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On the Robustness of the New Keynesian Phillips Curve Estimates*

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Abstract

In this paper, we examine parameter identification in the hybrid specification of the New Keynesian Phillips Curve proposed by Gali and Gertler (1999) by employing recently developed inference procedures. Our results cast doubts on the empirical validity of the NKPC.

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

JEL Classification: C22; E31; E32

1 Introduction

In this study, we re-evaluate the empirical validity of the hybrid version of the New Keynesian Phillips Curve (NKPC) proposed by Gali and Gertler (1999, henceforth GG) and recently refined by Gali, Gertler and López-Salido (2005, GGLS hereafter). In particular, we address the issue of parameter identification of the NKPC by applying recently developed moment-conditions inference methods. We employ Generalized Empirical Likelihood (GEL) procedures to obtain

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parameter confidence sets, conditional on model validity. These tests have been studied by Guggenberger and Smith (2005, 2006, GS hereafter) and Otsu (2006), based on the work of Kleibergen (2005), developed in a GMM framework. To our knowledge, this paper is the first empirical application of these methodologies.

GG derive their hybrid Phillips curve in a imperfectly competitive, Calvo-type price setting framework, combining forward and backward-looking behavior in the equation

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

where 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. Two main results were obtained by GG and GGLS: 1) forward-looking behaviour is dominant, i.e., γ_f is approximately as twice as large as γ_b, which, although statistically significant, was found to be quantitatively negligible; 2) real marginal cost (instead of traditional measures of the output gap) plays a major role in driving inflation, as suggested by a positive and significant λ.

Several authors[1] have questioned the validity of these results. The issue of identification was discussed in Mavroeidis (2005) and analysed by Ma (2002), who applies the Stock and Wright (2000, SW henceforth) statistics. However, SW tests are not fully informative with respect to parameter identification, since weak identification and instrument validity are being jointly tested. Also, in an independent work, Dufour, Khalaf and Kichian (2006) use identification-robust methods, but do so in a IV context and without taking into account the time-series nature of the data. These studies provide evidence against the NKPC's robustness to weak identification, meaning that conventional GMM asymptotic theory, used in GG and GGLS, is not valid. We rely on GEL methods, discussed in the next section, which are higher-order efficient

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

and have been found to have superior finite sample properties. Furthermore, by concentrating on the subset of crucial parameters (θ, ω), our analysis leads to more powerful tests.

2 Econometric Framework

Given the often disappointing small sample properties of GMM, a variety of alternative estimators has been proposed. Among these, the empirical likelihood (EL), the exponential tilting (ET) and the continuous-updating (CUE) estimators are very appealing from a theoretical perspective. Newey and Smith (2004) have shown that these methods pertain to the same class of 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's biases. For example, they show that, unlike GMM, the bias of EL does not grow with the number of moment conditions.

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 $y_t = (x_t, z_t)$. 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

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

Special cases arise when $\rho(v) = -(1+v)^2/2$, where $\boldsymbol{\theta}_{GEL}$ coincides with the CUE, while with $\rho(v) = \ln(1-v)$ we have the EL estimator and $\rho(v) = -\exp(v)$ leads to the ET case. When $g_t(\boldsymbol{\theta})$ is serially correlated, Anatolyev (2005) obtains similar results to Newey and Smith (2004) and demonstrates that the smoothed GEL estimator of Kitamura and Stutzer (1997) is efficient, obtained by replacing $g_t(\boldsymbol{\theta})$ in (2) with the smoothed counterpart $g_{tT}(\boldsymbol{\theta}) \equiv \frac{1}{2K_T+1} \sum_{k=-K_T}^{K_T} g_{t-k}(\boldsymbol{\theta})$. The SEL variant, in particular, removes important sources of bias associated with the GMM, namely the correlation between the moment function and its derivative, as well as third-order biases.

Another major source of misleading inferences with GMM is weak identification. SW 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 that allows the researcher to construct identification-robust confidence sets (S-sets) for $\boldsymbol{\theta}$. However, SW 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 their $S(\boldsymbol{\theta})$ statistic 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, GS and Otsu (2006) propose identification-robust procedures in a GEL framework, following the work of Kleibergen (2005). Here, we focus on the LM version of the Kleibergen-type test proposed by GS, which was found to have advantageous finite-sample properties:

$$K_{LM}(\boldsymbol{\theta}_0) = T\hat{g}_T(\boldsymbol{\theta}_0)'\hat{\Delta}(\boldsymbol{\theta}_0)^{-1}D_\rho(\boldsymbol{\theta}_0)[D_\rho(\boldsymbol{\theta}_0)'\hat{\Delta}(\boldsymbol{\theta}_0)^{-1}D_\rho(\boldsymbol{\theta}_0)]^{-1}D_\rho(\boldsymbol{\theta}_0)'\hat{\Delta}(\boldsymbol{\theta}_0)^{-1}\hat{g}_T(\boldsymbol{\theta}_0)/2 \quad (3)$$

with $\hat{g}_T(\boldsymbol{\theta}) = T^{-1}\sum_{t=1}^{T} g_{tT}(\boldsymbol{\theta})$, $\hat{\Delta}(\boldsymbol{\theta}) = S_T T^{-1}\sum g_{tT}(\boldsymbol{\theta})g_{tT}(\boldsymbol{\theta})'$ (with $S_T = K_T + 1/2$) 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. This statistic may be appropriately transformed if one wishes to test a sub-vector of $\boldsymbol{\theta}$ (see GS and Kleibergen, 2005 for details), for instance if one or more parameters are deemed to be strongly identified. If the assumption is correct, partialling out identified parameters will deliver a more powerful test, with a χ^2 asymptotic distribution with degrees of freedom equal to the number of parameters under test.

3 Empirical Results

For comparability, we use the same dataset of GG and GGLS (see papers for details), comprising quarterly US data (1960:1-1997:4). We concentrate on the most recent results reported in GGLS and therefore use the same set of instruments, i.e. 2 lags of each variable, with the exception of inflation with 4 lags. Thus, resorting to the analysis discussed in the previous section[2], we formed 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 10% significance level. We also present Kleibergen's (2005) GMM approach, i.e., combining his K statistic with an asymptotically independent $J(\boldsymbol{\theta})$ statistic for overidentifying restrictions, distributed as $\chi^2(m-p)$, which should enhance the power of the test. For the combined J-K test, we use $\alpha_J = 0.025$ and $\alpha_K = 0.075$, therefore emphasizing simple parameter hypothesis

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

testing[3]. To save space, we report sets based on EL estimation, as there are no significant differences with other GEL alternatives.

Moreover, 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.

As it is apparent, GMM and GEL 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. 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. Furthermore, a large portion of the sets lies above $\omega = 0.5$, hence contradicting the claim of GG and GGLS that the degree of backwardness is negligible.

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. 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.

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 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 GEL test points to non-rejection for almost the entire range of

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

ω considered here[4], both methods thus confirming identification problems.

4 Conclusion

In summary, by employing identification-robust statistics that allow us to disentangle tests on coefficients from tests on general model validity (and are therefore more appropriate than those used in previous studies), we question GGLS's claim that the NKPC is robust and empirically plausible. We corroborate the finding that the NKPC suffers from a weak identification problem, raising doubts on the significance of marginal costs as the forcing variable in inflation dynamics and on the relative magnitude backward-looking of behaviour. Our conclusions are strengthened by the use of two different approaches, GMM and GEL, which produce consistent results.

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5 Appendix

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

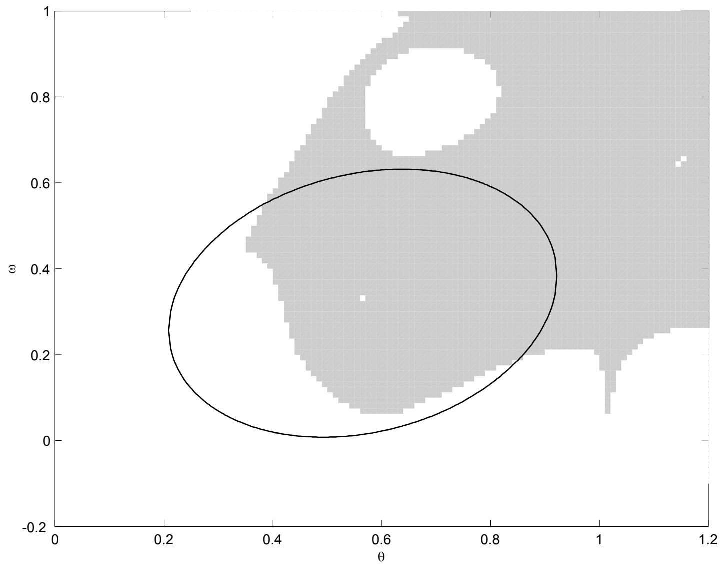

Figure 2: K_{LM} set concentrating at $\beta = 0.98$

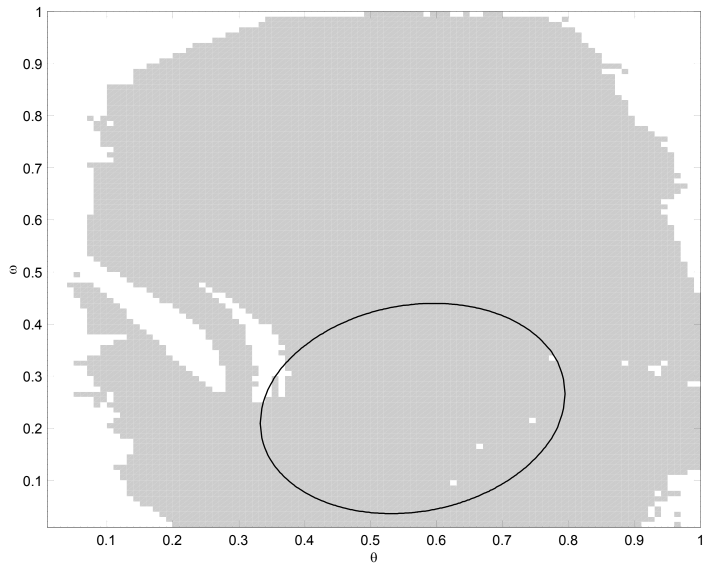

Figure 3: J-$K^{\hat{\beta}}$ set with $\hat{\beta}$ partialled out

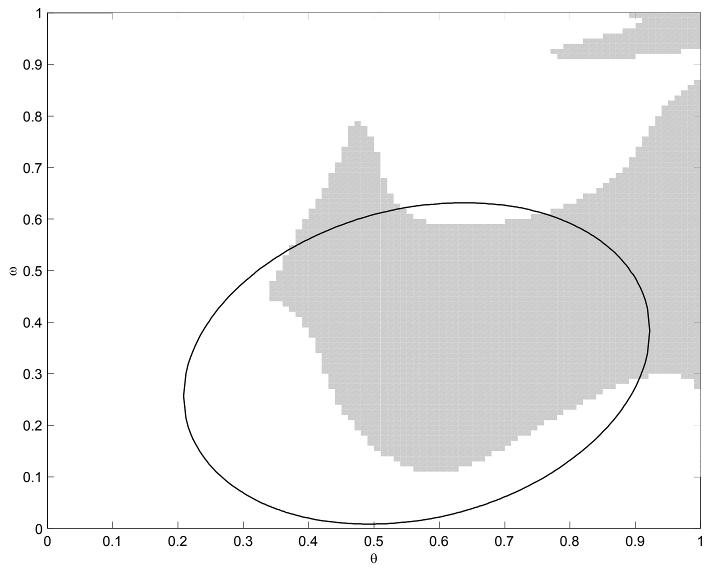

Figure 4: $K_{LM}^{\hat{\beta}}$ set with $\hat{\beta}$ partialled out

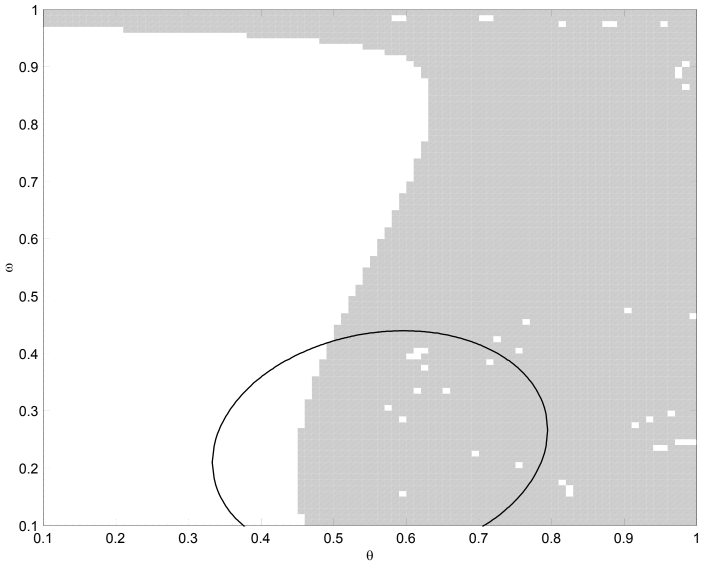

Figure 5: $K^{\hat{\beta}\hat{\theta}}$ sequence with $\hat{\beta}$ and $\hat{\theta}$ partialled out

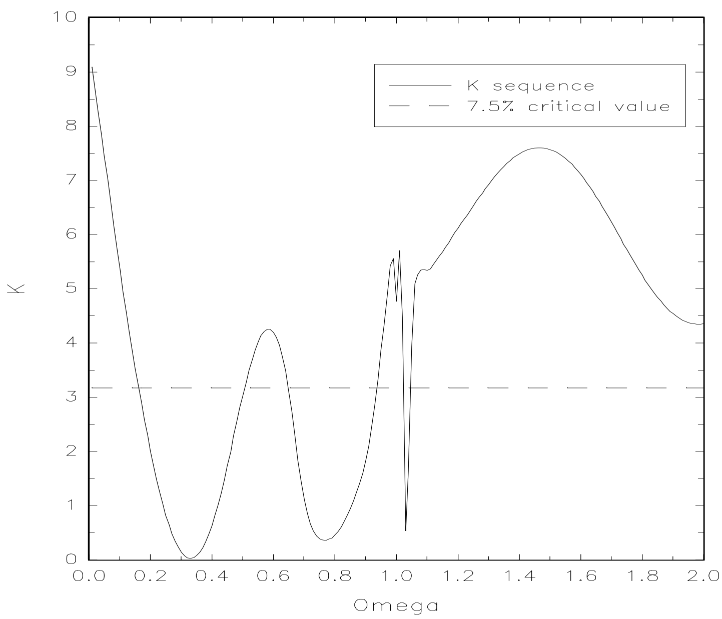

Figure 6: $K_{LM}^{\hat{\beta}\hat{\theta}}$ sequence with $\hat{\beta}$ and $\hat{\theta}$ partialled out