area inflation rates. However, use of the average labor share as a proxy for real marginal cost is not without criticism [see, e.g., Rudd and Whelan (2005)].

2. Stock and Watson (2007) and Kang et al. (2010) estimate univariate models in which U.S. inflation is decomposed into stochastic trend and cyclical components. Cecchetti et al. (2007) apply the Stock and Watson (2007) model to G7 inflation data.

3. An earlier literature, for example Kuttner (1994), Gerlach and Smets (1999), and Basistha and Nelson (2007), also works with Phillips curve models that have a bivariate UC structure. These models differ from that used in this paper in that they assume inflation is covariance-stationary.

4. Cecchetti et al. (2007) and Stock and Watson (2007) model the variance of the innovation to trend inflation as following a stochastic volatility process, where the change to the variance is a stochastic shock that comes from a high- or low-volatility regime. In the implementation of their model, they fix the probability of the high-volatility regime to be small, suggesting that large changes to the volatility of trend inflation occur only infrequently. Thus, their model is not completely inconsistent with the structural break model that we employ here, although it assumes an a priori degree of structural instability, whereas we make direct inferences about the number of structural breaks.

5. A substantial literature finds evidence for a statistically significant correlation between shocks to trend real activity and shocks to the real-activity gap in the United States [see, e.g., Morley et al.

(2003)]. For all countries, we have estimated a version of the model that allows for such a correlation, which in this case is between shocks to the natural rate and shocks to the unemployment gap. Overall, the results from this model regarding the importance of the various model components in explaining inflation and inflation gap variance are qualitatively similar to the results from the model that assumes a zero correlation. Thus, for simplicity of presentation, we focus on the results assuming uncorrelated shocks.

6. Kim et al. (in press) note that this serially correlated residual component can be given an interpretation within the NKPC theory. The stochastic component in the inflation gap equation is broadly labeled as a “markup” shock, capturing time variation in the markup of price over marginal cost. Serial correlation in this term can be justified through price indexation to past inflation as in Smets and Wouters (2003) or the interaction between trend inflation and nonlinearities in a Calvo price setting process as in Cogley and Sbordone (2008).

7. A similar procedure for outlier correction is used in Cecchetti et al. (2007) in their study of G7 inflation rates.

8. It is worth emphasizing that this multivariate normal approximation is only used for calibrating the variance of innovations to the MH random walk chain, and is not a restriction enforced on the posterior distribution.

9. Following the recommendation of Koop (2003), we calibrate c to yield acceptance rates between 0.2 and 0.5.

10. The SIC is defined in terms of the maximized value of the likelihood function. Exact maximization of the likelihood function for our bivariate UC model with multiple structural breaks is very computationally intensive, as it requires numerical optimization of the likelihood function for all possible combinations of potential break dates. For models with breaks, we instead maximize the likelihood function over the twenty break date combinations that received the highest posterior weight in the Bayesian estimation. We then define the SIC in terms of the maximum likelihood value achieved over these twenty maximizations. This is a generalization of the strategy followed by Wang and Zivot (2000), who define the SIC in terms of the maximized value of the likelihood function evaluated at the median of the posterior distribution for the structural break dates.

11. See, for example, Brock et al. (2003) and Doppelhofer et al. (2004). For additional discussion of the SIC-based approach to model averaging, see Raftery (1995).

12. All reported results are based on models for which the number of lags of the real-activity gap in the inflation gap equation (3) is set equal to four, the residual component of the inflation gap in equation (4) is an AR(1), and the real-activity gap in equation (7) is an AR(2).

REFERENCES

- Barnett, A., J.J.J. Groen, and H. Mumtaz (2010) Time-Varying Inflation Expectations and Economic Fluctuations in the United Kingdom: A Structural VAR Analysis. Bank of England working paper 392.
- Basistha, A. and C. Nelson (2007) New measures of the output gap based on the forward-looking New Keynesian Phillips Curve. *Journal of Monetary Economics* 54, 498–511.
- Bernanke, B. (2007) Inflation Expectations and Inflation Forecasting. Speech presented at the Monetary Economics Workshop of the National Bureau of Economic Research Summer Institute, Cambridge, MA.
- Beveridge, S. and C.R. Nelson (1981) A new approach to decomposition of economic time series into permanent and transitory components with particular attention to measurement of the business cycle. *Journal of Monetary Economics* 7, 151–174.
- Brock, W.A., S.N. Durlauf, and K.D. West (2003) Policy evaluation in uncertain economic environments. *Brookings Papers on Economic Activity* 1, 235–301.
- Bryan, M.F. and S.G. Cecchetti (1994) Measuring core inflation. In N.G. Mankiw (ed.), *Monetary Policy*. Chicago: Chicago University Press.

- Carter, C.K. and R. Kohn (1994) On Gibbs sampling for state space models. *Biometrika* 81, 541–553.
- Cecchetti, S.G., P. Hooper, B.C. Kasman, K.L. Schoenholtz, and M.W. Watson (2007) Understanding the evolving inflation process. In U.S. Monetary Policy Forum Report 1, Rosenberg Institute for Global Finance, Brandeis International Business School and Initiative on Global Financial Markets, University of Chicago Graduate School of Business.
- Clark, T.E. and T. Davig (2008) An Empirical Assessment of the Relationships among Inflation and Short- and Long-Term Expectations. Federal Reserve Bank of Kansas City Research working paper 08-05.
- Cogley, T., G.E. Primiceri, and T.J. Sargent (2010) Inflation-gap persistence in the U.S. *American Economic Journal: Macroeconomics* 2, 43–69.
- Cogley, T. and A.M. Sbordone (2008) Trend inflation, indexation, and inflation persistence in the New Keynesian Phillips Curve. *American Economic Review* 98, 2101–2126.
- Doppelhofer, G., R. Miller, and X. Sala-i-Martin (2004) Determinants of long-term growth: A Bayesian averaging of classical estimates (BACE) approach. *American Economic Review* 94, 813–835.
- Estrella, A. and J.C. Fuhrer (2002) Dynamic inconsistencies: Counterfactual implications of a class of rational-expectation models. *American Economic Review* 92, 1013–1028.
- Friedman, M. (1977) Nobel lecture: Inflation and unemployment. *Journal of Political Economy* 85, 451–472.
- Fuhrer, J.C. (1997) The (un)importance of forward looking behavior in price specifications. *Journal of Money, Credit and Banking* 29, 338–350.
- Fuhrer, J.C. and G. Moore (1995) Inflation persistence. *Quarterly Journal of Economics* 110, 127–159.
- Gali, J. and M. Gertler (1999) Inflation dynamics: A structural econometric analysis. *Journal of Monetary Economics* 44, 195–222.
- Gali, J., M. Gertler, and D. Lopez-Salido (2001) European inflation dynamics. *European Economic Review* 45, 1237–1270.
- Gerlach, S. and F. Smets (1999) Output gaps and monetary policy in the EMU area. *European Economic Review* 43, 801–812.
- Goodfriend, M. and R.G. King (2012) The great inflation drift. In *The Great Inflation: The Rebirth of Modern Central Banking*, pp. 181–209. Cambridge, MA: National Bureau of Economic Research.
- Gordon, R.J. (1982) Inflation, flexible exchange rates and the natural rate of unemployment. In M.N. Baily (ed.), *Workers, Jobs and Inflation*, pp. 89–158. Washington, DC: Brookings Institution.
- Gordon, R.J. (1997) The time-varying NAIRU and its implications for economic policy. *Journal of Economic Perspectives* 11, 11–32.
- Gordon, R.J. (1998) Foundations of the Goldilocks economy: Supply shocks and the time varying NAIRU. *Brookings Papers on Economic Activity* 2, 297–333.
- Harvey, A.C. (2008) Modeling the Phillips Curve with Unobserved Components. Cambridge Working Papers in Economics 0805.
- Kang, K.H., C.-J. Kim, and J. Morley (2010) Changes in U.S. inflation persistence. *Studies in Nonlinear Dynamics and Econometrics* 13.
- Kiley, M.T. (2008) Monetary Policy Actions and Long-Run Inflation Expectations. Federal Reserve Finance and Economics Discussion Series working paper 2008-03.
- Kim, C.-J., P. Manopimoke, and C.R. Nelson (in press) Trend inflation and the nature of structural breaks in the New Keynesian Phillips Curve. *Journal of Money, Credit and Banking*.
- Koop, G. (2003) *Bayesian Econometrics*. New York: Wiley.
- Kuttner, K.N. (1994) Estimating potential output as a latent variable. *Journal of Business and Economic Statistics* 12, 361–368.
- Laubach, T. (2001) Measuring the NAIRU: Evidence from seven economies. *Review of Economics and Statistics* 83, 218–231.
- Lee, J. and C.R. Nelson (2007) Expectation horizon and the Phillips Curve: The solution to an empirical puzzle. *Journal of Applied Econometrics* 22, 161–178.
- Morley, J.C., C.R. Nelson, and E. Zivot (2003) Why are the Beveridge–Nelson and unobserved components decompositions of GDP so different? *Review of Economics and Statistics* 85, 235–243.

- Okun, A. (1971) The mirage of steady inflation. *Brookings Papers on Economic Activity* 2, 485–498.
- Orphanides, A. and S. van Norden (2002) The unreliability of output-gap estimates in real time. *Review of Economics and Statistics* 84, 569–583.
- Orphanides, A. and S. van Norden (2005) The reliability of inflation forecasts based on output gap estimates in real time. *Journal of Money, Credit and Banking* 37, 583–601.
- Piger, J. and R.H. Rasche (2008) Inflation: Do expectations trump the gap? *International Journal of Central Banking* 4, 85–116.
- Raftery, A. (1995) Bayesian model selection in social research. *Sociological Methodology* 25, 111–163.
- Roberts, J. (2001) How Well Does the New Keynesian Sticky-Price Model Fit the Data? Federal Reserve Finance and Economics Discussion Series working paper 2001-13.
- Rudd, J. and K. Whelan (2005) Does labor's share drive inflation? *Journal of Money, Credit and Banking* 37, 297–312.
- Smets, F. and R. Wouters (2003) An estimated dynamic stochastic general equilibrium model of the Euro area. *Journal of the European Economic Association* 1, 1123–1175.
- Staiger, D., J. Stock, and M.W. Watson (1997) How precise are estimates of the natural rate of unemployment. In C. Romer and D. Romer (eds.), *Reducing Inflation: Motivation and Strategy*. Chicago: Chicago University Press.
- Stock, J.H. and M.W. Watson (2007) Why has U.S. inflation become harder to forecast? *Journal of Money, Credit and Banking* 39, 3–33.
- Stock, J.H. and M.W. Watson (2009) Phillips curve inflation forecasts. In J. Fuhrer, Y. Kodrzycki, J. Little, and G. Olivei (eds.), *Understanding Inflation and the Implications for Monetary Policy*, pp. 101–186. Cambridge, MA: MIT Press.
- Stock, J.H. and M.W. Watson (2010) Modeling Inflation after the Crisis. NBER working paper 16488.
- Wang, J. and E. Zivot (2000) A Bayesian time series model of multiple structural changes in level, trend, and variance. *Journal of Business and Economic Statistics* 18, 374–86.