THE INFORMATION VALUE OF MONEY FOR FORECASTING PURPOSE: THE CASES OF ARGENTINA AND CHILE

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The information value of money for forecasting purpose: The cases of Argentina and Chile*

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June 2012

Abstract

We evaluate the information content of money for forecasting purpose by introducing a real money gap into a New Keynesian Phillips Curve estimated for Argentina and Chile. We estimate models using high and low frequency data and conduct out-of-sample forecast for different horizons. The introduction of the real money gap does not improve forecast accuracy for quarterly data, but it significantly adds predictive power at lower frequencies.

JEL: E4, E31, E52, E47

Keywords: Money, Monetary Policy, Forecast, Economic Activity, Inflation

1 Introduction

A relevant empirical question beyond the ongoing debate on the role of money in monetary policy, is whether money can contribute to forecast inflation and at what frequencies. We try to answer this question for the cases of Argentina and Chile by comparing the out-of-sample predictive performance of a conventional Hybrid New Keynesian Phillips Curve (HNCPC) vis-à-vis that of a version that incorporates an estimated real money gap.1

One of the main empirical reasons argued to abandon monetary targeting policy frameworks has been that real money demand is quite volatile (Estrella and Mishkin, 1997).

*The opinions expressed here are of the authors and do not necessarily represent those of the Banco Central de la República Argentina.

1While the workhorse New Keynesian model used for the conduct of monetary policy does not attribute any explicit role to money (Woodford, 2003, Gali and Gertler, 2007), McCallum (2001), Christiano and Rostagno (2002) and Goodfriend and McCallum (2007) stress the importance of money and the lack of generality of the New Keynesian model.
However, Svensson (2000) and Gerlach and Svensson (2003) argue that despite the lack of theoretical and empirical support for the adoption of monetary targets, the gap between the actual real money stock and its long run equilibrium level can be an important indicator for future inflation.

Although the evidence on the information content of money for predicting future values of economic activity and inflation is mixed, several studies find that while real economic activity indicators can be very useful for short-run forecasting of inflation, money growth can be very informative at longer horizons (Assenmacher-Wesch and Gerlach 2006; Hoffman, 2008; Berger and Österholm, 2008).

We contribute to this literature by testing whether including the real money gap (the difference between the current real money stock and the long run equilibrium real money stock) into a HNKPC estimated for Argentina and Chile over the period 1995-2005 helps to improve inflation forecast. We conduct an out-of-sample forecast exercise using high and low frequency data and producing forecast at different horizons for the period 2006-2010. We compare the predictive accuracy of both models and test the statistical significance of the differences in their predictive performance using the Giacomini-White (2004) test.

The paper is organized as follows: In section 2 we revise the related literature. In section 3, we briefly review Argentina’s and Chile’s economic and monetary developments during the sample period. Section 4 describes the estimation methodology. In section 5, we present the estimation results. Section 6 presents the results of the forecasting exercise. We conclude in section 7.

2 A brief review of the literature

Due to the volatility in real money demand, monetary aggregates should not provide useful information about the future path of inflation. In fact, for the euro area, Gerlach and Svensson (2003) find that the growth rate of nominal M3 adds little to the forecasting accuracy of an output-gap based model of euro area inflation. This evidence seems to be consistent with the fact that the workhorse New Keynesian model used for the conduct of monetary policy does not attribute any explicit role to money.

However, several studies find that while money is not informative about future values of inflation for short-run forecasting, it can improve forecast accuracy at longer horizons. Assenmacher-Wesche and Gerlach (2006) show a significant contribution of low frequency movements in money growth to forecast inflation using a two-pillar Phillips-curve type dynamic model. Nicoletti-Altinari (2001), Hofmann (2008), and Scharnagl and Schumacher (2007) all find that M3 growth is useful for inflation forecasts at medium-term horizons. Also, Gerlach and Svensson (2003) find that a real money gap representation of the P* model adds to the predictive power of a conventional Phillips curve.

More recently, Berger and Stavrev (2008) analyze the information content of money in forecasting euro-area inflation, comparing the predictive performance
of various classes of structural and empirical models. They find that while money contains relevant information for inflation in some model classes, the marginal contribution of money to forecasting accuracy is often small. Berger and Österholm (2008) use mean-adjusted Bayesian VARs as an out-of-sample forecasting tool to test whether money growth Granger-causes inflation and find strong evidence that including money improves forecast accuracy.

Coenen et al. (2003) provide an alternative argument for using money as an indicator variable, which is that money demand depends on the true level of aggregate output, whereas the central bank only receives a noisy signal of aggregate actual income. Given this link, money can be informative about the real value of aggregate income depending on the relative variability of measurement errors vs. the magnitude of money demand fluctuations in response to unobserved velocity shocks.

Apart from any theoretical support for the use of money as a predictor of inflation, a practical reason to investigate the information content of money for forecasting purpose is that relying on more than one model for forecasting and policy advice is in general beneficial. Because models’ forecasts can be biased in different directions, diversifying should add robustness to policy and help to reduce the error’s variance in general, which would probably reduce the policy errors too.

The exercise we develop in this paper for Argentina and Chile relates to Gerlach and Svensson (2003) and Assenmacher-Wesche and Gerlach (2006) in that we investigate the contribution of introducing the money gap to a New Keynesian Phillips curve to improve inflation forecast accuracy at high and low frequencies.

3 Main macroeconomic and monetary developments in Argentina and Chile: 1995-2010

We conduct our forecasting exercise over the period 1995-2010. Both economies experienced changes in their monetary regimes over this time span. A brief review of the main policy developments and policy changes helps to put our forecasting exercise in context.

3.1 The Argentine Case

In the eighties, Argentina experienced very high macroeconomic instability and high inflation. During these years, inflation increased persistently in a context of repeated failed attempts by governments to stabilize inflation through the adoption of different monetary-exchange rate schemes and economics reforms.

After the adoption of the Convertibility, which fixed by law the exchange rate of the peso to the dollar, inflation dropped dramatically and quite permanently to much lower levels.

In addition to the adoption of a hard peg by law, a broad economic reform took place, including the privatization of the main public enterprises and
a reform of the Central Bank chart, which imposed restrictions to monetary financing of fiscal deficits.

During the 90s, the growth of the public debt in the context of a real appreciation of the local currency proved to be unsustainable and ended with a sharp devaluation of the currency and a default on its public debt in January 2002. Inflation reached a peak in April 2002 but it then returned to low levels.

A managed floating was adopted in the aftermath of the crisis combined with an international reserves accumulation strategy and an implicit objective on trying to keep the RER depreciated to foster growth. In fact, Argentina has achieved remarkable rates of economic growth combined with fiscal surpluses over the recent years. Inflation exhibits a positive correlation with both the output gap and money growth (see Figure 1).

The managed floating exchange rate mechanism was complemented after 2002 with regulations aiming at avoiding the currency risk of banks and, indirectly, of the private sector. The result has been a decreasing exposure to foreign currency mismatch in the financial system.

### Figure 1
Argentina: Inflation, Money Growth and Output Gap

**3.2 The case of Chile**

In the case of Chile, the Central bank granted its independence in 1989 and it was assigned the mandate to control inflation as its primary objective. Chile started targeting inflation in early 1990s, while at the same time the Central Bank of Chile operated a system of exchange rate bands until 1999, when inflation targeting was fully implemented with the adoption of a floating exchange rate regime.
Chile successfully reduced inflation from a peak of almost 30% year over year in 1990 to 4% in 1999 in less than a decade. In 2000 the Central Bank of Chile committed to a target of 2-4% for 2001 onwards.

During the sample selected, the Chilean economy grew at a significant pace, contrasting with its poor growth performance during the 80s. The figures for inflation and different output gap measures as well as money growth, depicted in Figure 2 for annual data show a statistically significant positive correlation over the last fifteen years.

Despite the adoption of a flexible exchange regime, the Central Bank continues to maintain a significant level of international reserves to act as a buffer against possible liquidity shocks; and two, because reserves allow monetary authorities to credibly intervene in the exchange market under exceptional circumstances.

The Central Bank of Chile has also established rules that limit currency mismatches of banks and that require them to evaluate the exposure to currency risk of their clients when assessing their creditworthiness in order to increase the resilience of the banking and corporate sectors to exchange rate shocks.

\textit{Figure 2}  
\textbf{Chile: Inflation, Money Growth and Output Gap}

4 The estimation methodology

In this paper, we rely on rather the same specification to estimate a HNKPC for Argentina and Chile over the period 1995:Q1–2005:Q4. We compare the predictive performance of this model with that of a HNKPC that incorporates the real money gap, defined as the difference between the actual real money stock and its long run equilibrium level.

\[ m_{\text{gap}} = m_t - m_t^* \]  

The long run equilibrium money stock \( m_t^* \) can be defined as the level of real money that is consistent with both, the output \( y_t^* \) and nominal interest rate \( r_t^* \) long run equilibrium levels.

Thus, in the long run the real equilibrium money demand should be equal to the long run equilibrium money stock.

\[ m_t^* = \kappa_y y_t^* - \kappa_r r_t^* \]  

When introduced into the HNKPC, the real money gap is a measure of demand pressure and can be considered as an indicator of real monetary overhang. As in D’Amato and Garegnani (2009) we specify the following HNKPC

\[ \pi_t = \phi_1 \pi_{t-1} + \phi_2 E_t(\pi_{t+1}) + \gamma \pi_t^* + \lambda \Delta e_t + \delta x_t + \varepsilon_t \]  

Where \( E_t(\pi_{t+1}) \) is the expectation of \( \pi_{t+1} \) in \( t \), \( \pi_t^* \) is foreign inflation, \( \Delta e_t \) is nominal depreciation and \( x_t \) is the output gap. We measure domestic inflation by the change in the log of the Consumer Price Index (CPI), foreign inflation by a weighted average of CPI inflation of the main trade partners. Finally, nominal depreciation is calculated as the change in the log of the nominal exchange rate with the same partners. The output gap is calculated as a weighted average of three estimations using: (i) the Hodrick-Prescott filter (ii) a Band-Pass Filter and (iii) an aggregate production function.\(^2\)

Thus, when the money gap is introduced into the HNKPC it can be written as

\[ \pi_t = \phi_1 \pi_{t-1} + \phi_2 E_t(\pi_{t+1}) + \gamma \pi_t^* + \lambda \Delta e_t + \delta x_t + \varphi m_{\text{gap}} + \mu_t \]  

5 Estimation results

5.1 Argentina

In order to construct a measure of the real money gap an estimation of a long run real money demand (equation 2) is required. Following the vast econometric literature on this topic, we consider that the real money demand depends on a measure of the volume of real transactions and the opportunity cost of money. Based on the model developed in Ahumada and Garegnani (2012) for Argentina

\(^2\)We thank the Central Bank of Chile for providing us a measure of the output gap calculated from an aggregate production function.
we use the aggregate supply as the measure of real transactions, taking into account three different measures of opportunity cost: inflation, the exchange rate depreciation and the domestic interest rate. We follow the system-based procedure suggested by Johansen (1988 and 1992) and Johansen and Juselius (1990) in order to validate a single-equation specification and the conditional model of real money.

In the case of Argentina the estimated long-run (equilibrium) money demand for the period 1995Q1-2005Q4 is

\[ m_t^* = 1.075y_t - 1.755r_t + 1.0498RER_t \]  

Where \( m_t^* \) is long run equilibrium level for the \( M2 \) monetary aggregate calculated in logs, \( y_t \) is the log of the aggregate supply, \( r_t \) is defined as log \((1 + R_t)\), where \( R_t \) is the 30 – 59 day time deposits nominal interest rate and \( RER_t \) is the real exchange rate peso/dollar.\(^3\)

We use (2) to calculate the real money gap according to (1) and estimate (4) in order to evaluate if it helps to improve inflation forecast relative to (3).

We estimate equations (3) and (4) using GMM on data at quarterly and annual frequencies. The estimation sample used for model selection is 1995Q1-2005Q4.\(^4\) In both cases six lags of all variables are used as instruments. Tests for over-identifying restrictions, applied to each estimations confirm that the instruments are valid in all cases.

\(^3\) In the Argentine case Ahumada and Garegnani (2012) find that it is the real exchange rate that enters the money demand with a coefficient not different from one and a positive sign. They interpret it as a deflator.

\(^4\) For details on estimation methodology see Appendix 1.
In Tables 1 and 2 we report results for quarterly and annual data respectively.

**Table 1**

<table>
<thead>
<tr>
<th>GMM estimates</th>
<th>Quarterly</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>with mgap</td>
<td>without mgap</td>
</tr>
<tr>
<td>$\phi_1$</td>
<td>0.307509</td>
<td>0.308612</td>
</tr>
<tr>
<td>Std. Error</td>
<td>0.015429</td>
<td>0.025342</td>
</tr>
<tr>
<td>$\phi_2$</td>
<td>0.308048</td>
<td>0.297165</td>
</tr>
<tr>
<td>Std. Error</td>
<td>0.019173</td>
<td>0.056712</td>
</tr>
<tr>
<td>$\delta$</td>
<td>0.045829</td>
<td>0.015733</td>
</tr>
<tr>
<td>Std. Error</td>
<td>0.013542</td>
<td>0.017504</td>
</tr>
<tr>
<td>$\gamma$</td>
<td>0.263956</td>
<td>0.175617</td>
</tr>
<tr>
<td>Std. Error</td>
<td>0.0311</td>
<td>0.028083</td>
</tr>
<tr>
<td>$\lambda^*$</td>
<td>0.049662</td>
<td>0.062667</td>
</tr>
<tr>
<td>Std. Error</td>
<td>0.006157</td>
<td>0.010059</td>
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<tr>
<td>$\phi^*$</td>
<td>0.062788</td>
<td></td>
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<tr>
<td>Std. Error</td>
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<td></td>
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<tr>
<td>J-statistic p-value</td>
<td>0.9935</td>
<td>0.9018</td>
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</table>

* These coefficients correspond to the first lag of each variable

**Table 2**

<table>
<thead>
<tr>
<th>GMM estimates</th>
<th>Annual</th>
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</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>with mgap</td>
<td>without mgap</td>
</tr>
<tr>
<td>$\phi_1$</td>
<td>0.337193</td>
<td>0.382383</td>
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<tr>
<td>Std. Error</td>
<td>0.012937</td>
<td>0.018664</td>
</tr>
<tr>
<td>$\phi_2$</td>
<td>0.371249</td>
<td>0.415804</td>
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<tr>
<td>Std. Error</td>
<td>0.010129</td>
<td>0.020636</td>
</tr>
<tr>
<td>$\delta$</td>
<td>0.141899</td>
<td>0.083548</td>
</tr>
<tr>
<td>Std. Error</td>
<td>0.013923</td>
<td>0.015799</td>
</tr>
<tr>
<td>$\gamma$</td>
<td>0.024592</td>
<td>0.064046</td>
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<tr>
<td>Std. Error</td>
<td>0.006717</td>
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<tr>
<td>$\lambda^*$</td>
<td>0.114006</td>
<td>0.082804</td>
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<tr>
<td>Std. Error</td>
<td>0.005361</td>
<td>0.005079</td>
</tr>
<tr>
<td>$\phi^*$</td>
<td>0.085345</td>
<td></td>
</tr>
<tr>
<td>Std. Error</td>
<td>0.012169</td>
<td></td>
</tr>
<tr>
<td>J-statistic p-value</td>
<td>0.9979</td>
<td>0.9216</td>
</tr>
</tbody>
</table>

* These coefficients correspond to the first lag of each variable

It can be seen from Table 1 that while there is a significant response of domestic inflation to changes in the output gap at the quarterly frequency (with no statistically significant difference in the coefficients between both specifications), the real money gap also has a significant impact on inflation at this
frequency. Regarding the backward and forward-looking components, both have rather the same weight in both specifications. Inflation responds to lagged values of nominal depreciation and current values of foreign inflation. While the response of domestic prices to changes in foreign inflation is quite important in both specifications, the response to nominal devaluation, although significant, is much weaker. A possible explanation for these findings is that the sample corresponds to a period in which the nominal exchange rate was kept fixed or rather administrated. It is important to note that the very different responses of domestic inflation to nominal devaluation and foreign inflation do not allow imposing the same coefficient to both variables, as it is usually done in the empirical literature.

As predicted by the theory, money should mostly contribute to explain inflation dynamics at the low frequencies. Table 2 shows that in fact, the real money gap has a significant impact on inflation at the annual frequency, but the output gap also contributes to explain inflation behavior at this frequency. Moreover, the response of inflation to the output gap increases when the real money gap is included in the estimation. Both, the backward and forward-looking components are relevant to explain price dynamics for annual data. Finally, the impact of foreign inflation is lower than that of nominal devaluation for annual data, although both contribute to explain inflation dynamics at this frequency.

5.2 Chile

In the case of Chile we also considered the real money demand depending on a measure of the volume of real transactions and the opportunity cost of money and we also follow the system-based procedure suggested by Johansen (1988 and 1992) and Johansen and Juselius (1990). The estimated long-run (equilibrium) money demand for the period 1995Q1-2005Q4 is

\[
m_t^* = 1.463y_t - 1.351r_t - 0.706e_t
\]  

(6)

Where again, \( m_t^* \) is the long run equilibrium level for the M2 monetary aggregate calculated in logs, \( y_t \) the log of GDP, \( r_t \) is the nominal interest rate calculated as the log of \((1 + R_t)\), where \( R_t \) is the interest rate on 30-90 days time deposits and \( e_t \) is the nominal exchange rate with respect to the main trade partners. As for the Argentine case we use this estimation to calculate the real money gap according to (1) and then use it to estimate (3) and (4).

In Tables 3 and 4 present the estimation results for equations (3) and (4) using quarterly and annual data respectively. In this case eight lags of the all variables are used as instruments.
For both quarterly and annual data, the real money gap has a significant positive effect on inflation in the case of Chile. Notably, inflation seems to be more forward looking in the Chilean case relative to Argentina.

Something to remark about the estimated HNKPC is that for both countries the use of annual data significantly improves the predictive capacity, something relevant for forecasting purpose.

In the next section we turn to evaluate and compare the out of sample predictive accuracy of the two specifications of the Phillips Curve using quarterly and annual data.
6 The Forecasting Excercise

We test for the statistical significance of the differences in predictive accuracy between the two HNKPC specifications using the Giacomini-White test. We are particularly interested in evaluating at what frequency does the real money gap contribute to improve forecast accuracy. We also want to investigate whether the relative accuracy of both models changes depending on the forecast horizon: (i) one quarter ahead, (i) one year ahead and (iii) two years ahead. The forecasting sample is 2006:1-2010:4.

The Giacomini and White approach focuses on finding the best forecast method for the following relevant future. Their methodology is suitable for forecasters who are interested in finding methodologies that improve the predictive ability of the forecast, rather than testing the validity of a theoretical model.

The test has many advantages: (i) it captures the effect of estimation uncertainty on relative forecast performance, (ii) it is useful for forecasts based on both nested and non-nested models, (iii) it allows the forecast to be produced by general estimation methods, and (iv) it is quite easy to be computed. Following a two-step decision rule that uses current information it allows to select the best forecast for the future date of interest.

The methodology consists on evaluating forecast by conducting an out of sample exercise using rolling windows. That is, using the \( R \) sample observations available at time \( t \), estimates of \( y_t \) are produced and used to generate forecast \( \tau \) step ahead. The test assumes that there are two methods, \( f_{Rt} \) and \( g_{Rt} \) to generate forecasts of \( y_t \) using the available set of information \( F_t \). Models used are supposed to be parametric.

\[
\begin{align*}
    f_{Rt} &= f_{Rt}(\hat{\gamma}_{R,t}) \\
    g_{Rt} &= g_{Rt}(\hat{\theta}_{R,t})
\end{align*}
\]

A total of \( P_n \) forecasts which satisfy \( R + (P_n - 1) + \tau = T + 1 \) are generated. The forecasts are evaluated using a loss function \( L_{t+\tau}(y_{t+\tau}, f_{R,t}) \), that depends on both, the realization of the data and the forecasts. The hypothesis to be tested is:

\[
\begin{align*}
    H_0 : \quad & E[h_t \left( L_{t+\tau}(y_{t+\tau}, f_{R,t}) - L_{t+\tau}(y_{t+\tau}, g_{R,t}) \right) \mid F_t] = 0 \\
    \text{or alternatively} \\
    H_0 : \quad & E[h_t \Delta L_{t+\tau} \mid F_t] = 0 \quad \forall \ t \geq 0
\end{align*}
\]

for all \( F_t \)-measurable function \( h_t \).

In practice, the test consists on regressing the differences in the loss functions on a constant and evaluating its significance using the \( t \) statistic for the null of a 0 coefficient, in the case of \( \tau = 1 \). When \( \tau \) is greater than one, standard
errors are calculated using the Newey-West covariances estimator, that allows for heteroskedasticity and autocorrelation.

In Tables 5 and 6 we report the results of our forecasting exercise for the Argentine case. They show that introducing the real money gap in the HNKPC significantly improves forecast accuracy at the annual frequency (Table 4) and that the accuracy of the HNKPC with the real money gap relative to that of the conventional one, increases with the length of the forecast horizon. In contrast, the two models do not exhibit significant differences in forecasting accuracy when quarterly data are used (Table 5).

Table 5

<table>
<thead>
<tr>
<th></th>
<th>t-Statistic</th>
<th>p-value</th>
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<tbody>
<tr>
<td>1 quarter ahead</td>
<td>1.6188</td>
<td>0.1136</td>
</tr>
<tr>
<td>1 year ahead</td>
<td>-1.4927</td>
<td>0.1434</td>
</tr>
<tr>
<td>2 year ahead</td>
<td>-0.8135</td>
<td>0.4209</td>
</tr>
</tbody>
</table>

Quarterly data
Sample forecast: 2006Q1 - 2010Q4

Table 6

<table>
<thead>
<tr>
<th></th>
<th>t-Statistic</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 quarter ahead</td>
<td>2.35426</td>
<td>0.02410</td>
</tr>
<tr>
<td>1 year ahead</td>
<td>3.24950</td>
<td>0.00250</td>
</tr>
<tr>
<td>2 year ahead</td>
<td>4.50748</td>
<td>0.00010</td>
</tr>
</tbody>
</table>

Annual data
Sample forecast: 2006Q1 - 2010Q4

The results for Chile are not very different. The money gap does not add any predictive power for quarterly data (Table 7), except for the longest horizon of 2 year, for which HNKPC including the money gap outperforms the conventional HNKPC, although at the 10% significance level. On the contrary, when using annual data, adding the money gap to the HNKPC significantly improves forecast accuracy. As in the Argentine case, the relative superiority of the HNKPC that incorporates the money gap for forecasting purpose increases with the forecast horizon (Table 8).
Table 7

<table>
<thead>
<tr>
<th></th>
<th>Quarterly data</th>
<th>Annual data</th>
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<tbody>
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<td></td>
<td>Sample forecast: 2006Q1 - 2010Q4</td>
<td>Sample forecast: 2006Q1 - 2010Q4</td>
</tr>
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<td>1 quarter ahead</td>
<td>t-Statistic 1.0809, p-value 0.2869</td>
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</tr>
<tr>
<td>1 year ahead</td>
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<tr>
<td>2 year ahead</td>
<td>t-Statistic 1.9625, p-value 0.0575</td>
<td>t-Statistic 4.50748, p-value 0.00010</td>
</tr>
</tbody>
</table>

7 Conclusions

While the workhorse monetary model does not attribute any role to money, its importance for monetary policy modelling continues to be a matter of debate. A relevant empirical question remains beyond this debate regarding the extent to which money can contribute to improve inflation forecast at low frequencies, in line with the predictions in the theory. To answer this question for the cases of Argentina and Chile, we evaluate the contribution to the out-of-sample predictive accuracy of a conventional Hybrid New Keynesian Phillips (HNKPC) to forecast inflation of incorporating the real money gap. We conduct this exercise using quarterly as well as annual data to produce out-of-sample forecast of inflation at different horizons.

We find that the predictive accuracy of the two models is rather the same when quarterly data are used for both countries, Argentina and Chile. On the contrary, when the real money gap is introduced into the HNKPC, it significantly improves inflation forecast at the annual frequency in both cases. Furthermore, using the Giacomini-White test we corroborate that this forecast improvement is statistically significant and the superiority of the model introducing the real money gap increases with the forecast horizon. Our results indicate that for the cases of Argentina and Chile the real money gap contains valuable information about the future path of inflation at low frequencies.
References


Appendix 1

A natural way to deal with the estimation of a Phillips Curve is to use the Generalized Method of Moments (GMM), developed by Hansen (1982) which is a generalization of the method of moments. In what follows we present a brief description of GMM and some methodological issues related to time series estimation using this method. We stress two main advantages of the GMM estimation: (i) it does not require imposing a certain probability distribution to the variables and (ii) it is consistent with the assessments of inter-temporal optimizing behavior by economic agents.

Suppose we have a set of observations of a random variable $y$, whose probability function depends on a vector of $k$ unknown parameters denoted by $\theta$. We can then define

$$ E(g(y_t, \theta)) = 0 \text{ for } \theta = \theta_0 $$

as the vector of moment conditions of $y$

The sample counterparty of the population moment condition is

$$ g_t(\theta) = \frac{\sum_{i=1}^{T} g(y_t, \theta)}{T} $$

If the number of moment conditions is equal to the number of parameters to be estimated, $a = k$, we have a system of $k$ equations and $k$ unknowns, which can be perfectly identified.

The Method of Moments estimator $\hat{\theta}$ can be defined as that which equals the sample moment with the population moment.

$$ g_t(\hat{\theta}) = \frac{\sum_{i=1}^{T} g(y_t, \hat{\theta})}{T} $$

If the number of moment conditions exceeds the number of unknown parameters, $a > k$, the system is over-identified, since there does not exist a unique $\theta$ satisfying (9). The Generalized Method of Moments proposes to use $\hat{\theta}_{GMM}$.

$$ \hat{\theta}_{GMM} = \arg \min \ g_t(\theta)' C_t g_t(\theta) $$

where $C_t$ is a symmetric positive definite matrix, known as the “weighting matrix” that weights the moment conditions as to solve (10)

Hansen (1982) proposes a method to choose $C_t$ optimally, that is, to obtain the $\hat{\theta}$ with the minimum asymptotic variance

$$ C_t \xrightarrow{p} \delta E \left[ g_t(\theta_0) g_t(\theta_0)' \right] $$

where $\delta$ is a constant.

Hansen shows that given $S$

$$ S = \lim_{T \to \infty} T E \left[ g_t(\theta_0) g_t(\theta_0)' \right] $$
the optimum value of the matrix $C_t$ is given by $S^{-1}$, the inverse of the asymptotic variance covariance matrix. Then, the minimum variance estimator of $\theta$ is obtained by choosing $\theta$ as to minimize

$$Q(\theta) = [gt(\theta)]' S^{-1} [gt(\theta)]$$

(11)

Assuming that $gt(\theta_0)$ is not serially correlated, $\theta$ is a consistent estimator of $\theta_0$.

$$\hat{S} = \frac{1}{T} \sum_{t=1}^{T} gt(\hat{\theta}) g_t(\hat{\theta})' P, S$$

(12)

The estimation of $\hat{S}$ requires having a previous estimation of $\hat{\theta}$. Thus, substituting $C_t$ in (10) by the identity matrix $I$, an initial estimation of $\hat{\theta}$ is obtained and then used in (12) to obtain an initial $\hat{S}_0$. The expression (11) is minimized using $S^{-1} = \hat{S}_p^{-1}$, to obtain a new estimation of $\hat{\theta}$. The process can be repeated until $\hat{\theta}^j = \hat{\theta}^{j+1}$.

If the vector $g_t(\theta_0)$ is serially correlated, the matrix $\hat{S}$ will have the following structure

$$\hat{\Omega}_{HAC} = \hat{\Gamma}(0) + \left[ \sum_{j=1}^{T-1} k(j, q) \left( \hat{\Gamma}(j) + \hat{\Gamma}'(-j) \right) \right]$$

(13)

where

$$\hat{\Gamma}(0) = \frac{1}{T} \left( \sum_{t=1}^{T} g_t(\hat{\theta}) g_t(\hat{\theta})' \right)$$

is the White’s heteroskedasticity consistent covariance matrix and

$$\hat{\Gamma}(j) = \frac{1}{T} \left( \sum_{t=j+1}^{T} g_t(\hat{\theta}) g_{t-j}(\hat{\theta})' \right)$$

describes the autocovariances and $k(j, q)$ is a kernel.

The matrix $\hat{\Omega}_{HAC}$ is known as the Heteroskedasticity and Autocorrelation Consistent (HAC) Covariance Matrix. The estimation $\hat{\Omega}_{HAC}$ of needs to specify a kernel, used to weight the covariances so $\hat{\Omega}_{HAC}$ that is positive semi-definite and a bandwidth which is a lag truncation parameter for the autocovariances.

Two type of kernel are commonly used in the estimation of $\hat{\Omega}_{HAC}$, Barlett and quadratic spectral.\(^5\)