Controlling Money Supply And Price Level With Unknown Regime Shifts: The Case Of Chile

Abdulnasser Hatemi-J, Deakin University, Australia
Manuchehr Irandoust, UAE University, UAE

ABSTRACT

This paper investigates the relationship between money supply and price level using new tests for cointegration with two unknown regime shifts and bootstrap causality tests. Quarterly Chilean data from 1973: I to 2006: III is used. We find empirical evidence that the variables establish a long-run steady state relationship in the presence of two regime shifts. The elasticity of price level with regard to money supply is close to unity during the first period (prior to 1978: II). The elasticity is reduced during the second period (1978: III-1986: I) and it is also reduced for the remaining period but the reduction is smaller. We also conducted bootstrap causality tests that reveal the following: in the first sub-period there is bidirectional causality between the underlying variables. In the last two sub-periods money supply causes the price level only. This implies that money supply is weakly exogenous concerning the price level and that the monetary authority had enough independence to execute an active monetary policy in Chile.

Keywords: Money supply; Structural break; Cointegration; Bootstrap Causality Test ; Price Level; Chile

1.   INTRODUCTION

*T*he potential relationship between money and prices and the directional of causality between these variables is of fundamental importance in economics discipline. In the long run inflation is generally believed to be a monetary phenomenon while in the short and medium term it is influenced by the relative elasticity of wages, prices and interest rates. The question of whether the short-term effects last long enough to be important is the central topic of debate between monetarist and Keynesian schools. In monetarism prices and wages adjust quickly enough to make other factors merely marginal behavior on a general trend line. In the Keynesian view, prices and wages adjust at different rates, and these differences have enough effects on real output to be "long term" in the view of people in an economy.

Since the pioneering work by Lucas (1972) and Sargent and Wallace (1975), the neoclassical doctrine declares that the anticipated money supply policy is impotent. Only monetary shocks may cause a significant impact on the major economic variables such as prices (Barro, 1977). However, this neoclassical point of view was subsequently challenged by neo-Keynesian economists both theoretically and empirically. Mishkin (1982) attempted to test the monetary neutrality hypothesis by providing empirical evidence. Mankiw and Romer (1991) put forward microeconomic foundations for wage and price rigidity that violate the conditions under which the money neutrality would prevail. Blanchard and Kiyotaki (1987) utilized an aggregate demand and aggregate supply dynamic model with monopolistic competition to study the effect of money supply on price. Recent advancements in this area have been done by Clarida et al. (2001).

According to Friedman (1968), the quantity theory of the money subject to the money velocity identity would also suggest that an increase in money supply will increase the price level. Nevertheless, the existing

empirical evidence on this issue is mixed and inconclusive. Barro (1990), Hallman et al. (1991), McCandless and Weber (1995), and Dwyer and Hafer (1999) showed that the correlation between money supply and price level is very strong positive. While Das (2003) found that the long-run relationship between money supply and price level is not statistically significant.

The purpose of this paper is to analyse empirically the impact of money supply on the price level and also to find out the direction of causality between the variables for Chilean economy using quarterly data from 1973: I to 2006: III. The choice of Chile is justified by the fact that Chile had relatively high inflation and her average inflation rate was 33.2 percent per year from 1940 to 1997 (Dwyer and Hafer, 1999). We have restricted the sample period to 1973: I-2006: III due to the availability of quarterly data. Nevertheless, with few exceptions, the empirical studies reviewed above are based on a conventional constant parameter and constant structure econometric approach that is subject to model misspecification due to the structural changes. To overcome this problem of structural changes, this paper adopts a new methodology suggested by Gregory and Hanson (1996) and extended by Hatemi-J (2008a). We also conduct leveraged bootstrap tests that are robust to non-normality and conditional hetersocedasticity (ARCH) effects.[1] The remainder of this paper is structured in the following way: Section 2 describes the econometric methodology and data used in the empirical analysis. Section 3 provides and describes the empirical findings. The last section concludes the paper.

2.   METHODOLOGY AND DATA

Our econometric methodology consists of tests for cointegration in the presence of two unknown structural breaks and tests for causality. To take into account the effect of two structural breaks on the parameters, we formulate and estimate the following regression model:

$$\ln P_t = v_0 + v_1 D_{1t} + v_2 D_{2t} + \phi_0 \ln M_t + \phi_1 D_{1t} \ln M_t + \phi_2 D_{2t} \ln M_t + e_t, \tag{1}$$

where D_{1t} and D_{2t} are binary indicator variables identified as:

$$D_{1t} = \begin{cases} 0 & if \quad t \le T_1 \\ 1 & if \quad t > T_1 \end{cases} \text{ and } D_{2t} = \begin{cases} 0 & if \quad t \le T_2 \\ 1 & if \quad t > T_2. \end{cases}$$

Where T_1 signifies the period before the first break and T_2 signifies the period before the second break. Note that $T_1 + T_2 = T$ and T is the sample size. To deal with two regime shifts with unknown timing, we make use of the procedure developed by Hatemi-J (2008a). This procedure is based on estimating the cointegration test statistics with two regime shifts for different possible breakpoints during the entire sample period. Then, we use the estimated test results of the breakpoints that provide the minimum value for that statistics (smaller test values sustaining the null hypothesis of no cointegration). Three tests statistics are used for this purpose: augmented Dickey-Fuller (ADF) test and two other tests developed by Phillips (1987) known as Z_α and Z_t. The distribution of these tests do not follow standard asymptotic distributions and new critical values are generated via Monte-Carlo simulations (Hatemi-J, 2008a). The ADF test is a t-test statistic calculated by the estimated slope in a regression of Δe_t on e_{t-1} divided by standard error of the slope parameter.

In the following we give a summary of Hatemi-J's (2008a) description of how the Z_α and Z_t test statistics are calculated. The test statistics are based on the calculation of the bias-corrected first-order serial correlation coefficient estimate $\hat{\rho}^*$, defined as:

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[1] Hatemi-J and Irandoust (2007) apply the same methodology without using leveraged bootstrap tests. In the present paper, we also extend and update our data.

$$\hat{\rho}^* = \frac{\sum_{t=1}^{T-1}\left(\hat{e}_t\hat{e}_{t+1} - \sum_{j=1}^{B}w(j/B)\hat{\gamma}(j)\right)}{\sum_{t=1}^{T-1}\hat{e}_t^2},$$

(2)

where $\hat{e}_t$ is the estimated value of e_t at time t for the estimated model with T observations, $w(\cdot)$ is a function determining kernel weights fulfilling the standard conditions for spectral density estimators, B (itself a function of T) is the bandwidth number with the properties $B \rightarrow \infty$ and $B/T^5 = O(1)$. Finally, $\hat{\gamma}(j)$ is an autocovariance function is defined by:

$$\hat{\gamma}(j) = \frac{1}{T}\sum_{t=j+1}^{T}(\hat{e}_{t-j} - \hat{\rho}\hat{e}_{t-j-1})(\hat{e}_t - \hat{\rho}\hat{e}_{t-1}),$$

(3)

here $\hat{\rho}$ signifies the estimated values of the effect of $\hat{e}_{t-1}$ on $\hat{e}_t$. The Z_α and Z_t test statistics are defined as:

$$Z_\alpha = T(\hat{\rho}^* - 1),$$

(4)

and

$$Z_t = \frac{(\hat{\rho}^* - 1)}{(\hat{\gamma}(0) + 2\sum_{j=1}^{B}w(j/B)\hat{\gamma}(j))\bigg/\sum_{1}^{T-1}\hat{e}_t^2},$$

(5)

here $\hat{\gamma}(0) + 2\sum_{j=1}^{B}w(j/B)\hat{\gamma}(j)$ represents the long-run variance of the residuals of a regression of $\hat{e}_t$ on $\hat{e}_{t-1}$.

The smallest values of these three tests across all values for τ_1 and τ_2, with $\tau_1 \in T_1 = (0.15, 0.70)$ and $\tau_2 \in T_2 = (0.15 + \tau_1, 0.85)$ are used. The reason for selecting the smallest value for each test is that the smallest value corresponds to the empirical evidence against the null hypothesis. These tests are defined as the following:

$$ADF^* = \inf_{(\tau_1,\tau_2)\in T} ADF(\tau_1,\tau_2),$$

(6)

$$Z_t^* = \inf_{(\tau_1,\tau_2)\in T} Z_t(\tau_1,\tau_2),$$

(7)

$$Z_\alpha^* = \inf_{(\tau_1,\tau_2)\in T} Z_\alpha(\tau_1,\tau_2).$$

(8)

The next step in our empirical analysis is to conduct tests for causality in the Granger (1969) sense by using the following vector autoregressive model of order p, VAR(p):

$$y_t = v + A_1 y_{t-1} + \ldots + A_p y_{t-p} + \varepsilon_t,$$

(9)

where y_t is the two by one vector of the variables, v is the two by one vector of intercepts, and ε_t is a the two by one vector of error terms. The matrix A_i is a the two by two matrix of parameters for lag order i ($i = 1, …, p$).

The optimal lag order (p) is selected by minimising an information criterion developed by Hatemi-J (2003, 2008b), which performs well if the variables are integrated and ARCH effects exist. This information criterion is defined as

$$\text{HJC} = \ln\left(\det \hat{\Omega}_j\right) + j\left(\frac{n^2 \ln T + 2n^2 \ln(\ln T)}{2T}\right), \qquad\qquad j = 0, \cdots, p. \tag{10}$$

where $det\,\hat{\Omega}_j$ is the determinant of the estimated maximum-likelihood variance-covariance matrix of ε_t when lag order j is used in estimating the VAR model, n is the number of variables and T is the number of observations.

The null hypothesis that there is no causation from kth element of y_t on the rth element of y_t is defined as

H_0: the row r, column k element in A_i is zero for $i = 1,…, p$. $\tag{11}$

The Wald test statistic for testing the statistical significance of the above null hypothesis is described using the following matrix denotations:

$Y := (y_1, \cdots, y_T) \quad (n \times T)$ matrix,

$D := (v, A_1, \cdots, A_p) \quad (n \times (1 + n \times p))$ matrix,

$$Z_t := \begin{bmatrix} 1 \\ y_t \\ y_{t-1} \\ \vdots \\ y_{t-p+1} \end{bmatrix} \quad ((1 + n \times \text{p}) \text{ matrix, for } t = 1, …, T,$$

$Z := (Z_0, \cdots, Z_{T-1}) \quad ((1 + n \times p) \times T)$ matrix, and

$\delta := (\varepsilon_1, \cdots, \varepsilon_T) \quad (n \times T)$ matrix.

By using this notation, the VAR(p) model becomes

$Y = DZ + \delta;$ $\tag{12}$

and the null hypothesis of no Granger causality can be defined as

$H_0 : C\beta = 0.$ $\tag{13}$

The Wald test statistic is calculated by first obtaining the ($n \times T$) matrix of estimated residuals from the unrestricted regression of equation (12), $\hat{\delta}_U$. The maximum-likelihood variance-covariance matrix of these residuals is then

calculated as $S_U = \dfrac{\hat{\delta}_U{}' \hat{\delta}_U}{T}.$

The null hypothesis of no causation from one variable to another variable is tested by using the following multivariate Wald test statistic:

$$WALD = (C\beta)' \left[C\left((Z'Z)^{-1} \otimes S_U \right) C' \right]^{-1} (C\beta) \sim \chi_p^2,$$ (14)

where $\beta = vec(D)$ and *vec* indicates the column-stacking operator; the denotation $\otimes$ is the Kronecker product (representing element by all element matrix multiplication), and C is a $p \times n(1+n \times p)$ indicator matrix with elements of either ones or zeros.

Based on the assumption of normality the WALD test statistic above has an asymptotic χ^2 distribution with the number of degrees of freedom equal to the number of restrictions to be tested (in this case equal to p). However, if the data is not normally distributed and ARCH effects prevail, the WALD test based on the asymptotic critical values does not have correct size properties as shown by Hacker and Hatemi-J (2006). The authors develop a test method based on leveraged bootstrap simulation techniques that produces more precise critical values. The leveraged bootstrap causality test ensures that the presence of heteroscedasticity does not affect the accuracy of estimated results. This method is described below.

1.   The first step in the bootstrap procedure consists of estimating the regression equation (12).

2.   Next simulate the bootstrapped residuals δ^* via resampling with replacement, that is,

$$\delta^* = \left\{ \delta_1^*, \delta_2^*, \cdots, \delta_n^* \right\}, \quad \delta_i^* \in \delta \; \forall \, i. $$ Where $i = 1, \cdots, n$. and n is the bootstrap sample.

3.   Then generate Y^* using the estimated coefficients from the regression, that is,

$$Y^* = \hat{D}Z + \delta^*.$$

4.   Calculate the parameter vector by using Y^* and denote it D^*, that is, estimate

$$D^* = Y^{*'} Z^* \left(Z^* Z^{*'} \right)^{-1}.$$

5.   Calculate the WALD test statistics presented in equation (14) by using the bootstrapped data. That is to estimate the following:

$$WALD^* = (C\beta)' \left[C\left((Z^{*'}Z^*)^{-1} \otimes S_U^* \right) C' \right]^{-1} (C\beta).$$

6.   Repeat step 2-5 *N* times and rank the estimated values of the WALD* test in order to produce its bootstrapped distribution.

7.   Take the (α)*th* upper quantile of the distribution of bootstrapped (WALD*) statistics, to obtain the α-level "bootstrap critical values" (c_α^*).

8.   The final step in the procedure is to calculate the WALD statistic using the original data. The null hypothesis is rejected at the α level of significance if $WALD > c_\alpha^*$.

It should be mentioned that the bootstrapped residuals, δ^*, are based on *T* random draws with replacement from the regression's modified residuals, each with equal probability of 1/*T*. The modified residuals are the regression's raw residuals modified through the use of *leverages* to ensure constant variance.[2] The bootstrapped residuals have been mean adjusted to fulfil the theoretical condition of having an expected value of zero. The bootstrap simulations were carried out 1000 times. Leveraged bootstrap critical values for the test at the 1%, 5% and

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[2] For more details on leverage adjustment the interested reader is referred to Davison and Hinkley (1999) and Hacker and Hatemi-J (2006). The latter authors generalized this adjustment for multivariate equation cases.

10% levels of significance are generated. The bootstrap simulations were conducted by a programme written in GAUSS.

We use quarterly Chilean data from 1973:I to 2006:III. The variables used here are money plus quasi-money as money supply and consumer price index (CPI) as an indicator of price level. The data were collected from *International Financial Statistics*.[3]

3.   ESTIMATION RESULTS

The estimated test results for cointegration with two unknown structural breaks and the critical values are presented in Table 1. The breaks were determined to be at 1978: II and 1986: II, respectively.

Table 1: Cointegration Test Results

Test statistics	The estimated value of the test	1% Critical Value	5% Critical Value	10% Critical Value
ADF^* (with two breaks)	-7.512	-6.803	-6.015	-5.653
Z_t^* (with two breaks)	-5.805	-6.803	-6.015	-5.653
Z_α^* (with two breaks)	-53.346	-90.794	-76.003	-52.232

The critical values are taken from Hatemi-J (2008a).

As these results reveal, the ADF test rejects the null hypothesis of no cointegration at the 1% significance level and the other two tests reject it at the 10% significance level. It should be mentioned that we conducted tests for unit roots in the presence of breaks prior to tests for cointegration. The results, not presented but available on request, showed that each variable is integrated of the first degree. The estimated elasticities from the cointegrating vector are presented in Table 2.

Table 2: The Estimated Parameters

Parameter	Estimated value	T-test
v_0	-2.338	-73.726 **
v_1	0.628	5.409 **
v_2	2.107	8.969 **
ϕ_0	0.931	68.331 **
ϕ_1	-0.274	-12.434 **
ϕ_2	-0.233	-8.387**

Notes: the notation (**) means that the null hypothesis of the parameter being equal to zero is rejected at the one percent significance level.

We can estimate parameters that are not spurious since it is found that the variables cointegrate when two regime shifts are introduced. The estimated parameters that are presented in Table 2 show that the elasticity of price level with regard to money supply is close to unity during the first period (prior to 1978: II). The elasticity reduces by a value of 0.274 during the second period (1978: III-1986: I). For the remaining period, there is a 0.233 decrease in the elasticity.

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[3] The computer programs written in Gauss for conducting the Hatemi-J (2008a) cointegration tests and the Hacker and Hatemi-J (2006) leveraged bootstrap tests are available on request from the authors.

The next step in our empirical enquiry is to determine the direction of causality in the Granger's (1969) sense. The results of the leveraged bootstrap tests that are robust to non-normality and ARCH effects are presented in Table 3.[4] This implies that prior to 1978: II there was bi-directional causality between money supply and price level. During the other two sub-periods there is causality running from money to price level only.

Table 3: Results of Leveraged Bootstrap Causality test

Period	The Null Hypothesis	The Estimated Test Value (WALD)	1% Bootstrap Critical Value	5% Bootstrap Critical Value	10% Bootstrap Critical Value
1973:I-1978:II	$M \neq> P$	7.921*	18.866	9.903	6.247
	$P \neq> M$	7.151**	9.791	5.169	3.671
1978:III-1986:I	$M \neq> P$	5.473**	7.895	5.12	3.218
	$P \neq> M$	0.015	8.990	4.478	3.052
1986:II-2006:III	$M \neq> P$	5.840**	7.316	4.182	2.751
	$P \neq> M$	0.337	6.093	3.85	2.700

Notes:
1. WALD is the Wald test statistics as defined by equation (14).
2. The null hypothesis $(A \neq> B)$ implies that variable A does not Granger cause variable B.
3. The notation * means that the null hypothesis on Non-Granger causality is rejected at the 10% significance level.
4. The lag order of the VAR model, p, was set to one based on the minimization of the information criterion.

5.   SUMMARY AND CONCLUSIONS

The objective of this paper is to explore empirically the relationship between money supply and price level between the period 1973:I and 2006:III in Chile. New tests for cointegration that allow for two regime shifts are used. The timing of each regime shift is selected endogenously. We find that the variables cointegrate when two regime shifts are presented. The estimated parameters show that the elasticity of price level with respect to money supply is close to unity during the first period (prior two 1978: II). The elasticity reduces by a value of 0.274 during the second period (1978: III-1986: I). For the remaining period, there is a 0.233 decrease in the elasticity. The conducted causality tests reveal that before 1978:II both variables cause each other. During the rest of the period only money supply causes the price level. This implies that money supply is weakly exogenous concerning the price level and that the monetary authority had enough independence to execute an active monetary policy in Chile.

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[4] It should be mentioned that we tested for the normality and no ARCH effects of the residuals in the VAR model. A multivariate test for normality developed by Doornik and Hansen (1994) and a multivariate test for ARCH effects developed by Hacker and Hatemi-J (2005) were used. The results revealed that the residuals are not normally distributed and ARCH effects exit.

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