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A Critical Review of Posch, J. and F. Rumler (2015), "Semi-Structural Forecasting of UK Inflation Based on the Hybrid New Keynesian Phillips Curve" *Journal of Forecasting* **34**(2): 145-62

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This article critically reviews and proposes further extensions to Posch, J. and F. Rumler (2015), "Semi-Structural Forecasting of UK Inflation Based on the Hybrid New Keynesian Phillips Curve," *Journal of Forecasting* **34**(2): 145-62.

JEL-Codes: *C22*; *C53*; *E31*; *E37*; *E47*.
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1. Introduction

Scarcity of consensus is a recognisable feature within the Macroeconomics field. However, a widely accepted computable result useful for policymaking is that more accurate forecasts lead to successful economic policies. A key example may be inflation forecasts for monetary policy. Nevertheless, and despite major improvements made towards microeconomic foundations, there is no such a consensus on which of the many devices delivers most accurate forecasts.

Since the rational expectations revolution that inflation modelling incorporate future expectations as part of the underlying driving process. However, lagged inflation still plays a crucial–and convenient–role when fitting a model to data. A common framework that amalgamates both subsequent dynamics comes after the so-called *Hybrid New Keynesian Phillips Curve* (HNKPC), introduced by Galí and Gertler (1999).[2]

A remaining setback for the HNKPC is in regard to the use of a reliable cost-push variable, *i.e.* marginal costs, especially due to the impossibility of being directly observed.[3] The baseline specification of the HNKPC is defined as:

$$\pi_t = \delta_1 \pi_{t-1} + \left(\frac{\lambda}{\delta_2 \gamma_f}\right) \sum_{s=0}^{\infty} \left(\frac{1}{\delta_2}\right)^s \mathbb{E}_t \left[rmc_{t+s}\right], \quad (1)$$

where π_t is price inflation, $\delta_1 = (1 - \sqrt{1 - 4\gamma_f \gamma_b})/2\gamma_f$, and $\delta_2 = (1 + \sqrt{1 - 4\gamma_f \gamma_b})/2\gamma_f$ are the stable and unstable roots of the HNKPC, with γ_f, γ_b, and λ being the coefficients to be estimated for the reduced-form NKPC, $\mathbb{E}_t$ stand for expected value, and rmc denotes real marginal costs.

Note that this specification, which is derived from an economical-based optimisation, possesses several identification challenges beyond the simultaneity that can be controlled by a GMM estimator. As the robustness discussion based on Instrumental Variables GMM (IVGMM) remains open (Rudd and Whelan, 2005; Lindé, 2005) less attention has been devoted to out-of-sample exercises. Some exceptions are Canova (2007), Rumler and Valderrama (2010), Jean-Baptiste (2012), and more recently, Posch and Rumler (2015; henceforth PR).

In this essay, I review and discuss the major forecasting results in PR for the UK economy covering the 1970-2010 period in quarterly frequency. Forecasts are made for 1-, 4-, and 8-steps ahead (h={1,4,8}) with a rolling scheme sample of a fixed-size window of 30-years length using a HNKPC as the preferred specification, and compared to several common benchmarking models.

2. PR: Preliminaries and Forecasting Exercise

PR analyse two extensions of the HNKPC model for forecast accuracy purposes: a time-series extension for the marginal costs measure, and an open-economy augmentation. As they use Equation 1 as a starting point (a structural specification) and the first extension corresponds to an AR(p) specification for marginal costs, the resulting model is labelled as "semi-structural". In principle, the motivation for this is to have the best of both worlds: accuracy from time-series models, and coefficients according to economic foundations. The open-economy augmentation consists of the incorporation of two additional gaps measures in the real marginal cost process, defined as:

$$\begin{aligned} rmc_t \quad = \quad & \widehat{s}_{n,t} + A\widehat{y}_t + B\left(\widehat{p}_t^d - \widehat{p}_t^f\right) - \quad (2) \\ & C\left(\widehat{w}_t - \widehat{p}_t^d\right) - D\left(\widehat{w}_t - \widehat{p}_t^f\right), \end{aligned}$$

where $\widehat{s}_{n,t}$ is real unit labour cost, $\widehat{y}_t$ is the output gap, and the variables w, p^d, and p^f represent the prices of inputs factors: labour (w) plus domestic

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[2] A summary of the major HNKPC results can be found in Galí *et al.* (2005).

[3] Some of the typical shortcomings with the output gap version can be found in Orphanides and Van Norden (2005) and Garratt *et al.* (2008).

(d) and foreign (f) inputs. Variables in hats represent deviations from the steady state. A, B, C, and D are convolutions of the steady-state values and might be viewed as weights in which the relative prices enter into real marginal cost function. For later reference, the close-economy case corresponds to A=B=C=D=0.

2.1. Baseline Specification and Data

As a multihorizon forecasting exercise, an auxiliary forecast for those horizons greater than the significant lag-length of the driving process should be incorporated. PR first depart from traditional estimations is made by assuming a present-value formulation of expectations, following Rumler and Valderrama (2010). Second, a bivariate VAR could alleviate this setback but as PR argue, this ensemble will impose a subjacent inflation dynamics different from the HNKPC. It is with this setback in mind that PR suggest the imposition of an AR(2) specification for real marginal costs, and hence incorporating it in an exogenous manner.

This treatment also allow the authors to analyse to what extent the joint estimation of both equations–for real marginal cost and for inflation–deliver more efficient estimates than a two-step estimator.[4] The reduced-form model (collapsed into a first-lag order equation) is the following:

$$\begin{bmatrix} \pi_t \\ X_t \end{bmatrix} = \begin{bmatrix} \delta_1 & \frac{\lambda}{\delta_2 \gamma_f} \overrightarrow{b_1} \\ \overrightarrow{0} & \mathbf{A} \end{bmatrix} \begin{bmatrix} \pi_{t-1} \\ X_{t-1} \end{bmatrix}, \qquad (3)$$

where $\overrightarrow{b_1}$ is the first row of the matrix $\mathbf{B} = \mathbf{A}\left[\mathbf{I} - (1/\delta_2)\mathbf{A}\right]^{-1}$, $X_t = \left[\begin{array}{ccc} rmc_t & \ldots & rmc_{t-p+1} \end{array}\right]'$, and $\overrightarrow{0}$ is a vector of dimension p containing zeros.[5] The final specification (comprising IV and its lag-length selection) relies on a criterion of individual significance plus the J-test for IV validation using the full sample in the final equation.

Actual inflation data correspond to the quarter-on-quarter change of GDP Deflator.[6] As a matter of robustness, PR makes use of a quarter-on-quarter version of CPI inflation. Rather than the use of a direct measure of inflation expectations, *e.g. Consensus Forecast*, PR makes use of the law of iterated expectations, and hence defining $\mathbb{E}_t(\pi_{t+\ell}) = \pi_t + \varepsilon_t^{\ell}$, where ε_t^{ℓ} is the ℓ-step-ahead forecast error.

[4]Results afterwards do not support the claim that the one-step estimator redound on efficient estimates nor fruitful forecasts.
[5]The fact that rmc enters to the baseline equation with two lags imply $rmc_t = \alpha_1 rmc_{t-1} + \alpha_2 rmc_{t-2}$.
[6]No formal discussion is made regarding seasonality. This issue may be cumbersome for forecasting exercises since traditional adjustment procedures includes already forecasted observations. This problem alongside the use of a fixed data vintage inherits the label of "pseudo"-out-of-sample to PR results.

2.2. Forecast Evaluation

After checking for the abovementioned in-sample diagnostics, PR provides their base estimation in which the forward looking coefficient is rather dominant.[7]

The forecast evaluation comprises the traditional two round procedure: the root mean squared forecast error (RMSFE) comparison, and statistical inference relative to a benchmark model. The benchmark model used is the random walk (RW), whereas several competing specification are analysed. These specifications are:

1. an AR(4) purely time-series model,
2. two bivariate VARs with marginal costs based on wages (labelled VAR-B) and in oil price (VAR-G),
3. the two-step estimator with a purely structural model (two versions: close and open economy; NKPC-CE and NKPC-OE), and
4. the two semi-structural HNKPC for close and open economy (SSNKPC-CE and SSNKPC-OE) using a one-step estimator. The postulated models of PR are these two SSNKPC.

The inclusion of the unrestricted VARs of (2) naturally evaluates the usefulness of imposing a structure in the model when comparing with the NKPC of (3) and (4). In the same line, the comparison between specifications (3) and (4) evaluates directly the usefulness of the marginal cost exogenous innovation in predictive gains.

An additional feature is added when decompose the RMSFE into a bias, variance, and unsystematic component, following the traditional Theil decomposition (Theil, 1967). These estimations carry out the advantage of investigate in which direction a specific forecast is better than other, either bias and variance.

Finally, an interesting modification of the traditional Diebold and Mariano (1995; DM) test is used for statistical evaluation. The modification accounts for the short sample using the correction proposed in Harvey *et al.* (1997). Then, inspired in the Clark and McCracken (2005) test for nested models, PR makes use of a *reality-check*-alike bootstrap of the original DM statistic within the short sample ensemble.[8]

[7]Note that the marginal cost is not always significant along the sample span. This is related to a recent view of the NKPC in which is supposed to be flat in the (π_t, X_t)-plane. See Kuester *et al.* (2009) for a brief discussion and empirics in this matter.
[8]This simulation exercise is conducted following the White (2000) *reality check* in the sense that replications are made for the sample-valued DM-statistic using the stationary block bootstrap resampling method of Patton *et al.* (2009).

2.3. Results

A concise summary of RMSFE results is the following. When using GDP Deflator, NKPC-OE is the best candidate at h=1, and the AR(4) for h=4 and 8. When using the CPI inflation, the best alternative is the AR(4) at any horizon.

There are five major findings shared for both inflation measures:

1. The SSNKPC-OE delivers forecasts that significantly outperform the RW at 1-step-ahead, while for 4- and 8-steps-ahead are indistinguishable close to the RW,
2. The AR(4) forecast turns to be the best forecasting method across all the candidates,
3. The use of expectations does not show significant predictive gains at longer horizons (comparing NKPC against SSNKPC models),
4. The OE augmentation delivers better forecast than their CE specifications, and
5. There is no an identifiable predictive gain when estimating the structural and semi-structural model in two steps or the two equations jointly.

The U-Theil decomposition reveals that the AR(4) and the two unrestricted VARs generally have a smaller bias than the structural and semi-structural models.

Statistical inference indicate that at the shortest horizon the model with the lowest RMSFE, NKPC-OE, outperforms all alternatives except the AR(4). The proposed SSNKPC-OE model outperforms significantly only the NKPC-CE, but none of the time-series models. When using the CPI inflation, there is found less variation in results, therefore, less significant results. Overall, the AR(4) is found the best when comparing point forecast and unbiasedness, confirmed with statistical significance tests.

3. Discussion

PR postulates that a semi-structural version of the NKPC seems as a "promising" avenue for inflation forecasting purposes (p. 145). Nevertheless, and taking a central banker point of view–whom the proposed innovation might be indeed promising–the evaluation of accuracy could involve different loss function rather than exhibit a quadratic shape.

In particular, considering an asymmetrical function with higher penalty for overestimation of inflation could shed a new light when comparing time-series with economics-based models as the latter exhibits a higher share of bias.[9]

Note that the best model is the AR(4); a textbook result since p=4 coincides with the annual frequency of a widely-known seasonal variable. This result may not to be useful for a central banker equipped with a storytelling device–a DSGE model, for instance–combined with a whole set of AR models delivering reasonable forecasting accuracy.[10] However, an unexplored avenue in the light of PR results aiming to persuade the use of the SSNKPC-OE can result in a statistical augmentation in the *inflation-related side* of the NKPC.

Assuming that the NKPC is described by $\pi_t = \varphi_1(\pi_{t-b}, \pi_{t+l}; \overrightarrow{\boldsymbol{\theta}_1}) + \varphi_2(X; \overrightarrow{\boldsymbol{\theta}_2}) + \varepsilon_t$, PR extension lies in the analytics of $\varphi_2(\cdot)$.[11] PR results suggest that a time series extensions would come in the $\varphi_1(\cdot)$ direction instead of $\varphi_2(\cdot)$. For instance, in regard to the estimation of the $\overrightarrow{\boldsymbol{\theta}_1}$ parameters, it is possible to use a bias correction procedure such a Andrews and Chen (1994) for the AR(p), p>1 case. The imposition of p=4 or a seasonal regressor should be considered. The expectations measures used also could be replaced for a directly observed variable. This is the case of expectations coming from surveys such as *Consensus Forecasts*, *Bloomberg*, or the European Commission, as used by Jean-Baptiste (2012).

PR departs from the baseline specification of Galí and Gertler (1999) not enough to do not inherit the criticism posed in Rudd and Whelan (2005) and Lindé (2005). In particular, the use of the Non Linear IVGMM should be explored as an alternative estimation method.[12]

Some standard criticism to forecasting exercises still applies. A discussion on how more structure would result in better predictive ability is always encouraged. Especially because the quest of accuracy is not necessarily related to a richer economic environment; as the PR results confirm afterwards.

As a multihorizon forecasting exercise, a comparison of iterated with a direct forecasting method would enrich the conclusions. In the same line, recursive estimation instead of a rolling-window-scheme remains as an open comparison.

Despite the U-Theil decomposition, the time dimension of the RMSFE will make a direct link of accuracy to the volatility of π_t. This figure is interesting to analyse with macroeconomic variables spanning the last financial crisis in the sample. Also, because is unlikely that the same model outperforms the candidates at every single observation.

[9] This minor twist also characterise to whom the model should seem promising.

[10] See Holan *et al.* (2010) for a revision of the plethora of currently computable AR models.

[11] Note also that as was mentioned, several papers found that $\overrightarrow{\boldsymbol{\theta}_2}$=0. See Kuester *et al.* (2009) for details.

[12] A *shrinkage*-alike estimation for the output gap coefficient is also an avenue for further analysis.

As a corollary, a forecast combination scheme in the Bates and Granger (1969) sense would also allow for a broad comparison between (semi-)structural and time-series models. Furthermore, the combined forecast may also compete in terms of accuracy depending on weights' election.

Finally, the RW RMSFE exhibits a declining profile across the horizons, reflecting inefficiency in the Patton and Timmermann (2012) sense.[13] A more demanding benchmark, or at least one fulfilling efficiency gives consistency to conclusions. A RW-related modelling technique could be the exponential smoothing family (Hyndman *et al.*, 2008) that nests the RW.

4. Final Remarks

PR proposes a NKPC-based semi-structural model to forecast inflation in the UK at multiple horizons, and compare it with structural and time-series models. The HNKPC of Galí and Gertler (1999) is augmented allowing the real marginal cost variable following an autoregressive process with some open-economy components (becoming SSNKPC-OE).

The SSNKPC-OE delivers more accurate forecast than most time series models *in the short-run only* (h=1). At longer horizons (h=4 and 8) is outperformed by time-series models, *i.e.* an AR(4). This result is obtained with the GDP Deflator, whereas using the CPI inflation the AR(4) outperforms remaining candidate models. Estimating the semi- and structural models in one step does not redound into more accurate results. Also, fully structural models do not perform worst than semi-structural models.

Roughly speaking, the best forecasting model for UK inflation is the AR(4). PR results are useful since investigate to what extent proposed structural models in the literature are a better device when forecasting inflation. The results are ultimately dependent on the characteristics of the economy; hence, encouraging the use of other datasets. Some minor methodological improvements are also proposed for further research.

[13] Last row of Table II in PR, p. 154.

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