The New Keynesian Phillips curve: an empirical assessment[1]

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Abstract

The recent works of Gali and Gertler (1999) and Gali, Gertler, and Lopez-Salido (2001a) provide evidence supporting the New Keynesian Phillips curve (NKPC) for the United States and the euro area. This model posits the dynamics of inflation as being forward looking and related to real marginal costs. In this paper we examine the empirical relevance of their results for the United States. Our approach addresses several important econometric issues with the standard approaches typically used for estimation and inference in NKPC models. Using the continously-updated GMM estimator proposed by Hansen, Heaton and Yaron (1996) and the 3-step GMM estimator developed by Bonnal and Renault (2003), the empirical evidence of the New Keynesian Phillips curve is mixed. Specifically, results are sensitive to the instruments sets, normalisation, estimators, the sample period and revisions of data.

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1. Introduction

The short-run dynamics of inflation and its cyclical interaction with real aggregates is an important question both in theory and in practice, especially for central banks in the conduct of monetary policy. The recent experience of high levels of economic activity coupled with low inflation observed in several countries casts doubt on the traditional Phillips curve as a model of inflation dynamics.

A recent class of dynamic stochastic general equilibrium models integrates Keynesian features, such as imperfect competition and nominal rigidities, resulting in a new view on the nature of inflation dynamics. These models are grounded in an optimizing framework where imperfectly competitive firms are constrained by costly price adjustments. Within this framework, the process of inflation is described by the so-called New Keynesian Phillips Curve (NKPC) which has two distinguishing features. First, the inflation process has a forward-looking component and second, it is related to real marginal costs. These features are a consequence of the fact that in this framework firms set prices in anticipation of future demand and factor costs. Compared to traditional reduced-form Phillips curves, which are subject to the Lucas critique, the NKPC is a structural model with parameters that are unlikely to vary as the policy regime changes. This aspect is particularly important and has been outlined in a number of papers: parameter instability in reduced-form models is a likely possibility. Furthermore, the New Keynesian Phillips Curve specification has dramatic implications for the conduct of monetary policy in that a fully credible central bank can bring about disinflation at no recessionary cost if inflation is a purely forward-looking phenomenon. A crucial issue is therefore whether the New Keynesian Phillips Curve is empirically relevant.

The recent works of Gali and Gertler (1999) and Gali, Gertler, and Lopez-Salido (2001a,henceforth GGLS) provide evidence supporting the NKPC for the United States and the euro area. These authors estimate hybrid versions of the NKPC, where lags of inflation are also incorporated, and conclude that the forward-looking component is more important and, furthermore, that real marginal costs are statistically significant. In these studies, parameter estimates are obtained by the Generalized Method of Moments (GMM) and statistical significance is assessed based on Newey-West estimates of the covariance matrix.

Several econometric problems have been discussed in the literature on the empirical relevance of their results.[2] On the one hand, Rudd and Whelan (2002), Lindé (2003) have suggested that their results may be the product of specification bias associated with GMM estimation procedure. Therefore, Rudd and Whelan (2002) showed that GMM produces biased estimates of the true parameters when instruments are used that belongs to the true inflation equation.[3] Lindé (2003) concluded that the mixed evidence for the NKPC can be explained by the extensive used of limited information estimation methods. In addition, it appears difficult to accurately

[2]The common criticisms of the NKPC include: (i) whether it captures actual inflation persistence (Fuhrer, 1997; Fuhrer and Moore, 1995), (ii) the plausibility of the implied dynamics (Ball, 1999; Mankiw, 2001) and (iii) the estimation methodology. We focus here on the third issue.

[3]Rudd and Whelan (2002) also argue that the hybrid model suffers from low power against the backward-looking model.

distinguish between a purely forward looking specification and a backward looking model in small samples and that the fully information maximum likelihood (FIML) approach leads to emphasise the backward component rather than the forward looking component of the hybrid NKPC. However, GGLS (2003) have shown that these claims are incorrect in the sense that their results are robust to a variety of estimation procedures, including GMM estimation of the closed form and nonlinear instrument variables. Specifically, the conclusions regarding the importance of the forward looking behavior seems to be robust. On the other hand, Mavroeidis (2002) discussed the issues of identification in the case of the single-equation formulations like the NKPC. Indeed, the properties of the non-modelled variables are important for the identification process. Overall, the hybrid NKPC may suffer from under-identification or misspecification. In this respect, identification is achieved in empirical applications by confining explanatory variables to the set of instruments, with misspecification as a result. Nason and Smith (2003) argued that GMM estimates typically lead to parameters that are near-identified. Hence, higher order dynamics in marginal cost or the output gap are necessary for identification and testing. In addition, Nason and Smith (2003) showed that the coefficient on lagged inflation in the hybrid NKPC can not be identified if inflation Granger causes marginal cost or the output gap. In this respect, they also conclude that FIML makes identification easier. Ma (2002) also discussed the question of identification and applied the test of weak instruments developed by Stock and Wright (2000). His results showed that the method of GG (1999) is inadequate due to observational equivalence in the pure forward-looking Phillips curve and weak identification in the hybrid NKPC. It is, however, to be noted that the identification problems do not mean that the NKPC is a poor approximation to inflation dynamics but rather that its interpretation is problematic. In addition, the redundancy of instruments and their number is a crucial issue for estimating the NKPC. Guay, Luger and Zhu (2002) demonstrated the sensitivity of standard GMM estimates to the choice of instruments. In effect, using the continuously-updated GMM estimator (CUE) developed by Hansen, Heaton and Yaron, empirical evidence for the NKPC is weak in all their specifications in Canada. Moreover, the test of instruments validity is rejected when considering the methodology proposed by Hall (2000). Finally, another important debate is the discussion of ML versus GMM estimates of the hybrid NKPC. While the two approaches are asymptotically equivalent, the finite sample performances may significantly differ. For example, Fuhrer (1997) rejects the importance of the forward-looking component in US inflation using the ML approach. In a related paper, Fuhrer and Rudebusch (2002) obtained a similar result for a hybrid IS curve. At the same time, Jondeau and LeBihan (2003), Kurman (2003) find evidence for the NKPC by using the implied cross-sections restrictions. Overall, the choice between the two approaches is an open debate.

This paper reexamines the empirical relevance of the New Keynesian Phillips Curve for the United States. In particular, several important econometric issues are addressed on the standard approaches typically used for estimation and inference in NKPC models. These are related to the potential bias of GMM estimates in the presence of many instruments, the low power of specification tests based on overidentifying restrictions, and the estimation of variance-covariance matrix. In order to mitigate these problems, we estimate different various specifications of the

NKPC by using the CUE and the 3-step GMM (3S-GMM) estimators proposed by Bonnal and Renault (2001, 2003).

Our results show that the empirical evidence of the real marginal cost in the NKPC is rather mixed and that the backward-looking component of inflation needs to be accounted for. In particular, results are sensitive to the instruments sets, normalisation, estimators, the sample period and revisions of data.

The rest of this paper is organized as follows. In section 2 we present the theoretical framework that yields the NKPC. In section 3, we describe the econometric issues associated with standard GMM estimation, discuss particular issues with estimation of the closed-form version of the NKPC, and present our estimation strategy based on the biased-corrected continuous updating estimator (CUE)and the 3 steps GMM estimator developed by Bonnal and Renault(2001, 2003). In particular, using the same data set as Gali and Gertler (1999), we demonstrate the sensitivity of standard GMM estimates to the choice of instruments. In section 4, we present the estimation results. A discussion of the main findings follows in section 5. Section 6 concludes.

2. The New Phillips Curves

2.1 Specifications

The New Keynesian Phillips Curve (NKPC), as advocated by Gali and Gertler (1999), is based on a model of price setting by monopolistically competitive firms. Adopting a price setting rule as in Calvo (1983) simplifies the aggregation problem. This price adjustment rule is in the spirit of Taylor's (1980) staggered contracts model. Following Calvo, each firm, in any given period, may reset its price with a fixed probability $1-\theta$ and, with probability θ, its price will be kept unchanged or proportional to trend inflation Ω.[4] These adjustment probabilities are independent of the firm's price history such that the proportion of firms that may adjust their price in each period is randomly selected. The average time over which a price is fixed is then given by $1/(1-\theta)$.[5] The firms face a common subjective discount factor, β.

Let mc_t be (log) real marginal cost, the NKPC (Woodford, 2003) is then given by:

$$\pi_t = \frac{(1-\theta)(1-\theta\beta)}{\theta-\theta\eta\mu} mc_t + \beta E_t \pi_{t+1}. \tag{1}$$

where

$$\frac{\alpha}{(1-\alpha)} = \eta.$$

The derivation in Yun (1996) and Goodfriend and King (1997) correspond to the particular case where the elasticity of marginal cost with respect to output (η) is equal to zero.[6]

[4]This adjustment is necessary if there is trend inflation in order to preserve monetary neutrality in the aggregate.

[5]Benigno and Lopez-Salido (2002) proposed to use an index of nominal rigidity given by: $\frac{1}{1-\theta}\frac{1}{1-\omega}$.

[6]Indeed, the hypothesis that individual firms can instantaneously adjust their own capital stocks implies that

Gali and Gertler (1999) extend the basic Calvo model to allow a subset of firms to use a backward-looking rule-of-thumb to capture the inertia in inflation. The net result is a hybrid Phillips curve that nests (1). From the three structural parameters, ω, θ and β, the three reduced-form parameters γ_f, γ_b and λ can be defined and the hybrid version of the Phillips developed by Woodford (2003) is given as follows:

$$\pi_t = \lambda \left(\frac{1}{(1-\eta\mu)} \right) mc_t + \gamma_f E_t \pi_{t+1} + \gamma_b \pi_{t-1}, \tag{2}$$

where

$$\begin{aligned}
\lambda &= \left(\frac{(1-\omega)(1-\theta)(1-\theta\beta)}{\theta} \right) \phi^{-1}, \\
\gamma_f &= \beta\theta\phi^{-1}, \\
\gamma_b &= \omega\phi^{-1}, \\
\phi &= \theta + \omega \left[1 - \theta(1-\beta) \right],
\end{aligned}$$

and where ω is the proportion of firms that use a backward-looking rule-of-thumb. The corresponding hybrid New Phillips curve for the aggregate assumption considered by Yun (1996) and Goodfriend and King (1987) is derived in Gali and Gertler (1999) and the one based on the assumption of Sbordone (2001) in Gali, Gertler, and Lopez-Salido (2001). One can easily retrieve these specific forms from the general one given above.

Three principle results emerge from the estimations of Gali and Gertler (1999) and Gali, Gertler and Lopez-Salido (2001): (1) the reduced-form coefficient on real marginal cost is positive and statistically significant; (2) tests rejects the pure forward-looking specification of the NKPC (1) and (3) forward looking behaviour is dominant and the coefficients γ_f and γ_b sum to close neighborhood of unity across a range of estimates.

2.2 Measure of Marginal Cost

Alternative measures of the marginal cost have been considered in empirical investigations of the New Keynesian Phillips curve. We consider here the simplest measure of real marginal cost based on the assumption of Cobb-Douglas technology (see Gali and Gertler 1999). Suppose the following Cobb-Douglas production function:

$$Y_t = K_t^{\alpha} \left(A_t H_t \right)^{(1-\alpha)},$$

where K_t is the capital stock, A_t is labor augmenting technology, and H_t is hours worked. Real marginal cost is then given by $S_t/(1-\alpha)$, where $S_t = W_t H_t / P_t Y_t$ is the labor income share. In

firms act as price takers in the input market. Combined with the assumption of a constant return to scale technology, real marginal cost is thus independent of output.

log-linear deviation from the steady state, we have:

$$mc_t = s_t = w_t + h_t - p_t - y_t.$$

The definition of marginal cost may be a critical issue in the estimation of the NKPC. For instance, the real marginal cost may be measured in different ways, which involve either the output gap or the real unit labour cost. In the first case, a reliable measure of the output gap is necessary while the standard approximation of the real marginal cost by real unit labour cost arises solely under the assumption of a constant return to scale production function (Rotemberg and Woodford, 1999). Under more realistic assumptions, the real unit labour cost needs to be corrected. For instance, Rotemberg and Woodford (1999) discuss possible appropriate corrections for different assumptions about technology. These include corrections to capture a non-constant elasticity of factor substitution between capital and labor and the presence of overhead costs and labor adjustment costs. Gagnon and Kahn (2003) derive the NKPC when firms use alternative productions functions and show that each technology introduces a specific "strategic complementarity parameter" and a modification to the real marginal cost measure. Finally, Eichenbaum and Fisher (2003) modify the real marginal cost by allowing the firms requiring working capital to finance payments to variable factors of production. Overall, these studies argue that these corrections do not affect the qualitative nature of the results discussed below. On the other hand, data may be revised over time and lead to different estimates. These two issues are further discussed later.

3. Estimation Issues

3.1 Standard GMM Approach

The hybrid model in reduced form can be written as

$$\pi_t = \gamma_f \pi_{t+1} + \gamma_b \pi_{t-1} + \lambda mc_t + \varepsilon_{t+1}, \tag{3}$$

where ε_{t+1} is an expectational error term orthogonal to the information set in period t, i.e.,

$$E_t \left[(\pi_t - \gamma_f \pi_{t+1} - \gamma_b \pi_{t-1} - \lambda mc_t) Z_t \right] = 0, \tag{4}$$

where Z_t is a vector of instruments dated t and earlier. The orthogonality condition in (4) then forms the basis for estimating the model by the generalized method of moments (GMM). Gali and Gertler (1999) use this technique with four lags each of inflation, the labour income share, the output gap,[7] the long-short interest rate spread, wage inflation, and commodity price inflation. Finally they use a 12-lag Newey-West estimate of the covariance matrix to obtain

[7] Typically, the output gap is obtained by application of the Hodrick-Prescott filter or by fitting a quadratic trend to the entire sample. Using filtered output gap measures as instruments could be invalid since they violate the basic GMM orthogonality conditions.

standard errors for the model parameters. Based on these choices, they conclude that: (i) the model is statistically significant, and (ii) γ_f is statistically larger than γ_b. They interpret these results as support for the New Keynesian Phillips Curve in the case of the United States. In contrast, GGLS (2001) choose a relatively smaller number of lags for instruments other than inflation in order to minimise the potential estimation bias arisen in small samples due to the number of overidentifying restrictions . In this respect, their instrument set reduce to four lags of inflation, two lags each of the output gap, wage inflation and the labour income share.

Given the relatively large number of moment conditions,[8] the estimates reported by Gali and Gertler (1999) are potentially biased since it is well-known that the estimation bias increases with the number of moment conditions in the standard GMM approach (Newey and Smith 2001). However, choosing a relative small number of instruments does not also prevent from estimation bias.[9] The two following issues are still present: the weak instruments and the instruments redundancy. In order to illustrate the finite-sample bias, we consider the following simple Monte Carlo experiment (Bonnal and Guay, 2003) in which the number of instruments is increased.[10] Suppose the data are generated by the AR process

$$y_t = \rho y_{t-1} + \varepsilon_t,$$

where $\rho = .1$ and $\varepsilon_t \sim i.i.d.\ N(0,1)$. Consistent estimates of ρ are obtained by GMM. The moment conditions are based on

$$E(\varepsilon_t Z_t) = 0,$$

where $Z_t = (y_{t-1}, y_{t-2}, \ldots, y_{t-k})'$ is a vector of valid instruments (since it excludes y_t). The sample size is fixed at 100 and we study the effect of an increase in the number of moment conditions. The Monte Carlo experiment is based on 10,000 replications and the automatic lag selection procedure of Newey and West (1994) is used to obtained an estimate of the weighting matrix. Finally, we compute the point estimate of the autoregressive parameter using the CUE and the 3S-GMM estimator.[11] Table 1 reports the bias of the different estimators as a function of the number of moment conditions $k-1$. The bias of the GMM estimator clearly increases with the number of moments (lags of y_t) included in the vector of instruments. With two instruments, the estimator is nearly unbiased. With ten instruments, the bias appears to be of the same order as the true parameter value. This simple Monte Carlo experiment concurs with the theoretical results of Newey and Smith (2001). In contrast, results are different for the CUE and 3S-GMM estimators. First, both estimators performs better in terms of bias or root mean square error (RMSE) than the GMM estimator. Second, the bias appears to increase less than linearly with

[8] In fact, 24 moment conditions to estimate 3 reduced-form parameters.

[9] It is to be noted that a number of studies have also estimated New Keynesian Phillips curves in countries other than the US applying equally arbitrary choices for the instrument set and the number of lags used in the construction of the Newey-West standard errors. See for example, Batini, Jackson and Nickell (2000), Balakrishman and Lopez-Salido (2002). A few notable exceptions are Jondeau and Le Bihan (2001, 2003) and Linde (2001) who consider full information maximum likelihood approaches.

[10] We do not examine whether or not the instruments are redundant and/ or weak.

[11] Both estimators are detailled in section 3.3.

Table 1. Bias of GMM, CUE and 3S-GMM estimators

$k-1$	$\hat{\rho}_{GMM}$	bias	rmse	$\hat{\rho}_{CUE}$	bias	rmse	$\hat{\rho}_{3S-GMM}$	bias	rmse
0	.0602	-.0398	.2263	.0697	-.0303	.2027	.0609	-.0391	.2269
1	.0953	-.0047	1745	.0726	-.0284	.1745	.9936	-.0064	.1753
2	.1109	.0109	.1654	.0784	-.0216	.1647	.1017	.0017	.1639
3	.1223	.0223	.1612	.0734	-.0266	.1622	.1110	.0110	1619
4	.1318	.0318	.1615	.0685	-.0315	.1648	.1175	.0175	.1606
5	.1441	.0441	.1646	.0655	-.0345	.1610	.1272	.0272	.1608
6	.1516	.0516	.1684	.0614	-.0386	.1725	.1327	.0327	.1639
7	.1607	.0607	.1713	.0586	-.0414	.1752	.1384	.0384	.1675
8	.1687	.0687	.1787	.0542	-.0458	.1823	.1473	.0473	.1726
9	.1761	.0761	.1813	.0488	-.0512	.1926	.1532	.0532	.1758
10	.1896	.0896	.1857	.0462	-.0538	.2004	.1583	.0583	.1775

the number of moment conditions.

To further appreciate the relative importance of the number of instruments within a standard GMM context, let $\gamma = \gamma_f$ and consider the reduced form under the constraint $\gamma_f + \gamma_b = 1$:

$$\pi_t(\gamma) = \lambda(\gamma) mc_t + \varepsilon_{t+1}, \tag{5}$$

where $\pi_t(\gamma) = \pi_t - \pi_{t-1} - \gamma(\pi_{t+1} - \pi_{t-1})$. For a fixed value of $\gamma \in [0, 1]$, the parameter $\lambda(\gamma)$ can be consistently estimated by instrumental variables using lagged values of real marginal cost dated t and earlier.

Using the same data set[12] as Gali and Gertler (1999), Figure 1 shows the effects of different instruments and those of various lags in constructing Newey-West estimates of the standard deviation. For a given instrument, it appears that there is little effect whether 8, 12, or 16 lags are used for the Newey-West standard errors. On the other hand, it is clear that the choice of instrument is crucial, especially at the upper end of the interval $[0, 1]$ where the forward-looking component in the new Phillips curve is more important. When the sixth lag of marginal cost is used as instrument, marginal costs tend to appear marginally significant for some values of the forward-looking component parameter near 0.7, while it is clearly insignificant when the fourth lag is used as instrument. Note also the increased precision when the fourth lag is used as instrument as reflected by the relatively tighter confidence bands. The difference in the width of the confidence bands is expected since the more recent lags are more strongly correlated with contemporaneous marginal cost and hence are better instruments.

Overall, these results suggest that the results reported by Gali and Gertler (1999) and GGLS (2001) may be sensitive to the number of instruments and hence the significance of marginal

[12] The data is quarterly for the U.S. over the period 1960:1-1997:4. Inflation is the annualized change in the logarithm of the GDP delator and real marginal costs are measured as deviations from the sample mean of the logarithm of labour income share in the non-farm business sector.

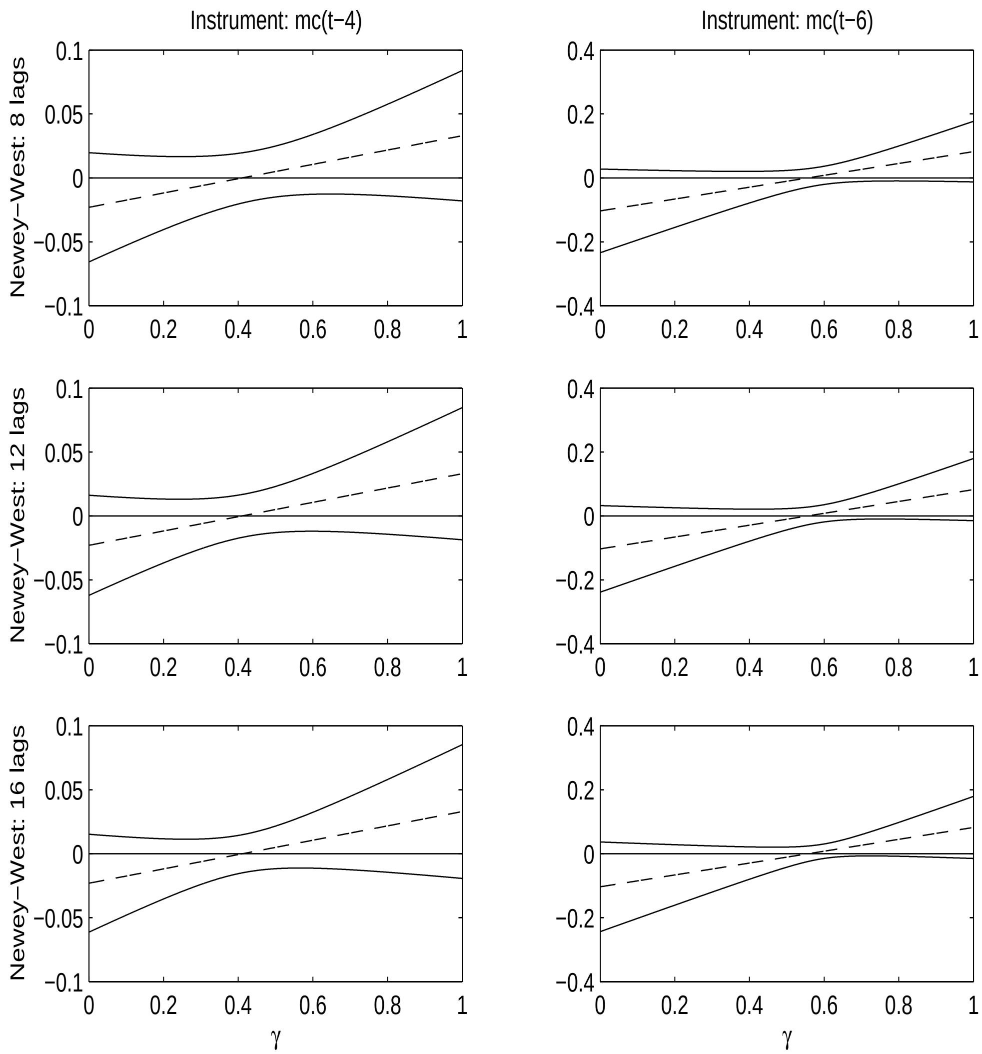

Figure 1. The dotted line in each graph shows the IV estimates of $\lambda(\gamma)$ in the model $\pi_t(\gamma) = \lambda(\gamma)mc_t + \varepsilon_{t+1}$, where the instrument used is either the fourth lag (left panel) or the sixth lag (right panel) of real marginal cost. Newey-West standard errors are used to construct the 95% confidence bands using either 8, 12, or 16 lags.

costs in explaining U.S. inflation must be further analysed.

3.2 Closed Form Estimation

Another way to estimate the structural parameters of the pure forward-looking NKPC curve or the hybrid NKPC is to derive the closed form representation. As shown in Gali and Gertler (1999), the hybrid Phillips curve has the following closed form, conditional on the expected path of real marginal cost:

$$\pi_t = \delta_1 \pi_{t-1} + \frac{\lambda}{\delta_2 \gamma_f} \sum_{k=0}^{\infty} \delta_2^{-k} E_t[mc_{t+k}], \tag{6}$$

where δ_1 and δ_2 are, respectively, the stable and unstable roots of the hybrid Phillips curve given by:

$$\delta_1 = \frac{1 - \sqrt{1 - 4\gamma_b \gamma_f}}{2\gamma_f}, \delta_2 = \frac{1 + \sqrt{1 - 4\gamma_b \gamma_f}}{2\gamma_f}.$$

An alternative to the standard GMM approach is to estimate directly the closed form representation as done in Rudd and Whelan (2003) and Gali, Gertler and Lopez-Salido (2001a, 2001b).[13] Under rational expectations, the closed form defines the following orthogonality conditions:

$$E_t \left[(\pi_t - \delta_1 \pi_{t-1} - \frac{\lambda}{\delta_2 \gamma_f} \sum_{k=0}^{\infty} \delta_2^{-k} mc_{t+k}) Z_t \right] = 0, \tag{7}$$

where Z_t is a vector of instrumental variables.

With this approach it is necessary to use a truncated sum to approximate the infinite discounted sum of real marginal costs. Based on an assumed value for the discount factor β, Rudd and Whelan (2001) use 12 leads of real marginal cost to construct the discounted stream of real marginal costs. Gali, Gertler and Lopez-Salido (2001), on the other hand, use 16 leads and differ by estimating the discount factor instead of fixing its value arbitrarily. In both cases however, there is loss of degrees of freedom due to the need to truncate the sum which can be important given the relatively small sample size (typically about 30 years of quarterly data). Furthermore, given the way the measure of the discounted stream of future marginal cost is constructed, there is a generated regressor problem. To see this, consider the limiting case of pure forward looking behavior. In that case the closed form, under rational expectations, becomes

$$\pi_t = \lambda \sum_{k=0}^{\infty} \beta^k mc_{t+k} + u_{t+1} \tag{8}$$

[13] However, as is noted by Gali, Gertler and Lopez-Salido (2003), the closed form model of Rudd and Whelan (2001, 3003) is inconsistent with the hybrid model in that their final form is not derived from the original hybrid equation. Therefore, the closed form of the pure forward looking model is appended on lagged inflation as opposed to be directly solved for the hybrid model.

where the new error term u_{t+1} is related to the original expectational error term ε_{t+1} by

$$u_{t+1} = \varepsilon_{t+1} + \gamma_f \pi_{t+1} - \lambda \sum_{k=1}^{\infty} \beta^k mc_{t+k}, \tag{9}$$

and from which the generated regressor problem is apparent. Since u_{t+1} in (9) is serially correlated (into to the indefinite future), it is essential that the efficiency of the GMM estimator and the consistency of the associated standard errors be evaluated. Clearly, this problem is also present in the hybrid Phillips curve. Estimation in the presence of generated regressors leads in general to inefficient estimates that require adjustments to obtain consistent estimates of their standard errors (see Pagan 1984, 1986, Murphy and Topel 1985, and McAller and McKenzie 1991a,b). Gali, Gertler, and Lopez-Salido (2001) recognize this problem, but no attempt is made to evaluate it.

Another problem associated with the closed form is that it involves locally almost unidentified (LAU) parameters such that use of Wald-type confidence intervals is invalid. The problem here is that the ratio $\lambda/(\delta_2\gamma_f)$ has a discontinuity at every point of the parameter space where $\gamma_f = 0$. From Dufour (1997), it is then known that one can find a value of this ratio such that the distribution of the Wald statistic will deviate arbitrarily from any "approximating distribution" (such as the standard normal distribution). This suggests that Wald-type inference on structural parameters that appear in NKPC models in ratio form is, in general, an issue for any of the usual estimation approaches. Other techniques, such as confidence sets based on the inversion of likelihood ratio tests, would yield valid inference on the LAU structural parameters. Note that Wald-type inference remains valid for the "non-LAU" reduced-form parameters.

Given that the econometric issues with the closed form solution are roughly the same as the issues used for estimation and inference in standard NKPC models, the estimates of the closed-form solutions are not reported in this paper.

3.3 Estimation Strategy

Our estimation strategy differs in three important ways compared to other empirical studies of the New Keynesian Phillips curve. First, an automatic lag selection procedure proposed by Newey and West (1994) is adopted to compute estimates of the variance-covariance matrix of the moment conditions. As shown by several studies, the small sample properties of method-of-moments estimators depends crucially on the number of lags used in the computation of this variance-covariance matrix.[14] Second, our estimator of the variance-covariance matrix uses the sample moments in mean deviation in order to increase the power of the overidentifying restrictions test as suggested by Hall (2000).[15] A more powerful specification test is clearly desirable as it addresses the issues raised by Dotsey (2002) who found that the conventional specification test used in Gali and Gertler (1999) lacks power. Third, two alternative estimators

[14] For a discussion, see *Journal of Business and Economic Statistics* (1996), vol. 14.
[15] The mean deviation is used for the GMM and 3S-GMM estimators.

are used for the non-linear specification - the CUE and 3S-GMM estimator. The CUE has the advantage that it does not depend on the normalization of the moment conditions in contrast to the conventional GMM estimator (invariance principle) while the 3S-GMM estimator is not sensitive to initial conditions. Moreover, they perform better in finite samples than the GMM estimator in terms of bias (see section 3.1 and Bonnal and Guay, 2003). In general, the differences between the CUE and the 3S-GMM estimator are expected to be relatively small, at least asymptotically, compared to the difference between them and the two-step GMM estimator.

We begin by first presenting the two alternative estimators to the conventional two-step GMM estimator: the CUE introduced by Hansen, Heaton and Yaron (1996) and the 3S-GMM estimator proposed by Bonnal and Renault (2001, 2003).

The optimal two-step GMM estimator of Hansen (1982) based on the moment conditions

$$E\left[g(z_t,\beta_0)\right]=0 \tag{10}$$

is defined as

$$\hat{\beta}=\arg\min_{\beta\in B}\frac{1}{T}\sum_{t=1}^{T}g(z_t,\beta)'\hat{\Omega}(\tilde{\beta})^{-1}\frac{1}{T}\sum_{t=1}^{T}g(z_t,\beta),$$

where $\tilde{\beta}$ is a first-step estimator usually obtained with the identity matrix as weighting matrix, and where $\hat{\Omega}^{-1}$ is a consistent estimator of the inverse of the variance-covariance matrix of the moments conditions.[16]

The CUE is analogous to GMM except that the objective function is simultaneously minimized over β and $\hat{\Omega}(\beta)$. In other words, the empirical variance-covariance matrix of moment conditions replaces the fixed metrics of the GMM, in which a norm of empirical moments is minimised. This estimator is given by[17]

$$\hat{\beta}=\arg\min_{\beta\in B}\frac{1}{T}\sum_{t=1}^{T}g(z_t,\beta)'\hat{\Omega}(\beta)^{-1}\frac{1}{T}\sum_{t=1}^{T}g(z_t,\beta).$$

This estimator has important advantages compared to the conventional two-step GMM estimator. First, unlike GMM, this estimator does not depend on the normalization of the moment

[16] In other words, a two-step GMM estimator $\widehat{\beta}$ is characterised by first order conditions:

$$\left[\frac{1}{T}\sum_{t=1}^{T}\frac{\partial g}{\partial\beta}(z_t,\widehat{\beta})\right]\left[\frac{1}{T}\sum_{t=1}^{T}g(z_t,\widetilde{\beta})g'(z_t,\widetilde{\beta})\right]\sum_{t=1}^{T}\frac{\partial g}{\partial\beta}(\widehat{\beta})=0$$

where $\widetilde{\beta}$ is a preliminary consistent estimator for β_0.

[17] As is pointed out by Newey and Smith (2003), the CUE can be computed as the solution of:

$$\widehat{\beta}=\arg\min_{\beta\in B}\frac{1}{T}\sum_{t=1}^{T}g(z_t,\beta)'\left[\frac{1}{T}\sum_{t=1}^{T}\left(g(z_t,\beta)-\overline{g}(z_t,\beta)\right)\overline{g}'(z_t,\beta)\right]^{-1}\frac{1}{T}\sum_{t=1}^{T}g(z_t,\beta)$$

where $\overline{g}(z_t,\beta)=\frac{1}{T}\sum_{t=1}^{T}g(z_t,\beta)$.

This is important since Hall (2000) shows that it is preferable to use the mean deviation form of the covariance matrix than the common form in two-step GMM.

conditions. As shown by Gali and Gertler (1999), Gali, Gertler and Lopez-Salido (2001), the results obtained for the New Phillips curve and the hybrid version depend on the normalization adopted for the GMM estimation procedure. Second, Newey and Smith (2001) have shown for i.i.d case that the asymptotic bias of CUE does not increase with the number of moment conditions. Specifically, Newey and Smith (2001) demonstrated that the CUE has the same minimal higher order bias as the empirical likelihood estimator (ELE) if the moments of order three are null.[18] One advantage of the CUE (or Minimum Chi-square) over the ELE is that it is less time-consuming and is not obtained through a saddle-point problem, which grows with the number of moment conditions. In contrast, the dimension of the optimisation problem for the CUE is equal to the number of moment conditions. At the same time, the CUE may be sensitive to initial conditions. Third, Hansen, Heaton, and Yaron (1996) show that in small samples the CUE has smaller bias for IV estimators of asset pricing models with several overidentifying restrictions compared to that of GMM.

On the other hand, the 3S-GMM estimator has the interesting property of being efficient with minimal higher order bias, like the ELE. In contrast to the standard two-step GMM estimator, the 3S-GMM estimator seeks to use all the information cointained in the moments restrictions (10) in order to estimate β_0 . In effect, the 3S-GMM estimator makes implicit use of the overidentifying restrictions to improve the estimatiom of the optimal selection of estimating equations. In contrast, the two-step GMM estimator does not use a technique of variance reduction. Indeed, the poor finite sample performance of GMM estimator can be explained by the fact that only the information used in the just-identified moment conditions are used.[19] As is pointed out by Back and Brown (1993), the remaining moment conditions can be used to improve the estimation of the data distribution by considering the empirical distribution. In other words, both moment conditions and the proximity between the estimated distribution and the empirical distribution are exploited, as in one-step alternatives. In this respect, the 3S-GMM estimator avoids the saddle-point problem and the numerical procedure's initialisation problem while possessing the optimal bias property. In addition, the computational implementation is not burdesone and only requires three quadratic optimisation steps. To describe the estimator, let us first consider the case of i.i.d process. In the first step, a consistent estimator $\widetilde{\beta}$ of β_0 is computed. In a second step, this estimator is used in order to define an efficient two-step GMM estimator $\widehat{\beta}_2$, i.e. $\widehat{\beta}_2$ solves the following equations:[20]

$$\left[\sum_{t=1}^{T} \pi_t\left(\widetilde{\beta}\right) \frac{\partial \overline{g}'}{\partial \beta}(z_t, \widetilde{\beta})\right] \left[\sum_{t=1}^{T} \pi_t\left(\widetilde{\beta}\right) g(z_t, \widetilde{\beta}) g'(z_t, \widetilde{\beta})\right]^{-1} \frac{1}{T} \sum_{t=1}^{T} g(z_t, \widetilde{\beta}) = 0$$

[18] These two estimators can be included in a general class based on the family of Cressie-Read power divergence statistics (Baggerly, 1998). The exponential tilting estimator also belongs to this class. Newey and Smith (2001) use the notation "Generalised Empirical Likelihood" estimators.

[19] It is to be noted that the CUE also uses all information contained in moment conditions since it can be interpreted as the empirical distribution on the set of all the distributions satisfying the moment conditions by using the Chi-square metric.

[20] It is to be noted that the 2S-GMM estimator can be computed by replacing $\pi_t(\widetilde{\beta})$ by $\frac{1}{T}$.

where the implied probabilities[21] are defined as follows:

$$\pi_t\left(\widetilde{\beta}\right) = \frac{1}{T} - \frac{1}{T}\overline{g}_T(\widetilde{\beta})V_T(\widetilde{\beta})^{-1}\left[g(z_t,\widetilde{\beta}) - \overline{g}_T(\widetilde{\beta})\right].$$

It is to be noted that an asymptotically equivalent to efficient GMM estimator, $\widehat{\beta}_2$, possessing the following property is derived:

$$\widehat{\beta}_2 - \beta_0 = (\Gamma'\Delta^{-1}\Gamma)^{-1}\Gamma'\Delta^{-1}\overline{g}_T(\beta_0) + \partial_p(T^{-1})$$

where

$$\begin{aligned}\Gamma &= E\left[\frac{\partial g}{\partial \beta'}(z_t,\beta_0)\right] \\ \Delta &= E\left[gg'(z_t,\beta_0)\right] = Var\left[g(z_t,\beta_0)\right].\end{aligned}$$

In a third step, the optimal inference of the implied probabilities is used to estimate the Jacobian and variance-covariance matrices. Specifically, $\widetilde{\beta}$ is used to solve the following p equations ($\beta \in \Re^p$) in $\widehat{\beta}_3$:

$$\left[\sum_{t=1}^{T}\pi_t\left(\widehat{\beta}_2\right)\frac{\partial \overline{g}}{\partial \beta'}(z_t,\widehat{\beta}_2)\right]'\left[\sum_{t=1}^{T}\pi_t\left(\widehat{\beta}_2\right)g(z_t,\widehat{\beta}_2)g'(z_t,\widehat{\beta}_2)\right]\frac{1}{T}\sum_{t=1}^{T}g(z_t,\widehat{\beta_3}) = 0.$$

The definition of the 3S-GMM estimator extends to the autocorrelated case, where an autocorrelation consistent covariance matrix is used to construct the estimator. In this case, $\widehat{\beta}_2$ solves the following equations:

$$\left[\sum_{t=1}^{T}\pi_t\left(\widetilde{\beta}\right)\frac{\partial \overline{g}'}{\partial \beta}(z_t,\widetilde{\beta})\right]\left[\widehat{\Omega}_t(\widetilde{\beta})\right]^{-1}\frac{1}{T}\sum_{t=1}^{T}g(z_t,\widetilde{\beta}) = 0$$

where

$$\widehat{\Omega}_t(\widetilde{\beta}) = \sum_{t=1}^{T}\pi_t\left(\widetilde{\beta}\right)\left(g(z_t,\widetilde{\beta})g'(z_t,\widetilde{\beta}) + 2\sum_{k=1}^{K}w_{kK}\,g(z_t,\widetilde{\beta})g'(z_{t+k},\widetilde{\beta})\right)$$

and w_{kK} are weights in order to make positive semi-definite the autocorrelation consistent estimator of the covariance matrix, and the implied probabilities are given by:

$$\pi_t\left(\widetilde{\beta}\right) = \frac{1}{T} - \frac{1}{T}\overline{g}_T(\widetilde{\beta})\widetilde{\Omega}_T(\widetilde{\beta})^{-1}\left[g(z_t,\widetilde{\beta}) - \overline{g}_T(\widetilde{\beta})\right].$$

The 3S-GMM has the advantage to give closed-form solutions for implied probabilities due to the use of a Chi-Square metric . At the same time, one potential problem associated with the

[21] See Back and Brown (1993), Bonnal and Renault (2003) for the definition of implied probabilities for the CUE.

implied probabilities is that they might be not positive in finite samples. Bonnal and Renault (2003) show that these probabilities are asymptotically positive and that signed measures can be used in order to guarentee the best fitting of the estimated distribution to the theoretical moments. Specifically, they proposed to estimate the implied probabilities as an optimally weighted average of the standard two-step GMM implied probabilities ($1/T$) and the computed implied probabilities ($\pi_t(\beta)$). This method know as shrinkage allows putting a non-zero weight on the two-step GMM implied probabilities when some of the implied probabilities ($\pi_t(\beta)$) are zero.[22]

4. Results for the United States

In this section, we report the results for the pure forward-looking NKPC and the hybrid NKPC using the original dataset of GG (1999). Specifically, we use several instruments sets including different lags of some variables; inflation, commodity prices, wage inflation, long-short interest rate spread and the output gaps. Different tests of robustness are performed by considering sub-samples estimation, different normalisations and different measures of inflation, marginal cost.

4.1 Baseline Model Estimates

We first present estimates for the reduced form of the New Keynesian Phillips curve (1) given by:

$$\pi_t = \kappa \lambda mc_t + \beta E_t \pi_{t+1},$$

where $\kappa = 1/(1-\eta\mu)$. If one follows Yun (1996) and Goodfriend and King (1997) then $\kappa = 1$, whereas following Sbordone (2001), $\kappa = \frac{-\alpha}{(1-\alpha)}\mu$.

This reduced form specification is first estimated over the sample period 1960:Q1-1997:Q4. Inflation is based on the GDP deflator and mc_t is the real marginal cost in log-deviation from its mean calculated as the labor share of nonfarm business. Several sets of instruments are used to investigate the robustness of the estimation results.[23] These are: [1] four lags of inflation and two lags of real marginal cost, wage inflation and commodity price inflation , [2] four lags of inflation and two lags of real marginal cost, wage inflation and output gap, [3] four lags of inflation and two lags of real marginal cost, wage inflation, [4] four lags of inflation, real marginal cost, wage inflation and commodity price inflation , [5] four lags of inflation, real marginal cost, wage inflation, commodity price inflation and output gap [6] four lags of inflation, real marginal cost, wage inflation, commodity price inflation, output gap and the long-short interest rate spread. Instruments dated $t-1$ and earlier are used to mitigate possible correlation with the measurement error of real marginal cost.

[22] Bonnal and Renault (2003) show that the shrinkage procedure may improve the finite sample properties.
[23] We discuss the choice of the instruments in section 5.

One econometric issue in small samples with nonlinear estimation using GMM or the 3S-GMM estimator is that these estimators are sensitive to the way the orthogonality conditions are normalised. In this respect, two different alternatives specifications of the orthogonality conditions are estimated. The first specification takes the following form:

$$E_t\left[(\theta\pi_t-(1-\theta)(1-\beta\theta)\kappa mc_t-\theta\beta\pi_{t+1})\,Z_t\right]=0$$

while the second is given by

$$E_t\left[\left(\pi_t-\theta^{-1}\,(1-\theta)(1-\beta\theta)\kappa mc_t-\beta\pi_{t+1}\right)Z_t\right]=0$$

For robustness, we consider a different sample period 1970Q1-1997Q4, use the non-farm deflator as opposed to the overall deflator, and consider different lag selection for the variance-covariance matrix. Finally, both forms are estimated with $\kappa=0.13$ and $\kappa=1$. These values are standard in the literature.[24] Finally, two important issues need to be considered. First, we check for potential weakness of instruments by performing an F-test applied to the first-stage regression. In effect, Staiger and Stock (1997) pointed out that this statistic is of concern, as conventional asymptotic results may break down under weak correlation between the instruments and endogenous regressor. In our estimated equations, there is no evidence of weak correlation between the instruments and the endogenous regressor. Second, Nason and Smith (2003) discussed two fundamental sources of non-identification in the NKPC: weak, higher-order dynamics and superior information. They suggested a pre-test in each case: a test of the lag length for the forcing variable (the real marginal cost) and a test of Granger non causality. Applying these tests, we find evidence that the real marginal cost Granger causes inflation but that inflation does not Granger cause the real marginal cost. It confirms earlier evidence of Nason and Smith (2003). Moreover, using standard information criteria, we find that a lag lenght of order up to one for the real marginal cost. Overall, these suggest that a backward-looking component of the Phillips curve may be necessary.

Tables (2a) and (2b) report the results for each specification when a 12-lag Newey-West estimate of the covariance matrix is used. The first two columns give the discount factor estimate, β, and the reduced form slope coefficient on real marginal cost λ.[25] The final column displays Hansen's J statistic of the overidentifying restrictions, together with the associated p-values. First, the GMM estimate of the slope coefficient on marginal cost depends on the normalisation.[26] The coefficient is statistically significant whatever the set of instruments when the first specification is estimated. This evidence is also supported in the case of the 3S-GMM estimator. However, there is no evidence for the CUE which is robust to normalisation. Second, in contrast to GG and GGLS, the estimate of β is close to one whatever the set of instruments and the estimator. Therefore, it implies a vertical "long-run" inflation -real marginal cost trade-off

[24] Results are robust to alternative values of κ. They are not reported here but are available on request.
[25] It is to be noted that the structural and the reduced form estimates lead to the same conclusions.
[26] GG (1999) and GGLS(2001) also point out the same result.

(and inflation-output gap trade-off under some specific assumptions). This is the specification of Roberts (1995). Nevertheless, we do not impose the discount factor to equal one. Overall, adding further instruments increases the precision slightly but does not lead to significant differences.

(Insert Tables 2a, 2b around here)

Tables 3 and 4 report the estimates for the first specification when the automatic lag selection procedure of Newey and West is used and the Hall correction is applied, respectively. First, in both cases, the 3S-GMM and GMM estimate of the real marginal cost are still significant at standard levels. Second, the overidentifying restrictions are rejected whatever the set of instruments when the estimator of the variance-covariance matrix uses the sample moments in mean deviation and the real marginal cost is not significant for the 3S-GMM. At the same time, using the second specification, the evidence is rather weak for each estimator (Tables 5 and 6).

(Insert Tables 3 and 4 around here)
(Insert Tables 5 and 6 around here)

These results are robust to different sample periods and different values for $\varkappa$. Specifically, the overidenfication restrictions are still rejected for each specification when $\kappa = 1$ and the real marginal cost is significant at standard level for the two-step GMM and the 3S-GMM estimator for the first specification. However, it is to be noted that the robustness analysis shows that there is some empirical evidence of the real marginal cost for some values of κ in the case of the CUE. Our results are also robust over the period 1970Q1-1997Q4. Finally, we find that the real marginal cost is almost always not significant when the non-farm business deflator is considered instead of the implicit GDP deflator in both specifications for the CUE and the 3S-GMM estimator.[27]

Our results clearly show that one important concern is the choice of the normalisation.[28] Asymptotically, it should not matter which normalisation is used but in small samples it can. As we discussed in section 3.3, the first specification has the advantage that the Wald test can be interpreted without involving LAU parameters such that use of Wald-type confidence intervals is invalid. In this respect, the first specification is our benchmark. However, results using the second specification will be reported in order to be consistent with other empirical studies.

Overall, these results suggest that the empirical evidence of the pure forward-looking NKPC is mixed. In fact, using the mean deviation correction of Hall (2000) leads to conclude that the model is misspecified and that richer dynamics would seem necessary to capture the persistance of US inflation.

[27] Results are not reported here but are available on request.

[28] Gali and Gertler (1999, p.207) note that "[the first specification] appears to minimize the non-linearities, while the second normalizes the inflation coefficient to unity".

4.2 Hybrid Model Estimates

In this section, we present estimates of the reduced form parameters and the structural parameters. The instrument sets are the same as we used in the previous section. To address the small sample normalisation problem with GMM and 3S-GMM that we discussed earlier, we also consider two different specifications. The first specification takes the form:

$$E_t\left[\left(\phi\pi_t - (1-\omega)(1-\theta)(1-\beta\theta)\kappa mc_t - \theta\beta\pi_{t+1}\right)Z_t\right] = 0$$

while the second is given by

$$E_t\left[\left(\pi_t - \phi^{-1}(1-\omega)\left(1-\theta\right)(1-\beta\theta)\kappa mc_t - \theta\phi^{-1}\beta\pi_{t+1}\right)Z_t\right] = 0$$

As in the previous section, we consider three cases: (i) a 12-lag Newey-West estimate of the covariance matrix, (ii) an automatic lag selection procedure and (iii) the Hall's correction.

Tables 7 and 8 report estimates setting $\kappa = .13$ for each specification. The first three columns give the estimated structural parameters. The next three give the implied values of the reduced form coefficients. Also reported are the average price duration D (in quarters) corresponding to the estimate of θ and the Hansen's J-test for overidentifying restrictions.

(Insert Tables 7a,b,c and 8a,b,c around here)

Using the first specification, we find evidence of a statistically signficant real marginal cost when a 12-lag Newey-West estimate of the variance-covariance matrix is used for the conventional 2-step GMM estimator and the 3-step GMM estimator. These two estimators lead to estimates of the same order for the reduced-form coefficients and the structural coefficients. At the same time, the real marginal cost is no longer significant in the case of CUE. Replacing the fixed bandwith with the automatic lag selection procedure of Newey and West (1994) does not alter the previous conclusions: the overidentifying restrictions are not rejected and the real marginal cost is statistically significant for the two-step GMM and the 3S-GMM estimators. However, when we use the demeaning procedure of Hall (2000), the validity of instruments is rejected more often, i.e. the overdidentifying restrictions are rejected when the fourth, fifth and sixth instruments sets are considered (Table 7c). Interestingly, the unconditional moments conditions are not rejected when the number of instruments is not too large ([1], [2] and [3]). Thus these three specifications provide some evidence for the hybrid NKPC. Nevertheless, this results still depends on the chosen estimator. Finally, as shown in the previous section, it is to be noted that the empirical evidence is weak when the second specification is used in order to estimate the structural and reduced-form parameters. This is consistent with the results of GG (1999) and GGLS (2001).[29]

[29] Using Monte-Carlo simulations, Sondergaard (2003) shows that the second normalisation overestimates the share of backward-looking firms.

Three other parameters are of particular interest: the degree of price stickness θ, the degree of "backwardness" in price setting ω and the discount factor β.

Regarding θ, we find lower estimates than GG (1999) and GGLS (2001). For example, depending on the estimator, the parameter θ is estimated to imply prices that are fixed for roughly 2 to 4 quarters on average. This result is robust across the different estimators. It is also consistent with survey evidence which suggests three to four quarters on average (see Rotemberg and Woodford, 1997). On the other hand, the parameter ω is estimated to be around 0.3 to 0.6, i.e the fraction of backward looking price setters is higher than the estimates suggested in GG and GGLS.

While the results suggest some imprecision in the estimate of degree of backwardness, one conclusion does not change across methods: in accounting for inflation dynamics, the forward looking behavior is larger than the backward looking component. In effect, the reduced-form coefficients γ_f and γ_b are significantly different from zero whatever the estimation method and the set of instruments. Therefore, the pure forward looking model is rejected by the data. At the same time, in contrast to GG and GGLS, the quantitative importance of the backward looking component for inflation dynamics is not negligible even if the forward-looking component remains dominant in the dynamics of inflation.

Finally, we find higher values of the discount factor than GG and GGLS. Specifically, the estimate of β is reasonnably similar across the two methods and the different estimators. In addition, restricting β equal to unity does not alter the results.

Overall, using the same data set of GG (1999), our results show that (i) the discount factor is close to one, (ii) the forward-looking behaviour is dominant, (iii) the duration is of the same order for the different estimators and prices are fixed for approximatively 2 to 4 quarters, (iv) the empirical evidence for the real marginal cost is mixed, i.e. it depends on the normalisation (for the 2-step GMM and the 3S-GMM), the estimator and the set of instruments and (v) tests do not always reject the hybrid specification of the NKPC when the mean deviation correction is applied. Results (ii), (iii) and (v) are roughly consistent with the results of GG (1999) and GGLS (2001). In this respect, the next step is whether these results are robust and to what extent we can explain the mixed evidence regarding the real marginal cost.

5. Discussion

The estimation strategy advocated in this paper allows us to obtain estimates of New Phillips curves which do not depend on either the normalization of the moment conditions or the initial conditions. When applied to US data, the CUE and 3S-GMM estimator result in more importance being given to the backward-looking vice forward-looking component in the hybrid version New Phillips curve compared to the GMM estimates obtained by GG (1999) and GGLS (2001). In this respect, the degree of price stickness and the degree of backwardness are higher than the results in the literature. This leads to a much higher significant part of backward-looking inflation in the NKPC.

In contrast to other empirical studies,[30] the specification test based on overidentifying restrictions rejects the New Phillips curve and its hybrid version for the two different normalisations considered in this paper (for some sets of instruments). The estimation of the weighting matrix is crucial for the small sample properties of Hansen's specification test, especially when the number of moment conditions is important relative to the number of observations.[31] These studies fixed at arbitrary values the number of lags used in kernel estimation of the weighting matrix. In this paper, we adopt a data-dependent automatic lag selection procedure and, the estimation of the weighting matrix is based on sample moments in deviation. This approach improves the power of the overidentifying restrictions test in small samples.

Finally, the empirical evidence for the real marginal cost is weak and seems to depend critically on the number of instruments and the estimator.

In order to further assess the reliability of our results and more generally the robustness of the results in the literature, we consider different issues in the estimation and inference of the NKPC: the choice of the instruments, the measurement of the real marginal cost, the misspecification of the dynamics of inflation, the inflation forecasting measures and the sample period. All these issues have been already discussed in the literature and may explain the weak evidence on the real marginal cost in the pure forward or hybrid NKPC for the United States.

- *The choice of instruments*

As we discussed in this paper, one important issue is the number of instruments in order to estimate the NKPC. Moreover, the choice of the instruments is of particular concern. Therefore, Hall and Peixe (2003) argue that it is desirable for the chosen instrument set to satisfy some properties, which they refer as being orthogonality, identification, efficiency and non-redundancy. For instance, their Monte-Carlo simulations report that the inclusion of redundant instruments leads to deterioration in the finite sample performances of the GMM estimator. In addition, it is important that the statistical properties of the instruments do not contaminate the limiting distribution of the parameter estimator. In this respect, we depart from earlier studies by excluding output gap measures from the instrument sets. Two measures of output gap are usually retained as instruments. One is based on quadratically detrended output. With standard unit root tests (such as the Augmented Dickey-Fuller), the presence of a unit root in US output cannot be rejected. Under the maintained hypothesis of a unit root, quadratically detrended output is then also characterized by a unit root. Unfortunately, the asymptotic properties of instrumental variables estimators in the presence of nonstationary instruments are not known. As a result, usual inference procedures are likely to be invalid. The other measure of output gap usually used is based on the Hodrick-Prescott filter. Output gap is then a combination of lags, leads, and contemporaneous values of output. Such measures of the output gap violate the basic GMM orthogonality conditions and is likely to be correlated with the measurement error of real marginal cost.[32]

[30] Balakrishnan and Lopez-Salido (2002), Gali and Gertler (1999), Gali, Gertler and Lopez-Salido (2001), Gali, Gertler and Lopez-Salido (2001) and Gali and Lopez-Salido (2000)

[31] For some of these studies, the ratio of the number of moment conditions to the number of observations equals 1/3.

[32] It is also to be noted that there is *a priori* no obvious reason to use a detrended output gap measure of one

In this respect, we reconduct estimations with the following sets of instruments: [1] four lags of inflation and two lags of real marginal cost and wage inflation, [2] six lags of inflation and two lags of real marginal cost and wage inflation, [3] four lags of inflation, real marginal cost and wage inflation, [4] six lags of inflation, real marginal costs and wage inflation and [5] six lags of inflation and four lags of real marginal cost and wage inflation. Instruments dated $t-1$ and earlier are also used to mitigate possible correlation with the measurement error of real marginal cost.

Tables 9 and 10 report the results for both normalisations in the case of the hybrid NKPC. We adopt the data-dependent automatic selecltion procedure of Newey and West (1994) and the J-stat is based on the Hall's correction.

(Insert Tables 9 and 10 around here)

We find empirical evidence for the real marginal cost in the first specification for the two-step GMM and the 3S-GMM estimators using these different sets of instruments. However, there is still no evidence in the case of the CUE and the evidence is rather weak for the second specification. At the same time, the validity of instruments is no longer rejected when the measures of output gap are ruled out. Therefore, if we compare these results with those of the previous section, the results appear to be sensitive to the inclusion of the output gap measure in the information set.

Finally, an important issue, which is also related to the number of instruments, is that agents that reoptimize their price do so on the basis of their time t information set. This means that when they make new price plans, these goes into effect immediately. Eichenbaum and Fisher (2003) test this assumption and assume that when firms reoptimise their price plans, it may not have a direct effect and the new plan may only go into effect at a latter date $t+\tau$ (delay effect).[33] Hence, by varying τ, the information set changes and it is possible to test whether any variable dated between $t-\tau$ and t has explantory power for the time t inflation. In that case, the model implies that inflation is a predetermined variable, depending upon past disturbances. Eichenbaum and Fisher (2003) find strong evidence against the standard Calvo model when $\tau = 0$ and that the model is no longer rejected once they allow for at least a lag. In this respect, we conduct a similar exercice with our five sets of instruments. Overall, we are not able to identify a significant effect of the starting date of the information set (or the degree of predetermination of inflation) and our previous results are not modified.

- *The definition of real marginal cost*

type or another. Specifically, in order to be consistent with the underlying theoretical definition of the natural rate output, the output gap should respond to real disturbances of several types. However, a smoothed measure of the output may not respond to these shocks.

[33] An alternative is to assume that a randomly chosen fraction of all prices are set optimally whereas the remaining fraction is adjusted according to an indexation rule (see Smets and Wouters, 2002, Christiano, Eichembaum and Evans, 1997) at a latter date for period t. In contract to Gali and Gertler (1999), inertia in the inflation dynamics is no longer explained by a backward-looking rule of thumb. Nevertheless, in the limiting case in which the discount factor equals one, the two models have the identical implications.

Since the real marginal cost is a latent variable, two dimensions can be considered. On the one hand, the results may depend on the calculation of the real marginal cost. For instance, Rotemberg and Woodford (1999), GGLS (2001), Gagnon and Kahn (2003), Sbordone (2001) have suggested to consider a Cobb-Douglas technology with overhead labor cost. In this case, the measure of marginal cost is augmented by a term that depends on hours worked. In addition, adjustment cost of labor, CES production function and complementaries may be taken into consideration in order to derive the measure of marginal cost.[34] On the other hand, the real marginal cost may be revised over time due to measurement errors etc. These two dimensions have been extensively discussed in the literature about the reliability of the output gap measures. Intuitively, both dimensions may be important in order to explain the lack of robustness of the marginal cost in the NKPC.

In order to illustrate the first point, Table 11 reports the results for a Cobb-Douglas production function with overhead labor. In this case, the real marginal cost is given by:

$$mc_t = s_t + bh_t$$

where $b = \frac{\overline{H}/H}{1-\overline{H}/H}$.[35] The series for hours worked is constructed as the number of employees multiplied by the average hours works per quarter. The resulting serie is stationary around a stable mean. Finally, we include lags of hours worked in the sets of instruments.

(Insert Table 11 around here)

Using the same sets of instruments (see section 4.1), the empirical evidence of the real marginal cost is still mixed. Once again, the specification is rejected in almost all cases when the mean deviation correction of Hall (2000) is taken into consideration. In contrast, the results are much more sensitive to the value of $\varkappa$. Specifically, as $\varkappa$ goes close to one, the statistical significance of the real marginal cost decreases.

Secondly, Figure 2 reports the real marginal cost in log-deviation from its mean calculated as the labor share of nonfarm business from the original database of GG and the revised real marginal cost (labelled mc1), which takes into account some revisions. We also report two other measures of the real marginal costs. The second measure "mc2" is based on the same deflator (Non-Farm Business, NFB) but used a different benchmark year (1996 instead of 1992). The third measure "mc3" is based on the GDP deflator instead of the NFB deflator. In effect, the end-of-sample properties of the original serie and "mc1"are different. At the same time, the change of the benchmark year (mc1) has minor effects in comparison with the change of the price deflator (mc3). In this respect, we conduct estimations on revised data. Our results are reported in Table 12.

(Insert Figure 2)
(Insert Table 12a around here)

[34]For a complete discussion, see Gagnon and Kahn (2003).
[35]The value of b is calibrated as in other studies of the NKPC.

According to both normalisations, the real marginal cost is mostly not significant except for the standard GMM estimator in the first specification. In fact, the real marginal cost is only significant for the 3S-GMM when the number of instruments is relatively large and thus the small-sample bias can not be ruled out. Results also show that almost one-third of the firms prices in a rule-of-thumb manner. It differs from our results in section 4 in the sense that the portion of backward-looking agents is less important. Therefore, it turns out that the hybrid NKPC displays less inertia than previously stated. It is to be noted that this result is robust over different sample period (see further) and different values of $\varkappa$. Hence, the revisions of the real marginal cost cast some doubts on the robustness of the NKPC.

- The misspecification of the dynamics of inflation

Two types of mis-specification have been mainly studied in the literature: measurement error and omitted dynamics. Omitted dynamics is also a plausible explanation of the non-significance of the real marginal cost and/ or the forward-looking nature of the dynamics of inflation. Hybrid NKPC in which additional lags of inflation have been introduced by some specific rule-of-thumbs or by other sources of lag dynamics in inflation (Kozicki and Tinsley, 2002). In this respect, we add extra lags of inflation to enter the right hand side of the dynamics of inflation. As is pointed out by GG and GGLS, one motivation is that the estimated importance of the forward looking behaviour of inflation may reflect the insufficient lagged dependence. Table 13 reports the results when three additional lags of inflation are added to the right hand side.

(Insert Table 13 around here)

Parameter φ denotes the sum of the coefficients on the additional lags. This sum is small and not statistically not significant. This result holds across all specifications. Thus it may appear that the hybrid NKPC can account for the inflation dynamics with relatively little reliance on arbitrary lags of inflation. At the same time, some lagged inflation coefficients are statistically significant despite the fact that the sum is not, i.e. a richer inflation dynamics may be necessary. Moreover, the test of overidentification moments is not rejected in several cases reinforcing the previous statement. Apart these coefficients, the broad picture is changed in the sense that the marginal cost does not have a significant impact on short run inflation dynamics in most cases. These results are robust for the non-farm business deflator and for different values of $\varkappa$.

- Inflation forecasting measures

One important issue may also be the measurement of inflation forecasts. Recent papers have estimated the NKPC for the US using data from the survey of professional forecasters as proxy for expected inflation. For instance Adam and Padula (2003) obtain significant and plausible estimates for the structural parameters independently of whether they use the output gap or unit labour costs as measure of marginal costs. An important concern is whether or not survey expectations are inefficient and thus biased. In effect, if these survey expectations are inefficient, the forecast errors will generally not be orthogonal to information available to agents at the time of forecast. Therefore, instrumental variable techniques are no longer necessary since we do not need to assume orthogonality of forecasts errors with respect to lagged information. At the same time, measurement error in real marginal cost is still present and instrumental variables techniques can be applied.

Figure 3 plots actual and expected inflation. Inflation expectations are approximated with data from the Survey of Professional Forecasters. We use the mean of the one-quarter ahead inflation forecast for the implicit GDP deflator as the measure for expected inflation.

(Insert Figure 3 around here)

Overall, the actual and expected inflation rates move closely together over the sample period.

To assess whether inflation forecasts are biased or inefficient, we regress actual inflation rates on a constant and on expected inflation and check whether the constant is equal to zero and the slope coefficient equal to one. Surprisingly, we reject the rationality of survey expectations using a Wald test.

Then we use our estimators. Table 14 reports the results.

(Insert Table 14 around here)

Overall, the use of inflation forecasts does not lead to improve the statistical significance of the real marginal cost and conduct to imprecise estimates.

- *Sample periods*

Finally, our results may be explained by sub-sample instability. We do not conduct here structural stability tests. However, we conduct estimations over different periods. For instance, Table 15 reports the structural and reduced-form estimates over the period 1960Q1-2001Q4. In effect, since the results may be sensitive to data revisions, we do not take into account the most recent data.

(Insert Table 15 around here)

Overall, the empirical evidence of the real marginal cost is rather mixed.

Moreover, following GG, we consider different intervals. Overall, the broad picture remains unchanged: there is no strong evidence for the real marginal cost.

6. Conclusion

The recent works of Gali and Gertler (1999) and Gali, Gertler amd Lopez-Salido (2001) provide evidence that the inflation dynamics in the United States and the Euro zone can be well-described by the hybrid New Keynesian Phillips Curve. Our approach has addressed several important econometrics issues with their results. Specifically, we discuss the finite sample performances of the two-step GMM estimators with other estimators recently proposed in the literature. In addition, we stress the importance to use the mean deviation correction of Hall (2000) and to avoid a fixed aribitrary bandwith. Using the Continuously-updating GMM estimator (Hansen, Heaton and Yaron, 1996) and the 3-step GMM estimator (2003), our results show that the empirical evidence of the New Keynesion Phillips curve is rather mixed.

In this respect, the rejection of alternative specifications of the New Phillips curve suggests that a richer dynamic structure in the explanatory variables will be needed to capture the dynamics of US inflation. In the case of the United States, other studies (as for instance Kurmann, 2002) also find considerable uncertainty between the observed persistent movements in inflation and what is predicted by a New Phillips curve model. Overall, these results and those of this paper represent an important step back from the conclusions of previous authors who argue that New Phillips curve models are a good representations of inflation dynamics. These new results suggest that, at the theoretical level, richer versions of the structural model from which the New Phillips curve is derived would need to be developed.

In addition, we show that the results are particularly sensitive to the well-know problem of the number of instruments, the choice of the instruments, data revisions and measurement of the real marginal cost and the sample periods.

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Table 2a: Estimates of the forward-looking NKPC using the first specification

Method	Instrument set	β	?	λ	J-stat
GMM	[1]	.979	.563	.347	8.46
		(.011)	(.036)	(.079)	
		[.000]	[.000]	[.000]	[.488]
	[2]	.991	.565	.338	8.11
		(.010)	(.044)	(.094)	
		[.000]	[.000]	[.000]	[.523]
	[3]	.999	.637	.131	7.16
		(.011)	(.053)	(.038)	
		[.000]	[.000]	[.000]	[.402]
	[4]	.974	.558	.361	10.53
		(.009)	(.031)	(.071)	
		[.000]	[.000]	[.000]	[.785]
	[5]	.964	.530	.434	10.89
		(.009)	(.030)	(.079)	
		[.000]	[.000]	[.000]	[.927]
	[6]	.976	.509	.482	11.07
		(.008)	(.025)	(.074)	
		[.000]	[.000]	[.000]	[.982]
CUE	[1]	1.020	.676	.148	7.12
		(.022)	(.098)	(.114)	
		[.000]	[.000]	[.196]	[.624]
	[2]	1.018	.671	.155	7.17
		(.021)	(.095)	(.114)	
		[.000]	[.000]	[.176]	[.619]
	[3]	1.022	.669	.156	7.09
		(.022)	(.102)	(.121)	
		[.000]	[.000]	[.203]	[.419]
	[4]	.999	.631	.217	9.69
		(.019)	(.069)	(.104)	
		[.000]	[.000]	[.035]	[.839]
	[5]	.997	.742	.090	10.21
		(.018)	(.120)	(.098)	
		[.000]	[.000]	[.361]	[.947]
	[6]	1.014	.596	.267	10.47
		(.019)	(.054)	(.097)	
		[.000]	[.000]	[.006]	[.987]
3S-GMM	[1]	.988	.597	.276	8.30
		(.010)	(.037)	(.068)	
		[.000]	[.000]	[.000]	[.504]
	[2]	1.003	.640	.201	7.53
		(.010)	(.052)	(.074)	
		[.000]	[.000]	[.007]	[.582]
	[3]	1.005	.636	.207	7.42
		(.011)	(.051)	(.075)	
		[.000]	[.000]	[.006]	[.386]
	[4]	.980	.579	.313	10.40
		(.009)	(.032)	(.073)	
		[.000]	[.000]	[.000]	[.794]
	[5]	.978	.578	.317	10.52
		(.008)	(.028)	(.058)	
		[.000]	[.000]	[.000]	[.938]
	[6]	.984	.546	382	11.09
		(.007)	(.022)	(.052)	
		[.000]	[.000]	[.000]	[.982]

Note: The p-values (in parenthesis) corresponding to the estimates of β, ? and λ are for the null hypothesis that these estimates are zero. A 12-lag Newey-West estimate of the covariance matrix is used . ? equals .13.

Table 2b: Estimates of the forward-looking NKPC using the second specification

Method	Instrument set	β	?	λ	J-stat
GMM	[1]	.987	.719	.113	7.64
		(.009)	(.070)	(.066)	
		[.000]	[.000]	[.088]	[.571]
	[2]	.995	.632	.216	7.63
		(.010)	(.051)	(.077)	
		[.000]	[.000]	[.028]	[.572]
	[3]	1.000	.673	.158	7.16
		(.010)	(.063)	(.075)	
		[.000]	[.000]	[.035]	[.412]
	[4]	.982	.818	.044	9.46
		(.008)	(.112)	(.057)	
		[.000]	[.000]	[.447]	[.852]
	[5]	.978	.753	.086	10.12
		(.007)	(.067)	(.052)	
		[.000]	[.000]	[.093]	[.949]
	[6]	.993	.753	.041	10.35
		(.007)	(.067)	(.046)	
		[.000]	[.000]	[.374]	[.988]
3S-GMM	[1]	.992	.725	.107	7.68
		(.009)	(.070)	(.063)	
		[.000]	[.000]	[.094]	[.566]
	[2]	1.000	.696	.132	7.40
		(.010)	(.069)	(.072)	
		[.000]	[.000]	[.069]	[.596]
	[3]	1.002	.692	.136	7.32
		(.011)	(.068)	(.073)	
		[.000]	[.000]	[.063]	[.396]
	[4]	.988	.716	.063	7.83
		(.010)	(.070)	(.072)	
		[.000]	[.000]	[.461]	[.617]
	[5]	.982	.809	.048	10.30
		(.007)	(.097)	(.052)	
		[.000]	[.000]	[.360]	[.945]
	[6]	.984	.802	.036	10.38
		(.007)	(.068)	(.069)	
		[.000]	[.000]	[.554]	[.967]

Note: The p-values (in parenthesis) corresponding to the estimates of β, ? and λ are for the null hypothesis that these estimates are zero. A 12-lag Newey-West estimate of the covariance matrix is used . ? equals .13.

Table 3: Estimates of the forward-looking NKPC using the first specification

Method	Instrument set	β	?	λ	J-stat
GMM	[1]	.994	.540	.394	16.45
		(.019)	(.058)	(.139)	
		[.000]	[.000]	[.005]	[.058]
	[2]	.999	.557	.353	15.00
		(.017)	(.056)	(.143)	
		[.000]	[.000]	[.015]	[.091]
	[3]	1.006	.589	.283	12.37
		(.020)	(.079)	(.146)	
		[.000]	[.000]	[.053]	[.088]
	[4]	.978	.562	.349	14.28
		(.012)	(.079)	(.089)	
		[.000]	[.000]	[.000]	[.505]
	[5]	.966	.532	.424	14.43
		(.011)	(.033)	(.086)	
		[.000]	[.000]	[.000]	[.758]
	[6]	.984	.531	.421	21.13
		(.014)	(.039)	(.102)	
		[.000]	[.000]	[.000]	[.543]
CUE	[1]	1.043	.614	.226	11.32
		(.022)	(.076)	(.121)	
		[.000]	[.000]	[.063]	[.255]
	[2]	1.005	.698	.129	11.29
		(.020)	(.099)	(.103)	
		[.000]	[.000]	[.213]	[.256]
	[3]	1.005	.783	.059	10.94
		(.020)	(.088)	(.117)	
		[.000]	[.000]	[.613]	[.141]
	[4]	1.002	.664	.169	12.59
		(.019)	(.078)	(..098)	
		[.000]	[.000]	[.088]	[.634]
	[5]	.975	.688	.149	11.74
		(.018)	(.075)	(.086)	
		[.000]	[.000]	[.084]	[.896]
	[6]	1.008	.631	.091	16.54
		(.019)	(.039)	(.098)	
		[.000]	[.000]	[.353]	[.830]
3S-GMM	[1]	1.000	.591	.281	15.00
		(.019)	(.067)	(.122)	
		[.000]	[.000]	[.224]	[.091]
	[2]	1.002	.639	.203	11.87
		(.017)	(.080)	(.114)	
		[.000]	[.000]	[.079]	[.221]
	[3]	1.003	.634	210	11.86
		(.019)	(.090)	(.131)	
		[.000]	[.000]	[.113]	[.105]
	[4]	.988	.588	.294	13.65
		(.012)	(.043)	(.081)	
		[.000]	[.000]	[.000]	[.552]
	[5]	.983	.593	.287	14.13
		(.010)	(.041)	(.076)	
		[.000]	[.000]	[.000]	[.776]
	[6]	.988	.553	.366	22.00
		(.013)	(.040)	(.091)	
		[.000]	[.000]	[.000]	[.520]

Note: The p-values (in parenthesis) corresponding to the estimates of β, ? and λ are for the null hypothesis that these estimates are zero. The automatic lag selection of Newey and West (1994) is used to estimate covariance matrix. ? equals .13.

Table 4: Estimates of the forward-looking NKPC using the second specification

Method	Instrument set	β	?	λ	J-stat
GMM	[1]	.991	.736	.097	14.68
		(.015)	(.116)	(.098)	
		[.000]	[.000]	[.323]	[.099]
	[2]	.997	.661	.174	11.81
		(.014)	(.072)	(.091)	
		[.000]	[.000]	[.058]	[.224]
	[3]	.996	.760	.076	11.12
		(.021)	(.181)	(.132)	
		[.000]	[.000]	[.563]	[.133]
	[4]	.985	.802	.051	12.62
		(.010)	(.131)	(.073)	
		[.000]	[.000]	[.485]	[.631]
	[5]	.979	.809	.103	11.27
		(.007)	(.132)	(.061)	
		[.000]	[.000]	[.096]	[.914]
	[6]	.990	.830	.003	15.81
		(.010)	(.135)	(.061)	
		[.000]	[.000]	[.957]	[.863]
3S-GMM	[1]	.995	.719	.110	14.44
		(.018)	(.122)	(.112)	
		[.000]	[.000]	[.328]	[.107]
	[2]	.999	.757	.078	11.10
		(.017)	(.148)	(.110)	
		[.000]	[.000]	[.478]	[.269]
	[3]	1.011	.793	.052	11.01
		(.019)	(.219)	(.125)	
		[.000]	[.000]	[.680]	[.138]
	[4]	.986	.798	.053	12.83
		(.010)	(.125)	(.072)	
		[.000]	[.000]	[.461]	[.614]
	[5]	.986	.762	.077	13.60
		(.009)	(.096)	(.069)	
		[.000]	[.000]	[.269]	[.806]
	[6]	.986	.834	.036	20.91
		(.012)	(.176)	(.079)	
		[.000]	[.000]	[.654]	[.586]

Note: The p-values (in parenthesis) corresponding to the estimates of β, ? and λ are for the null hypothesis that these estimates are zero. The automatic lag selection of Newey and West (1994) is used to estimate covariance matrix. ? equals .13.

Table 5: Estimates of the forward-looking NKPC using the first specification

Method	Instrument set	β	O	λ	J-stat
GMM	[1]	1.002	.542	.386	20.22
		(.019)	(.059)	(.139)	
		[.000]	[.000]	[.006]	[.017]
	[2]	1.003	.577	.309	20.42
		(.016)	(.059)	(.116)	
		[.000]	[.000]	[.008]	[.015]
	[3]	1.007	.581	.298	15.20
		(.020)	(.077)	(.148)	
		[.000]	[.000]	[.045]	[.034]
	[4]	.995	.589	.289	26.37
		(.012)	(.046)	(.086)	
		[.000]	[.000]	[.001]	[.034]
	[5]	.982	.572	.327	39.37
		(.009)	(.035)	(.073)	
		[.000]	[.000]	[.000]	[.004]
	[6]	.987	.550	.374	37.74
		(.012)	(.058)	(.088)	
		[.000]	[.000]	[.000]	[.027]
3S-GMM	[1]	.998	.620	.234	18.00
		(.022)	(.075)	(.120)	
		[.000]	[.000]	[.054]	[.035]
	[2]	1.003	.650	.187	13.90
		(.017)	(.083)	(.112)	
		[.000]	[.000]	[.096]	[.125]
	[3]	1.003	.650	.188	13.10
		(.019)	(.094)	(.130)	
		[.000]	[.000]	[.140]	[.053]
	[4]	.994	.608	.255	27.09
		(.012)	(.045)	(.077)	
		[.000]	[.000]	[.000]	[.028]
	[5]	.989	.611	.252	29.80
		(.010)	(.043)	(.072)	
		[.000]	[.000]	[.000]	[.055]
	[6]	.990	.559	.353	39.66
		(.013)	(.040)	(.089)	
		[.000]	[.000]	[.000]	[.017]

Note: The p-values (in parenthesis) corresponding to the estimates of β, ? and λ are for the null hypothesis that these estimates are zero. The automatic lag selection of Newey and West (1994) and the Hall's correction (2000) are used to estimate covariance matrix. ? equals .13.

Table 6: Estimates of the forward-looking NKPC using the second specification

Method	Instrument set	β	?	λ	J-stat
GMM	[1]	.995	.737	.095	18.01
		(.018)	(.137)	(.115)	
		[.000]	[.000]	[.410]	[.035]
	[2]	1.001	.687	.142	20.02
		(.014)	(.083)	(.091)	
		[.000]	[.000]	[.120]	[.017]
	[3]	.995	.695	.058	12.06
		(.022)	(.082)	(.132)	
		[.000]	[.000]	[.660]	[.098]
	[4]	.988	.768	.074	30.81
		(.010)	(.105)	(.073)	
		[.000]	[.000]	[.317]	[.009]
	[5]	.991	.724	.109	45.40
		(.008)	(.072)	(.067)	
		[.000]	[.000]	[.010]	[.000]
	[6]	.980	.840	.020	46.51
		(.010)	(.152)	(.061)	
		[.000]	[.000]	[.744]	[.003]
3S-GMM	[1]	.998	.708	.121	17.91
		(.018)	(.114)	(.112)	
		[.000]	[.000]	[.282]	[.036]
	[2]	1.001	.759	.076	13.13
		(.017)	(.151)	(.110)	
		[.000]	[.000]	[.491]	[.157]
	[3]	1.013	.800	.047	13.11
		(.019)	(.232)	(.126)	
		[.000]	[.000]	[.709]	[.693]
	[4]	.990	.768	.073	31.51
		(.010)	(.102)	(.072)	
		[.000]	[.000]	[.313]	[.007]
	[5]	.990	.716	.116	35.27
		(.009)	(.071)	(.069)	
		[.000]	[.000]	[.091]	[.012]
	[6]	.982	.815	.046	36.83
		(.012)	(.151)	(.079)	
		[.000]	[.000]	[.567]	[.034]

Note: The p-values (in parenthesis) corresponding to the estimates of β, ? and λ are for the null hypothesis that these estimates are zero. The automatic lag selection of Newey and West (1994) and the Hall's correction are used to estimate covariance matrix. ? equals .13.

Table 7a: Hybrid Phillips Curve Estimates 1960Q1- 1997Q4, form I (κ=.13)

Method	Instrument set	θ	β	ω	λ	γ_f	γ_b	Duration	J-stat
GMM	[1]	.583	.990	.385	.108	.577	.385	2.40	7.01
		(.052)	(.015)	(.047)	(.030)	(.054)	(.047)	(.301)	
		[.000]	[.000]	[.000]	[.000]	[.000]	[.000]	[.000]	[.535]
	[2]	.624	.997	.437	.080	.623	.437	2.66	6.12
		(.064)	(.015)	(.060)	(.032)	(.064)	(.060)	(.454)	
		[.000]	[.000]	[.000]	[.013]	[.000]	[.000]	[.000]	[.634]
	[3]	.628	.999	.160	.0.116	.628	.160	2.69	6.56
		(.053)	(.011)	(.073)	(.035)	(.053)	(.073)	(.386)	
		[.000]	[.000]	[.031]	[.001]	[.000]	[.031]	[.000]	[.363]
	[4]	.523	.981	.398	.139	.513	.398	2.10	10.30
		(.042)	(.015)	(.038)	(.026)	(.042)	(.038)	(.183)	
		[.000]	[.000]	[.000]	[.000]	[.000]	[.000]	[.000]	[.740]
	[5]	.531	.980	.395	.136	.521	.395	2.14	10.52
		(.041)	(.014)	(.035)	(.025)	(.041)	(.035)	(.187)	
		[.000]	[.000]	[.000]	[.000]	[.000]	[.000]	[.000]	[.913]
	[6]	.525	.983	.415	.135	.516	.415	2.10	10.70
		(.039)	(.013)	(.033)	(.024)	(.039)	(.033)	(.171)	
		[.000]	[.000]	[.000]	[.000]	[.000]	[.000]	[.000]	[.978]
CUE	[1]	.640	.999	.308	.094	.675	.324	2.78	6.00
		(.124)	(.034)	(.096)	(.086)	(.072)	(.070)	(.959)	
		[.000]	[.000]	[.000]	[.275]	[.000]	[.000]	[.000]	[.648]
	[2]	.665	.998	.414	.061	.616	.384	2.99	5.85
		(.170)	(.042)	(.135)	(.085)	(.071)	(.068)	(1.52)	
		[.000]	[.000]	[.000]	[.476]	[.000]	[.000]	[.052]	[.664]
	[3]	.670	.999	.375	.065	.641	.359	3.03	5.54
		(.178)	(.039)	(.138)	(.093)	(.086)	(.082)	(1.64)	
		[.000]	[.000]	[.007]	[.485]	[.000]	[.000]	[.066]	[.476]
	[4]	.6.91	.987	.276	.073	.707	.286	3.24	9.23
		(.147)	(.031)	(.104)	(.086)	(.079)	(.078)	(1.54)	
		[.000]	[.000]	[.009]	[.392]	[.000]	[.000]	[.037]	[.815]
	[5]	.714	.984	.298	.059	.697	.296	3.50	9.35
		(.157)	(.031)	(.111)	(.079)	(.073)	(.072)	(1.92)	
		[.000]	[.000]	[.008]	[.461]	[.000]	[.000]	[.0.071]	[.951]
	[6]	.776	.977	.281	.037	.720	.267	4.47	9.64
		(.200)	(.027)	(.119)	(.076)	(.073)	(.071)	(4.00)	
		[.000]	[.000]	[.019]	[.627]	[.000]	[.000]	[.266]	[.989]
3S-GMM	[1]	.603	.997	.353	.102	.601	.353	2.52	6.40
		(.050)	(.014)	(.045)	(.028)	(.051)	(.045)	(.314)	
		[.000]	[.000]	[.000]	[.000]	[.000]	[.000]	[.000]	[.602]
	[2]	625	1.000	.409	.083	.625	.409	2.66	6.01
		(.061)	(.015)	(.059)	(.031)	(.061)	(.059)	(.432)	
		[.000]	[.000]	[.000]	[.009]	[.000]	[.000]	[.000]	[.646]
	[3]	.625	1.003	.217	.110	.627	.217	2.67	6.21
		(.053)	(.012)	(.068)	(.033)	(.053)	(.068)	(.374)	
		[.000]	[.000]	[.000]	[.001]	[.000]	[.000]	[.000]	[.399]
	[4]	.540	.983	.381	.133	.531	.381	2.18	10.16
		(.041)	(.014)	(.038)	(.025)	(.041)	(.038)	(.192)	
		[.000]	[.000]	[.000]	[.000]	[.000]	[.000]	[.000]	[.750]
	[5]	.551	.982	.385	.127	.541	.384	2.23	10.41
		(.040)	(.013)	(.035)	(.024)	(.040)	(.035)	(.197)	
		[.000]	[.000]	[.000]	[.000]	[.000]	[.000]	[.000]	[.940]
	[6]	.543	.983	.408	.126	.534	.409	2.19	10.62
		(.038)	(.013)	(.034)	(.023)	(.038)	(.034)	(.182)	
		[.000]	[.000]	[.000]	[.000]	[.000]	[.000]	[.000]	[.980]

Notes: standard errors are in parenthesis, p-values are in square brackets. A 12-lag Newey-West estimate of the covariance matrix is used.

Table 7b: Hybrid Phillips Curve Estimates 1960Q1- 1997Q4, form I (κ=.13)

Method	Instrument set	θ	β	ω	λ	γ_f	γ_b	Duration	J-stat
GMM	[1]	.576	.991	.378	.113	.570	.378	2.36	8.16
		(.059)	(.018)	(.053)	(.034)	(.059)	(.053)	(.326)	
		[.000]	[.000]	[.000]	[.000]	[.000]	[.000]	[.000]	[.418]
	[2]	.611	.998	.404	.091	.610	.404	2.07	7.03
		(.070)	(.018)	(.068)	(.037)	(.070)	(.068)	(.463)	
		[.000]	[.000]	[.000]	[.016]	[.000]	[.000]	[.000]	[.533]
	[3]	.534	.999	.288	.154	.534	.288	2.15	6.45
		(.087)	(.028)	(.086)	(.058)	(.084)	(.087)	(.369)	
		[.000]	[.000]	[.000]	[.008]	[.000]	[.000]	[.000]	[.355]
	[4]	.521	.983	.375	.146	.513	.377	2.09	12.90
		(.048)	(.015)	(.048)	(.031)	(.047)	(.048)	(.208)	
		[.000]	[.000]	[.000]	[.000]	[.000]	[.000]	[.000]	[.534]
	[5]	.535	.980	.390	.135	.525	.390	2.15	11.25
		(.043)	(.013)	(.039)	(.027)	(.043)	(.038)	(.199)	
		[.000]	[.000]	[.000]	[.000]	[.000]	[.000]	[.000]	[.884]
	[6]	.523	.985	.394	.140	.515	.395	2.10	13.14
		(.044)	(.014)	(.042)	(.028)	(.045)	(.042)	(.193)	
		[.000]	[.000]	[.000]	[.000]	[.000]	[.000]	[.000]	[.926]
CUE	[1]	.619	.995	.352	.097	.635	.362	2.63	7.42
		(.115)	(.036)	(.094)	(.081)	(.062)	(.060)	(.798)	
		[.000]	[.000]	[.000]	[.236]	[.000]	[.000]	[.000]	[.492]
	[2]	.678	.996	.429	.054	.610	.388	3.11	6.34
		(.190)	(.044)	(.146)	(.086)	(.070)	(.067)	(1.83)	
		[.000]	[.000]	[.000]	[.534]	[.000]	[.000]	[.092]	[.608]
	[3]	.620	.999	.322	.103	.658	.341	2.63	5.64
		(.130)	(.035)	(.106)	(.093)	(.085)	(.082)	(.906)	
		[.000]	[.000]	[.000]	[.271]	[.000]	[.000]	[.000]	[.464]
	[4]	.666	.992	.219	.099	.747	.248	2.99	10.79
		(.117)	(.027)	(.087)	(.085)	(.082)	(.080)	(1.05)	
		[.000]	[.000]	[.000]	[.245]	[.000]	[.000]	[.004]	[.702]
	[5]	.799	.981	.256	.031	.745	.243	4.98	9.61
		(.238)	(.027)	(.123)	(.081)	(.078)	(.076)	(5.93)	
		[.001]	[.000]	[.000]	[.706]	[.000]	[.000]	[.402]	[.943]
	[6]	.642	.999	.499	.056	.562	.437	2.79	11.77
		(.141)	(.045)	(.146)	(.069)	(.056)	(.054)	(1.10)	
		[.000]	[.000]	[.000]	[.418]	[.000]	[.000]	[.000]	[.961]
3S-GMM	[1]	.584	.996	.338	.115	.581	.338	2.40	8.10
		(.060)	(.019)	(.056)	(.037)	(.060)	(.056)	(.348)	
		[.000]	[.000]	[.000]	[.002]	[.000]	[.000]	[.000]	[.424]
	[2]	.608	1.002	.357	.099	.609	.357	2.55	6.96
		(.065)	(.017)	(.066)	(.037)	(.065)	(.066)	(.424)	
		[.000]	[.000]	[.000]	[.009]	[.000]	[.000]	[.000]	[.541]
	[3]	.586	1.008	.274	.122	.592	.274	2.42	6.06
		(.099)	(.027)	(.097)	(.060)	(.096)	(.097)	(.582)	
		[.000]	[.000]	[.000]	[.042]	[.000]	[.000]	[.000]	[.417]
	[4]	.541	.983	.342	.142	.532	.342	2.18	12.48
		(.047)	(.014)	(.047)	(.031)	(.047)	(.047)	(.221)	
		[.000]	[.000]	[.000]	[.000]	[.000]	[.000]	[.000]	[.568]
	[5]	.558	.982	.375	.125	.548	.375	2.27	11.09
		(.042)	(.012)	(.039)	(.026)	(.042)	(.039)	(.215)	
		[.000]	[.000]	[.000]	[.000]	[.000]	[.000]	[.000]	[.891]
	[6]	.537	.986	.369	.137	.530	.369	2.16	13.11
		(.042)	(.014)	(.041)	(.027)	(.044)	(.041)	(.198)	
		[.000]	[.000]	[.000]	[.000]	[.000]	[.000]	[.000]	[.930]

Notes: standard errors are in parenthesis, p-values are in square brackets. The automatic lag selection of Newey and West (1994) is used to estimate the covariance matrix.

Table 7c: Hybrid Phillips Curve Estimates 1960Q1- 1997Q4, form I (κ=.13)

Method	Instrument set	θ	β	ω	λ	γ_f	γ_b	Duration	J-stat
GMM	[1]	.598	.996	.336	.108	.596	.336	2.49	11.83
		(.058)	(.016)	(.053)	(.033)	(.057)	(.053)	(.357)	
		[.000]	[.000]	[.000]	[.002]	[.000]	[.000]	[.000]	[.159]
	[2]	.607	.999	.369	.098	.607	.369	2.94	10.69
		(.060)	(.017)	(.065)	(.037)	(.066)	(.065)	(.427)	
		[.000]	[.000]	[.000]	[.009]	[.000]	[.000]	[.000]	[.220]
	[3]	.527	.999	.309	.158	.522	.309	2.09	7.11
		(.086)	(.029)	(.085)	(.057)	(.083)	(.085)	(.376)	
		[.000]	[.000]	[.000]	[.007]	[.000]	[.000]	[.000]	[.311]
	[4]	.567	.994	.252	.142	.563	.252	2.31	31.67
		(.042)	(.013)	(.042)	(.030)	(.042)	(.042)	(.226)	
		[.000]	[.000]	[.000]	[.000]	[.000]	[.000]	[.000]	[.004]
	[5]	.630	.986	.282	.101	.621	.282	2.70	45.37
		(.043)	(.010)	(.033)	(.025)	(.044)	(.033)	(.315)	
		[.000]	[.000]	[.000]	[.000]	[.000]	[.000]	[.000]	[.000]
	[6]	.592	.988	.254	.126	.585	.254	2.50	61.10
		(.038)	(.010)	(.037)	(.025)	(.038)	(.037)	(.225)	
		[.000]	[.000]	[.000]	[.000]	[.000]	[.000]	[.000]	[.000]
3S-GMM	[1]	.590	1.000	.315	.115	.590	.315	2.44	11.88
		(.059)	(.018)	(.056)	(.036)	(.058)	(.056)	(.352)	
		[.000]	[.000]	[.000]	[.002]	[.000]	[.000]	[.000]	[.156]
	[2]	.610	1.003	.341	.100	.612	.341	2.57	10.62
		(.064)	(.016)	(.065)	(.037)	(.064)	(.065)	(.422)	
		[.000]	[.000]	[.000]	[.008]	[.000]	[.000]	[.000]	[.224]
	[3]	.564	1.003	.306	.132	.566	.306	2.29	6.92
		(.079)	(.023)	(.075)	(.048)	(.077)	(.075)	(.417)	
		[.000]	[.000]	[.000]	[.007]	[.000]	[.000]	[.000]	[.328]
	[4]	.579	.993	.232	.137	.575	.232	2.38	29.40
		(.043)	(.013)	(.042)	(.030)	(.043)	(.042)	(.242)	
		[.000]	[.000]	[.000]	[.000]	[.000]	[.000]	[.000]	[.009]
	[5]	.613	.987	.259	.113	.605	.259	2.58	45.75
		(.040)	(.010)	(.032)	(.025)	(.041)	(.032)	(.268)	
		[.000]	[.000]	[.000]	[.000]	[.000]	[.000]	[.000]	[.000]
	[6]	.594	.986	.231	.129	.586	.231	2.46	59.23
		(.037)	(.010)	(.036)	(.025)	(.038)	(.036)	(.223)	
		[.000]	[.000]	[.000]	[.000]	[.000]	[.000]	[.000]	[.000]

Notes: standard errors are in parenthesis, p-values are in square brackets. The automatic lag selection of Newey and West (1994) and the Hall's correction (2000) are used to estimate the covariance matrix.

Table 8a: Hybrid Phillips Curve Estimates 1960Q1-1997Q4, form II (κ=.13)

Method	Instrument set	θ	β	ω	λ	γ_f	γ_b	Duration	J-stat
GMM	[1]	.646	.997	.472	.060	.576	.422	2.82	7.07
		(.068)	(.016)	(.069)	(.034)	(.031)	(.030)	(.538)	
		[.000]	[.000]	[.000]	[.079]	[.000]	[.000]	[.000]	[.528]
	[2]	.678	.998	.516	.042	.567	.432	3.11	6.19
		(.090)	(.018)	(.084)	(.034)	(.032)	(.031)	(.869)	
		[.000]	[.000]	[.000]	[.214]	[.000]	[.000]	[.000]	[.626]
	[3]	.687	.999	.557	.035	.553	.447	3.20	6.40
		(.107)	(.020)	(.118)	(.034)	(.040)	(.040)	(1.040)	
		[.000]	[.000]	[.000]	[.316]	[.000]	[.000]	[.002]	[.380]
	[4]	.649	.997	.553	.046	.539	.460	2.85	9.67
		(.070)	(.019)	(.074)	(.028)	(.028)	(.028)	(.569)	
		[.000]	[.000]	[.000]	[.101]	[.000]	[.000]	[.000]	[.786]
	[5]	.663	.997	.548	.043	.546	.453	2.97	9.76
		(.055)	(.019)	(.066)	(.024)	(.026)	(.026)	(.577)	
		[.000]	[.000]	[.000]	[.081]	[.000]	[.000]	[.000]	[.939]
	[6]	.649	.994	.542	.048	.543	.456	2.85	10.14
		(.055)	(.016)	(.058)	(.022)	(.025)	(.025)	(.443)	
		[.000]	[.000]	[.000]	[.033]	[.000]	[.000]	[.000]	[.984]
3S-GMM	[1]	.649	1.000	.423	.066	.606	.394	2.86	6.55
		(.062)	(.015)	(.059)	(.033)	(.030)	(.030)	(.506)	
		[.000]	[.000]	[.000]	[.050]	[.000]	[.000]	[.000]	[.586]
	[2]	.674	1.000	.477	.048	.586	.415	3.07	5.99
		(.081)	(.016)	(.075)	(.034)	(.032)	(.032)	(.772)	
		[.000]	[.000]	[.000]	[.162]	[.000]	[.000]	[.000]	[.648]
	[3]	.669	1.001	.459	.052	.593	.407	3.02	5.80
		(.078)	(.016)	(.086)	(.036)	(.040)	(.040)	(.713)	
		[.000]	[.000]	[.000]	[.147]	[.000]	[.000]	[.000]	[.445]
	[4]	.660	.995	.520	.048	.557	.441	2.94	9.57
		(.068)	(.018)	(.069)	(.028)	(.028)	(.027)	(.589)	
		[.000]	[.000]	[.000]	[.093]	[.000]	[.000]	[.000]	[.793]
	[5]	.723	1.001	.585	.024	.553	.447	3.62	9.75
		(.097)	(.020)	(.092)	(.024)	(.025)	(.025)	(1.273)	
		[.000]	[.000]	[.000]	[.325]	[.000]	[.000]	[.005]	[.940]
	[6]	.757	.994	.613	.017	.550	.448	4.12	10.11
		(.111)	(.019)	(.106)	(.022)	(.024)	(.024)	(1.892)	
		[.000]	[.000]	[.000]	[.441]	[.000]	[.000]	[.031]	[.985]

Notes: standard errors are in parenthesis, p-values are in square brackets. A 12-lag Newey-West estimate of the covariance matrix is used.

Table 8b: Hybrid Phillips Curve Estimates 1960Q1- 1997Q4, form II (κ=.13)

Method	Instrument set	θ	β	ω	λ	γ_f	γ_b	Duration	J-stat
GMM	[1]	.635	.996	.465	.064	.576	.422	2.74	8.23
		(.079)	(.019)	(.077)	(.041)	(.036)	(.036)	(.599)	
		[.000]	[.000]	[.000]	[.118]	[.000]	[.000]	[.000]	[.411]
	[2]	.668	.999	.492	.047	.575	.424	3.02	6.78
		(.100)	(.018)	(.092)	(.018)	(.037)	(.037)	(.919)	
		[.000]	[.000]	[.000]	[.003]	[.000]	[.000]	[.000]	[.559]
	[3]	.606	.999	.365	.101	.623	.376	2.54	5.79
		(.096)	(.024)	(.086)	(.064)	(.064)	(.064)	(.623)	
		[.000]	[.000]	[.000]	[.118]	[.000]	[.000]	[.000]	[.446]
	[4]	.654	.998	.538	.046	.548	.451	2.89	11.78
		(.090)	(.019)	(.090)	(.036)	(.032)	(.032)	(.756)	
		[.000]	[.000]	[.000]	[.210]	[.000]	[.000]	[.000]	[.623]
	[5]	.660	.996	.532	.045	.552	.446	2.94	10.37
		(.066)	(.017)	(.068)	(.026)	(.026)	(.026)	(.575)	
		[.000]	[.000]	[.000]	[.087]	[.000]	[.000]	[.000]	[.919]
	[6]	.647	.997	.521	.051	.553	.446	2.84	11.81
		(.061)	(.016)	(.066)	(.027)	(.025)	(.025)	(.494)	
		[.000]	[.000]	[.000]	[.068]	[.000]	[.000]	[.000]	[.961]
3S-GMM	[1]	.629	.999	.401	.079	.610	.389	2.70	7.73
		(.070)	(.017)	(.064)	(.043)	(.036)	(.036)	(.512)	
		[.000]	[.000]	[.000]	[.065]	[.000]	[.000]	[.000]	[.460]
	[2]	.661	1.000	.435	.058	.603	.397	2.96	6.80
		(.090)	(.018)	(.084)	(.044)	(.041)	(.041)	(.788)	
		[.000]	[.000]	[.000]	[.186]	[.000]	[.000]	[.000]	[.558]
	[3]	.594	1.008	.332	.116	.645	.358	2.47	5.70
		(.089)	(.024)	(.082)	(.068)	(.065)	(.066)	(.547)	
		[.000]	[.000]	[.000]	[.086]	[.000]	[.000]	[.000]	[.458]
	[4]	.654	.998	.481	.055	.576	.424	2.89	11.92
		(.081)	(.017)	(.079)	(.037)	(.034)	(.034)	(.679)	
		[.000]	[.000]	[.000]	[.144]	[.000]	[.000]	[.000]	[.613]
	[5]	.692	.996	.519	.038	.569	.429	3.24	10.20
		(.075)	(.016)	(.072)	(.027)	(.025)	(.025)	(.784)	
		[.000]	[.000]	[.000]	[.153]	[.000]	[.000]	[.000]	[.925]
	[6]	.666	.997	.494	.049	.573	.426	2.99	12.46
		(.069)	(.016)	(.072)	(.030)	(.029)	(.029)	(.617)	
		[.000]	[.000]	[.000]	[.106]	[.000]	[.000]	[.000]	[.947]

Notes: standard errors are in parenthesis, p-values are in square brackets. The automatic lag selection of Newey and West (1994) is used to estimate the covariance matrix.

Table 8c: Hybrid Phillips Curve Estimates 1960Q1 - 1997Q4, form II (κ=.13)

Method	Instrument set	θ	β	ω	λ	γ_f	γ_b	Duration	J-stat
GMM	[1]	.623	.999	.399	.083	.609	.390	2.66	11.97
		(.067)	(.018)	(.062)	(.042)	(.036)	(.036)	(.474)	
		[.000]	[.000]	[.000]	[.049]	[.000]	[.000]	[.000]	[.152]
	[2]	.654	.999	.427	.063	.605	.395	2.89	10.05
		(.084)	(.016)	(.076)	(.043)	(.038)	(.037)	(.706)	
		[.000]	[.000]	[.000]	[.146]	[.000]	[.000]	[.000]	[.261]
	[3]	.593	.999	.344	.115	.632	.367	2.46	6.52
		(.090)	(.024)	(.082)	(.065)	(.065)	(.064)	(.545)	
		[.000]	[.000]	[.000]	[.081]	[.000]	[.000]	[.000]	[.367]
	[4]	.684	.998	.413	.053	.622	.376	3.17	33.49
		(.084)	(.015)	(.070)	(.038)	(.033)	(.032)	(.842)	
		[.000]	[.000]	[.000]	[.165]	[.000]	[.000]	[.000]	[.002]
	[5]	.812	.994	.486	.014	.623	.375	5.33	41.87
		(.157)	(.014)	(.105)	(.028)	(.023)	(.023)	(.447)	
		[.000]	[.000]	[.000]	[.620]	[.000]	[.000]	[.000]	[.001]
	[6]	.731	.997	.401	.038	.645	.354	3.72	53.16
		(.085)	(.013)	(.066)	(.032)	(.027)	(.026)	(.119)	
		[.000]	[.000]	[.000]	[.236]	[.000]	[.000]	[.000]	[.000]
3S-GMM	[1]	.629	1.002	.373	.085	.628	.372	2.70	11.87
		(.067)	(.017)	(.061)	(.043)	(.037)	(.037)	(.489)	
		[.000]	[.000]	[.000]	[.050]	[.000]	[.000]	[.000]	[.157]
	[2]	.657	1.002	.406	.065	.619	.381	2.92	10.10
		(.084)	(.018)	(.079)	(.045)	(.042)	(.041)	(.723)	
		[.000]	[.000]	[.000]	[.151]	[.000]	[.000]	[.000]	[.258]
	[3]	.593	1.009	.330	.119	.647	.357	2.45	6.50
		(.089)	(.024)	(.082)	(.068)	(.066)	(.066)	(.536)	
		[.000]	[.000]	[.000]	[.082]	[.000]	[.000]	[.000]	[.368]
	[4]	.671	.995	.385	.063	.633	.365	3.04	31.12
		(.076)	(.014)	(.064)	(.039)	(.034)	(.034)	(.707)	
		[.000]	[.000]	[.000]	[.113]	[.000]	[.000]	[.000]	[.005]
	[5]	.761	.993	.443	.027	.629	.368	4.20	40.85
		(.101)	(.013)	(.073)	(.029)	(.024)	(.023)	(1.79)	
		[.000]	[.000]	[.000]	[.355]	[.000]	[.000]	[.021]	[.000]
	[6]	.707	.997	.380	.049	.649	.350	3.41	52.54
		(.072)	(.012)	(.058)	(.033)	(.027)	(.027)	(.835)	
		[.000]	[.000]	[.000]	[.132]	[.000]	[.000]	[.000]	[.000]

Notes: standard errors are in parenthesis, p-values are in square brackets. The automatic lag selection of Newey and West (1994) and the Hall's correction (2000) are used to estimate the covariance matrix.

Table 9: Hybrid Phillips Curve Estimates 1960Q1 - 1997Q4, form I (κ=.13)

Method	Instrument set	θ	β	ω	λ	γ_f	γ_b	Duration	J-stat
GMM	*[1]*	*.527*	*.999*	*.309*	*.158*	*.522*	*.309*	*2.09*	*7.11*
		(.086)	*(.029)*	*(.085)*	*(.057)*	*(.083)*	*(.085)*	*(.376)*	
		[.000]	*[.000]*	*[.000]*	*[.007]*	*[.000]*	*[.000]*	*[.000]*	*[.311]*
	[2]	.517	.997	.278	.169	.516	.278	2.07	7.91
		(.086)	(.034)	(.097)	(.062)	(.087)	(.097)	(.368)	
		[.000]	[.000]	[.005]	[.007]	[.000]	[.000]	[.000]	[.442]
	[3]	.512	.999	.223	.185	.512	.223	2.05	10.97
		(.072)	(.033)	(.091)	(.056)	(.072)	(.091)	(.303)	
		[.000]	[.000]	[.016]	[.001]	[.000]	[.000]	[.000]	[.359]
	[4]	.487	.986	.222	.207	.480	.222	1.97	21.15
		(.057)	(.023)	(.064)	(.045)	(.054)	(.064)	(.216)	
		[.000]	[.000]	[.000]	[.000]	[.000]	[.000]	[.000]	[.103]
	[5]	.511	.999	.209	.189	.511	.209	2.04	12.79
		(.068)	(.030)	(.089)	(.054)	(.069)	(.089)	(.285)	
		[.000]	[.000]	[.000]	[.000]	[.000]	[.021]	[.000]	[.385]
CUE	*[1]*	*.620*	*.999*	*.322*	*.103*	*.658*	*.341*	*2.63*	*5.64*
		(.130)	*(.035)*	*(.106)*	*(.093)*	*(.085)*	*(.082)*	*(.906)*	
		[.000]	*[.000]*	*[.000]*	*[.271]*	*[.000]*	*[.000]*	*[.000]*	*[.464]*
	[2]	.595	.963	.392	.105	.573	.392	2.47	4.91
		(.157)	(.047)	(.133)	(.090)	(.156)	(.133)	(.960)	
		[.000]	[.000]	[.000]	[.247]	[.000]	[.004]	[.012]	[.767]
	[3]	.571	.997	.418	.107	.570	.418	2.33	8.27
		(.136)	(.048)	(.120)	(.079)	(.143)	(.120)	(.741)	
		[.000]	[.000]	[.000]	[.176]	[.000]	[.000]	[.000]	[.602]
	[4]	.668	.999	.331	.073	.668	.331	3.02	12.33
		(.158)	(.034)	(.116)	(.074)	(.165)	(.115)	(1.441)	
		[.000]	[.000]	[.000]	[.321]	[.000]	[.000]	[.039]	[.464]
	[5]	.630	.966	.414	.084	.609	.414	2.71	10.07
		(.157)	(.049)	(.145)	(.079)	(.153)	(.145)	(1.164)	
		[.000]	[.000]	[.000]	[.284]	[.000]	[.005]	[.022]	[.610]
3S-GMM	*[1]*	*.564*	*1.003*	*.306*	*.132*	*.566*	*.306*	*2.29*	*6.92*
		(.079)	*(.023)*	*(.075)*	*(.048)*	*(.077)*	*(.075)*	*(.417)*	
		[.000]	*[.000]*	*[.000]*	*[.007]*	*[.000]*	*[.000]*	*[.000]*	*[.328]*
	[2]	.549	1.009	.210	.159	.554	.210	2.22	8.32
		(.086)	(.030)	(.100)	(.062)	(.087)	(.101)	(.421)	
		[.000]	[.000]	[.039]	[.012]	[.000]	[.038]	[.000]	[.403]
	[3]	.595	.997	.307	.114	.594	.306	2.47	9.74
		(.089)	(.028)	(.095)	(.051)	(.086)	(.095)	(.544)	
		[.000]	[.000]	[.001]	[.028]	[.000]	[.000]	[.000]	[.463]
	[4]	.583	.974	.263	.132	.568	.263	2.40	17.61
		(.075)	(.023)	(.079)	(.048)	(.072)	(.079)	(.433)	
		[.000]	[.000]	[.000]	[.007]	[.000]	[.001]	[.000]	[.347]
	[5]	.578	1.014	.221	.136	.586	.221	2.37	11.35
		(.084)	(.030)	(.102)	(.056)	(.084)	(.103)	(.470)	
		[.000]	[.000]	[.033]	[.017]	[.000]	[.000]	[.000]	[.498]

Notes: standard errors are in parenthesis, p-values are in square brackets. The automatic lag selection of Newey and West (1994) and the Hall's correction (2000) are used to estimate the covariance matrix for the GMM and 3S-GMM estimator. The automatic lag selection procedure is applied for the CUE.

Table 10: Hybrid Phillips Curve Estimates 1960Q1- 1997Q4, form I (κ=.13)

Method	Instrument set	θ	β	ω	λ	γ_f	γ_b	Duration	J-stat
GMM	*[1]*	*.593*	*.999*	*.344*	*.115*	*.632*	*.367*	*2.46*	*6.52*
		(.090)	*(.024)*	*(.082)*	*(.065)*	*(.065)*	*(.064)*	*(.545)*	
		[.000]	*[.000]*	*[.000]*	*[.081]*	*[.000]*	*[.000]*	*[.000]*	*[.367]*
	[2]	.613	.999	.332	.106	.648	.352	2.58	7.22
		(.115)	(.029)	(.103)	(.083)	(.079)	(.078)	(.766)	
		[.000]	[.000]	[.002]	[.202]	[.000]	[.000]	[.000]	[.513]
	[3]	.574	.999	.378	.118	.603	.397	2.35	11.92
		(.079)	(.025)	(.083)	(.062)	(.058)	(.058)	(.434)	
		[.000]	[.000]	[.000]	[.057]	[.000]	[.000]	[.000]	[.290]
	[4]	.587	.974	.492	.083	.534	.459	2.43	19.02
		(.119)	(.039)	(.114)	(.071)	(.058)	(.058)	(.706)	
		[.000]	[.000]	[.000]	[.245]	[.000]	[.000]	[.000]	[.268]
	[5]	.592	.999	.376	.107	.611	.389	2.45	11.85
		(.102)	(.031)	(.105)	(.075)	(.072)	(.076)	(.611)	
		[.000]	[.000]	[.000]	[.156]	[.000]	[.000]	[.000]	[.457]
3S-GMM	*[1]*	*.593*	*1.009*	*.330*	*.119*	*.647*	*.357*	*2.45*	*6.50*
		(.089)	*(.024)*	*(.082)*	*(.068)*	*(.066)*	*(.066)*	*(.536)*	
		[.000]	*[.000]*	*[.000]*	*[.082]*	*[.000]*	*[.000]*	*[.000]*	*[.368]*
	[2]	.593	1.005	.318	.123	.653	.349	2.46	7.40
		(.104)	(.028)	(.097)	(.083)	(.079)	(.078)	(.627)	
		[.000]	[.000]	[.001]	[.141]	[.000]	[.000]	[.000]	[.494]
	[3]	.587	1.013	.339	.119	.641	.365	2.42	9.77
		(.097)	(.030)	(.099)	(.078)	(.075)	(.073)	(.570)	
		[.000]	[.000]	[.000]	[.127]	[.000]	[.000]	[.000]	[.461]
	[4]	.625	1.003	.313	.102	.668	.333	2.67	14.88
		(.124)	(.033)	(.111)	(.093)	(.083)	(.081)	(.883)	
		[.000]	[.000]	[.000]	[.271]	[.000]	[.000]	[.000]	[.533]
	[5]	.580	1.004	.332	.128	.638	.364	2.38	11.57
		(.090)	(.029)	(.095)	(.076)	(.074)	(.073)	(.513)	
		[.000]	[.000]	[.000]	[.010]	[.000]	[.000]	[.000]	[.480]

Notes: standard errors are in parenthesis, p-values are in square brackets. The automatic lag selection of Newey and West (1994) and the Hall's correction (2000) are used to estimate the covariance matrix.

Table 12a: Hybrid Phillips Curve Estimates 1960Q1- 1997Q4, revised data, form I (κ=.13)

Method	Instrument set	θ	β	ω	λ	γ_f	γ_b	Duration	J-stat
GMM	[1]	.608	.980	.311	.109	.596	.311	2.55	5.11
		(.101)	(.043)	(.107)	(.054)	(.106)	(.107)	(.655)	
		[.000]	[.000]	[.000]	[.046]	[.000]	[.000]	[.000]	[.530]
	[2]	.624	.981	.298	.103	.612	.298	2.66	6.05
		(.103)	(.040)	(.107)	(.054)	(.109)	(.107)	(.725)	
		[.000]	[.000]	[.006]	[.062]	[.000]	[.000]	[.000]	[.641]
	[3]	.584	.986	.319	.119	.576	.319	2.41	8.41
		(.093)	(.042)	(.103)	(.052)	(.097)	(.103)	(.541)	
		[.000]	[.000]	[.000]	[.022]	[.000]	[.000]	[.000]	[.583]
	[4]	.646	.960	.222	.104	.621	.222	2.83	22.63
		(.067)	(.020)	(.070)	(.039)	(.071)	(.070)	(.539)	
		[.000]	[.000]	[.032]	[.008]	[.000]	[.002]	[.000]	[.124]
	[5]	.617	.980	.257	.112	.605	.257	2.62	12.02
		(.083)	(.028)	(.093)	(.045)	(.085)	(.093)	(.566)	
		[.000]	[.000]	[.000]	[.013]	[.000]	[.006]	[.000]	[.444]
CUE	[1]	.681	.979	.302	.076	.681	.309	3.14	4.48
		(.120)	(.038)	(.107)	(.069)	(.090)	(.089)	(1.186)	
		[.000]	[.000]	[.006]	[.261]	[.000]	[.000]	[.000]	[.612]
	[2]	.709	.980	.299	.062	.692	.298	3.44	6.05
		(.133)	(.036)	(.108)	(.066)	(.088)	(.087)	(1.580)	
		[.000]	[.000]	[.006]	[.353]	[.000]	[.000]	[.030]	[.641]
	[3]	.677	.972	.305	.078	.674	.312	3.10	7.11
		(.115)	(.037)	(.106)	(.064)	(.087)	(.088)	(1.106)	
		[.000]	[.000]	[.000]	[.227]	[.000]	[.000]	[.006]	[.715]
	[4]								
		-	-	-	-	-	-	-	-
	[5]	.702	.984	.365	.055	.650	.343	3.37	8.78
		(.141)	(.039)	(.119)	(.063)	(.084)	(.084)	(1.60)	
		[.000]	[.000]	[.000]	[.386]	[.000]	[.000]	[.037]	[.721]
3S-GMM	[1]	.651	.990	.310	.086	.644	.310	2.86	4.78
		(.114)	(.042)	(.115)	(.055)	(.120)	(.115)	(.937)	
		[.000]	[.000]	[.008]	[.123]	[.000]	[.008]	[.003]	[.572]
	[2]	.664	.981	.274	.085	.652	.274	2.98	5.56
		(.111)	(.036)	(.113)	(.055)	(.117)	(.113)	(.992)	
		[.000]	[.000]	[.000]	[.127]	[.000]	[.000]	[.003]	[.697]
	[3]	.682	.969	.347	.070	.662	.347	3.15	7.63
		(.125)	(.043)	(.120)	(.054)	(.129)	(.120)	(1.25)	
		[.000]	[.000]	[.000]	[.193]	[.000]	[.000]	[.013]	[.664]
	[4]	.643	.966	.246	.102	.621	.246	2.80	20.07
		(.076)	(.024)	(.081)	(.041)	(.077)	(.081)	(.594)	
		[.000]	[.000]	[.003]	[.015]	[.000]	[.000]	[.000]	[.217]
	[5]	.654	.976	.280	.090	.638	.280	2.89	11.00
		(.093)	(.027)	(.098)	(.045)	(.095)	(.098)	(.776)	
		[.000]	[.000]	[.000]	[.046]	[.000]	[.005]	[.000]	[.529]

Notes: standard errors are in parenthesis, p-values are in square brackets. The automatic lag selection of Newey and West (1994) and the Hall's correction are used to estimate the covariance matrix.

Table 12a (continued): Hybrid Phillips Curve Estimates 1960Q1- 1997Q4, revised data, form II (κ=.13)

Method	Instrument set	θ	β	ω	λ	γ_f	γ_b	Duration	J-stat
GMM	[1]	.653	.981	.345	.082	.645	.347	2.89	4.83
		(.123)	(.045)	(.121)	(.070)	(.097)	(.096)	(1.026)	
		[.000]	[.000]	[.005]	[.243]	[.000]	[.000]	[.005]	[.565]
	[2]	.674	.981	.343	.072	.653	.339	3.07	5.74
		(.131)	(.042)	(.124)	(.069)	(.097)	(.096)	(1.23)	
		[.000]	[.000]	[.000]	[.303]	[.000]	[.000]	[.014]	[.676]
	[3]	.673	.985	.319	.075	.670	.322	3.06	7.59
		(.124)	(.041)	(.120)	(.068)	(.096)	(.096)	(1.17)	
		[.000]	[.000]	[.000]	[.272]	[.000]	[.000]	[.010]	[.668]
	[4]	.757	.965	.368	.037	.655	.330	4.11	21.07
		(.119)	(.023)	(.096)	(.042)	(.059)	(.060)	(2.02)	
		[.000]	[.000]	[.000]	[.374]	[.000]	[.000]	[.043]	[.176]
	[5]	.680	.959	.309	.078	.665	.315	3.13	10.93
		(.106)	(.028)	(.103)	(.055)	(.087)	(.088)	(1.03)	
		[.000]	[.000]	[.000]	[.164]	[.000]	[.000]	[.000]	[.534]
3S-GMM	[1]	.644	.992	.310	.093	.670	.326	2.81	4.85
		(.113)	(.043)	(.115)	(.071)	(.098)	(.097)	(.891)	
		[.000]	[.000]	[.007]	[.131]	[.000]	[.001]	[.002]	[.562]
	[2]	.661	.984	.332	.076	.660	.333	3.01	5.77
		(.126)	(.041)	(.121)	(.070)	(.098)	(.096)	(1.14)	
		[.000]	[.000]	[.000]	[.276]	[.000]	[.000]	[.009]	[.674]
	[3]	.669	.971	.342	.076	.646	.341	3.02	7.60
		(.126)	(.043)	(.122)	(.068)	(.068)	(.095)	(1.15)	
		[.000]	[.000]	[.000]	[.268]	[.000]	[.000]	[.009]	[.667]
	[4]	.726	.980	.337	.050	.673	.318	3.65	18.37
		(.113)	(.027)	(.101)	(.047)	(.071)	(.072)	(1.52)	
		[.000]	[.000]	[.000]	[.301]	[.000]	[.000]	[.017]	[.302]
	[5]	.685	.978	.326	.069	.665	.3241	3.18	10.78
		(.111)	(.028)	(.107)	(.054)	(.087)	(.087)	(1.12)	
		[.000]	[.000]	[.000]	[.201]	[.000]	[.000]	[.000]	[.547]

Notes: standard errors are in parenthesis, p-values are in square brackets. The automatic lag selection of Newey and West (1994) and the Hall's correction are used to estimate the covariance matrix.

Table 13: Robustness to inflation specification, 1960Q1- 1997Q4, form II (κ=.13)

Method	Instrument set	θ	β	ω	λ	γ_f	γ_b	φ	D	J-stat
GMM	[1]	.645	.999	.418	.069	.607	.393	.001	2.82	2.76
		(.152)	(.213)	(.143)	(.054)	(.065)	(.096)	(.073)	(1.21)	
		[.000]	[.000]	[.004]	[.208]	[.000]	[.000]	[.987]	[.021]	[.429]
	[2]	.608	.999	.422	.086	.590	.392	.000	2.55	12.43
		(.142)	(.208)	(.132)	(.057)	(.063)	(.140)	(.069)	(.930)	
		[.000]	[.000]	[.004]	[.134]	[.000]	[.006]	[.998]	[.007]	[.087]
	[3]	.669	.999	.392	.063	.630	.370	.002	3.02	6.66
		(.149)	(.186)	(.140)	(.065)	(.065)	(.097)	(.070)	(1.36)	
		[.000]	[.000]	[.000]	[.242]	[.000]	[.000]	[.981]	[.028]	[.247]
	[4]	.648	.999	.622	.037	.510	.490	-.007	2.84	27.12
		(.256)	(.381)	(.191)	(.050)	(.056)	(.080)	(.071)	(2.07)	
		[.012]	[.009]	[.001]	[.464]	[.000]	[.000]	[.930]	[.171]	[.012]
	[5]	.612	.999	.412	.087	.598	.402	-.001	2.57	15.11
		(.146)	(.209)	(.130)	(.057)	(.068)	(.094)	(.071)	(.968)	
		[.000]	[.000]	[.002]	[.132]	[.000]	[.000]	[.983]	[.009]	[.088]
CUE	[1]	.650	.999	.380	.074	.631	.369	.003	2.86	2.33
		(.201)	(.240)	(.147)	(.095)	(.114)	(.099)	(.091)	(1.64)	
		[.002]	[.000]	[.000]	[.441]	[.000]	[.000]	[.978]	[.084]	[.506]
	[2]	.644	.999	.246	.107	.723	.276	.004	2.81	7.19
		(.147)	(.170)	(.118)	(.093)	(.120)	(.107)	(.099)	(1.16)	
		[.000]	[.000]	[.040]	[.251]	[.000]	[.011]	[.962]	[.017]	[.409]
	[3]	.658	.999	.288	.088	.696	.304	0.005	2.93	4.27
		(.168)	(.184)	(.130)	(.094)	(.116)	(.105)	(.087)	(1.44)	
		[.000]	[.000]	[.000]	[.352]	[.000]	[.000]	[.950]	[.043]	[.511]
	[4]	.766	.999	.282	.012	.505	.489	-.002	2.97	13.55
		(.102)	(.181)	(.121)	(.100)	(.103)	(.080)	(.098)	(1.47)	
		[.000]	[.000]	[.001]	[.980]	[.000]	[.000]	[.960]	[.041]	[.405]
	[5]									
		-	-	-	-	-	-	-	-	-
3S-GMM	[1]	.644	1.013	.364	.077	.646	.360	-.004	2.81	5.32
		(.122)	(.168)	(.122)	(.050)	(.042)	(.074)	(.064)	(.969)	
		[.000]	[.000]	[.000]	[.127]	[.000]	[.000]	[.953]	[.004]	[.377]
	[2]	.622	1.060	.380	.079	.648	.374	-.019	2.65	3.80
		(.117)	(.179)	(.103)	(.047)	(.050)	(.074)	(.060)	(.819)	
		[.000]	[.000]	[.000]	[.098]	[.000]	[.000]	[.745]	[.002]	[.578]
	[3]	.568	1.016	.459	.074	.616	.430	-.042	2.32	2.26
		(.167)	(.176)	(.153)	(.054)	(.065)	(.097)	(.074)	(.897)	
		[.000]	[.000]	[.000]	[.169]	[.000]	[.000]	[.565]	[.011]	[.521]
	[4]	.694	.944	.284	.078	.677	.294	.032	3.27	28.73
		(.098)	(.099)	(.069)	(.044)	(.030)	(.061)	(.054)	(1.05)	
		[.000]	[.000]	[.000]	[.077]	[.000]	[.000]	[.553]	[.002]	[.002]
	[5]	.714	.987	.324	.055	.681	.313	.007	3.50	34.41
		(.097)	(.100)	(.071)	(.033)	(.029)	(.056)	(.046)	(1.19)	
		[.000]	[.000]	[.000]	[.096]	[.000]	[.000]	[.877]	[.096]	[.003]

Notes: standard errors are in parenthesis, p-values are in square brackets. The automatic lag selection of Newey and West (1994) and the Hall's correction are used to estimate the covariance matrix for the 2S-GMM and 3S-GMM. The first procedure is only used for the CUE.

Table 14: Robustness to inflation forecasting measures, 1960Q1- 1997Q4, form II(κ=.13)

Method	Instrument set	θ	β	ω	λ	γ_f	γ_b	Duration	J-stat
GMM	[1]	.325	.999	.238	.616	.577	.423	1.48	16.65
		(.034)	(.052)	(.114)	(.198)	(.144)	(.129)	(.075)	
		[.000]	[.000]	[.000]	[.002]	[.000]	[.000]	[.000]	[.011]
	[2]	.323	.993	.307	.503	.510	.487	1.50	17.91
		(.037)	(.053)	(.106)	(.142)	(.114)	(.103)	(.081)	
		[.000]	[.000]	[.005]	[.000]	[.000]	[.000]	[.000]	[.056]
	[3]	.293	.937	.443	.391	.378	.608	1.42	21.95
		(.054)	(.113)	(.177)	(.175)	(.144)	(.132)	(.108)	
		[.000]	[.000]	[.013]	[.028]	[.000]	[.000]	[.000]	[.502]
	[4]	.242	.988	.571	.317	.274	.713	1.32	43.17
		(.043)	(.107)	(.117)	(.102)	(.086)	(.081)	(.073)	
		[.000]	[.000]	[.000]	[.002]	[.002	[.000]	[.000]	[.000]
	[5]	.235	.987	.522	.384	.289	.698	1.31	28.13
		(.055)	(.130)	(.144)	(.136)	(.117)	(.109)	(.094)	
		[.000]	[.000]	[.000]	[.006]	[.016]	[.000]	[.000]	[.000]
CUE	[1]	.358	.941	.279	.487	.533	.442	1.56	7.87
		(.048)	(.052)	(.126)	(.151)	(.139)	(.135)	(.116)	
		[.000]	[.000]	[.000]	[.002]	[.000]	[.001]	[.000]	[.248]
	[2]	.337	.917	.376	.406	.440	.535	1.51	8.30
		(.053)	(.073)	(.143)	(.139)	(.131)	(.127)	(.120)	
		[.000]	[.000]	[.000]	[.001]	[.001]	[.000]	[.000]	[.599]
	[3]								
		-	-	-	-	-	-	-	-
	[4]	.309	.946	.532	.275	.351	.640	1.45	13.21
		(.057)	(.091)	(.159)	(.117)	(.108)	(.105)	(.119)	
		[.000]	[.000]	[.001]	[.021]	[.002]	[.000]	[.000]	[.657]
	[5]	.385	.992	.522	.327	.753	241	1.63	8.51
		(.034)	(.026)	(.117)	(.112)	(.138)	(.132)	(.089)	
		[.000]	[.000]	[.000]	[.004]	[.000]	[.000]	[.000]	[.743]
3S-GMM	[1]	.345	.993	.214	.606	.614	.382	1.53	15.79
		(.036)	(.047)	(.108)	(.195)	(.142)	(.127)	(.084)	
		[.000]	[.000]	[.000]	[.000]	[.000]	[.000]	[.000]	[.015]
	[2]	.327	.971	.325	.478	.489	.501	1.49	17.28
		(.039)	(.058)	(.108)	(.137)	(.111)	(.101)	(.085)	
		[.000]	[.000]	[.003]	[.000]	[.000]	[.000]	[.000]	[.068]
	[3]	.336	1.003	.213	.630	.614	.387	1.51	19.37
		(.034)	(.042)	(.096)	(.175)	(.129)	(.117)	(.077)	
		[.000]	[.000]	[.028]	[.000]	[.000]	[.000]	[.000]	[.013]
	[4]	.362	.968	.231	.537	.593	.392	1.56	53.22
		(.028)	(.029)	(.061)	(.099)	(.078)	(.071)	(.069)	
		[.000]	[.000]	[.000]	[.000]	[.000]	[.000]	[.000]	[.000]
	[5]	.298	1.012	.301	.569	.503	.502	1.43	23.30
		(.035)	(.049)	(.098)	(.133)	(.114)	(.104)	(.071)	
		[.000]	[.000]	[.000]	[.000]	[.000]	[.000]	[.000]	[.025]

Notes: standard errors are in parenthesis, p-values are in square brackets. The automatic lag selection of Newey and West (1994) and the Hall's correction are used to estimate the covariance matrix for the 2S-GMM and the 3S-GMM. The first procedure is only used for the CUE.

Table 15: Hybrid Phillips Curve Estimates 1960Q1- 2001Q4, form I (κ=.13)

Method	Instrument set	θ	β	ω	λ	γ_f	γ_b	Duration	J-stat
GMM	[1]	.641	.987	.339	.087	.633	.339	2.79	5.24
		(.098)	(.043)	(.113)	(.047)	(.099)	(.113)	(.766)	
		[.000]	[.000]	[.003]	[.066]	[.000]	[.003]	[.000]	[.514]
	[2]	.658	.985	.331	.080	.649	.331	2.93	6.17
		(.101)	(.039)	(.113)	(.047)	(.103)	(.113)	(.869)	
		[.000]	[.000]	[.000]	[.091]	[.000]	[.004]	[.000]	[.628]
	[3]	.638	.991	.347	.087	.633	.347	2.76	7.87
		(.098)	(.042)	(.112)	(.046)	(.098)	(.112)	(.747)	
		[.000]	[.000]	[.000]	[.062]	[.000]	[.002]	[.000]	[.642]
	[4]	.702	.973	.246	.071	.683	.246	3.35	18.57
		(.068)	(.019)	(.079)	(.032)	(.069)	(.079)	(.762)	
		[.000]	[.000]	[.000]	[.028]	[.000]	[.000]	[.000]	[.292]
	[5]	.614	.984	.295	.082	.653	.295	2.97	10.82
		(.084)	(.027)	(.098)	(.039)	(.083)	(.097)	(.737)	
		[.000]	[.000]	[.000]	[.033]	[.000]	[.000]	[.000]	[.544]
CUE	[1]	.712	.981	.343	.054	.665	.327	3.48	4.64
		(.122)	(.038)	(.115)	(.053)	(.082)	(.083)	(1.48)	
		[.000]	[.000]	[.003]	[.316]	[.000]	[.000]	[.020]	[.590]
	[2]	.737	.979	.348	.044	.669	.323	3.81	6.30
		(.136)	(.037)	(.117)	(.053)	(.079)	(.080)	(1.97)	
		[.000]	[.000]	[.000]	[.408]	[.000]	[.000]	[.055]	[.614]
	[3]	.726	.975	.338	.050	.669	.319	3.66	6.81
		(.126)	(.037)	(.116)	(.053)	(.081)	(.083)	(1.69)	
		[.000]	[.000]	[.000]	[.345]	[.000]	[.000]	[.031]	[.743]
	[4]	.796	.983	.330	.026	.698	.294	4.91	12.32
		(.165)	(.033)	(.125)	(.048)	(.078)	(.077)	(1.39)	
		[.000]	[.000]	[.000]	[.588]	[.000]	[.000]	[.000]	[.721]
	[5]	.754	.975	.343	.039	.674	.314	4.07	8.55
		(.141)	(.034)	(.115)	(.051)	(.076)	(.078)	(2.33)	
		[.000]	[.000]	[.000]	[.449]	[.000]	[.000]	[.083]	[.740]
3S-GMM	[1]	.679	.994	.351	.068	.675	.351	3.12	4.95
		(.113)	(.043)	(.121)	(.048)	(.114)	(.121)	(1.10)	
		[.000]	[.000]	[.004]	[.159]	[.000]	[.004]	[.005]	[.551]
	[2]	.694	.987	.315	.066	.685	.315	3.27	7.16
		(.096)	(.028)	(.105)	(.039)	(.094)	(.106)	(1.02)	
		[.000]	[.000]	[.000]	[.095]	[.000]	[.003]	[.002]	[.520]
	[3]	.699	.973	.361	.061	.680	.362	3.33	7.22
		(.118)	(.042)	(.122)	(.047)	(.118)	(.122)	(1.31)	
		[.000]	[.000]	[.000]	[.196]	[.000]	[.004]	[.012]	[.704]
	[4]	.712	.982	.272	.063	.700	.272	3.47	16.67
		(.084)	(.024)	(.093)	(.036)	(.084)	(.093)	(1.02)	
		[.000]	[.000]	[.004]	[.083]	[.000]	[.004]	[.000]	[.408]
	[5]	.690	.983	.323	.067	.679	.323	3.23	10.03
		(.094)	(.028)	(.102)	(.038)	(.092)	(.102)	(.977)	
		[.000]	[.000]	[.002]	[.081]	[.000]	[.000]	[.001]	[.614]

Notes: standard errors are in parenthesis, p-values are in square brackets. The automatic lag selection of Newey and West (1994) and the Hall's correction are used to estimate the covariance matrix.

Table 15 (continued): Hybrid Phillips Curve Estimates 1960Q1- 2001Q4, form II (κ=.13)

Method	Instrument set	θ	β	ω	λ	γ_f	γ_b	Duration	J-stat
GMM	[1]	.704	.986	.368	.053	.649	.345	3.38	4.86
		(.130)	(.044)	(.131)	(.056)	(.089)	(.089)	(1.48)	
		[.000]	[.000]	[.005]	[.342]	[.000]	[.000]	[.024]	[.561]
	[2]	.716	.966	.338	.056	.662	.323	3.52	7.14
		(.107)	(.029)	(.107)	(.045)	(.089)	(.082)	(1.33)	
		[.000]	[.000]	[.000]	[.222]	[.000]	[.000]	[.009]	[.522]
	[3]	.712	.988	.351	.052	.664	.331	3.48	7.23
		(.129)	(.041)	(.128)	(.055)	(.088)	(.089)	(1.56)	
		[.000]	[.000]	[.000]	[.349]	[.000]	[.000]	[.027]	[.703]
	[4]	.784	.953	.428	.026	.624	.358	4.63	19.35
		(.118)	(.025)	(.109)	(.031)	(.059)	(.058)	(2.53)	
		[.000]	[.000]	[.000]	[.404]	[.000]	[.000]	[.068]	[.251]
	[5]	.721	.964	.339	.053	.661	.322	3.59	9.85
		(.107)	(.028)	(.107)	(.044)	(.079)	(.081)	(1.38)	
		[.000]	[.000]	[.000]	[.229]	[.000]	[.000]	[.010]	[.629]
3S-GMM	[1]	.676	.995	.338	.069	.665	.333	3.09	4.97
		(.111)	(.043)	(.119)	(.057)	(.089)	(.090)	(1.06)	
		[.000]	[.000]	[.005]	[.225]	[.000]	[.000]	[.004]	[.547]
	[2]	.697	.987	.379	.055	.642	.353	3.30	6.06
		(.127)	(.043)	(.131)	(.056)	(.088)	(.088)	(1.38)	
		[.000]	[.000]	[.000]	[.327]	[.000]	[.000]	[.018]	[.641]
	[3]	.721	.973	.357	.050	.655	.334	3.58	7.16
		(.134)	(.041)	(.130)	(.056)	(.088)	(.089)	(1.71)	
		[.000]	[.000]	[.000]	[.369]	[.000]	[.000]	[.038]	[.710]
	[4]	.771	.987	.369	.030	.669	.325	4.37	15.51
		(.126)	(.028)	(.113)	(.038)	(.069)	(.071)	(2.41)	
		[.000]	[.000]	[.001]	[.428]	[.000]	[.000]	[.072]	[.487]
	[5]	.726	.982	.371	.046	.652	.339	3.64	9.75
		(.111)	(.030)	(.112)	(.043)	(.078)	(.079)	(1.53)	
		[.000]	[.000]	[.001]	[.286]	[.000]	[.000]	[.018]	[.638]

Notes: standard errors are in parenthesis, p-values are in square brackets. The automatic lag selection of Newey and West (1994) and the Hall's correction are used to estimate the covariance matrix.

Figure 2: Different measures of real marginal costs and revisions

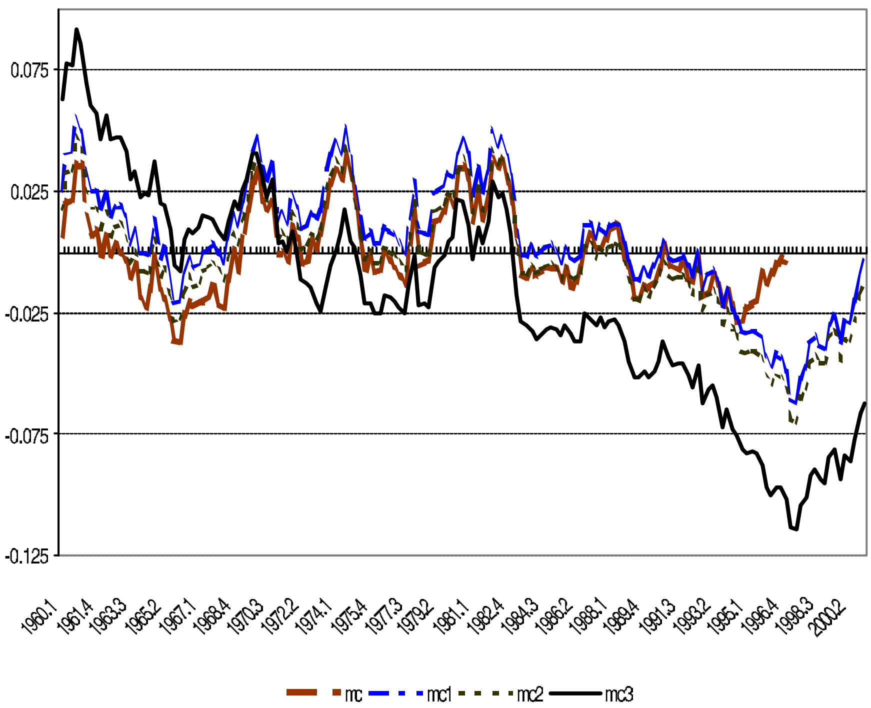

Figure 3: Inflation forecasting measures