Towards an estimation of money demand with forecasting purposes

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Abstract

This paper aims at producing forecasts of monetary aggregates which are useful in formulating monetary policy in Argentina; in particular, forecasts that allow evaluation of alternative economic scenarios, with a 5-quarter horizon and of both public and private monetary aggregates. With that aim, relationships between different aggregates – currency, M1*, M2*, M3*– and two of their determinants (GDP and interest rates) are estimated. The period selected (1993-2005) spans two different macroeconomic regimes, something problematic when analyzing long-run relationships: coefficients differ from those suggested by economic theory; and cointegration relationships are not stationary. In contrast, short-term models are estimated that exhibit acceptable goodness-of-fit, and evidence of stable parameters. In-sample forecasts do not display errors significantly different from zero, and observations between 2004:III and 2005:III are included within one-standard deviation confidence intervals. Additionally, forecast unbiasedness is obtained. Thus, models show good forecast capacity.

However, taking into account the Central Bank’s aims and constraints, more demanding criteria should be applied: although forecast errors are not significant, they turn more persistent as the forecast horizon is extended; and they currently seem to indicate underestimation of narrow aggregates and overestimation of broad ones. Such behaviour may be related to more “cash-intensive” money holdings after the crisis. An adjustment to forecasts is proposed in order to deal with this problem. The models obtained can be used to evaluate whether a given monetary target is consistent with a certain macroeconomic scenario, using as inputs variables whose forecasts can be obtained from models developed at BCRA.

Key words: forecasts – monetary aggregates – money demand - monetary policy – Argentina

JEL: E41, E47

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I. Introduction

Forecasting monetary aggregates is always a relevant task for a central bank; it is even more so in Argentina, where an annual program sets quantitative targets for certain monetary variables that, ultimately, serve as intermediate targets for achieving price stability. This paper aims at estimating relationships between currency held by the public, M1*, M2* and M3*, and certain observable variables, in order to produce forecasts which are useful to monetary policy making.

Estimating a function for the behaviour of monetary aggregates is a complex task—and somewhat infrequent in Argentina in recent times. It always requires at least three definitions (Johnson, 1962): what assets are considered money, of which variables is their behaviour dependent on, and how stable is the latter. Such matters are mere starting points: data frequency and seasonality have to be taken into account as well (Ericsson, 1998); and if for decades it was common practice to approach the problem from a “structural” equation, recent developments in cointegration, causality and exogeneity can only add to the complexity of any estimation.

Problems common to any strategy of empirical modelling of money demand are enhanced in the case of Argentina, given the series of monetary and foreign exchange regime changes, high and low inflation periods, macroeconomic volatility in general, and subsequent problems of data availability and methodology in particular. Recent research, that uses cointegration techniques, follows two broad lines: exploring the inflationary and post-inflationary experience (Melnick, 1990; Ahumada, 1992; Choudhry, 1995; Ericsson and Kamin, 2003); and accounting for money demand over an extended period using annual data (Ahumada and Garegnani, 2002; Gay, 2004). Such techniques have also been employed to understand the effects of monetary policy under a fixed exchange rate regime (Utrera, 2002). None of these papers focuses on forecasting monetary aggregates, with the only exception of Grubisic and Manteiga (2000); their analysis, however, was limited to the convertibility regime (or currency board), in place from 1991 to 2001.

In contrast, this paper aims at approaching monetary aggregates’ forecasts with quarterly frequency and including data of the post-Convertibility period, and focusing on monetary policy needs: assessing the consistency of possible targets and alternative macroeconomic scenarios; considering public and private aggregates on average of daily data; producing forecasts with quarterly frequency; and taking into account that forecasts have to be produced with an annual horizon—as the monetary program is formulated one year ahead, with quarterly targets.

The rest of the paper is organized as follows. Section II describes the methodology and data employed, putting them in the context of the literature on the subject (particularly that devoted to Argentina); section III presents long and short run models, explaining why ones are favoured with respect to others. Section IV is devoted to forecast evaluation. Section V concludes, and discusses guidelines for future work.

II. Data and methodology

In standard theory, money is demanded for two reasons: as a stock to smooth differences between flows of income and expenditure; and as one of several assets in a portfolio (Ericsson, 1998). This derives in a specification that necessarily includes a scale variable—with respect to which real balances are growing—and another one that captures the return of assets considered money vis-a-vis those which are not—that is, the opportunity cost of money holdings, with respect to which demand is decreasing. We choose a linear specification:

\[ \frac{M_i^d}{P_i} = \alpha Y_t + \beta i_t \]  \hspace{1cm} (1)
Four definitions of monetary aggregates are employed for $M^d_t$, in quarterly averages of daily data, deflated by the Consumer Price Index$^1$ ($P_t$):

ByM = currency held by the public (outside banks) + quasimonies;

$M1^* = ByM + $ checking accounts in AR pesos and US dollars, both public and private;

$M2^* = M1^* + savings accounts in AR pesos and US dollars, public and private$^2$;

$M3^* = M2^* + time deposits, public and private + other deposits, in AR pesos and US dollars$^3$.

The decision to include both the government and the private sector follows BCRA monetary programs since 2003. Including both public and private agents weakens the notion of money demand proper, as this refers to private agents’ decisions—that is why we prefer the expression “monetary aggregates’ estimates”; however, as long as the context is clear, the term “money demand” is also employed. In turn, the use of pesos and dollars arises from the need to include relevant behaviour during a sizable span of the estimation period: if we were to estimate aggregates in pesos, we would omit a significant portion of decisions made over real balances that, while the currency board was in place, were made over US dollars holdings. In addition, certain aggregates included in recent monetary programs were bi-monetary.

We estimated models between the second quarter of 1993 and the third of 2005 (in what follows, abbreviated as “year: quarter number”), a period that includes methodologically consistent data of all aggregates considered according to the definitions above.

Data frequency and seasonality may alter results: if agents’ decisions are taken over a shorter period than that covered by data frequency, dynamics may be confusing and inference may change (Ericsson, 1998). The same applies to series adjusted or not for seasonality, as well as to average or end-of-period data. We have used, alternatively, original data adjusted through dummy variables, and seasonally adjusted data according to the X-12 ARIMA methodology.

Regarding money demand determinants, we chose GDP$^5$ as scale variable ($Y_t$ in (1)). This just one possible choice of scale variable, and recent research confirms that such choice is far from irrelevant (Knell and Stix, 2004). For instance, Ahumada and Garegnani (2002) employ alternatively GDP and GDP plus imports, but prefer the latter as it improves goodness-of-fit and allows for a more satisfactory long-term representation$^6$.

As for the opportunity cost of money, we use the nominal interest rate (NIR) for peso time deposits of 30 to 59 days of maturity$^7$ ($i_t$ in (1)). This is certainly a measure of opportunity cost for ByM, $M1^*$ and $M2^*$, but not for all components of $M3^*$. Actually, we should estimate each aggregate’s own rate of return, as well as that of alternative assets. The own rate should be a weighted average of each component of the aggregate; and the same should apply to alternative assets$^8$. Likewise, both

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$^1$ CPI – general level, as informed by INDEC (National Institute of Census and Statistics), in quarterly average of monthly data.

$^2$ We include savings accounts in US dollars for 50% of their outstanding balances. While the currency board was in place, not all balances in US dollars could be considered of a “transactional” nature (something that should be reflected by $M2^*$); the fraction included here is considered an acceptable approximation.

$^3$ M2* as included in M3* includes savings accounts in AR pesos and US dollars for their complete balances.

$^4$ Daily information provided by BCRA. Time deposits include re-scheduled deposits (CEDRO) adjusted by a CPI-linked index, called “Coeficiente de Estabilización de Referencia” (CER).

$^5$ According to quarterly information as provided by INDEC.

$^6$ Gay (2004) includes only output; in turn, Grubisic and Manteiga (2000) do not find GDP to be significant in accounting for changes in monetary aggregates during the convertibility regime. Apparently, high correlation with country risk measures and capital flows would eliminate GDP from the estimated equation.

$^7$ According to daily information provided by BCRA.

$^8$ A possible interpretation of the specification we propose would be to consider return on sight deposits as virtually negligible in economic agents’ decisions.
rates should reflect each aggregate’s currency composition, instead of taking only the opportunity cost in pesos.

Disadvantages entailed by our specification are somewhat offset by the main aim of the exercise: producing forecasts, in order to which we should count on independent variables that can be forecasted systematically and consistently. There would be little value in the best specified model without a reliable procedure to produce forecasts of explanatory variables; with this aim, we rely on the Small Structural Model (Modelo Estructural Pequeño, MEP) developed by Economic Research staff at BCRA, upon whose simulations we can obtain forecasts of GDP, 30-59 day peso time deposits interest rates, inflation and the nominal exchange rate.

In an economy such as Argentina, inflation is a natural candidate for opportunity cost, as it approximates the rate of return of goods that are not money. Estimating money demand between 1935 and 2000, Ahumada y Garegnani (2002) find that the inflation rate is significant as opportunity cost only in high-inflation periods, whereas in low inflation ones the nominal interest rate is more suitable; in particular, this is verified in the 1991-2000 period, that spans most of the data we use.

Money demand can be treated in a different way in a small, open economy. Besides GDP and interest rates, Gay (2004) adds variables associated to the real exchange rate; he finds the latter to be significant, and the main source of money demand volatility in the 1963-2003. In turn, Ahumada and Garegnani (2002) find no effect of the rate of depreciation of the nominal exchange rate on money demand. Still, reflecting the behaviour of monetary aggregates in an economy where external shocks –and the foreign exchange rate in particular- play such a prominent role should be incorporated in the analysis.

A satisfactory representation of money demand in the chosen period is a challenge in itself: the 2001-2002 crisis marks a “break” in the series, something evident from visual inspection (figure 1). The economy appears to become more “cash-intensive” than in the past, something where both the government and private agents are involved. Money demand determinants may have changed, or economic agents’ response to them –and it is an open question whether changes we see are permanent or transitory.

The presence of breaks may not hinder a satisfactory estimation: Melnick (1990) estimates an error correction model before and after the launch of the Austral plan; Ericsson y Kamin (2003) proceed likewise during a period that includes the hyperinflationary episodes of 1989 and 1990; Choudhry (1995), in turn, estimates a system of equations including real income, M1, M2, inflation and foreign exchange depreciation, between the late 1970s and late 1980s. In each case, the authors find and empirical representation that they consider stable: Choudhry highlights that the result is sensitive to the inclusion of foreign exchange depreciation; Melnick suggests that parameter instability arises from inadequate treatment of inflation expectations. In turn, and only to take two cases from the international experience, Wolters, Terasvirta y Lütkepohl (1998) estimate M3 real demand for the 1976-1994 period, that includes re-unification in 1990; once the structural change entailed by reunification is accounted for, they find a stable function. Bjornland (2005) estimates M2 demand for Venezuela during the 1985-2000 period, marked by foreign exchange crises and foreign shocks. Introducing expected nominal currency depreciation, and a foreign interest rate, she is able to estimate a conditional, equilibrium correction equation, judged stable throughout the period.

The presence of breaks calls for cautiousness regarding long-term relationships between money demand and its determinants. One has to analyze results carefully in order to distinguish which of them make sense; and, if possible, contrast them with others, resulting from short-term models. The next section is devoted to this task.

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9 It should be noted that the US dollar interest rate (on domestic time deposits) series was virtually interrupted immediately after devaluation and subsequent financial de-dollarization in 2001-2002. With a forecasting aim in mind, the use of an AR peso interest rates looks more convenient.

10 However, only Melnick (1990) and Ericsson and Kamin (2003) test for stability of their models.
III. Exploring relationships between monetary aggregates, output and interest rates

We propose different models in order to capture the relationship between monetary aggregates, output and interest rates. A natural starting point is to consider cointegration relationships between the variables under study. These tend to show stochastic trends, and so spurious results may arise if conventional regression analysis is applied. Besides, these same variables may present an “equilibrium correction” movement through time, as predicted by economic theory, such that in the long run a steady state path is obtained: for instance, we would expect homogeneity between real balances and transactions (according to the quantity theory), so that any divergence between them may decrease until zero—provided, of course, that the existence of a long run relationship can be obtained.

Obtaining such a relationship may indeed be problematic when a sharp regime change as the one that took place in Argentina in 2001-2002 is included in the sample period. Even before estimating any model, we can have a flavour of the challenges this issue poses by inspecting two simple charts. In figure 2a, and following Lucas (1988), we plot the inverse of the velocity of money—assuming money-income elasticity equal to one—against the nominal interest rate. First, two distinct clouds appear, one for the currency board period (1993-2001) and another for the subsequent one; if one were to predict this relationship based on data from the convertibility period, estimates would surely differ from observed values in 2002-2006. What is more, it would be hard to obtain a good fit for a linear relationship between velocity and the interest rate, even during the currency board period. In turn, figure 2b shows the scatter plot of real M1 balances and GDP: in this case, linearity seems to hold, but once again, there would be no chance of adequately forecasting M1 in the post-convertibility period based on 1993-2001 data.

11 The currency board was in place from 1991 to 2001, but we use data from 1993 onwards (see section II).
III.1 Long run analysis: main results

In order to estimate long run models, we first apply the augmented Dickey-Fuller test in order to determine the order of integration of the variables (table 1). The null hypothesis of unit root is not rejected for all variables considered, except the nominal interest rate\(^{12}\). The latter is found to be I(1).

\(^{12}\) We also analyzed the order of integration of seasonally adjusted variables, and ADF tests yielded results similar to those presented here.
at 1% significance; however, and in line with other studies, it will be considered in the cointegration analysis\textsuperscript{13}.

\textbf{Table 1 / Order of integration of selected variables - 1993:II – 2005:III}

<table>
<thead>
<tr>
<th>Series</th>
<th>Number of lags included according to the Schwarz criterion. Exogenous variables: constant and trend</th>
</tr>
</thead>
<tbody>
<tr>
<td>ByM</td>
<td>ADF statistic p-value</td>
</tr>
<tr>
<td>M1*</td>
<td>ADF statistic p-value</td>
</tr>
<tr>
<td>M2*</td>
<td>ADF statistic p-value</td>
</tr>
<tr>
<td>M3*</td>
<td>ADF statistic p-value</td>
</tr>
<tr>
<td>PIB</td>
<td>ADF statistic p-value</td>
</tr>
<tr>
<td>TNA (constant only)</td>
<td>ADF statistic p-value</td>
</tr>
</tbody>
</table>

Cointegration analysis is performed according to the Johansen-Juselius methodology, that entails estimating a system of equations of the variables of interest through maximum likelihood. In order to isolate possible effects specifically associated to GDP or interest rates, and taking into account the lack of definition of the latter’s order of integration, we decided to start with the long-run relationship between money and output. We found a possible cointegration relationship between each aggregate and GDP—but such relationships were subject to the same limitations as those between money, output and interest rates; so in what follows we show the results of the latter analysis.

We found two possible cointegration relationships for each of the aggregates under study\textsuperscript{14}. GDP and the interest rate (table 2). The first vector, normalized with respect to money, shows a coefficient for GDP that ranges from 1.7 to 1.9, depending on the aggregate. The long run coefficient for the interest rate shows the expected sign, and it increases as the aggregate becomes broader. In the second relationship, normalized with respect to the interest rate, GDP shows a long run coefficient that increases as the aggregate’s liquidity decreases, while the value of the coefficient of this relationship is more or less constant no matter what definition of money is used.

In order to account for the change in monetary variables after the demise of the currency board, we introduced a step dummy from 2002 onwards, in addition to jump dummies that control for different episodes that took place during the sampling period. We also had to include a deterministic trend in the cointegration relationship of each aggregate. Residuals resulting from these systems turned out to be homoscedastic, non autocorrelated and normally distributed—so we could perform different tests in order to confirm or reject the cointegration relationships.

\textsuperscript{13} Ahumada (1992) points out that inflation –that she uses as the opportunity cost of money in Argentina from 1977 to 1988-, may not be I(1) according to the ADF test, but acknowledges that such test is extremely sensitive to the sampling period.

\textsuperscript{14} We were unable to find long-run relationships for M3*.
The cointegration vector normalized with respect to money presents certain features that cast doubts as to its usefulness for our purposes. The $\beta$ coefficient of such relationship (table 2) is not statistically different from 2, while the null hypothesis of $\beta$ equal to one is rejected for all aggregates so we discard homogeneity between money and output. These income elasticities, so different from those suggested by the quantitative theory (equal to 1) or the Baumol-Tobin hypothesis (0.5) may be the reflection of intense re-monetization that took place during most of the 1990s, and in the period that followed the crisis; likewise, de-monetization during the crisis occured at a pace that surpassed that of output fall\textsuperscript{15}. This could explain why each peso of change in output is virtually doubled by the change in real balances – something that should not be verified in the long run, but that we would expect to find during a period associated, successively, to a successful anti-inflationary program, a strong crisis and the ensuing recovery.

A higher than 1 income elasticity could also be interpreted in the light of international evidence: Knell and Stix (2004) survey 1000 money demand estimations across different countries in the last

\textsuperscript{15} Certainly, monetization phases could be captured by the deterministic trend included in the long run relationship.
three decades and find that OECD countries show income elasticities lower than the rest. They consider this as evidence of higher development of payment systems in more advanced countries, that allow individuals to better economize on cash holdings; along the same lines, they find that financial innovations are associated to lower elasticities. A possible interpretation of our results is that income elasticities are higher in an economy of relatively low financial development like Argentina, where agents are less able to economize on cash holdings; likewise, the crisis may be thought of as a (very) negative financial innovation, that led to strong deterioration of payment systems, evidenced through higher elasticity. These lines are far from being a complete explanation, but suggest possible rationalizations of the figures in table 2.

Next, we assess whether money, output and the interest rate respond to desequilibrium in the cointegration relationship—that is, we evaluate weak exogeneity. Tests reject the null hypothesis of weak exogeneity of the chosen variables: according to adjustment coefficients estimated for each possible cointegration vector, both money and GDP respond to long run desequilibria in the first cointegration relationship, while the interest rate responds to deviations in both relationships\(^{16}\). However, it should be noted that money is the variable showing the highest absolute valued response to desequilibria of long run relationships, followed by the interest rate, while output is the variable with smallest response\(^{17}\).

Lack of exogeneity of the variables under study is far from surprising: most of the sampling period includes the Convertibility regime, where other papers (Gay, 2004) find that money demand determinants are endogenous; and there are reasons to believe that money and interest rates, as we specify them here, are simultaneously determined. Thus, the analysis so far puts into question a single-equation approach, and suggests the need for system estimation.

However, a complete study should assess whether cointegration relationships are stable in the period considered: with that aim, we test parameter constancy through recursive tests, as well as stationarity of such relationships\(^{18}\). Different recursive Chow tests\(^{19}\), performed from the first quarter of 2000 onwards, reject the null hypothesis of parameter constancy in both the system and single equations—even after controlling with a step dummy since 2002. The interest rate equation shows prominent constancy problems throughout the period in question\(^{20}\); we interpret that interest rates may have “lost” their role as opportunity cost during the crisis due to, among other factors, the imposition of financial restrictions. Besides, unit root tests (table 3) indicate that cointegration relationships behave as non-stationary process at the usual levels of significance.

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16 Cointegration relationships for money and GDP, seasonally adjusted, and the interest rate, do not differ from those shown in table 2. Detailed results of the cointegration analysis are available from the authors upon request.
17 Exogeneity tests for monetary aggregates and GDP (without the interest rate) yield the following results: the adjustment coefficient of GDP to disequilibrium in the long run relationship differs from zero only for ByM and M1*, while coefficients for M2* and M3* are not significantly different from zero: that is why output may be treated as weakly exogenous. These results suggest validation of a conditional model of money as a function of GDP for wider aggregates like M2* and M3*. In addition, money always turns out to be exogenous.
18 Except for Ahumada and Garegnani (2002), we found no evaluations of this kind in the literature referred to Argentina.
19 Recursive Chow tests are available from the authors upon request. They were implemented in PCFIML; see Doornik and Hendry (1997)
20 Constancy parameter problems did not show in the money-GDP bivariate system.
Taken together, these results point against cointegration relationships between money, output and interest rates, for econometric and economic reasons: relationships are not stationary, and coefficients estimated for them are unstable; in addition, income elasticities are far from what could make sense under any known hypothesis of money demand. Even after controlling for structural change, it is extremely difficult to establish long run relationships between variables that correspond to different macroeconomic regimes\(^{21}\) and whose transition took place through a deep crisis—as was evident from mere visual inspection of figure 2. Certainly, detecting stability of these relationships may be just a matter of time: as long as observations since 2002 increase, we would have a better econometric standpoint to portray the post-convertibility period. All in all, the existence of long run relationships is an assumption previous to econometric analysis, that the latter can only help validate or discard—and it is the case that available evidence prevent us from validation. These reasons lead us to adopt, with the purpose of forecasting and as a preliminary approach, single equation, short run models.

### III.2 Approaching monetary aggregates’ estimation through short run models

In order to estimate the relationship between monetary aggregates and selected determinants, we followed the general to specific methodology, considering non-stationary variables in difference of logarithms, and the interest rate in levels. Seasonality was captured through dummies.\(^{22}\)

Table 4 presents ordinary least squares (OLS) estimates in rates of change of the different monetary aggregates, ByM, M1*, M2*, \(y\) M3*. It is first of all clear that the dependent variable is not, in general, persistent in time, except for ByM where it appears with a 1-quarter lag, though with a small coefficient. In turn, the scale variable turned out significant in all regressions, with the expected sign. In general, the scale variable’s coefficient is not significantly different from 1 in none of the models\(^{23}\).

Regarding the opportunity cost, the contemporaneous coefficient is significant, as are the first or second lag, depending on the aggregate. In all models, the contemporaneous coefficient carries the expected sign, whereas the lagged coefficient has the opposite sign, smoothing contemporaneous impacts. In general, the opportunity cost weighs less on relatively liquid aggregates, while its effect is much more important on wider forms of money. Results are in line with Knell and Stix’s (2004) findings: in models with only one interest rate, it carries negative sign for all aggregates\(^{24}\).

\(^{21}\) One may distinguish between regime change and structural break proper; see Hendry and Massman (2005).

\(^{22}\) Results for the series adjusted for seasonality using the X-12 ARIMA methodology do not differ substantially from those reported here, except where noted, and are available from the authors upon request.

\(^{23}\) This result appears sensitive to the definition of monetary aggregates employed. Indeed, using data of total aggregates (deposits by: public sector + private sector+ financial sector + foreign residents) the effect of output on money decreases with monetary aggregates’ illiquidity, ranging from 1 to 0.6.

\(^{24}\) In contrast, Knell and Stix (2004) point out that specifications of money demand with a short rate and a long rate show: i) a negative long rate coefficient, independently of the aggregate considered; ii) a negative short rate coefficient for narrow money and positive for broad money.
### Table 4 / Short run models (in differences): main results

1993:II – 2005:III

<table>
<thead>
<tr>
<th></th>
<th>∆LByM</th>
<th>AlM1*</th>
<th>AlM2*</th>
<th>AlM3*</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coef.</td>
<td>t-stat</td>
<td>p-value</td>
<td>Coef.</td>
</tr>
<tr>
<td>C</td>
<td>-0.032</td>
<td>-3.827</td>
<td>0.000</td>
<td>-0.003</td>
</tr>
<tr>
<td>Dependent variable (-1)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>D(LOG(GDP))</td>
<td>0.909</td>
<td>4.414</td>
<td>0.000</td>
<td>1.000</td>
</tr>
<tr>
<td>LOG(1+NIR)</td>
<td>-0.175</td>
<td>-3.282</td>
<td>0.002</td>
<td>-0.193</td>
</tr>
<tr>
<td>LOG(1+NIR(-1))</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>LOG(1+NIR(-1))/D2002.III ON</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>LOG(1+NIR(-2))</td>
<td>0.144</td>
<td>3.288</td>
<td>0.002</td>
<td>0.144</td>
</tr>
<tr>
<td>Seasonal-I</td>
<td>0.128</td>
<td>8.302</td>
<td>0.000</td>
<td>0.098</td>
</tr>
<tr>
<td>Seasonal-II</td>
<td>-0.083</td>
<td>-4.105</td>
<td>0.000</td>
<td>-0.081</td>
</tr>
<tr>
<td>Seasonal-III</td>
<td>0.096</td>
<td>9.125</td>
<td>0.000</td>
<td>0.048</td>
</tr>
<tr>
<td>D1995.I</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>D2001.IV</td>
<td>0.086</td>
<td>3.282</td>
<td>0.002</td>
<td></td>
</tr>
<tr>
<td>D2002.I</td>
<td>0.321</td>
<td>11.380</td>
<td>0.000</td>
<td>0.419</td>
</tr>
<tr>
<td>D2002.III</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Adjusted R²</td>
<td>0.860</td>
<td></td>
<td></td>
<td>0.866</td>
</tr>
<tr>
<td>Standard dev. of dependent variable</td>
<td>0.059</td>
<td></td>
<td></td>
<td>0.066</td>
</tr>
<tr>
<td>Standard deviation of regression</td>
<td>0.022</td>
<td></td>
<td></td>
<td>0.024</td>
</tr>
<tr>
<td>F statistic</td>
<td>34.490</td>
<td></td>
<td></td>
<td>46.281</td>
</tr>
<tr>
<td>Prob (F stat.)</td>
<td>0.000</td>
<td></td>
<td></td>
<td>0.000</td>
</tr>
</tbody>
</table>

Note: D(.) or ∆ are variables in differences; Dyear.quarter (eg: D1995.I) stand for jump dummy variables; Seasonal-quarter stand for seasonal dummy variables. GDP: gross domestic product; NIR: nominal interest rate.
The case of M3* merits further consideration, as recursive parameter stability tests detected a break in the interest rate coefficient at the time of the 2002 crisis. This was controlled by a multiplicative dummy variable from the third quarter of 2002 on, resulting in a higher effect (after two quarters), of the interest rate on the aggregate in question after the crisis. However, this coefficient looks particularly influenced by the behaviour of M3* during 2001 and 2002: the same model, estimated with data until the end of 2000, yields values close to 0.5 for interest rate elasticity, very similar to those obtained for the whole sample. As observed for the cointegration relationships, there seems to be a change of the effect of interest rates on monetary aggregates, and, in particular, on M3*. This makes economic sense if one takes into account that M3* is the form of money showing the highest “discontinuity” after the crisis (chart 1); and that it was the monetary aggregate more subject to changes derived from behaviour unexplained by conventional determinants (pesification, time deposit restructuring, exchange of deposits for bonds, adjustment through a CPI-linked coefficient, etc).

All models required the introduction of some kind of control associated to episodes of the 2001-2002 crisis, through jump dummy variables: 2002:1 is present in all models except for M3*; ByM incorporates 2001:4 –as financial restrictions affected, first of all, currency in circulation--; and M3* carries a dummy in 1995:1 –the Tequila crisis- and 2002:3.

Regressions’ residuals lack autoregressive and heteroscedastic behaviour, and are normally distributed, according to tests included in table 4. The Ramsey reset test allows us to accept the null hypothesis of correct specification. According to the Chow forecast test, no model entails rejection of the null hypothesis of parameter constancy and forecasting capability for the 2004:1-2005:III period –that is, a scenario as close as possible to that when out-of-sample forecast will have to be made. Besides, recursive estimation of coefficients for the different models show no structural breaks, and no significant breaks are revealed by n-descending and n-ascending recursive Chow tests, with both exercises being carried out from 1998:1 onwards. Estimated relationships, thus, look adequate for forecasting in the period after the crisis.

Forecasting with single equation models calls for checking Granger causality, in addition to weak exogeneity as examined in section III.1: the variable to be forecasted should not Granger-cause its determinants. Results differ according to the variable considered (table 5). There is no feedback
from money to output at a 1% significance: money does not anticipate output behaviour, and the same holds in the opposite way. In turn, the null hypothesis of monetary aggregates not preceding the interest rate is rejected, except for M3*; while Granger causation from the interest rate to money is unclear.

Summing up, single equation models reveal an acceptable goodness-of-fit, both globally and in terms of individual coefficients; residuals look normal, and lack autocorrelation and heteroscedasticity; the hypotheses of parameter stability and adequate forecasting ability cannot be rejected, at least for the period closest to that when out-of-sample forecasts will have to be made. However, a single equation approach is justified on limited grounds: although output may be exogenous with respect to certain aggregates, such is not the case of the opportunity cost. Moreover, absence of Granger causality from money demand to its determinants is verified for only one of them — output. Subject to these constraints, the following section presents and evaluates the models’ forecasts.

<table>
<thead>
<tr>
<th>Table 5 / Granger causality tests</th>
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<tbody>
<tr>
<td><strong>H0: no Granger causality</strong></td>
</tr>
<tr>
<td>Lags: 6</td>
</tr>
<tr>
<td>----------------------------------</td>
</tr>
<tr>
<td><strong>bym does not cause gdp</strong></td>
</tr>
<tr>
<td><strong>gdp does not cause bym</strong></td>
</tr>
<tr>
<td><strong>bym does not cause nir</strong></td>
</tr>
<tr>
<td><strong>nir does not cause bym</strong></td>
</tr>
<tr>
<td><strong>m1 does not cause gdp</strong></td>
</tr>
<tr>
<td><strong>gdp does not cause m1</strong></td>
</tr>
<tr>
<td><strong>m1 does not cause nir</strong></td>
</tr>
<tr>
<td><strong>nir does not cause m1</strong></td>
</tr>
<tr>
<td><strong>m2 does not cause gdp</strong></td>
</tr>
<tr>
<td><strong>gdp does not cause m2</strong></td>
</tr>
<tr>
<td><strong>m2 does not cause nir</strong></td>
</tr>
<tr>
<td><strong>nir does not cause m2</strong></td>
</tr>
<tr>
<td><strong>m3 does not cause gdp</strong></td>
</tr>
<tr>
<td><strong>gdp does not cause m3</strong></td>
</tr>
<tr>
<td><strong>m3 does not cause nir</strong></td>
</tr>
<tr>
<td><strong>nir does not cause m3</strong></td>
</tr>
</tbody>
</table>

IV. Forecasting monetary aggregates

In what follows, we present and assess 1- and 5-step forecasts of the different models estimated, in levels and in nominal terms. 1-step forecasts were made for the 2004:I - 2005:III period; 5-

---

26 Output turned out to be: a) exogenous with respect to all aggregates in the bivariate, seasonally adjusted, money-output relationship; b) the variable with smallest response to long run disequilibrium in the money-output-interest rates relationships.

27 The choice of variables in differences or in levels is far from trivial when it comes to forecast evaluation: the same model may be good at forecasting in differences, but not in levels, and viceversa (Clements and Hendry, 1998). We chose levels for our exercise only because monetary targets are set that way.
step forecasts, for 2004:III - 2005:III. The first exercise makes sense as a general way of evaluating model forecasting performance –under an “ideal” situation, being able to update forecasts with information available every quarter. The second tries to reproduce the situation when the monetary program is formulated, the latest information available dating from the third quarter of the year previous to that of the program. Certainly, forecast performance depends on forecast horizon: Clements and Hendry (1998) emphasize this, warning about limitations to forecast evaluation when only one step is taken into account.

An inspection of table 6 yields a remarkable result: forecast errors, at 1 and 5 steps, are always within the 95% confidence interval. From the point of view of usual measures of significance, these errors do not tend to be different from zero, so forecast capability is satisfactory. However, forecast evaluation should reflect the cost of errors for forecast users (Granger, 2001). In this case, the Central Bank may find deviations exceedingly costly, even if they are insignificant with a 95% confidence: our evaluation should be stricter than usual, and 1 standard deviation bands are considered –representing a 68% level of confidence. Even under this stricter criterion, forecast errors are seldom different from zero (figure 3).

One-step forecasts (table 6) show no systematic errors in the two most liquid aggregates; and errors’ magnitude does not generally exceed 2%. In M2* and M3* we notice errors of the same sign in the last four quarters: models seem to show a slight overestimation of wider monetary aggregates, even if by a small amount. This might have to do with more intensive use of cash by economic agents, still not fully captured by these models.

### Table 6 / H-step forecasts

<table>
<thead>
<tr>
<th></th>
<th>ByM</th>
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<th></th>
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<th></th>
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</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>h=1</td>
<td>h=5</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Forecast</td>
<td>Error</td>
<td>Confidence interval, 95%</td>
<td>Forecast</td>
</tr>
<tr>
<td>Mar-04</td>
<td>26.186</td>
<td>-0.4%</td>
<td>24.984</td>
<td>27.389</td>
<td></td>
</tr>
<tr>
<td>Jun-04</td>
<td>26.716</td>
<td>0.5%</td>
<td>25.503</td>
<td>27.929</td>
<td></td>
</tr>
<tr>
<td>Sep-04</td>
<td>29.116</td>
<td>-1.2%</td>
<td>27.787</td>
<td>30.445</td>
<td>29.116</td>
</tr>
<tr>
<td>Dec-04</td>
<td>29.467</td>
<td>1.3%</td>
<td>28.107</td>
<td>30.827</td>
<td>29.926</td>
</tr>
<tr>
<td>Mar-05</td>
<td>32.136</td>
<td>1.0%</td>
<td>30.648</td>
<td>33.624</td>
<td>32.126</td>
</tr>
<tr>
<td>Jun-05</td>
<td>34.026</td>
<td>-1.0%</td>
<td>32.424</td>
<td>35.628</td>
<td>33.525</td>
</tr>
<tr>
<td>Sep-05</td>
<td>36.499</td>
<td>1.4%</td>
<td>34.841</td>
<td>38.156</td>
<td>36.380</td>
</tr>
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</table>

<table>
<thead>
<tr>
<th></th>
<th>M1*</th>
<th></th>
<th></th>
<th></th>
<th></th>
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<tbody>
<tr>
<td></td>
<td></td>
<td>h=1</td>
<td>h=5</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Forecast</td>
<td>Error</td>
<td>Confidence interval, 95%</td>
<td>Forecast</td>
</tr>
<tr>
<td>Mar-04</td>
<td>48.542</td>
<td>1.2%</td>
<td>46.112</td>
<td>50.973</td>
<td></td>
</tr>
<tr>
<td>Jun-04</td>
<td>51.570</td>
<td>2.4%</td>
<td>48.991</td>
<td>54.149</td>
<td></td>
</tr>
<tr>
<td>Sep-04</td>
<td>55.984</td>
<td>0.5%</td>
<td>53.173</td>
<td>58.794</td>
<td>55.984</td>
</tr>
<tr>
<td>Dec-04</td>
<td>58.417</td>
<td>0.6%</td>
<td>55.448</td>
<td>61.387</td>
<td>58.154</td>
</tr>
<tr>
<td>Mar-05</td>
<td>62.376</td>
<td>-0.5%</td>
<td>59.244</td>
<td>65.508</td>
<td>61.700</td>
</tr>
<tr>
<td>Jun-05</td>
<td>66.760</td>
<td>-3.8%</td>
<td>63.362</td>
<td>70.157</td>
<td>66.357</td>
</tr>
<tr>
<td>Sep-05</td>
<td>67.996</td>
<td>0.6%</td>
<td>64.808</td>
<td>71.385</td>
<td>70.142</td>
</tr>
</tbody>
</table>

28 Nominal forecasts are obtained “inflating” real ones by observed CPI. This does not affect forecast evaluation, but adds uncertainty to forecasting, as we must specify not only the future path of explanatory variables, but also that of inflation.
### Table 6 (continued) / H-step forecasts

<table>
<thead>
<tr>
<th>h=1</th>
<th>M2*</th>
<th>h=5</th>
<th>M2*</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mar-04</td>
<td>64.652</td>
<td>2.5%</td>
<td>61.085</td>
</tr>
<tr>
<td>Jun-04</td>
<td>70.358</td>
<td>3.2%</td>
<td>66.479</td>
</tr>
<tr>
<td>Sep-04</td>
<td>78.764</td>
<td>1.1%</td>
<td>74.400</td>
</tr>
<tr>
<td>Dec-04</td>
<td>84.210</td>
<td>-1.8%</td>
<td>79.515</td>
</tr>
<tr>
<td>Mar-05</td>
<td>89.003</td>
<td>-2.4%</td>
<td>84.080</td>
</tr>
<tr>
<td>Jun-05</td>
<td>94.347</td>
<td>-5.6%</td>
<td>89.074</td>
</tr>
<tr>
<td>Sep-05</td>
<td>96.055</td>
<td>-0.9%</td>
<td>90.768</td>
</tr>
</tbody>
</table>

### Table 7 / Forecast evaluation measures, h-steps

<table>
<thead>
<tr>
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<tbody>
<tr>
<td>h=1</td>
<td>M1*</td>
</tr>
<tr>
<td>Mean squared error</td>
<td>209,4</td>
</tr>
<tr>
<td>Standardized mean squared error</td>
<td>0,010</td>
</tr>
<tr>
<td>Theil coefficient</td>
<td>0,005</td>
</tr>
<tr>
<td>Bias proportion</td>
<td>0,058</td>
</tr>
<tr>
<td>Variance proportion</td>
<td>0,073</td>
</tr>
<tr>
<td>Covariance proportion</td>
<td>0,870</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
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<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>ByM</td>
<td>M1*</td>
<td>M2*</td>
<td>M3*</td>
</tr>
<tr>
<td>Mean squared error</td>
<td>226,1</td>
<td>762,6</td>
<td>3550,4</td>
</tr>
<tr>
<td>Standardized mean squared error</td>
<td>0,011</td>
<td>0,019</td>
<td>0,062</td>
</tr>
<tr>
<td>Theil coefficient</td>
<td>0,006</td>
<td>0,010</td>
<td>0,032</td>
</tr>
<tr>
<td>Bias proportion</td>
<td>0,143</td>
<td>0,151</td>
<td>0,488</td>
</tr>
<tr>
<td>Variance proportion</td>
<td>0,744</td>
<td>0,657</td>
<td>0,493</td>
</tr>
<tr>
<td>Covariance proportion</td>
<td>0,113</td>
<td>0,193</td>
<td>0,018</td>
</tr>
</tbody>
</table>

Note: Standardized MSE is defined as $SMSE = (ECM^n) / (h^{-1} \Sigma y_{t+h})^{1/2}$, where $h$ is the number of steps and $y$ the observed value of the dependent variable. Theil decompositn is defined as $MSE = (h^{-1} \Sigma y_{t+h})^2 + (S_{y}S_{\hat{y}})^2 + (1-r^2) S_{\hat{y}}^2$, where $\hat{y}$ is the predicted value, $S$ is the sample standard deviation and $r$ the sample correlation coefficient between $y$ and $\hat{y}$; each term is included as a proportion of MSE.
Figure 3 / 5-step forecasts for 2004:III - 2005:III; 95% and 68% confidence intervals
Standard measures of forecast evaluation also reflect better performance at 1 step of ByM and M1* models (table 6); the standardized mean squared error increases as monetary aggregates’ liquidity decreases —with the exception of M3*. We can also look at the Theil decomposition of the mean squared error: a model with acceptable “goodness of fit” should reveal small bias and variance proportions, while concentrating the unexplained component in the covariance proportion. All models display very low bias proportions, with M3* showing the highest one. The variance proportion is generally high, except for ByM. Thus, the Theil decomposition reveals an acceptable fit of one step forecasts, in particular for ByM and M1* -the models that show highest covariance proportions.

When we look at five-step forecasts (table 6 and figure 3), certain issues just pointed out seem to become more accentuated. Although in an insignificant amount, currency holdings by the public present a positive error, implying a slight underestimation of that variable —but not exceeding 2% of observed values. This is consistent with behaviour noted after the crisis, that has entailed a decrease of the velocity of more liquid money (figure 1). In turn, the M1* model shows somewhat less systematic errors, and of similarly reduced magnitude. Once again, it is in the case of M2* and M3* where errors are higher and increasing through time. In this case, we might have some overestimation of these aggregates\(^29\), the mirror image of an economy that has not recovered pre-crisis bancarization levels. The mean squared error of 5-step forecasts (table 7) is inversely related to aggregates’ liquidity (except for M3*). However, the Theil decomposition yields higher bias and variance proportions than covariance ones.

If we calculated intervals from this point estimations, it would be enough to do it with a 1-standard deviation range in order to include observations within the intervals. The only exception is M2*, but only in the fourth and fifth step; and even if observed values fall beyond 1 standard deviation, the remain within two standard deviations from predicted values. This is renewed evidence of more than acceptable statistical behaviour, which is also relevant from the economic standpoint\(^30\).

So far, we have referred to the 2004:III – 2005:III period. It is worth examining if such satisfactory forecasting performance as we have found extends over a longer sampling period; in addition, we could check whether the apparent overestimation of wider aggregates only takes place during such period, or is more general and relates to some anomaly in forecasting.

There are additional criteria to assess forecasting performance: one of them is “forecast rationality”, and includes the concepts of forecast unbiasedness and efficiency\(^31\). Evaluating whether forecasts are unbiased leads us to measure whether they “hit” observed values on average throughout the whole sample —and not just in the last observations, as we have seen so far.

To carry out this analysis we built series of 1 to 5 step forecasts. Such series start in 1996:I and end in 2005:III. In each of them, the forecast horizon \(h\) remains fixed while the sampling period \(T\) changes. In order to test for unbiasedness, we estimate the following relationship using OLS:

\[
O_{T+h} = \alpha + \beta P_{T+h/T} + \epsilon_{T+h}
\]  

(2)

where \(O_{T+h}\) is the observed value in \(T+h\) and \(P_{T+h/T}\) is the predicted value in \(T+h\) at time \(T\). The null hypothesis \(\alpha=0\) and \(\beta=1\) implies that forecasts are unbiased; in so far as this hypothesis allows

\(^29\) Looking at errors associated to 5-step forecasts throughout the whole sample confirms that “overestimation” is higher in M3* than in M2*. This result, however, depends on the series used (see note 22).

\(^30\) When we say “relevant from an economic standpoint”, we refer to a possible trade off between certainty of achieving a given target and the latter’s capability to generate credibility: a target may be ample enough to be achieved, but with little or no value as a nominal anchor.

\(^31\) Weak rationality implies that the forecaster makes no systematic mistakes. This can be tested from observed and forecasted values without any further information. In contrast, strong rationality or efficiency requires forecast errors to be uncorrelated with any series or information available at the time of making forecasts. This analysis has been made to assess the performance of macroeconomic surveys’ forecasts at different horizons (Nordhaus, 1987; Brown and Maital, 1981).
us to accept or reject that forecasts and errors are correlated, it is also a test of efficiency. Although the estimators of coefficients $\alpha$ and $\beta$ are unbiased and consistent, the variance-covariance matrix associated to them is inconsistent, as errors are serially correlated; this invalidates any inference based on $t$ statistics. Correlation is due to the fact that forecasts for any $h>1$ are made on samples that overlap, in the sense that forecasts are made before knowing the error made in the previous forecast (Clements and Hendry, 1998; Elkayam and Illek, 2004). To solve this problem we corrected the variance-covariance matrix using the Newey-West method. Table 8 shows OLS estimates of equation (2), corrected for autocorrelation for $h=1, 2, \ldots, 5$, together with the results of testing the above mentioned null.

The condition $\alpha=0$ and $\beta=1$ is sufficient but not necessary for unbiasedness: Holden and Peel (1990) suggest testing unbiasedness through a test of $\tau=0$ in the following regression

$$O_{T+h} - P_{T+h/T} = \tau + \epsilon_{T+h} \quad (3)$$

According to results included in table 8, we accept the null hypothesis about forecasts posed for equation (2) at the usual 1% and 5% significance levels, except for M3* at the fourth and fifth steps. When testing equation (3), we do not reject the null hypothesis for any of the aggregates considered, no matter what step $h=1\ldots, 5$, at 1% and 5% significance levels. Thus, evidence indicates that forecasts from short run models are unbiased for forecasting horizons that range from 1 to 5 steps. This points towards lack of systematic forecasting errors; the possible exception is M3*, something that could be related to structural change problems detected in the model's specification (see section III.1).

### Table 8 / Forecast unbiasedness tests

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<tbody>
<tr>
<td></td>
<td>ByM</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>$h=1$</td>
<td>$h=2$</td>
<td>$h=3$</td>
<td>$h=4$</td>
<td>$h=5$</td>
</tr>
<tr>
<td>$H_0: \alpha = 0 \text{ y } \beta = 1$</td>
<td>F(2,33) 1,882</td>
<td>1,422</td>
<td>1,405</td>
<td>1,676</td>
<td>1,835</td>
</tr>
<tr>
<td></td>
<td>p-value</td>
<td>0,168</td>
<td>0,256</td>
<td>0,260</td>
<td>0,203</td>
</tr>
<tr>
<td>$H_0: \tau = 0$</td>
<td>F(2,33) 1,456</td>
<td>2,006</td>
<td>2,434</td>
<td>3,102</td>
<td>3,581</td>
</tr>
<tr>
<td></td>
<td>p-value</td>
<td>0,236</td>
<td>0,166</td>
<td>0,128</td>
<td>0,087</td>
</tr>
<tr>
<td>$H_0: \alpha = 0 \text{ y } \beta = 1$</td>
<td>F(2,33) 0,810</td>
<td>2,191</td>
<td>2,599</td>
<td>1,060</td>
<td>0,803</td>
</tr>
<tr>
<td></td>
<td>p-value</td>
<td>0,454</td>
<td>0,128</td>
<td>0,090</td>
<td>0,358</td>
</tr>
<tr>
<td>$H_0: \tau = 0$</td>
<td>F(2,33) 0,014</td>
<td>0,003</td>
<td>0,003</td>
<td>0,042</td>
<td>0,060</td>
</tr>
<tr>
<td></td>
<td>p-value</td>
<td>0,906</td>
<td>0,959</td>
<td>0,954</td>
<td>0,838</td>
</tr>
</tbody>
</table>
Although forecasts from 1 to 5 steps are unbiased, and errors associated to them insignificant, during the 1996:I-2005:III period the latter become more persistent as the forecasting horizon extends; that is, although forecasts reveal no bias, there may be variance problems –something suggested already by the Theil decomposition in 2004:III - 2005:II-. One-step forecast errors of the model in differences are uncorrelated (table 4); but as forecasts are made in levels, models become dynamic, in the sense that the variable of interest in t’s partially determined by its value in t-1. In the latter case, forecast errors’ correlation occurs as long as the forecasting horizon exceeds one step.\textsuperscript{32} We propose an adjustment to deal with this problem: correct the forecast in $T+h$ for the value of the forecast error in $T-1+h$, taking into account error autocorrelation, that is:

$$P_{T+h/T}^C = P_{T+h/T} + \phi e_{T-1+h}$$

(4)

where $P_{T+h/T}^C$ denotes the corrected $h$-step forecast made in $T$, $P_{T+h/T}$ the original $h$-step forecast made in $T$, $e_{T-1+h}$ the $h$-step forecast error made in $T-1$, and $\phi$ the autocorrelation coefficient between $e_{T-1+h}$ and $e_{T+h}$.

The proposed adjustment can be justified on econometric grounds, as well as by the analyst’s judgment. From an econometric standpoint, taking into account the structure of errors improves forecasts\textsuperscript{33}; it can be considered a sort of “learning mechanism” to foster forecast accuracy. In particular, using the adjusted model incorporating errors’ autocorrelation yields better results in terms of error variance and MSE (except for MSE in the M1* model); in table 9, values lower than 1 indicate that corrected forecasts have lower variance than uncorrected ones. Besides, once corrections are incorporated, all observations fall within a range of one standard deviation\textsuperscript{34}.

\textsuperscript{32} Strictly speaking correlation between the errors of forecasts made in $T$ and $T-j$ appears as long as the forecast horizon $h$ exceeds the distance $j$.

\textsuperscript{33} This kind of correction may be advantageous for other reasons: if the presence of a structural break gives way to serially correlated forecasts, correction through the error made in the previous step entails an improvement in forecast accuracy; see Ahumada (2005).

\textsuperscript{34} Models adjusted in this way were compared to the performance of ARIMA models in 2004:I-2005:III, in terms of Mean Squared Error (MSE). We found no difference in 1-step forecasts between both kind of models for ByM; but ARIMA yielded better M1*, M2* and M3* forecasts. For 5-step forecasts, our corrected ByM model surpasses ARIMA; in M1*, both models perform just as well; and in M2* and M3*, ARIMA models display lower MSEs.
Besides, the analyst must assess whether behaviour towards more intensive use of cash, which could explain the sign of errors observed towards the end of the sampling period, have to be incorporated to forecasts. Models estimated for 1993:II-2005:III reflect, during an important part of that period, the behaviour of agents whose sensitivity to determinantes like GDP or interest rates is different from now; thus, using estimated coefficients for forecasting must entail some error, even if it is neither statistically significant nor does it hamper the models’ forecasting ability under conventional criteria. We can only guess whether this behaviour will be sustained through time, or it will revert from now on towards more liquid definitions of real balances’ holdings. Evidence available so far is far from indicating that such reversion is to take place in the short run; taking into account the “short” forecasting horizon of this paper, we believe it makes sense to make an adjustment to forecasts.

Table 9/


<table>
<thead>
<tr>
<th></th>
<th>ByM</th>
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<th>M3*</th>
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<td>h=2</td>
<td>0.938</td>
<td>0.854</td>
<td>0.814</td>
<td>0.885</td>
</tr>
<tr>
<td>h=3</td>
<td>0.895</td>
<td>0.737</td>
<td>0.660</td>
<td>0.816</td>
</tr>
<tr>
<td>h=4</td>
<td>0.866</td>
<td>0.635</td>
<td>0.607</td>
<td>0.677</td>
</tr>
<tr>
<td>h=5</td>
<td>0.778</td>
<td>0.566</td>
<td>0.494</td>
<td>0.612</td>
</tr>
</tbody>
</table>

Mean squared error ratios 2004:III-2005:III

<table>
<thead>
<tr>
<th></th>
<th>ByM</th>
<th>M1*</th>
<th>M2*</th>
<th>M3*</th>
</tr>
</thead>
<tbody>
<tr>
<td>MSE Ratio</td>
<td>0.482</td>
<td>1.385</td>
<td>0.848</td>
<td>0.876</td>
</tr>
</tbody>
</table>

V. Concluding remarks

This paper estimates relationships between different monetary aggregates, output and interest rates, aiming at making forecasts useful to monetary policy making. Single-equation models show: acceptable global (as well as individual) goodness-of-fit; residuals that are non-autocorrelated, homoscedastic and normal; and evidence of parameter constancy. Forecasts do not display errors significantly different from zero, both at 1 and at 5 steps, and daily observed values fall within average quarterly ranges with 68% of confidence. In addition, two tests confirm forecast unbiasedness throughout the 1996:I-2005:III period. Thus, more demanding criteria than usual support the models’ forecasting capability.

We apply more demanding criteria in order to reflect the costs associated to forecast error faced by the monetary authority. Such criteria lead us to detect errors that, although insignificant, seem to indicate overestimation of wider aggregates and –to a lesser extent- underestimation of the more liquid ones. Possible underestimation of liquid forms of money may lead to unnecessarily restrictive targets; possible overestimation of wider aggregates, to excessively expansive targets. Thus, we found it convenient to introduce an adjustment based on econometric grounds as well as on analysts’ judgment: forecast errors show higher persistence as the forecast horizon increases; and evidence shows that, after the crisis, economic agents hold more cash-intensive portfolios than before, disregarding more illiquid forms of money. The adjustment we propose consists of correcting each estimate by the last observed error in the corresponding step, taking into account the forecast errors’ autocorrelation structure.
Models thus obtained are a tool for evaluating what level of monetary targets is consistent with certain macroeconomic scenario, using as inputs variables that can be systematically and consistently provided by the Small Structural Model developed at BCRA. Thus, forecasts are useful to determine whether possible monetary policy targets are too “accomodative” or, on the contrary, unnecessarily restrictive.

Making forecasts in the 1993-2005 period is particularly challenging, as it spans two different macroeconomic regimes. This turns out to be problematic when analyzing long run relationships between the chosen variables: estimated coefficients do not correspond to long-run values suggested by economic theory; and cointegration relationships are non-stationary —even controlling for certain breaks—, contradicting their very raison d’être. We believe it would make little sense to make forecasts based on an income elasticity almost equal to 2, when we know it was obtained from data that belong to a period of intense remonetization of the economy, followed by a crisis and renewed remonetization of liquid aggregates. It is true that exogeneity tests, as well as Granger causality tests, do not always suggest a single-equation approach; but we find it more costly to estimate a VECM that we know beforehand it is incorrectly specified.

There are several lines for further research, comprising both money demand determinants and the relationship between such determinants and real balances. As for the former: it looks convenient to introduce transactions through the sum of output and imports; it is important to discriminate the most suitable opportunity cost for each aggregate, as well as to include the nominal exchange rate; finally, modelling public sector deposits, either explained by tax collection or financing needs, should go a long way in improving estimates of total deposits. It must be noted, of course, that increasing the number of determinants is costly as to obtain a variable set that has to be forecasted consistently with a yearly horizon. Regarding the relationship between money holdings and its determinants: even if no equilibrium correction representation is attainable, we should try VAR models; we cannot rule out more disaggregated models, by type of deposit; finally, we could resort to tools such as co-breaking (Hendry and Massmann, 2005) or a variable coefficient approach, useful under the presence of structural breaks.
Annex A
Recursive parameter estimation - ByM

Recursive parameter estimation - M1*
Annex A (continued)
Recursive parameter estimation -M2*

Recursive parameter estimation -M3*

22
Annex B
Recursive Chow Forecast Tests (n-descending)

ByM

M1*

M2*

M3*
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