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Has US inflation really become harder to forecast?

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ABSTRACT

Since the mid-1980s, Phillips curve forecasts of US inflation have been inferior to those of a conventional causal autoregression. However, little change in forecast accuracy is detected against the benchmark of a noncausal autoregression, more accurately characterizing US inflation dynamics.

1. Introduction

In their recent, widely cited article, Stock and Watson (2007, SW henceforth) argued that while US inflation in general has become easier to forecast after 1983, it has also become more difficult to improve upon univariate models by means of backward-looking Phillips curve (PC) forecasts. Specifically, they claimed that before 1983, PC models were superior to the univariate autoregressive (AR) model, but after 1984, the situation has reversed. We argue that SW's benchmark model is not the appropriate univariate model, especially in the 1970–1983 period, but, in fact, inflation dynamics are better captured by a noncausal, instead of a conventional causal AR model. This claim is backed up by the findings of Lanne and Saikkonen (2011) and Lanne, Luoma and Luoto (forthcoming) for the CPI inflation and Lanne et al. (forthcoming) for the GDP price inflation. Also, in contrast to SW, we do not force a unit root in the inflation process.

Our results show that once the noncausal AR benchmark is adopted, the changes in the forecastability of US GDP inflation are minor, and mainly confined to the two-year forecast horizon. As to the other inflation measures (personal consumption expenditure deflator for core items (PCE-core) and all items (PCE-all), and the consumer price index (CPI-U)) considered by SW, the PC forecasts very rarely beat the noncausal AR forecast in either forecast period.

The plan of the paper is as follows. In Section 2, we present the noncausal AR model, and discuss estimation and forecasting. Section 3 presents the forecasting results and comparisons to SW's findings. Finally, Section 4 concludes.

2. Noncausal AR model

Let us consider the following noncausal AR model for inflation π_t $(t = 0, \pm 1, \pm 2, \ldots)$:

$$\varphi\left(B^{-1}\right)\phi\left(B\right)\pi_t = \epsilon_t, \tag{1}$$

where $\phi(B) = 1 - \phi_1 B - \cdots - \phi_r B^r$, $\varphi\left(B^{-1}\right) = 1 - \varphi_1 B^{-1} - \cdots - \varphi_s B^{-s}$, and ϵ_t is a sequence of independent, identically distributed (continuous) random variables with mean zero and variance σ^2 or, briefly, $\epsilon_t \sim i.i.d.\left(0, \sigma^2\right)$. Moreover, B is the usual backward shift operator, that is, $B^k \pi_t = \pi_{t-k}$ $(k = 0, \pm 1, \ldots)$, and the polynomials $\phi(z)$ and $\varphi(z)$ have their zeros outside the unit circle so that

$$\phi(z) \neq 0 \quad \text{for } |z| \leq 1 \quad \text{and} \quad \varphi(z) \neq 0 \quad \text{for } |z| \leq 1. \tag{2}$$

This formulation was recently suggested by Lanne and Saikkonen (2011). We use the abbreviation AR(r, s) for the model defined

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by (1). If $\varphi_1 = \cdots = \varphi_s = 0$, model (1) reduces to the conventional causal AR(r) model.

The conditions in (2) imply that π_t has the two-sided moving average representation

$$\pi_t = \sum_{j=-\infty}^{\infty} \psi_j \epsilon_{t-j}, \tag{3}$$

where ψ_j is the coefficient of z^j in the Laurent series expansion of $\phi(z)^{-1} \varphi\left(z^{-1}\right)^{-1} \overset{def}{=} \psi(z)$. Note that this implies that past observations can be used to predict future errors. From (1) one also obtains the representation

$$\pi_t = \phi_1 \pi_{t-1} + \cdots + \phi_r \pi_{t-r} + \upsilon_t, \tag{4}$$

where $\upsilon_t = \varphi\left(B^{-1}\right)^{-1} \epsilon_t = \sum_{j=0}^{\infty} \beta_j \epsilon_{t+j}$ with β_j the coefficient of z^j in the power series expansion of $\varphi\left(B^{-1}\right)^{-1}$. This representation can be used to obtain forecasts. Taking conditional expectations conditional on past and present inflation of (4) yields

$$\pi_t = \phi_1 \pi_{t-1} + \cdots + \phi_r \pi_{t-r} + E_t\left(\sum_{j=0}^{\infty} \beta_j \epsilon_{t+j}\right),$$

which shows that in a noncausal AR model, future errors are predictable by past values of inflation. If the true model is noncausal, but this is ignored in forecasting, i.e., forecasts are based on a causal AR model, this predictability is dismissed, leading to inferior forecast accuracy despite the causal and noncausal forecasts being based on the same information.

A well-known feature of noncausal autoregressions is that a non-Gaussian error term is required to achieve identification (see, e.g., Breidt et al. (1991), and Brockwell and Davis (1987, pp. 124–125)). This follows from the fact that the same autocovariance function can be obtained irrespective of whether the roots of $\phi(z)$ and $\varphi(z)$ in (1) are inside or outside the unit circle, i.e., whether π_t is causal or noncausal. Since the Gaussian likelihood is completely determined by the autocovariance function, causal and noncausal processes cannot be distinguished under Gaussianity. Therefore, following Lanne and Saikkonen (2011), we specify Student's t-distribution for ϵ_t. In addition to these authors, also Lanne, Luoma and Luoto (forthcoming), and Lanne et al. (forthcoming) have shown this distribution to fit US inflation series well. A small value of the degrees-of-freedom parameter is required for identification, as otherwise the t-distibution comes close to the normal distribution, and identification is not achieved (or it is weak).[1] Under this assumption, the noncausal AR model can be estimated by maximizing the approximate likelihood function proposed by Lanne and Saikkonen (2011). The approximation involves conditioning on the first r and last s observations. As the orders of the polynomials are typically small, the approximation error is likely to be negligible.

To compute forecasts based on representation (4), simulation methods are called for. Let $E_T(\cdot)$ signify the conditional expectation operator given the observed data vector $\boldsymbol{\pi} = (\pi_1, \ldots, \pi_T)'$. From (4) it is seen that the optimal predictor of π_{T+h} ($h > 0$) based on $\boldsymbol{\pi}$ satisfies

$$E_T(\pi_{T+h}) = \phi_1 E_T(\pi_{T+h-1}) + \cdots + \phi_r E_T(\pi_{T+h-r}) + E_T(\upsilon_{T+h}).$$

Thus, if we are able to forecast the variable υ_{T+h}, we can compute forecasts of inflation recursively. In the purely noncausal case of particular interest in this paper, the optimal forecast of π_{T+h} reduces to $E_T(\upsilon_{T+h})$. To calculate υ_{T+h} in practice we use the approximation $\upsilon_{T+h} \approx \sum_{j=0}^{M-h} \beta_j \epsilon_{T+h+j}$, where the integer M is supposed to be so large that the approximation error is negligible for all forecast horizons h of interest. To a close approximation we then have

$$E_T(\pi_{T+h}) \approx \phi_1 E_T(\pi_{T+h-1}) + \cdots + \phi_r E_T(\pi_{T+h-r}) + E_T\left(\sum_{j=0}^{M-h} \beta_j \epsilon_{T+h+j}\right). \tag{5}$$

Lanne et al. (forthcoming) show how to generate by simulation the conditional density of future errors needed in the computation of the conditional expectation of $\sum_{j=0}^{M-h} \beta_j \epsilon_{T+h+j}$. Following their recommendations based on simulation experiments, we set $M = 50$, and the number of replications, N, in the simulation procedure equals 100 000.

3. Forecast results

We focus on quarterly GDP price index inflation, but we also considered a number of other inflation measures (PCE-core, PCE-all and CPI-U).[2] All data are downloaded from Mark Watson's web page. The PC forecasts are calculated using autoregressive distributed lag models with various activity variables and potentially gap variables based on them as additional regressors (SW's Eq. (3)). The specifications PC-Δu, PC-Δy, PC-ΔCapUtil and PC-ΔPermits omit gap variables. For detailed variable definitions, see SW.

The noncausal AR models are estimated recursively, with data from 1960:I–1969:IV used for initial parameter estimation. Following SW, forecast results are presented separately for the periods 1970:I–1983:IV and 1984:I–2004:IV. Unlike SW, we only consider iterated multistep forecasts that SW found quantitatively quite similar to their direct forecasts. Lanne and Saikkonen (2011) propose a model selection procedure that was employed in forecasting by Lanne et al. (forthcoming). However, in this paper all noncausal forecasts are based on the recursively estimated fixed AR(0, 4) model that should be adequate for quarterly data. SW mainly rely on the Akaike information criterion (AIC) in model selection, i.e., they recursively select the order of the AR model (denoted AR(AIC) below). However, they also show that the fixed AR(4, 0) model produces similar results.

Table 1 reproduces, from SW's Tables 1 and 4, the root mean squared forecast errors (RMSFEs) of the AR(AIC) forecast and the relative mean squared forecast errors (MSFEs) of a number of alternative models in relation to that model. Compared to the benchmark AR(AIC) model, the predictive performance of virtually all PC models is inferior in the latter compared to the former subsample period at all horizons. This is even more clearly seen in the left panel of Table 3 that presents the percentage changes of the relative MSFEs. There are only two negative entries, both of which are small in absolute value compared to the positive percentage changes. Moreover, while in the 1970–1983 period, the relative MSFEs in Table 1 are, in general, less than unity, indicating the superiority of the PC models, the situation is reversed in the 1984–2004 period. This evidence warrants SW's claim that since the mid-1980s it has been difficult for inflation forecasts to improve on univariate models.

[1] For the inflation series considered in Section 3, the degrees-of-freedom parameter is estimated small, indicating strong identification. For instance, for the GDP price inflation series, the estimate for the entire sample period is 4.94 with a standard error of 1.82.

[2] To save space, the results are not reported, but they are available upon request. The general conclusion are the same as those for GDP price inflation.