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Revisiting the empirics of inflation in China: A smooth transition error correction approach

Lingxiang Zhang

School of Management and Economics, Beijing Institute of Technology, Beijing, Haidian district, 100081, People's Republic of China

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ABSTRACT

Using the same data as Chow and Wang (2010) [Chow, Gregory C., Wang, Peng, 2010. The empirics of inflation in China. Economics Letters 109, 28–30], as well as a smooth transition regression model, this paper reconsiders the empirics of inflation in China. The estimated smooth transition error correction model indicates the significant regime-switching behavior of inflation in China, in contrast to the results derived with Chow and Wang's model of constant parameters.

1. Introduction

On the basis of the classical quantity theory of money, Chow (1987) estimates a residual-based error correction model proposed by Granger and Engle (1987) to explain inflation in China. Chow and Wang (2010) update the aforementioned model by using 1952 to 2008 data. The estimated model shows that the parameters remain constant. However, when we reexamine the linear model of Chow and Wang (2010), we find strong evidence that shows some form of misspecification, which makes us doubt whether the linear model adequately describes the empirics of inflation in China. Therefore, considering nonlinearity is promising in explaining the inflation in China.

This paper aims to reconsider the empirics of inflation in China by using a smooth transition error mechanism. Results show that the inflation dynamics in China have significant regime-switching characteristics, and that the estimated smooth transition error correction model exhibits better fit than the linear model.

2. Nonlinear unit root tests

We use the same variables and data as those employed by Chow and Wang (2010). For simplicity, we define $p = \log(P)$, $m = \log(M2/Y)$, where P is the retail price index, $M2$ is the money supply, and Y is the real GDP index.

The Augmented Dickey–Fuller tests strongly suggest the presence of a unit root in p and m. However, simulation studies by Balke and Fomby (1997) and Taylor et al. (2001) show that, the power of conventional unit root tests can be dramatically low when tested against nonlinear alternatives. Recently, Kapetanios et al. (2003), Park and Shintani (2005), and Kiliç (2011) proposed nonlinear unit root tests (denoted by t_{NL}, inf-t, and t_{ESTAR}, respectively) based on a smooth transition autoregressive model.[1]

Table 1 presents the results of the three nonlinear unit root tests mentioned above. All the three tests reject the unit root null at the 10% level, but for the inf-t and t_{ESTAR} tests, the results are more significant for both the p_t and m_t series. We therefore believe that these two series are global stationary processes.

3. Reconsidering the error-correction mechanism

Given that p and m are global stationary, we can directly regress p on m and on other deterministic terms without performing a cointegration test; an error correction model can also be derived on the basis of this regression. Nevertheless, the estimated

[1] For the details about the three tests, the readers are directed to the related references.

E-mail address: lingxiangzh@163.com.

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Table 1
Nonlinear unit root tests for the inflation rate in China and money supply-to-output ratio.

Test	p_t			m_t		
	Statistic value	Lag length	Transition variable	Statistic value	Lag length	Transition variable
inf-t	-3.779^{**}	9	Δp_{t-4}	-8.536^{***}	9	Δm_{t-4}
t_{NL}	-3.370^{*}	9	p_{t-4}	-3.925^{**}	9	m_{t-2}
t_{ESTAR}	-2.642^{**}	1	Δp_{t-2}	-2.662^{**}	10	Δm_{t-2}

Notes: We follow Caner and Hansen (2001) and select a transition variable that minimizes the residual sum of squares of corresponding regressions. Lag lengths are selected by using BIC. The 1%, 5%, and 10% critical values for the inf-t test are −3.99, −3.45, and −3.16, respectively. Those for the t_{NL} test are −3.93, −3.40, and −3.13, respectively, and those for the t_{ESTAR} test are −3.19, −2.57, and −2.23, respectively.
*** Denote significance at the 1% level.
** Denote significance at the 5% level.
* Denote significance at the 10% level.

cointegrating equation and the error correction equation used by Chow and Wang (2010) are still available. This estimate is determined by a direct regression of p on a constant m and on structural break dummy variables in level and slope.[2]

Therefore, we construct the linear baseline model according to the last equation used by Chow and Wang (2010):

$$\Delta p_t = -0.0015 + 0.6044\Delta p_{t-1} + 0.1633\Delta m_t - 0.2429u_{t-1} + \hat{\varepsilon}_t \quad (0.0053) \quad (0.0846) \quad (0.0373) \quad (0.0591), \qquad (1)$$

$$\bar{R}^2 = 0.66, \quad \hat{\sigma}_l = 0.031, \quad p\text{JB} = 0.001,$$
$$p\text{LM}_{ARCH}(1) = 0.647, \quad p\text{LM}_{ARCH}(4) = 0.046,$$
$$p\text{LM}_{AR}(1) = 0.435, \quad p\text{LM}_{AR}(4) = 0.375,$$
$$p\text{LM}_{RESET}(1) = 0.011$$

where u_t denotes the error correction term and $\hat{\sigma}_l$ is the residual standard deviation. Furthermore, the figures in parentheses below the parameter estimates are estimated standard deviations. Misspecification tests are also conducted for model evaluation.[3] The JB test rejects normality, and the p-value of the McLeod–Li statistic shows heteroskedasticity in the residual at the 5% significant level when the maximum lag in the statistic is 4. Moreover, the RESET result shows that the linear error correction model is inadequate for predicting inflation in China. These outcomes may be interpreted as evidence of nonlinearity. Therefore, the next step is to test linearity against smooth transition regression (STR) nonlinearity.

Here, we introduce the specification test only briefly. As for the modeling cycle and corresponding tests of the STR model, interested readers are referred to Teräsvirta (1994), van Dijk et al. (2002), and Teräsvirta et al. (2010). Consider the following logistic STR model (LSTR):

$$y_t = \boldsymbol{\theta}_1'\mathbf{x}_t + \boldsymbol{\theta}_2'\mathbf{x}_t \left(1 + \exp\{-\gamma(s_t - c)\}\right)^{-1} + \varepsilon_t, \qquad (2)$$

where $\mathbf{x}_t = \left(1, y_{t-1}, \ldots, y_{t-p}, x_{1t}, \ldots, x_{kt}\right)'$; γ is the transition speed coefficient; c is the threshold value; and s_t represents the transition variable. A Taylor series approximation about $\gamma = 0$ is used and the tests are based on the following transformed equation:

$$y_t = \boldsymbol{\beta}_0'\mathbf{x}_t + \boldsymbol{\beta}_1'\mathbf{x}_t s_t + \boldsymbol{\beta}_2'\mathbf{x}_t s_t^2 + \boldsymbol{\beta}_3'\mathbf{x}_t s_t^3 + e_t, \qquad (3)$$

where $\boldsymbol{\beta}_i$, $i = 0, \ldots, 3$ are the reparameterized coefficient vectors; hence, the null hypothesis of linearity test corresponds to $H_0 : \boldsymbol{\beta}_1 = \boldsymbol{\beta}_2 = \boldsymbol{\beta}_3 = \mathbf{0}$, which can be tested using the Lagrange multiplier (LM) test statistic with a standard asymptotic χ^2-distribution. In small samples, using the F-version of the LM test statistic is a good strategy because it has a better size. Furthermore, Teräsvirta (1994) suggests computing this LM statistic for various candidate transition variables $s_{1t}, \ldots, s_{mt}$, say, and selecting the one for which the p-value of the test is the smallest.

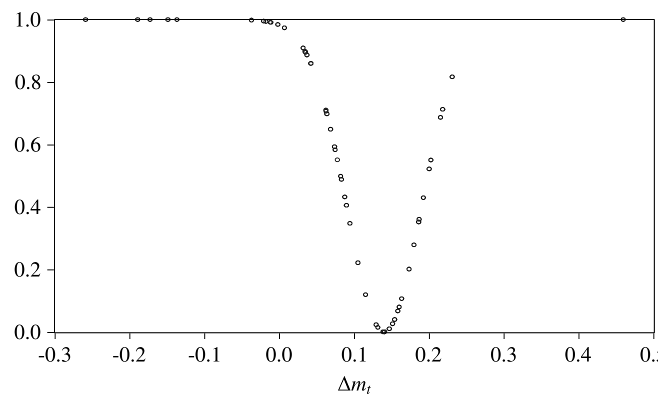

Fig. 1. Values of the transition function of estimated model (5). Each dot corresponds to an observation.

To select the appropriate form of the transition function, consider the sequence of the null hypotheses

$$H_{03} : \boldsymbol{\beta}_3 = \mathbf{0}$$
$$H_{02} : \boldsymbol{\beta}_2 = \mathbf{0} | \boldsymbol{\beta}_3 = \mathbf{0}$$
$$H_{01} : \boldsymbol{\beta}_1 = \mathbf{0} | \boldsymbol{\beta}_2 = \boldsymbol{\beta}_3 = \mathbf{0}$$

in Eq. (3), all of which can be tested by LM-type tests. Teräsvirta (1994) reexamine : if the p-value of the test that corresponds to H_{02} is the smallest, an exponential STR (ESTR) model should be selected; in all other cases, an LSTR model is the preferred choice.

Escribano and Jordá (1999) propose an alternative transition function selection procedure, which is based on the following auxiliary test equation:

$$y_t = \boldsymbol{\beta}_0'\mathbf{x}_t + \boldsymbol{\beta}_1'\mathbf{x}_t s_t + \boldsymbol{\beta}_2'\mathbf{x}_t s_t^2 + \boldsymbol{\beta}_3'\mathbf{x}_t s_t^3 + \boldsymbol{\beta}_4'\mathbf{x}_t s_t^4 + e_t. \qquad (4)$$

They suggest testing the hypotheses

$$H_{0E} : \boldsymbol{\beta}_2 = \boldsymbol{\beta}_4 = \mathbf{0}$$
$$H_{0L} : \boldsymbol{\beta}_1 = \boldsymbol{\beta}_3 = \mathbf{0}$$

in Eq. (4) and selecting an LSTR (ESTR) model if the minimum p-value is obtained for H_{0L} (H_{0E}).

On the basis of linear baseline model (1), we perform specification tests, whose p-values are shown in Table 2. The table indicates that, linearity is rejected at the 5% significance level for $s_t = \Delta m_t, \Delta p_{t-1}, \Delta p_{t-2}$ and that Δm_t may be considered the transition variable because it presents the smallest corresponding p-value.

We find that ESTR is better not only in terms of goodness of fit, but also in terms of diagnostic test results. We therefore present only the results for this ESTR model. Following van Dijk et al. (2002), we retain the variables whose parameters have t-statistics that exceed 1 in absolute value. The smooth transition error correction model is estimated as

[2] Note that this equation does not have a cointegration interpretation as in Chow and Wang (2010).
[3] These misspecification tests are not provided in Chow and Wang (2010).