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

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Abstract

We 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 is well-described by the New Keynesian Phillips curve (NKPC). Specifically, we address several important econometrics issues that arise in estimating the NKPC model. Using the continuously updated generalized method of moments estimator proposed by Hansen, Heaton, and Yaron (1996) and a new bias-corrected estimator based on a time series extension of the three-step GMM estimator developed by Bonnal and Renault (2005), we show that the empirical evidence casts serious doubt on the empirical relevance of the NKPC. In almost all cases, either the NKPC specification is rejected or the real marginal cost is not significant.

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1 Introduction

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.

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-explained 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 bandwidth).

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. Furthermore, we propose a time series extension of the three-step GMM estimator developed by Bonnal and Renault (2005) as well as a bias-corrected version of this new estimator. Both estimators seek to overcome part of the standard problems encountered in economic applications with the 2S-GMM estimator, and especially the following three problems identified in the literature of the New Keynesian Phillips Curve.

First, as is well known, the usual two-step GMM estimator (henceforth, 2S-GMM) has questionable finite sample properties.[2] 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

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

asymptotic bias of the usual 2S-GMM estimator has been well-documented in Newey and Smith (2004) and Antolyev (2005). Using higher-order asymptotic expansions for members of a class of generalized empirical likelihood estimators, they show that, in particular, 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 large 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 allow to judge 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 do not reject 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 bias problem is addressed by using the continuously updated GMM estimator (CUE) developed by Hansen, Heaton, and Yaron (1996) and a bias-corrected time series extension of the three-step GMM (3S-GMM) estimator proposed by Bonnal and Renault (2005). In itself, the time series extension of the 3S-GMM estimator as well as its bias-corrected version are original contributions of this paper. We show that the bias-corrected version of this estimator is asymptotically unbiased up to order T^{-1} while the class of GMM estimators including the usual 2S-GMM, the 3S-GMM and the CUE are asymptotically biased at order T^{-1}. Furthermore, we also apply a new specification test based on the concept of implied probabilities proposed by Back and Brown (1993). Second, although the bias corrected estimator has shown to have better asymptotic unbiased properties that the CUE, this latter estimator 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 bandwidth.[3] 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. Finally, the empirical relevance of the NKPC is also addressed by reconsidering the choice of instruments, the measurement of the real marginal cost and, specifically, how the results are robust to data revisions.

The main conclusions are the followings. First, a more appropriate choice of the weighting matrix improves greatly the power of the specification test. For the sample used by GG and GGLS, the J-test rejects the Forward-Looking and the Hybrid NKPC. Second, the CUE, which is invariant to the normalization, allows us to discriminate between conflicting results from the first and the second specifications. The CUE favors the second normalization for which the estimated values for the parameter relative to the real marginal cost is lower than for the first normalization and generally insignificant. Moreover, these estimates are for almost cases lower with CUE and 3S-GMM than with GMM estimator. Finally, for the revised and extended data sets, while the Hybrid NKPC is generally not rejected by the specification J-test, the real marginal cost is not statistically significant.

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 a bias-corrected time-dependent 3S-GMM estimator. In section 4, we present the estimation results. Section 5 concludes. Proofs are in appendices.

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 or proportional to trend inflation, Ω. These adjustment probabilities are independent of the firm's price history such that the proportion of firms that may

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

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.

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 behavior 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).

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):

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

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, 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—it is model-dependent. In addition, since the real marginal cost is a latent variable, it is also sensitive to data revisions. These issues are discussed in more details in section 4.

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

$$\widehat{\beta}_T^{2S} = \arg\min_{\beta \in B} \frac{1}{T}\sum_{t=1}^{T} g(z_t,\beta)' \widehat{\Omega}(\widehat{\beta}_T^{1S})^{-1} \frac{1}{T}\sum_{t=1}^{T} g(z_t,\beta),$$

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

Let us now consider the methodology of GG and GGLS. In the case of the hybrid model, the reduced form can be written as

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

where ε_{t+1} is an expectations 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 labor income share, the output gap,[4] 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 labor income share.[5] In both GG and GGLS, the variance-covariance matrix used to obtain standard errors for the model parameters is estimated with a fixed bandwidth 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, two alternative estimators are used for the nonlinear specification: the CUE and a bias-corrected time series extension of the 3S-GMM estimator. According to the higher-order asymptotic expansions derived by Newey and Smith (2004) and Anatolyev (2005), the empirical likelihood estimator (ELE) affords a minimal higher-order estimation bias. The ELE, however, is computationally 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 and achieves an asymptotic higher order efficiency (see Bonnal and Renault (2005) in the i.i.d case). These properties still hold in the time series context. Moreover, the bias-corrected 3S-GMM estimator is shown to be asymptotically unbiased up to order T^{-1} whereas other estimators are asymptotically biased at this order (GMM, CUE, EL and 3S-GMM). Second, the

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

[5]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).

automatic lag-selection procedure proposed by Newey and West (1994) is adopted to compute estimates of the variance-covariance matrix of the moment conditions. Third, 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, 2005). 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.

Let us now describe the alternative estimators. The CUE is analogous to the 2S-GMM estimator, except that the objective function is simultaneously minimized over β and $\widehat{\Omega}(\beta)$. 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

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

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 2005). This property is generally true in the autocorrelated case for an estimator of the covariance matrix that has the same bandwidth.[6]

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) in the i.i.d. case and Anatolyev (2005) with dependent data show that the higher-order 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 of the moment conditions 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 two drawbacks of using an unconstrained estimator of the weighting matrix and to be more sensitive to initial conditions than the 2S-GMM.[7] At the same time, two obvious advantages of the

[6]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.

[7]The estimator of the weighting matrix is unconstrained in the sense that the variance-covariance matrix used for its computation is weighted by the unconstrained empirical probabilities $1/T$.

CUE with respect to 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. 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, proposed by Bonnal and Renault (2005) in the i.i.d. context, 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. 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) pointed 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.

Using the methodology proposed by Bonnal and Renault (2005), we first provide a time series extension of their estimator. Then we develop a bias-corrected 3S-GMM estimator for dependent data. To do so, let us introduce the concept of implied probabilities for GMM estimators (Back and Brown 1993). These are defined as the constrained probabilities such that the moment conditions are respected at the GMM estimator, $\widehat{\beta}$. Thus,

$$\sum_{t=1}^{T} \widehat{p}_t^{GMM} g(z_t, \widehat{\beta}_T) = 0.$$

where $\widehat{p}_t^{GMM}$ are the implied probabilities evaluated at the GMM estimator $\widehat{\beta}$ defined as

$$\widehat{p}_t^{GMM} = \frac{1}{T} - \frac{1}{T}\left[g(z_t, \widehat{\beta}_T) - \overline{g}_T(\widehat{\beta}_T)\right]' \widehat{\Omega}_T(\widehat{\beta}_T)^{-1}\overline{g}_T(\widehat{\beta}_T)$$

where $\overline{g}_T(\widehat{\beta}_T) = \frac{1}{T}\sum_{t=1}^{T} g(z_t, \widehat{\beta}_T)$ (see Back and Brown 1993; Bonnal and Renault 2001, 2005).[8] Note that the unconstrained empirical probabilities used in the standard GMM are given by the empirical frequencies, $\frac{1}{T}$.

Before presenting the two main results of this section, we briefly describe the 3S-GMM estimator for the i.i.d. case. Let $\widehat{\beta}$ be now an estimator asymptotically equivalent to the optimal 2S-GMM estimator, $\widehat{\beta}_T^{2S}$. The 3S-GMM estimator, $\widehat{\beta}_T^{3S}$, is defined as the solution of the following p equations:

$$\left[\sum_{t=1}^{T}\widehat{p}_t^{GMM}\frac{\partial g}{\partial\beta'}(z_t,\widehat{\beta}_T)\right]'\left[\sum_{t=1}^{T}\widehat{p}_t^{GMM}g(z_t,\widehat{\beta}_T)g'(z_t,\widehat{\beta}_T)\right]^{-1}\frac{1}{T}\sum_{t=1}^{T}g(z_t,\beta_3)=0.$$

where the $\widehat{p}_t^{GMM}$'s are evaluated at the optimal estimator $\widehat{\beta}_T$. These equations are nothing but the first order conditions of the empirical likelihood with the gradient and the moments matrix evaluated at an asymptotic efficient estimator of β. To obtain the 3S-GMM estimator, the implied probabilities are used to estimate the Jacobian and variance-covariance matrices. The 3S-GMM then uses efficiently the information content of moment conditions as the empirical likelihood estimator does.

One major feature of the 3S-GMM is that implied probabilities have now an explicit closed-form solution since this estimator relies on a chi-square metric. At the same time, one potential problem might be that implied probabilities might be undefined (e.g., not positive) in finite samples.[9] Nevertheless, Bonnal and Renault (2005) 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 ($\widehat{p}_t^{GMM}$). 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 are zero.

Similarly, a 3S-GMM estimator for dependent data can be proposed based on the first order conditions of the empirical likelihood estimator. In order to take account the temporal dependence, the moment conditions has to be smoothed with an appropriate kernel. In general, the smoothed moment conditions are given by:

$$\widetilde{g}_{tT}(\beta)=\frac{1}{S_T}\sum_{s=t-T}^{t-1}k\left(\frac{s}{S_T}\right)g(z_{t-s},\beta)$$

[8]In the following, $\widehat{\Omega}_T$ is considered as a consistent estimator of the variance-covariance matrix of the moments conditions in mean deviation or not depending on the estimator used.

[9]In contrast to the empirical likelihood estimator, no inequality constraint is imposed *a priori* on the existence of the implied probabilities.

for $t = 1, \ldots, T$ and S_T is a bandwidth parameter and $k(\cdot)$ a kernel function. Smith (2004) presents examples of appropriate kernels to smooth the moment conditions and their resulting induced kernel for the estimation of the variance-covariance matrix of the moment conditions. For instance, the uniform kernel proposed by Kitamura and Stutzer (1997) induces the Bartlett kernel for the estimation of the variance-covariance matrix. Defining the smoothed derivative of the moment conditions as:

$$\widetilde{G}_{tT}(\beta) = \frac{1}{S_T} \sum_{s=t-T}^{t-1} k\left(\frac{s}{S_T}\right) \frac{\partial g}{\partial \beta'}(z_{t-s}, \beta).$$

the time dependent 3S-GMM is the solution of the first order conditions of the ELE, as in the i.i.d. case, but for its smoothed version. These first order conditions of the smoothed empirical likelihood (SEL) estimator are shown by Smith (2004) and Anatolyev (2005) to imply the following equations:

$$\left[\sum_{t=1}^{T} \widehat{p}_t^{SEL} \widetilde{G}_{tT}(\widehat{\beta}_T^{SEL})\right]' \left[S_T \sum_{t=1}^{T} \widehat{p}_t^{SEL} g_{tT}(\widehat{\beta}_T^{SEL}) g_{tT}(\widehat{\beta}_T^{SEL})'\right]^{-1} \frac{1}{T} \sum_{t=1}^{T} \widetilde{g}_{tT}(\widehat{\beta}_T^{SEL}) = 0.$$

where the implied probabilities, $\widehat{p}_t^{SEL}$, are computed from those of the SEL (see Smith 2004).

As proposed by Bonnal and Renault (2005) in the i.i.d. case, the Jacobian matrix and the variance-covariance matrix can be evaluated at an efficient GMM estimator. With dependent data, the corresponding implied probabilities are defined respective to the smoothed moments, namely:

$$\widehat{p}_t^{GMM} = \frac{1}{T} - \frac{1}{T}\left[\widetilde{g}_{tT}(\widehat{\beta}_T) - \overline{g}_T(\widehat{\beta}_T)\right]' \widehat{\Omega}_T(\widehat{\beta}_T)^{-1} \overline{g}_T(\widehat{\beta}_T) \tag{5}$$

where $\overline{g}_T(\widehat{\beta}_T) = \frac{1}{T}\sum_{t=1}^{T} \widetilde{g}_{tT}(\widehat{\beta}_T) = \frac{1}{T}\sum_{t=1}^{T} g(\widehat{\beta}_T)$ and

$$\widehat{\Omega}_T = \frac{S_T}{T} \sum_{s=-2K}^{2K} \kappa^*(s) g_t(\beta) g_{t-s}(\beta)'$$

where $\kappa^*(s)$ is the induced kernel resulting from the kernel used to smooth the moment conditions (see Smith (2004) or Anatolyev (2005)). This is a consistent and positive definite estimator of the variance-covariance matrix and it has the usual form of a heteroskedasticity and autocorrelation consistent (HAC) weight matrix. For the uniform kernel proposed by Kitamura and Stutzer (1997), the smoothed moment conditions are:

$$\widetilde{g}_{tT}(\beta) = \frac{1}{2K+1} \sum_{s=-K}^{K} g(z_{t-s}, \beta)$$

and the corresponding estimator of the variance-covariance matrix is the one that uses the Bartlett kernel.

Similarly to Newey and Smith for i.i.d. context, Anatolyev (2005) derives second order asymptotic biases of smoothed generalized empirical likelihood with dependent data. As in i.i.d. case, second order asymptotic bias of smoothed empirical likelihood lacks some components, which exists for the 2S-GMM estimator. In particular, the SEL removes the bias component resulting from the correlation between the moment conditions and their derivatives, which grows with the degree of overidentification. By an appropriate choice of the kernel, the SEL also removes the bias component associated with third moments. The smoother proposed by Kitamura and Stutzer (1997) belongs to this class of appropriate kernels. The next proposition sets forth the higher order equivalence efficiency for the SEL estimator and the 3S-GMM proposed here in the context of time dependence.

Proposition 1 *Let the Three-step GMM estimator $\widehat{\beta}_T^{3S}$ be defined as the solution of the p equations*

$$\left[\sum_{t=1}^{T} \widehat{p}_t^{GMM} \widetilde{G}_{tT}(\widehat{\beta}_T)\right]' \left[S_T \sum_{t=1}^{T} \widehat{p}_t^{GMM} \widetilde{g}_{tT}(\widehat{\beta}_T)\widetilde{g}_{tT}(\widehat{\beta}_T)'\right]^{-1} \frac{1}{T}\sum_{t=1}^{T} \widetilde{g}(z_t,\beta) = 0.$$

where $\widehat{\beta}_T$ is an efficient GMM estimator, then

$$\widehat{\beta}_T^{3S} - \widehat{\beta}_T^{SEL} = O_p(T^{-3/2})$$

and $\widehat{\beta}_T^{3S}$ achieves the same higher order efficiency that the smoothed empirical likelihood estimator.

Proof: see Appendix.

The 3S-GMM estimator then shares the same higher order asymptotic properties than the SEL estimator. In the following, we considered the uniform kernel proposed by Kitamura and Stutzer (1997). For the applications, the smoothed parameter K is chosen according to the data-dependent procedure proposed by Newey and West (1994).

By Proposition 1, the bias-order $O(T^{-1})$ for the 3S-GMM estimator and the SEL are the same. The higher order asymptotic derivations in Anatolyev (2005) allows us to propose a bias-corrected 3S-GMM estimator for dependent data. The next proposition gives the expression for this bias corrected 3S-GMM estimator.

Proposition 2 *Suppose a Three-step estimator $\widehat{\beta}_T^{3S}$ such as defined in Proposition* 1 *obtained with the smoothed uniform kernel proposed by Kitamura and Stutzer (1997).*

Under Assumptions 1-5 in Anatolyev (2005), a consistent estimator of the asymptotic bias of order T^{-1} is given by:

$$\widehat{Bias}(\widehat{\beta}_T^{3S}) = \widehat{B}_{G\Xi g}/T + \widehat{B}_{\partial^2 g}/T$$

where $\widehat{B}_{G\Xi g}$ and $\widehat{B}_{\partial^2 g}$ are consistent estimators of:

$$B_{G\Xi g} = \Xi \sum_{u=-\infty}^{\infty} E\left[\frac{\partial g}{\partial \beta'}(z_t,\beta)\Xi g(z_{t-u},\beta)\right]$$

$$B_{\partial^2 g} = \Xi \sum_{j=1}^{p} E\left[\frac{\partial^2 g}{\partial \beta' \partial \beta_j}(z_t,\beta)\frac{\Sigma}{2}e_j\right]$$

and e_j is the jth column of the identity matrix with dimension $p \times p$, $\Sigma = \left(G'\Omega^{-1}G\right)^{-1}$, $\Xi = \Sigma G'\Omega^{-1}$, $G = E\left[\frac{\partial g}{\partial \beta'}(z_t,\beta)\right]$ and $\Omega = \sum_{s=-\infty}^{\infty} E\left[g(z_t,\beta)g(z_{t-s},\beta)'\right]$.

The bias corrected Three-step GMM estimator $\widehat{\beta}_T^{3SC}$ defined as $\widehat{\beta}_T^{3SC} = \widehat{\beta}_T^{3S} - \widehat{Bias}(\widehat{\beta}_T^{3S})$ is asymptotically unbiased up to order T^{-1}.

Proof: see Appendix.

Consistent estimators of $B_{G\Xi g}$ and $B_{\partial^2 g}$ are obtained following an appropriate replacement of moment conditions or their derivatives by their respective smoothed versions (see Lemmas 2 and 3 in Anatolyev). Thus,

$$\widehat{G} = \sum_{t=1}^{T} \widehat{p}_t^{3S} \widetilde{G}_{tT}(\widehat{\beta}_T^{3S}),$$

$$\widehat{\Omega}_T = S_T \sum_{t=1}^{T} \widehat{p}_t^{3S} \widetilde{g}_{tT}(\widehat{\beta}_T^{3S}) \widetilde{g}_{tT}(\widehat{\beta}_T^{3S})'$$

and a consistent estimator of $\sum_{u=-\infty}^{\infty} E\left[\frac{\partial g}{\partial \beta'}(z_t,\beta)\Xi g(z_{t-u},\beta)\right]$ is given by:

$$S_T \sum_{t=1}^{T} \widehat{p}_t^{3S} \widetilde{G}_{tT}(\widehat{\beta}_T^{3S}) \widehat{\Xi} \widetilde{g}_{tT}(\widehat{\beta}_T^{3S}).$$

where $\widehat{\Xi} = \left(\widehat{G}'\widehat{\Omega}^{-1}\widehat{G}\right)^{-1} \widehat{G}'\widehat{\Omega}^{-1}$ (see Lemma 3b in Anatolyev (2005)).

Finally, we perform two specification tests. On the one hand, we consider the usual J-statistic but evaluated at the bias-corrected 3S-GMM estimator. On the other hand, we propose a new specification test based on the results of Brown and Back (1993), Baggerly (1998), and Bonnal and Renault (2001, 2005). In effect, as suggested by Back and Brown (1993), implied probabilities may provide a useful diagnostic device. We then perform a specification test, which measures the discrepancy between the estimated probabilities and the unconstrained empirical probabilities $1/T$. The statistic called IPS_T for implied probabilities statistic has the following form

$$IPS_T = S_T \sum_{t=1}^{T} \left[T^2 \left(\widehat{p}_t^{3SC} \right)^2 - 1 \right].$$

where $\widehat{p}_t^{3S}$'s are the implied probabilities defined in equation (5) but evaluated at the bias-corrected 3S-GMM estimator. Under usual regularity conditions, in i.i.d. settings (S_T=1), this statistic is asymptotically distributed as $\chi^2(q-p)$ (see Baggerly (1998), Theorem 1 and Bonnal and Renault (2001) for the case where $\lambda = -2$ in their papers). In the Appendix, we show that for dependent data, this statistic calculated with an appropriate S_T is asymptotically distributed also as $\chi^2(q-p)$. This statistic is then asymptotically equivalent to the J-statistic at the first order but can differ in small samples.

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).[10] As a first step, we use the same instrument sets as GG and GGLS, before considering alternative instrument sets in a robustness analysis.

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), $\kappa = 0.12$.[11]

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

[10] 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.

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

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

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

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 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 that non-identification is not an issue. In particular, our results suggest 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.

Table 1 reports the results for each specification when a 12-lags Newey-West estimate of the covariance matrix is used.[12] 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 the p-values of the Hansen's J-statistic of the overidentifying restrictions for GMM, CUE and the bias-corrected 3S-GMM (denoted 3SC-GMM in the tables) and the p-values of the IPS_T for the bias-corrected 3S-GMM. 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.[13] 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

[12]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.

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

GG's instrument set, but not with GGLS's instrument set.[14] Second, the overidentifying restrictions test is far from rejecting the NKPC specification with the usual J_T-statistic while the specification is rejected with the IPS_T. We will see below that, in general, the J_T-statistic and the IPS_t yield the same conclusion except in the case when the bandwidth is fixed as in this set of results. The IPS_T seems to be less sensitive to the computation of the weighting matrix than that the J_T statistic. This merits more investigations by a simulation study.[15]

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 each normalization, the 2S-GMM, CUE, and 3SC-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 3SC-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 3SC-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 and GGLS's instrument sets when the estimator of the variance-covariance matrix is calculated with the sample moments in mean deviation except for GMM in the case of the second specification with GG's instrument set and CUE also with GG's instrument set. For results obtained with the bias corrected estimator, the NKPC specification in both forms is clearly rejected with the J_T-statistic and the IPS_T.

(Insert Tables 1 and 2 around here)

Overall, these results suggest that the empirical evidence for the Forward-Looking NKPC is rather weak. In particular, 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.

[14]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 (2004).

[15]For Monte-Carlo simulations of alternative GMM estimators (including the 3S-GMM and its bias-corrected version) and specification tests, see Guay and Pelgrin (2005a).

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 both statistics for overidentifying restrictions.

(Insert Tables 3 and 4 around here)

According to the 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 bias-corrected 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 bias corrected 3S-GMM estimators. Again here, the J_T-statistic and the IPS_T deliver opposite conclusions.

When we use Hall's mean deviation correction, however, the validity of instruments is rejected more often. For example, the overidentifying restrictions are rejected with GG's instrument set for the 2S-GMM, CUE and bias corrected 3S-GMM estimators. Interestingly, the real marginal cost is significant in the case of the CUE, but the overidentifying test rejects the specification with GG's instrument set. As before, the real marginal cost is not significant for the second specification.

Our results therefore provide few 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. The hybrid specification is rejected for the GG's instrument set 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 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. However, these results have to be interpreted with caution since in several cases the hybrid NKPC specification is rejected.

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 revisions of the dataset, an updated dataset, and the definition of the real marginal cost.[16]

[16] We also examine the following issues in an earlier version of this paper (see Guay and Pelgrin 2004). First, we test how informative additional lags of inflation are in the NKPC. Second, we analyze 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). Third, following Sbordone (2001) and Banerjee and Batini (2004), we conduct sensitivity analysis to examine if our results are not specific to the particular model of staggered prices adopted (Calvo's specification) and thus use fixed-length contracts introduced by Taylor (1980). Finally, as Adam and Padula (2003) discuss, the inflation-forecasting measure may be of concern. In this respect, we re-estimate the NKPC with data from the Survey of Professional Forecasters. Our results are robust and this refinements do not improve the statistical significance of the real marginal cost in our sample. Detailed results are available on request.

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. In particular, 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 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 conduct 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_T and IPS_T statistics are based on Hall's mean deviation correction.

(Insert Tables 5a and 5b around here)

As expected, the results are similar for the 2S-GMM and CUE estimation methods (for both normalizations) in the just-identified case. The results differ for the bias-corrected 3S-GMM due to the applied correction. 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 bias corrected 3S-GMM estimators. The estimated value of λ for the first specification is substantially lower with the 3SC-GMM than with the 2S-GMM estimator. Both specifications are not rejected by the overidentifying test, except in two cases (at the 6 per cent level with the bias corrected 3S-GMM). 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. Overall, the results are more encouraging for the Hybrid NKPC specification. However, the estimations with few instruments generally reject the model and the real marginal cost is not significant. Interestingly here, the J_T and IPS_T statistics yield the same conclusion for all cases.

4.3.2 *Revised and updated data*

As we explained earlier, 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 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). In this respect, Figure 1 reports the real marginal cost in log deviation from its mean, calculated as the labor 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 Table 6 for the instrument sets of GG and GGLS.

(Insert Figure 1 and Table 6 around here)

According to both normalizations, the real marginal cost is not significant except for the standard GMM and bias corrected 3S-GMM estimators in the first specification. However, for the GG’s instruments, the specification is rejected by overidentifying restrictions test. In contrast to our results in Tables 4a, 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 additional 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 favor of the NKPC, particularly for the estimation with instrument sets [1] to [6].

(Insert Tables 7a and 7b around here)

Results with the sample size extended to 1960Q1–2001Q3 are provided in Table 8 for GGLS's instrument set, and in Tables 9a and b for instrument sets [1] to [6]. Results for GGLS's instrument set are very close to the ones obtained with revised data, specially the real marginal cost is significant only with the 2S-GMM and bias corrected 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. Unfortunately for the NKPC, the results with the CUE seem to favor 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.

(Insert Tables 8 and 9a,b around here)

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

4.4 The definition of real marginal cost

As we noted earlier, the definition of the real marginal cost may be a critical issue in the estimation of the NKPC. The standard approximation of the real marginal cost by real unit labor 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 labor 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 labor and the presence of overhead costs and labor 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.

Following Rotemberg and Woodford (1999), Gagnon and Khan (2004), and Sbordone (2001), we re-estimate the NKPC using (i) a Cobb-Douglas technology with overhead labor costs, or (ii) a specification with adjustment costs for labor.[17] In both cases, the marginal cost is no longer proportional to the average labor 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 $\frac{\phi}{2}\left(H_t - H_{t-1}\right)^2$, the real marginal cost can be defined as follows (in logarithm):

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

We first try to estimate the parameter ϕ. Unfortunately, it 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 labor," 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 labor, $\overline{H} \geq 0$.

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.[18]

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

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

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 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 bias corrected 3S-GMM. In all other cases, the real marginal cost is not significant.

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

5 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 and that the real marginal cost is statically significant. The main contribution of this paper is to deliver a comprehensive evidence on the empirical performance of the NKPC by considering critical issues in the 2S-GMM method of GG and GGLS and thus by comparing and proposing alternative estimation techniques. In particular, we develop a time series extension of the 3S-GMM estimator, as suggested by Bonnal and Renault (2005), and a bias-corrected version of this estimator for dependent data.

Our empirical results suggest that, at the theoretical level, more refined models would have to be developed in closed or open economies. 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). Regarding the estimation techniques, some further extensions would be to develop the inference in GMM by using the implied probabilities (Guay and Pelgrin, 2005b) and to compare the finite sample performances of a wide range of GMM-based estimators by Monte-Carlo simulations.

Appendix

Proof of Proposition 1:

The sketch of the proof follows Bonnal and Renault (2005). Define the respective p equations corresponding to the FOC for the SEL and 3S-GMM estimators as:

$$f_T(\widehat{\beta}_T^{SEL}) = \left[\sum_{t=1}^{T} \widehat{p}_t^{SEL} \widetilde{G}_{tT}\left(\widehat{\beta}_T^{SEL}\right)\right]' \left[\widehat{\Omega}_T\left(\widehat{\beta}_T^{SEL}\right)\right]^{-1} \frac{1}{T}\sum_{t=1}^{T} \widetilde{g}_{tT}(\widehat{\beta}_T^{SEL}) = 0.$$

where $\widehat{\Omega}_T\left(\widehat{\beta}_T^{SEL}\right) = S_T \sum_{t=1}^{T} \widehat{p}_t^{SEL} \widetilde{g}_{tT}(\widehat{\beta}_T^{SEL})\widetilde{g}_{tT}(\widehat{\beta}_T^{SEL})'$ and $\widehat{p}_t^{SEL}$ is defined in Smith (2004),

$$h_T(\widehat{\beta}_T^{3S}) = \left[\sum_{t=1}^{T} \widehat{p}_t^{GMM} \widetilde{G}_{tT}\left(\widehat{\beta}_T\right)\right]' \left[\widehat{\Omega}_T\left(\widehat{\beta}_T\right)\right]^{-1} \frac{1}{T}\sum_{t=1}^{T} \widetilde{g}_{tT}(\widehat{\beta}_T^{3S}) = 0.$$

where $\widehat{\Omega}_T\left(\widehat{\beta}_T\right) = S_T \sum_{t=1}^{T} \widehat{p}_t^{GMM} \widetilde{g}_{tT}(\widehat{\beta}_T)\widetilde{g}_{tT}(\widehat{\beta}_T)'$ and $\widehat{p}_t^{GMM}$ is defined in Section 3.

The objective is to show that $\widehat{\beta}_T^{3S} - \widehat{\beta}_T^{SEL} = O_p(T^{-3/2})$. The proof is based on Theorem 1 in Robinson (1988). This theorem allows to evaluate the order of magnitude for the stochastic difference between two alternative estimators. In order to apply the theorem, two assumptions need to be fulfilled. The Assumption A1 in Robinson (1988) is directly verified and Assumption A2 is supposed to hold. For instance, the latter assumption is respected when the derivative of $h_T(\beta)$ respective to β is continuous uniformly in large T with probability arbitrarily close to one in the neighborhood of β_0.

Under these Assumptions, Theorem 1 in Robinson implies that:

$$\widehat{\beta}_T^{3S} - \widehat{\beta}_T^{SEL} = O_p\left(\|h_T\left(\widehat{\beta}_T^{SEL}\right) - f_T\left(\widehat{\beta}_T^{SEL}\right)\|\right).$$

Since $\frac{1}{T}\sum\limits_{t=1}^{T} \widetilde{g}_{tT}(\widehat{\beta}_T^{SEL}) = O_p(1/\sqrt{T})$, we only need to show that:

$$\left\|\widehat{p}_t^{GMM} \widetilde{G}_{tT}\left(\widehat{\beta}_T\right) - \widehat{p}_t^{SEL} \widetilde{G}_{tT}\left(\widehat{\beta}_T^{SEL}\right)\right\| = O_p(1/T) \tag{6}$$

and

$$\left\|\widehat{\Omega}(\widehat{\beta}_T) - \widehat{\Omega}(\widehat{\beta}_T^{SEL})\right\| = O_p(1/T). \tag{7}$$

First examine equation (6). Consider the continuous updated estimator $\widehat{\beta}_T^{CUE}$. The corresponding implied probabilities $\widehat{p}_t^{CUE}$ have the same analytic expression as in GMM's ones. By the triangle inequality

$$\begin{aligned}\left\|\widehat{p}_t^{GMM} \widetilde{G}_{tT}\left(\widehat{\beta}_T\right) - \widehat{p}_t^{SEL} \widetilde{G}_{tT}\left(\widehat{\beta}_T^{SEL}\right)\right\| &\leq \left\|\widehat{p}_t^{GMM}\ \widetilde{G}_{tT}\left(\widehat{\beta}_T\right) - \widehat{p}_t^{CUE} \widetilde{G}_{tT}\left(\widehat{\beta}_T^{CUE}\right)\right\| \\ &+ \left\|\widehat{p}_t^{CUE} \widetilde{G}_{tT}\left(\widehat{\beta}_T^{CUE}\right) - \widehat{p}_t^{SEL} \widetilde{G}_{tT}\left(\widehat{\beta}_T^{SEL}\right)\right\|\end{aligned}$$

The first expression at the right hand side is $O_p(1/T)$ by an usual Taylor expansion and $\widehat{\beta}_T - \widehat{\beta}_T^{CUE} = O_p(1/T)$. The second expression is also $O_p(1/T)$ by a direct implication of Theorem 3.1 in Smith (2004) for efficient moment estimators of $G_{tT}\left(\widehat{\beta}_T\right)$ by CUE and SEL. The same arguments holds for (7). The result follows. The third step estimator $\widehat{\beta}_T^{3S}$ is then higher-order equivalent to the smoothed empirical likelihood estimator $\widehat{\beta}_T^{SEL}$.

Proof of Proposition 2:

Theorem 1 in Anatolyev provides the asymptotic bias of the SEL estimator. Since by Proposition 1, the Three-step GMM estimator achieves the same higher order efficiency, the asymptotic bias of this estimator is the same as the one for the SEL estimator. The first term appearing in the asymptotic bias of the SEL estimator in the expression of Theorem 1 in Anatolyev is removed by the use of the uniform kernel. The asymptotic bias at order T^{-1} of the Three-step GMM estimator obtained by using this kernel is then given by: $B_{G\Xi g} + B_{\partial^2 g}$.

Derivation of the asymptotic distribution of IPS_T statistic:

The implied probabilities evaluated at the bias-corrected 3S-GMM is defined as:

$$\widehat{p}_t^{3SC} = \frac{1}{T} - \frac{1}{T}\left[\widetilde{g}_{tT}(\widehat{\beta}_T^{3SC}) - \overline{g}_T(\widehat{\beta}_T^{3SC})\right]' \widehat{\Omega}_T(\widehat{\beta}_T^{3SC})^{-1}\overline{g}_T(\widehat{\beta}_T^{3SC})$$

or equivalently:

$$\widehat{p}_t^{3SC} = \frac{1}{T} - \frac{1}{T}\overline{g}_T(\widehat{\beta}_T^{3SC})'\widehat{\Omega}_T(\widehat{\beta}_T^{3SC})^{-1}\left[\widetilde{g}_{tT}(\widehat{\beta}_T^{3SC}) - \overline{g}_T(\widehat{\beta}_T^{3SC})\right].$$

Now we compute $\sum_{t=1}^{T}\left(\widehat{p}_t^{3SC}\right)^2$, this yields:

$$\begin{aligned}\sum_{t=1}^{T}\left(\widehat{p}_t^{3SC}\right)^2 \;&=\; \frac{1}{T} + \frac{1}{T}\overline{g}_T(\widehat{\beta}_T^{3SC})'\widehat{\Omega}_T(\widehat{\beta}_T^{3SC})^{-1}\frac{1}{T}\sum_{t=1}^{T}\left[\widetilde{g}_{tT}(\widehat{\beta}_T^{3SC}) - \overline{g}_T(\widehat{\beta}_T^{3SC})\right] \\ &\quad\times\left[\widetilde{g}_{tT}(\widehat{\beta}_T^{3SC}) - \overline{g}_T(\widehat{\beta}_T^{3SC})\right]' \widehat{\Omega}_T(\widehat{\beta}_T^{3SC})^{-1}\overline{g}_T(\widehat{\beta}_T^{3SC})\end{aligned}$$

An consistent estimator of Ω in mean deviation is obtained by:

$$\frac{S_T}{T}\sum_{t=1}^{T}\left[\widetilde{g}_{tT}(\widehat{\beta}_T^{3SC}) - \overline{g}_T(\widehat{\beta}_T^{3SC})\right]\left[\widetilde{g}_{tT}(\widehat{\beta}_T^{3SC}) - \overline{g}_T(\widehat{\beta}_T^{3SC})\right]'.$$

This gives that:

$$S_T\sum_{t=1}^{T}\frac{1}{T}\left[\left(T\widehat{p}_t^{3SC}\right)^2 - 1\right] = \overline{g}_T(\widehat{\beta}_T^{3SC})'\widehat{\Omega}_T(\widehat{\beta}_T^{3SC})^{-1}\overline{g}_T(\widehat{\beta}_T^{3SC})$$

where the right hand side expression corresponds to the GMM criteria evaluated at the bias-corrected 3S-GMM. Multiplying by T, this yields:

$$S_T \sum_{t=1}^{T} \left[\left(T \widehat{p}_t^{3SC} \right)^2 - 1 \right] = T \overline{g}_T (\widehat{\beta}_T^{3SC})' \widehat{\Omega}_T (\widehat{\beta}_T^{3SC})^{-1} \overline{g}_T (\widehat{\beta}_T^{3SC}).$$

Hence, the IPS_T statistic corresponds to the optimal GMM statistic J. The IPS_T statistic is then asymptotically distributed as $\chi^2(q-p)$.

References

Adam, K.K. and M. Padula. 2003. "Inflation Dynamics and Subjective Expectations in the United States." Unpublished manuscript.

Ambler S., A. Guay, and L. Phaneuf. 2003. "Labor Market Imperfections and the Dynamics of the Postwar Business Cycles." Unpublished manuscript.

Anatolyev, S. 2005. "GMM, GEL, Serial Correlation, and Asymptotic Bias." *Econometrica* 73: 983-1002.

Ascari, G. 2004. "Staggered Prices and Trend Inflation: Some Nuisances." *Review of Economic Dynamics* 7(3): 642-67.

Back, K. and D.P. Brown. 1993. "Implied Probabilities in GMM Estimators." *Econometrica* 61: 971-75.

Baggerly, K.A. 1998. "Empirical Likelihood as a Goodness-of-Fit Measure." *Biometrika* 85: 535-47.

Bakhshi, H., P. Burriel-Llombart, H. Khan, and B. Rudolf. 2003. "Endogenous Price Stickiness, Trend Inflation, and the New Keynesian Phillips Curve." Working Paper No. 191, Bank of England.

Balakrishnan, R. and J.D. Lopez-Salido. 2002. "Understanding UK Inflation: The Role of Openness." Working Paper No. 164, Bank of England.

Banerjee, R. and N. Batini. 2004. "Inflation Dynamics in Seven Industrialised Open Economies." Forthcoming Working Paper, Bank of England.

Batini, N., B. Jackson, and S. Nickell. 2002. "Inflation Dynamics and the Labor Share in the U.K." External MPC Unit Discussion Paper No. 2, Bank of England.

Bonnal, H. and E. Renault. 2001. "Minimal Chi-Square Estimation with Conditional Moment Restrictions." Document de Travail, CESG, September 2001.

Bonnal, H, and E. Renault. 2005. "On the Efficient Use of the Informational Content of Estimating Equations: Implied Probabilities and Euclidean Empirical Likelihood."*Journal of Econometrics*, forthcoming.

Calvo, G. 1983. "Staggered Prices in a Utility-Maximizing Framework." *Journal of Monetary Economics* 12: 383-98.

Cogley, T. and A. Sbordone. 2004. "A Search For a Structural Phillips Curve." Working Paper, Federal Reserve Bank of New York.

Dotsey, M. 2002. "Pitfalls in Interpreting Tests of Backward-Looking Pricing in New Keynesian Models." *Economic Quarterly* Federal Reserve Bank of Richmond: 88.

Eichenbaum, M. and A. Fisher. 2003. "Evaluating the Calvo Model of Sticky Prices." Federal Reserve Bank of Chicago, Working Paper No. 2003-23.

Gagnon, E. and H. Khan. 2004. "New Phillips Curve with Alternative Marginal Cost Measures for Canada, the United States, and the Euro Area." *European Economic Review*, forthcoming.

Galí, J. and M. Gertler. 1999. "Inflation Dynamics: A Structural Econometrics Analysis." *Journal of Monetary Economics* 44: 195-222.

Galí, J., M. Gertler, and J. D. Lopez-Salido. 2001. "European Inflation Dynamics." *European Economic Review* 45: 1237-70.

———. 2003. "Robustness of the Estimates of the Hybrid New Keynesian Phillips Curve." New York University. Unpublished manuscript.

Goodfriend, M. and R. King. 1997. "The New Neoclassical Synthesis." *NBER Macroeconomics Annual.* Cambridge, MA, MIT Press.

Guay, A., R. Luger, and Z. Zhu. 2004. "The New Phillips Curve in Canada." In *Price Adjustment and Monetary Policy*, 59-94. Proceedings of a conference held by the Bank of Canada, November 2002. Ottawa: Bank of Canada.

Guay, A. and F. Pelgrin. 2005a. "A Monte-Carlo Study of Alternative GMM estimators." Paper in progress.

Guay, A. and F. Pelgrin. 2005b. "Testing Parameters in GMM with Implied Probabilities." Paper in progress.

Guay, A. and F. Pelgrin. 2004. "The U.S. New Keynesian Phillips Curve: An Empirical Assessment." Working paper, Bank of Canada.

Hall, A.R. 2000. "Covariance Matrix Estimation and the Power of the Overidentifying Restrictions." *Econometrica* 68: 1517-28.

Hansen, L.P. 1982. "Large Sample Properties of Generalized Method of Moments Estimators." *Econometrica* 50: 1029-54.

Hansen, L.P., J. Heaton, and A. Yaron. 1996. "Finite-Sample Properties of Some Alternative GMM Estimators." *Journal of Business and Economic Statistics* 14: 262-80.

Kitamura, Y. and M. Stutzer, 1997. "An Information-Theoretic Alternative to Generalized Method of Moments Estimation," *Econometrica* 65: 861-74.

Lindé, J. 2001. "Estimating New-Keynesian Phillips Curves: A Full Information Maximum Likelihood Approach." Working Paper No. 129, Sveriges Riksbank.

Mankiw, N.G. and R. Reis. 2002. "Sticky Information Versus Sticky Prices: A Proposal to Replace the New Keynesian Phillips Curve." *The Quarterly Journal of Economics* 117: 1295-1328.

Mavroeidis, S. 2004. "Identification and Misspecification Issues in Forward Looking Monetary Models." *Oxford Bulletin of Economics and Statistics* 66(s1): 609-36.

Nason, J.M. and G.W. Smith. 2004. "Identifying the New Keynesian Phillips Curve." University of British Columbia and Queen's University. Unpublished paper.

Newey, W.K. and R.J. Smith. 2004. "Higher Order Properties of GMM and Generalized Empirical Likelihood Estimators." *Econometrica* 72: 219-55.

Newey, W.K. and K. West. 1994. "Automatic Lag Selection in Covariance Matrix Estimation." *Review of Economic Studies* 61: 631-53.

Orphanides, A. 2001. "Monetary Policy Rules Based on Real-Time Data." *American Economic Review* 91: 964-85.

Robinson, P.M. 1988. "The Stochastic Difference between Econometric Statistics." *Econometrica* 56: 531-548.

Rotemberg, J.J. and M. Woodford. 1999. "The Cyclical Behavior of Prices and Costs." In *Handbook of Macroeconomics,* edited by J.B. Taylor and M. Woodford. North-Holland, Elsevier Science E.V.

Sbordone, A. 2001. "Prices and Unit Labor Costs: A New Test of Price Stickiness." *Journal of Monetary Economics* 49: 265-92.

Smith, R.J. 2004. "GEL Criteria for Moment Condition Models, " mimeo.

Staiger, D. and J. Stock. 1997. "Instrumental Variables Regression with Weak Instruments." *Econometrica* 65(3): 557-86.

Stock, J. and W. Wright. 2000. "GMM with Weak Identification." *Econometrica* 68: 1055-96.

Taylor, J.B. 1980. "Aggregate Dynamics and Staggered Contracts." *Journal of Political Economy* 88: 1-23.

West, K. 1997. "Another Heteroskedasticity and Autocorrelation Consistent Covariance Matrix Estimator." *Journal of Econometrics* 76: 171-91.

Woodford, M. 2003. *Interest and Prices.* Princeton University Press.

Yun, T. 1996. "Nominal Price Rigidity, Money Supply Endogeneity, and Business Cycles." *Journal of Monetary Economics* 37: 345-70.

Table 1: Forward-Looking NKPC, $\kappa = .12$

Method	Instrument	θ	β	λ	D	J-stat
				Form I		
GMM	GGLS	.538	.846	.468	2.16	.513
		(.040)	(.043)	(.120)	(.189)	
		[.000]	[.000]	[.000]	[.000]	
	GG	.503	.823	.580	2.01	.984
		(.024)	(.029)	(.087)	(.097)	
		[.000]	[.000]	[.000]	[.000]	
CUE	GGLS	.659	1.018	.170	2.93	.523
		(.101)	(.046)	(.136)	(.872)	
		[.000]	[.000]	[.212]	[.000]	
	GG	.543	.856	.449	2.19	.987
		(.043)	(.043)	(.122)	(.208)	
		[.000]	[.000]	[.000]	[.000]	
3SC-GMM	GGLS	.527	.850	.494	2.12	.450
		(.039)	(.040)	(.121)	(.174)	
		[.000]	[.000]	[.000]	[.000]	[.000]
	GG	.513	.832	.545	2.05	.984
		(.023)	(.027)	(.076)	(.094)	
		[.000]	[.000]	[.000]	[.000]	[.012]
				Form II		
GMM	GGLS	.566	.865	.392	2.30	.518
		(.045)	(.042)	(.115)	(.239)	
		[.000]	[.000]	[.000]	[.000]	
	GG	.567	.849	.395	2.31	.987
		(.058)	(.023)	(.065)	(.138)	
		[.000]	[.000]	[.000]	[.000]	
3SC-GMM	GGLS	.567	.881	.382	2.31	.440
		(.044)	(.038)	(.110)	(.236)	
		[.000]	[.000]	[.000]	[.000]	[.000]
	GG	.565	.857	.397	2.30	.986
		(.025)	(.021)	(.064)	(.134)	
		[.000]	[.000]	[.000]	[.000]	[.033]

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.. The values in the J-stat column correspond to the p-values of the J_T statistic and the values in brackets to the p-values of the IPS_T statistic.

Table 2: Forward-Looking NKPC, $\kappa = .12$

Method	Instrument	θ	β	λ	D	J-stat
		Form I				
GMM	GGLS	.531	.872	.475	2.13	.022
		(.056)	(.050)	(.164)	(.255)	
		[.000]	[.000]	[.004]	[.000]	
	GG	.540	.846	.463	2.17	.038
		(.037)	(.036)	(.108)	(.174)	
		[.000]	[.000]	[.000]	[.000]	
CUE	GGLS	.606	1.008	.252	2.54	.057
		(.073)	(.038)	(.129)	(.470)	
		[.000]	[.000]	[.053]	[.000]	
	GG	.613	1.016	.238	2.59	.440
		(.067)	(.039)	(.117)	(.448)	
		[.000]	[.000]	[.044]	[.000]	
3SC-GMM	GGLS	.561	.898	.387	2.28	.012
		(.053)	(.040)	(.128)	(.273)	
		[.000]	[.000]	[.002]	[.000]	[.000]
	GG	.539	.853	.463	2.17	.039
		(.031)	(.029)	(.082)	(.156)	
		[.000]	[.000]	[.000]	[.000]	[.000]
		Form II				
GMM	GGLS	.649	.916	.218	2.85	.044
		(.093)	(.048)	(.145)	(.758)	
		[.000]	[.000]	[.134]	[.000]	
	GG	.597	.891	.316	2.48	.134
		(.045)	(.032)	(.096)	(.278)	
		[.000]	[.000]	[.001]	[.000]	
3SC-GMM	GGLS	.657	.934	.201	2.92	.021
		(.078)	(.032)	(.110)	(.666)	
		[.000]	[.000]	[.067]	[.000]	[.001]
	GG	.598	.890	.315	2.49	.016
		(.040)	(.027)	(.082)	(.244)	
		[.000]	[.000]	[.000]	[.000]	[.006]

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.The values in the J-stat column correspond to the p-values of the J_T statistic and the values in brackets to the p-values of the IPS_T statistic.

Table 3: Hybrid NKPC: $\kappa = .12$

Method	Instrument	θ	β	ω	λ	γ_f	γ_b	D	J-stat
		Form I							
GMM	GGLS	.571	.923	.281	.174	.629	.335	2.33	.541
		(.053)	(.044)	(.060)	(.071)	(.040)	(.045)	(.288)	
		[.000]	[.000]	[.000]	[.016]	[.000]	[.000]	[.000]	
	GG	.509	.886	.248	.272	.607	.334	2.04	.967
		(.033)	(.032)	(.027)	(.058)	(.030)	(.027)	(.136)	
		[.000]	[.000]	[.000]	[.000]	[.000]	[.000]	[000]	
CUE	GGLS	.634	.988	.389	.082	.614	.382	2.73	.584
		(.124)	(.089)	(.107)	(.079)	(.077)	(.069)	(.923)	
		[.000]	[.000]	[.000]	[.300]	[.000]	[.000]	[.004]	
	GG	.800	.964	.323	.028	.692	.290	5.00	.982
		(.170)	(.062)	(.114)	(.053)	(.074)	(.069)	(4.244)	
		[.000]	[.000]	[.005]	[.601]	[.000]	[.000]	[.240]	
3SC-GMM	GGLS	.569	.951	.310	.156	.622	.356	2.32	.494
		(.052)	(.037)	(.054)	(.061)	(.039)	(.038)	(.279)	
		[.000]	[.000]	[.000]	[.012]	[.000]	[.000]	[.000]	[.004]
	GG	.521	.886	.243	.261	.616	.324	2.09	.968
		(.031)	(.031)	(.028)	(.055)	(.030)	(.027)	(.135)	
		[.000]	[.000]	[.000]	[.000]	[.000]	[.000]	[.000]	[.055]
		Form II							
GMM	GGLS	.638	.974	.426	.074	.588	.403	2.76	.580
		(.076)	(.035)	(.068)	(.046)	(.033)	(.032)	(.578)	
		[.000]	[.000]	[.000]	[.110]	[.000]	[.000]	[.000]	
	GG	.638	.993	.522	.055	.547	.451	2.76	.981
		(.062)	(.038)	(.065)	(.031)	(.027)	(.026)	(.473)	
		[.000]	[.000]	[.000]	[.079]	[.000]	[.000]	[.000]	
3SC-GMM	GGLS	.626	.977	.416	.082	.590	.402	2.67	.553
		(.074)	(.033)	(.069)	(.049)	(.034)	(.033)	(.526)	
		[.000]	[.000]	[.000]	[.097]	[.000]	[.000]	[.000]	[.214]
	GG	.651	.986	.558	.046	.533	.464	2.87	.957
		(.097)	(.062)	(.119)	(.047)	(.028)	(.030)	(.799)	
		[.000]	[.000]	[.000]	[.331]	[.000]	[.000]	[.000]	[.285]

Note: See note to Table 1.

Table 4: Hybrid NKPC, $\kappa = .12$

Method	Instrument	θ	β	ω	λ	γ_f	γ_b	D	J-stat
		Form I							
GMM	GGLS	.557	.941	.296	.176	.622	.351	2.26	.201
		(.065)	(.048)	(.065)	(.079)	(.051)	(.052)	(.329)	
		[.000]	[.000]	[.000]	[.027]	[.000]	[.000]	[.000]	
	GG	.553	.868	.162	.277	.683	.231	2.24	.000
		(.039)	(.032)	(.034)	(.073)	(.041)	(.038)	(.196)	
		[.000]	[.000]	[.000]	[.000]	[.000]	[.000]	[.000]	
CUE	GGLS	.620	.968	.353	.102	.621	.366	2.63	.293
		(.061)	(.039)	(.102)	(.053)	(.042)	(.040)	(.424)	
		[.000]	[.000]	[.000]	[.018]	[.000]	[.000]	[.000]	
	GG	.545	.874	.082	.351	.766	.135	2.20	.050
		(.018)	(.028)	(.032)	(.046)	(.045)	(.046)	(.856)	
		[.000]	[.000]	[.011]	[.000]	[.000]	[.005]	[.000]	
3SC-GMM	GGLS	.572	.954	.309	.154	.625	.354	2.33	.224
		(.059)	(.038)	(.059)	(.064)	(.046)	(.044)	(.321)	
		[.000]	[.000]	[.000]	[.018]	[.000]	[.000]	[.000]	[.021]
	GG	.550	.874	.160	.280	.687	.229	2.22	.006
		(.033)	(.033)	(.033)	(.064)	(.038)	(.036)	(.137)	
		[.000]	[.000]	[.000]	[.000]	[.000]	[.000]	[.000]	[.000]
		Form II							
GMM	GGLS	.622	.979	.415	.084	.591	.402	2.65	.207
		(.078)	(.037)	(.075)	(.053)	(.039)	(.037)	(.548)	
		[.000]	[.000]	[.000]	[.119]	[.000]	[.000]	[.000]	
	GG	.754	.990	.472	.027	.610	.386	4.07	.000
		(.134)	(.033)	(.108)	(.040)	(.030)	(.029)	(2.208)	
		[.000]	[.000]	[.002]	[.501]	[.000]	[.000]	[.068]	
3SC-GMM	GGLS	.617	.970	.371	.099	.610	.378	2.61	.283
		(.076)	(.038)	(.072)	(.058)	(.044)	(.043)	(.525)	
		[.000]	[.000]	[.000]	[.093]	[.000]	[.000]	[.000]	[.020]
	GG	.667	.975	.406	.065	.610	.381	3.01	.000
		(.118)	(.033)	(.095)	(.067)	(.030)	(.030)	(1.079)	
		[.000]	[.000]	[.000]	[.338]	[.000]	[.000]	[.013]	[.000]

Note: See note to Table 2.

Table 5a: Hybrid NKPC: Form I, $\kappa = .12$

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	.070
		[.000]	[.000]	[.359]	[.175]	[.000]	[.249]	[.000]	
	[3]	.503	.991	.206	.279	.703	.291	2.01	.336
		[.000]	[.000]	[.217]	[.104]	[.000]	[.125]	[.000]	
	[4]	.517	.975	.172	.289	.734	.251	2.07	.440
		[.000]	[.000]	[.262]	[.053]	[.000]	[.182]	[.000]	
	[5]	.490	.935	.278	.263	.603	.366	1.96	.575
		[.000]	[.000]	[.003]	[.038]	[.000]	[.000]	[.000]	
	[6]	.461	.900	.226	.360	.613	.334	1.86	.482
		[.000]	[.000]	[.021]	[.030]	[.000]	[.004]	[.000]	
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	.080
		[.000]	[.000]	[.071]	[.140]	[.003]	[.024]	[.003]	
	[3]	.665	.963	.210	.109	.737	.241	2.99	.218
		[.000]	[.000]	[.115]	[.442]	[.000]	[.071]	[.062]	
	[4]	.617	.963	.207	.150	.725	.253	2.61	.488
		[.000]	[.000]	[.102]	[.256]	[.000]	[.056]	[.004]	
	[5]	.555	.957	.320	.164	.612	.369	2.25	.522
		[.000]	[.000]	[.000]	[.039]	[.000]	[.000]	[.000]	
	[6]	.550	.984	.316	.164	.627	.366	2.22	.404
		[.000]	[.000]	[.000]	[.048]	[.000]	[.000]	[.000]	
3SC-GMM	[1]	.539	1.001	.415	.130	.565	.434	2.17	
		[.000]	[.000]	[.094]	[.122]	[.028]	[.028]	[.000]	
	[2]	.632	1.029	.141	.143	.838	.182	2.71	.006
		[.000]	[.000]	[.768]	[.147]	[.007]	[.485]	[.000]	[.003]
	[3]	.591	1.017	.141	.191	.819	.192	2.44	.118
		[.000]	[.000]	[.406]	[.057]	[.002]	[.335]	[.000]	[.110]
	[4]	.574	.999	.156	.210	.787	.213	2.35	.302
		[.000]	[.000]	[.324]	[.069]	[.000]	[.251]	[.000]	[.236]
	[5]	.508	.943	.305	.222	.596	.379	2.03	.486
		[.000]	[.000]	[.000]	[.038]	[.000]	[.000]	[.000]	[.441]
	[6]	.529	.953	.314	.192	.604	.376	2.12	.406
		[.000]	[.000]	[.000]	[.046]	[.000]	[.000]	[.000]	[.399]

Note: See note to Table 2.

Table 5b: Hybrid NKPC: Form II, $\kappa = .12$

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	.144
		[.001]	[.000]	[.278]	[.481]	[.016]	[.107]	[.047]	
	[3]	.547	.982	.319	.165	.623	.369	2.21	.390
		[.000]	[.000]	[.166]	[.288]	[.003]	[.065]	[.005]	
	[4]	.556	.966	.286	.176	.641	.342	2.25	.375
		[.000]	[.000]	[.137]	[.050]	[.001]	[.062]	[.000]	
	[5]	.546	.960	.338	.163	.598	.386	2.20	.499
		[.000]	[.000]	[.000]	[.043]	[.000]	[.000]	[.000]	
	[6]	.526	.951	.369	.169	.565	.417	2.11	.396
		[.000]	[.000]	[.000]	[.088]	[.000]	[.000]	[.000]	
3SC-GMM	[1]	.540	.997	.417	.129	.563	.436	2.18	
		[.000]	[.000]	[.092]	[.122]	[.028]	[.027]	[.000]	
	[2]	.633	1.063	.358	.077	.669	.356	2.72	.000
		[.000]	[.000]	[.227]	[.270]	[.018]	[.099]	[.004]	[.000]
	[3]	.595	1.024	.226	.149	.739	.274	2.47	.106
		[.000]	[.000]	[.219]	[.106]	[.000]	[.128]	[.000]	[.135]
	[4]	.574	1.002	.299	.145	.658	.342	2.35	.269
		[.000]	[.000]	[.009]	[.056]	[.000]	[.034]	[.000]	[.350]
	[5]	.542	.964	.344	.163	.594	.391	2.19	.507
		[.000]	[.000]	[.000]	[.051]	[.000]	[.000]	[.000]	[.587]
	[6]	.537	.960	.365	.159	.577	.408	2.16	.302
		[.000]	[.000]	[.000]	[.047]	[.000]	[.000]	[.000]	[.338]

Note: See note to Table 2.

Table 6: Hybrid NKPC, $\kappa = .12$ and Revised Data

Method	Instrument	θ	β	ω	λ	γ_f	γ_b	D	J-stat
		Form I							
GMM	GGLS	.565	.963	.287	.167	.643	.339	2.30	.201
		(.072)	(.053)	(.082)	(.073)	(.075)	(.076)	(.379)	
		[.000]	[.000]	[.000]	[.024]	[.000]	[.000]	[.000]	
	GG	.505	.868	.154	.363	.676	.237	2.02	.027
		(.038)	(.041)	(.038)	(.090)	(.045)	(.046)	(.154)	
		[.000]	[.000]	[.000]	[.000]	[.000]	[.000]	[.000]	
CUE	GGLS	.552	1.018	.267	.175	.684	.325	2.23	.309
		(.088)	(.108)	(.084)	(.110)	(.094)	(.078)	(.438)	
		[.000]	[.000]	[.002]	[.114]	[.000]	[.000]	[.000]	
	GG	.565	1.077	.354	.118	.651	.379	2.30	.155
		(.095)	(.116)	(.090)	(.090)	(.068)	(.061)	(.503)	
		[.000]	[.000]	[.000]	[.191]	[.000]	[.000]	[.000]	
3SC-GMM	GGLS	.576	.967	.288	.156	.649	.335	2.36	.164
		(.067)	(.046)	(.076)	(.069)	(.069)	(.068)	(.374)	
		[.000]	[.000]	[.000]	[.025]	[.000]	[.000]	[.000]	[.086]
	GG	.505	.864	.145	.371	.681	.227	2.02	.099
		(.041)	(.042)	(.033)	(.094)	(.046)	(.046)	(.166)	
		[.000]	[.000]	[.000]	[.000]	[.000]	[.000]	[.000]	[.003]
		Form II							
GMM	GGLS	.668	.977	.331	.078	.657	.33	3.01	.068
		(.087)	(.043)	(.081)	(.055)	(.056)	(.057)	(.792)	
		[.000]	[.000]	[.000]	[.157]	[.000]	[.000]	[.000]	
	GG	.669	.948	.363	.076	.621	.356	3.02	.001
		(.066)	(.036)	(.063)	(.042)	(.035)	(.036)	(3.02)	
		[.000]	[.000]	[.000]	[.073]	[.000]	[.000]	[.068]	
3SC-GMM	GGLS	.647	.982	.339	.083	.647	.345	2.84	.098
		(.092)	(.045)	(.092)	(.058)	(.063)	(.065)	(.807)	
		[.000]	[.000]	[.000]	[.166]	[.000]	[.000]	[.000]	[.099]
	GG	.666	.943	.343	.082	.630	.345	3.00	.004
		(.077)	(.038)	(.064)	(.051)	(.034)	(.035)	(.690)	
		[.000]	[.000]	[.000]	[.114]	[.000]	[.000]	[.013]	[.000]

Note: See note to Table 2.

Table 7a: Hybrid NKPC: Form I, $\kappa = .12$ 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	.102
		[.000]	[.000]	[.503]	[.207]	[.001]	[.466]	[.004]	
	[3]	.576	1.011	.215	.176	.734	.271	2.36	.304
		[.000]	[.000]	[.163]	[.201]	[.000]	[.092]	[.000]	
	[4]	.553	1.006	.198	.212	.740	.263	2.24	.530
		[.000]	[.000]	[.202]	[.146]	[.000]	[.129]	[.000]	
	[5]	.524	.955	.296	.206	.616	.364	2.10	.656
		[.000]	[.000]	[.013]	[.136]	[.000]	[.0003	[.00]	
	[6]	.508	.972	.299	.218	.615	.372	2.03	.521
		[.000]	[.000]	[.009]	[.041]	[.000]	[.002]	[.000]	
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	.105
		[.000]	[.000]	[.117]	[.203]	[.002]	[.061]	[.011]	
	[3]	.656	.968	.216	.113	.732	.249	2.91	.190
		[.000]	[.000]	[.084]	[.316]	[.000]	[.046]	[.012]	
	[4]	.615	.970	.240	.139	.702	.282	2.60	.394
		[.000]	[.000]	[.051]	[.205]	[.000]	[.021]	[.001]	
	[5]	.634	1.004	.315	.096	.670	.332	2.73	.589
		[.000]	[.000]	[.003]	[.373]	[.000]	[.000]	[.012]	
	[6]	.678	1.031	.309	.068	.704	.311	3.10	.507
		[.000]	[.000]	[.010]	[.525]	[.000]	[.000]	[.068]	
3SC-GMM	[1]	.606	1.011	.349	.104	.640	.365	2.54	
		[.000]	[.000]	[.118]	[.248]	[.014]	[.066]	[.009]	
	[2]	.705	1.036	.100	.089	.905	.124	3.39	.040
		[.000]	[.000]	[.646]	[.263]	[.002]	[.614]	[.013]	[.024]
	[3]	.617	1.021	.192	.141	.776	.237	2.61	.096
		[.000]	[.000]	[.194]	[.133]	[.000]	[.127]	[.000]	[.068]
	[4]	.604	1.023	.186	.156	.780	.234	2.52	.205
		[.000]	[.000]	[.187]	[.096]	[.000]	[.126]	[.000]	[.174]
	[5]	.559	.965	.298	.168	.633	.350	2.27	.607
		[.000]	[.000]	[.000]	[.197]	[.000]	[.000]	[.000]	[.657]
	[6]	.583	.987	.289	.145	.661	.332	2.40	.618
		[.000]	[.000]	[.135]	[.282]	[.000]	[.003]	[.003]	[.724]

Note: See note to Table 2.

Table 7b: Hybrid NKPC: Form II, $\kappa = .12$ 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	.140
		[.000]	[.000]	[.364]	[.386]	[.006]	[.259]	[.052]	
	[3]	.629	1.037	.294	.098	.701	.316	2.70	.401
		[.000]	[.000]	[.138]	[.479]	[.000]	[.055]	[.046]	
	[4]	.614	1.027	.282	.113	.700	.313	2.59	.529
		[.000]	[.000]	[.109]	[.374]	[.000]	[.044]	[.015]	
	[5]	.608	.997	.345	.106	.637	.362	2.55	.640
		[.000]	[.000]	[.008]	[.370]	[.000]	[.000]	[.011]	
	[6]	.631	1.013	.347	.088	.651	.354	2.71	.548
		[.000]	[.000]	[.011]	[.446]	[.000]	[.000]	[.029]	
3SC-GMM	[1]	.600	.982	.353	.111	.620	.372	2.50	
		[.000]	[.000]	[.114]	[.224]	[.015]	[.064]	[.008]	
	[2]	.707	1.048	.186	.069	.823	.207	3.42	.005
		[.000]	[.000]	[.443]	[.355]	[.003]	[.369]	[.035]	[.003]
	[3]	.624	1.051	.263	.107	.733	.294	2.66	.078
		[.000]	[.000]	[.104]	[.267]	[.000]	[.048]	[.005]	[.069]
	[4]	.618	1.019	.273	.115	.704	.306	2.61	.239
		[.000]	[.000]	[.082]	[.202]	[.000]	[.035]	[.002]	[.262]
	[5]	.575	1.005	.356	.124	.620	.382	2.36	.339
		[.000]	[.000]	[.000]	[.164]	[.000]	[.000]	[.000]	[.390]
	[6]	.576	1.032	.310	.133	.666	.348	2.36	.449
		[.000]	[.000]	[.016]	[.416]	[.000]	[.002]	[.014]	[.424]

Note: See note to Table 2.

Table 8: Hybrid NKPC: Form I, $\kappa = .12$ for sample: 1960Q1-2001Q3

Method	Instrument	θ	β	ω	λ	γ_f	γ_b	D	J-stat
		Form I							
GMM	GGLS	.593	.955	.319	.133	.627	.353	2.46	.211
		(.074)	(.055)	(.082)	(.064)	(.071)	(.070)	(.445)	
		[.000]	[.000]	[.000]	[.041]	[.000]	[.000]	[.000]	
CUE	GGLS	.681	.995	.274	.067	.664	.334	3.13	.188
		(.096)	(.048)	(.095)	(.054)	(.068)	(.066)	(.680)	
		[.000]	[.000]	[.000]	[.216]	[.000]	[.000]	[.000]	
3SC-GMM	GGLS	.604	.966	.322	.122	.635	.350	2.53	.137
		(.070)	(.048)	(.080)	(.060)	(.067)	(.064)	(.448)	
		[.000]	[.000]	[.000]	[.045]	[.000]	[.000]	[.000]	[.051]
		Form II							
GMM	GGLS	.665	.996	.392	.065	.630	.372	2.98	.150
		(.094)	(.053)	(.091)	(.050)	(.061)	(.060)	(.838)	
		[.000]	[.000]	[.000]	[.195]	[.000]	[.000]	[.000]	
3SC-GMM	GGLS	.655	.995	.395	.069	.622	.376	2.90	.173
		(.096)	(.052)	(.097)	(.054)	(.065)	(.062)	(.805)	
		[.000]	[.000]	[.000]	[.199]	[.000]	[.000]	[.000]	[.161]

Note: See note to Table 2.

Table 9a: Hybrid NKPC: Form I, $\kappa = .12$ 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	.161
		[.000]	[.000]	[.346]	[.290]	[.001]	[.256]	[.021]	
	[3]	.597	.997	.245	.147	.707	.291	2.48	.264
		[.000]	[.000]	[.139]	[.259]	[.000]	[.066]	[.021]	
	[4]	.588	.983	.228	.165	.711	.280	2.43	.404
		[.000]	[.000]	[.138]	[.188]	[.000]	[.073]	[.000]	
	[5]	.567	.945	.298	.165	.626	.349	2.31	.637
		[.000]	[.000]	[.017]	[.190]	[.000]	[.004]	[.000]	
	[6]	.558	.954	.310	.166	.619	.361	2.26	.414
		[.000]	[.000]	[.005]	[.063]	[.000]	[.001]	[.000]	
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	.134
		[.000]	[.000]	[.040]	[.131]	[.007]	[.020]	[.003]	
	[3]	.688	.970	.260	.082	.708	.276	3.20	.148
		[.000]	[.000]	[.052]	[.428]	[.000]	[.019]	[.044]	
	[4]	.691	1.000	.271	.072	.718	.282	3.24	.366
		[.000]	[.000]	[.051]	[.477]	[.000]	[.016]	[.060]	
	[5]	.699	1.012	.327	.058	.688	.318	3.32	.580
		[.000]	[.000]	[.010]	[.565]	[.000]	[.000]	[.109]	
	[6]	.743	1.027	.328	.038	.708	.304	3.90	.502
		[.003]	[.000]	[.025]	[.706]	[.000]	[.000]	[.293]	
3SC-GMM	[1]	.638	1.032	.366	.077	.651	.362	2.76	
		[.000]	[.000]	[.118]	[.267]	[.011]	[.066]	[.016]	
	[2]	.738	1.056	.200	.049	.823	.211	3.82	.005
		[.000]	[.000]	[.407]	[.413]	[.003]	[.335]	[.058]	[.001]
	[3]	.634	1.015	.240	.113	.735	.274	2.73	.065
		[.000]	[.000]	[.118]	[.172]	[.000]	[.062]	[.001]	[.047]
	[4]	.624	1.016	.243	.120	.729	.280	2.66	.169
		[.000]	[.000]	[.101]	[.145]	[.000]	[.050]	[.000]	[.151]
	[5]	.638	1.011	.330	.089	.665	.340	2.76	.403
		[.000]	[.000]	[.004]	[.263]	[.000]	[.000]	[.005]	[.433]
	[6]	.597	.980	.281	.137	.669	.321	2.48	.624
		[.000]	[.000]	[.027]	[.332]	[.000]	[.006]	[.008]	[.766]

Note: See note to Table 2.

Table 9b: Hybrid NKPC: Form II, $\kappa = .12$ 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	.217
		[.000]	[.000]	[.288]	[.448]	[.006]	[.185]	[.100]	
	[3]	.669	1.027	.345	.067	.673	.338	3.02	.289
		[.002]	[.000]	[.100]	[.578]	[.000]	[.026]	[.112]	
	[4]	.631	1.002	.380	.083	.625	.376	2.71	.307
		[.000]	[.000]	[.046]	[.318]	[.000]	[.012]	[.015]	
	[5]	.662	.999	.361	.071	.647	.353	2.96	.614
		[.000]	[.000]	[.014]	[.509]	[.000]	[.001]	[.062]	
	[6]	.682	1.003	.368	.060	.651	.350	3.15	.515
		[.000]	[.000]	[.016]	[.568]	[.000]	[.000]	[.107]	
3SC-GMM	[1]	.636	1.038	.370	.077	.650	.364	2.75	
		[.000]	[.000]	[.114]	[.268]	[.011]	[.063]	[.015]	
	[2]	.733	1.056	.269	.043	.764	.266	3.75	.002
		[.000]	[.000]	[.290]	[.456]	[.004]	[.207]	[.082]	[.000]
	[3]	.643	1.046	.312	.083	.697	.323	3.24	.060
		[.000]	[.000]	[.068]	[.368]	[.000]	[.025]	[.018]	[.053]
	[4]	.648	1.023	.325	.082	.678	.332	2.84	.215
		[.000]	[.000]	[.054]	[.333]	[.000]	[.017]	[.014]	[.230]
	[5]	.612	1.018	.366	.095	.634	.373	2.58	.338
		[.000]	[.000]	[.002]	[.292]	[.000]	[.000]	[.005]	[.350]
	[6]	.594	.967	.315	.131	.636	.348	2.46	.382
		[.001]	[.000]	[.026]	[.433]	[.000]	[.002]	[.023]	[.341]

Note: See note to Table 2.

Figure 1: The real marginal cost and data revisions