

Modelling and forecasting money demand:

divide and conquer

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Modelling and forecasting money demand: divide and conquer[†]

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Abstract:

The literature on money demand suggests several specification forms of empirical functions that better describe observed data on money in circulation. In a first stage, we select the best long-run model specification for a money demand function at the aggregate level based on forecast performance. On a second stage we divide the money in circulation by denomination and argue that determinants of a low-level denomination is different than those of a high-level. We then estimate the best model specification for each denomination and aggregate each forecast in order to have an aggregate proyection. We finally compare forecasts between these strategies. Our results indicate that the bottom-up approach has a better performance than the traditional view of directly forecasting the aggregate.

JEL Classification: C16, F31, F41

Key words: Money demand, bottom-up, co-integration, forecast.

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1. INTRODUCTION

Central banks all over the world hold a vow on achieving and maintaining the stability of the price level in their economies. In this commitment, a central banker needs a good understanding of the money demand function because it links the monetary development to its fundamental determinants. The literature agrees that the most important determinants are real income measures and the opportunity cost of holding money however there is not consensus yet of what variables have to be taken into account in order to achieve good forecasts for this key equation.

According to Walsh (2010) the monetary base are liabilities of the central bank that can be affected by open market operations and is usually viewed as the variable set by the policy authority. In this paper we use monthly data for one of the components of the monetary base. At this point, we focus on the demand for note bills. From a managerial point of view, the reasoning behind this division are twohold: (i) difference in the life expectancy between bills and coins, and (ii) dependence from an external source for the production of note bills. From the stand point of the policy maker, a central bank has to be ready to face any demand for domestic currency. In that line, the life expectancy of a bill is far shorter than the one of a coin so a central bank should plan ahead the amount of note bills in circulation and the need for replacement of those note bills when they deteriorate.

Regarding the estimation of the money demand, the traditional consensus is to use cointegration techniques based on a linear combination of two or more non-stationary time series. The linear combination then is referred as the long-run equilibrium relationship among those variables. In line with this approach, the forecasting procedure departs from a vector error correction model (VEC) that takes care of the short run dynamics and relies on the relationship dynamics among these variables. Even though there is consensus on the technique, most of the discussion is about the specification. The literature tends to focus on the set of variables that is included in the long-run relationship. The most standar representation uses nominal money balances, price level, real GDP, and a nominal short term interest rate so the most important reasons for demanding money are taken into account: transaction volume in the economy and the opportunity costs of holding money.

Departing from the basic specification, Dreger and Wolters (2014) use financial wealth and Howells and Hussein (1997) total transactions as the scale variable. In addition to the short term interest rate, the nominal long term interest rate (Dreger and Wolters, 2014), the spread between bank lending rate and money's own rate (Howells and Hussein, 1997), and the differential between the interest rate on overnight deposits and short-term deposits (Jung, 2016) are considered in this literature. The inflation rate is also considered as an opportunity cost of holding money instead of real assets (Dreger and Wolters, 2014, 2015).

Under the argument of currency substitution, any expectation of a depreciation in a domestic currency would lead to a re-composition in individual portfolios leading to hold more foreign currency rather than domestic currency. Then variables such as exchange rate and expected rate of inflation are also included in the money demand equation (see Kumar and Rao, 2012; and Kumar et al., 2013).

The first round in this paper is to let the models with different specifications compete in terms of forecasting accuracy. Each specification has a number of co-integration vectors. Once this step is determined, we search for the best VEC representation (lags, variables, and specification). We evaluate 10 specifications following this procedure and select the best possible model based on forecast accuracy.

We then add another level of *divide* and challenge the already best representation of money demand under the traditional view of forecasting the aggregate level of money. We model the

bill notes at the denomination level. This alternative strategy has the advantage to take into account the dynamics implied by the determinants for each denomination. In short, low-level denomination determinants are different than those of high-level denomination bill notes. So at the time of aggregating individual denominations we obtain fine-tuned forecasts for the aggregate.

The bottom-up strategy improves the forecast ability of the traditional strategy and beats the results obtained in the first round. Taking into consideration fundamentals at the denomination level greatly improve the forecasting performance of traditional model specifications on money demand.

The remainder of this paper is organized as follows: Part 2 briefly discuss the related literature on money demand, Part 3 describe the data used in this paper, Part 4 includes estimations, and Part 5 concludes.

2. BRIEF LITERATURE REVIEW

This review briefly discusses the main literature regarding the specification of the money demand and, therefore, the variables behind the structural equation.¹ The consensus about the most standar representation which takes into account the transaction volume in the economy and the opportunity costs of holding money is given by:

$$(m-p)_t = \alpha_0 + \alpha_1 \ y_t + \alpha_2 \ R_t + \varepsilon_t \tag{1}$$

where *m* denotes nominal money balances taken in logs, *p* is the log of the price level, *y* is the log of real GDP, *R* is the nominal short term interest rate, ε is an error term, and the index *t* denotes time.

¹ See, for example, Ireland (2009) and Walsh (2010) for comprenhensive discusions and surveys and Lucas and Nicolini (2015) and Ireland (2015) for modelling the money demand in times of a financial crisis.

This group of standar variables has some support in cross-country studies. In terms of panel co-integration and following Pedroni (1999, 2002), Kumar and Bhaskara (2012) and Carrera (2016) use FMOLS to test for cointegration of money demand for Asian and Latinamerican countries and find a welldefined long-run demand for money. Zuo and Park (2011) argue that the money demand of a transition economy requires a time-varying cointegration approach and find that the overall effect of the interest rate on the money holding is weak.

Regarding the scale variable, the traditional view is that GDP is the variable that best describe transactions in the economy. However, there is a possibility that non-GDP transactions might have an important influence on the demand for money. In the absence of a total transactions series Palley (1995) sugest the use of transactions in real estate (value of sales of existing family homes) and of financial assets (value of transactions on the NYSE) as proxies for total transactions and finds that they improved the out-of-sample forecasts on money demand. Howells and Hussein (1997) find that a direct measure of total transactions (estimated by adding payments recorded by payments systems) outperforms the proxies used in Palley (1995) for money demand. More recently, Dreger and Wolters (2014, 2015) use real financial wealth in their study of money demand, in order to identify stability in times of unconventional monetary policy in the US.

In addition to the short-term interest rate, the opportunity costs of holding money are proxied by nominal long-term interest rate (see Dreger and Wolters, 2014). Howells and Hussein (1997) considers the spread between bank lending rate and money's own rate and Jung (2016) takes the differential between the interest rate on overnight deposits (the "typical" alternative investment) and short-term deposits (the own rate of return).

The inflation rate is also considered as an opportunity cost of holding money. The underlying fact is families get an incentive to increase their consumption as they are able to buy less goods and services in future than now as prices keep increasing (see for example, Dreger and Wolters 2014, 2015). Another variable to be considered is expected inflation because agents tend to be rational and so they take future decisions based on current conditions (see Darrat and Al-Sowaidi, 2009).

The inclusion of the exchange rate in the money demand function is based on the argument of currency substitution. Any expectation of a depreciation in a domestic currency would lead to a re-composition in individual portfolios leading to hold more foreign currency rather than domestic currency. Some authors such as Kumar and Bhaskara (2012) and Kumar et al. (2013) argue that exchange rate movements are also used as a proxy for the expected rate of inflation (exchange rate pass-through literature).

3. DATA CHARACTERISTICS

For this study we consider the period 2002 - 2015, thus including observations during the World economic and financial crisis. This period is choosen because the central bank of Peru changed its monetary policy strategy in 2002, specifically, it decided to adopt an inflation targeting regime. The interest rate rather than a monetary aggregate is used as a cross-check and signal for the medium to the long-run perspective. The analysis produces money in circulation forecasts for the period 2014 – 2015 that is evaluated with out-of-sample data.

This paper uses monthly data for the components of the monetary base i.e. bill notes of different denomination in circulation. At this point, we ignore the component of coins in circulation. As part of the strategy we divide the monetary base into demand for bill notes and for coins, and then conquer by focusing, estimating, and forecasting the demand for bill notes. The reasoning behind this division are twohold: (i) difference in the life expectancy between bill notes and coins, and (ii) dependence from an external source for the production of bill notes.

From the stand point of the policy maker, a central bank has to be ready to face any demand for domestic currency. In that line, the life expectancy of a bill is far shorter than the one of a coin. That is why a central bank should plan ahead the amount of this type of money in circulation and the need for replacement of those bills when they deteriorate.

Measures of monetary base components, interest rates, inflation expectations, and electronic transactions are taken from the Peruvian central bank web page. Real GDP and inflation are the series reported by the National Accounts Division, National Institute of Statistics of Peru.

The short term interest rate is the 1 month interest rate, the long term interest rate is 1 year interest rate, the inflation rate is Peruvian 12-months CPI variations and the exchange rate is measured as US dollar per unit of domestic currency. Following Carrera (2012), the 12-months ahead expectation is a lineal combination from the end-of-the year and next year expected inflation taken from the Survey for Macroeconomic Conditions from the Central Bank of Peru.

4. ESTIMATIONS AND EMPIRICS

As Jung (2016) points out, linear models embodying error-correction mechanisms have become the standard macroeconometric tool in the empirical literature on money demand. We begin this section with a selection criteria for the best specification of a money demand by following the cointegration strategy at the aggregate level. Then we replicate the same methodology at the denomination level. We close this section with the collusion between results from aggregate and from bottom-up strategy.

4.1 Traditional approach: Co-integration and VEC

Engle and Granger (1987) motivate most of the co-integration literature by pointing out that a linear combination of two or more non-stationary time series may be stationary. If a stationary linear combination among those variables exists, those non-stationary series are cointegrated. The stationary linear combination is usually called the cointegrating equation and referred as the long-run equilibrium relationship among those variables.

The development of the theory of non-stationary time series analysis includes those studies on money demand. Here the discussion turns around the specification. The literature focuses on the set of variables that is included in the long-run relationship. The most standar representation is given by Equation (1) that takes into account the transaction volume in the economy and the opportunity costs of holding money.²

Alternatibe scale variable are different measures of wealth: financial wealth and total financial transactions (see Dreger and Wolters, 2014; and, Howells and Hussein, 1997).

Alternative variables for opportunity costs of holding money are the long-term interest rate (see Dreger and Wolters, 2014), the spread between bank lending rate and money's own rate (see Howells and Hussein, 1997), and the differential between the interest rate on overnight deposits and short-term deposits (see Jung, 2016). The inflation rate and its expected value are also considered as opportunity cost of holding money (see for example, Dreger and Wolters 2014, 2015).

For currency substitution reasons, the exchange rate and related variables are included in the set of fundamentals for the money demand function. Any depreciation in a domestic currency lead to a re-composition in individual portfolios and agents hold more foreign currency rather than domestic currency.

² Nakashima and Saito (2012) study the case of different forms to introduce the interest rate (in log or in levels) for the case of Japan, given the extremely low insterest rate regime observed in the Japanese economy.

Given the large list of variables that cointegrate with money in circulation, we let all these specifications to compete with each other in terms of forecasting accuracy. In Table 1 we present all the models (and their associated variables) that are estimated.

Model	Variables						
M1	Real GDP, short interest rate						
M2	Real GDP, short interest rate, long term interest rate						
M3	Real GDP, short interest rate foreign currency, long term interest rate foreign currency						
M4	Real GDP, short interest rate, long term interest rate, exchange rate						
M5	Real GDP, short interest rate, long term interest rate, exchange rate, inflation						
M6	Real GDP, short interest rate, long term interest rate, exchange rate, expected inflation						
M7	Electronic transactions, short interest rate, long term interest rate, exchange rate, inflation						
M8	Electronic transactions, short interest rate, long term interest rate, exchange rate, expected inflation						
M9	Real GDP, short interest rate, dollarization coefficient						
M10	Real GDP, dollarization coefficient						

In our estimations we first consider the number of cointegrating vectors (some specifications have up to 2 vectors). Then, we estimate the vector error correction model (VEC) that best describe the data and use this model to forecast futures values on money in circulation.³ As part of our strategy, we estimate every model by using a sample from 2002 to 2013, forecast the period 2014 - 2015, and calculate the out-of-sample root mean squared error (RMSE).

Forecasts are divided by forecasting windows (H). The minimum number of periods ahead to be considered is 1 month (H=1) while the maximum is 24 months (H=24, 2 years). We use rolling windows in order to achieve consistency through different sample periods and generate one RMSE for each window and model.

To conclude this first round of forecasting, we set the RMSE coming from model 10 (M10) as the benchmark to the remaining models, in other words, we present the ratio of the RMSE

³ The optimal lag of each VEC is determined by AIC y SIC.

from any forecast from any estimated model relative to the RMSE coming from M10 forecasts. We refer to this ratio as relative root mean squared error (relative RMSE).

In Table 2 we present the relative root mean squared error. From this table we conclude that most simple standard model M1 does better in the long-run while more complex models such as M6 and M5 perform better in the short run.

	H=1	H=3	H=6	H=12	H=18	H=24	
M1	113.7	119.0	110.4	84.4	85.7	83.5	
M2	109.8	113.7	107.3	82.6	84.7	84.1	
М3	115.6	115.7	111.0	85.5	82.9	89.3	
M4	107.2	97.8	95.7	78.0	83.5	90.2	
M5	96.2	89.0	83.3	78.1	89.2	90.8	
M6	85.1	85.5	86.0	83.5	89.7	90.8	
M7	105.9	102.0	86.4	85.2	99.0	95.0	
M8	101.5	107.1	93.4	90.7	100.2	100.2	
M9	99.9	97.4	94.6	95.7	96.5	98.4	

NOTES: RELATIVE RSME IS THE ROOT SQUARED OF THE MEAN FORECAST ERROR OF MODEL I WITH RESPECT TO MODEL 10. H STANDS FOR THE HORIZON WINDOW OF FORECASTING. A RELATIVE RSME ABOVE ONE HUNDRED MEANS THAT THE ALTERNATIVE APPROACH PERFORMS WORSE THAN M10 model.

4.2 *The bottom-up approach*

A natural extension of this analysis is the use of the same strategy for each denomination note bill (10, 20, 50, 100, and 200). For each denomination, we estimate 10 different models and forecast with the best possible model. We then aggregate those forecasts, and generate an aggregate forecast.

Simple model M3 based on foreign interest rates performs better for 10 soles bill. For 20 soles bill, M8 that has electronic transactions as the scale variable performs better in longer periods of forecasting. M9 with the coefficient of dollarization does better than other model specifications forecasting longer periods of 50 soles bill. In the case of 100 soles bill, exchange rate and expected inflation do better in forecasting up to two years ahead. Finally, 200 soles bill determinants are the benchmark variables GDP and coefficient of dollarization (see Table

			10							20			
	H=1	H=3	H=6	H=12	H=18	H=24		H=1	H=3	H=6	H=12	H=18	H=24
M1	94.9	97.2	97.4	97.0	97.9	173.8	М1	92.7	89.0	91.0	104.5	104.7	113.2
		-	-					92.7 91.6					
M2	82.7	96.0	91.7	75.2	97.9	138.5	M2		89.1	91.8	105.4	106.3	119.8
M3	77.2	91.5	86.4	68.4	94.2	28.4	M3	92.3	84.1	94.5	91.4	88.7	91.2
M4	100.6	106.3	99.7	97.8	92.0	548.7	M4	106.2	98.7	105.5	101.3	105.1	167.0
M5	91.7	106.0	93.1	64.7	92.9	84.4	M5	93.5	85.4	90.1	92.8	103.7	137.2
M6	102.7	127.5	107.1	70.7	112.5	453.5	M6	93.3	87.8	96.1	88.5	87.6	66.7
M7	101.1	123.5	91.6	95.3	90.1	421.0	M7	103.7	101.0	96.8	84.8	84.8	89.8
M8	99.0	122.6	93.3	97.8	87.6	554.1	M8	104.8	102.9	96.8	78.3	74.7	0.3
M9	99.4	103.5	101.4	97.4	95.3	344.3	M9	100.1	101.5	101.2	107.1	100.4	90.7
	50									100			
	H=1	H=3	H=6	H=12	H=18	H=24		H=1	H=3	H=6	H=12	H=18	H=24
M1	88.9	88.8	91.0	107.0	77.8	50.6	M1	100.8	109.6	103.0	100.8	102.8	93.5
M2	76.3	91.2	102.7	139.2	98.8	115.7	M2	96.4	104.7	100.4	100.2	102.9	93.7
M3	96.0	94.6	97.3	154.9	111.2	116.5	М3	97.8	103.3	99.5	97.7	98.8	95.9
M4	88.9	90.4	89.3	112.6	105.6	110.5	M4	76.5	76.9	70.0	83.5	94.3	89.4
M5	89.1	89.0	88.2	126.0	108.9	112.3	M5	83.3	77.3	73.6	88.8	102.0	91.4
M6	96.1	94.2	96.3	117.8	100.7	110.2	M6	78.9	74.8	73.3	87.5	87.9	87.2
M7	95.4	110.0	100.8	293.7	159.2	100.8	M7	89.8	84.3	69.6	86.2	105.5	88.5
M8	101.5	108.1	93.1	146.9	118.6	106.0	M8	87.7	84.9	60.7	80.1	100.7	90.7
IVIA													

 TABLE 3 – RELATIVE ROOT MEAN SQUARED ERROR

200									
	H=1	H=3	H=6	H=12	H=18	H=24			
M1	107.7	183.8	271.0	285.1	211.6	214.2			
M2	122.0	221.1	320.8	329.2	234.3	228.9			
M3	113.6	168.5	242.4	247.1	179.1	167.6			
M4	69.9	104.3	116.3	179.7	165.5	180.0			
M5	108.9	197.5	308.5	324.9	230.5	218.4			
M6	85.2	98.1	99.3	170.6	161.1	167.7			
M7	61.5	97.5	155.7	252.5	223.9	220.8			
M8	86.0	96.1	108.4	112.5	119.2	145.6			
M9	92.7	97.5	96.4	101.2	102.7	102.7			

NOTES: RELATIVE RSME IS THE ROOT SQUARED OF THE MEAN FORECAST ERROR OF MODEL I WITH RESPECT TO MODEL 10. H STANDS FOR THE HORIZON WINDOW OF FORECASTING. A RELATIVE RSME ABOVE ONE HUNDRED MEANS THAT THE ALTERNATIVE APPROACH PERFORMS WORSE THAN M10 MODEL.

This bottom-up strategy has better forecasts than the original traditional approach. The RMSE from M1 in directly forecast the aggregate is 4639 while the RMSE from aggregating the forecast from the 5 best models is 3834. By dividing and conquering, we uncovered the fact that determinants for each denomination tend to differ, according to the denomination we intend to forecast in the long-run.

5. CONCLUSIONS

The bottom-up approach of forecasting components and then aggregate them has more accurate proyections than the traditional approach of straight forecasting the aggregate money in circulation. The most important determinants (real income measures and opportunity cost of holding money) are tested in terms of forecasting power and the best models are choosen according to the RMSE in an out-of-sample evaluation.

In a first round, we select the best model by testing different variables that co-integrate with the money demand and have support in the literature. The winner is a simple standard model that has GDP and a short-term interest rate as the fundamental variables that best forecast under a long-run perspective.

Then we extend the same methodology but for each denomination (here we divide) under the view that determinants of a low-level denomination are different than those of a high-level. For each denomination we get the best model. We out-of-sample forecast the money demand for each denomination and finally bottom-up those forecast in order to have an aggregate proyection.

Comparing results in terms of long-run forecast error suggests that the bottom-up approach leads to more accurate proyections of the money demand. We do not find anyother specification at the aggregate that change the ultimate outcome.

The literature on money demand is still very active, shedding light and spewing new forecasting strategies. But no doubt it considers the actual state of the art a work in progress along that long march of forecasting acuracy. For example, forecasting with a mix of large BVARs and bottom-up strategy in line with Carrera and Ledesma (2015) is still another way to go in this arena.

REFERENCES

Carrera, C. (2016). "Long-Run Money Demand in Latin-American countries: A Nonstationary Panel Data Approach", Monetaria, CEMLA, forthcoming.

Carrera, C. (2012). "Estimating Information Rigidity Using Firms' Survey Data," The B.E. Journal of Macroeconomics, De Gruyter, vol. 12(1), pages 1-34, June.

Carrera, C., Ledesma, A. (2015). "Aggregate Inflation Forecast with Bayesian Vector Autoregressive Models," Working Papers 2015-50, Peruvian Economic Association.

Darrat, A., Al-Sowaidi, S. (2009). "Financial progress and the stability of long-run money demand: Implications for the conduct of monetary policy in emerging economies." *Review of Financial Economics* 18, 124-131.

Dreger, C., J. Wolters (2014). "Money demand and the role of monetary indicators in forecasting euro area inflation." *International Journal of Forecasting* 30, 303-312.

Dreger, C., J. Wolters (2015). "Unconventional monetary policy and money demand." *Journal of Macroeconomics* 46, 40-54.

Engle, R., Granger, C. (1987). "Co-integration and error correction: Representation, estimation and testing." Econometrica, 35, 251–276.

Howells, P., Hussein, K. (1997). "The demand for money: Total transactions as the scale variable." Economics letters 55, 371-377.

Ireland, P. (2009). "On the Welfare Cost of Inflation and the Recent Behavior of Money Demand." American Economic Review, 99:3, 1040–1052

Ireland, P. (2015). "Comment on: On the stability of money demand." *Journal of Monetary Economics* 73, 66-69.

Jung, A. (2016). "Is euro area money demand for M3 still stable?" *The Quarterly Review of Economics and Finance, forthcoming.*

Kumar S., Webber, D., Fargher, S. (2013). "Money demand stability: A case study of Nigeria." *Journal of Policy Modeling* 35, 978-991.

Kumar, S., Bhaskara, B. (2012). "Error-correction based panel estimates of the demand for money of select Asian countries with extreme bounds analysis." *Economic Modelling* 29, 1181-1188.

Lucas Jr., R., Nicolini, J. (2015). "On the stability of money demand." *Journal of Monetary Economics* 73, 48-65.

Nakashima, K., Saito, M. (2012). "On the comparison of alternative specifications for money demand: The case of extremely low interest rate regimes in Japan." *Journal of the Japanese and International Economies* 26, 454-471.

Palley, T. (1995). "The demand for money and non-GDP transactions." Economics Letters 48, 145-154.

Pedroni, P. (1999). "Critical values for cointegration tests in heterogeneous panels with multiple regressors." Oxford Bulletin of Economics and Statistics 61, 653-70.

Pedroni, P. (2002). "Fully modified ols for heterogeneous cointegrated panels." In B. H. Baltagi (Ed.), Recent Developments In The Econometrics Of Panel Data, Volume 1, Chapter 20, pp. 424-461. Edward Elgar Academic Publications.

Walsh, C. (2010). "Monetary Theory and Policy." Third Edition, MIT Press Books, The MIT Press, edition 3, volume 1.

Zuo, H., Park, S. (2011). "Money demand in China and time-varying cointegration." China Economic Review 22, 330–343.