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Forecasting Canadian inflation: A semi-structural NKPC approach

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ABSTRACT

We examine whether alternative versions of the New Keynesian Phillips Curve equation contain useful information for forecasting the inflation process. We notably consider semi-structural specifications which combine, for closed- and open-economy versions of the model, the structural New Keynesian equation with time series features. Estimation and inference are conducted using identification-robust methods to address the concern that NKPC models are generally weakly identified. Applications using Canadian data show that all the considered versions of the NKPC have a forecasting performance that comfortably exceeds that of a random walk equation, and moreover, that some NKPC versions also significantly outperform forecasts from conventional time series models. We conclude that relying on single-equation structural models such as the NKPC is a viable option for policymakers for the purposes of both forecasting and being able to explain to the public structural factors underlying those forecasts.

1. Introduction

One of the main concerns of Central Banks around the world is to understand the dynamics of the inflation process and to forecast as accurately as possible the future path of this variable. With respect to the former objective, the popular strategy has been to rely on New Keynesian Dynamic Stochastic General Equilibrium (DSGE) setups, as these models are rooted in optimization-based principles, and because they also allow uncertainty in various structural variables to affect general equilibrium outcomes. The DSGE literature is vast and it has shown that models belonging to this class are fairly successful in explaining the behavior of some key macroeconomic variables. On the other hand, when it comes to the forecasting objective, preference has been given to using statistical models. Indeed, it is well known that simple time series models have a superior performance compared to theory-based structural models, especially over short or medium term forecasting horizons.

Forecast accuracy is clearly paramount for policymakers, yet decision-makers would also like to be able to explain to the public the economic reasons for their policy actions, as well as any risks associated with the forecasts underlying those decisions. Unfortunately, in this respect, time series models have, at best, cursory links to the various theoretical and economic channels giving rise to the forecasts, and thus have only limited information to provide in this regard. In addition, while formal attempts were made, for example, by Del Negro and Schorfheide (2006), Del Negro et al. (2007) and by Bernanke et al. (2005), to marry aspects of DSGE and time-series features so as to generate models that can better explain the dynamics of macroeconomic variables simultaneously, such models face important challenges as forecasting devices. This is because they often feature a multitude of parameters, including some that may be difficult to estimate with any precision, which negatively affects forecast accuracy, and also because linearization of first-order conditions around steady-states required for obtaining the equilibrium relationships among variables of interest makes it difficult to predict values for these variables that considerably stray from their historic mean. Such forecasts are more appropriate for long run forecasting but could be fairly inaccurate in the short term, specially at turning points, at times of structural change, or during periods of atypical economic turbulence.

Rather than relying on fully-specified highly constrained multi-equation DSGE setups, it might be preferable to use single-equation economic models instead. Such models incorporate a certain amount of structural information that can be useful in interpreting the economic reasons and risks underlying its forecast. They also have far fewer parameters to estimate, yielding potentially more precise forecasts. Furthermore, they are considerably less constrained than their full DSGE counterparts and are therefore more likely to be compatible with the data. Such an approach was followed by Rumler and Valderrama (2010) who examined the forecasting performance of the New Keynesian Phillips Curve (NKPC) for inflation in Austria and showed that it performed equally well as, and sometimes better than, some pure time series models.

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While focusing on single-equation structural models is a promising enterprise, a major challenge nonetheless needs to be met in this context, namely that such models face identification difficulties (for the case of the NKPC, see for example Dufour et al., 2006). In the presence of identification problems, standard estimation and inference methods such as Generalized Method of Moments (GMM) yield unreliable outcomes. Given that the advantage of the NKPC relative to pure time series models is precisely in its story-telling dimension, it becomes important that the applied econometric methods yield structural coefficient estimates and related precision estimates that policymakers can be confident in. Only then can a particular forecast be properly attributed to its various underlying structural components, and therefore be used to tell a meaningful story to the public. To this end, one can resort to using identification-robust methodology for model quantification. Such methods produce reliable inference even in the presence of identification difficulties, while, at the same time, preserving all of the structural constraints of the model. Moreover, they can also formally account for any calibrated parameter values in the equation, providing further statistically-justified information to policymakers.

In this paper we apply identification-robust estimation and inference methods to the NKPC equation to obtain forecasts for Canadian inflation. Different versions of the model are estimated and their forecasts are compared to ones obtained from various other model alternatives. We notably focus on open-economy versions of the NKPC as Canada is a small open economy, and the habitually-used (closed-economy) NKPC equation would likely be misspecified for our purposes. In addition, we propose semi-structural versions of our models which additionally incorporate time series features into the equations. The latter are aimed at better capturing some of the shorter-term dynamics in the data that the purely structural models are likely to miss.

The reason why we focus on the NKPC is that it is the current predominant paradigm for explaining inflation, being firmly rooted in theory and a key ingredient of DSGE models. Another reason is that it assigns a role to inflation expectations which may prove very important in the context of forecasting; many developed countries have been following successful inflation targeting monetary policies for a number of years, and as a consequence, expectations have become anchored to implicit or explicit inflation targets (see, for example Fuhrer and Olivei, 2010). In other words, expectations are an important explanatory variable and need to be accounted for when forecasting inflation.

Our results show that the identification-robust-estimated NKPC has good forecasting performance for our sample, both in the short and medium runs (that is, one and four quarters ahead), and that, in general, its various versions perform as well as or better than conventional time series models in forecasting inflation. In particular, among all of our different model versions, we find that the semi-structural model (SSM), and notably its open-economy version, generally performs the best. Indeed, compared to the random walk model, forecast improvements with the SSM reach 26% at the short-term forecasting horizon, and 34% at the medium-term forecasting horizon. Moreover, the SSM versions have a superior performance (of up to 12%) relative to their purely structural counterparts, as do the open-economy specifications compared with their closed-economy versions (up to 7% in this case). We thus conclude that such models should be included in the forecaster's toolbox and can be used when needed to explain certain elements of policy decisions.

In the next section we outline our methodology. Section 3 discusses the identification-robust estimation strategy. Section 4 describes the time series models used in the forecasting comparison and evaluation. The results along with significance tests for equal predictive accuracy are then presented in Section 5. Finally, Section 6 concludes the paper.

2. Methodology

Our starting point is the method by Rumler and Valderrama, (2010) that proposes to generate forecasts from the NKPC equation using the present-value formulation of the model. Writing the equation in the original difference formulation would have allowed for obtaining only a 'nowcast' for inflation rather than a forecast, given that inflation expectations of future periods would have been needed for forecasting future inflation, and that despite the existence of some survey measures this data is often not available over the required time horizons. The present-value formulation of the NKPC helps to avoid this problem.

To describe the forecasting technique, consider the hybrid version of the NKPC as defined by Galí and Gertler (1999):

$$\pi_t = \frac{\theta\beta}{\Delta}E_t\pi_{t+1} + \frac{\omega}{\Delta}\pi_{t-1} + \frac{(1-\theta)(1-\omega)(1-\theta\beta)}{[\varepsilon(\phi-1)+1]\Delta}rmc_t \tag{1}$$

where π_t is inflation and rmc_t denotes real marginal cost. θ represents the Calvo probability that a firm adjusts its price in a given period, β is the steady-state discount factor, ω is the fraction of firms following a backward-looking rule of thumb in price setting, ε is the elasticity of demand, ϕ is the substitution elasticity in production and $\Delta = \theta + \omega[1 - \theta(1 - \beta)]$. For ease of notation we can rewrite this equation in reduced form as:

$$\pi_t = \gamma_f E_t(\pi_{t+1}) + \gamma_b \pi_{t-1} + \lambda rmc_t. \tag{2}$$

To arrive at fundamental inflation, Eq. (2) is solved forward, yielding an expression for current inflation as a function of the discounted sum of present and future marginal costs:

$$\pi_t = \delta_1\pi_{t-1} + \left(\frac{\lambda}{\delta_2\gamma_f}\right)\sum_{s=0}^{\infty}\left(\frac{1}{\delta_2}\right)^s E_t\left[rmc_{t+s}\right] \tag{3}$$

where $\delta_1 = \frac{1-\sqrt{1-4\gamma_f\gamma_b}}{2\gamma_f}$ and $\delta_2 = \frac{1+\sqrt{1-4\gamma_f\gamma_b}}{2\gamma_f}$ are the stable and unstable roots of the hybrid NKPC.

Computing fundamental inflation according to the present-value formulation in Eq. (3) requires multi-period forecasts of real marginal cost. Campbell and Shiller, (1987) propose to generate such forecasts from an auxiliary time-series model; specifically, they use a bivariate Vector Autoregression (VAR) model including inflation and real marginal cost. This is also the approach followed in Rumler and Valderrama (2010). However, using a bivariate VAR to generate forecasts of real marginal cost, in our view, induces an inconsistency as it implicitly assumes a different process for inflation than the NKPC itself. To avoid this, in this paper we assume a univariate autoregressive (AR) process of order p for real marginal cost, which makes this variable exogenous. In addition, AR models are usually a good choice if the process to be forecasted exhibits high autocorrelation, which is usually the case for empirical marginal cost proxies.

As is well known, any general AR(p) process can be written in "companion form" as a VAR(1) of dimension p:

$$X_t = AX_{t-1} + \epsilon_t. \tag{4}$$

This companion form representation is general enough to capture different time series processes and at the same time can conveniently be integrated into expression (3). In the case of a univariate AR(p) process for real marginal cost, the vector X contains current and up to $p-1$ lags of rmc_t, i.e. '$X_t = \left[rmc_t \quad rmc_{t-1} \quad \cdots \quad rmc_{t-p+1}\right]$' and A is the companion matrix. Note that multi-period forecasts of X_t in this framework are given by $\hat{X}_{t+h} = A^h X_t$. Using this relation and applying the summation formula to Eq. (3), a one-step-ahead forecast of fundamental inflation is then given as:[2]

$$\pi_{t+1} = \delta_1\pi_t + \left(\frac{\lambda}{\delta_2\gamma_f}\right)e_1'\left[I - \frac{1}{\delta_2}A\right]^{-1}AX_t \tag{5}$$

[2] For convergence we need that the sum of the first-row elements of A, i.e. the autoregressive coefficients of marginal cost, is less than 1.