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Improving inflation prediction with the quantity theory

Ying Wang[a], Yundong Tu[a,*], Song Xi Chen[a,b]

[a] Guanghua School of Management and Center for Statistical Science, Peking University, Beijing, 100871, China

[b] Department of Statistics, Iowa State University, Ames, IA50011, USA

HIGHLIGHTS

- We consider the role of the quantity theory in improving inflation forecasts.
- We find that the cointegration-based quantity theory does not hold for the period after 1995 for the US data.
- That period is well explained by an adaptive quantity theory based on a functional-coefficient cointegration that adapts to the unemployment rate.
- The forecasting exercises show that the adaptive quantity theory has superior pre-dictive power for targeting future inflation.

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ABSTRACT

This paper focuses on the role of the quantity theory in improving inflation forecasts. We find that the cointegration-based quantity theory does not hold for the period after 1995 for the U.S. data. However, that period is well explained by an adaptive quantity theory based on a functional-coefficient cointegration that adapts to the unemployment rate. The forecasting exercises show that the adaptive quantity theory has superior predictive power for targeting future inflation.

1. Introduction

Inflation forecasting has played an important role in US monetary policy, which leads to continuous effort to search for good indicators of future inflation. This paper focuses on the role of the quantity theory in targeting inflation. Inspired by Chow (1987, 2007), Chow and Wang (2010) and Bachmeier and Swanson (2005), we consider the cointegrating relationship between price and excess money supply suggested by the quantity theory.

Motivated from parameter instability in empirical applications (De Grauwe and Grimaldi, 2001; Moroney, 2002), we study a functional-coefficient cointegration (Xiao, 2009; Cai et al., 2009) between price and excess money supply, with the cointegrating vector adapting to the unemployment rate. Such a choice of the state variable provides close linkage to the Phillips Curve, which emphasizes the relationship between the unemployment rate and the inflation level. We further compare the forecasting performance of various cointegration models, built upon the adaptive quantity theory, in predicting the US inflation. We find that the quantity theory, particularly the functional-coefficient cointegration, is effective in predicting future inflation. Due to space limitation, details not reported in this paper can be found in an earlier working paper, Wang et al. (2015).

The rest of the paper is organized as follows. Section 2 introduces the quantity theory and provides cointegration analysis between price and excess money supply. Section 3 reports the inflation forecasting results and Section 4 concludes.

2. The quantity theory

2.1. Preliminaries

We begin with the Fisher Identity,

$$M_t V_t = P_t Y_t, \tag{1}$$

* Corresponding author.
E-mail address: yundong.tu@gsm.pku.edu.cn (Y. Tu).

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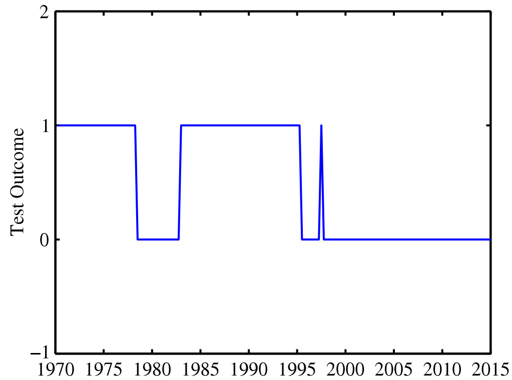


Fig. 1. Testing outcomes for cointegration between p and m. Here "1" stands for the existence of one cointegration and "0" for none.

where M stands for the money stock, V for velocity of the circulation, P for the price level and Y for the real output. In our analysis, we use the Consumer Price Index for P, the Gross Domestic Product in chained 2009 dollars as a measure of Y, and M2 for measure of M. All data are seasonally adjusted quarterly US figures ranging from 1959:1 to 2015:1.

Taking the logarithm on (1) and rearranging yield

$$v_t = p_t - m_t, \tag{2}$$

where $p_t \equiv \log P_t$, and $m_t \equiv \log(M_t/Y_t)$ is referred to as excess money supply. The velocity $v_t \equiv \log(V_t)$ has been often argued to be stationary (Feldstein and Stock, 1994; Estrella and Mishkin, 1997), while the Augmented Dickey–Fuller (Dickey and Fuller, 1981) test suggests that both p and m are unit root processes. As a result, Eq. (2) suggests that p_t and m_t are cointegrated with cointegrating vector $(1, -1)$, using the terminology of Engle and Granger (1987). This observation leads to studies (Chow, 1987, 2007; Chow and Wang, 2010) that investigate whether the quantity theory of money is congruent with the real world economy.

We consider a general cointegration model as in Bachmeier and Swanson (2005),

$$p_t = \beta m_t + v'_t, \tag{3}$$

where β may be different from 1 and v'_t is the regression residual. Using Johansen's maximum eigenvalue test (Johansen, 1995), we check on the cointegration relationship between p_t and m_t. The results based on an expanding window basis (with the samples starting from 1959:1, and 1970:1 being the first testing point) are displayed in Fig. 1. It is observed that p_t and m_t were not cointegrated anymore after 1995, consistent with the findings of Bachmeier and Swanson (2005), who attributed the lack of cointegration since mid-1990s to a structural break.

2.2. The adaptive quantity theory

To incorporate possible structural breaks and parameter instability, we consider a functional-coefficient cointegration model (Xiao, 2009; Cai et al., 2009),

$$p_t = \beta(z_t)m_t + v''_t \tag{4}$$

where the cointegration between p_t and m_t is adapting to an economic variable, z_t, for which we shall use the unemployment rate in the subsequent analysis, and v''_t is the regression residual. The above model is referred to as the "Adaptive Quantity Theory of Money". See Wang et al. (2015).

Two questions of central importance here are: (i) whether the functional cointegration is supported by the US data; and (ii) whether it is necessary to use functional cointegration instead of conventional cointegration that has constant (stable) cointegrating parameters. Xiao (2009) laid down the theoretical underpinnings to address both questions with his functional cointegration test and stability test.

We implement both tests of Xiao (2009) to the data sample recursively on an expanding window basis with 1995:1 as the first test point, and the smoothing bandwidth is set as $h = c \cdot \hat{\sigma}_z \cdot n^{-9/20}$ for $c = 0.8, 1, 1.2$, with $\hat{\sigma}_z$ denoting the sample standard deviation of z_t, and n the sample size. The test results are reported in Fig. 2. It is observed that p_t and m_t are functionally cointegrated for almost all of the subsamples after 1998:2 under different choices of bandwidths. Furthermore, the constancy of the functional cointegrating vector is rejected most of the time under various choices of bandwidths. These results strongly suggest the existence of functional cointegration and are consistent with those from the Johansen test that p_t and m_t are not cointegrated in the conventional way after 1995.

3. Empirical results

In this section, we provide empirical evidence to show that the adaptive quantity theory of money is useful in improving inflation prediction accuracy. We first present the forecasting models and then provide the empirical forecasting performance of these models.

3.1. Forecasting models

We consider the error-correction models (ECMs) derived from cointegrations between p and m to form the forecasting models. Also included for comparison is a frequently used model based on the Phillips Curve (Stock and Watson, 1999). The benchmark model is chosen to be the Autoregression of order ℓ (AR(ℓ)). For forecasting horizon $s = 1, 2, \ldots, 20$, models under consideration are listed below.

- AR(ℓ)

$$\Delta p_{t+s} = \xi_0 + \sum_{i=0}^{\ell-1} \xi_i \Delta p_{t-i} + \epsilon_{t+s}.$$

- AR with excess money supply (AR-m)

$$\Delta p_{t+s} = \xi_0 + \sum_{i=0}^{\ell_1-1} \xi_i \Delta p_{t-i} + \sum_{i=0}^{\ell_2-1} \zeta_i \Delta m_{t-i} + \epsilon_{t+s}.$$

- ECM with error correction from QTM (QTM-ECM)

$$\Delta p_{t+s} = \xi_0 + \sum_{i=0}^{\ell_1-1} \xi_i \Delta p_{t-i} + \sum_{i=0}^{\ell_2-1} \zeta_i \Delta m_{t-i} + \delta \cdot ecm_t + \epsilon_{t+s},$$

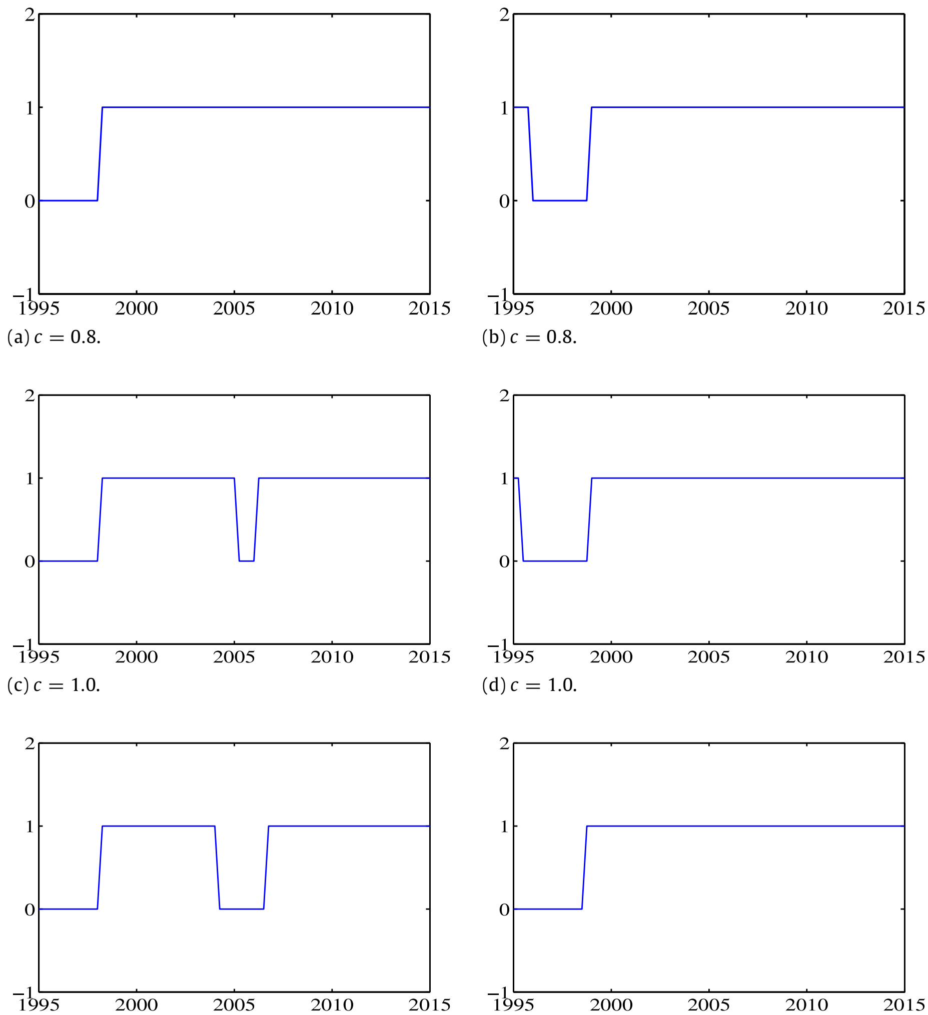
with $ecm_t = p_t - m_t$.
- ECM with error correction from Constant-coefficient Cointegration (C-CI-ECM)

$$\Delta p_{t+s} = \xi_0 + \sum_{i=0}^{\ell_1-1} \xi_i \Delta p_{t-i} + \sum_{i=0}^{\ell_2-1} \zeta_i \Delta m_{t-i} + \delta \cdot \widetilde{ecm}_t + \epsilon_{t+s},$$

with $\widetilde{ecm}_t = p_t - \tilde{\beta} m_t$, and $\tilde{\beta}$ denotes the least square estimate of β in (3).
- ECM with error correction from Functional-coefficient Cointegration (F-CI-ECM)

$$\Delta p_{t+s} = \xi_0 + \sum_{i=0}^{\ell_1-1} \xi_i \Delta p_{t-i} + \sum_{i=0}^{\ell_2-1} \zeta_i \Delta m_{t-i} + \delta(z_t) \cdot \widehat{ecm}_t + \epsilon_{t+s},$$

with $\widehat{ecm}_t = p_t - \hat{\beta}(z_t) m_t$, where $\hat{\beta}(z_t)$ is obtained by the kernel estimator of Xiao (2009).



(a) $c = 0.8$. (b) $c = 0.8$.
(c) $c = 1.0$. (d) $c = 1.0$.
(e) $c = 1.2$. (f) $c = 1.2$.

Fig. 2. Functional-coefficient cointegration test results (left panel, with "1" standing for the existence of functional cointegration between p and m and "0" for none) and stability test results (right panel, with "0" indicating failing to reject the null of constant coefficient and "1" the rejection of constancy), with bandwidth $h = c \cdot \hat{\sigma}_z \cdot n^{-9/20}$, for $c = 0.8$, 1.0 and 1.2.

- Phillips Curve

$$\Delta p_{t+s} = \xi_0 + \sum_{i=0}^{\ell_1-1} \xi_i \Delta p_{t-i} + \sum_{i=0}^{\ell_1-1} \theta_i z_{t-i} + \epsilon_{t+s}.$$

Estimation of F-CI-ECM is carried out following the procedure proposed by Fan and Huang (2005), while the least squares are used for the other models.

To evaluate the out of sample forecasting performance of these models, we consider two measures, i.e., the root of mean squared forecast error (RMSFE) and the mean absolute forecast error (MAFE). We select two forecasting samples, with the first spanning the period 2001:1–2007:4 and the second 2010:1–2015:1, avoiding 2008:1–2009:4 due to the financial crisis.[1] All the lags ℓ, ℓ_1, ℓ_2 are recursively determined by the Bayesian information criterion and the parameters are recursively estimated with a rolling window,[2] with the window width determined by the first forecasting point automatically. The bandwidth used for the estimation of $\beta(z_t)$ is $h = 10 \cdot \hat{\sigma}_z \cdot n^{-1/5}$, and that for the estimation of $\delta(z_t)$ is $h = 5 \cdot \hat{\sigma}_z \cdot n^{-1/5}$. We remark that relatively larger bandwidths are used here as it is often the case that simpler models (i.e., larger bandwidth in nonparametric estimation) perform better in forecasting exercises.

3.2. *Forecasting results*

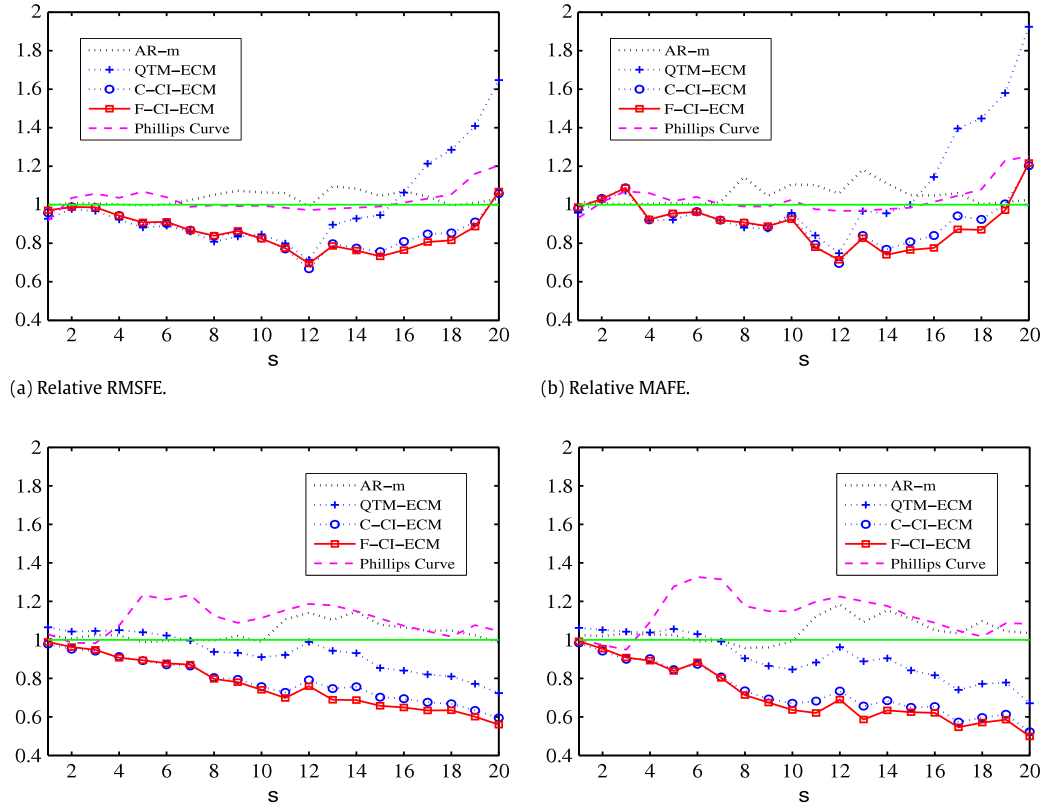
We plot in Fig. 3 the relative RMSFE and MAFE of the latter five models to those of AR model over different forecasting horizons, for the sample periods 2001:1–2007:4 and 2010:1–2015:1, respectively. In both periods, the plots of RMSFE and MAFE share similar patterns. From Fig. 3, we can draw the following conclusions:

(i) The use of the quantity theory leads to competitive forecasting performance compared to AR(ℓ) for short run ($s \leq 4$). This suggests inflation has strong self-persistency within one year horizon, and the cointegrating relationship that reflects long run equilibrium often has little marginal effect.

(ii) AR-*m* and Phillips Curve seem to provide little help to inflation forecasting at all horizons. This indicates that the lagged growth rate of the excess money supply and the rate of unemployment do not contain much predictive power for inflation in a linear fashion.

[1] In this period, the unemployment rate is rather high, around which there are very few observations in the sample data. This limitation in data availability often leads to unstable performance of nonparametric smoothing.

[2] We use rolling window instead of expanding window because the former is known for allowing more timely adaptation to possible parameter instability than the latter.



(a) Relative RMSFE.

(b) Relative MAFE.

(c) Relative RMSFE.

(d) Relative MAFE.

Fig. 3. Relative forecasting performance to AR(ℓ) for 2001:1–2007:4 (upper panels) and 2010:1–2015:1 (lower panels).

(iii) All the three ECM-type models outperform AR(ℓ) significantly in middle run forecasting ($5 < s \leq 12$). This shows that the quantity theory contains valuable information for inflation targeting toward two to three years ahead.

(iv) As to long term forecasting ($s \geq 13$), the performance of the QTM-ECM deteriorates quickly for the first sample period. The other two ECM-type models continue outperforming AR(ℓ) significantly for both sample periods, even though their relative advantages start to decline as the forecasting horizon increases for the first sample. The adaptive quantity theory clearly stands out as the winner for its overall superiority.

In summary, the above analysis suggests that the functional-coefficient cointegration, or the adaptive quantity theory, is more useful in inflation targeting.

4. Conclusion

In this paper, we examine whether the quantity theory based on the cointegration relationship between price and excess money supply can help to improve inflation forecast. In the two periods we examined, it gains substantial improvement compared to the benchmark AR(ℓ) for middle and long run forecast. Particularly, the adaptive quantity theory based on the functional-coefficient cointegration demonstrates superior and more stable performance, especially for long run inflation forecast, and thus should be preferred for inflation forecasting.

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