New Keynesian Phillips Curves and Potential Identification Failures: a Generalized Empirical Likelihood Analysis*

Luis F. Martins

Department of Quantitative Methods and UNIDE, ISCTE, Portugal

Vasco J. Gabriel†

Department of Economics, University of Surrey, UK and NIPE-UM

20th January 2009

Abstract

In this paper, we examine parameter identification in the hybrid specification of the New Keynesian Phillips Curve proposed by Gali and Gertler (1999). We employ recently developed moment-conditions inference procedures, which provide a more efficient and reliable econometric framework for the analysis of the NKPC. In particular, we address the issue of parameter identification, obtaining robust confidence sets for the model's parameters. Our results cast serious doubts on the empirical validity of the NKPC.

*The authors thank the editor and a referee for useful comments. The second author acknowledges financial support from ESRC grant RES-061-25-0115. A previous version of the paper circulated with the title "On the robustness of NKPC estimates". We are grateful to Jordi Gali and J. David López-Salido for providing the data used in their papers. We are also indebted to Patrik Guggenberger for discussions on the implementation of GEL procedures. The usual disclaimer applies.

†Corresponding author. Address: Department of Economics, University of Surrey, Guildford, Surrey, GU2 7XH, UK. Email: v.gabriel@surrey.ac.uk. Tel: + 44 1483 682769. Fax: + 44 1483 689548.

Keywords: Weak identification; Generalized Empirical Likelihood; GMM; Phillips curve

JEL Classification: C22; E31; E32

1 Introduction

The New Keynesian Phillips Curve (NKPC) has become a fundamental macroeconomic specification in the context of inflation modelling. In particular, work by Gali and Gertler (1999, henceforth GG) suggests that firms set prices in a forward-looking fashion, with real marginal costs driving inflation dynamics. These authors, and more recently, Gali, Gertler and López-Salido (2005, GGLS hereafter) present empirical estimates of this NKPC for the US case, claiming that the NKPC is able to explain inflation dynamics very well.

In this study, we re-evaluate the empirical validity of the hybrid version of the NKPC proposed by GG and refined by GGLS. For that purpose, we employ recently developed moment-conditions inference methods, namely Generalized Empirical Likelihood (GEL) estimation, as well as identification-robust methods. We do so for several reasons. First, the papers above rely on a standard 2-step GMM estimator, which may deviate substantially from its small sample distribution - as discussed in Hansen, Heaton and Yaron (1996), for example, and in the two special issues of the *Journal of Business and Economic Statistics* (1996, vol. 14(3) and 2002, vol. 20(4)) dedicated to GMM. A further advantage of GEL methods is that, unlike standard GMM, estimation is invariant to the specification of the moment conditions, which means that the results do not depend on the normalization adopted for the estimation. This will allow us to focus on the economic specifications, rather than on their econometric implementation. Thirdly, it is known that results of tests of statistical significance hinge on the weighting matrix used in the estimation. GG and GGLS estimate the variance-covariance matrix based on a Bartlett kernel with fixed bandwidth, so it is important to assess how the main results are affected by this choice. Lastly, the inference method employed by GG and GGLS is not reliable with respect to weak parameter identification. Recent papers, focusing on US data, show that this is an important issue that should be taken into consideration (see Ma, 2002, Mavroeidis, 2005 and Dufour, Khalaf and Kichian, 2006, for example).

We propose using GEL estimation, given that it possesses superior large and finite sample properties (as shown by Anatolyev, 2005) and is more efficient than the GMM estimator used in the papers cited above. Within this framework, it is also possible to compute identification-robust parameter confidence sets, conditional on model validity.

This is of great importance, since the usual standard errors will be invalid if parameters are only weakly identified, as shown by Stock and Wright (2000). These procedures have been studied by Guggenberger and Smith (2005 and 2008) and Otsu (2006) for GEL estimators, based on the work of Kleibergen (2005), developed in a GMM CUE framework.

Several authors have recently questioned the validity of GG results[1]. Closely related to the present paper, the issue of identification was analyzed empirically by Ma (2002), who found evidence of weak parameter identification, meaning that conventional GMM asymptotic theory, used in GG and GGLS, is not valid. In turn, however, Dufour *et al.* (2006), using identification-robust methods and inflation expectations data, provide evidence of some support for the NKPC specification with US data.

From a methodological point of view, we depart from the existing literature by resorting to an integrated inference approach based on GEL methods, thus bridging the gaps between existing papers on the empirical analysis of the NKPC. Previous papers have relied only on standard GMM, despite its known flaws. On the other hand, Ma (2002) applies the Stock and Wright (2000) identification-robust statistics, but these tests are not fully informative with respect to parameter identification. Indeed, rejections of the model may be due to either weak identification or invalid overidentifying restrictions, as these are being jointly tested. We, in turn, conduct our analysis conditional on model validity, thus separating the two problems. Moreover, we improve on Dufour *et al.* (2006), as these authors resort to a more restrictive, standard, linear i.i.d., IV approach, which may not be fully efficient - especially if there is non-negligible serial correlation and heteroskedasticity, as it seems to be the case. We account for these potential sources of misspecification by using appropriate HAC variance-covariance estimators in a GEL context. Finally, the procedures employed in our analysis allow us to concentrate both on the full parameter vector, as well as on the subset of crucial parameters, thus potentially leading to more powerful tests. To our knowledge, this paper is the first empirical application of these particular methodologies.

Next, we briefly summarize the results in GG and GGLS and then describe the eco-

[1]See Rudd and Whelan (2005) and Linde (2005) in the special issue on "The econometrics of the New Keynesian price equation" of the *Journal of Monetary Economics*, vol. 52(6), or Rudd and Whelan (2007), for example.

nometric procedures used in our analysis. Section 4 presents the results and a discussion finalizes this paper.

2 The New Keynesian Phillips Curve

GG start from a Calvo-type price setting framework with imperfectly competitive firms, where a proportion θ of firms do not change their prices in any given period, independently of past price changes. Furthermore, they assume that a fraction ω of firms are backward-looking price-setters, that is, they use a simple rule-of-thumb based on lagged inflation. The remaining firms set prices optimally, considering expected future marginal costs. The resulting equation for inflation is a hybrid Phillips curve, combining forward and backward-looking behavior:

$$\pi_t = \lambda mc_t + \gamma_f E_t(\pi_{t+1}) + \gamma_b \pi_{t-1} + \varepsilon_t. \tag{1}$$

Here, mc_t represents real marginal cost, $E_t(\pi_{t+1})$ is the expected inflation in period t and ε_t captures measurement errors or unexpected mark-up shocks. The reduced-form parameters are expressed as

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

with structural parameters β, the subjective discount rate, θ measuring price stickiness and ω the degree of backwardness.

Using the orthogonality conditions implied by (1) and assuming rational expectations, GG estimate the parameters via GMM with quarterly US data (1960:1-1997:4). Three main results were obtained: 1) γ_b is statistically significant, implying that the hybrid variant of the NKPC supplants the pure forward-looking model, although being quantitatively negligible; 2) nevertheless, forward-looking behavior is dominant, i.e., γ_f is approximately as twice as large as γ_b; 3) GG stress the role played by real marginal cost (instead of traditional measures of the output gap) in driving inflation, as suggested by a positive and significant λ. GGLS later refined the initial analysis in GG, albeit maintaining the main conclusions.

However, as explained in section 1, several econometric issues that may hinder inference based on the method used by GG and GGLS must be carefully considered. In the next section, we discuss alternative methods to deal with these problems.

3 Econometric Framework

3.1 GEL Estimation

Given the often disappointing small sample properties of GMM, a variety of alternative estimators have been proposed recently. Among these, the empirical likelihood (EL), the exponential tilting (ET) and the continuous-updating (CUE) estimators are very appealing from a theoretical point of view. Newey and Smith (2004) have shown that these methods pertain to the same class of Generalized Empirical Likelihood (GEL) estimators. These authors demonstrate that, while GMM and GEL estimators have identical first-order asymptotic properties, the latter are higher order efficient, in the sense that these estimators are able to eliminate some sources of GMM biases[2]. For example, they show that the bias of the EL estimator does not grow with the number of moment conditions, unlike GMM. Similar properties have been recently established by Anatolyev (2005), in a time series setting.

Consider the estimation of a p-dimensional parameter vector $\boldsymbol{\theta} = (\theta_1, ..., \theta_p)$ based on $m \geq p$ moment conditions of the form $E[g(y_t, \boldsymbol{\theta}_0)] = 0, \forall t = 1, ..., T$, where, in our case, $g(y_t, \boldsymbol{\theta}_0) \equiv g_t(\boldsymbol{\theta}_0) = \varepsilon(x_t, \boldsymbol{\theta}_0) \otimes z_t$ for some set of variables x_t and instruments z_t, such that $y_t = (x_t, z_t)$. Using Newey and Smith (2004) typology, for a concave function $\rho(v)$ and a $m \times 1$ parameter vector $\lambda \in \Lambda_T(\boldsymbol{\theta})$, the GEL estimator solves the following saddle point problem

$$\hat{\boldsymbol{\theta}}_{GEL} = \arg \min_{\boldsymbol{\theta} \in \Re^p} \sup_{\lambda \in \Lambda_T} T^{-1} \sum_{t=1}^{T} \rho[\lambda' g_t(\boldsymbol{\theta})]. \tag{2}$$

[2] Guay and Pelgrin (2007) suggest a 3-step GMM that also corrects for GMM biases by using implied probabilities. A potential caveat with this procedure is that, as it relies on the 2-step GMM, it will not be invariant to the normalization of the moment conditions.

Special cases arise when $\rho(v) = -(1+v)^2/2$, where $\boldsymbol{\theta}_{GEL}$ coincides with the CUE; if $\rho(v) = \ln(1-v)$ we have the EL estimator, whereas $\rho(v) = -\exp(v)$ leads to the ET case. The class of estimators defined by $\hat{\boldsymbol{\theta}}_{GEL}$ is generally inefficient when $g(y_t, \boldsymbol{\theta})$ is serially correlated. However, Anatolyev (2005) demonstrates that, in the presence of correlation in $g(y_t, \boldsymbol{\theta})$, the smoothed GEL estimator of Kitamura and Stutzer (1997) is efficient, obtained by smoothing the moment function with the truncated kernel[3], so that

$$\hat{\boldsymbol{\theta}}_{SGEL} = \arg \min_{\boldsymbol{\theta} \in \Re^p} \sup_{\lambda \in \Lambda_T} T^{-1} \sum_{t=1}^{T} \rho[\lambda' g_{tT}(y_t, \boldsymbol{\theta})]. \tag{3}$$

with $g_{tT}(\boldsymbol{\theta}) \equiv \frac{1}{2K_T+1} \sum_{k=-K_T}^{K_T} g_{t-k}(\boldsymbol{\theta})$. The SEL variant, in particular, removes important sources of bias associated with the GMM, namely the correlation between the moment function and its derivative[4], as well as third-order biases. Furthermore, Anatolyev (2005) shows that even when there is no serial correlation, using smoothing and an appropriate HAC weight matrix, as in Andrews (1991) or Newey and West (1994), leads to a reduction in estimation biases. Thus, it is clearly worthwhile to compare GG and GGLS 2-step GMM inefficient results with GEL estimates.

3.2 Identification-robust analysis

Another major source of misleading inferences with GMM is weak parameter identification, due to instruments being poorly correlated with the excluded endogenous variables, or, more formally, the Jacobian of the first order conditions of GMM is not full rank. Stock and Wright (2001) derived the appropriate asymptotic theory for this case, concluding that GMM is inconsistent and conventional tests are therefore flawed. They developed an asymptotically valid test based on the statistic

$$S(\boldsymbol{\theta}_0) = T^{-1} \hat{g}_T(\boldsymbol{\theta}_0)' \hat{\Omega}(\boldsymbol{\theta}_0)^{-1} \hat{g}_T(\boldsymbol{\theta}_0), \tag{4}$$

with $\hat{g}_T(\boldsymbol{\theta}_0) = \sum_{t=1}^{T} g_t(\boldsymbol{\theta}_0)$ and $\hat{\Omega}(\boldsymbol{\theta}_0)$ as a (possibly HAC) weight matrix, which is simply the renormalized objective function of the CUE evaluated at the simple null hypothesis

[3] In the empirical analysis, we use $K_T = 5$, since the optimal bandwidth rate for the truncated kernel used in the Kitamura-Stutzer estimator is $O(T^{1/3})$ (the results are largely insensitive to the choice of this parameter).

[4] This correlation leads to an increasing bias deterioration as the number of moment conditions increase.

$\boldsymbol{\theta} = \boldsymbol{\theta}_0$. This allows the researcher to construct identification-robust confidence sets (S-sets) for $\boldsymbol{\theta}$ by inverting the statistic, that is, performing a grid search over the parameter space and collect the values of $\boldsymbol{\theta}$ for which the null is not rejected at a given significance level. However, Stock and Wright (2001) acknowledge difficulties with the interpretation of their method, since their procedure jointly tests simple parameter hypotheses *and* the validity of the overidentifying restrictions. This may be problematic since $S(\boldsymbol{\theta}_0)$ is asymptotically $\chi^2(m)$, with degrees of freedom growing with the number of moment conditions and, therefore, less powerful to test parameter hypotheses, with the resulting confidence sets being less informative.

Recently, Kleibergen (2005) devised a reliable approach that is robust to weak identification, conditional on instrument validity. Indeed, his K-statistic may be written as a quadratic form in the first-order conditions of the CUE:

$$K(\boldsymbol{\theta}_0) = T^{-1}\hat{g}_T(\boldsymbol{\theta}_0)'\hat{\Omega}(\boldsymbol{\theta}_0)^{-1}\hat{D}(\boldsymbol{\theta}_0)[\hat{D}(\boldsymbol{\theta}_0)'\hat{\Omega}(\boldsymbol{\theta}_0)^{-1}\hat{D}(\boldsymbol{\theta}_0)]^{-1}\hat{D}(\boldsymbol{\theta}_0)'\hat{\Omega}(\boldsymbol{\theta}_0)^{-1}\hat{g}_T(\boldsymbol{\theta}_0), \quad (5)$$

with a $\chi^2(p)$ limiting distribution that depends only on the number of parameters. The key element is $\hat{D}(\boldsymbol{\theta}_0)$, a modified Jacobian estimator asymptotically uncorrelated with the sample average of the moments, such that

$$\hat{D}(\boldsymbol{\theta}_0) = [\hat{G}_1(\boldsymbol{\theta}_0) - \hat{\Omega}_{\boldsymbol{\theta}g,1}(\boldsymbol{\theta}_0)\hat{\Omega}(\boldsymbol{\theta}_0)^{-1}\hat{g}_T(\boldsymbol{\theta}_0) \ \cdots \ \hat{G}_p(\boldsymbol{\theta}_0) - \hat{\Omega}_{\boldsymbol{\theta}g,p}(\boldsymbol{\theta}_0)\hat{\Omega}(\boldsymbol{\theta}_0)^{-1}\hat{g}_T(\boldsymbol{\theta}_0)]$$

where $\hat{G}_i(\boldsymbol{\theta}_0) = \sum_{t=1}^{T} \frac{\partial g_t(\boldsymbol{\theta}_0)}{\boldsymbol{\theta}_i}$, $i = 1, .., p$ and $\hat{\Omega}_{\boldsymbol{\theta}g,i}(\boldsymbol{\theta}_0)$ is a HAC estimate of the $m \times m$ covariance matrix between $g_t(\boldsymbol{\theta}_0)$ and $G_i(\boldsymbol{\theta}_0)$, see Kleibergen (2005, p. 1112) for details. In addition, this statistic is not affected by the strength or weakness of identification.

In order to enhance the power of the $K(\boldsymbol{\theta}_0)$ statistic, Kleibergen (2005) recommends combining $K(\boldsymbol{\theta}_0)$ with an asymptotically independent $J(\boldsymbol{\theta}_0)$ statistic for overidentifying restrictions[5] with a similar form, but using an orthogonal projection of $\hat{D}[\hat{D}'\hat{\Omega}^{-1}\hat{D}]^{-1}\hat{D}'$ as its central term, asymptotically distributed as $\chi^2(m-p)$. In fact, Kleibergen (2005) stresses the fact that $S(\boldsymbol{\theta}_0) = K(\boldsymbol{\theta}_0) + J(\boldsymbol{\theta}_0)$, thus confirming Stock and Wright (2001) precautions regarding the use of $S(\boldsymbol{\theta}_0)$. We can see that the $S(\boldsymbol{\theta}_0)$ test employed by Ma (2002) may have its power negatively affected, as it does not distinguish between weak identification and overidentifying restrictions.

[5]Although with a similar role, this is different from the traditional J-test for overidentifying restrictions.

Following Kleibergen (2005), Guggenberger and Smith (2008) and Otsu (2006) propose identification-robust procedures in a GEL framework. The tests are based on quadratic forms in the FOC of the GEL estimator, or, alternatively, given as renormalized GEL criterion functions. For the sake of conciseness, we focus on the LM version of the Kleibergen-type test proposed by Guggenberger and Smith (2008). This statistic was found to have advantageous finite-sample properties in their Monte Carlo study. Indeed, although the CUE-GMM and the CUE-GEL are numerically identical (see Newey and Smith, 2004), their FOC are different and one should expect the LM version and the K statistic to differ, especially with dependent data.

The LM statistic can be written as

$$K_{LM}(\boldsymbol{\theta}_0) = T\hat{g}_T(\boldsymbol{\theta}_0)'\hat{\Delta}(\boldsymbol{\theta}_0)^{-1}D_\rho(\boldsymbol{\theta}_0)[D_\rho(\boldsymbol{\theta}_0)'\hat{\Delta}(\boldsymbol{\theta}_0)^{-1}D_\rho(\boldsymbol{\theta}_0)]^{-1}D_\rho(\boldsymbol{\theta}_0)'\hat{\Delta}(\boldsymbol{\theta}_0)^{-1}\hat{g}_T(\boldsymbol{\theta}_0)/2 \tag{6}$$

with $\hat{\Delta}(\boldsymbol{\theta}) = S_T T^{-1}\sum g_{tT}(\boldsymbol{\theta})g_{tT}(\boldsymbol{\theta})'$ ($S_T = K_T+1/2$) and $D_\rho(\boldsymbol{\theta}) = T^{-1}\sum \rho_1(\lambda' g_{tT}(\boldsymbol{\theta}))G_{tT}(\boldsymbol{\theta})$, where $G_{tT}(\boldsymbol{\theta}) = (\partial g_{tT}/\partial\boldsymbol{\theta})$ and $\rho_1(v) = \partial\rho/\partial v$. The statistic has a $\chi^2(p)$ limiting distribution that depends only on the number of parameters, so its power will not be affected in overidentified situations.

This statistic may be appropriately transformed if one wishes to test a sub-vector of $\boldsymbol{\theta}$, for instance if one or more parameters are deemed to be strongly identified. Let $\boldsymbol{\theta} = (\alpha', \beta')'$ with dimensions $p_\alpha \times 1$ and $p_\beta \times 1$, respectively, so that $p_\alpha + p_\beta = p$. Assuming that α is the subset of parameters of interest[6], we then wish to conduct tests for $H_0 : \alpha_0 = \alpha$. This can be carried out by concentrating out the subset of "nuisance", strongly identified parameters β, which is replaced by a consistent GEL estimator $\hat{\beta}(\alpha)$ with fixed α. The relevant statistic is then

$$K^{\beta}_{LM}(\alpha_0) = T\hat{g}_T(\hat{\boldsymbol{\theta}}_0)'\hat{\Delta}(\hat{\boldsymbol{\theta}}_0)^{-1}D_\rho(\alpha_0)[D_\rho(\alpha_0)'\hat{M}(\alpha_0)^{-1}D_\rho(\alpha_0)]^{-1}D_\rho(\alpha_0)'\hat{\Delta}(\hat{\boldsymbol{\theta}}_0)^{-1}\hat{g}_T(\hat{\boldsymbol{\theta}}_0)/2, \tag{7}$$

with $\hat{\boldsymbol{\theta}}_0 = (\alpha', \hat{\beta}(\alpha)')'$ and $\hat{M}(\alpha_0)$ is the new covariance matrix of the problem (see Guggenberger and Smith, 2008, eq. 26 for details). If the testing assumptions are correct, partialling out identified parameters will deliver a more powerful test, with a χ^2 asymp-

[6] Regardless of whether α is strongly or weakly identified, see Guggenberger and Smith (2008) for details.

totic distribution with degrees of freedom equal to the number of parameters under test, i.e., $\chi^2(p_\alpha)$.

In summary, GEL estimators provide a powerful alternative to standard GMM methods. Nevertheless, identification-robust sets should be also computed, in case weak identification is an issue.

4 Empirical Results

We begin by discussing the results based on standard GMM and GEL estimation of (1). We first conduct estimations using the original dataset of GG (quarterly data for the period 1960:1-1997:4). We then consider a more recent vintage of the data, which spans until 2006:4. Following GG and GGLS, real marginal cost is proxied by real unit labour costs and inflation is the percent change in the GDP deflator. Lagged variables are used as instruments, as well as lags of quadratically detrended log output, wage inflation, an interest rate spread and commodity price inflation. In addition, we distinguish between the set of instruments used by GG (4 lags of each variable) and the restricted set employed by GGLS, chosen with the purpose of minimizing potential biases due to the large number of identifying restrictions (2 lags of each variable, except for inflation with 4 lags).

< Insert Table 1 here >

We start by presenting in Table 1 estimation results using the standard 2-step GMM estimator used in GG and GGLS. One of problems mentioned above with the 2-step estimator is that results differ depending on the normalization of the moment conditions[7]. Indeed, estimates vary considerably across specifications, with the slope of the NKPC ranging from 0.02 to 0.3, for example. On the other hand, results for the slope of the NKPC obtained with the updated dataset indicate that the coefficient may not be statistically significant. Next, we turn to GEL estimation for further clarification.

[7] Specification 1 is based on $E_t\{\phi\pi_t - \phi\omega\pi_{t-1} - \phi\beta\theta\pi_{t+1} - (1-\omega)(1-\theta)(1-\beta\theta)mc_t)z_t\} = 0$, while Specification 2 is based on $E_t\{\pi_t - \omega\pi_{t-1} - \beta\theta\pi_{t+1} - \phi^{-1}(1-\omega)(1-\theta)(1-\beta\theta)mc_t)z_t\} = 0$, with z_t representing the set of instruments. We also allow for increasing real marginal cost and variation across firms, as in Sbordone (2002), following the calibration proposed in GGLS.

< Insert Table 2 here >

In contrast with standard GMM, GEL estimators are invariant to the normalization of moment conditions, so we need to present only one specification. Table 2 reports point estimates of both "deep" and "reduced-form" parameters, using the three estimators discussed above, with the top panel presenting results for the original sample period and the bottom panel using the updated dataset. Some issues are worth mentioning. First, we observe that, overall, the three estimators produce consistent and comparable results. Secondly, estimates of ω increase slightly when the updated set is used, suggesting either an identification problem with this parameter (which will be considered below), or some sort of structural instability. However, the corresponding reduced-form coefficients (γ_f and γ_b) are within the expected range.

A crucial element in the analysis of the NKPC is the importance of the effect of aggregate activity, as measured by real marginal costs and given by λ. We find that, unlike results in Table 1, this coefficient is never different from 0, statistically speaking. Indeed, point estimates are in some cases larger in magnitude than previously estimated, but, in general, less precisely estimated, and insignificant at the 5% level when obtained with the CUE and GG broader instrument set. When estimation is carried out using the updated dataset, the coefficient associated with the real marginal cost is never statistically significant (except for ET and GG instruments). This implies that the NKPC may have become flatter in more recent years. Alternatively, one can interpret this result as reflecting a substantial degree of price stickiness, but this seems to be at odds with evidence from micro-studies (see Bils and Klenow, 2004 for example), which suggest that prices change with a frequency below 4 quarters, even for goods with 'stickier' prices[8].

< Insert Table 3 here >

[8]However, Altig et al. (2005) show that it is possible to reconcile aggregate price inertia with frequent price changes by firms. They develop a model allowing for complete firm-specific capital, in which firms may change their stock of capital and index non-re-optimized prices to lagged inflation, which offers more flexibility than the assumptions in Sbordone (2002) and GGLS. We thank a referee for help in clarifying this point.

As a robustness check, we also consider the possibility of fixing β given that the data itself provides information on the discount rate. We present results for $\beta = 0.99$ in Table 3, but estimates change very little if other values in the vicinity are used. As expected, there is little numerical variation in the estimates and earlier conclusions are not altered. In addition, we also analyse the benchmark case of imposing $\gamma_f + \gamma_b = 1$ in the reduced-form specification, considered in Gali and Gertler (1999) - which may also lead to improved identification. Direct reduced-form estimates of λ are presented in the last column of Table 2 (under λ^*). Once again, the results point to non-significant estimates of the NKPC slope, regardless of the dataset used, which reinforces our previous conclusions.

< Insert Table 4 here >

Still, in order to further assess our results, we present in Table 4 CUE estimates and respective standard errors for λ, obtained using different variance-covariance matrices. As argued before, the choice of the weighting matrix for CUE estimation may affect inference on the NKPC, in particular whether or not the marginal cost variable is statistically significant. Given the range of existing estimators, we focus on the Andrews (1991) data-dependent method with Parzen and Bartlett kernels, as well as the latter kernel with fixed bandwidths (4 and 8; 12 lags was the original choice in GG). Clearly, if one does not arbitrarily choose the lag truncation parameter, the results do not support the marginal cost as the driving variable of the inflation process. The use of different kernels with the Andrews method does not alter the conclusions of Tables 2, obtained with the Quadratic Spectral kernel. On the other hand, increasing the bandwidth in an ad-hoc fashion leads to higher, and more significant, estimates of λ, especially if one uses the original datasets. Interestingly, λ is never significant across different methods, even for fixed bandwidths, when the updated dataset is employed. Thus, the results in GG and GGLS seem to be data and method-specific, and do not withstand a simple sensitivity analysis.

Nevertheless, the above conclusions may be invalid if weak identification pervades. Hence, resorting to the analysis discussed in the previous section, one can form 95% and 90% confidence sets for the set of parameters (ω, θ, β) by performing a grid search over the parameter space (restricted to the interval $(0, 1)$, with increments of 0.01) then tested

$H_0 : \omega = \omega_0$, $\theta = \theta_0$, $\beta = \beta_0$ and collected the values $(\omega_0, \theta_0, \beta_0)$ for which the p-value exceeded the 5% and 10% significance level. We also present Kleibergen's (2005) GMM CUE approach, i.e., combining his K statistic with the asymptotically independent $J(\boldsymbol{\theta})$ statistic for overidentifying restrictions. For the combined J-K test, we use $\alpha_J = 0.025$ and $\alpha_K = 0.075$ for a 10% significance level and $\alpha_J = 0.01$ and $\alpha_K = 0.04$ for the 5% significance level, therefore emphasizing simple parameter hypothesis testing[9].

< Insert Figures 1 and 2 here >

We focus on the main points of contention, i.e. the relative magnitude of the coefficients θ and ω. The latter parameter, in particular, displayed a wide range of estimated values across the different specifications studied in GG, ranging from 0.077 to 0.522, whereas β is estimated with more precision. Hence, in Figures 1 and 2 we present bi-dimensional confidence sets obtained from the J-K and K_{LM} tests, concentrated at particular values of β (here $\beta = 0.98$, but results are the same for different values of this parameter). These sets are plotted together with 90% confidence ellipses based on standard asymptotic theory. To save space, we report sets based on CUE (Figure 1) and EL (Figure 2) estimation, as there are no significant differences among other GEL alternatives. Also, we focus on results obtained with the original data, as this seems to offer more support for the claims of GG and GGLS.

As it is apparent, the CUE and EL methods produce similar results, despite their intrinsic differences. Indeed, in both cases the robust confidence sets are much larger than standard ellipses, with a significant proportion outside the unit cube[10]. This feature is not only a clear indication of weak parameter identification, but it also means that the confidence sets contain several combinations of the reduced-form parameters that are inconsistent with the findings of GG and GGLS. In particular, large ω's and θ's correspond to values of λ close to 0, which questions the significance of the marginal cost as the forcing variable in inflation dynamics. In addition, a large portion of the sets

[9] See paper for details, choosing different significance levels does not change the results qualitatively.

[10] The large gap in Figure 1 for the 90% confidence set is due to the fact that the p-values for these data points are between 5% and 10% and hence do not enter the 90% confidence set, but are included in the 95% one.

lies above $\omega = 0.5$, hence contradicting the claim of GG and GGLS that the degree of backwardness is negligible.

$<$ Insert Figure 3 and 4 here $>$

More powerful tests may be conducted if one assumes that some parameters are well identified. This involves obtaining a consistent estimate of these parameters for each value in the grid of the parameters under test (see Kleibergen, 2005, section 3.2 and Guggenberger and Smith, 2008, section 2.3 for details). Even when we do this, the above conclusions remain unaltered. Figures 3 and 4 reproduce the confidence sets when β is assumed to be well identified (noted with the superscript $\hat{\beta}$) and the null $H_0 : \omega = \omega_0$, $\theta = \theta_0$ is tested. As expected, the confidence sets are tighter, mainly due to the reduction in the degrees of freedom. Nevertheless, they are still unreasonably large and contain far too high values for ω when compared to what has been reported by GG and GGLS.

$<$ Insert Figures 5 and 6 here $>$

Furthermore, when both β and θ are partialled out, the values of ω for which the null $H_0 : \omega = \omega_0$ is not rejected reinforce the weak identification conclusion. Figures 5 and 6 plot sequences of K and K_{LM} statistics against the corresponding $\chi^2_\alpha(1)$ critical value. The CUE-GMM procedure points to a region of non-rejection formed, roughly speaking, by the intervals $(0.2, 0.5) \cup (0.7, 0.95)$, while the EL test points to non-rejection for almost the entire range of ω considered here[11], both methods thus confirming identification problems.

5 Conclusion

The NKPC has become a standard tool for macroeconomic analysis. However, there is mounting evidence questioning its empirical validity. In this paper, we revisit the results presented in Gali and Gertler (1999) and Gali *et al.* (2005), by employing state-of-the-art inference techniques. Though very recent, the literature on GEL methods suggest that there may be advantages in their use in empirical situations, both asymptotically and in

[11]The ridge at $\omega = 1$ corresponds to the point where $\{\beta\theta\omega = 1\}$, as noted by Ma (2002).

finite samples. In particular, we resort to procedures that disentangle tests on coefficients from tests on general model validity, which allow us to focus on the potential sources of misspecification.

Thus, using an alternative approach, our results question some of the earlier findings regarding the empirical plausibility of the NKPC for the US. Although GEL estimates of the structural parameters are in line with those in the original papers, our results raise serious doubts on the significance of real marginal cost as the forcing variable in inflation dynamics. This seems to be even more acute if one considers more recent vintages of data. Moreover, while our "classical" estimation results agree with the result of a dominant forward-looking component, the use of identification-robust tools reveals the existence of a weak identification problem. Indeed, robust confidence sets associated with the parameter estimates are too large, including cases where: i) the backward-looking component of inflation is more important than the forward-looking part; and/or ii) the marginal cost variable is not significant. Therefore, these results contrast dramatically with the published work of Gali and Gertler (1999) and Gali *et al.* (2005). Also, this contradicts the findings of Dufour *et al.* (2006), who found support for the US hybrid NKPC even when employing identification-robust methods. This may be explained by the more restrictive (and perhaps less appropriate) approach employed by these authors. Our conclusions seem to be robust, as they are confirmed by the use of three different GEL estimators (the CUE, EL and ET), which produced similar results.

Although the main focus of the paper is on the econometric issues surrounding the empirical analysis of the NKPC, our results suggest that alternative specifications of the NKPC should be considered, which is in line with results surveyed in Rudd and Whelan (2007). Alternatively, different proxies for the driving variable, the marginal cost, should be analyzed, see Gwin and VanHoose (2007), for example. Thus, a comparison of different specifications, using appropriate methods, should be entertained. We leave this for future research.

References

[1] Altig, D., Christiano, L., Eichenbaum, M. and Linde, J. (2005), Firm-specific Capital, Nominal Rigidities and the Business Cycle, NBER Working Paper 11034.

[2] Anatolyev, S. (2005), GMM, GEL, Serial Correlation and Asymptotic Bias, *Econometrica*, 73, 983-1002.

[3] Andrews, D. W. K. (1991), Heteroskedasticity and Autocorrelation Consistent Covariance Matrix Estimator, *Econometrica,* 59, 817-858.

[4] Bils, M. and Klenow, P. J. (2004), Some Evidence on the Importance of Sticky Prices, *Journal of Political Economy*, 112, 947-985.

[5] Dufour, J. M., Khalaf, L. and Kichian, M. (2006), Inflation dynamics and the New Keynesian Phillips Curve: an identification robust econometric analysis, *Journal of Economic Dynamics and Control*, 30, 1707-1727.

[6] Gali, J. and Gertler, M. (1999), Inflation dynamics: A structural econometric analysis, *Journal of Monetary Economics*, 44, 195-222.

[7] Gali, J., Gertler, M. and López-Salido, J. D. (2005), Robustness of the estimates of the hybrid New Keynesian Phillips curve, *Journal of Monetary Economics*, 52, 1107-1118.

[8] Guay, A. and Pelgrin, F. (2007), Using Implied Probabilities to Improve Estimation with Unconditional Moment Restrictions, CIRPEE Working Paper 07-47.

[9] Guggenberger, P. and Smith, R. J. (2005), Generalized Empirical Likelihood Estimators and Tests under Partial, Weak and Strong Identification, *Econometric Theory*, 21, 667-709.

[10] Guggenberger, P. and Smith, R. J. (2008), Generalized Empirical Likelihood Tests in Time Series Models With Potential Identification Failure, *Journal of Econometrics*, 142, 134-161.

[11] Gwin, C. R. and VanHoose, D. D. (2007), Alternative measures of marginal cost and inflation in estimations of new Keynesian inflation dynamics, *Journal of Macroeconomics*, forthcoming.

[12] Hansen, L. P., Heaton, J. and Yaron, A. (1996), Finite-Sample Properties of Some Alternative GMM estimators, *Journal of Business and Economic Statistics*, 1996, 14, 262-80.

[13] Kitamura, Y. and Stutzer, M. (1997), An Information-Theoretic Alternative to Generalized Method of Moments Estimation, *Econometrica*, 65, 861-874.

[14] Kleibergen, F. (2005), Testing parameters in GMM without assuming that they are identified, *Econometrica*, 73, 1103-1123.

[15] Linde, J. (2005), Estimating New-Keynesian Phillips Curves: A full information maximum likelihood approach, *Journal of Monetary Economics*, 52, 1135-1149.

[16] Ma, A. (2002), GMM estimation of the new Phillips curve, *Economics Letters*, 76, 411-417.

[17] Mavroeidis, S. (2005), Identification Issues in Forward-Looking Models Estimated by GMM, with an Application to the Phillips Curve, *Journal of Money, Credit and Banking*, 37, 421-448.

[18] Newey, W. K. and Smith, R. J. (2004), Higher Order Properties of GMM and Generalized Empirical Likelihood Estimators, *Econometrica*, 72, 219-255.

[19] Newey, W. K. and West, K. D. (1994), Automatic Lag Selection in Covariance Matrix Estimation, *Review of Economic Studies*, 61, 631-653.

[20] Otsu, T. (2006), Generalized empirical likelihood inference under weak identification, *Econometric Theory*, 22, 513-528.

[21] Rudd, J. and Whelan, K. (2005), New tests of the new-Keynesian Phillips curve, *Journal of Monetary Economics*, 52, 1167-1181.

[22] Rudd, J. and Whelan, K. (2007), Modeling Inflation Dynamics: a Critical Review of Recent Research, *Journal of Money, Credit and Banking*, 39, 155-170.

[23] Stock, J. H. and Wright, J. H. (2000), GMM With Weak Identification, *Econometrica,* 68, 1055-1096.

6 Appendix

Figure 1: J-K set concentrating at $\beta = 0.98$

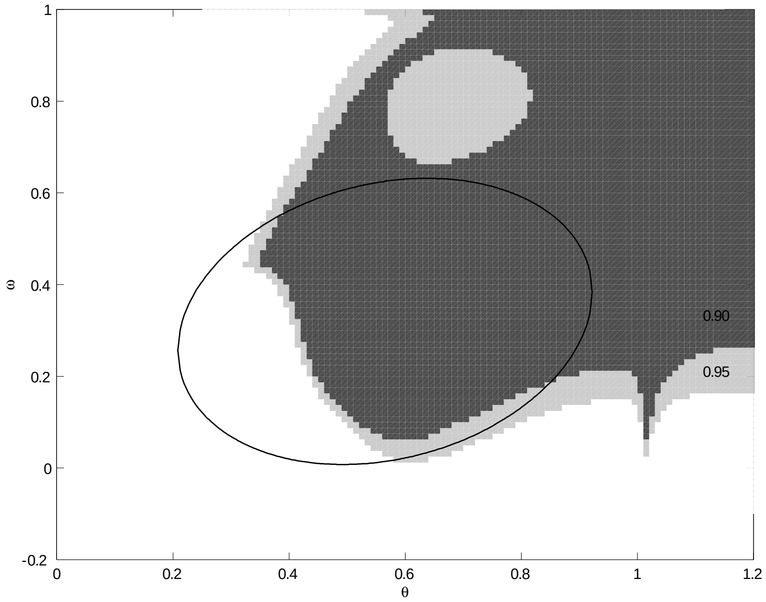

Figure 2: K_{LM} set concentrating at $\beta = 0.98$

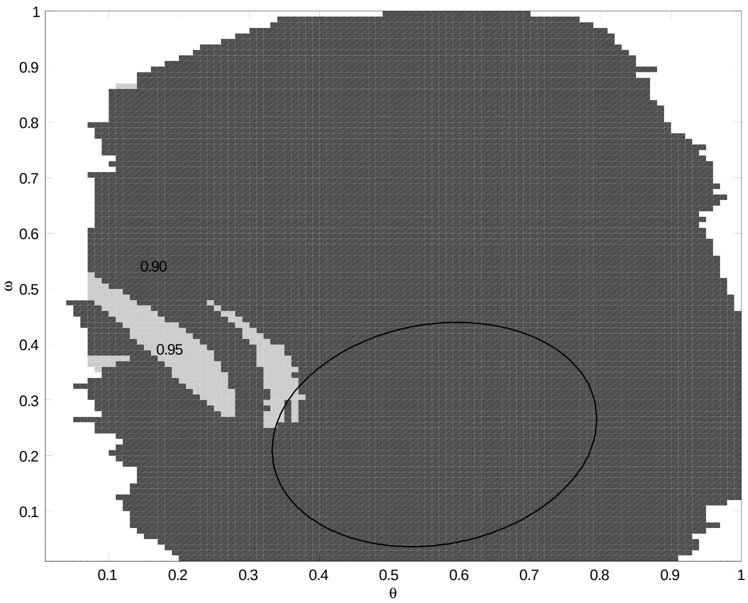

Figure 3: J-$K^{\hat{\beta}}$ set with $\hat{\beta}$ partialled out

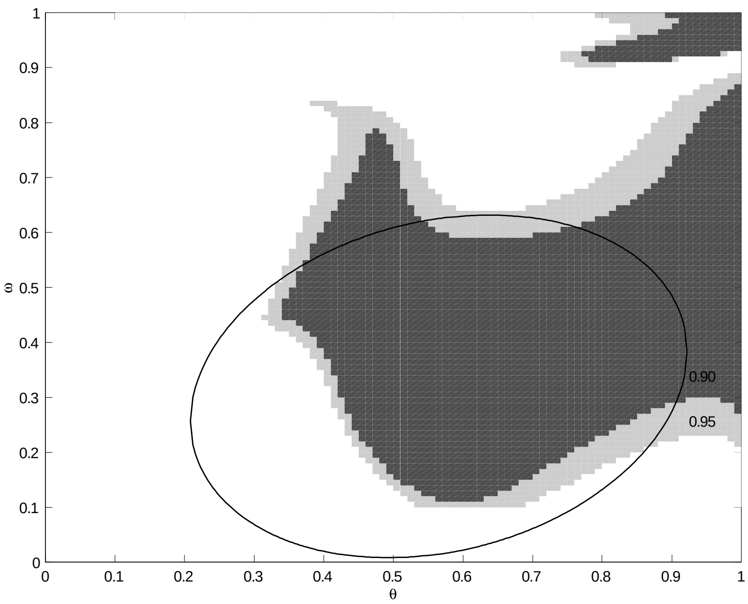

Figure 4: $K_{LM}^{\hat{\beta}}$ set with $\hat{\beta}$ partialled out

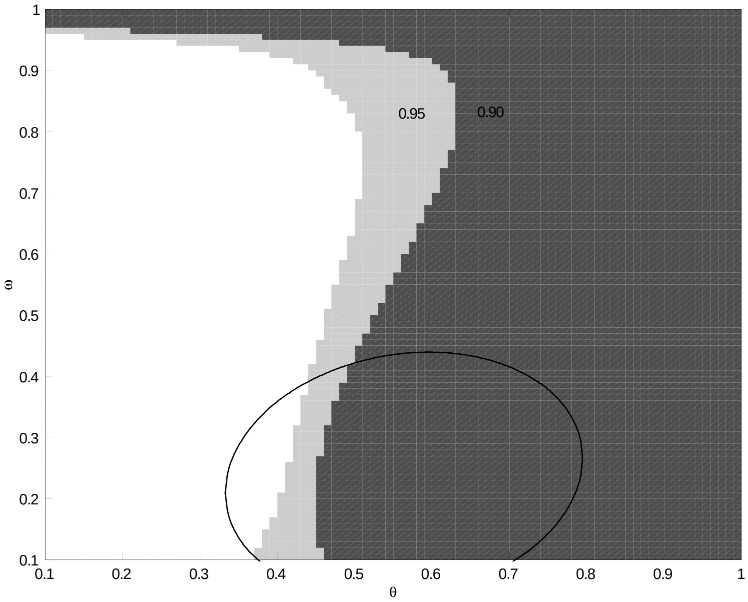

Figure 5: $K^{\hat{\beta}\hat{\theta}}$ sequence with $\hat{\beta}$ and $\hat{\theta}$ partialled out

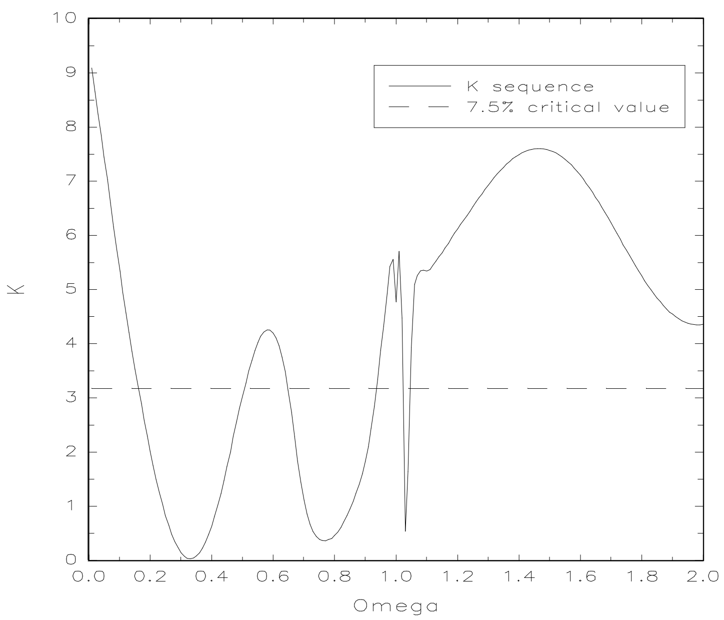

Figure 6: $K_{LM}^{\hat{\beta}\hat{\theta}}$ sequence with $\hat{\beta}$ and $\hat{\theta}$ partialled out

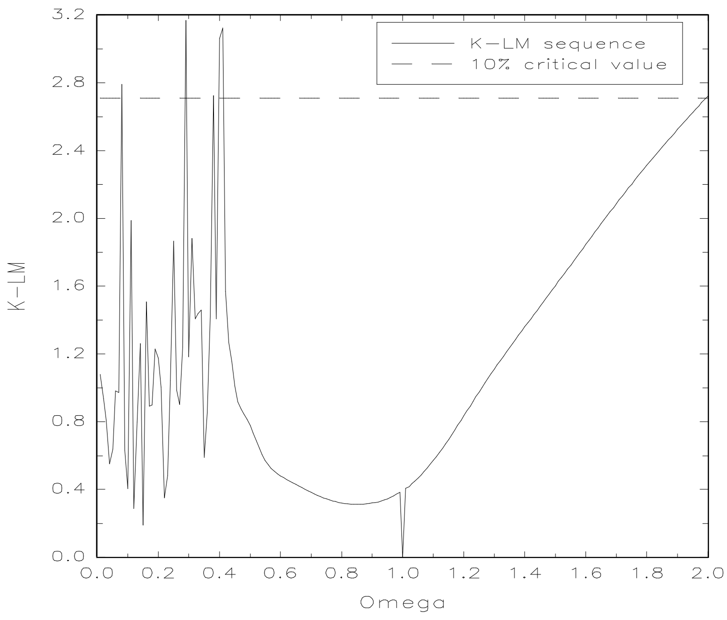

Table 1: Standard 2-step GMM of the hybrid NKPC, US data

1960-1996		β	ω	θ	γ_b	γ_f	λ	λ^*
Specification 1	GG	0.823 (0.014)	0.168 (0.019)	0.418 (0.031)	0.293 (0.021)	0.599 (0.021)	0.293 (0.027)	0.306 (0.029)
	GGLS	0.881 (0.049)	0.229 (0.035)	0.488 (0.043)	0.325 (0.035)	0.611 (0.021)	0.320 (0.094)	0.222 (0.058)
Specification 2	GG	0.927 (0.025)	0.352 (0.036)	0.591 (0.039)	0.380 (0.021)	0.590 (0.021)	0.129 (0.038)	0.072 (0.029)
	GGLS	0.943 (0.034)	0.332 (0.050)	0.602 (0.053)	0.360 (0.029)	0.615 (0.029)	0.125 (0.051)	0.079 (0.034)
1960-2006								
Specification 1	GG	0.945 (0.019)	0.467 (0.037)	0.649 (0.032)	0.425 (0.013)	0.558 (0.022)	0.066 (0.016)	0.020 (0.011)
	GGLS	0.954 (0.021)	0.480 (0.058)	0.677 (0.042)	0.420 (0.016)	0.565 (0.029)	0.052 (0.018)	0.019 (0.013)
Specification 2	GG	0.958 (0.019)	0.237 (0.037)	0.486 (0.069)	0.330 (0.026)	0.648 (0.030)	0.292 (0.129)	0.167 (0.099)
	GGLS	0.979 (0.027)	0.189 (0.037)	0.487 (0.086)	0.280 (0.033)	0.707 (0.037)	0.323 (0.176)	0.258 (0.150)

Note: standard errors in brackets; λ^* obtained imposing $\gamma_f + \gamma_b = 1$; GG instruments: 4 lags of inflation, labour share, output gap, interest rate spread, wage and commodity price inflation; GGLS instruments: 2 lags of above variables and 4 lags of inflation

Table 2: GEL estimates of the hybrid NKPC, US data

1960-1996		β	ω	θ	γ_b	γ_f	λ	λ^*
CUE	GG	0.965	0.357	0.700	0.340	0.645	0.059	0.022
		(0.022)	(0.081)	(0.109)	(0.039)	(0.066)	(0.055)	(0.039)
	GGLS	1.001	0.279	0.634	0.306	0.695	0.106	0.080
		(0.013)	(0.056)	(0.059)	(0.022)	(0.041)	(0.046)	(0.052)
EL	GG	0.963	0.285	0.669	0.301	0.681	0.088	0.011
		(0.008)	(0.034)	(0.061)	(0.020)	(0.034)	(0.041)	(0.040)
	GGLS	0.977	0.278	0.618	0.312	0.677	0.122	0.062
		(0.011)	(0.045)	(0.059)	(0.019)	(0.036)	(0.048)	(0.045)
ET	GG	0.961	0.230	0.641	0.266	0.711	0.123	0.012
		(0.004)	(0.019)	(0.031)	(0.010)	(0.018)	(0.027)	(0.021)
	GGLS	0.978	0.286	0.609	0.321	0.669	0.126	0.091
		(0.007)	(0.033)	(0.035)	(0.013)	(0.026)	(0.031)	(0.029)
1960-2006								
CUE	GG	0.960	0.461	0.808	0.368	0.619	0.018	0.006
		(0.017)	(0.075)	(0.061)	(0.019)	(0.040)	(0.014)	(0.010)
	GGLS	0.965	0.404	0.769	0.348	0.639	0.031	0.016
		(0.019)	(0.083)	(0.069)	(0.019)	(0.044)	(0.046)	(0.016)
EL	GG	0.940	0.348	0.740	0.324	0.649	0.048	0.058
		(0.016)	(0.060)	(0.076)	(0.020)	(0.039)	(0.031)	(0.024)
	GGLS	0.956	0.305	0.729	0.298	0.680	0.056	0.057
		(0.016)	(0.107)	(0.101)	(0.029)	(0.081)	(0.057)	(0.040)
ET	GG	0.947	0.304	0.732	0.297	0.677	0.056	0.019
		(0.007)	(0.028)	(0.036)	(0.009)	(0.019)	(0.027)	(0.009)
	GGLS	0.964	0.317	0.859	0.272	0.710	0.014	0.003
		(0.006)	(0.042)	(0.078)	(0.013)	(0.033)	(0.016)	(0.015)

See notes to Table 1; CUE, EL and ET: Continuous Updating, Empirical Likelihood and Exponential Tilting estimators

Table 3: GEL estimates of the NKPC, restriction $\beta = 1$

1960-1996		ω	θ	γ_f	γ_b	λ
CUE	GG	0.462 (0.081)	0.838 (0.066)	0.358 (0.022)	0.635 (0.045)	0.012 (0.052)
	GGLS	0.421 (0.087)	0.788 (0.070)	0.350 (0.022)	0.642 (0.046)	0.023 (0.058)
EL	GG	0.363 (0.062)	0.748 (0.060)	0.328 (0.019)	0.663 (0.039)	0.038 (0.023)
	GGLS	0.302 (0.110)	0.776 (0.099)	0.281 (0.031)	0.709 (0.082)	0.035 (0.043)
ET	GG	0.338 (0.027)	0.790 (0.036)	0.301 (0.010)	0.689 (0.020)	0.028 (0.012)
	GGLS	0.316 (0.045)	0.874 (0.086)	0.267 (0.021)	0.723 (0.039)	0.011 (0.016)
1960-2006						
CUE	GG	0.369 (0.084)	0.709 (0.114)	0.344 (0.040)	0.648 (0.047)	0.052 (0.052)
	GGLS	0.337 (0.076)	0.570 (0.086)	0.373 (0.037)	0.618 (0.057)	0.140 (0.073)
EL	GG	0.315 (0.049)	0.691 (0.077)	0.314 (0.026)	0.676 (0.045)	0.068 (0.044)
	GGLS	0.308 (0.049)	0.615 (0.059)	0.335 (0.023)	0.656 (0.038)	0.115 (0.046)
ET	GG	0.242 (0.022)	0.686 (0.036)	0.262 (0.011)	0.727 (0.021)	0.084 (0.024)
	GGLS	0.286 (0.033)	0.613 (0.035)	0.319 (0.013)	0.671 (0.026)	0.123 (0.029)

See notes to Tables 1 and 2

Table 4: CUE estimates of the real marginal cost parameter λ

Sample	Instruments	Parzen	Bartlett	Bartlett, $l = 4$	Bartlett, $l = 8$
1960-1996	GG	0.070 (0.052)	0.074 (0.057)	0.102 (0.046)	0.248 (0.053)
	GGLS	0.142 (0.070)	0.136 (0.072)	0.106 (0.046)	0.116 (0.051)
1960-2004	GG	0.026 (0.027)	0.010 (0.019)	0.029 (0.032)	0.009 (0.026)
	GGLS	0.029 (0.032)	0.016 (0.030)	0.026 (0.035)	0.015 (0.029)

See notes to Tables 1 and 2