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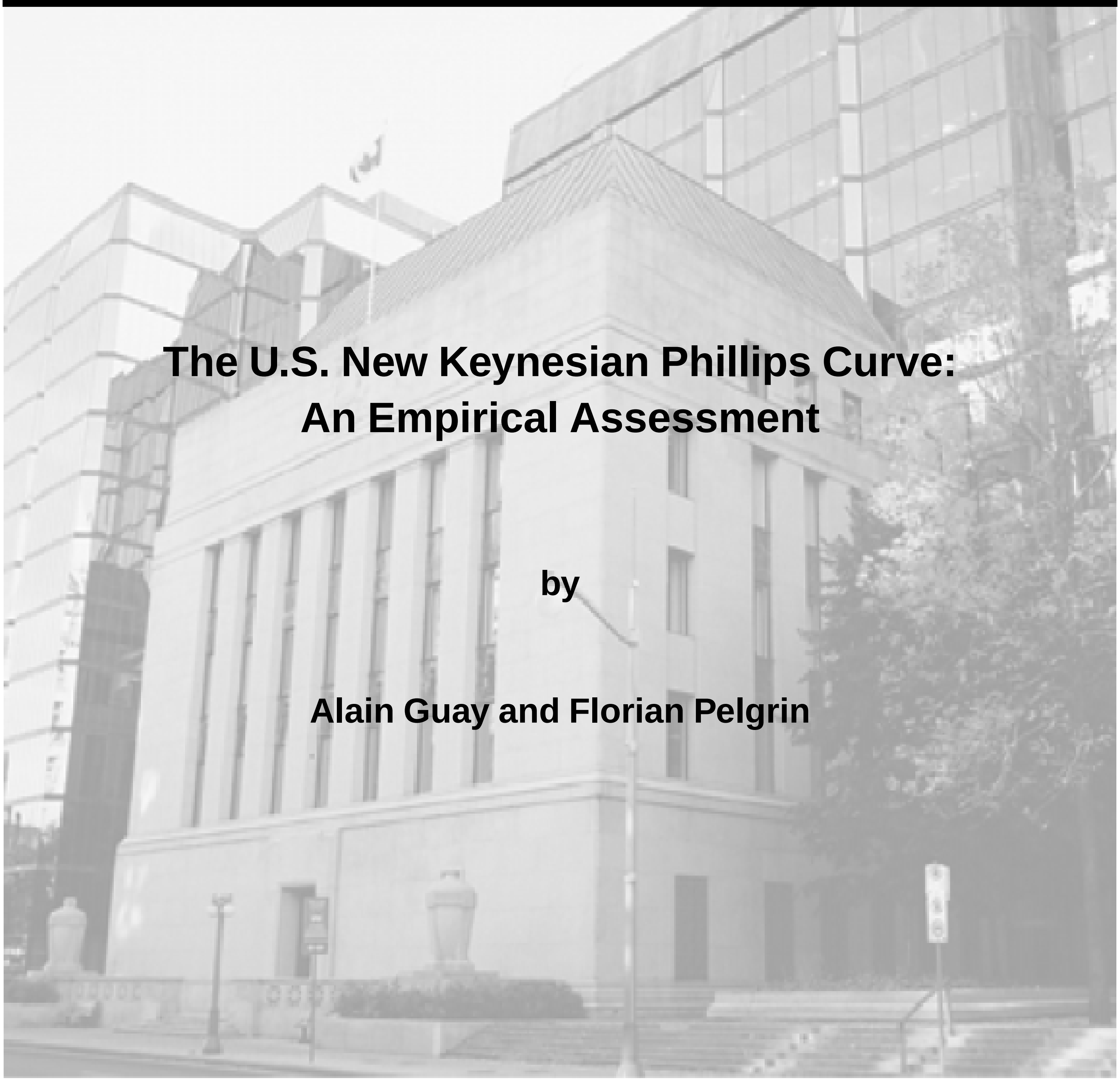
Working Paper 2004-35 / Document de travail 2004-35



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ISSN 1192-5434

Printed in Canada on recycled paper

Bank of Canada Working Paper 2004-35

September 2004

The U.S. New Keynesian Phillips Curve: An Empirical Assessment

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Acknowledgements

We would like to thank Stéphane Adjemian, Brian Campbell, Antoine D'Autume, Pierre Duguay, Patrick Fève, Jean-Olivier Hairault, Éric Jondeau, Glen Keenleyside, Richard Luger, Sophocles Mavroeidis, Benoît Perron, Éric Renault, and Gregor Smith for helpful comments and suggestions, as well as the participants of the Société canadienne de science économique (Quebec, 2004) the Canadian Economic Association (Toronto, 2004), the North American Summer Meeting of the Econometric Society (Brown University, 2004), the Society of Computational Economics (Amsterdam, 2004), the EEA-ESEM meeting (Madrid, 2004), the Seminar of Macroeconomics (Paris, 2004), the participants of the workshops at the Bank of Canada (Ottawa, 2004), and the OFCE (Paris, 2004).

Abstract

The authors examine the evidence presented by Galí and Gertler (1999) and Galí, Gertler, and Lopez-Salido (2001, 2003) that the inflation dynamics in the United States can be well-described by the New Keynesian Phillips curve (NKPC). The authors address several important econometrics issues that arise in estimating the NKPC model. Using the continuously updated generalized method of moments (GMM) estimator proposed by Hansen, Heaton, and Yaron (1996) and the three-step GMM estimator developed by Bonnal and Renault (2003), the authors find that the empirical evidence for the real marginal cost is rather weak. Specifically, results are sensitive to the instrument sets, normalization, estimators, sample period, and data revisions.

JEL classification: C13, C52, E31
Bank classification: Inflation and prices; Econometric and statistical methods

Résumé

Les auteurs examinent les résultats de Galí et Gertler (1999) et de Galí, Gertler et Lopez-Salido (2001 et 2003) selon lesquels la dynamique de l'inflation aux États-Unis est correctement décrite par la nouvelle courbe de Phillips keynésienne. Ils considèrent différents problèmes économétriques importants que soulève l'estimation de la nouvelle courbe de Phillips keynésienne. À l'aide de l'estimateur « constamment actualisé » de la méthode des moments généralisés (GMM) proposé par Hansen, Heaton et Yaron (1996) et de l'estimateur GMM en trois étapes mis au point par Bonnal et Renault (2003), les auteurs montrent que le rôle du coût marginal réel n'est pas bien étayé sur le plan empirique. En effet, les résultats sont sensibles au choix de l'ensemble d'instruments, de la méthode de normalisation, de l'estimateur et de la période étudiée, de même qu'aux révisions des données.

Classification JEL : C13, C52, E31
Classification de la Banque : Inflation et prix; Méthodes économétriques et statistiques

1 Introduction

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

A recent class of dynamic stochastic general-equilibrium models integrates Keynesian features, such as imperfect competition and nominal rigidities, allowing new perspectives on 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: (i) the inflation process has a forward-looking component, and (ii) it is related to real marginal costs. Compared with traditional reduced-form Phillips curves, which are subject to the Lucas critique, the NKPC is a structural model with parameters that do not vary as policy regimes change. This aspect is particularly important and has been outlined in a number of papers: parameter instability in reduced-form models is likely. Furthermore, the NKPC specification has dramatic implications for the conduct of monetary policy in that, for example, a fully credible central bank can bring about disinflation at no recessionary cost if inflation is a purely forward-looking phenomenon. A crucial issue, therefore, is whether the NKPC is empirically relevant.

Work by Galí and Gertler (1999, henceforth GG) and Galí, Gertler, and Lopez-Salido (2001, 2003, henceforth GGLS) provides evidence that the inflation dynamics in the United States (and the euro area) can be well-described by the NKPC. Their results suggest that: (i) the hybrid specification of the NKPC outperforms the purely forward-looking version of the NKPC (without a lag of inflation in the dynamics) over the period and the countries considered, (ii) the forward-looking component is much more important than the backward-looking component, and (iii) the real marginal cost variable is statistically significant at the standard level and, in contrast to the traditional output-gap measure, greatly improves the statistical fit of the inflation dynamics. In both studies, parameter estimates are obtained by the generalized method of moments (GMM) and statistical significance is based on Newey-West estimates of the covariance matrix (with a fixed bandwith).

In the literature, several econometric issues have been raised regarding the empirical relevance of the results obtained by GG and GGLS. The common criticisms of the NKPC include: (i) whether it actually captures inflation persistence (Fuhrer 1997; Fuhrer and Moore 1995), (ii) the plausibility of its implied dynamics (Mankiw and Reis 2002), and (iii) its estimation methodology. We focus on the third issue, about which different econometrics concerns have already been expressed. For instance, Rudd and Whelan (2001, 2003) and Lindé (2001) suggest that GG and GGLS's results may be the product of specification bias associated with the GMM estimation procedure. Mavroeidis (2001) discusses identification issues in the case of single-equation formulations like the NKPC. Indeed, the properties of the non-modelled variables are important for the identification process. In empirical applications, identification is achieved by confining important explanatory variables to the instrument sets, and misspecification results. Nason and Smith (2004) argue that GMM estimates typically lead to parameters that are near-identified. Hence, higher-order dynamics in marginal cost or the output-gap are required for identification and testing. Ma (2002) also assesses the question of identification and applies the test of weak instruments developed by Stock and Wright (2000). Dufour, Khalaf, and Kichian (2004) use exact tests and discuss the weak identification and the optimal instruments in the NKPC. Another important debate concerns maximum likelihood (ML) versus GMM estimates of the hybrid NKPC (Jondeau and Le Bihan 2003; Kurmann 2002).

In this paper, we re-examine the empirical relevance of the NKPC for the United States, focusing on three problems that emerge from the estimation strategy adopted by GG and GGLS. First, as is well known, the usual two-step GMM estimator (henceforth, 2S-GMM) has questionable finite sample properties.[1] Given the relatively large number of moment conditions, the estimates reported in GG and GGLS are potentially biased. For instance, Guay, Luger, and Zhu (2004) show that standard GMM estimates of the NKPC in Canada are sensitive to the number of instrumental variables. On the other hand, the bias of the usual 2S-GMM estimator has been well-documented in the independent, identically distributed (i.i.d.) case by Newey and Smith (2004). Using higher-order asymptotic expansions for members of a class of generalized empirical likelihood estimators, they show that this bias grows with the number of moment conditions. This may be the case in GG and to some extent in GGLS, since they use an arbitrary number of instruments.

Second, the 2S-GMM procedure suffers from a lack of invariance to transformations of the original moment conditions. As GG and GGLS report, the results obtained for the NKPC and the hybrid version depend on the normalization adopted for the GMM estimation procedure. In this respect, results based on a GMM estimator invariant to normalization may help distinguish between the two specifications and may illustrate the robustness of the NKPC's estimates.

Third, as shown by several studies, the small-sample properties of method-of-moments estimators depend crucially on the number of lags used in the computation of the variance-covariance matrix. There is no a priori reason to use, as GG and GGLS do, a fixed window (12 lags) to compute the optimal weighting matrix. Moreover, the power of the overidentifying restrictions depends critically on this weighting matrix. For instance, the standard J-test may lead to no rejection of the specification, although the NKPC (forward looking or hybrid) is misspecified. Consequently, all these issues are pertinent to a discussion of the three conclusions by GG and GGLS: (i) the reduced-form coefficient on real marginal cost is positive and statistically significant, (ii) overidentification tests reject the pure forward-looking specification of the NKPC and accept the hybrid form, and (iii) the forward-looking component of price inflation is dominant.

Our estimation strategy differs from GG, GGLS, and other 2S-GMM-related studies of the NKPC in three important ways. First, the small-sample bias is addressed by using the continuously updated GMM estimator (CUE) developed by Hansen, Heaton, and Yaron (1996) and

[1] See the special issue of *Journal of Business and Economic Statistics (1996)* volume 14.

the three-step GMM (3S-GMM) estimator proposed by Bonnal and Renault (2001, 2003). To our knowledge, this is the first empirical study to apply the 3S-GMM estimator. Both estimators have better finite sample properties than the standard 2S-GMM estimator in Monte Carlo simulations. Second, the CUE allows us to distinguish between the two specifications proposed by GG and GGLS, since it is robust to normalization. Third, we compute an automatic lag-selection procedure proposed by Newey and West (1994), and therefore we do not rely on an arbitrary truncation lag of the bandwith.[2] Our estimator of the variance-covariance matrix also uses the sample moments in mean deviation to improve the low power of the standard J-test as suggested by Hall (2000). Hence, we address the issues raised by Dotsey (2002), who finds that the conventional specification test used in GG lacks power. The empirical relevance of the NKPC is also addressed by reconsidering the measurement of the real marginal cost and, specifically, how robust it is to data revisions.

Our estimation strategy leads to the following conclusions. First, our results show that the forward-looking component of the NKPC is dominant regardless of the estimator that we use. Second, the J-test suggested by Hall rejects the purely forward-looking specification of the NKPC curve and generally accepts the hybrid form. The results, however, depend on the normalization of the NKPC and the instrument sets chosen. Third, the CUE, which is invariant to the normalization, allows us to distinguish between the conflicting results regarding the normalization retained. Fourth, the empirical evidence for the real marginal cost is rather mixed, and is particularly sensitive to the well-known problem of the choice of instrument set. In effect, there exists some empirical support for the original dataset used by GG and GGLS. In contrast to those studies, the output-gap variable must not belong to the information set. Nevertheless, the real marginal cost is no longer significant when we consider revised data or an updated version of the dataset. Our conclusions are robust to the definition of the real marginal cost and the inclusion of additional lags of inflation.

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 econometrics issues associated with standard GMM estimation, and present our estimation strategy based on the CUE and the 3S-GMM estimator developed by Bonnal and Renault (2001, 2003). In section 4, we present the estimation results. A discussion of the main findings follows in section 5. Section 6 concludes.

2 The New Keynesian Phillips Curves

2.1 Specifications

The NKPC, as advocated by GG, is based on a model of price-setting by monopolistically competitive firms. Following Calvo (1983), each firm, in any given period, may reset its price with a fixed probability of $1 - \theta$ and, with probability θ, its price will be kept unchanged

[2] We also use the method proposed by West (1997). Our main conclusions remain unchanged.

or proportional to trend inflation, Ω.[3] 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 given by $1/(1-\theta)$. 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 μ is the firm's demand elasticities, η the elasticity of marginal cost, and $E_t\pi_{t+1}$ the expectation of inflation at time $t+1$ with the information set at period t. Note that the derivations 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.[4]

GG 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). The corresponding hybrid version of the NKPC is then given as follows:

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

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 ω is the proportion of firms that use a backward-looking rule of thumb.

Note that the hybrid New Phillips curve for the aggregate assumption considered by Yun (1996) and Goodfriend and King (1997) is derived in GG and the one based on the assumption of Sbordone (2001) is derived in GGLS.

Three principal results emerge from the estimations of GG and GGLS: (i) the reduced-form coefficient on real marginal cost, λ, is positive and statistically significant; (ii) tests reject the pure forward-looking specification of the NKPC; and (iii) the forward-looking behaviour is dominant and the coefficients γ_f and γ_b sum close to unity across a range of estimates. GG and GGLS interpret these results as evidence in support of the robustness of the NKPC for the United States (and the euro area).

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

[4] Indeed, the hypothesis that individual firms can instantaneously adjust their own capital stocks implies that firms act as price-takers in the input market. Combined with the assumption of a constant-returns-to-scale technology, real marginal cost is thus independent of output.

2.2 Measure of marginal cost

Alternative measures of the marginal cost have been considered in empirical investigations of the NKPC. We consider the simplest measure of real marginal cost based on the assumption of Cobb-Douglas technology (see GG 1999)[5]:

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

where K_t is the capital stock, A_t is labour-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 labour income share, W_t the nominal wage, and P_t the price level. In log-linear deviation from the steady state, one obtains:

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

The definition of the marginal cost may be a critical issue in the estimation of the NKPC. The standard approximation of the real marginal cost by real unit labour cost arises solely under the assumption of a constant-returns-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 regarding technology. These include corrections to capture a non-constant elasticity of factor substitution between capital and labour and the presence of overhead costs and labour adjustment costs. Gagnon and Khan (2004) derive the NKPC when firms use alternative production functions, and show that each technology introduces a specific "strategic complementarity parameter" and a modification to the real marginal cost measure. Eichenbaum and Fisher (2003) modify the real marginal cost by allowing the firms that require 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.

The real marginal cost is a latent variable (e.g., unobservable) and is thus sensitive to both its definition (as well as the underlying assumptions of the model considered—it is model-dependent) and the data revisions. The latter issue has not yet been discussed in the literature. It is similar, however, to the standard problems encountered for the measurement of the output gap or the time-varying non-accelerating-inflation rate of unemployment (see Orphanides 2001). This issue is discussed in more detail in section 4.

[5] We discuss this issue further in sections 4 and 5.

3 Estimation Issues

3.1 Standard GMM approach

GG and GGLS use the standard 2S-GMM estimator developed by Hansen (1982) to estimate the NKPC. The optimal 2S-GMM estimator, based on the moment conditions

$$E\left[g(z_t, \beta_0)\right] = 0, \tag{2}$$

is defined as

$$\widehat{\beta}_2 = \arg\min_{\beta \in B} \frac{1}{T}\sum_{t=1}^{T} g(z_t, \beta)' \hat{\Omega}(\widehat{\beta}_1)^{-1} \frac{1}{T}\sum_{t=1}^{T} g(z_t, \beta),$$

where $\widehat{\beta}_1$ is a first-step estimator, usually obtained with the identity matrix as a weighting matrix, and $\hat{\Omega}^{-1}$ is a consistent estimator of the inverse of the variance-covariance matrix of the moments conditions.[6]

Let us now consider the methodology of GG and GGLS. In the case of the hybrid model, the 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.

The corresponding moment conditions are

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

where Z_t is a vector of instruments dated t and earlier.

The orthogonality condition in (4) forms the basis for estimating the model using the GMM. GG use the following instrument set: 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. GGLS choose a smaller number of lags for instruments other than inflation, in order to minimize the potential estimation bias that arises in small samples due to the number of overidentifying restrictions. Their instrument set reduces to four lags of inflation, and two lags each of the output gap, wage inflation, and the labour income share.[8] In both GG and GGLS, the variance-

[6] In other words, a 2S-GMM estimator, $\widehat{\beta}_2$, is characterized by the first-order conditions:

$$\left[\frac{1}{T}\sum_{t=1}^{T} \frac{\partial g'}{\partial \beta}(z_t, \widehat{\beta}_2)\right] \hat{\Omega}(\widehat{\beta}_1) \frac{1}{T}\sum_{t=1}^{T} g(z_t, \widehat{\beta}_2) = 0,$$

where $\widehat{\beta}_1$ is a preliminary consistent estimator for β_0. These first-order conditions are called identifying restrictions.

[7] Typically, the output gap is obtained by applying the Hodrick-Prescott filter or by fitting a quadratic trend to the entire sample.

[8] A number of studies have also estimated the NKPC in countries other than the United States, 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, Banerjee and Batini (2004), Batini, Jackson, and Nickell (2002), and Balakrishnan and Lopez-Salido (2002).

covariance matrix used to obtain standard errors for the model parameters is estimated with a fixed bandwith in which the truncation lag is 12.

3.2 Estimation strategy

Our estimation strategy differs in three important ways from other empirical studies of the NKPC. 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. Second, our estimator of the variance-covariance matrix uses the sample moments in mean deviation to increase the power of the overidentifying restrictions test, as suggested by Hall (2000) and Bonnal and Renault (2001, 2003). A more powerful specification test is clearly desirable, because it addresses the issues raised by Dotsey (2002), who finds that the conventional specification test used by GG (1999) lacks power. Third, two alternative estimators are used for the nonlinear specification: the CUE and the 3S-GMM estimator. According to the higher-order asymptotic expansions derived by Newey and Smith (2004), the empirical likelihood estimator (ELE) affords a minimal higher-order estimation bias. The ELE, however, is computionally demanding. For this reason, we perform these two alternative estimation methods. The CUE has the advantage that it does not depend on the normalization of the moment conditions, in contrast to the conventional 2S-GMM estimator (invariance principle), whereas the 3S-GMM estimator is less sensitive than the CUE to initial conditions. Moreover, these estimators seem to perform better in a finite sample than the 2S-GMM.

The CUE is analogous to the 2S-GMM estimator, 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 minimized. This estimator is given by

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

The solution of the minimization problem is numerically equivalent with the optimal weighting matrix in mean deviation or not, in the i.i.d. case (see Newey and Smith 2004; Bonnal and Renault 2003). This property is generally true in the autocorrelated case for an estimator of the covariance matrix that has the same bandwidth.[9]

The CUE has important advantages over the conventional 2S-GMM estimator. First, unlike the 2S-GMM estimator, the CUE does not depend on the normalization of the moment conditions. Second, in contrast to the 2S-GMM estimator, Newey and Smith (2004) show for the i.i.d.

[9]The results will not be systematically identical for the CUE, regardless of whether the variance-covariance matrix is calculated in mean deviation. As mentioned before, the solution of the objective function for CUE is numerically equivalent only for the same lag selection necessary to compute the covariance. In fact, there is no guarantee that the automatic lag-selection procedure will select the same number of lags for the covariance matrix whether or not it is calculated in deviation. In particular, if the model is misspecified, the number of lags selected will differ.

case that the asymptotic bias of the CUE does not increase with the number of overidentifying restrictions. In addition, they demonstrate that the CUE has the same minimal higher-order bias as the ELE if the third moments are null. In fact, the CUE uses the relevant constrained estimator of the Jacobian matrix by taking into account implied probabilities (defined below). It has, however, the drawback of using an unconstrained estimator of the weighting matrix.[10] Two advantages the CUE has over the ELE are that it is less time-consuming and it is not obtained through a saddle-point problem, which grows with the number of moment conditions. In contrast, the dimension of the optimization problem for the CUE is equal to the number of moment conditions. Also, the CUE may be sensitive to initial conditions. Furthermore, Hansen, Heaton, and Yaron (1996) show that, in small samples, the CUE has the smallest bias among the instrumental variable (IV) estimators when one estimates standard asset-pricing models.

On the other hand, the 3S-GMM estimator has the two interesting properties of being efficient with minimal asymptotic higher-order bias, like the ELE, and preserving the user-friendly features of least squares. Unlike the standard 2S-GMM estimator, it uses all the information contained in the moments conditions (4) to estimate β_0. In effect, the 3S-GMM estimator makes implicit use of the overidentifying restrictions to improve the estimation of the optimal selection of estimating equations. The 2S-GMM estimator and the CUE, in contrast, do not use variance reduction. The poor finite sample performance of the 2S-GMM estimator can therefore be explained by the fact that only the information in the just-identified moment conditions is used. Nevertheless, as Back and Brown (1993) point out, the remaining moment conditions can be used to improve the estimation of the data distribution by considering the empirical distribution of the moment conditions. In other words, 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 initialization problem, while possessing the optimal-bias property. In addition, the computational implementation is less burdensome and requires only three quadratic optimization steps.

To describe the estimator, we first introduce the concept of implied probabilities in GMM estimators (Back and Brown 1993). The implied probabilities are the constrained probabilities such that the moment conditions are respected at the GMM estimator, $\widehat{\beta}$. Thus,

$$\sum_{t=1}^{T} p_t(\widehat{\beta}) g(z_t, \widehat{\beta}) = 0.$$

The unconstrained empirical probabilities used in the standard GMM are given by the empirical frequencies, $\frac{1}{T}$.

We next describe the 3S-GMM estimator for the i.i.d. case. Let $\widetilde{\beta}$ be an estimator asymptotically equivalent to the optimal 2S-GMM estimator, $\widehat{\beta}_2$. The implied probabilities that cor-

[10] 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 (2004) use the concept of "generalized empirical likelihood" estimators.

respond to this optimal GMM estimator are defined as follows:

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

where $\overline{g}_T(\widetilde{\beta}) = \frac{1}{T}\sum_{t=1}^{T} g(z_t,\widetilde{\beta})$ (see Back and Brown 1993; Bonnal and Renault 2001, 2003). The 3S-GMM estimator, $\widehat{\beta}_3$, is defined as the solution of the following equation:

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

Therefore, to obtain the 3S-GMM estimator, the implied probabilities are used to estimate the Jacobian and variance-covariance matrices.

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, $\widehat{\beta}_3$ solves the following equations:

$$\left[\sum_{t=1}^{T} p_t\left(\widetilde{\beta}\right)\frac{\partial g'}{\partial \beta}(z_t,\widetilde{\beta})\right]\left[\widehat{\Omega}_t(\widetilde{\beta})\right]^{-1}\frac{1}{T}\sum_{t=1}^{T} g(z_t,\widehat{\beta}_3) = 0,$$

where

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

and w_{kK} are weights to make the autocorrelation-consistent estimator of the covariance matrix positive semi-definite (see Andrews and Monahan 1992; Newey and West 1994).

The implied probabilities are given by:

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

where

$$g^*(z_t,\widetilde{\beta}) = \sum_{j=-K}^{K}\left(\sum_{h,l,l-h=j}\alpha(h)\alpha(l)\right) g(z_t,\widetilde{\beta}),$$

and $\alpha(\cdot)$ is a flat kernel such that

$$\alpha(h) = \frac{1}{2K+1}, \quad h = -K,\ldots,+K.$$

Bonnal and Renault (2001) show the tight relationship between the weighting matrix for GMM and the relevant weights, $\alpha(\cdot)$, on the implied probability distributions. In particular, the flat weighting of $\alpha(\cdot)$ implies the usual Newey and West estimator of the long-run covariance matrix. Consequently, the parameter K is chosen according to the data-dependent procedure proposed by Newey and West (1994).

The 3S-GMM, with its use of a chi-square metric, has the advantage of giving closed-form solutions for implied probabilities. One potential problem with this estimator is that implied probabilities might be undefined (e.g., not positive) in finite samples. Nevertheless, Bonnal and Renault (2003) show that these probabilities are asymptotically positive and that signed measures can be used to guarantee the best fit of the estimated distribution to the theoretical moments. They propose estimating the implied probabilities as an optimally weighted average of the standard 2S-GMM's implied probabilities ($1/T$) and the computed implied probabilities ($p_t(\beta)$). This method, known as the shrinkage procedure, allows a non-zero weight to be put on the 2S-GMM implied probabilities when some of the implied probabilities ($p_t(\beta)$) are zero.[11]

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 (1960Q1-1997Q4), a revised dataset, and an updated dataset (1960Q1-2001Q3).[12] As a first step, we use the same instrument sets as GG and GGLS, before considering alternative instrument sets in a robustness analysis. We address the issues of the number of instruments and the choice of instruments.

4.1 Estimates of the baseline model

We first present estimates of the NKPC (1), given by:

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

where $\kappa = 1/(1-\eta\mu)$ and $\lambda = \frac{(1-\theta)(1-\theta\beta)}{\theta}$.

If one follows Yun (1996) and Goodfriend and King (1997), then $\kappa = 1$; following Sbordone (2001) and GGLS (2001), $\kappa = 0.12$.[13]

One econometrics issue in small samples with nonlinear estimation using the 2S-GMM or the 3S-GMM estimator is the way the orthogonality conditions are normalized. In this paper, two alternative specifications of the orthogonality conditions are estimated. The first specification takes the following form:

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

and the second is given by

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

Before estimating both specifications, two important issues need to be considered. First, we check for weakness of instruments by performing an F-test on the first-stage regression. Staiger

[11] Bonnal and Renault (2003) show that the shrinkage procedure may improve the finite sample properties.

[12] The sample period of the updated dataset does not include the most recent data, to avoid taking account of the last revisions of the real marginal cost, which appear to be large at the end-of-sample.

[13] Results are robust to alternative values of κ. They are not reported here, but are available on request.

and Stock (1997) point out that this statistic is of concern because conventional asymptotic results may break down under a weak correlation between the instruments and the endogenous regressor. In our estimated equations, there is no evidence of a weak correlation between the instruments and the endogenous regressor. Second, Nason and Smith (2004) discuss two fundamental sources of non-identification in the NKPC: weak, higher-order dynamics and superior information. They suggest a pretest in each case: a test of the lag length for the forcing variable (the real marginal cost) and a test of Granger 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. This finding confirms earlier evidence of Nason and Smith (2004). Moreover, using standard information criteria, we find a lag length of order up to one for the real marginal cost. Overall, these results suggest that a backward-looking component of the Phillips curve may be necessary.

Tables 1a and b report the results for each specification when a 12-lags Newey-West estimate of the covariance matrix is used.[14] The first four columns show the probability, θ, the discount factor estimate, β, the reduced-form slope coefficient on real marginal cost, λ, and the corresponding duration, D. The final column shows Hansen's J-statistic of the overidentifying restrictions, together with the associated p-values. First, the GMM estimates of the slope coefficient on marginal cost depend on the normalization. Overall, the coefficient is statistically significant for both instrument sets and both specifications.[15] This evidence is also supported in the case of the 3S-GMM estimator. The evidence with the CUE, however, which is robust to normalization, is mixed. The coefficient on the real marginal cost, λ, is significant with GGLS's instrument set, but not with GG's instrument set.[16] Second, the overidentifying restrictions test is far from rejecting the NKPC specification.

Table 2 reports the results of applying the automatic lag-selection procedure of Newey and West (1994), and Hall's (2000) mean deviation correction. For both normalizations, the 2S-GMM, CUE, and 3S-GMM estimates of the real marginal cost are significant for almost all cases at standard level. The estimates of λ are, in general, lower with the 3S-GMM than with the 2S-GMM, but this difference is not significant. Other things being equal, the estimates obtained with the CUE are closer to those obtained with the 2S-GMM and 3S-GMM estimators for the second specification. This may suggest that the empirical evidence for the real marginal cost is weak, since the second specification yields more mixed results for this variable. However, the overidentifying restrictions are rejected for GG's instrument set when the estimator of the variance-covariance matrix is calculated with the sample moments in mean deviation. It is also the case for GGLS's instrument set with the GMM and the first specification.[17]

Overall, these results suggest that the empirical evidence for the pure forward-looking NKPC

[14] The results reported are not directly comparable with GG (1999) and GGLS (2001), but the same conclusions hold. Tables 1 and 2 in GG (1999) report estimation results for $\kappa = 1$, whereas we report results for $\kappa = 0.12$, and GGLS (2001) do not use the same sample period.

[15] GG (1999) and GGLS (2001) describe the same result.

[16] The non-rejection of the null hypothesis $H_0 : \lambda = 0$ leads to an identification problem. Specifically, the reduced form can still be estimated. The structural parameters, however, cannot be retrieved from this reduced form if the null hypothesis is not rejected. For a complete discussion on identification, see Mavroeidis (2001).

[17] These results are robust to different sample periods and different values of $\varkappa$.

is mixed. Specifically, Hall's (2000) mean deviation correction suggests that the model is misspecified and that richer dynamics are necessary to capture the persistence of U.S. inflation.

4.2 Estimates of the hybrid model

In this section, we present estimates of the reduced-form parameters and the structural parameters for the hybrid version. Two specifications (normalizations) are also considered:

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

and

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

Tables 3 and 4 report results obtained by setting $\kappa = 0.12$ 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 Hansen's J-test for overidentifying restrictions.

According to GGLS's results, there is evidence of a statistically significant real marginal cost with the first specification, but not with the second specification, when a 12-lag Newey-West estimate of the variance-covariance matrix is used for the conventional 2S-GMM estimator. Results are similar for the 3S-GMM estimator. At the same time, the real marginal cost is no longer significant in the case of the CUE, and the estimate of λ is close to that obtained for the second specification with the 2S-GMM and 3S-GMM estimators.

When we use Hall's mean deviation correction, however, the validity of instruments is rejected more often; i.e., the overidentifying restrictions are rejected with GGLS's instrument set for both the 2S-GMM estimator and the CUE.[18] Interestingly, the real marginal cost is significant in the case of the CUE, but the overidentifying test rejects the specification with GGLS's instrument set. As before, the real marginal cost is not significant for the second specification.

Our results therefore provide some evidence for the robustness of the hybrid NKPC. Nevertheless, they still depend on the chosen estimator and the instrument set. The empirical evidence is rather weak when the second specification is used to estimate the structural and reduced-form parameters. This is consistent with the results of GGLS, but for a different sample period. The hybrid specification is rejected when the optimal weighting matrix is calculated in mean deviation.

Three other parameters are of interest: the degree of price stickiness, θ, the degree of "backwardness" in price-setting, ω, and the discount factor, β. Regarding θ, we find lower estimates than GG and GGLS. For example, depending on the estimator, the parameter θ is estimated

[18] If the hybrid Phillips curve is well-specified, the error term should be serially uncorrelated and should have a moving-average (MA) representation. More precisely, the disturbance will follow an MA process of order one. The automatic lag-selection procedure of Newey and West (1994), however, suggests that the dynamics of the disturbance is characterized by higher-order MA representation. This may suggest that the NKPC is misspecified. Therefore, to some extent, our results differ from those obtained with the long-run covariance matrix estimator proposed by West (1997), unless we specify the same order.

to imply prices that are fixed for 2 to 3 quarters, on average. This result is robust across the different estimators. It is also fairly consistent with survey evidence that suggests 3 to 4 quarters, on average (see Rotemberg and Woodford 1999). The parameter ω, however, 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 by GG and GGLS.

Although the results suggest some imprecision in the estimate of the degree of backwardness, one conclusion is robust across methods: in accounting for inflation dynamics, the forward-looking component 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 set of instruments used. Therefore, the pure forward-looking model is rejected by the data. At the same time, 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. Furthermore, as in GG and GGLS, we find similar values for the discount factor. Specifically, the estimate of β is reasonably similar across the two normalizations and the different estimators.

Overall, using the same data set as GG (1999), our results show that (i) the forward-looking behaviour is dominant, (ii) the duration is of the same order for the different estimators and prices are fixed for approximately 2 to 3 quarters, (iii) the empirical evidence for the real marginal cost is mixed, i.e., it depends on the normalization (for the 2S-GMM and the 3S-GMM estimators), and (iv) tests reject for several cases the hybrid specification of the NKPC when the mean deviation correction is applied. Because the normalization matters for the empirical evidence of the real marginal cost, the results obtained with the CUE cast doubt on the importance of the real marginal cost in explaining inflation. In this respect, the next step is to examine whether these results are robust and to what extent we can explain the mixed evidence regarding the real marginal cost.

4.3 Robustness of the results

To further assess the reliability of our previous results and, more generally, the robustness of the results in the literature, we consider the following issues in estimating the NKPC model: the choice of instruments, the revision of the dataset, and the updating of the dataset.

4.3.1 *The choice of instruments*

As noted earlier, one important issue is the number of instruments used to estimate the NKPC. The choice of instruments is of particular concern. Hall and Peixe (2003) argue that it is desirable for the chosen instrument set to satisfy certain properties: 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 2S-GMM estimator. In addition, it is important that the statistical properties of the instruments 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 the 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 test), the presence of a unit root in U.S. output cannot be rejected. Under the hypothesis of a unit root, quadratically detrended output is also characterized by a unit root. Unfortunately, the asymptotic properties of instrumental variable estimators are not known in the presence of non-stationary instruments. As a result, the usual inference procedures are likely to be invalid. The other measure of the output gap is based on the Hodrick-Prescott filter. In this measure, the output gap is a combination of lags, leads, and contemporaneous values of output. Such measures of the output gap violate the basic GMM orthogonality conditions and are likely to be correlated with the measurement error of the real marginal cost.

Therefore, we reconduct estimations with the following sets of instruments: [1] two lags of inflation and one lag of the real marginal cost (just-identified case), [2] two lags of inflation and two lags of the real marginal cost, [3] four lags of inflation and two lags of the real marginal cost, [4] four lags of inflation and the real marginal cost, [5] four lags of inflation and the real marginal cost and two lags of wage inflation, and [6] four lags of inflation, the real marginal cost, and wage inflation. Instruments dated $t-1$ and earlier are also used to mitigate possible correlation with the measurement error of the real marginal cost.

Tables 5a and b report the results for both normalizations in the case of the hybrid NKPC. We adopt the data-dependent automatic selection procedure of Newey and West (1994), and the J-statistic is based on Hall's mean deviation correction.

As expected, the results are similar for the three estimation methods and both normalizations in the just-identified case. Interestingly, the results are more encouraging for the NKPC. Specifically, for instrument sets [4], [5], and [6], the real marginal cost is significant whatever the estimation method and normalization. The empirical evidence, however, is found when the number of instruments is relatively large. As before, the CUE values of λ are close to the ones obtained for the second specification with the 2S-GMM and 3S-GMM estimators. The estimated value of λ for the first specification is substantially lower with the 3S-GMM than with the 2S-GMM estimator. Both specifications are not rejected by the overidentifying test, except in two cases (at the 5 per cent level). The discount factor is estimated at more realistic higher values, around 0.95 and 0.999, and the forward-looking parameter is more important. The estimates of θ give an average price duration around 2 quarters.

4.3.2 *Revised and updated datasets*

Figure 1 reports the real marginal cost in log deviation from its mean, calculated as the labour share of non-farm business from the original database of GG and the revised real marginal cost (labelled as mc1). One can easily see that the end-of-sample properties of the original series and "mc1"are different. The revisions of the output measure account for a large part of the differences observed between these two variables. Therefore, to assess how sensitive the results are to data revisions, we conduct estimations using the instrument sets of GG and GGLS and the six instrument sets described in section 4.3.1. Our results are reported in Tables 6a and b for the instrument sets of GG and GGLS.

According to both normalizations, the real marginal cost is not significant except for the standard GMM and 3S-GMM estimators in the first specification. In contrast to our results in Tables 4a and b with GG's instrument set, we find that the real marginal cost is not significant for the estimation obtained using the CUE. Hence, the revisions of the real marginal cost cast some doubts on the robustness of the NKPC.

Tables 7a and b report the results for alternative instrument sets [1] to [6]. The real marginal cost is significant for only one case: estimation with GMM for the first specification with instrument set [6]. Remember that, with the original data, the real marginal cost is significant whatever the estimation methods and normalization for instrument sets [4], [5], and [6]. The data revisions weaken the empirical evidence in favour of the NKPC, particularly for the estimation with instrument sets [1] to [6].

Results with the sample size extended to 1960Q1–2001Q3 are provided in Tables 8a and b for GG's instrument set, and in Tables 9a and b for instrument sets [1] to [6]. Results for GG's instrument set are very close to the ones obtained with revised data; the real marginal cost is significant only with the 2S-GMM and 3S-GMM estimators in the case of the first specification. The real marginal cost is never significant with the CUE and for the second normalization. In the cases of alternative instrument sets [1] to [6], the real marginal cost is not significant (at the 5 per cent level) whatever the normalization and estimation methods.

The empirical evidence for the real marginal cost is weak and depends critically on the normalization and the instrument set. In fact, the real marginal cost is significant only for the instrument sets of GG and GGLS and the first specification. Unfortunately, the estimator, which is invariant to the adopted normalization, does not favour empirical evidence for the NKPC. In all other cases, the real marginal cost is not significant.

5 Discussion

In this section, we examine the issue of how sensitive the results are to the particular measure of marginal cost that we used, and how informative additional lags of inflation are in the NKPC. We also test whether the starting date of the information set (i.e., the degree of predetermination of inflation) matters for the dynamics of inflation, as in Eichenbaum and Fisher (2003). Our main conclusions are unchanged. Moreover, as Sbordone (2001) and Banerjee and Batini (2004) show, our results are not specific to the particular model of staggered prices adopted (Calvo's specification), but also hold with fixed-length contracts introduced by Taylor (1980). In addition, as Adam and Padula (2003) discuss, the inflation-forecasting measure may be of concern. Overall, using data from the Survey of Professional Forecasters does not improve the statistical significance of the real marginal cost in our sample. Detailed results are available on request.

5.1 The definition of real marginal cost

As we noted earlier, our results may depend on the calculation of the real marginal cost. For instance, Rotemberg and Woodford (1999), Gagnon and Khan (2004), and Sbordone (2001) suggest (i) a Cobb-Douglas technology with overhead labour costs, or (ii) a specification with adjustment costs for labour.[19] In both cases, the marginal cost is no longer proportional to the average labour cost, since there is, respectively, (i) a "productivity bias" and (ii) a "real wage bias."

In the first case, when firms face adjustment costs for increasing hours of work, of the form $\frac{\phi}{2}(H_t - H_{t-1})^2$, the real marginal cost can be defined as follows (in logarithm):

$$mc_t = s_t + \phi H \left(\frac{H}{(1-\alpha)Y}\right) \Delta H_t - \beta\phi \left(\frac{H}{(1-\alpha)Y}\right) E_t \Delta H_{t+1}.$$

The parameter ϕ was never significant across estimation methods. Therefore, we calibrate this parameter following the estimates reported by Ambler, Guay, and Phaneuf (2003), and by conducting a sensitivity analysis. Increasing the size of the adjustment costs, however, does not lead to significant changes in our estimates; we obtain a slightly higher degree of nominal rigidity (see Sbordone 2001). Overall, we find only weak empirical evidence for the adjustment cost-based measure of the real marginal cost.

On the other hand, the second model allows for "overhead labour," which is defined as the number of hours that need to be hired regardless of the level of production. The production function is thus modified as

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

where $H_t - \overline{H}$ is the number of hours in excess of the overhead labour, $\overline{H} \geq 0$.

In this case, the real marginal cost is given by:

$$mc_t = s_t + bh_t,$$

where $b = \frac{\overline{H}/H}{1-\overline{H}/H}$ and H is the number of hours worked at steady state.[20]

The series for hours worked is calculated as being the number of employees multiplied by the average hours worked per quarter. The resulting series is stationary around a stable mean. In contrast to the series used by Sbordone (2001) and Gagnon and Khan (2004), no detrending is necessary. We also include lags of hours worked in the instrument sets considered before. We first try to estimate the parameter b. Unfortunately, the estimates are generally not significant. Instead, we also calibrate this scalar and conduct sensitivity analysis. Following Rotemberg and Woodford (1999), the benchmark value is calibrated to 0.4. Our conclusions are not sensitive to variations in the value of this parameter—only the degree of nominal rigidity rises (see Sbordone 2001). Overall, the empirical evidence of the robustness of the NKPC is still unchanged. In

[19] Other changes may be considered; for instance, a CES production function. For a complete discussion, see Gagnon and Khan (2004).

[20] The value of b is calibrated as in other studies of the NKPC.

particular, the real marginal cost is significant only for the instrument sets of GG and GGLS augmented with lags of hours worked, with the first specification estimated by 2S-GMM and 3S-GMM. In all other cases, the real marginal cost is not significant.

Therefore, modifications to the unit labour cost measure do not significantly alter our main conclusions.

5.2 The misspecification of the dynamics of inflation

Two main types of misspecification have been studied in the literature: measurement error and omitted dynamics. Because we have already discussed the former, we analyze whether omitted dynamics is a plausible explanation for our results. We therefore consider a hybrid NKPC, in which additional lags of inflation are introduced by some specific rules of thumb or by other sources of lag dynamics in inflation (see Kozicki and Tinsley 2002). To do so, we add extra lags of inflation to enter the right-hand side of the dynamics of inflation. As GG and GGLS point out, one reason is that the estimated importance of the forward-looking behaviour of inflation may reflect the insufficient lagged dependence.

In the estimation, three additional lags of inflation are added to the right-hand side. The sum of these additional lags is small and not statistically different from zero. 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. The broad picture is unchanged, in the sense that the marginal cost does not have a significant effect for most of the specifications.

6 Conclusion

Work by Galí and Gertler (1999) and Galí, Gertler, and Lopez-Salido (2001) provides evidence that the inflation dynamics in the United States (and the euro area) can be well-described by the New Keynesian Phillips curve. The approach adopted in our paper has addressed several important econometrics issues. First, our results show that the forward-looking component of the NKPC is dominant regardless of the estimator we use. Second, the J-test proposed by Hall rejects the purely forward-looking specification of the NKPC curve and yields mixed results for the hybrid form. The results, however, depend on the normalization of the NKPC and the instrument sets chosen. Third, the CUE, which is invariant to the normalization, allows us to distinguish between the different normalization results. Specifically, the CUE results tend to favour the second specification, for which the real marginal cost is generally not statistically significant at the standard level. Fourth, the empirical evidence for the real marginal cost is rather mixed and is particularly sensitive to the well-known problem of the choice of instrument set. In effect, there exists some empirical support for the original dataset used by GG and GGLS. In contrast to those studies, however, the output-gap variable must not belong to the information set. Nevertheless, the real marginal cost is no longer significant when we consider revised data or an updated version of the dataset. Furthermore, our conclusions are robust to the definition of the real marginal cost and the inclusion of additional lags of inflation.

Our results suggest that, at the theoretical level, richer versions of the structural model from which the NKPC is derived would need to be developed. For instance, as Ascari (2004), Bakhshi et al. (2003), and Cogley and Sbordone (2004) discuss, one interesting approach is to relax the particularly restrictive assumption that the steady-state inflation is zero (e.g., to allow for trend inflation). Earlier evidence suggests that such models fit the observed inflation well, and enough persistence is generated without specifying a hybrid version of the NKPC.

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Table 1a: Forward-Looking NKPC: Form I, $\kappa = 0.12$

Method	Instrument	θ	β	λ	D	J-stat
GMM	GG	.538	.846	.468	2.16	7.22
		(.040)	(.043)	(.120)	(.189)	
		[.000]	[.000]	[.000]	[.000]	[.513]
	GGLS	.503	.823	.580	2.01	10.25
		(.024)	(.029)	(.087)	(.097)	
		[.000]	[.000]	[.000]	[.000]	[.984]
CUE	GG	.659	1.018	.170	2.93	7.12
		(.101)	(.046)	(.136)	(.872)	
		[.000]	[.000]	[.212]	[.000]	[.523]
	GGLS	.543	.856	.449	2.19	9.96
		(.043)	(.043)	(.122)	(.208)	
		[.000]	[.000]	[.000]	[.000]	[.987]
3S-GMM	GG	.537	.854	.468	2.16	8.33
		(.038)	(.039)	(.114)	(.178)	
		[.000]	[.000]	[.000]	[.000]	[.401]
	GGLS	.515	.832	.540	2.06	11.05
		(.023)	(.026)	(.077)	(.096)	
		[.000]	[.000]	[.000]	[.000]	[.974]

Note: Standard errors appear in parentheses and p-values appear in brackets for the null hypothesis that the estimate is equal to zero. A 12-lags Newey-West estimator of the weighting matrix is used.

Table 1b: Forward-Looking NKPC: Form II, $\kappa = 0.12$

Method	Instrument	θ	β	λ	D	J-stat
GMM	GG	.566	.865	.392	2.30	7.18
		(.045)	(.042)	(.115)	(.239)	
		[.000]	[.000]	[.000]	[.000]	[.518]
	GGLS	.567	.849	.395	2.31	9.87
		(.058)	(.023)	(.065)	(.138)	
		[.000]	[.000]	[.000]	[.000]	[.987]
3S-GMM	GG	.579	.884	.355	2.38	8.13
		(.045)	(.037)	(.105)	(.253)	
		[.000]	[.000]	[.000]	[.000]	[.421]
	GGLS	.572	.859	.382	2.33	10.60
		(.025)	(.021)	(.063)	(.139)	
		[.000]	[.000]	[.000]	[.000]	[.980]

Note: See note to Table 1a.

Table 2a: Forward-Looking NKPC: Form I, $\kappa = 0.12$

Method	Instrument	θ	β	λ	D	J-stat
GMM	GG	.531	.872	.475	2.13	17.89
		(.056)	(.050)	(.164)	(.255)	
		[.000]	[.000]	[.004]	[.000]	[.022]
	GGLS	.540	.846	.463	2.17	35.04
		(.037)	(.036)	(.108)	(.174)	
		[.000]	[.000]	[.000]	[.000]	[.038]
CUE	GG	.606	1.008	.252	2.54	15.13
		(.073)	(.038)	(.129)	(.470)	
		[.000]	[.000]	[.053]	[.000]	[.057]
	GGLS	.613	1.016	.238	2.59	22.33
		(.067)	(.039)	(.117)	(.448)	
		[.000]	[.000]	[.044]	[.000]	[.440]
3S-GMM	GG	.592	.911	.317	2.45	21.17
		(.049)	(.032)	(.100)	(.292)	
		[.000]	[.000]	[.002]	[.000]	[.007]
	GGLS	.555	.868	.415	2.25	21.56
		(.031)	(.029)	(.082)	(.156)	
		[.000]	[.000]	[.000]	[.000]	[.486]

Note: The p-values appear in brackets for the null hypothesis that the estimate is equal to zero. The automatic lag selection of the Newey-West (1994) estimator of the weighting matrix in mean deviation is used.

Table 2b: Forward-Looking NKPC: Form II, $\kappa = 0.12$

Method	Instrument	θ	β	λ	D	J-stat
GMM	GG	.649	.916	.218	2.85	15.90
		(.093)	(.048)	(.145)	(.758)	
		[.000]	[.000]	[.134]	[.000]	[.044]
	GGLS	.597	.891	.316	2.48	29.38
		(.045)	(.032)	(.096)	(.278)	
		[.000]	[.000]	[.001]	[.000]	[.134]
3S-GMM	GG	.672	.932	.183	3.05	14.71
		(.075)	(.031)	(.099)	(.698)	
		[.000]	[.000]	[.067]	[.000]	[.067]
	GGLS	.618	.902	.273	2.62	20.72
		(.039)	(.024)	(.072)	(.267)	
		[.000]	[.000]	[.000]	[.000]	[.566]

Note: See note to Table 2a.

Table 3a: Hybrid NKPC: Form I, $\kappa = 0.12$

Method	Instrument	θ	β	ω	λ	γ_f	γ_b	D	J-stat
GMM	GG	.571	.923	.281	.174	.629	.335	2.33	5.99
		(.053)	(.044)	(.060)	(.071)	(.040)	(.045)	(.288)	
		[.000]	[.000]	[.000]	[.016]	[.000]	[.000]	[.000]	[.541]
	GGLS	.509	.886	.248	.272	.607	.334	2.04	10.79
		(.033)	(.032)	(.027)	(.058)	(.030)	(.027)	(.136)	
		[.000]	[.000]	[.000]	[.016]	[.000]	[.000]	[.000]	[.967]
CUE	GG	.634	.988	.389	.082	.614	.382	2.73	5.62
		(.124)	(.089)	(.107)	(.079)	(.077)	(.069)	(.923)	
		[.000]	[.000]	[.000]	[.300]	[.000]	[.000]	[.004]	[.584]
	GGLS	.800	.964	.323	.028	.692	.290	5.00	9.74
		(.170)	(.062)	(.114)	(.053)	(.074)	(.069)	(4.244)	
		[.000]	[.000]	[.005]	[.601]	[.000]	[.000]	[.240]	[.982]
3S-GMM	GG	.577	.947	.305	.153	.626	.350	2.36	6.67
		(.052)	(.036)	(.053)	(.060)	(.038)	(.038)	(.289)	
		[.000]	[.000]	[.000]	[.012]	[.000]	[.000]	[.000]	[.464]
	GGLS	.520	.887	.246	.257	.614	.328	2.08	11.27
		(.032)	(.031)	(.027)	(.054)	(.029)	(.026)	(.137)	
		[.000]	[.000]	[.000]	[.016]	[.000]	[.000]	[.000]	[.957]

Note: See note to Table 1a.

Table 3b: Hybrid NKPC: Form II, $\kappa = 0.12$

Method	Instrument	θ	β	ω	λ	γ_f	γ_b	D	J-stat
GMM	GG	.638	.974	.426	.074	.588	.403	2.76	5.66
		(.076)	(.035)	(.068)	(.046)	(.033)	(.032)	(.578)	
		[.000]	[.000]	[.000]	[.110]	[.000]	[.000]	[.000]	[.580]
	GGLS	.638	.993	.522	.055	.547	.451	2.76	9.82
		(.062)	(.038)	(.065)	(.031)	(.027)	(.026)	(.473)	
		[.000]	[.000]	[.000]	[.079]	[.000]	[.000]	[.000]	[.981]
3S-GMM	GG	.643	.983	.424	.071	.595	.399	2.80	6.12
		(.074)	(.033)	(.068)	(.044)	(.033)	(.032)	(.583)	
		[.000]	[.000]	[.000]	[.110]	[.000]	[.000]	[.000]	[.526]
	GGLS	.685	1.032	.625	.026	.534	.472	3.17	10.22
		(.094)	(.060)	(.114)	(.029)	(.026)	(.026)	(.948)	
		[.000]	[.000]	[.000]	[.376]	[.000]	[.000]	[.001]	[.976]

Note: See note to Table 1a.

Table 4a: Hybrid NKPC: Form I, $\kappa = 0.12$

Method	Instrument	θ	β	ω	λ	γ_f	γ_b	D	J-stat
GMM	GG	.557	.941	.296	.176	.622	.351	2.26	9.79
		(.065)	(.048)	(.065)	(.079)	(.051)	(.052)	(.329)	
		[.000]	[.000]	[.000]	[.027]	[.000]	[.000]	[.000]	[.201]
	GGLS	.553	.868	.162	.277	.683	.231	2.24	60.37
		(.039)	(.032)	(.034)	(.073)	(.041)	(.038)	(.196)	
		[.000]	[.000]	[.000]	[.000]	[.000]	[.000]	[.000]	[.000]
CUE	GG	.620	.968	.353	.102	.621	.366	2.63	8.48
		(.061)	(.039)	(.102)	(.053)	(.042)	(.040)	(.424)	
		[.000]	[.000]	[.000]	[.018]	[.000]	[.000]	[.000]	[.293]
	GGLS	.545	.874	.082	.351	.766	.135	2.20	32.65
		(.018)	(.028)	(.032)	(.046)	(.045)	(.046)	(.856)	
		[.000]	[.000]	[.011]	[.000]	[.000]	[.005]	[.000]	[.050]
3S-GMM	GG	.578	.954	.308	.149	.629	.351	2.37	7.99
		(.059)	(.036)	(.056)	(.062)	(.045)	(.043)	(.329)	
		[.000]	[.000]	[.000]	[.017]	[.000]	[.000]	[.000]	[.333]
	GGLS	.564	.888	.170	.250	.692	.236	2.29	19.16
		(.033)	(.030)	(.029)	(.056)	(.036)	(.032)	(.172)	
		[.000]	[.000]	[.000]	[.000]	[.000]	[.000]	[.000]	[.575]

Note: See note to Table 2a.

Table 4b: Hybrid NKPC: Form II, $\kappa = 0.12$

Method	Instrument	θ	β	ω	λ	γ_f	γ_b	D	J-stat
GMM	GG	.622	.979	.415	.084	.591	.402	2.65	9.68
		(.078)	(.037)	(.075)	(.053)	(.039)	(.037)	(.548)	
		[.000]	[.000]	[.000]	[.119]	[.000]	[.000]	[.000]	[.207]
	GGLS	.754	.990	.472	.027	.610	.386	4.07	50.75
		(.134)	(.033)	(.108)	(.040)	(.030)	(.029)	(2.208)	
		[.000]	[.000]	[.002]	[.501]	[.000]	[.000]	[.068]	[.000]
3S-GMM	GG	.625	.973	.373	.093	.613	.376	2.67	7.23
		(.076)	(.038)	(.070)	(.055)	(.043)	(.041)	(.543)	
		[.000]	[.000]	[.000]	[.094]	[.000]	[.000]	[.000]	[.405]
	GGLS	.731	.993	.438	.036	.622	.376	3.71	14.57
		(.108)	(.032)	(.088)	(.040)	(.027)	(.026)	(1.487)	
		[.000]	[.000]	[.000]	[.376]	[.000]	[.000]	[.013]	[.844]

Note: See note to Table 2a.

Table 5a: Hybrid NKPC: Form I, $\kappa = 0.12$

Method	Instrument	θ	β	ω	λ	γ_f	γ_b	D	J-stat
GMM	[1]	.531	.858	.409	.166	.501	.450	2.13	
		[.000]	[.000]	[.099]	[.089]	[.037]	[.034]	[.000]	
	[2]	.568	.983	.177	.212	.751	.239	2.31	3.29
		[.000]	[.000]	[.359]	[.175]	[.000]	[.249]	[.000]	[.070]
	[3]	.503	.991	.206	.279	.703	.291	2.01	3.38
		[.000]	[.000]	[.217]	[.104]	[.000]	[.125]	[.000]	[.336]
	[4]	.517	.975	.172	.289	.734	.251	2.07	4.80
		[.000]	[.000]	[.262]	[.053]	[.000]	[.182]	[.000]	[.440]
	[5]	.490	.935	.278	.263	.603	.366	1.96	5.70
		[.000]	[.000]	[.003]	[.038]	[.000]	[.000]	[.000]	[.575]
	[6]	.461	.900	.226	.360	.613	.334	1.86	8.53
		[.000]	[.000]	[.021]	[.030]	[.000]	[.004]	[.000]	[.482]
CUE	[1]	.531	.858	.409	.166	.501	.450	2.13	
		[.000]	[.000]	[.099]	[.089]	[.037]	[.034]	[.000]	
	[2]	.618	.935	.404	.096	.574	.402	2.62	3.06
		[.000]	[.000]	[.071]	[.140]	[.003]	[.024]	[.003]	[.080]
	[3]	.665	.963	.210	.109	.737	.241	2.99	4.43
		[.000]	[.000]	[.115]	[.442]	[.000]	[.071]	[.062]	[.218]
	[4]	.617	.963	.207	.150	.725	.253	2.61	4.44
		[.000]	[.000]	[.102]	[.256]	[.000]	[.056]	[.004]	[.488]
	[5]	.555	.957	.320	.164	.612	.369	2.25	6.15
		[.000]	[.000]	[.000]	[.039]	[.000]	[.000]	[.000]	[.522]
	[6]	.550	.984	.316	.164	.627	.366	2.22	9.36
		[.000]	[.000]	[.000]	[.048]	[.000]	[.000]	[.000]	[.404]
3S-GMM	[1]	.531	.858	.409	.166	.501	.450	2.13	
		[.000]	[.000]	[.099]	[.089]	[.037]	[.034]	[.000]	
	[2]	.621	.973	.186	.152	.752	.232	2.64	4.04
		[.000]	[.000]	[.393]	[.110]	[.002]	[.292]	[.000]	[.044]
	[3]	.584	.997	.150	.202	.794	.204	2.40	6.09
		[.000]	[.000]	[.292]	[.058]	[.002]	[.224]	[.000]	[.107]
	[4]	.578	.987	.154	.210	.781	.211	2.37	7.34
		[.000]	[.000]	[.263]	[.040]	[.000]	[.196]	[.000]	[.197]
	[5]	.520	.939	.304	.210	.599	.374	2.08	8.55
		[.000]	[.000]	[.000]	[.027]	[.000]	[.000]	[.000]	[.287]
	[6]	.534	.943	.309	.191	.604	.371	2.15	22.89
		[.000]	[.000]	[.000]	[.031]	[.000]	[.000]	[.000]	[.006]

Note: See note to Table 2a.

Table 5b: Hybrid NKPC: Form II, $\kappa = 0.12$

Method	Instrument	θ	β	ω	λ	γ_f	γ_b	D	J-stat
GMM	[1]	.531	.858	.409	.166	.501	.450	2.13	
		[.000]	[.000]	[.099]	[.089]	[.037]	[.034]	[.000]	
	[2]	.624	.949	.383	.095	.595	.385	2.66	2.13
		[.001]	[.000]	[.278]	[.481]	[.016]	[.107]	[.047]	[.144]
	[3]	.547	.982	.319	.165	.623	.369	2.21	3.01
		[.000]	[.000]	[.166]	[.288]	[.003]	[.065]	[.005]	[.390]
	[4]	.556	.966	.286	.176	.641	.342	2.25	5.35
		[.000]	[.000]	[.137]	[.050]	[.001]	[.062]	[.000]	[.375]
	[5]	.546	.960	.338	.163	.598	.386	2.20	6.35
		[.000]	[.000]	[.000]	[.043]	[.000]	[.000]	[.000]	[.499]
	[6]	.526	.951	.369	.169	.565	.417	2.11	9.47
		[.000]	[.000]	[.000]	[.088]	[.000]	[.000]	[.000]	[.396]
3S-GMM	[1]	.531	.858	.409	.166	.501	.450	2.13	
		[.000]	[.000]	[.094]	[.085]	[.034]	[.031]	[.000]	
	[2]	.628	.939	.385	.094	.591	.386	2.69	3.24
		[.000]	[.000]	[.184]	[.215]	[.013]	[.070]	[.002]	[.072]
	[3]	.598	.999	.184	.169	.764	.236	2.49	6.26
		[.000]	[.000]	[.230]	[.053]	[.000]	[.155]	[.000]	[.100]
	[4]	.580	.984	.225	.174	.710	.281	2.38	6.73
		[.000]	[.000]	[.155]	[.038]	[.000]	[.086]	[.000]	[.241]
	[5]	.549	.963	.331	.163	.605	.379	2.22	7.31
		[.000]	[.000]	[.000]	[.045]	[.000]	[.000]	[.000]	[.398]
	[6]	.548	.962	.354	.154	.589	.396	2.21	11.51
		[.000]	[.000]	[.000]	[.048]	[.000]	[.000]	[.000]	[.242]

Note: See note to Table 2a.

Table 6a: Hybrid NKPC: Form I, $\kappa = 0.12$ and Revised Data

Method	Instrument	θ	β	ω	λ	γ_f	γ_b	D	J-stat
GMM	GG	.565	.963	.287	.167	.643	.339	2.30	8.51
		(.072)	(.053)	(.082)	(.073)	(.075)	(.076)	(.379)	
		[.000]	[.000]	[.000]	[.024]	[.000]	[.000]	[.000]	[.201]
	GGLS	.505	.868	.154	.363	.676	.237	2.02	35.13
		(.038)	(.041)	(.038)	(.090)	(.045)	(.046)	(.154)	
		[.000]	[.000]	[.000]	[.000]	[.000]	[.000]	[.000]	[.027]
CUE	GG	.552	1.018	.267	.175	.684	.325	2.23	8.28
		(.088)	(.108)	(.084)	(.110)	(.094)	(.078)	(.438)	
		[.000]	[.000]	[.002]	[.114]	[.000]	[.000]	[.000]	[.309]
	GGLS	.565	1.077	.354	.118	.651	.379	2.30	15.54
		(.095)	(.116)	(.090)	(.090)	(.068)	(.061)	(.503)	
		[.000]	[.000]	[.000]	[.191]	[.000]	[.000]	[.000]	[.155]
3S-GMM	GG	.576	.975	.284	.155	.656	.332	2.36	10.15
		(.066)	(.044)	(.075)	(.066)	(.068)	(.068)	(.368)	
		[.000]	[.000]	[.000]	[.020]	[.000]	[.000]	[.000]	[.180]
	GGLS	.505	.860	.144	.374	.680	.225	2.02	20.29
		(.040)	(.040)	(.033)	(.093)	(.045)	(.042)	(.162)	
		[.000]	[.000]	[.000]	[.000]	[.000]	[.000]	[.000]	[.503]

Note: See note to Table 2a.

Table 6b: Hybrid NKPC: Form II, $\kappa = 0.12$. and Revised Data

Method	Instrument	θ	β	ω	λ	γ_f	γ_b	D	J-stat
GMM	GG	.668	.977	.331	.078	.657	.33	3.01	13.16
		(.087)	(.043)	(.081)	(.055)	(.056)	(.057)	(.792)	
		[.000]	[.000]	[.000]	[.157]	[.000]	[.000]	[.000]	[.068]
	GGLS	.669	.948	.363	.076	.621	.356	3.02	45.58
		(.066)	(.036)	(.063)	(.042)	(.035)	(.036)	(3.02)	
		[.000]	[.000]	[.000]	[.073]	[.000]	[.000]	[.068]	[.001]
3S-GMM	GG	.662	.979	.333	.080	.654	.336	2.95	10.23
		(.092)	(.045)	(.092)	(.058)	(.063)	(.065)	(.807)	
		[.000]	[.000]	[.000]	[.169]	[.000]	[.000]	[.000]	[.176]
	GGLS	.686	.945	.353	.070	.632	.344	3.18	19.49
		(.078)	(.037)	(.064)	(.046)	(.033)	(.034)	(.787)	
		[.000]	[.000]	[.000]	[.135]	[.000]	[.000]	[.013]	[.554]

Note: See note to Table 2a.

Table 7a: Hybrid NKPC: Form I, $\kappa = 0.12$ and Revised Data

Method	Instrument	θ	β	ω	λ	γ_f	γ_b	D	J-stat
GMM	[1]	.598	.910	.359	.125	.580	.383	2.49	
		[.000]	[.000]	[.108]	[.186]	[.017]	[.062]	[.008]	
	[2]	.648	1.001	.140	.135	.823	.177	2.84	2.68
		[.000]	[.000]	[.503]	[.207]	[.001]	[.466]	[.004]	[.102]
	[3]	.576	1.011	.215	.176	.734	.271	2.36	3.64
		[.000]	[.000]	[.163]	[.201]	[.000]	[.092]	[.000]	[.304]
	[4]	.553	1.006	.198	.212	.740	.263	2.24	4.14
		[.000]	[.000]	[.202]	[.146]	[.000]	[.129]	[.000]	[.530]
	[5]	.524	.955	.296	.206	.616	.364	2.10	5.02
		[.000]	[.000]	[.013]	[.136]	[.000]	[.0003	[.000]	[.656]
	[6]	.508	.972	.299	.218	.615	.372	2.03	8.13
		[.000]	[.000]	[.009]	[.041]	[.000]	[.002]	[.000]	[.521]
CUE	[1]	.598	.910	.359	.125	.580	.383	2.49	
		[.000]	[.000]	[.108]	[.186]	[.017]	[.062]	[.008]	
	[2]	.657	.941	.334	.089	.633	.341	2.92	2.63
		[.000]	[.000]	[.117]	[.203]	[.002]	[.061]	[.011]	[.105]
	[3]	.656	.968	.216	.113	.732	.249	2.91	4.76
		[.000]	[.000]	[.084]	[.316]	[.000]	[.046]	[.012]	[.190]
	[4]	.615	.970	.240	.139	.702	.282	2.60	5.18
		[.000]	[.000]	[.051]	[.205]	[.000]	[.021]	[.001]	[.394]
	[5]	.634	1.004	.315	.096	.670	.332	2.73	5.58
		[.000]	[.000]	[.003]	[.373]	[.000]	[.000]	[.012]	[.589]
	[6]	.678	1.031	.309	.068	.704	.311	3.10	8.28
		[.000]	[.000]	[.010]	[.525]	[.000]	[.000]	[.068]	[.507]
3S-GMM	[1]	.598	.910	.359	.125	.580	.383	2.49	
		[.000]	[.000]	[.108]	[.186]	[.017]	[.062]	[.008]	
	[2]	.663	.986	.219	.103	.742	.249	2.97	3.23
		[.000]	[.000]	[.281]	[.153]	[.000]	[.202]	[.004]	[.072]
	[3]	.616	1.015	.203	.139	.762	.247	2.61	7.56
		[.000]	[.000]	[.142]	[.108]	[.000]	[.087]	[.000]	[.056]
	[4]	.606	1.015	.192	.154	.769	.240	2.54	8.91
		[.000]	[.000]	[.144]	[.072]	[.000]	[.091]	[.000]	[.113]
	[5]	.589	.965	.307	.138	.639	.345	2.43	11.76
		[.000]	[.000]	[.000]	[.110]	[.000]	[.000]	[.000]	[.109]
	[6]	.612	.947	.301	.127	.642	.333	2.58	16.92
		[.000]	[.000]	[.000]	[.134]	[.000]	[.000]	[.000]	[.050]

Note: See note to Table 2a.

Table 7b: Hybrid NKPC: Form II, $\kappa = 0.12$ and Revised Data

Method	Instrument	θ	β	ω	λ	γ_f	γ_b	D	J-stat
GMM	[1]	.598	.910	.359	.125	.580	.383	2.49	
		[.000]	[.000]	[.108]	[.186]	[.017]	[.062]	[.008]	
	[2]	.674	.992	.256	.087	.720	.276	3.07	2.18
		[.000]	[.000]	[.364]	[.386]	[.006]	[.259]	[.052]	[.140]
	[3]	.629	1.037	.294	.098	.701	.316	2.70	2.94
		[.000]	[.000]	[.138]	[.479]	[.000]	[.055]	[.046]	[.401]
	[4]	.614	1.027	.282	.113	.700	.313	2.59	4.14
		[.000]	[.000]	[.109]	[.374]	[.000]	[.044]	[.015]	[.529]
	[5]	.608	.997	.345	.106	.637	.362	2.55	5.17
		[.000]	[.000]	[.008]	[.370]	[.000]	[.000]	[.011]	[.640]
	[6]	.608	.997	.345	.106	.637	.362	2.55	5.17
		[.000]	[.000]	[.008]	[.370]	[.000]	[.000]	[.011]	[.640]
3S-GMM	[1]	.598	.910	.359	.125	.580	.383	2.49	
		[.000]	[.000]	[.108]	[.186]	[.017]	[.062]	[.008]	
	[2]	.708	.993	.220	.073	.758	.238	3.43	2.66
		[.000]	[.000]	[.359]	[.284]	[.002]	[.278]	[.028]	[.103]
	[3]	.640	1.024	.249	.104	.734	.279	2.78	7.30
		[.000]	[.000]	[.093]	[.220]	[.000]	[.048]	[.004]	[.063]
	[4]	.622	1.023	.256	.116	.722	.290	2.65	8.13
		[.000]	[.000]	[.083]	[.168]	[.000]	[.040]	[.001]	[.149]
	[5]	.585	.994	.355	.120	.619	.378	2.41	9.34
		[.000]	[.000]	[.000]	[.137]	[.000]	[.000]	[.000]	[.229]
	[6]	.647	1.024	.329	.081	.676	.335	2.84	13.36
		[.000]	[.000]	[.006]	[.432]	[.000]	[.000]	[.026]	[.147]

Note: See note to Table 2a.

Table 8a: Hybrid NKPC: Form I, $\kappa = 0.12$ for sample: 1960Q1-2001Q3

Method	Instrument	θ	β	ω	λ	γ_f	γ_b	D	J-stat
GMM	GG	.593	.955	.319	.133	.627	.353	2.46	9.63
		(.074)	(.055)	(.082)	(.064)	(.071)	(.070)	(.445)	
		[.000]	[.000]	[.000]	[.041]	[.000]	[.000]	[.000]	[.211]
CUE	GG	.601	1.026	.274	.119	.705	.308	2.56	8.11
		(.103)	(.098)	(.097)	(.097)	(.097)	(.084)	(.680)	
		[.000]	[.000]	[.005]	[.218]	[.000]	[.000]	[.000]	[.323]
3S-GMM	GG	.604	.975	.320	.120	.641	.348	2.53	11.50
		(.069)	(.046)	(.078)	(.058)	(.065)	(.063)	(.441)	
		[.000]	[.000]	[.000]	[.040]	[.000]	[.000]	[.000]	[.118]

Note: See note to Table 2a.

Table 8b: Hybrid NKPC: Form II, $\kappa = 0.12$ for sample: 1960Q1-2001Q3

Method	Instrument	θ	β	ω	λ	γ_f	γ_b	D	J-stat
GMM	GG	.665	.996	.392	.065	.630	.372	2.98	10.75
		(.094)	(.053)	(.091)	(.050)	(.061)	(.060)	(.838)	
		[.000]	[.000]	[.000]	[.195]	[.000]	[.000]	[.000]	[.150]
3S-GMM	GG	.670	1.011	.398	.060	.632	.372	3.03	10.48
		(.098)	(.053)	(.097)	(.050)	(.063)	(.061)	(.903)	
		[.000]	[.000]	[.000]	[.233]	[.000]	[.000]	[.000]	[.163]

Note: See note to Table 2a.

Table 9a: Hybrid NKPC: Form I, $\kappa = 0.12$ for sample: 1960Q1-2001Q3

Method	Instrument	θ	β	ω	λ	γ_f	γ_b	D	J-stat
GMM	[1]	.634	.928	.351	.101	.607	.362	2.74	
		[.000]	[.000]	[.134]	[.195]	[.013]	[.083]	[.014]	
	[2]	.689	.988	.221	.085	.749	.244	3.21	1.97
		[.000]	[.000]	[.346]	[.290]	[.001]	[.256]	[.021]	[.161]
	[3]	.597	.997	.245	.147	.707	.291	2.48	3.98
		[.000]	[.000]	[.139]	[.259]	[.000]	[.066]	[.021]	[.264]
	[4]	.588	.983	.228	.165	.711	.280	2.43	5.09
		[.000]	[.000]	[.138]	[.188]	[.000]	[.073]	[.000]	[.404]
	[5]	.567	.945	.298	.165	.626	.349	2.31	5.19
		[.000]	[.000]	[.017]	[.190]	[.000]	[.004]	[.000]	[.637]
	[6]	.558	.954	.310	.166	.619	.361	2.26	9.26
		[.000]	[.000]	[.005]	[.063]	[.000]	[.001]	[.000]	[.414]
CUE	[1]	.634	.928	.351	.101	.607	.362	2.74	
		[.000]	[.000]	[.134]	[.195]	[.013]	[.083]	[.014]	
	[2]	.616	.869	.393	.111	.548	.402	2.60	2.25
		[.000]	[.000]	[.040]	[.131]	[.007]	[.020]	[.003]	[.134]
	[3]	.688	.970	.260	.082	.708	.276	3.20	5.34
		[.000]	[.000]	[.052]	[.428]	[.000]	[.019]	[.044]	[.148]
	[4]	.691	1.000	.271	.072	.718	.282	3.24	5.42
		[.000]	[.000]	[.051]	[.477]	[.000]	[.016]	[.060]	[.366]
	[5]	.699	1.012	.327	.058	.688	.318	3.32	5.66
		[.000]	[.000]	[.010]	[.565]	[.000]	[.000]	[.109]	[.580]
	[6]	.743	1.027	.328	.038	.708	.304	3.90	8.32
		[.003]	[.000]	[.025]	[.706]	[.000]	[.000]	[.293]	[.502]
3S-GMM	[1]	.634	.928	.351	.101	.607	.362	2.74	
		[.000]	[.000]	[.134]	[.195]	[.013]	[.083]	[.014]	
	[2]	.726	.990	.218	.064	.763	.231	3.65	1.89
		[.000]	[.000]	[.344]	[.311]	[.001]	[.271]	[.040]	[.169]
	[3]	.645	1.007	.247	.105	.727	.277	2.82	9.34
		[.000]	[.000]	[.085]	[.162]	[.000]	[.042]	[.001]	[.025]
	[4]	.637	1.006	.248	.110	.723	.280	2.76	10.15
		[.000]	[.000]	[.074]	[.132]	[.000]	[.035]	[.000]	[.071]
	[5]	.666	1.006	.328	.074	.673	.330	2.99	13.07
		[.000]	[.000]	[.002]	[.294]	[.000]	[.000]	[.005]	[.007]
	[6]	.678	.990	.317	.073	.676	.320	3.10	18.59
		[.000]	[.000]	[.003]	[.298]	[.000]	[.000]	[.007]	[.029]

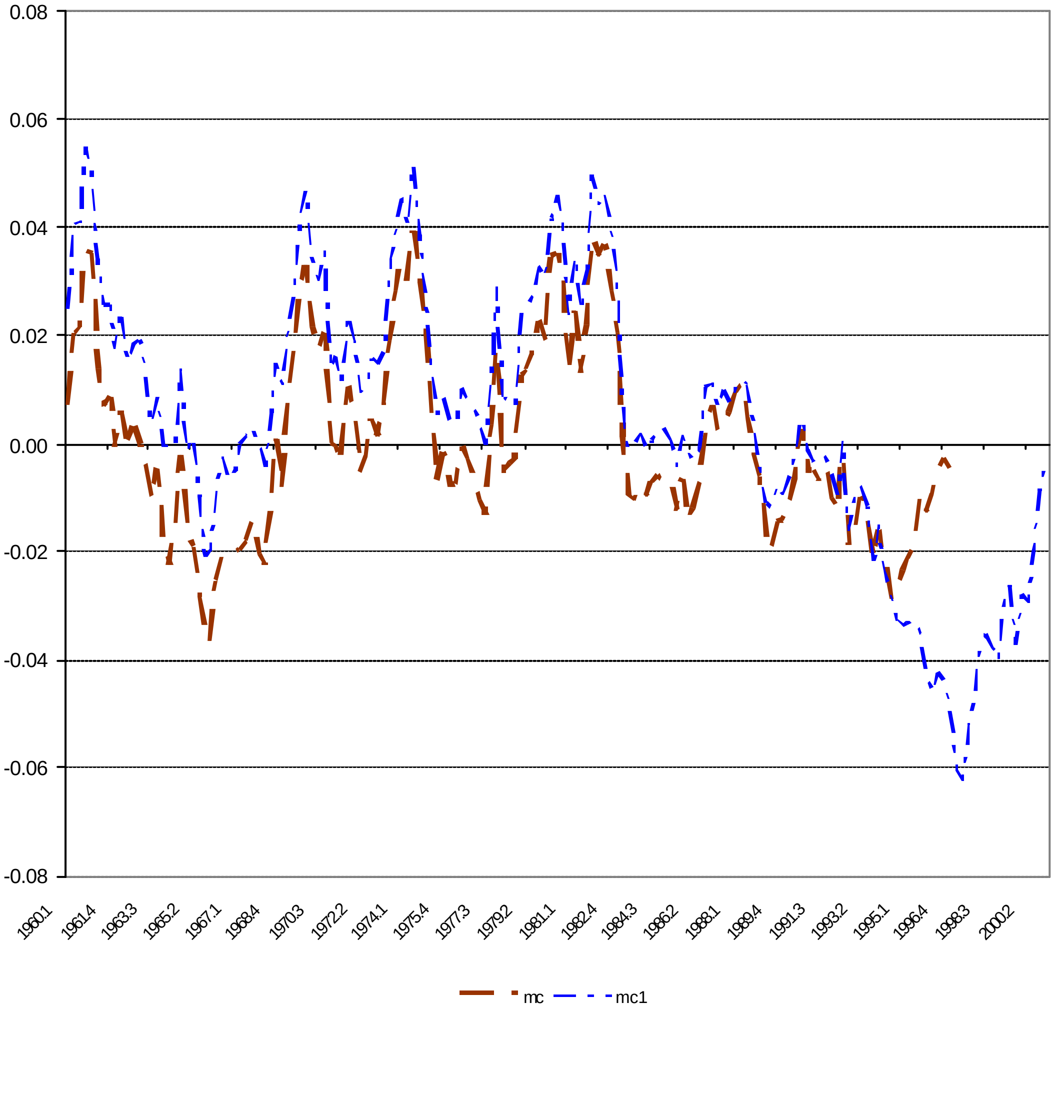
Note: See note to Table 2a.

Table 9b: Hybrid NKPC: Form II, $\kappa = 0.12$ for sample 1960Q1-2001Q3

Method	Instrument	θ	β	ω	λ	γ_f	γ_b	D	J-stat
GMM	[1]	.635	.928	.351	.101	.607	.362	2.74	
		[.000]	[.000]	[.134]	[.196]	[.013]	[.083]	[.015]	
	[2]	.709	.981	.306	.061	.688	.302	3.44	1.53
		[.000]	[.000]	[.288]	[.448]	[.006]	[.185]	[.100]	[.217]
	[3]	.669	1.027	.345	.067	.673	.338	3.02	3.75
		[.002]	[.000]	[.100]	[.578]	[.000]	[.026]	[.112]	[.289]
	[4]	.631	1.002	.380	.083	.625	.376	2.71	5.99
		[.000]	[.000]	[.046]	[.318]	[.000]	[.012]	[.015]	[.307]
	[5]	.662	.999	.361	.071	.647	.353	2.96	5.38
		[.000]	[.000]	[.014]	[.509]	[.000]	[.001]	[.062]	[.614]
	[6]	.682	1.003	.368	.060	.651	.350	3.15	8.20
		[.000]	[.000]	[.016]	[.568]	[.000]	[.000]	[.107]	[.515]
3S-GMM	[1]	.635	.928	.351	.101	.607	.362	2.74	
		[.000]	[.000]	[.134]	[.196]	[.013]	[.083]	[.015]	
	[2]	.731	.984	.274	.055	.718	.273	3.72	1.71
		[.000]	[.000]	[.272]	[.366]	[.003]	[.195]	[.070]	[.191]
	[3]	.680	1.021	.303	.069	.703	.307	3.12	8.54
		[.000]	[.000]	[.058]	[.364]	[.000]	[.024]	[.026]	[.036]
	[4]	.674	1.015	.306	.073	.696	.311	3.066	9.39
		[.000]	[.000]	[.048]	[.317]	[.000]	[.017]	[.016]	[.095]
	[5]	.647	1.005	.377	.075	.634	.370	2.83	9.07
		[.000]	[.000]	[.000]	[.304]	[.000]	[.000]	[.009]	[.247]
	[6]	.754	1.041	.367	.030	.693	.324	4.06	13.64
		[.009]	[.000]	[.032]	[.760]	[.000]	[.000]	[.385]	[.136]

Note: See note to Table 2a.

Figure 1: The real marginal cost and data revisions



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