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Testing for the New Keynesian Phillips Curve. Additional international evidence

Eric Jondeau[a], Hervé Le Bihan[b,*]

[a]HEC-Lausanne, Route de Chavannes 33, 1007 Lausanne-Vidy, Switzerland, and FAME
[b]Banque de France, Centre de recherche, 41-1391 DGEI, 31, rue Croix des Petits-Champs, 75049 Paris Cedex 01, France

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Abstract

The "New Keynesian" Phillips Curve (NKPC) states that inflation has a purely forward-looking dynamics. In this paper, we test whether the inflation dynamics in European countries can be adequately described by this model. For this purpose, we estimate hybrid Phillips curves, which include both backward- and forward-looking components, for major European countries, the euro area, and the US. Using both GMM and ML estimation procedures, we examine the sensitivity of the estimates to the choice of output gap or real unit labor cost (ULC) as forcing variable and to the number of lags and leads in the inflation dynamics. Then, we provide several specification tests for the models estimated. Our findings can be summarized as follows. First, the forward-lookingness of the inflation dynamics is not altered by the choice of the forcing variable. In contrast, it is strongly affected by the lag and lead structure of inflation. Two specifications emerge: the real ULC specification with a single lag and lead and a large forward-looking component which is relevant in the US and the UK. The output gap specification with three lags and leads and a low degree of forward-lookingness provides a better fit for continental Europe.

JEL classification: E31

Keywords: Forward-looking Phillips curve; Euro area; GMM estimator; ML estimator

* Corresponding author.
E-mail addresses: eric.jondeau@banque-france.fr (E. Jondeau), herve.lebihan@banque-france.fr (H. Le Bihan).

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1. Introduction

The traditional Phillips curve has been over the last decade challenged by the so-called "New Keynesian" Phillips Curve (NKPC). Unlike its predecessor, the NKPC states that inflation has a forward-looking dynamics. An appealing characteristic of the NKPC is that it can be derived from optimal price-setting by firms. For instance, in the model proposed by Calvo (1983), firms set their price optimally, subject to a constraint on the frequency of price adjustment. Hence, estimated parameters can be viewed as structural ones, providing some immunity with respect to the Lucas critique. As is widely acknowledged, the precise specification of the Phillips curve has dramatic implications from a central bank perspective. In particular, a fully credible central bank can engineer a disinflation at no cost in terms of output if inflation is a forward-looking phenomenon, whereas lowering steady-state inflation requires a recession in the context of the traditional, backward-looking Phillips curve.

The empirical relevance of the NKPC is hence a crucial issue. Recently, several studies have tested the empirical validity of the NKPC. These tests typically involve estimating a "hybrid" model that incorporates, in addition to the forward-looking component, lags of inflation that are not predicted by the core theory. The hybrid model nests the traditional Phillips curve and the NKPC as polar cases. Empirical estimates of the hybrid model have yielded conflicting results and interpretations. On one hand, Fuhrer (1997) finds the forward-looking component in inflation to be essentially unimportant. Roberts (2001) compares several Phillips curve specifications and obtains a large backward-looking component on US data. Estrella and Fuhrer (2002) also document the poor fit of a purely forward-looking Phillips curve. Söderlind et al. (2002) show, in a calibrated model, that a large backward-looking component is needed to replicate the auto-correlation patterns of inflation and output. On the other hand, Galí and Gertler (1999, henceforth GG) for the US, and Galí et al. (2001, henceforth GGL) for the euro area, obtain that the forward-looking component is dominant. Empirical evidence presented by Sbordone (2002) and Amato and Gerlach (2000) also suggests that the baseline forward-looking NKPC provides a reasonably good description of US and European inflation dynamics.

Rationalizing these results is quite challenging, because the empirical approaches adopted by the above-mentioned studies differ in many respects, namely the forcing variable introduced in the Phillips curve, the lag and lead structure of inflation dynamics, and the estimation method. This is illustrated by the contrast between two typical and influential empirical studies of the US hybrid Phillips curve: Fuhrer (1997) estimates a model with output gap allowing for three lags and leads of inflation and using Maximum-Likelihood (ML) estimation, yielding a value of the forward-looking component equal to 0.2; GG estimate a model with real unit labor cost (ULC) and one single lag and lead of inflation, using the Generalized-Method-of-Moment (GMM) and find the forward-looking component to be 0.68. GG explain the discrepancy between the two sets of estimates by the choice of the forcing variable. In fact, the relevant forcing variable suggested by the typical New Keynesian model is the real marginal cost, so that output gap and real ULC enter the equation as proxy variable for the real marginal cost.

Yet, another important difference between the two sets of estimates is the structures of lags and leads in the inflation dynamics that are not nested across existing studies. On one hand, Christiano et al. (2001) and GG provide theoretical foundations for a model with a single lag and lead and report some evidence suggesting the empirical relevance of this model. On the other hand, Fuhrer and Moore (1995b) and Fuhrer (1997) report evidence that lags and leads of inflation have to be added to the baseline hybrid model to fit the data. Guerrieri (2001) also describes a model with optimizing firms, in which price commitments last for a fixed length of several periods. Galí et al. (2002) provide an extension of the model developed by GG that incorporates additional lags.

Finally, two different econometric approaches have been used to cope with the presence of expected inflation in the hybrid Phillips curve. Fuhrer (1997) and, more recently, Lindé (2001) and Kurmann (2002) use the ML approach, while GG followed by a number of studies adopt the GMM approach. Whereas GMM requires only weak assumptions on the innovation process, ML provides model-consistent inflation expectations. As is well known, the two methods are asymptotically equivalent, but they are likely to provide significant differences in parameter estimates in finite sample. Rudd and Whelan (2001), Mavroeidis (2001), Guerrieri (2001), Lindé (2001), and Kurmann (2002) have questioned the robustness of the results obtained using the GMM approach from various points of view.

The aim of the present paper is to provide additional evidence on the empirical importance of the forward-looking component in inflation, and to investigate in a systematic fashion, the sources of the discrepancy between existing estimates. As in many previous studies, we estimate hybrid Phillips curves to assess the relative weight of past and expected inflations and compare the ability of output gap and real ULC to explain the dynamics of inflation. The distinctive features of our approach are the following. First, we investigate for several countries different specifications of the hybrid Phillips curve studied in the literature. In particular, we consider models with output gap and real ULC as forcing variables and models with different lag-and-lead structures. While most existing studies were concerned with US data, we focus our analysis on Europe. We consider the four largest European countries (Germany, France, Italy, and the UK) as well as the euro area. Comparing results obtained at the euro-area level and at individual-country level is an important cross-check of the results obtained at the area level. Second, we investigate the influence of the estimation method in estimating the hybrid model. We implement both the GMM and the ML techniques, controlling for the specification used. Finally, we perform specification tests on the estimated relations. Stability tests provide indication on the robustness with respect to the Lucas critique and are helpful in discriminating among the alternative specifications. In addition, specification tests based on ML residuals also provide valuable insights.

The paper is organized as follows. Various specifications of the Phillips curve, including the traditional, the New Keynesian, and the hybrid Phillips curves are reviewed in Section 2. Section 3 is devoted to a brief description of the GMM and ML estimation procedures. The estimation results are presented in Section 4. Section 5 provides several specification tests based on both GMM and ML estimates. To anticipate our empirical evidence, two models emerge: The real ULC model with one lag and lead appears to be consistent with US and UK data, while the output gap specification with three lags and leads is relevant in continental Europe. Section 6 summarizes our main findings and suggests topics for further investigation.

2. Overview of Phillips curves

2.1. The traditional Phillips curve

In the traditional Phillips curve, inflation is related to output gap and lagged values of inflation.[1] Such a relationship can be written as:

$$\pi_t = \sum_{k=1}^{K} \alpha_k \pi_{t-k} + \gamma \hat{y}_t + \eta_t, \tag{1}$$

where π_t denotes the inflation rate, $\hat{y}_t$ is the log deviation of output from its steady-state value, and η_t is an error term.

Such a backward-looking Phillips curve has been shown to fit US postwar inflation quite well (Fuhrer, 1997; Rudebusch and Svensson, 1999). The output-gap parameter γ is found to be statistically significant, while the sum of lagged inflation parameters does not statistically differ from unity. However, the traditional Phillips curve is a reduced-form equation that may be subject to the Lucas critique. Indeed, since the estimated parameters are not deep parameters (reflecting preferences or technologies), they are likely to change as the policy regime varies. More precisely, parameter instability of the traditional Phillips curve may occur because the relationship between past inflation and expected future inflation may change over time. In addition, the output gap may be a poor proxy for the relevant forcing variable, namely real marginal cost.

2.2. The core NKPC

The explicit introduction of rational expectations is the main feature of the forward-looking Phillips curve. An early derivation was the rational-expectation wage staggering model of Taylor (1980). In the core version of the NKPC developed by Rotemberg (1982) and Calvo (1983), aggregate price is derived from the optimizing behavior of firms. Combining nominal rigidities and optimizing behavior produces a forward-looking dynamics of inflation. The main interest of this model is to embed nominal rigidities in the dynamic stochastic general equilibrium (DSGE) framework. In Rotemberg's model, firms experience a cost of adjustment, that depends on the change in price. In Calvo's model, firms are allowed to reset their price at each date with a given probability. Thus, firms adjust their price to take into account expectations

[1] We abstract in this paper from the original "wage-price" form of the Phillips curve.

concerning future costs and future demand conditions. In both models, aggregating across firms yields the following Phillips curve equation:[2]

$$\pi_t = \beta E_t \pi_{t+1} + \lambda \widehat{mc}_t, \qquad (2)$$

where β denotes the discount factor, and $\widehat{mc}_t$ is the log deviation of average real marginal cost from its steady-state value. Parameter λ is a function of the structural parameters (in particular, the demand elasticity and the adjustment cost).

Note that, consistently with the theoretical derivation of the NKPC proposed by Rotemberg (1982) and Calvo (1983), no error term enters Eq. (2). However, several arguments suggest to introduce a random disturbance in the estimated relationship. First, as pointed out by Neiss and Nelson (2002), there may be price-level shocks, i.e., shocks that permanently affect the price level, but only temporarily affect inflation. Second, the error term may capture approximation errors related to the linearization of the theoretical model. Alternatively, it may correspond to errors in measuring real marginal cost and/or inflation.

The real marginal cost is an unobservable variable that has to be estimated. Under some assumptions about the labor supply process (Rotemberg and Woodford, 1997), the output gap is linearly related to the real marginal cost, providing a rationale for introducing the output gap in the Phillips curve. Such a proxy is advocated in particular by Fuhrer and Moore (1995a, 1995b), Fuhrer (1997), as well as Neiss and Nelson (2002). The purely forward-looking specification (NKPC) with output gap as forcing variable has been estimated, for instance, by GG, GGL, and Estrella and Fuhrer (2002). In most studies, the estimate of λ is found to be insignificant. Using the GMM approach, GG and GGL report negative estimates of λ, for both US and euro-area data.[3] One explanation of the failure of the NKPC based on output gap is that conventional measures of output gap are likely to be ridden with error. The standard approach typically involves a deterministic trend or an Hodrick–Prescott filter that is not likely to capture variations in the natural rate of output due, e.g., to supply shocks. Neiss and Nelson (2002) propose an alternative measure of potential output based on a DSGE model. Implied output gap and detrended output do not appear to be very closely related. When using the theory-based output gap, Neiss and Nelson (2002) find positive estimates of λ.

More recently, Sbordone (2002) and GG have argued that the real marginal cost may be well proxied by real ULC. These contributions have found empirical support for the NKPC. Parameter λ is found to be significantly positive, so that real ULC is a quantitatively important determinant of inflation. As pointed out by Sbordone (2002) and Gagnon and Khan (2001), however, the approximation of real marginal cost by real ULC requires that firms operate using a Cobb–Douglas technology. These authors extend the approach toward two directions. First, Sbordone derives a measure of the real marginal cost that is consistent with a Cobb–Douglas technology with overhead

[2] Chari et al. (2000) and Kiley (2002) derive such an equation under Taylor-type price staggering. An appendix containing the derivation of the pure and hybrid Phillips curves, given by Eqs. (2) and (3), is available upon request.

[3] In contrast, using proxies for inflation expectations from surveys, Roberts (1995, 1997) obtains significantly positive estimates of λ.

labor. In addition, Gagnon and Khan allow for a constant elasticity of substitution technology. They obtain that both extensions improve the fit of the NKPC relative to the Cobb–Douglas technology.

2.3. The hybrid NKPCs

2.3.1. The hybrid Phillips curve with a single lag and lead

In order to introduce some persistence in the purely forward-looking model, Fuhrer and Moore (1995b) propose a model of relative real wage contract. With a two-period contract, their key specification is written as a hybrid model, in which both lagged and expected inflation appear in the reduced form of the Phillips curve. The output gap is introduced as a forcing variable to capture demand pressure. An early formulation of the hybrid model was proposed by Masson et al. (1992). GG rationalize the hybrid model by the existence of two types of firms, in a DSGE framework. A fraction of firms set their price optimally, subject to the constraint on the frequency of price adjustment as in Calvo's model, while the remaining firms use a rule of thumb, based on recent aggregate price developments, and therefore behave in a backward-looking fashion. In Christiano et al. (2001), all firms adjust their price at each period, but some of them are not able to re-optimize their price, so that their price is indexed to last period's inflation rate. An extension proposed by Sbordone (2003) and Smets and Wouters (2003) assumes that the price set by firms that are not allowed to re-optimize is only partially indexed to past inflation.

In all models, the general hybrid Phillips curve can be written as:

$$\pi_t = \omega_f E_t \pi_{t+1} + \omega_b \pi_{t-1} + \lambda \widehat{mc}_t + \eta_t, \tag{3}$$

where η_t denotes a composite shock. This specification nests, with output gap as empirical forcing variable, the traditional Phillips curve (ω_b=1, ω_f=0), the two-period Taylor (1980) contracting model (ω_b=0, ω_f=1), and the Fuhrer and Moore (1995b) model with two-period contracts (ω_b=ω_f=1/2). It also nests, with real ULC as forcing variable, the models proposed by Rotemberg (1982) and Calvo (1983) (ω_b=0, ω_f=β), Christiano et al. (2001) (ω_f=1$-\omega_b$=$\beta/(1+\beta)$), GG, Sbordone (2003), and Smets and Wouters (2003) ($\beta \leq \omega_f + \omega_b \leq 1$).

The weights on lagged inflation and expected future inflation do not necessarily sum to one in the model developed by GG and its partial-indexation extension, while they are assumed to sum to one in the other specifications. It is worth emphasizing that this assumption is not really restrictive, since the sum of weights lies theoretically between the discount factor β (typically set equal to 0.99 in calibrated models for quarterly data) and 1.[4] In some preliminary GMM estimations, we estimated ω_f and ω_b

[4] In GG, ω_f and ω_b are related to "deeper" parameters as follows: ω_f=$\phi^{-1}\beta\alpha$, and ω_b=$\phi^{-1}\omega$, where ϕ=[α+(1$-\alpha$)ω+$\omega\alpha\beta$], with α the probability of a firm being able to change price and ω the fraction of rule-of-thumb price setters. In Sbordone (2003) and Smets and Wouters (2003), ω_f and ω_b are defined as ω_f=$\beta/(1+\beta\kappa)$ and ω_b=$\kappa/(1+\beta\kappa)$ with κ the partial indexation parameter. For the typical calibration β=0.99 and α=0.5, ω=0.5, and κ=0.5, we obtain ω_f=0.496 and ω_b=0.501 in the GG model and ω_f=0.662 and ω_b=0.334 in the model with partial indexation.

freely and obtained that in many cases, ω_f and ω_b summed to a value larger than 1, a value that is precluded in theoretical models. In addition, ML estimation revealed that, in some of these cases, allowing $\omega_f+\omega_b$ to exceed 1 would result in a non-stationary dynamics of inflation. Therefore, each specification is estimated under the constraint $\omega_f+\omega_b$=0.995, a value very close to that typically met in the model of GG and its partial-indexation extension.[5] Notice that imposing such a restriction eases identification of the model parameters.[6]

GG and GGL find empirical support for such a hybrid specification on US and European data, respectively. In both papers, a large weight (ranging from 0.6 to 0.8) on the forward-looking component is reported. While these studies suggest that real ULC is a more relevant forcing variable for inflation than output gap, Roberts (2001) obtains more balanced results from his comparison of output gap and real ULC in the case of the US. Using a Bayesian procedure for estimating a complete DSGE, Smets and Wouters (2003) find a forward-looking component of 0.69 on euro-area data.

2.3.2. The hybrid Phillips curve with additional lags and leads

The last type of specification we consider is a hybrid Phillips curves in which additional lags and leads of inflation are incorporated. Such a model was first suggested by Taylor (1980), Fuhrer and Moore (1995b) and Fuhrer (1997) as an extension of the two-period contract model, under the assumption that prices are set for several quarters at a time. As a result, agents are concerned for inflation several quarters ahead. An empirically undesirable prediction of the multi-period Taylor contracting is that lags of inflation are expected to have a negative weight in the reduced-form inflation equation (see, e.g., Fuhrer 1997). In contrast, in the relative wage contracting model of Fuhrer and Moore, lags and leads with the same horizon have the same positive weight. An additional feature of this model is that an m-period contracting model results in an inflation dynamics with $(m-1)$ lags and leads of inflation. Guerrieri (2001) extends the Taylor multi-period contract model by allowing for a fraction of rule-of-thumb price setters. While the lag and lead structure of the inflation dynamics is rather complex in these specifications, Rudebusch (2002) proposes a simpler model, where additional lags and leads are viewed as a way to cope with annual contracts when quarterly data are used. Galí et al. (2002) investigate an extension to the hybrid model developed in GG, in which firms adopting a backward-looking rule of thumb do not consider the one-lag inflation, but instead an average of several lags.

Such Phillips curves with additional lags and leads have been investigated on US and European data (Fuhrer and Moore, 1995a; Fuhrer, 1997; Coenen and Wieland, 2000; Roberts, 2001; Rudebusch, 2002; Galí et al., 2002). A comparison of several specifications is performed by Kozicki and Tinsley (2002) on the basis of their empirical performance. In this paper, we adopt a very stylized version of the relative wage contracting model with four-period contracts, following Fuhrer (1997) and Roberts (2001). We estimate a model

[5] We also estimated the hybrid models, with $\omega_f+\omega_b$=0.99 and 1. The results of these experiments, available upon request from the authors, indicate that changing the value of $\omega_f+\omega_b$ within this range does not affect parameter estimates.

[6] Identification of the NKPC is discussed by Mavroeidis (2001) and Nason and Smith (2003).

with a three-quarter average of inflation, labelled "three lags and leads" model and written as:[7]

$$\pi_t = \omega_f \left(\frac{1}{3} \sum_{i=1}^{3} E_t \pi_{t+i} \right) + \omega_b \left(\frac{1}{3} \sum_{i=1}^{3} \pi_{t-i} \right) + \lambda \widehat{mc}_t + \eta_t, \tag{4}$$

Although it does not explicitly result from individual optimization, this specification allows to cope with multi-colinearity between lags (or leads) of inflation and avoids relying too heavily on restrictions implied by a particular contracting specification.[8] Since specification (4) does not nest the standard model with one lag and lead (3), it is not clear a priori which model would outperform the other.

3. Estimation methodology

In the hybrid Phillips curve, current inflation depends on expected future inflation, an unobservable variable. A first, widely used approach to deal with this issue under the rational-expectation assumption is the GMM, in which expected inflation is implicitly built using an information set chosen by the econometrician. An alternative approach is the ML technique, which conditions upon forecasts of the forcing variable, obtained from a prediction model.

3.1. GMM estimation

In the GMM estimation technique, expected inflation is replaced by realized inflation in Eq. (3) or (4). Then, orthogonality conditions are defined between the error term $\epsilon_t = \eta_t - (\pi_{t+1} - E_t \pi_{t+1})$ and a vector of instruments Z_t in the information set available at date t, so that $E[\epsilon_t Z_t] = E[g_t(\theta)] = 0$, where θ denotes the vector of unknown parameters. An efficient GMM estimator of θ is obtained by minimizing with respect to θ the expression

$$\bar{g}_T(\theta)' \left(S_T(\tilde{\theta}_T) \right)^{-1} \bar{g}_T(\theta),$$

where $\bar{g}_T(\theta) = (1/T) \sum_{t=1}^{T} g_t(\theta)$ and the weighting matrix $S_T(\tilde{\theta}_T)$ is a consistent estimator of the covariance matrix of $\sqrt{T}\bar{g}_T(\theta)$, obtained using $\tilde{\theta}_T$ as a consistent estimator of θ.

Provided instruments are correlated with endogenous regressors and uncorrelated with the error term, GMM estimators are consistent and asymptotically normal (Hansen, 1982).

[7] Parameter estimates are not altered when the model is estimated with four lags and leads instead of three.

[8] It may be argued that Eq. (4) is an overly constrained version of a model with additional lags and leads. For this reason, we also investigated alternative specifications with several lags and leads. In particular, we estimated a specification with four lags and a four-quarter average of leads (as in Rudebusch, 2002), and a specification with four lags and one lead (as in Galí et al., 2002). Unreported evidence (available upon request from the authors) suggests that additional lags help improve the fit of the data. Additional leads also seem to matter, although the precise structure of leads is difficult to disentangle due to the high degree of colinearity between expected inflation terms. As for specification (4), we generally obtained that the weight of the forward-looking component reduces significantly as compared to the specification with a single lag and lead.

In the context of rational-expectation models, the GMM approach is very appealing, because it only requires identifying relevant instruments and does not necessitate strong assumptions on the underlying model.

A common practice is to use instruments dated $t-1$ or earlier, although the error term is theoretically assumed to be uncorrelated with all variables known at date t. One reason is that some current information may be unavailable at the date agents form their expectations. In addition, there may be dramatic measurement errors of some series, such as output gap and real ULC, that are subsequently corrected. We adopt a baseline information set, that includes four lags of inflation, the forcing variable, the short-term interest rate, and a constant term. This choice appears to be sufficient to capture the economy's dynamics. We use the same information set structure for all specifications estimated in order to ensure direct comparability of results between GMM and ML estimates. Estimation of say, specification (3), relies on the q postulated orthogonality conditions:

$$E\left[g_t(\theta)\right]=0 \qquad \text{with} \qquad g_t(\theta)=\left(\pi_t-\omega_f\pi_{t+1}-\omega_b\pi_{t-1}-\lambda\widehat{mc}_t\right)Z_{t-1},$$

where Z_{t-1} denotes the $(q,1)$ vector of instruments available at time $t-1$ and $\theta=(\omega_f,\omega_b,\lambda)'$. The same approach applies for estimating specification (4). While there exist several ways of constructing GMM estimators, with similar asymptotic properties (see, e.g., Ferson and Foerster, 1994; Hansen et al., 1996), most previous work on the NKPC used the two-step GMM estimator, initially proposed by Hansen (1982). We also adopt this estimator below, in order to match previous estimates.

Estimating the weighting matrix S_T has been widely discussed in the theoretical literature. An asymptotically efficient estimator is obtained by choosing a consistent estimator of $V=E[\bar{g}_T(\theta)\bar{g}_T(\theta)']$, i.e., the long-run covariance matrix of $g_t(\theta)$. When the error term is likely to be heteroskedastic and serially correlated, the covariance matrix may be consistently estimated by the widely used estimator proposed by Newey and West (1987). This estimator, used for instance by GG, is based on a constant number of covariances whose weights decrease linearly. Here, we favor an alternative approach proposed by West (1997) that exploits the moving-average structure of the error term ϵ_t. Indeed, ϵ_t is expected to be an MA(1) with specification (3) and an MA(3) with specification (4). Thus, moment conditions are preliminary filtered before computing the weighting matrix. This matrix is likely to be more efficiently estimated, since it is computed using the correct structure of the moment conditions. Additional details on the implementation of the GMM technique are provided in Appendix A.

The relevance of the GMM approach has been investigated, on both theoretical and empirical grounds in the context of the hybrid Phillips curve. Most of the issues are common to forward-looking models with rational expectations. First, tests of the forward-lookingness of the Phillips curve may provide highly misleading results, in case of slight specification errors. As shown by Rudd and Whelan (2001), large estimated values of ω_f and low estimated values of ω_b may be consistent with a purely backward-looking model, when a variable that belongs to the true model for inflation is erroneously omitted from the specification. Lindé (2001) finds that the GMM estimator is biased when the innovation associated with the dynamics of the forcing variable is assumed to be serially correlated.

Mavroeidis (2001) also raises the issue of identification of parameters in forward-looking models with rational expectations. He shows, in the context of the US Phillips curve, that lack of identification may lead to inconsistent estimates of the un-identifiable parameters, so that virtually any estimate for these parameters may be obtained, depending on the information set. Bårdsen et al. (2002) also point out the lack of robustness of GMM estimates of the hybrid Phillips curve.

Another concern is that the motivation for GMM is essentially asymptotic. The poor finite-sample properties of GMM have been pointed out in a number of studies (see, for instance, the 1996 special issue of the Journal of Business and Economic Statistics, vol. 14, no. 3). One reason for these poor finite-sample performances comes from the use of a single-equation estimation, which does not incorporate information on the process followed by the forcing variable. A strong implication is that the finite-sample distribution of statistical tests based on GMM should be evaluated using Monte Carlo experiments (Burnside and Eichenbaum, 1996; Diebold and Chen, 1996). Thus, in the following, we adopt this strategy systematically and compute finite-sample critical values for all test statistics based on GMM.

3.2. ML estimation

An alternative approach to GMM is the ML technique, which solves the model forward using a prediction model for the forcing variable. This prediction model may be a univariate equation, a VAR model, or a more structural model. For instance, Fuhrer and Moore (1995b) estimate a forward-looking structural model for the output gap and the short rate. In most cases, however, forecasts of the forcing variable are obtained from a VAR-type approach (see Kozicki et al., 1995; Fuhrer and Moore, 1995a). Several procedures have been proposed to solve a forward-looking model and rewrite it in a backward-looking form. In this paper, the model is solved using the AIM procedure developed by Anderson and Moore (1985). This procedure works as follows: First, the forward-looking model is written in the following general form

$$\sum_{i=1}^{\tau_B} H_{-i}X_{t-i} + H_0X_t + \sum_{j=1}^{\tau_F} H_jE_t\left(X_{t+j}\right) = v_t, \tag{5}$$

where X_t contains all variables in the model, τ_B and τ_F denote the maximum number of lags and leads respectively, and v_t is the vector of error terms. Then, the procedure computes the following autoregressive form of this model, using a generalized saddlepath procedure:

$$\sum_{i=0}^{\tau_B} S_iX_{t-i} = v_t. \tag{6}$$

This so-called observable structure is then used to compute the log-likelihood function. Under non-normality of residuals, this procedure yields Quasi-ML estimators of parameters, and requires the covariance matrix of parameter estimators to be adjusted accordingly.

Recent contributions using the ML estimation method are by Lindé (2001) and Kurmann (2002). Both authors use models in which the forcing variable depends on inflation. In particular, Lindé estimates a small macroeconomic model, in which both the Phillips curve and the *I–S* curve have a hybrid structure, with the dynamic of output gap depending on expected inflation through the short real rate. We do not adopt such structural equations for the forcing variable, but instead we estimate a VAR-like model. The reason is that we wish to compare the relative ability of the output gap and the real ULC to explain the dynamic of inflation, using the same framework. Hence, a VAR approach allows more comparability between estimates obtained with output gap and real ULC. Therefore, in addition to the hybrid Phillips curve, we estimate a VAR-like model for the marginal-cost proxy (output gap or real ULC) and the short nominal rate. Both variables depend on four lags of the inflation rate, the forcing variable, and the short nominal rate:

$$\widehat{mc}_t = \mu_1 + \sum_{k=1}^{4} \delta_{yk}\widehat{mc}_{t-k} + \sum_{k=1}^{4} \delta_{ik} i_{t-k} + \sum_{k=1}^{4} \delta_{\pi k}\pi_{t-k} + u_{1t} \tag{7}$$

$$i_t = \mu_2 + \sum_{k=1}^{4} \theta_{yk}\widehat{mc}_{t-k} + \sum_{k=1}^{4} \theta_{ik} i_{t-k} + \sum_{k=1}^{4} \theta_{\pi k}\pi_{t-k} + u_{2t}. \tag{8}$$

For the model with output gap, Eqs. (7) (8) can be viewed as an *I–S* curve and a reaction function, respectively. As far as the real ULC model is concerned, these equations can be interpreted as describing the dynamics of labor cost and capital cost, respectively.[9]

Note that several constraints have been imposed in the estimation process. As for the GMM technique, parameters ω_f and ω_b have been restricted so that $\omega_f+\omega_b$=0.995. Furthermore, in contrast to GMM, ML requires model stationarity, implying that the roots of the autoregressive observable structure satisfy the Blanchard–Kahn conditions (Blanchard and Kahn, 1980). We impose this restriction in the course of estimation.[10]

The ML estimate is performed in two steps, following the approach proposed by Fuhrer and Moore (1995b): the parameters of the hybrid Phillips curve are estimated, conditionally on the VAR parameter estimates obtained in the previous step. With this approach, once the above-mentioned stationarity problem is properly taken into account, we systematically obtain the convergence of the optimization algorithm.[11]

[9] Amato and Gerlach (2000) estimate a model in which the real ULC is defined as the difference between the real wage and the labor productivity. They therefore estimated a VAR model with real wage change and labor productivity change. We also estimated such a model and did not find significant differences between both approaches.

[10] The optimization is performed using the CML procedure of the GAUSS package.

[11] We also considered a full-information ML approach, in which all equations were estimated simultaneously. However, in a few cases, we had some difficulties to obtain convergence of VAR models, presumably because of the near non-stationarity of the model. Since the results obtained with both approaches were otherwise very close, we only report results obtained with the two-step approach.

4. Empirical results

4.1. Data

We estimate the hybrid Phillips curves described above for the euro area and four major European countries (Germany, France, Italy, and the UK). We also report results using US data for two purposes: First, we aim at understanding the conflicting results of Fuhrer (1997) and GG; second, we examine whether similar conflicts occur on European data. The sample period runs from 1970:1 to 1999:4 at the quarterly frequency. The data are drawn from OECD Business Sector Data Base for individual countries. As regards the euro area, we use the updated Area-Wide Model database from Fagan et al. (2000). In the case of Germany, we corrected for the mechanical impact of re-unification on GDP and GDP deflator data using data for West Germany for the year 1991.

Fig. 1 displays the historical path of the various series under consideration for each country or area. We measure inflation as the annualized quarterly percent change in the implicit GDP deflator. The interest rate is the three-month money-market rate. Output is simply defined as real GDP. From a theoretical standpoint, potential output is the level that would prevail under fully flexible prices. It is well documented that the use of detrended GDP as a proxy for the output gap does not have strong theoretical grounds. Since estimating structural measure of potential output is beyond the scope of this paper, we concentrate on the output-gap measure computed with a Hodrick–Prescott filter.[12] Subsequently, detrended output may fail to account adequately for supply shocks or labor market frictions affecting real marginal cost.

Real ULC is computed using deviation of the (log) labor income share from its average value. The labor income share is the ratio of total compensation in the economy over nominal GDP.

4.2. Parameter estimates

We now present and discuss GMM and ML estimates of the hybrid models described above. Table 1 reports parameter estimates using the GMM technique with the weighting matrix computed using the optimal West (1997) procedure. Table 2 reports estimates of the ML approach.

Our empirical evidence can be summarized as follows.

(1) GMM estimates of the hybrid model with a single lag and lead (Table 1, Panel A) indicate that the choice of the forcing variable does not affect significantly the degree of forward-lookingness in inflation. Differences in estimates of ω_f in the first two columns are barely noticeable, less than 0.1 in most countries. Even in Germany, where the difference exceeds 0.13, it is not statistically different from 0. An explanation for this

[12] We used the recommended value, λ=1600, for the smoothness parameter. We also examined measures of output gap computed using the regression on a quadratic time trend or on a segmented trend as alternative indicators of excess demand. All statistical trends were computed over the 1965:Q1–1999:Q4 period. Using a Hodrick–Prescott filter provided more conclusive results, apparently because the resulting output gap displays a more stationary dynamics.

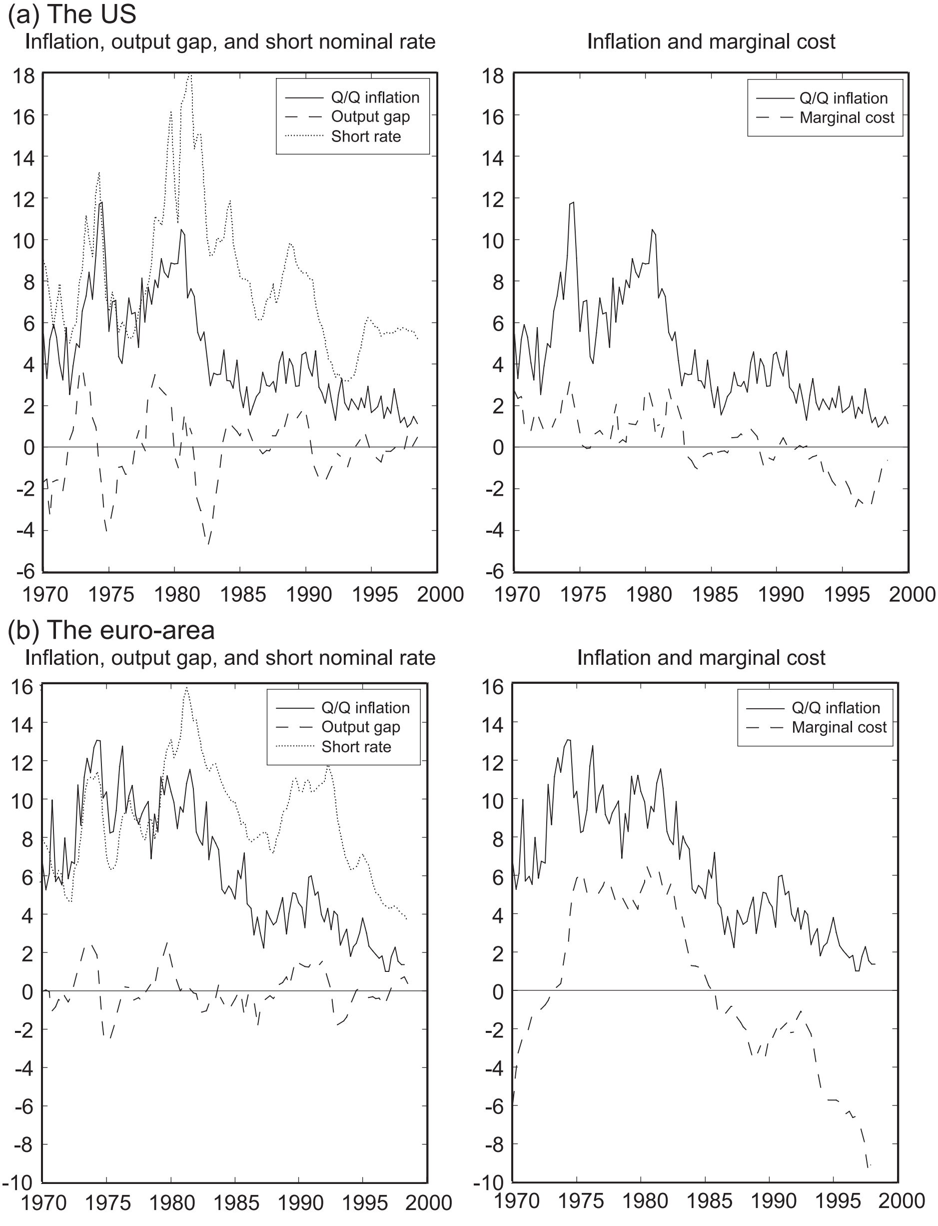

Fig. 1. This figure illustrates the historical path of the various series under considerations for each country or area: ‘QQ inflation’ is the annualized quarterly percent change in the implicit GDP deflator, ‘short rate’ is the 3-month money-market rate, ‘output gap’ is the percent deviation of real GDP from its trend computed using the Hodrick–Prescott filter, ‘real ULC’ is the percent deviation of the real unit labor cost from its sample average value.

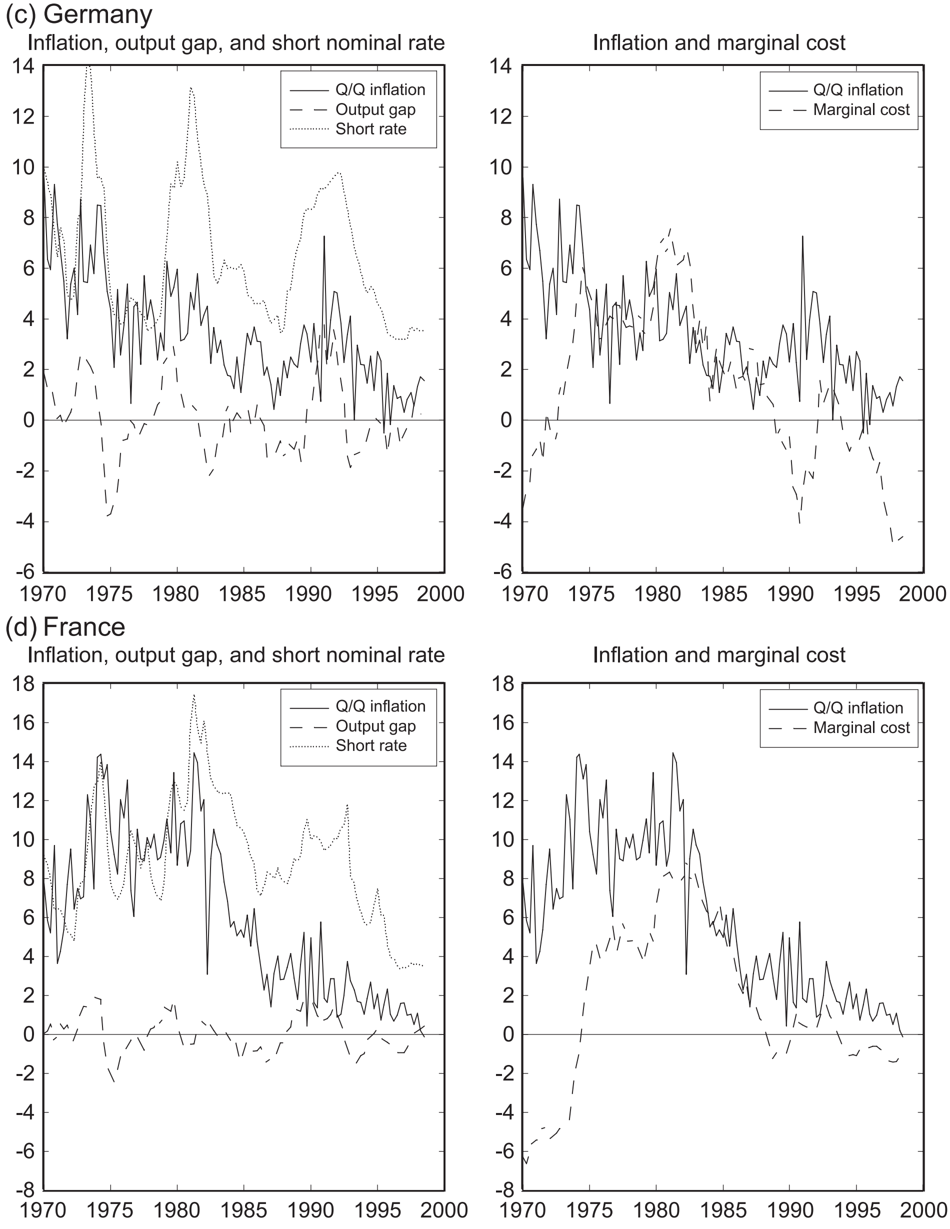

Fig. 1 (*continued*).

result may be that the two forcing variables are proxies for the real marginal cost, so that it is not surprising that the estimates of other parameters are very similar. It may also be argued that the GMM estimates of the forcing variable parameter λ is in most cases insignificant. In the model with one lag and lead, λ is found to be significantly positive for

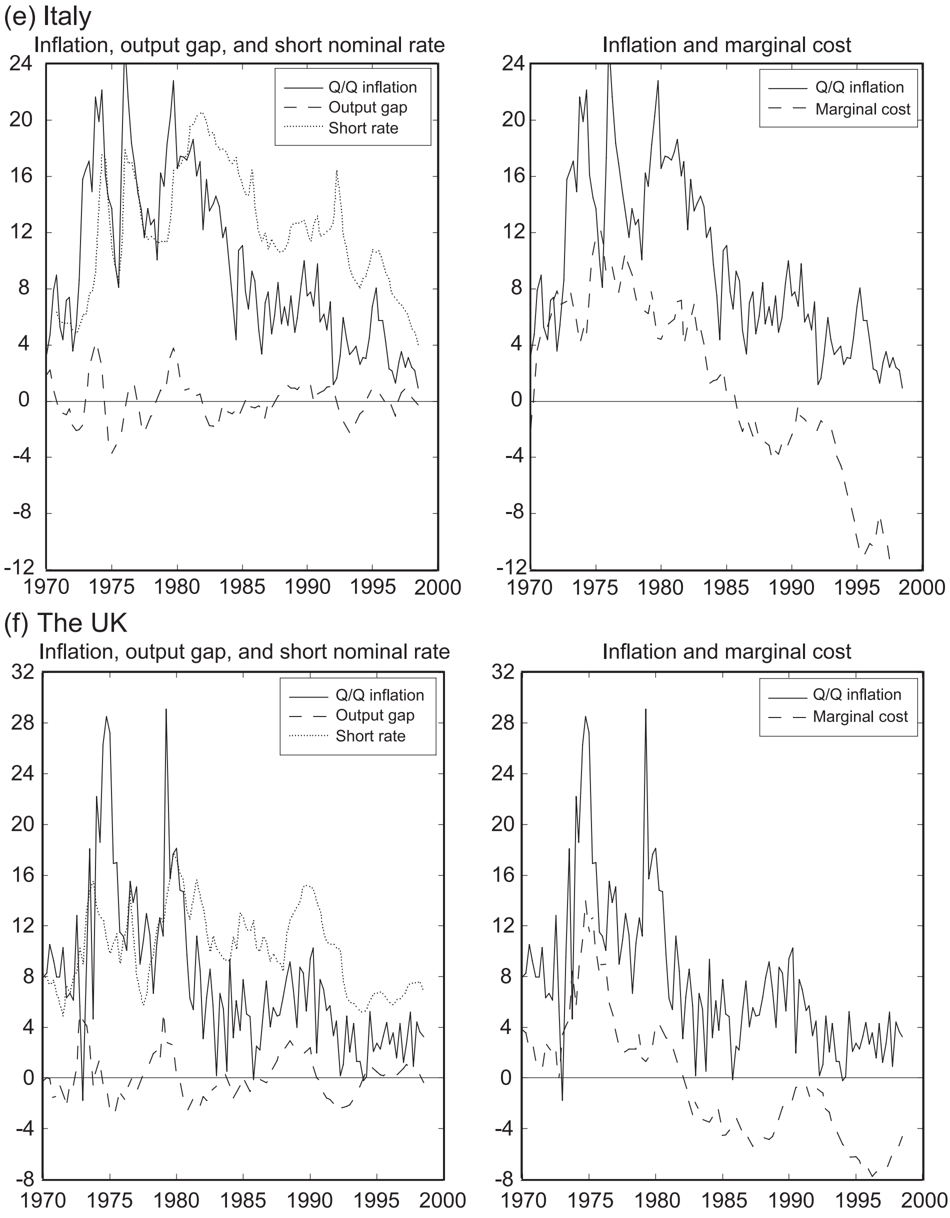

Fig. 1 (*continued*).

Germany only, when the forcing variable is the output gap. This clearly raises the issue of the relevance of the hybrid model, because with λ=0 the reduced-form equation of the hybrid Phillips curve (3) collapses to an AR(1) model, with root equal to $\left(1-\sqrt{1-4\omega_b\omega_f}\right)/\left(2\omega_f\right)$.

Table 1
GMM estimation of the hybrid model using the West (1997) procedure

	Panel A: model with one lag and lead				Panel B: Model with three lags and leads			
	Output gap		Real ULC		Output gap		Real ULC	
	Parameter	S.E.	Parameter	S.E.	Parameter	S.E.	Parameter	S.E.
The US								
ω_f	0.606*	0.075	0.677*	0.061	0.445*	0.080	0.586*	0.084
ω_b	0.389*	0.075	0.318*	0.061	0.550*	0.080	0.409*	0.084
λ	−0.025	0.035	0.009	0.027	0.089	0.071	0.053	0.057
J-stat	18.413	0.048	16.165	0.095	13.022	0.222	12.791	0.236
Euro area								
ω_f	0.628*	0.091	0.608*	0.059	0.415*	0.130	0.550*	0.097
ω_b	0.367*	0.091	0.387*	0.059	0.580*	0.130	0.445*	0.097
λ	0.121	0.094	0.000	0.005	0.556*	0.149	0.003	0.010
J-stat	15.835	0.104	25.318**	0.005	16.370	0.090	26.961*	0.003
Germany								
ω_f	0.808*	0.099	0.687*	0.079	0.425*	0.067	0.440*	0.094
ω_b	0.187	0.099	0.308*	0.079	0.570*	0.067	0.555*	0.094
λ	0.086**	0.042	0.000	0.008	0.153*	0.052	−0.008	0.015
J-stat	21.228**	0.020	25.843*	0.004	18.348	0.049	18.382	0.049
France								
ω_f	0.548*	0.076	0.600*	0.082	0.212	0.124	0.368*	0.133
ω_b	0.447*	0.076	0.395*	0.082	0.783*	0.124	0.627*	0.133
λ	−0.040	0.064	0.013	0.007	0.287	0.217	−0.001	0.024
J-stat	22.987**	0.011	21.302**	0.019	14.854	0.137	12.555	0.250
Italy								
ω_f	0.471*	0.032	0.431*	0.030	0.528*	0.070	0.502*	0.055
ω_b	0.524*	0.032	0.564*	0.030	0.467*	0.070	0.493*	0.055
λ	−0.006	0.053	0.004	0.002	0.350**	0.171	0.013	0.009
J-stat	33.054*	0.000	36.854*	0.000	15.796	0.106	18.603	0.046
The UK								
ω_f	0.725*	0.081	0.817*	0.078	0.319*	0.037	0.617*	0.070
ω_b	0.270*	0.081	0.178**	0.078	0.676*	0.037	0.378*	0.070
λ	−0.142	0.128	0.030	0.024	0.381*	0.138	0.044**	0.022
J-stat	13.547	0.195	10.319	0.413	14.465	0.153	16.379	0.089

This table reports GMM estimates of the hybrid model using the West (1997) procedure. Panel A corresponds to the specification with one lag and lead (Eq. (3)) and Panel B corresponds to the specification with three lags and leads (Eq. (4)). Column 'S.E.' reports the standard error of parameter estimates and the p-value of the J statistics.

* Indicates that the parameter or the J statistic is significant at the 1% level.

** Indicates that the parameter or the J statistic is significant at the 5% level.

More generally, the estimates of ω_f obtained with both output gap and real ULC are very close, regardless the lag and lead structure and the estimation method. For instance, when three lags and leads are introduced in the dynamics of inflation (Panel B), the difference between the two GMM estimates of ω_f is significant in the UK only (0.32 vs. 0.62).

Table 2
ML estimation of the hybrid model estimated by ML

	Panel A: model with one lag and lead				Panel B: model with three lags and leads			
	Output gap		Real ULC		Output gap		Real ULC	
	Parameter	S.E.	Parameter	S.E.	Parameter	S.E.	Parameter	S.E.
The US								
ω_f	0.480*	0.047	0.525*	0.014	0.275	0.150	0.429	0.053
ω_b	0.515*	0.047	0.470*	0.014	0.720*	0.150	0.566*	0.053
λ	0.017	0.022	0.010*	0.003	0.178**	0.083	0.014	0.023
see	1.199		1.179		1.145		1.210	
log-lik.	−180.464		−178.801		−175.142		−181.624	
Euro area								
ω_f	0.496*	0.030	0.540*	0.015	0.401*	0.046	0.436*	0.049
ω_b	0.499*	0.030	0.455*	0.015	0.594*	0.046	0.559*	0.049
λ	0.049	0.045	0.002*	0.000	0.323*	0.090	−0.001	0.005
see	1.752		1.733		1.548		1.665	
log-lik.	−215.529		−214.257		−201.830		−209.918	
Germany								
ω_f	0.604*	0.029	0.607*	0.030	0.382	0.105	0.480*	0.059
ω_b	0.391*	0.029	0.388	0.030	0.613*	0.105	0.515*	0.059
λ	0.008	0.025	0.000	0.002	0.093	0.054	−0.009	0.010
see	1.651		1.652		1.385		1.419	
log-lik.	−216.572		−216.627		−196.691		−199.489	
France								
ω_f	0.513*	0.026	0.537*	0.020	0.264	0.251	0.194	0.422
ω_b	0.482*	0.026	0.458*	0.020	0.731*	0.251	0.801	0.422
λ	0.016	0.049	0.003	0.002	0.342	0.228	−0.042	0.071
see	2.159		2.147		1.829		1.868	
log-lik.	−240.230		−239.684		−221.968		−224.311	
Italy								
ω_f	0.505*	0.025	0.525*	0.014	0.443*	0.028	0.447*	0.037
ω_b	0.490*	0.025	0.470*	0.014	0.552*	0.028	0.548*	0.037
λ	−0.006	0.043	0.003*	0.001	0.255**	0.101	0.004	0.006
see	2.739		2.642		2.979		3.050	
log-lik.	−256.702		−253.688		−266.204		−268.811	
The UK								
ω_f	0.589*	0.025	0.585*	0.023	0.164	0.251	0.485*	0.044
ω_b	0.406*	0.025	0.410*	0.023	0.831*	0.251	0.510*	0.044
λ	−0.029	0.025	0.004*	0.001	0.722	0.432	−0.005	0.009
see	4.353		4.303		3.923		4.088	
log-lik.	−326.212		−325.184		−314.295		−319.397	

This table reports ML estimates of the hybrid model. Panel A corresponds to the specification with one lag and lead (Eq. (3)) and Panel B corresponds to the specification with three lags and leads (Eq. (4)). Column 'S.E.' reports the standard error of parameter estimates. 'see' is the standard error of estimate. 'log-lik.' is the sample log-likelihood of the model.

* Indicates that the parameter is significant at the 1% level.

** Indicates that the parameter is significant at the 5% level.

Similarly, when ML estimates are considered (Table 2), the difference in ω_f estimates is significant in the same case only.

This evidence suggests that in general the choice of the forcing variable cannot be viewed as affecting the degree of forward-lookingness of inflation. This result contradicts the claim by GG that the forcing variable is the major rationale for contrasts in existing estimates.

(2) Now, comparing the one lag/lead model (Panel A) with the three lags/leads model (Panel B) indicates that, in all countries except Italy, the forward-looking component decreases when additional lags and leads are introduced. In some cases, the difference is very significant. For instance, the GMM estimates of ω_f in the output gap model with three lags and leads is about half the estimates of ω_f in the model with one lag and lead in Germany, France, and the UK. Hence, the broad picture is that the model with one lag and lead puts more weight on the forward-looking component while the model with three lags and leads puts more weight on the backward-looking component. The contrast is even more marked in the ML estimates reported in Table 2. It should be mentioned that the role of the forcing variable is empirically more compelling in the model with three lags and leads.

(3) Before discussing the differences between GMM and ML estimates, it is interesting to compare the GMM estimates obtained using the optimal West (1997) procedure (reported in Appendix A, Table A) and those obtained using the Newey and West (1987) procedure, widely used in the literature (reported in Table 1). A forceful result is that estimates of ω_f with West procedure are systematically lower than those obtained with the Newey–West procedure. In several cases, this difference is very significant. For instance, in the model with one lag and lead, the estimates of ω_f with West procedure are about 0.15–0.2 lower than the estimates with Newey–West procedure for the euro area, Germany, and the UK. Therefore, it seems that in the context of the Phillips curve, using the sub-optimal Newey–West procedure for computing the GMM weighting matrix implies systematic over-estimation of the forward-looking component.

(4) Last, comparing optimal GMM estimates and ML estimates reveals that in most cases the GMM estimates of the forward-looking component in the one lag/lead model is larger than the ML estimates. In several countries (the US, the euro area, Germany, and the UK), the gap between both estimates is as high as 0.1–0.2. In France and Italy, ω_f is estimated to be very close to 0.5 with both estimation methods. As far as the model with three lags and leads is concerned, the differences between the estimates of ω_f are much smaller: in the euro area and in countries of the area, GMM and ML yield basically the same estimates of the hybrid curve. In the US and the UK, the GMM estimate is slightly larger than the ML estimate.

The broad picture that emerges from these estimates can be summarized as follows: the choice of the forcing variable does not affect the weight of the forward-looking component significantly; introducing additional lags and leads in the dynamics of inflation induces a lower forward-looking component; last, the GMM estimate of ω_f appears to be over-stated as compared to the ML estimate, especially under a Newey–West weighting matrix.

Now, considering the GMM estimate of ω_f found in the real ULC model with one lag and lead (corresponding to the estimates reported by GG) and the ML estimate in the output gap model with three lags and leads (reported by Fuhrer, 1997), we observe that a similar gap exists in all countries except Italy: the difference between both estimates of ω_f is as high as 0.4 in the US, 0.2 in the euro area, 0.3 in Germany and France, and 0.6 in the UK. Such gaps can be partially explained by the differences in the lag and lead structure and by the estimation method. It is worth emphasizing that the two aspects are not independent. In a related paper, Jondeau and Le Bihan (2003) propose an explanation of the empirical finding that GMM tends to provide a larger estimate of the forward-looking component than ML. Under mis-specification (for instance in case of omitted dynamics or measurement error in the forcing variable), the ML estimate of ω_f is generally biased downwards, while the GMM estimate is generally biased upwards. Now, if the output gap model with three lags and leads is assumed to be the correct model in the euro area, one should observe large differences in GMM and ML estimates of ω_f for the model with one lag/lead, and essentially no difference in the two estimates for the model with three lags/leads. This is basically what we obtain since estimates of ω_f are 0.63 with GMM and 0.5 with ML in the model with one lag and lead and 0.42 and 0.4, respectively, in the model with three lags and leads. A similar result obtains in Germany.

Basically, two types of models emerge from the above investigation of parameter estimates: a model with one lag and lead and a dominant forward-looking component, and a model with three lags and leads and a dominant backward-looking component. This pattern appears to be broadly independent of the estimation method. Yet, a further investigation of parameter estimates suggests that real ULC is more appropriate for the model with one lag and lead, while output gap is more relevant for the model with three lags and leads. Unlike the others, these two specifications provide economically meaningful and often significant values for the forcing variable parameter.

5. Specification tests

Since GMM and ML estimators are asymptotically equivalent, the discrepancy between parameter estimates is likely to be explained by small-sample biases and/or mis-specification. Evidence of mis-specification should be apparent from the properties of residuals. Exploring the properties of GMM residuals is not a promising way, however, since they incorporate expectation errors that are presumed to be serially correlated. In contrast, GMM provides the opportunity to perform various specification tests.

5.1. Tests based on GMM estimation

The first specification test we consider is the well-known J test of over-identifying restrictions (Hansen, 1982). When the instrument set contains more instruments than unknown parameters ($q>n$), a correctly specified model should lead to sample moments being very close to zero. The J statistic tests whether the $(q-n)$ restrictions on the moment conditions are satisfied by the data. Under the null hypothesis that the model is correctly specified, it is asymptotically distributed as a $\chi^2(q-n)$. However, as argued above, several studies have highlighted that the asymptotic distribution provides only a poor approximation of the finite-sample distribution of estimators and test statistics.

Thus, as recommended by Burnside and Eichenbaum (1996) and Diebold and Chen (1996), we evaluate the finite-sample distribution of GMM-based specification test statistics using Monte–Carlo experiments. The finite-sample distributions are computed as follows. We simulate 1000 samples of the whole model using parameter estimates obtained by ML estimation (with the same number of observations as in the sample). Then for each simulated sample, we compute the corresponding statistic. We thus obtain the finite-sample distribution of the statistic, from which we select the 1% and 5% critical values.

Table 1 reports the J statistic, its asymptotic p-value and the indication whether the J statistic is rejected at the 1% (*) and 5% (**) significance level using finite-sample critical values. The finite-sample critical values of the J statistic are slightly larger than the asymptotic ones.[13] Inspection of the table reveals that the diagnosis is very similar with both finite-sample and asymptotic critical values: On one hand, the over-identifying restrictions are strongly rejected in countries of the euro area for the model with one lag and lead, regardless the forcing variable. On the other hand, they are not rejected for the model with three lags and leads.

Another important hypothesis that can be investigated using GMM estimation is parameter stability. Tests for parameter stability are important in our set-up for two reasons. First, the Lucas critique may be a concern for the estimated equations, because these specifications rely only partially on the underlying optimizing behavior of agents under rational expectations (in particular, Eq. (4)). As shown by Favero and Hendry (1992) and Ericsson and Irons (1995), the Lucas critique can be seen as a testable hypothesis: a specification is said to be structural, if it is policy-invariant. Hence, stability over the sample period is here viewed as a test of policy invariance. Second, even models with micro-foundations may be subject to the Lucas critique. Indeed, parameters may not be structural ones, if the model inaccurately reflects the true behavior of agents or the way they form expectations (see Estrella and Fuhrer, 2002). We therefore test the temporal stability of all hybrid models. We consider the Wald test for parameter stability with unknown break-point, following the approach developed by Andrews (1993) and Andrews and Ploberger (1994). The test statistic is described in Appendix B. Note that stability tests and the J statistic should be viewed as complementary. First, any rejection of parameter stability should be in general expected to lead to rejection of orthogonality conditions by the J statistic. However, given that stability tests are devised against one specific alternative, they should have more power against this type of mis-specification. Second, rejection of moment condition cannot be expected to be systematically associated with rejection of stability. Indeed under certain types of mis-specification (e.g., omitted variables), the estimated parameters may be stable within the sample, although asymptotically biased.

[13] It should be noticed that we also computed the finite-sample critical values for the GMM estimation with the Newey and West (1987) procedure, as reported in Appendix A (Table A). In no case, we were able to reject the over-identifying restrictions, suggesting that the estimated model is not rejected by the data. However, the estimation of the J statistic with the Newey–West weighting matrix has been shown to be severely biased in rational-expectation models (Hansen et al., 1996; Jondeau et al., 2004).

Table 3
Specification tests

	Panel A: GMM-based test		Panel B: ML-based tests		
	Stability		Normality	No serial correlation	Homoskedasticity
	Sup-W_T	Break-point	KS	QW(8)	LM(8)
The US					
1 lag–1 lead/Output gap	13.766	1982:3	0.408	10.775	12.708
1 lag–1 lead/Real ULC	7.689	1982:4	0.512	8.755	11.448
3 lags–3 leads/Output gap	5.812	1981:4	0.740	14.036	31.114*
3 lags–3 leads/Real ULC	19.554	1981:4	0.642	10.177	27.940*
Euro area					
1 lag–1 lead/Output gap	11.545	1980:3	1.278*	15.418	10.003
1 lag–1 lead/Real ULC	37.023**	1986:1	1.209*	13.752	6.443
3 lags–3 leads/Output gap	26.625	1987:1	1.067*	12.913	2.366
3 lags–3 leads/Real ULC	15.693	1986:1	1.064*	12.186	7.403
Germany					
1 lag–1 lead/Output gap	19.077	1987:1	0.929**	21.953*	6.361
1 lag–1 lead/Real ULC	19.614	1980:2	0.953**	21.648*	5.784
3 lags–3 leads/Output gap	14.93	1987:1	0.577	15.590**	4.044
3 lags–3 leads/Real ULC	10.224	1979:2	0.793	8.891	1.659
France					
1 lag–1 lead/Output gap	17.347	1982:2	1.071*	18.264**	8.756
1 lag–1 lead/Real ULC	47.337*	1981:2	1.047*	16.009**	10.189
3 lags–3 leads/Output gap	30.769**	1986:3	0.680	13.299	8.061
3 lags–3 leads/Real ULC	13.206	1981:2	0.744	10.042	14.025
Italy					
1 lag–1 lead/Output gap	37.165**	1980:1	0.859	19.927**	8.541
1 lag–1 lead/Real ULC	62.767*	1982:3	0.777	19.778*	9.031
3 lags–3 leads/Output gap	2.811	1983:3	0.940**	18.819**	12.900
3 lags–3 leads/Real ULC	13.363	1986:4	0.899**	16.783**	11.217
The UK					
1 lag–1 lead/Output gap	11.027	1978:3	1.122*	12.688	9.292
1 lag–1 lead/Real ULC	9.325	1979:3	1.017**	11.098	9.584
3 lags–3 leads/Output gap	29.869**	1978:3	1.396*	6.813	23.605**
3 lags–3 leads/Real ULC	26.794**	1979:4	1.010**	5.404	11.689

This table reports specification test statistics for hybrid models. Panel A is devoted to the GMM-based Wald test statistic for the null hypothesis of parameter stability. The breaking date is reported rightward. The test statistic and the computation of critical values using Monte Carlo simulations are described in Appendix B. Panel B is devoted to ML-based specification tests: the Kolmogorov–Smirnov test (KS) for normality; the (corrected for heteroskedasticity) Ljung–Box statistic (QW(K)) of the null hypothesis that the first K serial correlations of residuals are jointly zero; the LM statistic ($R(K)$) of the null that the first K serial correlations of squared residuals are jointly zero. Critical values for ML-based test statistics are obtained from Monte Carlo simulations, as described in the text.

* Indicates that the statistics is significant at the 1% level.

** Indicates that the statistics is significant at the 5% level.

Table 3 presents the Sup-W_T statistic and the date for which the largest statistic is obtained.[14] If we first consider the model with a single lag and lead, our results indicate that the hybrid Phillips curve is unstable in Italy with output gap as the forcing variable, and in the euro area, France, and Italy with real ULC. The 'sup' of Wald statistics is attained around 1981 in France and Italy, whereas the break is found to occur in 1986 in the euro area. Turning to the specification with three lags and leads, stability is rejected in France and in the UK for the output gap model and in the UK only for the real ULC model.

This evidence suggests that the specification with one lag and lead displays some undesirable properties in euro-area countries. But on the whole, structural stability does not seem to be a major problem for the hybrid curve. Moreover, in spite of its loose theoretical grounds, the model with three lags and leads exhibits some robustness to the Lucas critique.

5.2. Tests based on ML residuals

The difficulty in comparing the various specifications under study is that they are not nested. Since they are based on the same number of estimated parameters, comparing the log-likelihoods is equivalent to using information criteria, however no formal test is available. We thus use two approaches: first, we compare log-likelihoods and second we investigate the properties of residuals, that should be white noise if the theoretical model is consistent with the data.

Inspection of log-likelihoods in Table 2 reveals that, in most countries, the best fit of the data is obtained for the output gap model with three lags and leads. The only exception is Italy, where the real ULC with one lag and lead obtains the better fit. It should be noticed also that in the US, the difference with the real ULC model with one lag and lead is rather small, suggesting that both models may correctly adjust to the data.

Table 3 also reports three specification tests based on ML residuals: the Kolmogorov–Smirnov test for normality; the (corrected for heteroskedasticity) Ljung–Box test for the null hypothesis of no serial correlation; and the LM test of the null hypothesis of homoskedasticity. The last two tests are performed with eight lags of (squared) residuals. As for GMM-based specification tests, we computed the critical values of these tests using Monte Carlo simulations.[15] In most cases, they were found to be rather close to the asymptotic ones.

Table 3 reveals that, while non-normality is not a problem on US data, residuals are found to be non-normal for all models in the euro area and the UK. In Germany and

[14] We also estimated and evaluated the finite-sample distribution of two other Wald statistics, the 'average' and 'exponential' statistics proposed by Andrews and Ploberger (1994). Since we found essentially no difference in the conclusion of the three tests, only the sup statistic, which provides an indication of the break point, is reported. Results for the other tests are available upon request.

[15] Critical values for the normality test were obtained with error terms drawn from a $N(0,\hat{\Sigma})$ distribution, where $\hat{\Sigma}$ is the estimated covariance matrix of sample residuals. For serial correlation and heteroskedasticity tests, since the finite-sample distribution of the statistics may be sensitive to the non-normality of innovation, we simulated using a bootstrap procedure, in which error terms v_t are drawn uniformly from the empirical distribution of residuals. Thus, critical values are corrected for both finite-sample bias and non-normality of the error term.

France, three lags and leads appears to be necessary to obtain normal residuals. In contrast, in Italy, the model with three lags and leads is unable to yield normality. Due to the presence of non-normality, we adjusted, for the subsequent tests, the critical value to the possibility of non-normal innovations. We were unable to detect serial correlation of residuals in the US, the euro area, and the UK. In Germany and France, the model with one lag and lead induces auto-correlated residuals, while in Italy residuals are correlated for all models, suggesting mis-specification of all Phillips curves. Finally, heteroskedasticity is detected only for the US and the UK for the model with three lags and leads.

5.3. Who is the winner?

As for the US, two models are likely to be the winners in view of parameter estimates and log-likelihood: the real ULC specification with one lag and lead, and the output gap specification with three lags and leads. Since residuals of the latter model are strongly heteroskedastic, we have a slight preference for the former model. This specification is very close to that estimated by GG, but the backward-looking and forward-looking components of inflation are here found to have equal weights. Interestingly, models proposed by GG and Fuhrer (1997) provide a very similar fit on US data.

In the euro area, Germany, and France, specification tests are not able to reject the output gap specification with three lags and leads. In all cases, residuals are found to be homoskedastic, and non-auto-correlated. Since this model has the largest log-likelihood and a large effect of the output gap, this is our preferred specification. These results contrast rather sharply with those reported for the euro area by GGL and for Germany and France by Benigno and López-Salido (2002), who found using GMM very large forward-looking components.

In the UK, we notice that the model with three lags and leads offers the largest log-likelihood, but its parameter estimates appear to be unstable over time. We therefore have a preference for the real ULC model with one lag and lead.

Finally, for Italy, we are unable to select a winner. The best fit is attained for the real ULC model with one lag and lead, but it is found to provide strongly unstable parameter estimates, so that it would not be robust to the Lucas critique. In addition, all residual series are serially correlated.

Overall, our empirical investigation suggests that the degree of inflation stickiness may be larger in continental Europe than in the US and the UK. Additional dynamics appears to be necessary to explain some characteristics of inflation dynamics in continental Europe.

6. Conclusion

In this paper, we estimate several empirical specifications of the hybrid Phillips curve for four European countries, the euro area, and the US. Our starting point is the conflicting results obtained on US data by Fuhrer (1997) and GG. Whereas the former found the forward-looking component to be empirically unimportant, the latter obtained inflation to be essentially a forward-looking phenomenon.

Our main findings are the following. First, the use of the Newey–West procedure for computing the weighting matrix in the GMM approach may imply an over-estimation of the degree of forward-lookingness. In most cases, using the optimal West (1997) procedure leads to significantly lower estimates of the forward-looking parameter that appear to be much more in line with their ML counterparts.

Second, the choice of the empirical forcing variable is not the major determinant of the estimated degree of forward-lookingness in inflation. In particular, regardless of the chosen specification, the backward-looking component in inflation is significant and quantitatively important. Using the GG specification, the forward-looking component lies in the range 0.5–0.6 for all countries. This estimate is lower than the weights reported by GG and GGL for the US and the euro area. Using the output gap specification, point estimates of the forward-looking component lie in the range 0.2–0.5.

Third, introducing additional lags and leads provides in most cases a better fit of the data and a significant decrease in the degree of forward-lookingness. Thus, two specifications turn out to be alternative, plausible representations of inflation dynamics with economically meaningful interpretation of parameters. Interestingly, these two specifications are those put forward by Fuhrer (1997) and GG, respectively: The first one relates inflation to output gap with three lags and leads of inflation, while the second one relates inflation to real ULC with a single lag and lead. In addition, we find that, in all countries, the first specification is characterized by a rather low weight of the forward-looking component, while the second specification is characterized by a large weight of the forward-looking component. Specification tests and residual check suggest that the (arguably better micro-founded) GG model has a slight edge for the US and the UK, while the Fuhrer specification dominates in continental Europe. Our results also suggest that the simple hybrid Phillips curve is not an appropriate data summary for Italy.

This empirical analysis suggests several topics for future investigation. One issue is to explain why two specifications featuring different forcing variables and different dynamic specifications of inflation yield a similar empirical fit, together with a contrasting assessment of the weight of the forward-looking component in inflation. One route is to study the estimators in a hybrid model under mis-specification (see Jondeau and Le Bihan, 2003). Yet, another issue is to rationalize the empirical evidence concerning the euro area and the individual countries of the area. In many cases, the backward-looking component appears to be too small in the euro area, as compared to the weight obtained in individual countries. A first avenue to address this issue would be to analyze the possible consequences of an aggregation bias. Another option would be to use pooled estimation of the NKPC in European countries in order to test for heterogeneity.[16]

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[16] Turner and Seghezza (1999) followed such an approach in the context of a backward-looking Phillips curve.

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Appendix A. GMM estimators

Let Eq. (3) or (4) be expressed in standard regression notation as

$$y = X\theta + \varepsilon$$

with y a $(T\times 1)$ vector and X a $(T\times n)$ matrix. $X_t=(x_{1t},\cdots,x_{nt})'$ is a vector of observations, ϵ denotes the error term, and θ is the $(n\times 1)$ vector of unknown parameters. Note that X_t may include actual future variables such as π_{t+1} in the case of Eq. (3). Let $Z=(Z_0,\cdots,Z_{T-1})'$ be a $(T\times q)$ matrix of instruments, with $q>n$. The q instruments are assumed to be predetermined, in the sense that they are orthogonal to the current error term. For simplicity, instruments are assumed to be in the information set available at date $t-1$, so that $E(\epsilon_t Z_{it-1})=0$, $\forall t$ and $i=1,\ldots,q$. This can be written as $Eg_t(\theta)=0$, where $g_t(\theta)=(y_t-Xt'\theta)\cdot Z_{t-1}=\epsilon_t\cdot Z_{t-1}$.

The GMM estimator, denoted θ_{GMM}, is the value of θ that minimizes the scalar

$$Q_T(\theta) = \bar{g}_T(\theta)'\left(S_T\left(\hat{\theta}_T^1\right)\right)^{-1}\bar{g}_T(\theta) \tag{A1}$$

where the $(q\times 1)$ vector $\bar{g}_T(\theta)=1/T\sum_{t=1}^{T}g_t(\theta)$ denotes the sample mean of $g_t(\theta)$. $S_T(\hat{\theta}_T^1)$ is a consistent estimator of the $(q\times q)$ covariance matrix of $\sqrt{T}\bar{g}_T(\theta)$, obtained using $\hat{\theta}_T^1$, a consistent estimator of θ. The GMM estimator is then provided by:

$$\hat{\theta}_T = \left(X'Z\left(S_T\left(\hat{\theta}_T^1\right)\right)^{-1}Z'X\right)^{-1} \quad X'Z\left(S_T\left(\hat{\theta}_T^1\right)\right)^{-1}Z'y \tag{A2}$$

with asymptotic covariance matrix $\hat{\Omega}=(X'Z(S_T(\hat{\theta}_T^1))^{-1}Z'X)^{-1}$.

The parameter vector is estimated with the two-step two-stage least squares, or "two-step GMM", initially proposed by Hansen (1982). Assuming an initial guess for the covariance matrix, such as $S_T^{(0)}=1/T\ \sum_{t=1}^{T}Z_tZ_t'$, a first estimate of the parameter vector, $\hat{\theta}_T^{(1)}$, is obtained using $S_T^{(0)}$ to weight the moment conditions. Then, the covariance matrix $S_T(\hat{\theta}_T^{(1)})$ is estimated with $\hat{\epsilon}_t=y_t-X_t'\hat{\theta}_T^{(1)}$ using the procedure described below. Last, the two-step GMM estimator, denoted $\hat{\theta}_T^{(2)}$, is obtained by formula (A2).

Estimating the covariance matrix S_T has been widely discussed in the theoretical literature. An asymptotically efficient estimator is obtained by choosing a consistent estimator of $V=E(\bar{g}_T(\theta)\bar{g}_T(\theta)')$, the so-called long-run covariance matrix of $g_t(\theta)$, i.e., the spectral density of $g_t(\theta)$ at frequency zero up to a constant. When the error term is likely to be heteroskedastic and serially correlated, the covariance matrix can be consistently estimated by the estimator proposed by Newey and West (1987):

$$\hat{S}_T\left(\hat{\theta}_T\right) = S_0 + \sum_{l=1}^{L} w(l)(S_l + S_l') \qquad \text{with} \qquad S_l = \frac{1}{T}\sum_{t=l+1}^{T} \hat{\varepsilon}_t\hat{\varepsilon}_{t-l}(Z_{t-1}Z'_{t-1-l})$$

where $\hat{\epsilon}_t = y_t - X_t'\theta_T$ and $w(l)=1-(l/L+1)$ denotes the Bartlett kernel. The bandwidth parameter L can be chosen either in a data-dependent or non-data-dependent fashion, but should be increasing with T at a sufficient rate. The estimator with fixed bandwidth is likely to provide inconsistent estimators, since weights on some non-zero auto-covariances in S_T do not approach one asymptotically. Here, we use the Newey–West estimator with bandwidth parameter L=8. (We computed the optimal bandwidth as suggested by Den Haan and Levin, 1997, and found that it ranged between 4 and 7.) Parameter estimates obtained with the Newey–West procedure are reported in Table A. Though it has been widely used in the empirical literature for its simplicity, it is not optimal in some applications, where the correlation structure of moment conditions is known a priori (including our set-up where the error term is presumed to follow an MA(1) or MA(3) process). In cases when the maximum order of non-zero auto-covariance can be inferred from the structure of the model, West (1997) has proposed to incorporate this information by filtering out the MA component in a preliminary step, while guaranteeing the covariance matrix to be definite positive. Assuming that the error term ϵ_t is driven by an MA(q) process, so that

$$\varepsilon_t = u_t + \gamma_1 u_{t-1} + \ldots + \gamma_q u_{t-q},$$

the correction proposed by West (1997) consists in estimating the process $\{u_t\}$ using a consistent non-linear least-square estimation method and then to compute the weighting matrix as

$$\hat{S}_T = \frac{1}{T-q}\sum_{t=1}^{q} \hat{d}_{t+q}\hat{d}'_{t+q}$$

where $\hat{d}_{t+q}=(Z_t+Z_{t-1}\gamma_1+\ldots+Z_{t-q}\hat{\gamma}_q)\ \hat{u}_t$. $\hat{S}_T$ is, by construction, positive semi-definite and converges to the true value of the weighting matrix at a higher rate than other widely used estimators (such as those proposed by Newey and West, 1987; Andrews and Monahan, 1992, or Newey and West, 1994).

Table A
GMM estimation of the hybrid model using the Newey and West (1987) procedure

	Panel A: hybrid model with one lag and lead				Panel B: hybrid model with three lags and lead			
	Output gap		Real ULC		Output gap		Real ULC	
	Parameter	S.E.	Parameter	S.E.	Parameter	S.E.	Parameter	S.E.
The US								
ω_f	0.626*	0.067	0.736*	0.053	0.462*	0.078	0.706*	0.046
ω_b	0.369*	0.067	0.259*	0.053	0.533*	0.078	0.289*	0.046
λ	−0.025	0.029	0.030	0.037	0.052	0.051	0.096	0.058
J-stat	8.806	0.551	8.399	0.590	7.573	0.670	8.517	0.578
Euro area								
ω_f	0.764*	0.053	0.734*	0.049	0.739*	0.145	0.709*	0.091
ω_b	0.231*	0.053	0.261*	0.049	0.256	0.145	0.286*	0.091

Appendix A (*continued*)

	Panel A: hybrid model with one lag and lead				Panel B: hybrid model with three lags and lead			
	Output gap		Real ULC		Output gap		Real ULC	
	Parameter	S.E.	Parameter	S.E.	Parameter	S.E.	Parameter	S.E.
Euro area								
λ	0.135**	0.067	−0.001	0.009	0.296**	0.122	0.005	0.014
J-stat	8.231	0.606	9.839	0.455	8.480	0.582	10.304	0.414
Germany								
ω_f	0.946*	0.086	0.848*	0.076	0.425*	0.105	0.350*	0.107
ω_b	0.049	0.086	0.147	0.076	0.570*	0.105	0.645*	0.107
λ	0.077	0.052	0.005	0.016	0.170*	0.053	−0.029	0.021
J-stat	8.487	0.581	8.407	0.589	8.244	0.605	8.154	0.614
France								
ω_f	0.630*	0.056	0.641*	0.052	0.256*	0.071	0.399*	0.080
ω_b	0.365*	0.056	0.354*	0.052	0.739*	0.071	0.596*	0.080
λ	−0.068	0.093	0.019	0.017	0.176	0.200	−0.007	0.029
J-stat	7.758	0.652	7.965	0.632	8.398	0.590	7.342	0.693
Italy								
ω_f	0.505*	0.032	0.477*	0.030	0.589*	0.063	0.518*	0.044
ω_b	0.490*	0.032	0.518*	0.030	0.406*	0.063	0.477*	0.044
λ	0.033	0.079	0.000	0.008	0.509*	0.096	−0.014	0.017
J-stat	9.864	0.453	10.247	0.419	8.351	0.595	9.788	0.459
The UK								
ω_f	0.826*	0.069	0.901*	0.056	0.488*	0.114	0.626*	0.049
ω_b	0.169**	0.069	0.094	0.056	0.507*	0.114	0.369*	0.049
λ	−0.115	0.125	0.035	0.025	0.203	0.190	0.062**	0.030
J-stat	4.964	0.894	5.441	0.860	5.296	0.871	8.310	0.599

This table reports GMM estimates of the hybrid model using the Newey and West (1987) procedure. The bandwidth is chosen to be L=8 lags. Panel A corresponds to the specification with one lag and lead (Eq. (3)) and Panel B corresponds to the specification with three lags and leads (Eq. (4)). Column ‘S.E.’ reports the standard error of parameter estimates and the p-value of the Hansen’s J statistics.

* Indicates that the parameter or the J statistic is significant at the 1% level.

** Indicates that the parameter or the J statistic is significant at the 5% level.

Appendix B. Stability tests

This section briefly describes the Wald test for parameter stability with unknown break-point, developed by Andrews (1993).[17] The break is assumed to occur in the subsample $[\pi_0 T, (1-\pi_0)T]$, where π_0 denotes a fraction of the sample and T the sample size. Since our sample is fairly short, we choose a subsample covering 40 percent of the initial sample, so that π_0=0.3. Hence, for each date of this subsample (or for each fraction π, for

[17] As mentionned above, we also considered the “average” and “exponential” Wald statistics proposed by Andrews and Ploberger (1994). We do not report results of these tests, however, because they are very close to those obtained with the test considered in the paper.

simplicity), we estimate the hybrid Phillips curve for the period before and after the break sequentially. Then, the 'sup Wald' test statistic is defined as (Andrews, 1993):

$$Sup - W_T = \sup_{\pi \in [\pi_0, (1-\pi_0)]} W_T(\pi)$$

with

$$W_T(\pi) = T\left(\hat{\theta}_1(\pi) - \hat{\theta}_2(\pi)\right)' \left(\frac{\hat{V}_1(\pi)}{\pi} + \frac{\hat{V}_2(\pi)}{1-\pi}\right)^{-1} \left(\hat{\theta}_1(\pi) - \hat{\theta}_2(\pi)\right)$$

where $\hat{\theta}_1(\pi)$ and $\hat{\theta}_2(\pi)$ are the vectors of parameter estimates obtained over the first and second subsamples, respectively. $\hat{V}_i(\pi)$ denotes the covariance matrix of parameter estimates for each subperiod (see Andrews, 1993, for additional technical details).

The asymptotic distribution of the sup statistic is nonstandard, because the break-point parameter, π_0, appears under the alternative hypothesis only. Critical values of the test, that depend on the break-point parameter and on the number of shifting parameters, are reported in Andrews (1993) and Andrews and Ploberger (1994). As shown by Burnside and Eichenbaum (1996) and Diebold and Chen (1996), however, the finite-sample size of the Wald test exceeds its asymptotic size, so that the asymptotic distribution leads to reject the null hypothesis too often. Consequently, we computed critical values by Monte Carlo simulations for each hybrid model. We simulated 1000 samples of size T for each specification. For each sample, we computed the three Wald statistics for the model estimated by GMM. We thus obtained the empirical distribution for the Wald statistics under the null hypothesis of stability. Last, we defined the α percent critical value as the value of the statistic that is exceeded by α percent of the 1,000 samples.

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