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# Inflation and the steeplechase between economic activity variables: evidence for G7 countries

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**Abstract:** A sharp increase in unemployment accompanied by a relatively muted response of inflation during the Great Recession and a consecutive inflationless recovery cast further doubts on the very existence of the Phillips curve as a systemic relation between real activity and inflation. With the aid of dynamic model averaging, this paper aims to highlight that this relation resurfaces if (i) inflationary pressures are captured by a richer set of real activity measures, and (ii) one accounts for the existence of a non-linear response of inflation to the driving variable. Based on data for the US and other G7 countries, our results show that the relation between economic activity and inflation is quite sturdy when one allows for more complex assessment of the former. We find that measures of economic activity describe inflation developments to a varying degree across time and space. This can blur the picture of inflation–real economy comovements in models where only a single variable of economic activity is considered. The output gap is often outperformed by unemployment-related variables. Our results also confirm a weakening of the inflation–activity relationship (i.e. a flattening of the Phillips curve) in the last decade that is robust both across activity measures and across countries.

**Keywords:** dynamic model averaging; inflation dynamics; Phillips curve; real economic activity.

## 1 Introduction

The relationship between price inflation and domestic economic activity has been constantly reassessed over recent decades. While the concept of the Phillips curve

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is deeply rooted in macroeconomics and most (Keynesian-style) macroeconomic models begin with its very existence, the empirical evidence on the impact of domestic slack on inflation is (if anything) very ambiguous. One possible explanation for this ambiguity is that it is not easy to extract the appropriate inflation-driving signal from the available data on real economic activity. In reality, there are several potential "economic" variables tracking domestic economic activity, most notably output versus employment measures. Besides, the number of real economy measures expands substantially when statistical methods start working to extract the appropriate signal that might be linked to inflation. While policy makers can use their intuition to take on board all relevant real activity signals simultaneously, econometric models usually shrink these "mental" projections into models containing only one inflation-driving variable.

The link between economic activity and price inflation regained importance as the global financial crisis caused a significant decline in economic activity elsewhere, while the decline in inflation was much less general. Although the very recent downward pressures on inflation seem to suggest otherwise, there is a general impression that during the recent Great Recession inflation fell by less than one might have expected. This has been attributed variously to long-term inflation expectations being firmly anchored at pre-defined inflation targets (e.g. IMF 2013), a flatter Phillips curve, implying a weakening of the trade-off between inflation and unemployment (Matheson and Stavrev 2013), and to an increase in structural unemployment and a related decline in potential output, implying that the output gaps are not as negative as they might appear and therefore that the downward pressures on inflation from the real economy are not that strong (e.g. Kocherlakota 2010).

While the empirical literature has long strived to uncover the nature of the inflation–real activity trade-off, the results are very dispersed and often ambiguous. The empirical research on the inflation–real activity nexus has faced various uncertainties, namely (i) uncertainty about the appropriate variable for tracking economic activity (or, in fact, also the appropriate measure of price inflation that can be related to domestic economic activity), (ii) uncertainty about whether the relationship between economic activity and inflation is linear or state-dependent, and (iii) uncertainty about whether the relationship between inflation and economic activity is subject to permanent changes due to structural changes in the economy and monetary policy.[1]

**1** There is an ongoing discussion about the identification strategy for inflation expectations in the context of the New Keynesian Phillips curve. Since our goal is to study the link between economic activity and inflation in a broader context, we leave aside the discussion on this lively topic and we refer the reader to the most current and extensive review of the identification problem in Mavroeidis et al. (2014).

The first issue has commonly been addressed by using various measures of domestic economic activity. Traditional measures such as the unemployment gap and the output gap have been coupled with new model-based measures such as real marginal cost (Galí and Gertler 1999). Still, it has proved difficult to find a measure that performs well and is superior to others across time and space. The identification of the inflation-forcing variable is further complicated for small open economies (Batini, Jackson, and Nickell 2005; Mihailov, Rumler, and Scharler 2011). Consequently, recent empirical literature studies directly the extent to which global developments are able to explain domestic inflation developments (Ciccarelli and Mojon 2010; Mumtaz and Surico 2012; Eickmeier and Pijnenburg 2013). The second issue has been dealt with using empirical models allowing for potential nonlinearities. The idea that the trade-off between inflation and economic activity can be nonlinear, for example due to downward price and wage stickiness (Ball, Mankiw, and Romer 1988), seems to be supported by empirical studies based on micro data (see Klenow and Malin 2011, for a recent review). Yet, at the macroeconomic level the empirical evidence is rather mixed (Laxton, Rose, and Tambakis 1999; Aguilar and Martins 2005; Dolado, María-Dolores, and Naveira 2005). The nonlinearity hypothesis has also been discussed during the recent turmoil (Meier 2010; Stock and Watson 2010). Finally, the third issue is partially reflected in studies focused on structural changes in the inflation process across time (Cogley and Sbordone 2008; Zhang, Osborn, and Kim 2008; Kang, Kim, and Morley 2009; Cogley, Primiceri, and Sargent 2010). Popular explanations of the permanent decrease in comovement between inflation and domestic economic activity – often referred to as a flattening of the Phillips curve – include globalization (Borio and Filardo 2007; Razin and Binyamini 2007) and good monetary policy (Roberts 2006; Ball and Mazumder 2011), but there is no full consensus yet (Kuttner and Robinson 2010).

This paper aims to address the above-mentioned uncertainties in a consistent manner, focusing on the United States and other G7 countries. The choice of G7 countries was driven by their share in world output, and also by superior data quality and longer available time series. Our empirical framework can be described as follows. First, we focus on the inflation gap, i.e. the deviation of inflation from the trend. Our baseline trend is derived from the unobserved component model with stochastic volatility (the UC-SV model) of Stock and Watson (2007), which can be interpreted as long-term inflation expectations.[2] We thus

**2** The issue of the inflation trend has recently gained in popularity in the context of long-term inflation expectations and inflation forecasting. Diverse methods for estimating the inflation trend have been proposed in recent literature (Clark and Doh 2014; Chan, Clark, and Koop 2015; Garnier, Mertens, and Nelson 2015; Stock and Watson 2015).

assume that real economic activity can affect the cyclical component of inflation whereas its long-term level is given by other factors.[3] Second, we address the fact that one can choose between various measures of domestic economic activity rather than stick to a single one. Besides traditional measures (the output gap, unit labor costs, employment) we employ measures that potentially allow for a nonlinear relationship between inflation and economic activity by their very construction without any need to resort explicitly to a nonlinear estimation framework. In particular, we follow the idea of Stock and Watson (2010) that inflation can be affected asymmetrically along the business cycle (it has a higher tendency to fall in a recession). Besides their "unemployment recession gap" we construct its expansion-type counterpart, the "unemployment expansion gap," where both these measures stress the importance of local extremes. In addition, we control for potential foreign inflation determinants, in particular oil prices and the nominal exchange rate. Third, we allow for potential permanent change in the inflation process and its determinants across time. We use dynamic model averaging, or DMA (Raftery, Kárny, and Ettler 2010), which marries the flexibility of the time-varying parameter framework (e.g. Harvey 1989) with a model-uncertainty treatment similar to Bayesian model averaging, or BMA (Hoeting at al. 1999). In particular, we assume the existence of a single model to drive inflation (defined in terms of various different measures of real economic activity), which, however, can switch in each period.[4] To the best of our knowledge, this approach is new in the literature.

Our paper is particularly related to studies which try to uncover comovement between inflation and domestic economic activity in diverse empirical settings. Most of this empirical work is related to the US (Stock and Watson 2010; Ball and Mazumder 2011; Koop and Korobilis 2012). The studies for other countries usually analyze the somewhat wider issue of Phillips curve stability and nonlinearity (e.g. Aguilar and Martins 2005; Dolado, María-Dolores, and Naveira 2005; Musso, Stracca, and van Dijk 2007) rather than dealing specifically with the complexity of the inflation–real activity trade-off. Notable exceptions include Andrle, Brůha, and Solmaz (2013), who study aggregated euro area inflation using the frequency rather than the time domain, Bankovskis et al. (2011), who use a suite of models

**3** For example, the credibility of monetary policy, which, in turn, determines the level of inflation expectations, and also supply shocks with persistent effects (e.g. significant changes in commodity prices).

**4** Our primary focus on model selection (i.e. we employ dynamic model selection or DMS) rather than averaging is related to the fact that DMA is commonly used to identify the most relevant variables across different models, while our task is to assess what measure of the meta-variable "economic activity" can be linked to inflation in each period.

such as TVP VAR and DSGE aimed at both the aggregated euro area and selected individual EU countries, and Morley, Piger, and Rasche (2011), who test the importance of trend inflation and the real activity gap for explaining the inflation variation in G7 countries. These studies find a positive relationship between inflation and economic activity, although the importance of this relationship varies (in the frequency/time domain).

The spirit of this paper is closest to Stock and Watson (2010) in terms of our use of the inflation gap and our quest for a measure of domestic economic activity which can be linked to the former. Besides considering a wider sample of countries, we extend Stock and Watson (2010) to include the DMA technique, which allows us to (i) deal with the uncertainty related to the real economy measure, and (ii) model the relationship between inflation and a given variable on real economic activity in a time-varying manner. We are not the first to use DMA for the analysis of inflation dynamics. In particular, Koop and Korobilis (2012) used DMA to analyze its forecasting potential vis-à-vis other methods and found it to be a promising avenue for inflation forecasting. Koop and Onorante (2012) employed DMA to investigate the relative importance of forward-looking and backward-looking expectations in the New Keynesian Phillips curve. Though these authors use a similar methodology, their research questions are different from ours. In addition, our approach differs in the set of admissible models. While the former authors generally consider a wide range of models arising from an arbitrary combination of variables, in our baseline case we restrict the model universe to quite a small set of models, all of which, however, have a clear structural and economic interpretation.

In broader terms, our research can also be linked to studies trying to identify changes in inflation dynamics across time, such as Baxa, Plašil, and Vašíček (2015), Cogley and Sbordone (2008), Cogley, Primiceri, and Sargent (2010), Kang, Kim, and Morley (2009), and Zhang, Osborn, and Kim (2008). While this literature on the whole agrees on the changing nature of inflation dynamics (Pivetta and Reis 2007, being an exception to this), and in particular on a decline in inflation persistence, the specific issue of the inflation–activity nexus has not been well researched yet.

Our results can be summarized as follows. First and foremost, we find a positive and statistically significant relationship between inflation and domestic economic activity. However, inflation responds to (or at least comoves with) different measures of economic activity with varying intensity across time and space, and no measure of economic activity clearly dominates for the entire sample. Second, while the traditional output gap often performs rather poorly, the recently proposed unemployment recession gap (Stock and Watson 2010) did not prove to be as promising as claimed. In general, this measure does not convincingly outperform the others in terms of its impact on the inflation gap, nor is its short-term relationship found to be stable. Third, the relationship between (any measure of) economic activity and inflation exhibits a highly nonlinear pattern over time, with the observable weakening of the relationship (i.e. the flattening of the Phillips curve) being robust both across activity measures and across countries. Fourth, foreign factors are found to be relevant for all countries, although their relevance varies across time. Finally, our results seem to clarify why the empirical evidence on the use of an individual measure of domestic economic activity comes to rather ambiguous or even negative conclusions about the inflation–activity nexus. Proper selection of the variable representing economic activity seems to be a promising way to go.

The paper is organized as follows. In Section 2, we discuss the relationship between inflation and economic activity from the point of view of an appropriate measure of both. Section 3 presents our empirical framework. Section 4 presents the empirical evidence, with more country-specific narratives detailed in Appendix D. The final section concludes.

## 2 Inflation and economic activity

We noted that the empirical relationship between inflation and domestic economic activity can be obscured by numerous uncertainties. One of the most prominent ambiguities is related to the choice of real domestic activity measure. In what follows we discuss several economic activity variables that will be subsequently placed in an empirical horse race, while full details on the data used can be found in Appendix B. It should be stressed that our aim is not to construct the best measure of economic activity, but rather to choose between measures that are commonly used.[5] In general, they are based on either output or employment.

The prominent example of the output-based variable is the output gap as an encompassing measure of capacity utilization in the economy. However, the very idea that the productive capacity of the economy can be identified is rather controversial, especially in the case of open economies, where production factors are mobile (Bermingham et al. 2012). In addition, the statistical derivation of the unobservable potential output is subject to statistical uncertainty and none of

5 In other words, we do not try to find the best existing horse, but instead try to select between the horses that normally run in the steeplechase. For example, we use the common measure of the output gap derived from the HP filter rather than using alternative methods for its construction.

the methods for deriving it can be seen as superior (Orphanides and van Norden 2002; Billmeier 2009). Therefore, we resort to the common HP filter, which for most countries in the sample is very close to the production-function based estimation published by the OECD.[6]

In terms of the employment-based measures there are more alternatives. The traditional Phillips curve is based on the unemployment rate, in particular its deviation from the NAIRU. Therefore, actual unemployment above its equilibrium level implies downward pressures on wages, whereas below-equilibrium unemployment implies upward pressures. Consequently, the NAIRU can be seen as the counterpart of potential output, and also shares with it all the problems related to the estimation of an unobserved variable. However, it has been suggested (see also Blanchard and Wolfers 2000) that the long-term (structurally as opposed to cyclically) unemployed are not able to compete for existing jobs and therefore do not exert wage pressure. Therefore, it might be preferable to track unemployment slack only in terms of cyclical unemployment. However, it is empirically difficult to distinguish between the two (structural unemployment corresponds to the NAIRU, which is unobserved and is commonly estimated only at lower, i.e. annual, frequency), so as a proxy we use the short-term unemployment component, assuming that long-term employment corresponds to structural unemployment (cf. Stock 2011).

An alternative employment-based measure that is a determinant of disposable income is (the change of) total employment. Indeed, different levels of unemployment rates can be consistent with different levels of employment, depending on labor market flows from temporary inactivity to the work force and vice versa. Total employment also affects the aggregate income of the economy and therefore also determines effective demand, which is in turn a key driver of inflation impulses (from the demand side).

Another employment-based measure compatible with the micro-funded model of the New Keynesian Phillips curve is marginal cost, which is proxied by real unit labor costs (Galí and Gertler 1999; Galí, Gertler, and López-Salido 2001). While this measure was proposed as a viable alternative to the empirical pitfalls of traditional measures such as the output gap, the empirical evidence on its performance as an inflation driver is rather ambiguous. The

6 It should be noted that as a two-sided filter, the HP filter is in a different position than the other variables employed, where only past information is used. However, given that our focus is not on forecasting but rather on the assessment of the relationship between inflation and economic activity, and the output gap derived from the HP filter is the most popular measure of the former, we consider its use to be reasonable.

measure was further refined (Mazumder 2010) in order to deal with its intrinsic countercyclicality (Rudd and Whelan 2007). Still, real unit labor costs can be a relevant inflation driver as they contain information about changes in productivity and other changes in the economy relevant to the price-setting behavior of firms.

Finally, Stock and Watson (2010) proposed an employment-based measure that explicitly takes into account the idea that there might be a nonlinear relationship between inflation and economic activity. They construct an "unemployment recession gap" as the difference between the current (quarterly) unemployment rate and the minimum value in the last (in their case eleven) quarters (including the current one). The idea behind this one-sided gap is to pay attention to economic downturns, or in other words to track whether unemployment is higher than in recent years (in this case the gap is positive with the value of current unemployment and zero otherwise). The unemployment recession gap is in fact a concept related to deviations from the NAIRU based on the idea that the NAIRU follows the trend in the unemployment rate and that stable levels of unemployment are less likely to cause inflationary pressures in the economy. Hence, the concept of the unemployment recession gap is more simple, albeit more intuitive. In addition, we extend the idea that local rather than global extremes are what might matter by constructing the inverse measure – the "unemployment expansion gap" – as the difference between the current unemployment rate and the maximum value of observed unemployment over the last few quarters (including the current one), which is a measure of higher unemployment than usual. Adding the unemployment expansion gap to the set of regressors allows us to take into account the possible nonlinear behavior of inflation associated with either economic downturns or economic upturns.

Although our focus is on domestic economic activity, in line with numerous papers documenting the importance of external inflation factors in explaining domestic inflation dynamics (Batini, Jackson, and Nickell 2005; Mihailov, Rumler, and Scharler 2011), we also include variables representing external inflationary pressures in our study. External cost-push factors related to commodity prices and exchange rates might even affect relatively large countries, as was evident not only in the Great Inflation of the 1970s, but also in the rising inflation rates around the world at the onset of the Great Recession due to the peak in oil prices.[7]

7 In general, accounting for oil prices and other external factors corresponds to the logic of the triangle model by Gordon (1982), where current inflation is explained by its lag, a measure of domestic economic slack, and a supply-side variable (representing a cost-push shock).

Consequently, we use two additional variables for tracking this: the nominal effective exchange rate and oil prices.[8]

# 3 Model and estimation strategy

To analyze the relationship between inflation and real economy variables in the US and other G7 countries we follow and further enrich the methodology of Stock and Watson (2010). We consider a simple multivariate framework in which a measure of economic activity, $x_t$, is used to explain the forecast error as represented by the difference between the rate of inflation at time $t+h$, $\pi_{t+h}$, and the inflation trend, $\tau_t$. The model can be expressed in the following state-space form:

$$\begin{aligned} &\pi_{t+h} = \tau_{t|t} + \gamma_t x_t + e_{t+h}, \quad \mathrm{var}(e_{t+h}) = \sigma^2_{e,t+h} \\ &\gamma_t = \gamma_{t-1} + \xi_t, \quad \mathrm{var}(\xi_t) = \sigma^2_{\xi,t}, \ \mathrm{cov}(e_{t+h}, \xi_t) = 0 \end{aligned} \tag{1}$$

where $\pi_{t+h}$ is the year-on-year inflation rate at time $t+h$, $\pi_{t|t}$ is the best estimate of the trend at time $t$ using the information available up to time $t$, and $e_{t+h}$ is an error term. The approach to estimating the inflation trend is presented in the next section. In our empirical analysis we set the horizon $h$ to four quarters, which corresponds to the common horizon identified by VAR studies at which real activity affects price developments.[9] Similarly to Koop and Onorante (2012), our primary focus is not on inflation forecasting. Using a pseudo forecasting exercise, we rather investigate how much economic activity variables tell us about the future path of inflation. Given this objective, we rely on ex-post data and ex-post estimates of the output gap instead of using real-time data.

Our approach extends that of Stock and Watson (2010) in several directions. Importantly, we consider a time-varying parameter model where $\gamma_t$ follows a random walk. This allows us to explicitly account for potential evolution in the

**8** Some papers also use relative import prices as measured by the terms of trade, but in our view this may represent an endogeneity problem, as relative import prices can be affected by definition by the relative foreign vs. domestic price level, and hence also by the change in it. Some studies have also used measures of global slack such as the trade-weighted output gap (Borio and Filardo 2007), but more recent research on the global dimension of inflation using factor models (e.g. Eickmeier and Pijnenburg 2013) has cast some doubt on their importance.
**9** We also checked the results for $h=1$ quarter, which are largely consistent with the baseline horizon. These results are available upon request.

relationship between inflation and economic activity measures[10] and ideally pin down the shifts to structural and/or policy changes. As the estimated path of the time-varying coefficient is sensitive to changes in the volatility of the error term (see, for example, Nakajima 2011), we further assume that the variances of the disturbance terms in the observation equation and transition equation (1) may evolve over time.

Along with the coefficient $\gamma_t$ in (1), the explanatory power of different variables may change dramatically over time as well, either depending on the phase of the cycle or as a result of deeper structural changes in the economy. This implies that the structure of the domestic inflation-driving variable in the first equation of (1) might be subject to change over time, too. To account for the possibility of model switching, we consider a set of competing models for the inflation gap with a different set of variables that are allowed to switch from one to another at any time. The model switching is implemented through dynamic model averaging (DMA, Raftery, Kárny, and Ettler 2010).

Below we provide further details on our approach to deriving the inflation gap and to the model-switching framework, while the technical discussion on computational details and estimation issues is left for Appendix A.

## 3.1 Inflation and inflation gap

Inflation can have different drivers at different frequencies. Whereas the high-frequency dynamics can be driven by one-off non-systemic shocks, for example, shocks to oil prices, the low-frequency dynamics can be determined by institutional factors such as the central bank's inflation target and its credibility. However, most concern relates to the evolution of inflation at business cycle frequencies, which makes the concept of the inflation gap – the deviation of the inflation rate from the inflation trend – particularly appealing. Also, the inflation gap, in terms of deviations of inflation from the inflation target, enters most of the existing DSGE models aiming to analyze the effects of monetary policy.[11]

**10** Stock and Watson (2010) claim that when their newly proposed measure of economic activity – called the unemployment recession gap – is used, the relationship implied by the Phillips curve is much more stable than that based on the real economy measures traditionally exploited in the literature. Our time-varying model approach represents a convenient and straightforward way to reinvestigate their findings.

**11** There are some differences in the literature in the consideration of the inflation trend and its related statistical treatment. See, for example, Cogley and Sbordone (2008) and Kim and Kim (2008). Ascari and Sbordone (2014) provide the most recent review on this issue. Therefore, in turn, there is single consensus measure of the inflation gap, which has a parallel to the uncertainty related to the estimation of potential output and, in turn, the output gap.

We use a narrower definition of inflation (Ball and Mazumder 2011), namely, core inflation, which excludes some non-systemic inflation components (food and energy)[12] (with the exception of the UK, where we made use CPI inflation – see Appendix B). We additionally control for volatile external factors arguably driving the non-systemic component of inflation, which, by their very nature, cannot be attributed to domestic economic activity. As noted above, we opt for removing the inflation trend, which is likely determined by other factors (e.g. monetary policy credibility, long-term developments in commodity prices) unrelated to domestic economic activity. In practice, we use a two-step procedure where the inflation trend $\tau_t$ in (1) is estimated in the first step by the univariate unobserved components model with stochastic volatility (UC-SV) proposed in Stock and Watson (2007).[13]

The UC-SV model assumes that the rate of inflation can be decomposed into a permanent (stochastic trend) component and a transitory component

$$\begin{aligned} \pi_t &= \tau_t + \eta_t, \quad E\eta_t = 0, \mathrm{var}(\eta_t) = \sigma^2_{\eta,t} \\ \tau_t &= \tau_{t-1} + \varepsilon_t, \quad E\varepsilon_t = 0, \mathrm{var}(\varepsilon_t) = \sigma^2_{\varepsilon,t}, \ \mathrm{cov}(\eta_t, \varepsilon_t) = 0 \end{aligned} \tag{2}$$

where the variances of the permanent and transitory disturbances ($\varepsilon_t$ and $\eta_t$, respectively) both vary over time and can be described by the standard stochastic volatility model. Stock and Watson (2010) suggest thinking of the trend $\tau_t$ in (2) as capturing long-term inflation expectations, where the degree to which they are "anchored" is allowed to change over time.

The UC-SV model was chosen as our baseline for two main reasons. First, the model has gained some prominence within the statistical community in recent

**12** Particularly questionable is the presence of some non-systemic (and typically also the most volatile) components, such as food and energy, which are by nature unrelated to domestic economic activity (headline vs. core inflation) and increases in which generally do not spawn second-round effects (Cecchetti and Moessner 2008). However, another problematic item is tax changes, whose effect on prices can be direct (first-round effects) and also indirect (second-round effects) in the sense that a tax increase can give rise to wage pressures.

**13** Note that in theory it is possible to estimate all the parameters in (1) jointly in a single step, which may potentially lead to some efficiency gains. We experimented with this possibility, but it is rather problematic in our setting due to different variability in the trend inflation and regression parameters, which are all regulated by a single forgetting factor (see Appendix A). It should be noted that the confidence intervals presented below do not take into account the uncertainty related to the first step (estimation of the trend in inflation) and thus in general underestimate the true variability in the coefficients. We used a bootstrap procedure to assess how much the uncertainty in the first step inflates the final confidence intervals and we found that (once the prior parameters are set) the width of the reported intervals is not seriously affected.

years and is most commonly used in practice (cf. Chan, Koop, and Potter 2016). Moreover, most recent models usually encompass it as a special case (see Chan, Clark, and Koop 2015; Stock and Watson 2015; Chan, Koop, and Potter 2016). Second, the model is known to have good forecasting properties and matches the basic features of the US inflation dynamics well (Clark and Doh 2014). Nevertheless, as a robustness check we also consider four other options for obtaining the trend. Robustness checks using alternative methods to estimate the inflation trend are further discussed in Section 4.1.3 and full results are provided in Appendix C. Once the trend is estimated, the resulting inflation gap is related in the second step to a set of variables measuring economic activity (see below).

To the extent that $\tau_t$ captures (forward-looking) inflation expectations, equation (1) can be viewed as a New-Keynesian Phillips curve model and should thus have a structural nature. On the other hand, since these "expectations" are solely based on past information, one can also show that (1) is just a tightly parameterized backward-looking Phillips curve with potentially long lags. Therefore, our approach to inflation expectations is eclectic, as it allows for a compromise between the accelerationist Phillips curve and the New Keynesian Phillips curve. To put it differently: we prefer to stay agnostic about the underlying interpretation of the model, as we believe it is not crucial to make our main point, which can be encapsulated as a significant and sturdy impact of real activity on inflation.[14]

When the inflation trend is estimated and deducted from inflation, one can clearly see that model (1) focuses on the issue of how much the economic activity measure $x_t$ can tell us about the deviation $\pi_{t+h} - \tau_{t|t}$, which is commonly referred to as the inflation gap (see Cogley, Primiceri, and Sargent 2010). In addition to the interpretations of (1) offered above, we can also think of the inflation gap as filtering out low frequencies, which are unlikely to be related to movements in economic activity and the business cycle.[15]

**14** Moreover, it should be noted that the nature of our exercise (i.e. selection between alternative measures of economic activity as drivers of inflation) leaves out the possibility of estimating any form of "structural model" of inflation, which always rests on numerous restrictive assumptions that might be appropriate for one forcing variable but not another. For example, alongside a measure of real marginal cost the New Keynesian Phillips curve also relies, as a forcing variable, on a forward-looking inflation term derived under the assumption that agents form their expectations rationally. Interestingly, even when one sticks to the New Keynesian Phillips curve model the empirical results vary greatly according to the empirical strategy employed (Mavroeidis, Plagborg-Møller, and Stock 2014).

**15** Recently, Andrle, Brůha, and Solmaz (2013) and Basturk et al. (2013) showed that a blurred relationship between inflation and economic activity resurfaces once one focuses on business cycle frequencies. In this light, extraction of the trend in the rate of inflation seems necessary when analyzing the inflation–real activity nexus. This makes model (1) empirically appealing.

## 3.2 Specification of competing models for the inflation gap

In our baseline setting we assume that each model only contains a single economic activity variable. Such an assumption corresponds to the idea of a steeplechase where we look for a single winner (albeit a different winner in each period).[16] We believe that using a model with a single measure has economic rationale, as both empirical Phillips curves and many structural models commonly work with a single measure of economic slack. Yet, as a robustness check we also consider a full model universe with models containing any possible number of variables in a model (from one up to six). This way we can also assess how realistic one-variable models are vis-à-vis their more complex alternatives.

The switching mechanism between models is implemented through dynamic model averaging (DMA; readers unfamiliar with this technique are referred to Raftery, Kárny, and Ettler 2010, or Appendix A). The DMA procedure can be understood as a nexus between the time-varying parameter framework (e.g. Harvey 1989) and Bayesian model averaging, or BMA (Hoeting et al. 1999). While the former ensures that the strength of the relation between the endogenous variable (the inflation gap) and exogenous variables (domestic economic slack) can vary across time, the latter deals with the fact that the actual model (i.e. the model linking the inflation gap to domestic slack) is uncertain in each period. The key output of DMA is a posterior model probability for each model and period. Raftery, Kárny, and Ettler (2010) and Koop and Korobilis (2012) show that the posterior predictive model probabilities for the model $k$, $\rho_{t|t-1,k}$, can be related to the weighted product of the predictive densities

$$\rho_{t|t-1,k} \propto \prod_{i=1}^{t-1} \left[ p_k(y_{t-i} \,|\, y^{t-i-1}) \right]^{\alpha^i}. \tag{3}$$

This means that model $k$ will receive higher probability at time $t$ if it has exhibited good forecast performance in the recent past, where the performance is measured by the predictive density. The definition of "recent past" depends on the value of the forgetting factor $\alpha$. Values close to unity imply that the forecast performance in the relatively distant past still receives quite a high weight, while lower values of the forgetting factor tend to ignore the forecasting ability of the model in more distant periods. In our empirical analysis, we use $\alpha = 0.95$ as a benchmark value, but values closer to one did not alter the overall picture substantially. Along with

**16** Note, however, that the information content of the individual variables can be combined via the averaging techniques presented below.

DMA, dynamic model switching (DMS) can be based on the highest posterior model probability in a given period.

Since all the models only differ by the economic activity variable(s) included in the model, they all share the same economic structure as given by (1). Such a design can help us answer several interesting research questions, such as (i) whether the information content of the economic activity variables varies over time, (ii) what the best-performing variables are in any given period, and importantly (iii) whether recently proposed measures (such as the unemployment recession gap) really outperform traditional measures over the entire sample, or at least in the period after the recent financial crisis. We also include external factors such as crude oil prices and effective exchange rates to analyze their impact on inflation dynamics. The list of 13 competing models is shown in Table 1.

It can be seen that we indeed focus on the inflation gap in all models, as the trend is always included (in practice, the trend was estimated in the first step and then deduced). In the baseline case, the first six models each contain one of the domestic economic activity measures, but no external factors are included. The cohort of the subsequent six models is the same as before, but this time the models also contain external factors. Finally, the very last model assumes that only external factors drive the inflation gap. It should be stressed again that the coefficients in all the models are allowed to vary over time so as to capture the process of potential flattening of the Phillips curve in the recent decade (a phenomenon reported by several authors; see, for example, Ball and Mazumder 2011, and IMF 2013).

## 4 Results

We first present comprehensive results for the US inflation dynamics as a benchmark. The time span of available and comparable data is by far the best[17] and thus allows for comparing the current characteristics of inflation dynamics not only with the era of the Great Inflation, but also with the relatively low inflation period of the 1960s. Furthermore, most comparable studies have been carried out for the US economy. The results for other countries are described on the aggregate level in the subsequent part, and more detailed country-specific results are relegated to Appendix D.

17 The data availability is limited mainly by the availability of the short-term or long-term unemployment rate. For European countries, these data are available since 1983.

**Table 1:** Summary of models used for the DMA/DMS estimation.

| Model | Trend $\tau_{t\|t}$ | Output gap | RULC | Growth in employment | Short-term unemployment | Unemployment recession gap | Unemployment expansion gap | Oil price | Effective exchange rate |
|---|---|---|---|---|---|---|---|---|---|
| 1 | • | • | | | | | | | |
| 2 | • | | • | | | | | | |
| 3 | • | | | • | | | | | |
| 4 | • | | | | • | | | | |
| 5 | • | | | | | • | | | |
| 6 | • | | | | | | • | | |
| 7 | • | • | | | | | | • | • |
| 8 | • | | • | | | | | • | • |
| 9 | • | | | • | | | | • | • |
| 10 | • | | | | • | | | • | • |
| 11 | • | | | | | • | | • | • |
| 12 | • | | | | | | • | • | • |
| 13 | • | | | | | | | • | • |

RULC stands for real unit labor costs. Inclusion of the variable in the model is indicated by "•". The models can be divided into three subgroups depending on whether they contain domestic economic activity variables and/or external factors.

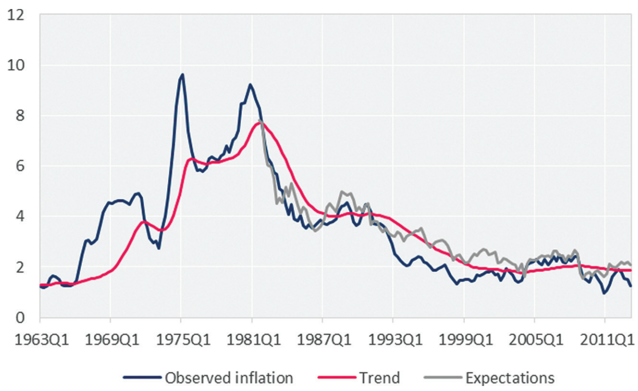


**Figure 1:** Net inflation, 1-year-ahead inflation expectations (SPF), and UC-SV inflation trend, US.

## 4.1 Role of economic activity in US inflation dynamics

### 4.1.1 Estimated trend inflation and expectations

First, we report the estimates of the UC-SV model, which we use to estimate the inflation trend (Figure 1). To assess the degree of coherence with inflation expectations we compare the trend from the UC-SV model with 1-year-ahead inflation expectations taken from the Survey of Professional Forecasters (SPF).[18] Overall, the model-based trend tracks the long-term signal in inflation expectations quite well, which suggests that it can be considered a candidate measure for the former.

Notably, the model-based expectations reflect the stabilization of inflation expectations after the sharp disinflation of the early 1980s. Initially, inflation expectations are anchored to a 4% level of inflation, and then, starting at the beginning of the 1990s, the survey expectations and the UC-SV trend gradually decrease and approach the 2% level. Inflation expectations stabilize at 2% and somewhat surprisingly stay at that level during the Great Recession. In particular, the downturn in SPF expectations around 2008 was subsequently revised back to the 2% level.

**18** Note that we compare the UC-SV trend in core CPI with the SPF forecast of overall inflation because the core inflation expectations forecasts are not available for a sufficiently long period of time. Additionally, Ball and Mazumder (2011) argue that survey inflation expectations have been "shock-anchored" since the 1980s, that is, supply shocks have had little effect on inflation expectations and so the survey expectations track core inflation.

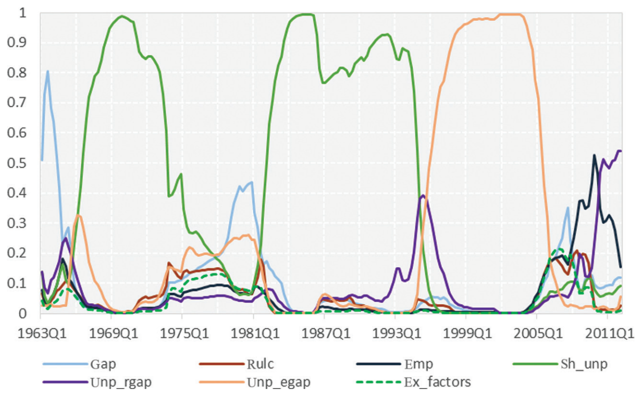


**Figure 2:** Posterior model probabilities, US.

The path of the estimated trend seems to support the hypothesis that inflation expectations were not anchored in the US before the sequence of supply shocks hit the US economy in the 1970s. As found by Benati and Goodhart (2010) and Clarida, Galí, and Gertler (2000), the start of the Great Inflation seems to coincide with the monetary policy loosening in the second half of the 1960s. With respect to the Great Moderation, our results support[19] the interpretation given by Ball and Mazumder (2011) that the anchoring of inflation expectations was a gradual process consisting of two stages: First, *shock anchoring* occurred, with inflation expectations becoming unresponsive to temporary changes in inflation after the inflation trend stabilized in the first half of the 1980s. Second, inflation expectations gradually became *level-anchored* to an inflation level of 2% and continued to be level-anchored in the Great Recession.

### 4.1.2 Which variable drives the inflation gap?

We now focus on the impact of economic activity on the size of the inflation gap, as defined as the deviation of inflation from the estimated trend (i.e. the de-facto cyclical component of inflation), employing six different variables to represent domestic economic activity and the effect of external inflation drivers stemming from oil prices.[20] Figure 2 presents the posterior model probabilities of all the

**19** This assessment is supported by the estimated volatility of the trend in the UC-SV model (see Appendix A for a detailed description of the results of the UC-SV model and the implications for inflation dynamics).
**20** Given that the availability of the NEER would substantially limit our time span, and also given that the US is a large and rather closed economy, we use oil prices as the only proxy of external inflation factors for the US (unlike in the case of the other six countries).

models. Not to clutter the figure, we sum the probabilities of the models without the external variables and the models augmented for the external variables (for example, the model probability of the output gap corresponds to the sum of the probabilities of models 1 and 7 in Table 1). Our results show that in general economic activity has explanatory power with respect to the inflation gap (see also Figure 5); however, the contributions of the candidate measures of domestic economic activity differ and change significantly over time. The results point to the importance of the model-switching approach in accounting for changes in inflation drivers in the context of the inflation–activity nexus, alongside the commonly considered parameter instability.

Overall, the short-term unemployment rate (sh_unp) and the unemployment expansion gap (unp_egap) dominate the other variables in most parts of the sample. The traditional output gap (gap) and the unemployment recession gap (unp_rgap) have the highest inclusion probabilities only on a few, temporary occasions, pointing to the importance of disaggregation of economic activity and to the possibility of changing inflation drivers in the context of the inflation–activity nexus. On the contrary, (the changes of) total employment (emp) and real unit labor costs (rucl) emerge as the worst performers. Whereas the failure of the traditional output gap to take a lead in the steeplechase might resonate with the views of some practitioners, the results for some of the other variables might be seen (vis-à-vis some previous empirical findings) as disappointing. In particular, the real unit labor costs fiercely advocated by Galí and Gertler (1999) and their followers do not seem to leave much footprint when compared with alternative variables.[21] Rather unconvincing results also apply to the unemployment recession gap, which was suggested by Stock and Watson (2010) as a measure of economic activity having a stable relationship with the inflation gap and outperforming other measures of economic activity. We find instead that this variable did not gain a considerable lead over its competitors and its relevance for explaining the inflation gap changes over time. However, it seems to be the best-performing variable in the very recent period, which is (rather paradoxically) not considered in Stock and Watson (2010).

**21** In fact, the certain degree of correlation between real unit labor costs and the output gap that was apparent between 1960 and 1997, which was analyzed in Galí and Gertler (1999), entirely disappears in the subsequent period and it is hard to argue that there is any proportionality between these two variables at all. As noted above, we believe that alternative ways of modeling inflation expectations should not significantly affect the relationship between inflation and economic activity. Besides, our approach is close in spirit to the hybrid New Keynesian Phillips curve, which allows for both adaptive and rational expectations formation.

From our point of view, the most promising results are obtained for short-term unemployment, which dominates from the 1960s to the mid-1990s. More specifically, the short-term unemployment rate has the highest posterior model probability from the second half of the 1960s until the first oil shock in 1973, especially when supply shocks are also considered as additional inflation drivers. During the period of the Great Inflation, the picture is rather blurred and none of the models dominates strongly over the others. Nevertheless, beside the supply shock stemming from rising oil prices, inflation is still driven by short-term unemployment, the output gap, and the unemployment expansion gap. After the Volcker disinflation and the early 1980s recession, the pattern of the inflation dynamics changes and the short-term unemployment rate again takes the lead over the other variables. The robust growth of the 1990s, a decreasing NAIRU, and low inflation lead to a decrease in the posterior probabilities of all the other variables besides the unemployment expansion gap, which emerges as the most relevant measure of real economy pressures in this period of bonanza ending in 2007. Since the global financial crisis and the Great Recession the picture has become a bit more blurred again, with no variable being clearly dominant, but with the unemployment recession gap gaining in relevance.

Besides the posterior model probabilities, which provide information on the relative performance of each model, it is also important to assess the individual impacts of the various real economy measures on the inflation gap. Figure 3 presents the time-varying coefficients (with 95% credible intervals) for the output gap and the unemployment-related variables that have the highest inclusion probabilities consistently throughout the sample. The most notable finding is that the impact of economic activity on inflation has decreased markedly over the last decade and this decrease is broad and visible across all the variables under consideration.

The contribution of the output gap to the inflation gap (upper left graph) is positive and significant throughout the sample (with the exception of the 1960s). However, the absolute values of all the coefficients decreased markedly in the 2000s, along with stabilization of inflation, a decrease in the deviations from trend inflation, and level-anchoring of inflation expectations. The coefficient on short-term unemployment (upper right graph) is again often significant with the correct negative sign and shows rather inverse movement to the coefficient on the output gap. The short-term unemployment coefficient shows an increasing impact (i.e. a lower coefficient) of economic activity up to the mid-1970s, when the impact starts decreasing, arguably as a consequence of commodity shocks (see also Figure 2), increasing again only in the early 1980s. The short-term unemployment coefficient enters insignificant territory (very similar to the coefficient on the output gap), confirming a flattening of the Phillips curve. Our results do not

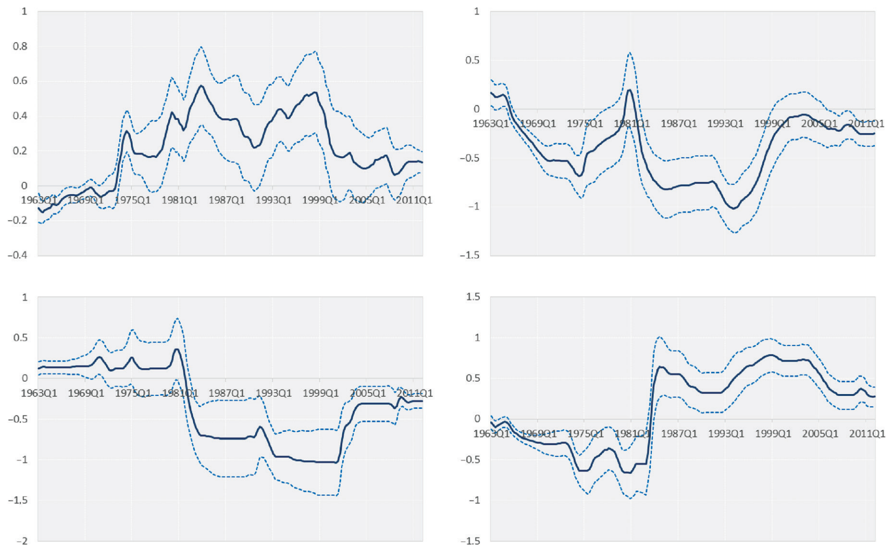

**Figure 3:** Time-varying coefficients of selected measures of economic activity, US.
Note: Output gap (upper left), short-term unemployment (upper right), unemployment recession gap (lower left), unemployment expansion gap (lower right).

provide a clear-cut picture of what the forces behind this flattening might be.[22] The short-term unemployment coefficient significantly decreases only in the late 1990s, which seems to coincide with the process of globalization. On the contrary, the output gap coefficient shows a decreasing trend from the mid-1980s onwards, which coincides with the period when a strong anti-inflationary monetary policy stance was adopted.

The coefficient on the unemployment recession gap (lower left graph) has a rather counterintuitive positive coefficient in the 1970s, which seems to be related to stagflation as a phenomenon that is entirely inconsistent with the inflation–employment trade-off and the Phillips curve. In the early 1980s the coefficient turns significant and stays so until the 2000s, confirming (similarly to the above-mentioned two coefficients) that the correspondence between inflation and economic activity has weakened in the last 15 years. Contrary to Stock and Watson (2010) we do not find that the impact of this variable on the inflation gap is stable

22 Ball and Mazumder (2011) use unemployment as the only variable representing economic activity and they provide tests of several hypotheses of why the Phillips curve has flattened in recent years. Their hypotheses are that the causes lie in anchored inflation expectations and in overall lower levels and variability of inflation. The role of inflation expectations is further elaborated in chapter 3 of the IMF's WEO 2013 (IMF 2013).

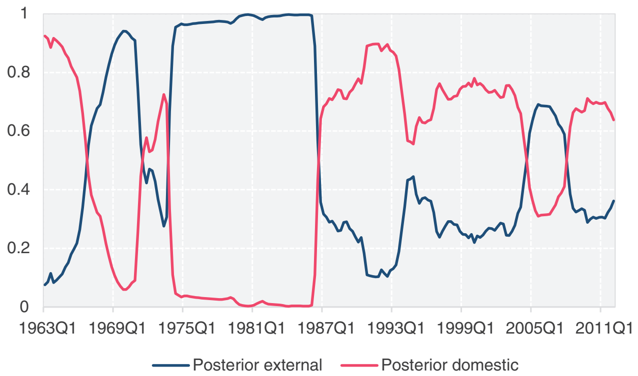


**Figure 4:** Relative importance of domestic vs. foreign inflation drivers, US.

over time or that the coefficient is significantly less volatile than that for other variables.

The coefficient on the unemployment expansion gap (lower right graph) has been positive over recent decades, meaning that decreasing unemployment has been accompanied by a reduction in the inflation gap. Although this result seems counterintuitive at first sight, it is in line with the observed non-inflationary growth of the 1990s, boosted by growth in productivity. Therefore, this result seems to be driven by the presence of a supply shock, e.g. productivity, which cannot be accounted for by any measure of economic activity, and as suggested recently by Gordon (2013), productivity might be explicitly considered an additional inflation driver (alongside measures of domestic economic activity and foreign variables).

Figure 4 compares the relative performance (in terms of posterior model probability) of the models with external inflation drivers, namely, oil prices, and the models without this variable. The main finding is that the importance of external factors also varies over time. Although the model with oil prices but without any activity variable has generally low posterior model probabilities (below 0.2 – see Figure 2, dashed line), Figure 4 shows that the models augmented by oil prices and hence accounting for supply shocks have higher posterior probabilities than those with purely domestic inflation drivers, since the oil shocks hit in the 1970s until the mid-1980s and then again shortly before the Great Recession, when oil prices and prices of other commodities hit historical highs. It should be noted that the differences in the estimated coefficients between the models with and without external variables were negligible (the coefficients in the models without external variables are reported in Figure 3), so Figure 4 indicates the periods in which the external drivers contain additional explanatory power to the inflation gap given by the predictions based on domestic inflation drivers only.

#### 4.1.3 Robustness checks

To supply the reader with a wider picture and more convincing outcomes, we performed two robustness checks. The first one consisted in using alternative inflation trends in the first step. In particular, we alternatively use inflation gaps derived from the following inflation trend estimates that have appeared in the literature recently: (i) the 5-year moving average, (ii) the trend derived using a model-free method, namely, singular spectrum analysis (Alexandrov 2009; Hassani, Soofi, and Zhigljavsky 2013), (iii) the inflation trend model proposed in Chan, Clark, and Koop (2015), and (iv) inflation expectations from the Survey of Professional Forecasters.[23] We present the comprehensive results of these alternative measures of the inflation trend and the corresponding inflation gaps in Appendix C. At this point, however, we note that while the size of the estimated inflation gap may differ in some periods, the overall dynamics are quite similar. This is confirmed by a correlation of 0.9.

Analogously to our baseline case, we fed alternative specifications of the inflation gap through the DMA exercise. The results (reported in Appendix C) are largely consistent with the baseline results, suggesting the short-term unemployment rate (sh_unp) and the unemployment expansion gap (unp_egap) as the two variables most significantly linked to the US inflation gap, with the unemployment recession gap (unp_rgap) performing well in the recent period.

The second robustness check is related to the enlargement of the model universe. Rather than selecting between models containing just one measure of economic activity, we performed a robustness check using all models with one to all six economic activity variables. With this experiment, we investigate, first, whether the resulting model switching sustains after more variables are included within one model and, second, whether the dynamics of the inclusion probabilities of different variables change markedly or not. This experiment follows Koop and Korobilis (2012), who used DMA not only to select the variables that most drive inflation, but also to distinguish between the performance of small and large models. The full model universe implies a pool of 120 models containing one to six measures of economic activity. Based on the pool, posterior inclusion probabilities for each variable were calculated.

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**23** The 5-year moving average is a simple method based on the idea that the underlying inflation trend can be tracked by a reasonably chosen one-sided low-pass filter. Singular spectrum analysis is a model-free method that does not rely on any specific model and only uses data to obtain the trend. Additionally, the model of Chan, Clark, and Koop (2015) is one of the most recent contributions in the field of estimation of inflation trends. Finally, inflation expectations are frequently linked to trend inflation, so we also examine expectations from the Survey of Professional Forecasters as an alternative representation of the inflation trend.

The results are presented in Appendix C in a way comparable with the benchmark model, i.e. we sum the model probabilities for each variable (across all the models where it appears). Unlike the baseline with one variable, there are more chances for variables that did not perform that well before to score in combination with other variables. Consequently, the difference between the best-performing variable in each *t* and the others is less striking than in the baseline case (when the variables are forced to show their relative performance one against one).

In terms of model size, more complex models with more than three variables are selected notably in the period from the mid-1960s to the mid-1990s. Nevertheless, the overall findings are generally consistent with those based on DMA with one-variable models both in terms of the prevalence of model-switching behavior and in terms of the importance of unemployment-related variables for the overall inflation dynamics. We also repeated the same exercise with models containing at most two economic activity variables (the results are not reported but are very similar to those based on the "full" model space). Hence, we believe our results based on parsimonious models with just one variable representing economic activity can be considered robust.

## 4.2 Economic activity and inflation in G7 countries

The economic activity–inflation nexus in other G7 countries shares a number of common features with that in the US. First of all, for no country is there a variable that can robustly be considered the best performer in explaining the inflation gap. Our country-level results (see Appendix D) show that models with the output gap, traditionally representing economic activity in macro models, dominate other models only rarely, with the exceptions of the UK and Germany in the 1990s. Other variables, such as unemployment and related gaps, usually perform better, as can be seen from the posterior model probabilities.

The results are also rather heterogeneous for the period of the Great Recession. DMS selects the unemployment recession gap in Japan, the UK, and Germany, whereas in France and Italy short-term unemployment dominates the other variables. Hence, the unemployment-related variables recorded the highest posterior model probabilities in all countries in the period of the Great Recession. The richness of the dynamics over time in terms of both the size of the coefficients (Figure 5) and the model inclusion probabilities (see Appendix D) explains why most of the models estimated on the pre-Great Recession sample fail to predict the inflation gap correctly: the answer lies in the inherent instability of the forms of the inflation–activity nexus.

The key observation that can be drawn from Figure 5 is that real activity has a significant but very time-dependent impact on inflation. The width of the

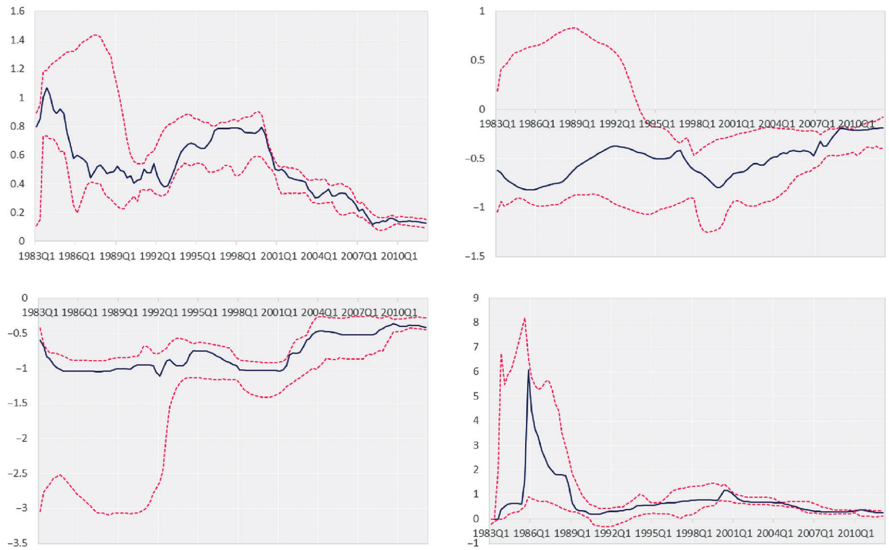


**Figure 5:** Time-varying coefficients of various measures of economic activity, Medians for G7 countries.
Note: Output gap (upper left), short-term unemployment (upper right), unemployment recession gap (lower left), unemployment expansion gap (lower right). The intervals represent the 25%–75% quantiles.

"confidence" interval (constructed as the 25%–75% quantiles of the country observations) is substantial until the late 1990s, suggesting a lot of country heterogeneity that disappears during the next decade. This is arguably related to globalization. Whereas in the 1980s there was greater heterogeneity of the business cycle across countries and also greater heterogeneity in the strength of the relationship between inflation and economic activity, globalization has contributed to the alignment of both, and the evolution of the response coefficients has become much more similar across countries. A more detailed inspection of the time-varying coefficients reveals some similarity in the findings to those for the US. In particular, the coefficients on the output gap, unemployment, and the unemployment recession gap are consistent with the economic intuition about the slope of the Phillips curve, whereas the coefficient on the unemployment expansion gap is positive, with large dispersion across countries.[24] Specifically,

24 It should be noted that the unemployment expansion gap usually has low posterior probabilities in this period, with the exception of the US and the UK – countries with robust non-inflationary growth in the 1990s fostered by increasing productivity (see the previous section and Appendix D for the posterior inclusion probabilities for individual countries).

the slopes of the Phillips curves have decreased over recent decades (due to the limited availability of data for some G7 countries the overall figures start only in 1983). This decrease is broad, shared by almost all the time series and all the countries under consideration, and not only for the output gap and the unemployment rate, which are traditionally reported in most of the recent studies. These results support the hypothesis that the slope of the Phillips curve is probably time-varying, depending on the level and variability of inflation, which are now at historically unprecedented low levels.

It has been an ongoing trial to augment the Phillips curves for the effects of external inflation drivers (Galí and Monacelli 2005) to account for the openness of economies and possible inflationary supply shocks. We augmented all the models with oil prices and the nominal effective exchange rate, and these external drivers (see the second figure for each country in Appendix D for posterior probabilities of models without and with external inflation drivers) are generally significant in all the G7 countries except Italy and Germany, although usually only temporarily. As in the case of the United States, the posterior model probability is rather low for the model containing only external variables, so domestic economic activity can be considered the main determinant of the inflation gap.

## 4.3 Overall importance of economic activity for inflation

Our steeplechase is not a single race to determine the winner at the finish line, as it is apparent that different models can win in different historical phases of this race. Moreover, we rather act as the owners of all horses at once and are chiefly interested in their combined performance. The results are summarized in Table 2, where we present the percentage of time each economic activity variable outperformed the others, i.e. the percentage of the time each model had the highest posterior probability, for each country. The cross-country variation is very significant. In general terms, the best-performing variable is the short-term unemployment rate. By contrast, the worst score is retained by total employment growth, while the importance of the other variables lies in between. Particularly notable is the predominance of the output gap for Germany and the UK and the unemployment recession gap for Japan. As noted, the external factors without any measure of domestic economic activity are hardly ever able to explain a material part of the inflation dynamics.

So far we have been dealing with the relative importance of various measures of economic activity in explaining inflation by means of the posterior probabilities of various models. Now we turn to assessing the overall importance of domestic economic activity in explaining inflation (the inflation gap). First, we

**Table 2:** Percentage of the time each model with a specific measure of economic activity outperformed the others.

| Country | Output gap | RULC | Growth in employment | Short-term unemployment | Unemployment recession gap | Unemployment expansion gap | External factors |
|---|---|---|---|---|---|---|---|
| United States | 12.69 | 0.00 | 4.57 | 50.76 | 5.58 | 24.87 | 1.52 |
| Canada | 11.68 | 8.76 | 0.73 | 50.36 | 11.68 | 16.79 | 0.00 |
| Germany | 50.46 | 10.09 | 0.92 | 22.94 | 15.60 | 0.00 | 0.00 |
| France | 0.00 | 18.35 | 2.75 | 36.70 | 22.94 | 19.26 | 0.00 |
| Italy | 14.68 | 23.85 | 5.50 | 33.94 | 6.42 | 15.60 | 0.00 |
| United Kingdom | 40.37 | 0.00 | 13.76 | 1.83 | 17.43 | 26.60 | 0.00 |
| Japan | 0.00 | 0.00 | 6.02 | 31.58 | 62.40 | 0.00 | 0.00 |

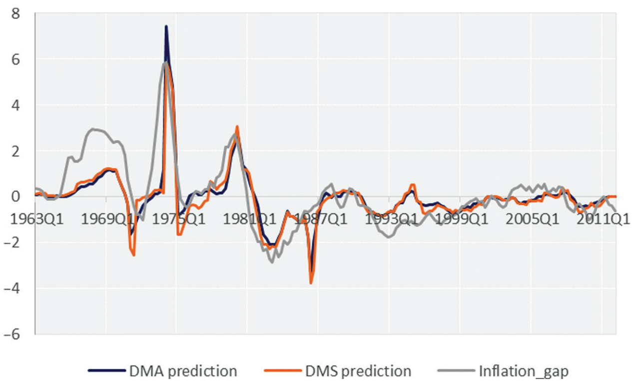


**Figure 6:** Inflation gap vs. DMA/DMS results, US.

compare the DMS and DMA pseudo out-of-sample predictions of the inflation gap over time. Figure 6 provides such a comparison for the US. The results for the other countries are given in Appendix D (see the third figure for each country). The figures suggest that the relationship between inflation and economic activity is strong and robust. Indeed, most of the major inflation upturns and downturns are well explained by the real economy variables. However, these results also confirm that the relationship between inflation and economic activity is rather complex and cannot be traced by a Phillips curve depending on a single measure of economic activity and assuming a stable and linear relationship between inflation and economic activity. Therefore, this nexus can only be seen when a more subtle approach that explicitly accounts for the uncertainty of this relationship, such as DMA/DMS, is used.

Table 3 then reports several statistics of the model's fit, with R squared ranging roughly between 0.2 and 0.5. While these results are far from being fully satisfactory from the perspective of an inflation analyst, they simply reflect the fact that it is rather difficult to fully explain inflation dynamics. On the other hand, we note that using our approach we obtained considerably higher R squared than that reported in Stock and Watson (2010), which points to the importance of exploiting dynamically the information content of all competing variables characterizing economic activity. The same applies to the RMSE measure, where again one can see larger efficiency gains vis-à-vis Stock and Watson (2010) when compared to the null model (i.e. the model only capturing the long-term inflation trend without any other explanatory variables describing the real economy). It can also be seen that even if individual models do not always work better than the null model, their switching across time leads to significant improvements over the null model in all cases.

**Table 3:** Model fit: R Squared, RMSE From Pseudo forecasting regressions.

| Country | DMA model | DMS model |
|---|---|---|
| United States | 0.514 | 0.480 |
| Canada | 0.661 | 0.611 |
| Germany | 0.424 | 0.378 |
| France | 0.493 | 0.174 |
| Italy | 0.354 | 0.232 |
| United Kingdom | 0.385 | 0.393 |
| Japan | 0.490 | 0.337 |

| Country | Mean RMSE across models | DMA model | Null model | Relative RMSE DMA/Null |
|---|---|---|---|---|
| United States | 1.302 | 1.007 | 1.500 | 0.784 |
| Canada | 1.430 | 0.927 | 1.523 | 0.575 |
| Germany | 1.604 | 0.932 | 1.207 | 0.772 |
| France | 1.169 | 0.674 | 0.893 | 0.755 |
| Italy | 2.070 | 0.991 | 1.132 | 0.875 |
| United Kingdom | 1.521 | 1.201 | 1.524 | 0.788 |
| Japan | 1.163 | 0.705 | 0.877 | 0.804 |

RMSE stands for Root Mean Square Error. The mean RMSE across models was calculated as a simple average of the RMSEs obtained from all 13 individual models. The null model is a model without any explanatory variables characterizing the real economy, and its RMSE can be identified with the RMSE of the UC-SV model.

# 5 Conclusions

The aim of this paper is to shed some new light on the economic activity–inflation nexus through the lens of dynamic model averaging (DMA). This approach addresses the uncertainty inherent in the dynamic selection of an appropriate measure of real economic activity (vis-à-vis its impact on inflation) within the time-varying parameter framework. To investigate for the existence of the Phillips curve, defined broadly as stable comovement between inflation and real activity, we simply look at the correlations between the inflation gap and several real activity measures. Our approach can be best described as eclectic, with structural and purely statistical models being reconciled. Six variables tracking real economic activity took part in our steeplechase. Four of them are rather traditional: the output gap, real unit labor costs, growth of the employment rate, and the short-term unemployment rate. In addition, following the recent contribution by Stock and Watson (2010), we examine the unemployment recession gap, focused on periods with increasing unemployment, and also create its counterpart, the unemployment expansion gap, targeted at periods with decreasing unemployment rates. Finally, variables representing foreign supply shocks, in particular oil prices and the nominal effective exchange rate, also run in our steeplechase.

We find evidence in favor of both "model switching" and time variance of the individual coefficients in the context of the inflation–activity relationship. Our results show that inflation responds significantly to economic activity in general, but does so to a varying extent across different measures. Evidently, no measure of economic activity clearly dominates in all countries or over the whole sample; however, a Phillips curve-like relationship seems to be clearly present. The traditional output gap is often outperformed by unemployment-related variables, which calls for their more frequent use in empirical practice. The performance of real unit labor costs, which are employed in some empirical studies on the NKPC, is rather disappointing, limiting their potential as an inflation driver.

Our results also suggest that foreign factors play an important role for inflation even in relatively large and closed economies, as many G7 countries are. Although their relevance varies over time, there are long periods where external factors contribute significantly to explaining inflationary pressures. Nevertheless, it should be noted that external variables on their own outperform variables representing domestic economic activity only in a few isolated periods. Thus they have additional rather than leading explanatory power for the inflation gap.

Whereas our main finding corroborates the existence of a Phillips curve-like relationship, we also document a weakening of the inflation–real activity trade-off (i.e. a flattening of the Phillips curve) in the recent decade that is robust both across activity measures and across countries. Although the weakening trade-off between inflation and economic activity might suggest that policy geared toward supporting economic growth might have a rather limited effect on inflation in the medium term, this result is conditional on inflation expectations remaining anchored in most countries. There is no guarantee that a flat Phillips curve would persist if inflation expectations were to break away from (more or less explicit) inflation targets.

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# Appendix A: Empirical framework

## A.1 The unobserved component model with stochastic volatility-UC-SV (Stock and Watson 2007)

The UC-SV is a parsimonious local-level model that has gained some prominence in recent years as it seems to capture the main features of inflation dynamics very well. The UC-SV model (2) has a standard state space representation with stochastic volatility and can be estimated using well-defined MCMC techniques (see Stock and Watson 2007). To spare computation time, we estimated the model using fast approximations for both time-varying variances. Such approximations are commonly used within the DMA framework (presented below). Given our multi-country analysis where many models need to be estimated, this is not only a practical, but in some respects also a more flexible approach which opens the door to some new insights. In particular, the forgetting factor – approximating the path of the volatility of the trend component – can be used to investigate how inflation expectations are formed. Roughly speaking, very low values of the forgetting factor indicate that economic agents take into account only actual (and the most recent) level of inflation to adjust their expectations. This means that expectations are not anchored and react instantly to changes in the price level. For example, for the US, the forgetting factor of 0.6 reached during the 1970s suggests that the inflation rate observed a year ago receives only 13% as much weight as the very last observation when the formation of expectations takes place (see Figure 7).

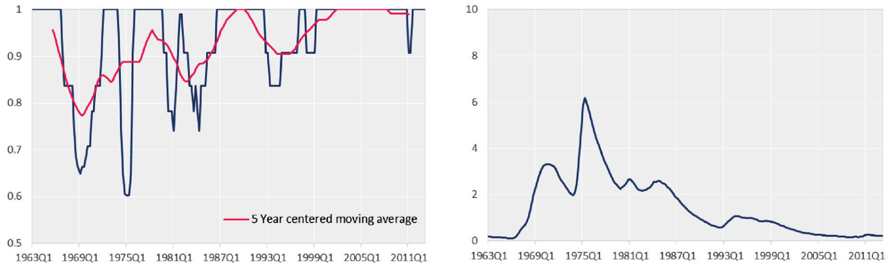



**Figure 7:** Estimated value of forgetting factor and standard deviation of transitory component, US.

## A.2 Model estimation and dynamic model averaging (Raftery et al. 2010)

Following Raftery, Kárny, and Ettler (2010), we will first turn to the estimation of the individual models and later describe how the switching between models can be done via dynamic model averaging (DMA).

*Model estimation*

We start by noting that if the variances $\sigma^2_{e,t+h}$ and $\sigma^2_{\xi,t}$ in (1) were known then a filtered estimate of the time-varying coefficient $\gamma_t$ could easily be obtained by standard Kalman filter prediction and updating formulas with almost no computational effort. If $\sigma^2_{e,t+h}$ and $\sigma^2_{\xi,t}$ are not known, it is always possible to estimate them, but this can be computationally demanding, especially if we assume time-varying volatility, which is usually modeled by stochastic volatility models and estimated via MCMC techniques.

Since we work with large sets of competing models within a multi-country environment, the total computational burden may become prohibitive when the variances need to be estimated. Drawing on the earlier literature (e.g. Fagin 1964, and Jazwinsky 1970), Raftery, Kárny, and Ettler (2010) suggest using fairly simple but generally effective approximations of $\sigma^2_{e,t+h}$ and $\sigma^2_{\xi,t}$. If we restrict our attention only to the relevant Kalman filter formulas, then the traditional prediction formula for the variance of the prediction error

$$P_{t|t-1} = P_{t-1|t-1} + \mathrm{var}(\xi_t) \tag{A.1}$$

can be specified in terms of a forgetting factor $\lambda$ and replaced by

$$P_{t|t-1} = \frac{1}{\lambda} P_{t-1|t-1} \tag{A.2}$$

where the forgetting factor $\lambda$ is typically set slightly below 1. The resulting approximation still leads to a properly defined state space model, with $\sigma^2_{\xi,t} = (\lambda^{-1} - 1)P_{t-1|t-1}$. The forgetting factor $\lambda$ regulates the uncertainty in the state (i.e. time-varying coefficient) evolution. Values close to one would lead to a fairly stable model. On the contrary, lower values enable higher variation in the coefficients (see Raftery, Kárny, and Ettler 2010, for the detailed motivation of this approach). Typically, $\lambda$ is set to a fixed value by the user prior to the estimation; however, we follow Koop and Korobilis (2012) and estimate $\lambda$ in a time-varying, data-driven manner. In our analysis we replace $\lambda$ by $\lambda_t$, where

$$\lambda_t = \lambda_{\min} + (1-\lambda_{\min}) L^{f_t} \tag{A.3}$$

where $\lambda_{\min}$ and $L$ are values pre-specified by the researcher that control the time-varyingness of the estimated coefficients:[25] $\lambda_{\min}$ is the minimum value of the forgetting factor and $L$ defines the sensitivity of the coefficients' variation to (large) prediction errors. We further define $f_t$ as $f_t = -\text{round}(\hat{e}'_{t-1+h}\hat{e}_{t-1+h})$, where $\hat{e}_{t-1+h}$ is a one-step-ahead prediction error produced by the Kalman filter and the *round* function rounds to the nearest integer. In the empirical analysis we set $\lambda_{\min}=0.9$ and $L=1.2$. We also checked for the robustness using other values, but the main story remained unchanged.

To obtain the value of $\sigma^2_{e,t+h}$ Koop and Korobilis (2012) suggest replacing it with an exponentially weighted moving average estimate, which can be computed recursively as

$$\hat{\sigma}^2_{e,t+h} = \kappa \hat{\sigma}^2_{e,t+h-1} + (1-\kappa)(\pi_{t+h} - \tau_{t|t} - \gamma_t x_t)^2 \tag{A.4}$$

where $\kappa$ is called a decay factor and has a proposed value of 0.98 for quarterly data. Armed with these approximations, we can now obtain estimates of $\gamma_t$ for all the models in Table 1 (and for the inflation trend) in a standard way. To initialize the Kalman filter we set our prior on $\gamma_t$ to zero for each model and, following Raftery, Kárny, and Ettler (2010), we use $P_{0|0}=\text{Var}(y_t)/\text{Var}(x_t)$. The data-driven choice of $P_{0|0}$ can be advocated on the grounds of Cauchy-Schwarz inequality. In the sample of countries and variables selected, its value varied between 3 and 15. As a robustness check we also initialized the filter with $P_{0|0}=10$ and $P_{0|0}=100$ uniformly across all models and obtained almost identical results. Final results are presented after discarding the first 2 years, which were used as an initialization period.

In the case of the inflation trend it is necessary to take into account the specific nature of model (2) and adjust the values of $\lambda_{\min}$, $L$, and $\kappa$ correspondingly. To estimate the inflation trend in (2), we set (after some experimenting) $L=1.2$, $\kappa=0.94$, and $\lambda_{\min}$ between 0.6 and 0.8 depending on the overall volatility of the observed inflation.

**25** In a certain sense, they can be interpreted similarly to the tightness of the priors on the coefficients.

*Model switching*

We now consider the multiple case where the model universe is formed by $K$ competing models and there is uncertainty about the "true" model governing the inflation process at time $t$. There are several approaches to producing switching between individual models, with Markov-switching models being arguably the most popular. However, some evidence (see, for example, Belmonte and Koop 2013) suggests that they only provide satisfactory results for a relatively small number of competing models, as it is quite difficult to specify (or estimate) large transition matrices. In addition, even up-to-date algorithms would require long computational time. Raftery, Kárny, and Ettler (2010) offer a solution to this problem in the form of dynamic model averaging (DMA). They propose to avoid specifying the transition matrix explicitly by introducing another forgetting factor $\alpha$, which is again typically set to a value slightly below 1. The simplification consists in replacing the traditional model prediction equation (which requires knowledge of the probability transition matrix) by

$$\rho_{t|t-1,k} = \frac{\rho^{\alpha}_{t-1|t-1,k}}{\sum_{l=1}^{K} \rho^{\alpha}_{t-1|t-1,l}} \tag{A.5}$$

where $\rho_{t|t-1,k}$ denotes the probability[26] of model $k$ being "true" at time $t$. Forgetting factor $\alpha$ works similarly as $\lambda$ in (A.3), as it slightly inflates the distribution of model probabilities. Although this step is computationally simple, Raftery, Kárny, and Ettler (2010) argue that it represents an empirically sensible approach. Recent empirical evidence (Belmonte and Koop 2013) seems to support this claim.

Obtaining the updated model probabilities is also computationally simple. The model-updating equation takes the form

$$\rho_{t|t,k} = \frac{\rho_{t|t-1,k}\, p_k(y_t \mid y^{t-1})}{\sum_{l=1}^{K} \rho_{t|t-1,l}\, p_l(y_t \mid y^{t-1})} \tag{A.6}$$

where $p_l(y_t|y^{t-1})$ is the predictive density for model $l$ obtained by the Kalman filter and evaluated at $y_t$. Similarly to traditional BMA, model probabilities $\rho_{t|t-1,k}$ can then be used for model averaging (DMA) and model selection (DMS) purposes or for summarizing the relative performance of each model and variable. We make

26 We use the symbol $\rho$ for the model probability instead of the traditional $\pi$ so as not to be confused with the rate of inflation.

a non-informative choice on the model probability prior and set $\rho_{0|0,k}=1/K$, which means that at the beginning all the models are equally probable.

To better understand the role of the forgetting factor, Raftery, Kárny, and Ettler (2010) and Koop and Korobilis (2012) show that $\rho_{t|t-1,k}$ can be related to the weighted product of the predictive densities

$$\rho_{t|t-1,k} \propto \prod_{i=1}^{t-1} \left[ p_k(y_{t-i} \,|\, y^{t-i-1}) \right]^{\alpha^i}. \tag{A.7}$$

This means that model $k$ will receive higher probability at time $t$ if it has exhibited good forecast performance in the recent past, where the performance is measured by the predictive density. The definition of the "recent" past depends on the value of the forgetting factor. Values close to unity imply that the forecast performance in the relatively distant past still receives quite a high weight, while lower values of the forgetting factor tend to ignore the forecasting ability of the model in more distant periods. In our empirical analysis, we use $\alpha=0.95$ as a benchmark value, but values closer to one did not alter the overall picture substantially.

# Appendix B: Data

G7 countries in our sample: Canada (1976:01–2013:01), France (1983:01–2013:01), Germany (1983:01–2013:01), Italy (1983:01–2013:01), Japan (1977:01–2013:01), the UK (1983:01–2013:01), and the US (1961:01–2013:01). The data span varies according to data availability. All series are seasonally adjusted. Most series are from the OECD's Main Economic Indicators and Economic Outlook. Some series were taken from national sources.

Inflation: year-on-year difference of the price index measuring core inflation (i.e. the consumer price index excluding food and energy prices, OECD MEI). For the UK, where time series is discontinued, the entire consumer price index is used.

The inflation gap is defined as the deviation of year-on-year CPI inflation (in $t+4$) from its trend value (for t) from the UC-SV model of Stock and Watson (2007). The survey inflation expectations series used for comparison with the UC trend are from the Survey of Professional Forecasters. Longer time-series starting in 1960 are taken from Chan, Koop, and Potter (2016).

The various domestic forcing variables are:
- the output gap: derived using the Hodrick–Prescott (HP) filter for real GDP
- real unit labor costs: year-on-year change of the index
- the employment rate: year-on-year change

– the short-term unemployment rate
– the (short-term) unemployment recession gap
– the (short-term) unemployment expansion gap

The external control variables are:
– the crude oil price: year-on-year change
– the nominal effective exchange rate: year-on-year change

## Appendix C: Robustness checks for the US

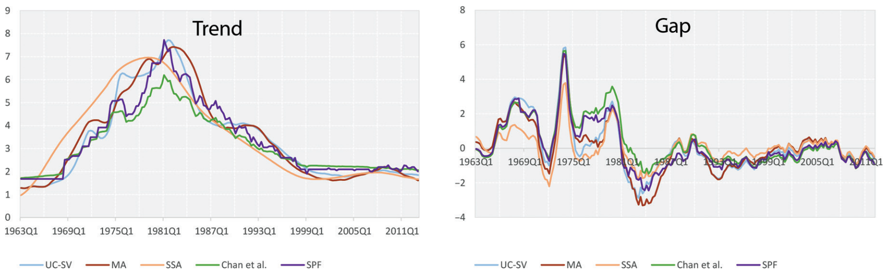



**Figure 8:** Alternative estimates of inflation trend and inflation gaps.

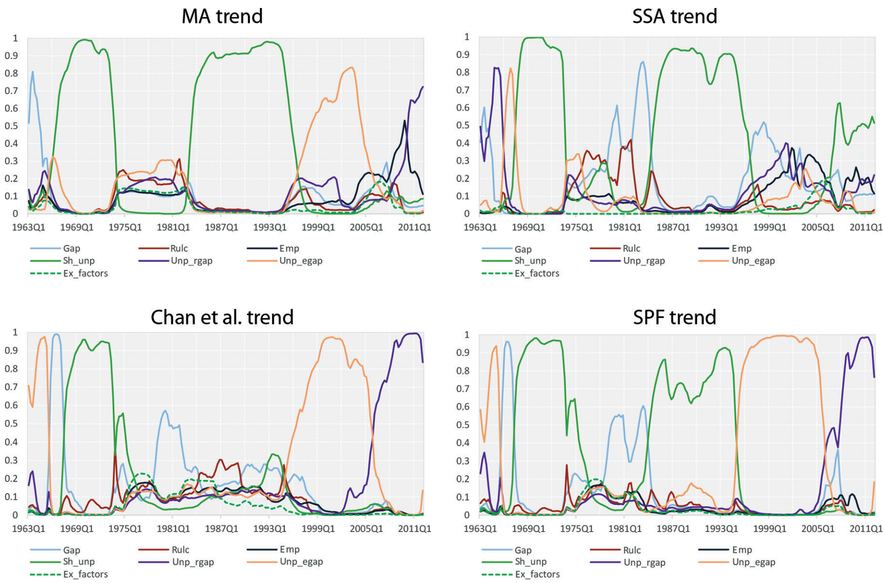



**Figure 9:** Posterior model probabilities for models in Table 1 using alternative inflation gaps.

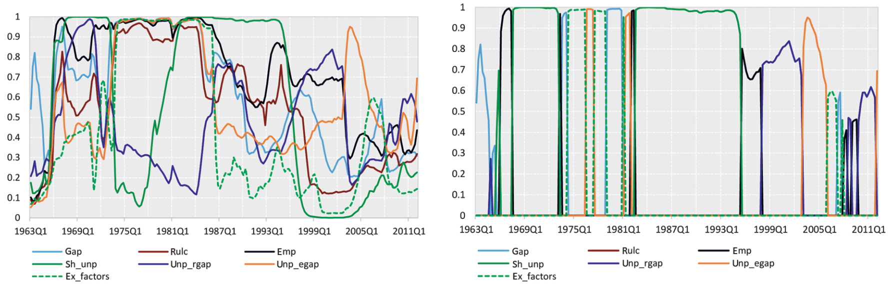
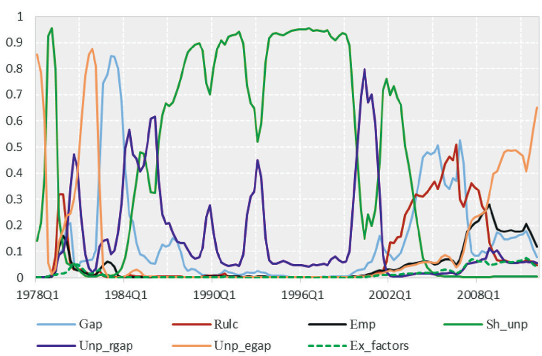


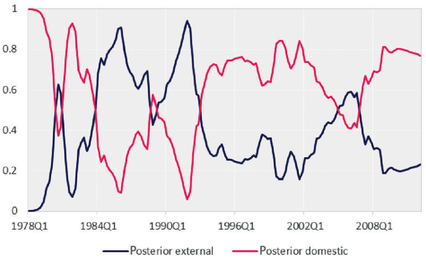

Figure 10: Posterior inclusion probabilities using DMA with any arbitrary combination of variables.
1. All variables shown (left), 2. Only best performing variable at time t shown (right).

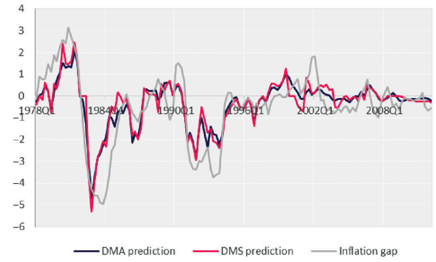
## Appendix D: Results for individual G7 countries (besides the US)

1. Posterior model probabilities, 2. Relative importance of domestic vs. foreign inflation drivers, 3. Inflation gap vs. DMA/DMS predictions.

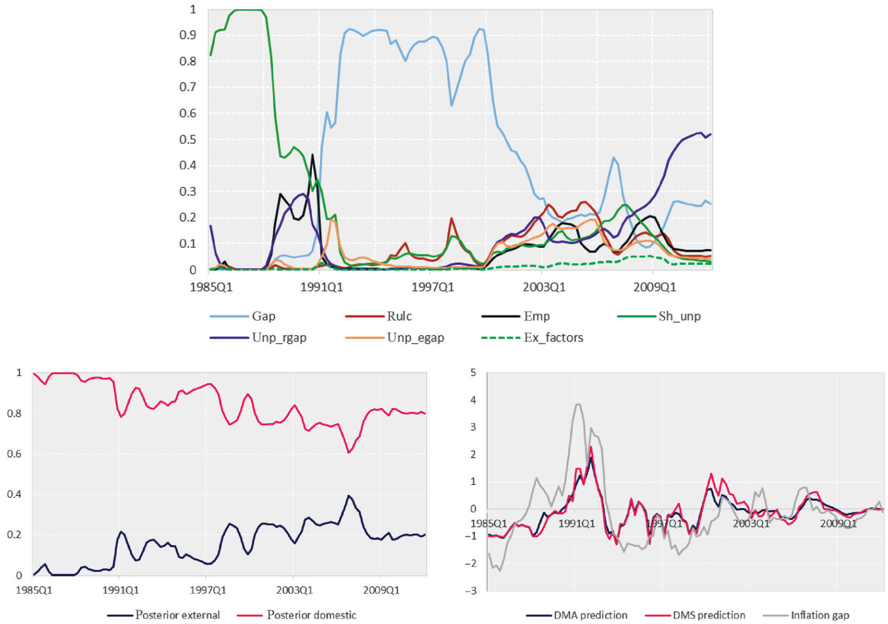
Canada



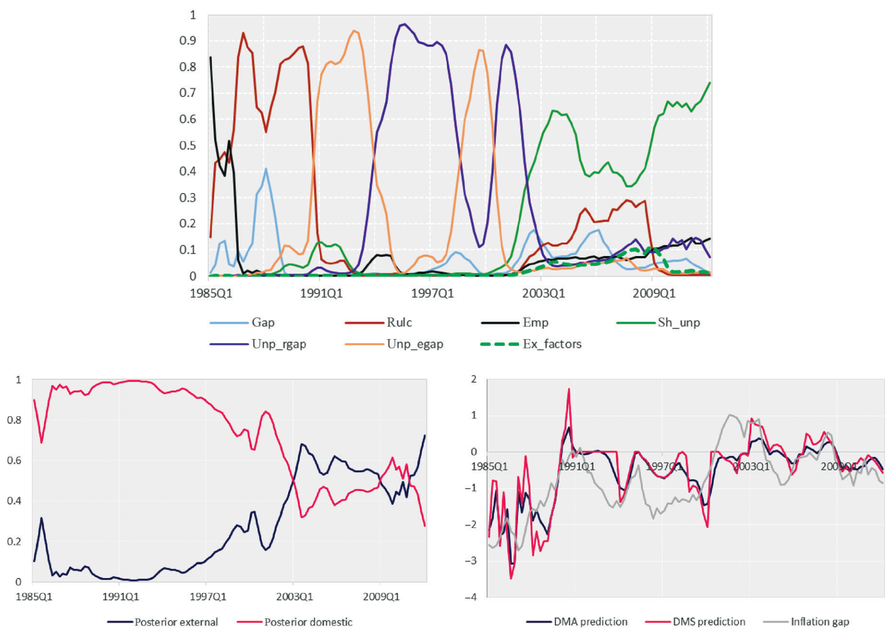



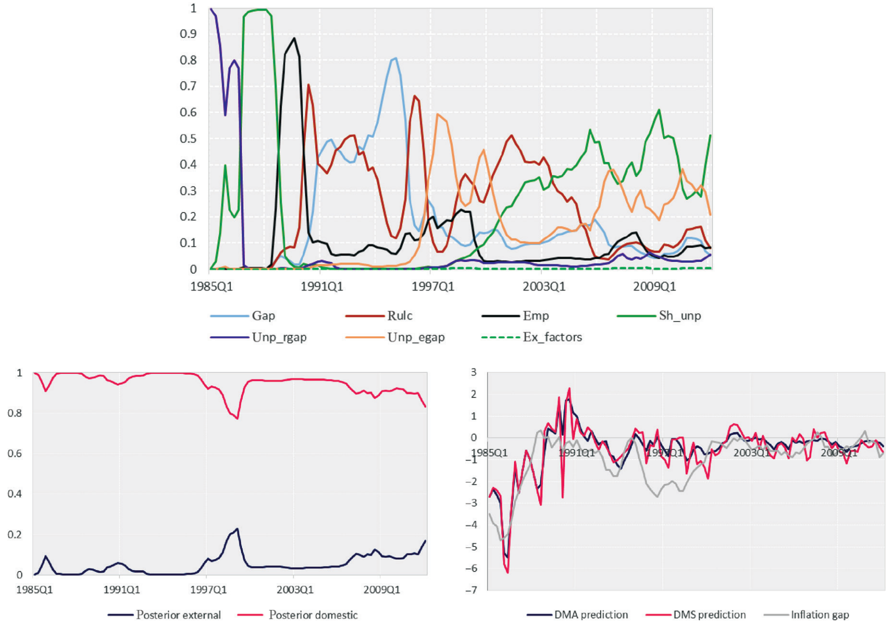
Germany



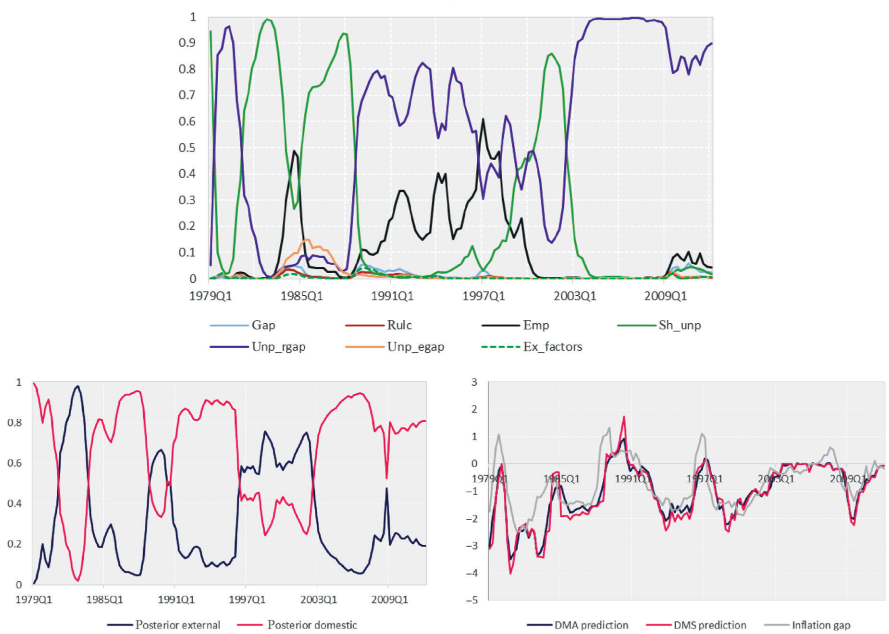

France



Italy


1985Q1
1991Q1
1997Q1
2003Q1
2009Q1
Gap
Rulc
Emp
Sh_unp
Unp_rgap
Unp_egap
Ex_factors
Posterior external
Posterior domestic
DMA prediction
DMS prediction
Inflation gap

Japan


1979Q1
1985Q1
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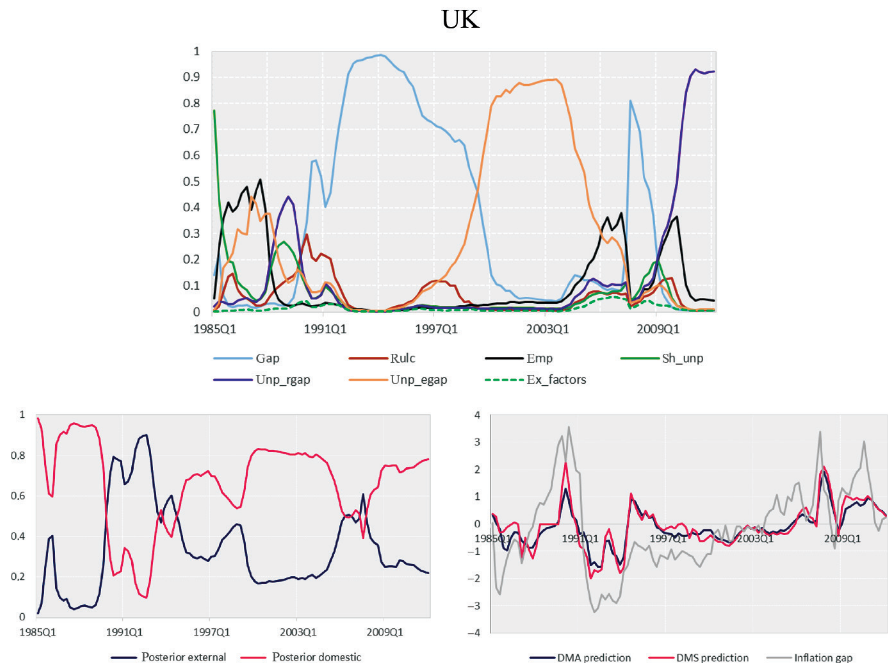
Posterior external
Posterior domestic
DMA prediction
DMS prediction
Inflation gap

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