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# ABOUT THE ROLE OF MONETARY AGGREGATES FOR MONETARY POLICY: THE CASE OF PERU

**Erick Lahura y Donita Rodríguez**

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# ABOUT THE ROLE OF MONETARY AGGREGATES FOR MONETARY POLICY: THE CASE OF PERU

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## RESUMEN

El propósito principal de la presente investigación es analizar la relevancia de los agregados monetarios para la política monetaria como indicadores de la actividad económica real. La principal hipótesis de este trabajo es que los agregados monetarios más líquidos ayudan a predecir el producto real. El análisis empírico combina la descomposición de las series de tiempo usando funciones "wavelets" y la posible existencia de relaciones de cointegración entre dinero, producto y precios. Usando datos recientes para la economía peruana, se encuentra evidencia a favor de la hipótesis planteada. En particular, los resultados sugieren la existencia de co-integración entre series no estacionarias construidas a partir de funciones wavelets. En este contexto, las pruebas de exogeneidad revelan que los agregados monetarios más líquidos son débil y fuertemente exógenos, y por lo tanto ayudan a predecir el producto real. Estos resultados sugieren que el dinero puede ser útil para la política monetaria como indicador de la actividad económica real.

## ABSTRACT

The purpose of this paper is to analyze the relevance of monetary aggregates for monetary policy as indicators of real activity. The main hypothesis of this paper is that narrow monetary aggregates can help forecasting real output. The empirical analysis combines the time scale decomposition of time series using wavelets and the possible existence of cointegrating relationships between money, output and prices. Using recent Peruvian data, evidence is found to support the proposed hypothesis. In particular, the results suggest the existence of co-integration between non-stationary series built using wavelet filtering. In this context, exogeneity tests reveal that narrow monetary aggregates are weakly and strongly exogenous; i.e., they are helpful for forecasting real output. These results suggest that money has a role for monetary policy as an indicator of real activity.

# ABOUT THE ROLE OF MONETARY AGGREGATES FOR MONETARY POLICY: THE CASE OF PERU[1]

Erick Lahura[2] and Donita Rodriguez[3]

## 1. INTRODUCTION

The purpose of this paper is to provide some insights about the empirical relationship between money and real output in Peru, in order to establish if there is any role of monetary aggregates for monetary policy as indicators of real activity[4]. The motivation of this paper is associated with recent theoretical literature and practices of central banks, which reveal a tendency to discard the use of monetary aggregates in the conduction of monetary policy (the European Central Bank is an important exception). However, monetary aggregates can be useful for monetary policy as long as they could provide relevant information about future real output. Therefore, the main hypothesis analyzed in this paper is that narrow monetary aggregates can help forecasting real output.

The empirical analysis is based on orthogonal decomposition of series by time scale using wavelets, following Ramsey and Lampart (1998), and subsequent research by Chew (2001) and Gençay et al. (2002). These authors have applied wavelets to the analysis of the short-run relationship between money and output, achieving two main results: (1) the link between money and real output is not unique, and (2) the direction of Granger causality depends on the timescale considered.

In this paper we go a little bit further in the empirical analysis of money-output relationship using wavelets. Specifically, we propose the application of wavelet filtering to analyze cointegrating relationships. For the Peruvian case, the data show no evidence of co-

[1] This paper is an extension of Lahura (2003) and it was presented in the Latin American Meeting of the Econometric Society 2004 (LAMES 2004), Santiago de Chile. The authors would like to thank the participants in the Time Series Econometrics session of LAMES 2004, Paul Castillo (Central Bank of Peru and London School of Economics), Rocío Gondo (Central Bank of Peru) and the anonymous referee. They also thank Pierre Perron for his helpful comments and suggestions on an early version of the paper.

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[4] A natural extension of this paper would be to replicate the analysis for Latin American countries and other developing countries.

integration between money, real output and prices. However, it is found evidence that support the hypothesis of cointegration between non-stationary series constructed from the original ones. The main feature of this result is that these non-stationary series that co-integrate are obtained from their time scale descomposition based on wavelet functions. In particular, each time series is the sum of different components associated to a different time scale. Given the nature of the cointegrating relationship found in this paper, this result could be considered as an alternative way to represent hidden co-integration, as proposed by Granger and Yoon (2002).

In this context, evidence is found to support the hypothesis that narrow monetary aggregates can help forecasting real output, but at intermediate time scales. Specifically, exogeneity tests reveal that narrow monetary aggregates are weakly and strongly exogenous, i.e., they are helpful for forecasting real output. These results suggest that money has a role for monetary policy as an indicator of real activity.

The paper is organized as follows. In section 2, a short review of recent literature about the role of money for monetary policy is presented. In section 3, it is introduced the time scale decomposition of time series using wavelets. Section 4 provides a description of the data. Section 5 shows how the traditional approach —standard time series econometrics techniques— provides no clear evidence about the relationship between money and real output in the long run. In section 6, non-stationary series are constructed from the original series (money, real output and prices), adding different components obtained from their time scale decomposition. Then, it is found evidence of co-integration between these non-stationary components of the series. Furthermore, the resulting error correction model is not based on just the first difference of series, but on specific time scales. Within this empirical framework, evidence is found on the fact that narrow monetary aggregates can help forecasting real output, but at intermediate time scales. In section 7, conclusions are presented.

## 2. THE ROLE OF MONEY FOR MONETARY POLICY: A BRIEF REVIEW

In contrast with the traditional monetarist approach leaded by Friedman (1969) in which money is the key variable for monetary policy, Taylor (1993) establishes that monetary policy decisions can be well-approximated by a simple interest-rate rule —known in the literature as Taylor' s rule— in which the interest rate responds to observed movements of

the inflation rate and deviations of output from a trend (or a measure of potential output). After Taylor's work, most models of monetary policy usually have incorporated the "Taylor's rule" or some variant, but with a common feature: the absence of money (monetary aggregates). New Keynesian models are the main examples of monetary analysis with no explicit reference to monetary aggregates (Clarida et al., 1999; Woodford, 2003).

In this context, many authors have re-examined the role of monetary aggregates for monetary policy. Coenen et al. (2005) and Dotsey and Hornstein (2003) are two recent empirical papers that analyze the role of money for monetary policy. Coenen et al. (2005) perform a quantitative assessment of the role of money as an indicator variable for monetary policy in the euro area. They show that monetary aggregates may have substantial information in an environment with high variability of output measurement errors, low variability of money demand shocks, and a strong contemporaneous linkage between money demand and real output. However, as a practical matter, they conclude that money has fairly limited information content as an indicator of contemporaneous aggregate demand in the euro-area.

Dotsey and Hornstein (2003) evaluate how useful is money for monetary policy within the context of optimal monetary policy in a general equilibrium environment. They found that even though money gives information on aggregate output, it is of limited use for a policy maker. Nevertheless, they emphasize that (a) it is an empirical matter if money is useful as a signal, and (b) if money demand is more stable than it appears for the United States, the role of money could dramatically change. In particular, money would be a useful signal in an environment driven by productivity shocks, but not in the presence of money demand disturbances. This finding suggests that the policymaker's responsiveness to money could be time varying.

Despite this unclear evidence about the role of monetary aggregates for monetary policy, Nelson (2003) performs a theoretical analysis and concludes that money is useful for monetary policy. According to Nelson (2003, p. 1030), "the use of Taylor's rule for monetary policy analysis is neutral on the issue of the importance of monetary aggregates. The fact that actual policy is well characterized by a rule with no explicit money terms does not preclude a role for monetary aggregates in the transmission of monetary policy or in the analysis of inflation". According to this argument, Taylor (1992) stated that money should continue to play an important role for monetary policy formulation in the future, as long as there is evidence that large movements in inflation are related to money growth. This advice

has been followed by the European Central Bank, in contrast with the decreasing importance of money observed in several central banks, as in the case of the Federal Reserve.

New Keynesian models of monetary policy do not give an explicit role to monetary aggregates. For Nelson (2003), this implies that New Keynesian models do not consider one important element of most monetarist models: the notion that a spectrum of yields matters for the determination of aggregate demand and money demand. The main implication of this feature is that money conveys information about monetary conditions that the short-term interest rate does not. In others words, the most fruitful area in which money can play a greater role for cyclical analysis is as a proxy for yields that matter for aggregate demand, some of which do not have a ready counterpart in securities-market interest rates. As a conclusion, Nelson (2003, p.1054) states that "The information imparted to money by its relationship to yields that matter for aggregate demand, gives money value to monetary policy, even when money is absent from the key structural relationship".

In this paper, considering the above literature and recent practices implemented by central banks which do not take into account explicitly monetary aggregates, the hypothesis that money can help to forecast movements in real output for the Peruvian case is empirically analyzed. In particular, and considering wavelet-based filtering of time series (usually called "time scale decomposition"), we hypothesized that intermediate time scales of money can help to forecast intermediate time scales of real output. In terms of monetary policy, this would be a useful indicator for future expansions or contractions of real activity of approximately 4-to-8 months of duration.

## 3. AN INTRODUCTION TO *WAVELETS*[5]

*Wavelets* are mathematical functions that can be used to decompose a signal into components associated to information in the frequency (scale) and time domain. The analysis of a signal using wavelets can be compared to a camera with sophisticated lens, which provides a panoramic view of a city (i.e., buildings, avenues), and also a detailed view[6] (i.e., trees, cars, windows). As far as it is known, wavelet functions appeared in

[5] This section is based on Lahura (2004).
[6] This analogy follows Schleicher (2002).

Alfred Haar's Thesis (1910). However, as a mathematical theory, wavelets were not known until mid-80's, due to Morlet (1984) and Mallat (1988)[7].

The Wavelet transform (WT) is a mathematical instrument that describes a signal in the frequency and time domain in contrast to traditional filtering methods as Hodrick-Prescott, Baxter & King and Kalman filter, as can be seen in Gencay et al. (2002). WT is similar to Window Fourier Transform (WFT), but presents some important differences. As stated by Gencay et al. (2002, p.3), "the wavelet transform intelligently adapts itself to capture features across a wide range of frequencies and thus has the ability to capture events that are local in time. This makes the wavelet transform and ideal tool for studying non-stationary or transient time series. [In particular, WT is useful for] seasonality filtering, de-noising, identification of structural breaks, separating observable data into timescales (the so-called multiresolution analysis) and comparing multiple time series."

3.1. Definition of wavelet

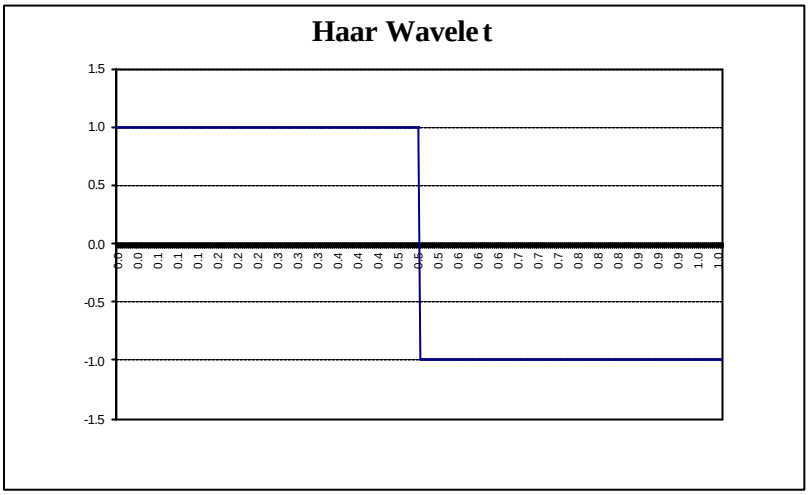
A ***wavelet*** $\psi(t)$ is a function that depends on time that presents two important properties: (1) admissibility condition, and (2) the unit energy. One of the most famous *wavelets* is the Haar wavelet, defined as:

$$\psi(x) = \begin{cases} 1 & 0 \le x < 0.5 \\ -1 & 0.5 \le x < 1 \\ 0 & other \end{cases} \qquad (3.1)$$

In general, conditions (1) and (2) stated above determine the shape of a wavelet: a waveform with zero mean, which is shown below:

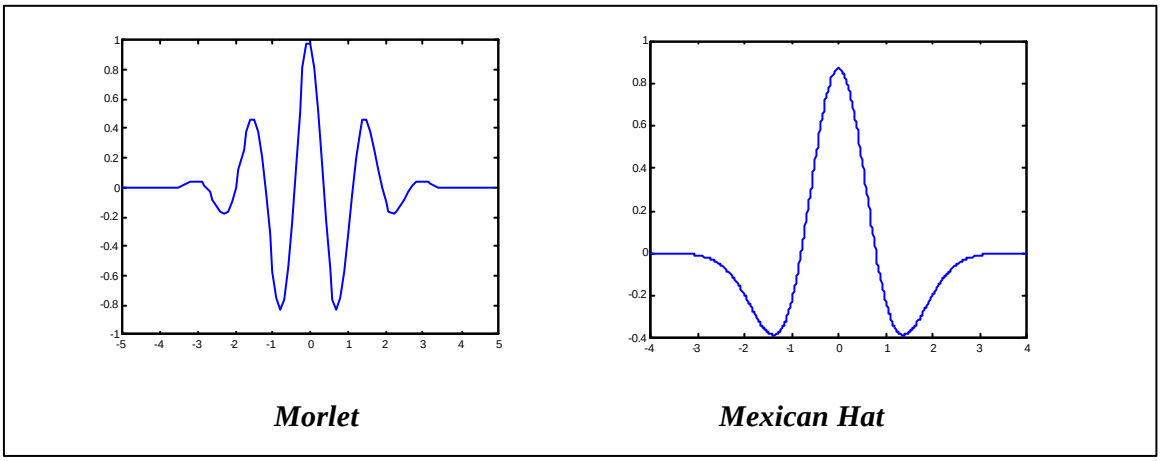
[7] As stated in Misiti, et al. (2002), the concept of wavelets -as it is known in the present- was first proposed by Jean Morlet and the team at the Marseille Theoretical Physics Center while working under Alex Grossmann in France. The main algorithm dates back to Stephane Mallat (1988).

**Figure 1**




Other well-known wavelet functions are Morlet and Mexican Hat, which are shown in Figure 2:

**Figure 2**




3.2. Wavelet families

A wavelet $\psi(t)$ can be used to generate a family of wavelet functions, by dilating and translating $\psi(t)$:

$$\psi^{a,b}(t) = \frac{1}{\sqrt{a}}\psi\left(\frac{t-b}{a}\right) \qquad (3.3)$$

Parameter "$a$" is called "scalar" or "dilation" factor, which allows to expand the range of a wavelet: when "$a$" is high, $\psi(t)$ is a wave that completes its movement along a wider range than when "a" is "low". Parameter "b" is denominated the translation factor, which allows moving the range of $\psi(t)$. In this way, translating and dilating a wavelet $\psi(t)$ generates a family of wavelet functions $\psi^{a,b}$, in which each member of the family is associated to a specific scale and temporal location (time scale). When a wavelet $\psi$ generates a family of wavelets, it is called "mother wavelet".

The dilation and translation parameters "a" and "b" could take discrete values. For example, if $a = a_0^j$ y $b = nb_0a_0^j$, then each element of the wavelet family is given by:

$$\psi_{j,k} = \frac{1}{\sqrt{a_0^j}}\psi\left(\frac{t - kb_0a_0^j}{a_0^j}\right) \tag{3.3}$$

or:

$$\psi_{j,k} = a_0^{-j/2}\psi(a_0^j t - kb_0) \tag{3.4}$$

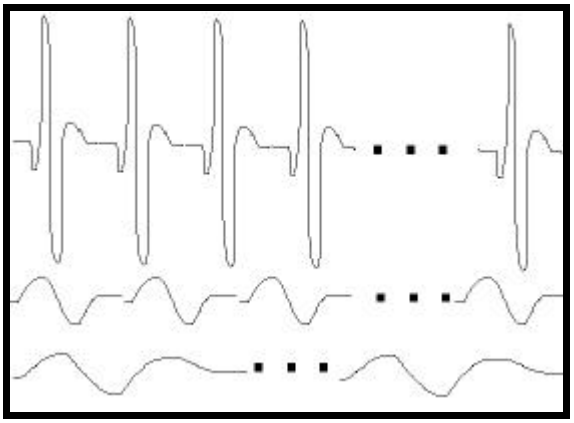
where $j$ and $k$ take integer values, $a_0 > 1$ y $b_0 > 0$. As Figure 3 illustrates, values of $j$ will determine the amplitude and translation factor of a wavelet:

a) ***Compressed or low scale wavelets*** (usually, associated to high frequency components) correspond to low values of $j$. This means that to cover the entire range over which the signal is defined, wavelet functions are translated into small intervals.

b) ***Stretched, dilated or high scale wavelets*** (usually, associated to low frequency components) correspond to high values of $j$. This means that to cover the entire range over which the signal is defined, wavelets functions are translated into big intervals.

**Figure 3**

**Dilation and translation of a wavelet**



Given the main features of wavelets, it can be seen that they make possible the analysis of a signal with varying frequency components, i.e. a **non-stationary signal**. This is explained by the capability of wavelets to adapt their form —through dilation and translation— to capture the main characteristics of a given signal, and so they are able to identify different features at different frequencies (in terms of scales) and time periods. In this sense, it is possible to obtain a better representation of a signal using wavelets than using WFT[8].

3.3. Multiresolution Analysis (MRA).

Multiresolution analysis is the mathematical formalization of a simple idea: to obtain successive approximations of a signal, so that each new approximation is better than the last one. If

$$\ldots, S_J, S_{J-1}, S_{J-2}, \ldots \qquad (3.5)$$

represents a MRA, then $S_{J-1}$ is a better approximation than $S_J$, i.e. with a better resolution. The differences between the various successive approximations are called details:

$$D_J \equiv S_{J-1} - S_J \qquad (3.6)$$

[8] See Kaiser (1994) for a reference of Windowed Fourier Transform.

Given this, an approximation can be expressed as the sum of a lower-resolution approximation plus a detail:

$$S_{J-1} = S_J + D_J \tag{3.7}$$

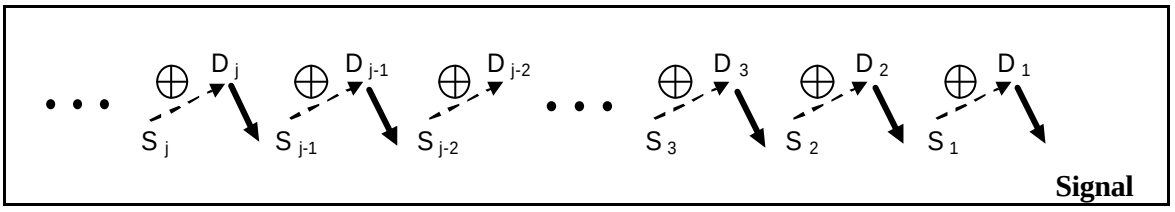
In general, if $S_1$ denotes the best approximation (the one with the highest resolution) of a signal $f(t)$, the it is true that:

$$f(t) = S_1 + D_1 \tag{3.8}$$

If there exists a MRA for a signal, then it is possible to obtain different approximations of the signal expressed as the sum of an approximation of lower resolution and a detail:

$$\begin{aligned} S_1 &= S_2 + D_2 \\ S_2 &= S_3 + D_3 \\ &\vdots \\ S_{j-1} &= S_j + D_j \\ S_{j-2} &= S_{j-1} + D_{j-1} \end{aligned} \tag{3.9}$$

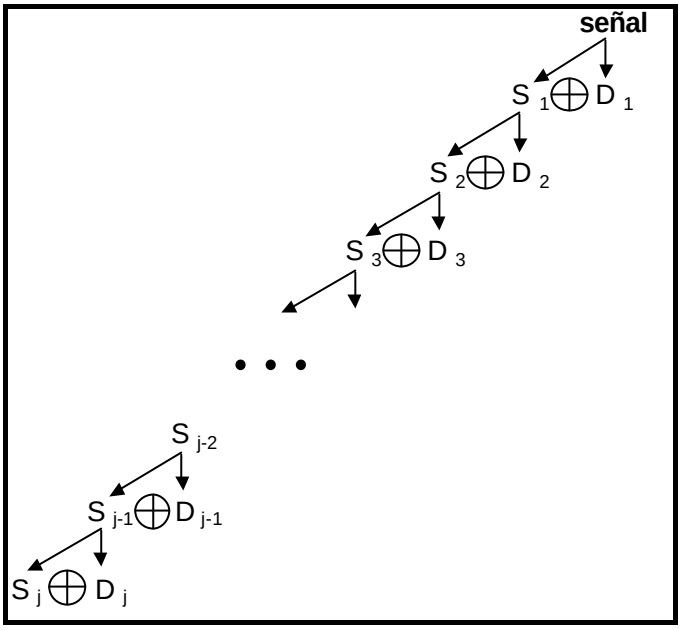
which yields the following process to approximate the original signal:




In this way, multiresolution analysis is able to express a signal $f(t)$ as the (orthogonal) sum of an approximation $S_J$ and different details $D_J$:

$$f(t) = S_J + D_J + D_{J-1} + \ldots D_j + \ldots + D_1 \tag{3.10}$$

The following diagram illustrates the multiresolution approach:




3.4. Multiresolution analysis and *wavelets*.

Daubechies (1992, p. 10), shows that given that a family of wavelets constitute an orthonormal basis for $L^2$ functions, then there exists a MRA that allows a signal to be decomposed into its orthogonal components. Furthermore, these components depend on two wavelet functions: (i) a ***father wavelet***, which captures trend or smoothing components of a signal, and (ii) a ***mother wavelet***, which captures cyclical movements associated to specific time scales. The existence and properties of the MRA are key elements of the wavelet-based analysis necessary to evaluate the hypothesis of the present paper.

One of the most important results of wavelet theory is the existence of a correspondence between multiresolution analysis of a signal and a wavelet family. In particular, Daubechies (1992, p. 129-135) shows that if there exists a MRA for a signal in the $L^2(\Re)$ space[9] (or square integrable signal), then there exists an associated orthonormal wavelet basis for $L^2(\Re)$, such that it allows decomposing a signal into orthonormal components $S_J$ and various $D_j$ which depend on a family of *wavelets*:

[9] A function $f$ belongs to the $L^2(\Re)$ space if the integral of $|f|^2$ is finite. For further details, see for example Kaiser (1994).

$$D_j = \sum_k d_{j,k}\psi_{j,k}(t) \quad , j = 1, 2, \ldots, J-1 \qquad (3.11)$$

$$S_J = \sum_k s_{J,k}\phi_{J,k}(t) \qquad (3.12)$$

On one hand, the details $D_j$ (equation 3.11) are associated to scales lower than $J$. Formally, these details are obtained from discrete wavelet transforms, which are projections of the signal on a family of wavelets $\psi_{j,k}(t)$, which is generated by translation and dilation of a ***mother wavelet*** $\psi$, using as the translation factor $k = 0, 1, 2, \ldots$ and as the dilation factor $a = 2^j$, with $j = 1, 2, 3, \ldots$. On the other hand, the approximation $S_J$ (equation 3.12) is the component associated to the highest scale $J$ of the signal. This detail is obtained using the discrete wavelet transform, which is the projection of the signal on a wavelet family $\phi_{J,k}(t)$, generated by the translation of the level of dilation $J$ of a wavelet $\phi$ using the factor $k = 0, 1, 2, \ldots$ of the details.

The wavelet function $\phi$ is called ***father wavelet***, and satisfies the property that $\int_{-\infty}^{+\infty}\phi(t)dt = 1$. A father wavelet is used to capture trend components usually associated to low frequencies (this means that the wavelet is long in time). A mother wavelet is used to capture components associated to lower scales, which correspond usually to higher frequencies. In other words, $S_J$ represents the trend components of the signal as long as it is associated to longer scales, while the details $D_J, D_{J-1}, \ldots, D_j, \ldots, D_1$ represent low scale (high frequency) movements (deviations from $S_J$). In this way, a signal can be expressed as:

$$f(t) = \sum_k s_{J,k}\phi_{J,k}(t) + \sum_k d_{J,k}\psi_{J,k}(t) + \sum_k d_{J-1,k}\psi_{J-1,k}(t) + \ldots + \sum_k d_{1,k}\psi_{1,k}(t) \qquad (3.13)$$

where $J$ denotes the wavelet ***scale***. The decomposition of the signal $f(t)$ into different time scales (associated to different frequencies) is referred to as ***time scale decomposition***, and it can be represented by:

$$\{S_J, D_J, D_{J-1}, \ldots, D_1\} \qquad (3.14)$$

The detail 1 (scale 1) contains information of the signal that take place between $2^1$ y $2^2$ periods, short-term movements that can be linked to high-frequency movements. In general, detail $j$ contains information of the signal associated to movements from $2^j$ to $2^{j+1}$ periods. In this way, greater details (higher scales), contain information of long-term movements, which are usually associated to low-frequency movements. This decomposition of the signal in time scales that are power of 2 is called dyadic multiresolution analysis. In this paper, the time series are decomposed into different time scales using wavelets, in order to analyze the possible relationship between money and output that can be hidden at some time scales[10].

## 4. PERUVIAN DATA

The analysis is based on monthly data from the Central Bank of Peru (May 1992-December 2002). In this way, the sample used to make the decomposition of the series using wavelets has a size that is a power of 2 (in this case $n=2^7=128$)[11]. Nevertheless, the econometric analysis was made using the results from January 1993 to December 2001, a period when monetary policy followed a nominal anchor regime, where the anchor or the intermediate target was the monetary base[12].

Five nominal monetary aggregates were chosen as proxies of money: monthly average monetary base (BASE), currency (CIR), "money" (DIN), broad money in domestic currency (LIQMN) and broad money in foreign currency denominated in domestic currency (LIQME)[13]. The monetary aggregate called "money" (M1) is the sum of currency and demand deposits; broad money in domestic currency (M2) is the sum of "money" and saving deposits, time deposits and other values denominated in domestic currency; broad money in foreign currency is the sum of demand deposits, saving deposits, time deposits and other values denominated in foreign currency. The real activity was approximated through the real Gross Domestic Output (GDP) in terms of 1994 soles and the nominal Gross Domestic Output. Finally, the GDP Implicit Price deflator and the CPI (consumer

10 See Lahura (2004) for further discussion about the practical implementation of wavelets.

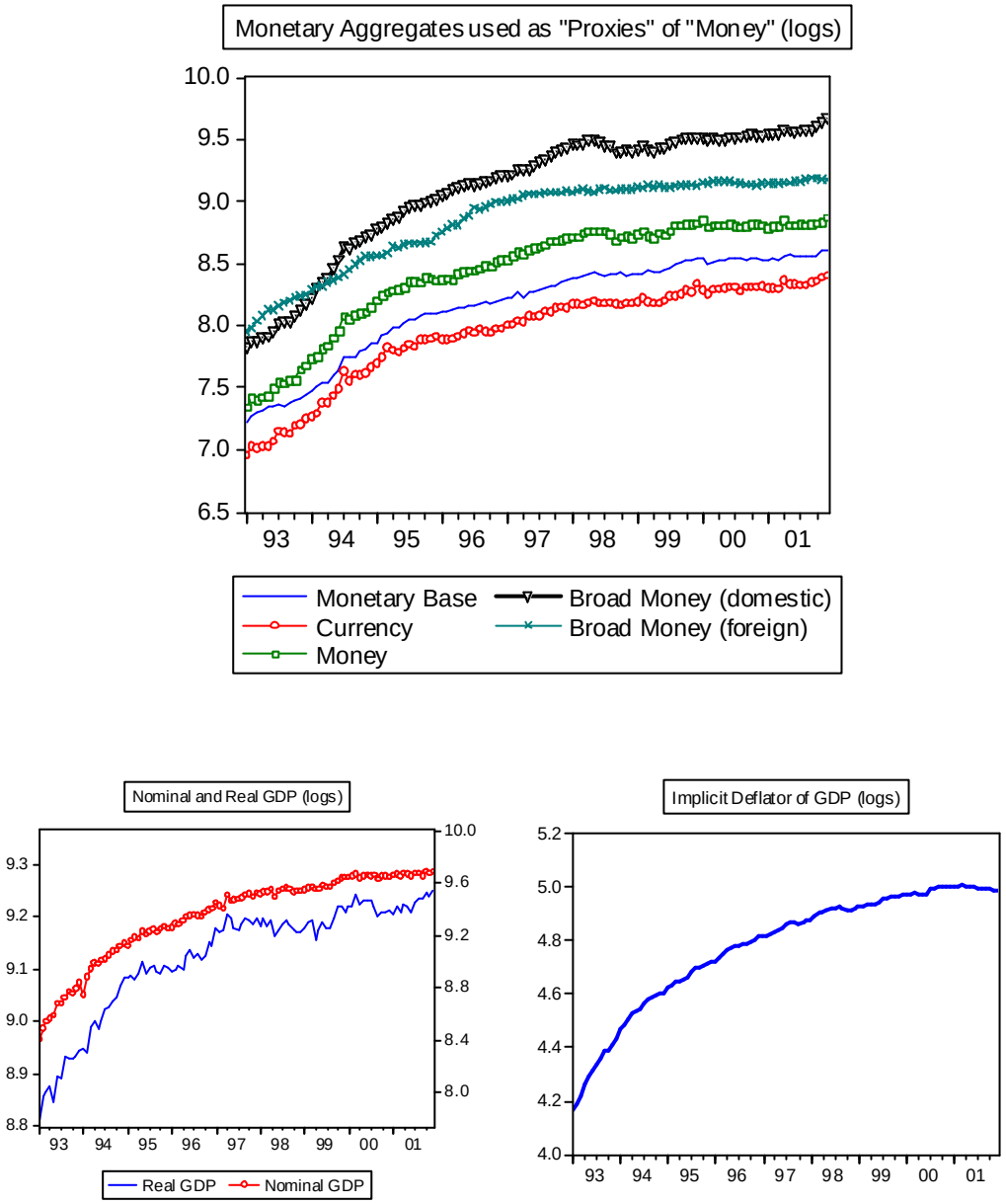
11 Since the filtration of the time series through wavelets has considered 20 additional periods to the analyzed ones (12 previous and eight later ones), this aids to eliminate possible problems in the ends of each one of the filtered series.

12 From January of 2002 the monetary policy follows an inflation objective scheme (inflation targeting), where the intermediate target is a specific inflation level. Preliminary estimations shows that the results presented in this paper remain the same.

13 The sum of M2 and broad money in foreign currency is denominated total liquidity, and is the broaden monetary aggregate of the Peruvian economy.

price index) have been used as proxies of the price level. The series were seasonally adjusted[14] and used in logarithms. Figure 4 present three graphs with the data.

**Figure 4: Peruvian data**




[14] Wavelets can capture the seasonal components of the series. However, the seasonal adjusted series were chosen to be able to compare the results of the analysis using traditional econometrics with the alternative approach using wavelets.

## 5. TRADITIONAL APPROACH

The first step was the evaluation of the existence of unit root in the series. First, the ADF and Phillip-Perron tests showed that it is not possible to reject the hypothesis of unit root. Then, in order to evaluate the possibility of breaks in the series that make them appeared as non-stationary, Zivot and Andrews (1992) and Perron (1997) tests were applied to evaluate the hypothesis of unit root vs. the alternative of stationary series with breaks; the results showed no evidence in favor of the stationary hypothesis[15]. In this context, the time series econometric analysis —the one we called "traditional approach"— involves the analysis of the series in terms of their first differences, their gaps or, if there exists any cointegrating vector, the combination of their levels and first differences in an Error Correction Model (ECM).

To evaluate the existence of any cointegrating vector, the Johansen methodology was implemented[16], as developed in Johansen (1991, 1995). This methodology showed evidence in favor of cointegrating vectors at 1 and 5 percent of significance level, between different monetary aggregates (in logs) denominated in domestic currency and the log of real output, but only under the following assumptions: (a) there is no deterministic trend in the data, (b) the cointegrating vector does not present neither intercept nor a linear trend, and (c) there is no intercept in the error correction model. The existence of a cointegrating relation between output and broad money in foreign currency was statistically significant under the same assumptions except (b): it was necessary to assume that the cointegrating vector had an intercept but not a linear trend.[17]

Given the existence of a cointegrating relationship between each monetary aggregate and real output (all variables in logs), it was estimated a Vector Error Correction Model (VECM) using the first difference of the log of series; these first-differenced series are denoted as: BASE (base money), CIR (currency), DIN (money), LIQMN (broad money in domestic currency) and LIQME (broad money in foreign currency denominated in domestic currency) and PBIR (real output). In order to analyze exogeneity in a cointegrating context, Table 1 shows the results of Granger causality (Granger, 1969) tests between each pair of

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15 The authors upon request can provide these results.

16 Johansen methodology was used because there is no clear reason (theoretical and practical) to consider either some monetary aggregate or output as "exogenous" in a bivariate relationship between them.

17 The authors upon request can provide these results.

variables (null hypothesis in the first column and the corresponding p-value in the second column) and the significance of the error correction terms in the VECM (third column). In the case of the first line, it can be read the following:

(a) The cointegrating error of the "BASE" equation (the first difference of the log of base money) is significant at 10 percent (it appears "YES" in the third column). This implies that in the short run (the first difference of the log of) base money responds to a deviation of the long run relationship, so base money would be endogenous.

(b) The first difference of the log of real output (PBIR) does not Granger cause the first difference of the log of base money (BASE); this is because the null hypothesis "PBIR does not Granger cause BASE" can not be rejected as long as the p-value is 0.4618.

**Table 1**

**COINTEGRATION, GRANGER CAUSALITY AND EXOGENEITY:**
1993:01 - 2001:12 [1/]

| Granger Causality test | | Error correction |
|---|---|---|
| **Null hypothesis** | **p-value** | **significative?** |
| **PBIR does not cause BASE** | 0.4618 | YES |
| **BASE does not cause PBIR** | 0.0592 | YES |
| Lags | **12** | **12** |
| **PBIR does not cause CIR** | 0.0164 | YES |
| **CIR does not cause PBIR** | 0.0651 | NO |
| Lags | **14** | **14** |
| **PBIR does not cause DIN** | 0.0060 | YES |
| **DIN does not cause PBIR** | 0.0472 | NO |
| Lags | **14** | **14** |
| **PBIR does not cause LIQMN** | 0.0000 | YES |
| **LIQMN does not cause PBIR** | 0.0645 | NO |
| Lags | **24** | **24** |
| **PBIR does not cause LIQME** | 0.5739 | NO |
| **LIQME does not cause PBIR** | 0.1010 | YES |
| Lags | **21** | **21** |

1/ In all cases, exists a cointegrating vector at 1% y 5% of significance, except for the case of the model with currency (only at 5%)

*Source: Own elaboration.*

And from the second line, it can be stated that:

(a) The cointegrating error of the PBIR equation (the first difference of the log of real output) is significant at 10 percent (it appears "YES" in the third column). This implies that in the short run (the first difference of the log of) real output also responds to a deviation of the long run relationship, so real output would be endogenous.

(b) The first difference of the log of base money (BASE) does not Granger cause the first difference of the log of real output (PBIR); this is because the null hypothesis "BASE does not Granger cause PBIR" can not be rejected (at 5 percent of significance) as long as the p-value is 0.0592.

Then, considering all this information from lines 1 and 2, it can be analyzed if either real output or base money (both in logs) are exogenous, considering the definition of exogeneity as it was defined by Engle, et al. (1983) and the methodology proposed by Hendry (1996) for the case of co-integrated time series. In particular, given that the cointegrating error of the BASE equation is statistically significant (YES) as well as the cointegrating error of PBIR equation, then neither base money nor real output are ***weakly exogenous***. If base money were supposed to be weakly exogenous, then a "NO" would have to appear in the first line of the third column (indicating that the cointegrating error of BASE equation is not statistically significant) and a "YES" in the second line of the third column (indicating that the cointegrating error of PBIR equation is statistically significant). Finally, the third line labeled "lags" shows that the optimal lags selected to estimate the VECM between PBIR and BASE was 12.

The analysis of the remaining lines should be done in the same manner as above (by pairs and taking into account the "lags" line). Now, to illustrate a case where it can be found weak exogeneity and strong exogeneity, it can be considered the relationship between LIQME and PBIR (lines 13, 14 and 15). From line 13 it can be seen that:

(a) The cointegrating error of LIQME equation (first difference of the log of "total liquidity in foreing currency") is not significant at 10 percent (it appears "NO" in the third column). This implies that in the short run (the first difference of the log of) liquidity in foereign currency does not respond to a deviation of the long run relationship.

(b) The first difference of the log of real output (PBIR) does not Granger cause the first difference of the log of total liquidity in foreing currency (LIQME); this is because the null hypothesis "PBIR does not Granger cause LIQME" cannot be rejected as long as the p-value is 0.5739.

whereas from line 14:

(a) The cointegrating error of the equation for "PBIR" (first difference of the log of real output) is significantive at 10 percent (it appears "YES" in the third column). This implies that in the short run (the first difference of the log of) real output responds to a deviation of the long run relationship, so real output would be endogenous.

(b) The first difference of the log of total liquidity in foreing currency (LIQME) does not Granger cause the first difference of the log of real output (PBIR); this is because the null hypothesis "LIQME does not Granger cause PBIR" cannot be rejected (at 5 percent of significance) as long as the p-value is 0.1010.

In this case, given that the cointegrating error of the equation for LIQME is not statistically significant, but only the cointegrating error for PBIR, then the log of liquidity in foreign currency is said to be ***weakly exogenous***[18]. Furthermore, given that it is weakly exogenous, it can be tested if it is also ***strongly exogenous***. Following Hendry (1996), if the log of liquidity in foreign currency is weakly exogenous and PBIR does not Granger cause LIQME, then the log of this monetary aggregate is also ***strongly exogenous*** and can be used to forecast the log of real output. As can be seen from line 14 of Table 1, PBIR does not Granger cause LIQME because the p-value is 0.5739; then, it can be said that the log of liquidity in foreign currency is strongly exogenous.

For the remaining cases, it can be read from Table 1 that output is weakly exogenous when "money"(DIN) is considered, but strongly exogenous (at 5 percent of significance) when currency (CIR) and broad money in domestic currency (LIQMN) are considered. The way information is presented in Table 1 and the interpretation of the results will be done in the same manner for subsequent tables.

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[18] Indeed, it should be said that the log of liquidity in foreign currency is "weakly exogenous" for its parameter in the equation where the left-hand side variable is the log of real output. The same applies for "strong exogeneity".

These results outlined above should be taken with care because the assumptions that underlie the cointegrating vectors of Table 1 are not consistent with the nature of the data. In particular, the assumption of no deterministic trend in the data is not suitable, especially for monetary aggregates. In particular, assumptions (a), (b) and (c) become relevant only when the series have zero average. Under assumption (c) it was not possible to find any cointegrating vector between each monetary aggregate, the real GDP and the GDP Implicit Price deflator.

As long as cointegration could not be found in the data, the next step was to analyze the existence of causality in Granger sense on the relationship between money and output using the first differences of the logarithms of the series and their gaps. The results are shown in Table 2.

**Table 2**

**STATIONARY SERIES AND GRANGER CAUSALITY:**
1993:01 - 2001:12

| Null Hypothesis | First Differences | Gaps HP |
|---|---|---|
| **PBIR does not cause BASE** | 0.0082 | 0.0812 |
| **BASE does not cause PBIR** | 0.3290 | 0.4044 |
| Lags | **4** | **6** 1/ |
| **PBIR does not cause CIR** | 0.0181 | 0.0899 |
| **CIR does not cause PBIR** | 0.1046 | 0.0001 |
| Lags | **14** 1/ | **22** |
| **PBIR does not cause DIN** | 0.0092 | 0.1350 |
| **DIN does not cause PBIR** | 0.0339 | 0.0017 |
| Lags | **20** | **21** |
| **PBIR does not cause LIQMN** | 0.3630 | 0.0467 |
| **LIQMN does not cause PBIR** | 0.0221 | 0.0945 |
| Lags | **1** | **21** |
| **PBIR does not cause LIQME** | 0.4795 | 0.4172 |
| **LIQME does not cause PBIR** | 0.0029 | 0.0145 |
| Lags | **24** | **26** |

1/ First order autocorrelation

*Source: Own elaboration.*

Using the first differences of the logarithms of the series (growth rates), it was found that output Granger causes money when the latter is represented by monetary base, currency, or currency plus demand deposits (money). The causality reverses when broader monetary aggregates are considered, in both domestic currency and foreign currency. In the

case of "gaps", money Granger causes output when currency, currency plus demand deposits (money) and broad money in foreign currency are considered. The only case where output Granger causes money is when the latter is measured as the gap of broad money in foreign currency. Finally, when the gap of monetary base is considered, nothing can be concluded about the existence of Granger causality.

In short, the results provided by the "traditional approach" do not show a clear Granger causality between output and the different monetary aggregates[19]. Then, nothing can be concluded about the relevance of some monetary aggregate for forcasting real output.

## 6. ALTERNATIVE APPROACH: WAVELETS AND MULTIRESOLUTION ANALYSIS

As an alternative to the traditional approach, the empirical analysis of the relationship between output and different monetary aggregates was done based on the multiresolution analysis of the series using wavelets, following Ramsey and Lampart (1998). Specifically, the series were filtered using the mother wavelet function denominated Symmlet of order 12 (Sym12) characterized by orthonormality, compact support and for being almost symmetric[20].

The multiresolution analysis was made considering six details for each series: $D_1, D_2, D_3, D_4, D_5, D_6$ and a smoothed component $S_6$. The detail $D_1$ contains information of movements from the series (mainly of high frequency) that occur between $2^1 = 2$ and $2^2 = 4$ months; the detail $D_2$ movements from the series between $2^2 = 4$ and $2^3 = 8$ months, the detail $D_3$ movements from the series between $2^3 = 8$ and $2^4 = 16$ months, …, the detail $D_6$ movements from the series between $2^6 = 64$ and $2^7 = 128$ months[21].

[19] These results are similar to those obtained when the real GDP implicit price deflator is included in the VECM.

[20] It was chosen a length of 12 for the wavelet filter denominated Symmlet, to get good properties in terms of regularity. See Gencay, et al. (2002) and Odgen (1997) for a discussion about desired properties of wavelets.

[21] The multiresolution graphs are presented in the annex.

The analysis considered two measures of output: the real output and the nominal output. The following relations were analyzed:

(a) A short run relationship between the real money and the GDP. For that reason, the causality analysis based on "Granger causality" was made through a vector autoregressive or VAR model.

(b) Two long run relationships: (1) the money and the nominal GDP, and (2) money, the real GDP and the price level. In these cases, the causality analysis in the sense of Granger was made through a vector error correction model (VECM) for the cointegrated series.

6.1. Nominal Money and Real Output

Table 3 presents the Granger causality test results between different nominal monetary aggregates and the real GDP (short run relation), using each one of the details of the series obtained from the *MRA* of the same variables. It is seen that the causality relation between money (measured by different monetary aggregates) and output (measured by the real GDP) **is not unique** and **it changes with the time scale considered;** furthermore, the results about causality in the sense of Granger differs between monetary aggregates. These results can be summarized as follows:

(1) For all monetary aggregates, output Granger causes money at scale 1. This means that when it is considered movements from 2 to 4 months of the series ("detail 1" of the multiresolution analysis), real GDP leads movements in output. This result is consistent with the approach that in the short run money reacts at real output.

(2) When considering greater scales, Granger causality changes: unidirectional causality of money to output and vice versa, double causality and absence of causality are observed.

(3) The most interesting case is when the monetary aggregate called "money" is considered, which is defined as the sum of currency plus demand deposits. In this case, at scale 1 (movements from 2 to 4 months) output Granger causes money; then Granger causality reverses at scale 2 (movements from 4 to 8 months) and money

Granger causes output. When movements from 8 to 16 months (scale 3) are considered, output Granger causes money again[22]; and finally, at scales 4 and 5 (movements from 16 to 32 and from 32 to 64 months), double causality between output and money[23] is found.

**Table 3**
**GRANGER CAUSALITY USING WAVELETS: 1993:01 - 2001:12**
(Seasonal adjusted monthly series)

| Null Hypothesis | D1 (2 a 4 m.) | D2 (4 a 8 m.) | D3 (8 a 16 m.) | D4 (16 a 32 m.) | D5 (32 a 64 m.) | D6 (64 a 128 m.) |
|---|---|---|---|---|---|---|
| **PBIR does not cause BASE** | 0.0157 | 0.0138 | 0.2558 | 0.0005 | 0.3396 | |
| **BASE does not cause PBIR** | 0.7242 | 0.0119 | 0.3445 | 0.0000 | 0.0018 | **UNSTABLE** |
| Lags | **16** | **23** | **9** | **18** | **19** | |
| Autocorrelation | **NO** | **NO** | **YES** | **NO** | **NO** | |
| **PBIR does not cause CIR** | 0.0000 | 0.0000 | 0.0020 | 0.0017 | 0.0000 | |
| **CIR does not cause PBIR** | 0.2075 | 0.2754 | 0.0079 | 0.0000 | 0.0000 | **UNSTABLE** |
| Lags | **13** | **22** | **23** | **18** | **27** | |
| Autocorrelation | **NO** | **NO** | **YES** | **NO** | **NO** | |
| **PBIR does not cause DIN** | 0.0472 | 0.3146 | 0.0032 | 0.0000 | 0.0000 | 0.1856 |
| **DIN does not cause PBIR** | 0.9915 | 0.0004 | 0.2547 | 0.0000 | 0.0000 | 0.0000 |
| Lags | **23** | **18** | **13** | **23** | **23** | **9** |
| Autocorrelation | **NO** | **NO** | **YES** | **NO** | **NO** | **YES** |
| **PBIR does not cause LIQMN** | 0.0007 | 0.0289 | 0.2545 | 0.1518 | 0.3431 | 0.0000 |
| **LIQMN does not cause PBIR** | 0.6918 | 0.2427 | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
| Lags | **29** | **20** | **13** | **20** | **13** | **20** |
| Autocorrelation | **NO** | **NO** | **YES** | **NO** | **YES** | **NO** |
| **PBIR does not cause LIQME** | 0.0206 | 0.5486 | 0.0258 | 0.0001 | 0.1929 | 0.0001 |
| **LIQME does not cause PBIR** | 0.9991 | 0.2839 | 0.0002 | 0.0000 | 0.0000 | 0.0000 |
| Lags | **10** | **14** | **5** | **26** | **6** | **20** |
| Autocorrelation | **YES** | **YES** | **YES** | **NO** | **YES** | **NO** |

*Source: Own elaboration.*

In contrast to the traditional approach, these results shows how the use of wavelets and multiresolution analysis —"the alternative approach"— allows to establish the existence of causality in the sense of Granger and the possibility of different directions, depending on the time scales[24] considered. These results show evidence that the relationship between money and real output is not unique and that money could help to forecast output at intermediate time scales.

[22] Although in this case, exists an autocorrelation generated by an autoregressive process of order 4, only 2 and 4 lags are significant.

[23] This result is in the line of the evidence presented by Ramsey and Lampart (1998b), Chew (2001) and Gencay et. al (2002).

[24] This diversity of causality relations in the sense of Granger also is obtained when the price level is included in the analysis.

6.2. Money and Output: Long run Relationship

The theoretical reference for analyzing a long run relationship between money and output is the money quantitative equation $MV = PY$. This equation relates the nominal amount of money, $M$, the velocity of circulation $V$, the price level $P$ and the level of real activity $Y$. The empirical implications of this equation come from two long-run assumptions: (a) the velocity of money is stationary, and (b) output is constant (at its equilibrium level).

The quantitative equation can be expressed in logarithms as it follows:

$$\log M + \log V = \log PY \qquad (6.1)$$

or, in terms of the logarithm of the velocity:

$$\log PY - \log M = \log V \qquad (6.2)$$

The equation (6.2) implies that, if $\log V$ is stationary, $\log M$ and $\log PY$ are ***cointegrated*** and the cointegrating vector is also a vector with parameters equal to one (in absolute value). An alternative expression is given by:

$$\log M + \log V = \log P + \log Y \qquad (6.3)$$

or, in terms of the logarithm of the velocity:

$$\log P + \log Y - \log M = \log V \qquad (6.4)$$

The equation (6.4) implies that, under the assumption that $\log V$ is stationary (a stable velocity of money), $\log M$, $\log P$ and $\log Y$ ***are cointegrated*** and the cointegrating vector is a vector with parameters equal to one (in absolute value).

Since the data considered present unit roots, it was analyzed the existence of a cointegrating vector for models (6.2) and (6.4) in terms of the logs of the series. The Engle

and Granger (1987) and Johansen (1991) cointegration tests[25] were applied for this purpouse, but it was not possible to find any cointegrating vector. Nevertheless, and due to the existence of a possible cointegrating relationship between these variables, it was evaluated the existence of cointegration between "non-stationary components" of the series, the ones that were constructed using ***the details and the smooth components of the multiresolution analysis of the series.*** This kind of cointegration is similar to the concept of ***hidden cointegration,*** proposed by Granger and Yoon (2002). According to these authors, it is possible to find components of each series that are nonstationary, integrated of order 1 such that there is a cointegrating relationship. When this occurs, ***a hidden cointegrating vector*** for the original variables exists, or ***they cointegrate in a hidden way*** and the ECM is called ***crouching error correction model***. Under these considerations, Granger and Yoon (2002) show that even though the levels of short and long run interest rates do not cointegrate, there is evidence of hidden cointegration between the accumulated positive changes of the same series.

6.3. Cointegration between the money and the nominal GDP

To evaluate the presence of hidden cointegration between money and nominal GDP, the details 5 and 6 (D5 and D6) were eliminated of each original series, producing:

$$LDINSA\_65 = LDINSA - LDINSA\_D6 - LDINSA\_D5$$
$$LPBINSA\_65 = LPBINSA - LPBINSA\_D6 - LPBINSA\_D5$$

where *LDINSA* is the logarithm of seasonally adjusted money and *LPBINSA* is the logarithm of seasonally adjusted nominal GDP, both nonstationary and integrated of order 1. Engle and Granger (1987) and Johansen (1991) methodologies showed evidence of a cointegrating vector between *LDINSA_65* and *LPBINSA_65* or a ***hidden cointegrating vector*** between money and output**.** The first row of Table 4 shows that there is a bi-directional Granger causality between the first differences of *LDINSA_65* and *LPBINSA*_65 and that the latter is weakly exogenous.

[25] Only for the model with two variables represented by (4.2).

**Table 4**

**GRANGER CAUSALITY, EXOGENEITY AND HIDDEN COINTEGRATION BETWEEN MONEY AND NOMINAL GDP USING WAVELETS : 1993:01 - 2001:12**

(Seasonal adjusted monthly series)

| Granger Causality test | | Error correction | eliminated |
|---|---|---|---|
| **Null hypothesis** | **p-value** | **significative?** | **components** |
| **PBIN does not cause DIN** | **0.0455** | YES | |
| **DIN does not cause PBIN** | **0.0057** | NO | D6, D5 |
| Lags | 10 | | |
| **PBIN does not cause DIN** | **0.0000** | YES | |
| **DIN does not cause PBIN** | 0.0692 | YES | D6, D5, D3, D2 |
| Lags | 2 | | |
| **PBIN does not cause DIN** | 0.0735 | YES | |
| **DIN does not cause PBIN** | **0.0000** | NO | D6, D5, D1 |
| Lags | 8 | | |

*Source: Own elaboration.*

The next step was the analysis of various hidden cointegrating vectors considering ***different time scales in the ECM.*** This strategy makes the ***evaluation of the different causality directions between money and nominal output*** possible considering the existence of a long run relationship.

Two additional hidden cointegrating relationships were obtained. The hidden cointegration relationship 1 was defined in terms of the original series after removing details 2 and 3 (D2 and D3), which contain movements from 4 to 8 months and 8 to 16 months, respectively:

$$LDINSA\_6532 = LDINSA - LDINSA\_D6 - LDINSA\_D5 - LDINSA\_D3 - LDINSA\_D2$$

$$LPBINSA\_6532 = LPBINSA - LPBINSA\_D6 - LPBINSA\_D5 - LPBINSA\_D3 - LPBINSA\_D2$$

Thus, the series involved in the hidden cointegrating relationship 1 contains —in addition to the component *D4*— the first detail or *D1*. Engle and Granger (1987) and Johansen (1991) methodologies show the existence of a cointegrating vector between *LDINSA_6532* and *LPBINSA_6532* or a ***hidden cointegrating vector*** between money and output**.** The second row of Table 5 establishes that both series are weakly exogenous.

The hidden cointegration relationship 2 was defined in terms of the original series after removing only detail 1 of the series, which contains movements from 4 to 8 months and 8 to 16 months:

$$LDINSA\_651 = LDINSA - LDINSA\_D6 - LDINSA\_D5 - LDINSA\_D1$$
$$LPBINSA\_651 = LPBINSA - LPBINSA\_D6 - LPBINSA\_D5 - LPBINSA\_D1$$

Again, it was possible to obtain a cointegrating vector between the filtered series *LDINSA_651* and *LPBINSA_651*, and so a hidden cointegrating vector between money and nominal output. The third row of Table 5 shows that the first difference of *LDINSA_651* Granger causes the first difference of *LPBINSA_651*, but that nominal output is weakly exogenous.

6.4. Cointegration between money, real GDP and prices

The first step in the analysis of hidden cointegration between money, prices and real GDP, was the elimination of details 5 and 6 (D5 and D6) of each original series, producing:

$$LDINSA\_65 = LDINSA - LDINSA\_D6 - LDINSA\_D5$$
$$LPBIRSA\_65 = LPBIRSA - LPBIRSA\_D6 - LPBIRSA\_D5$$
$$LDEFLACTOR\_65 = LDEFLACTOR - LDEFLACTOR\_D6 - LDEFLACTOR\_D5$$

where *LDINSA* is the logarithm of the seasonally adjusted money, *LPBIRSA* is the logarithm of the seasonally adjusted real GDP and *LDEFLACTOR* is the logarithm of the real GDP Implicit Price deflator. The Johansen (1991) test suggests the existence of a cointegrating vector between the filtered series and thus the existence of hidden cointegration between money, prices and the real GDP. The first row of Table 5 shows that the first difference of *LPBIRSA* Granger causes *LDINSA* and that both "money" and real output are weakly exogenous.

The next step was the evaluation of the existence of ***various hidden cointegrating vectors considering different time scales in the ECM.*** The hidden cointegration relationship 1 was defined in terms of the original series after removing detail 2 (D2), which contains movements from 4 to 8 months:

$$LDINSA\_652 = LDINSA - LDINSA\_D6 - LDINSA\_D5 - LDINSA\_D2$$

$$LPBIRSA\_652 = LPBIRSA - LPBIRSA\_D6 - LPBIRSA\_D5 - LPBIRSA\_D2$$

$$LDEFLACTOR\_652 = LDEFLACTOR - LDEFLACTOR\_D6 - LDEFLACTOR\_D5 - LDEFLACTOR\_D2$$

The Johansen (1991) test shows the existence of a cointegrating vector between the filtered series *LDINSA_652*, *LPBIRSA_652* and *LDEFLACTOR_652*. Thus, there is evidence of hidden cointegration between money, prices and real GDP. The second row of Table 5 shows that considering scales 1, 3 and 4, *LPBIRSA_652* Granger causes *LDINSA_652*, but they both "money" and real output weakly exogenous.

**Table 5:**

**GRANGER CAUSALITY, EXOGENEITY AND HIDDEN COINTEGRATION BETWEEN MONEY, REAL GDP AND PRICES USING WAVELETS: 1993:01 - 2001:12**

(Seasonal adjusted monthly series)

**Model with money, real GDP and prices**

| Granger Causality test | | Error correction significative? | Eliminated components |
|---|---|---|---|
| **Null hypothesis** | **p-value** | | |
| **PBIR does not cause DIN** | **0.0228** | YES | |
| **DIN does not cause PBIR** | 0.2349 | YES | D6, D5 |
| Lags | 6 | | |
| **PBIR does not cause DIN** | **0.0495** | YES | |
| **DIN does not cause PBIR** | 0.1961 | YES | D6, D5, D2 |
| Lags | 6 | | |
| **PBIR does not cause DIN** | 0.6896 | NO | |
| **DIN does not cause PBIR** | **0.0062** | YES | D6, D5, D3, D1 |
| Lags | 2 | | |

*Source: Own elaboration.*

The hidden cointegration relationship 2 was defined in terms of the original series after removing details 1 and 3, which contains movements from 4 to 8 months and from 16 to 32 months:

$$LDINSA\_6531 = LDINSA - LDINSA\_D6 - LDINSA\_D5 - LDINSA\_D3 - LDINSA\_D1$$

$$LPBIRSA\_6531 = LPBIRSA - LPBIRSA\_D6 - LPBIRSA\_D5 - LPBIRSA\_D3 - LPBIRSA\_D1$$

$$LDEFLACTOR\_6531 = LDEFLACTOR - LDEFLACTOR\_D6 - LDEFLACTOR\_D5 - LDEFLACTOR\_D3 - LDEFLACTOR\_D1$$

Again, it was possible to obtain a cointegrating vector between the filtered series *LDINSA_6531* and *LPBINSA_6531*, i.e. a hidden cointegrating vector between money, real GDP and prices. The third row of Table 5 shows that *LDINSA_6531* Granger causes *LPBINSA_6531* and that money is strongly exogenous. Then, money would be useful for forecasting real output considering movements at scale 2.

Tables 6 and Table 7 show the results when the remaining monetary aggregates are considered. The results in Table 6 involve series for which details 1 and 3 were removed, while the results in Table 7 involves series where only detail 2 was not considered:

**Table 6**

**GRANGER CAUSALITY, EXOGENEITY AND HIDDEN COINTEGRATION BETWEEN DIFFERENT MONETARY AGGREGATES, REAL GDP AND PRICES, USING WAVELETS: 1993:01 - 2001:12**

(Seasonal adjusted monthly series)

**Model with money, real GDP and prices**

| Granger Causality test | | Error correction significative? | Eliminated components |
|---|---|---|---|
| **Null hypothesis** | **p-value** | | |
| **PBIR do not cause BASE** | 0.1862 | NO | |
| **BASE do not cause PBIR** | 0.1233 | YES | D6, D5, D3, D1 |
| Lags | 10 | | |
| **PBIR do not cause CIR** | 0.1236 | YES | |
| **CIR do not cause PBIR** | **0.0022** | NO | D6, D5, D3, D1 |
| Lags | 4 | | |
| **PBIR do not cause DIN** | 0.6896 | NO | |
| **DIN do not cause PBIR** | **0.0062** | YES | D6, D5, D3, D1 |
| Lags | 2 | | |
| **PBIR do not cause LIQMN** | **0.0386** | YES | |
| **LIQMN do not cause PBIR** | 0.5415 | NO | D6, D5, D3, D1 |
| Lags | 4 | | |
| **PBIR do not cause LIQME** | 0.4531 | YES | |
| **LIQME do not cause PBIR** | 0.0902 | NO | D6, D5, D3, D1 |
| Lags | | | |

*Source: Own elaboration.*

**Table 7**

**GRANGER CAUSALITY, EXOGENEITY AND HIDDEN COINTEGRATION BETWEEN DIFFERENT MONETARY AGGREGATES, REAL GDP AND PRICES, USING WAVELETS: 1993:01 - 2001:12**

(Seasonal adjusted monthly series)

**Model with money, real GDP and prices**

| Granger Causality test | | Error correction significative? | Eliminated components |
|---|---|---|---|
| **Null hYpothesis** | **p-value** | | |
| **PBIR does not cause BASE** | **0.0152** | YES | |
| **BASE does not cause PBIR** | 0.2093 | YES | D6, D5, D2 |
| Lags | 4 | | |
| **PBIR does not cause CIR** | **0.0380** | YES | |
| **CIR does not cause PBIR** | 0.2830 | NO | D6, D5, D2 |
| Lags | 3 | | |
| **PBIR does not cause DIN** | **0.0495** | YES | |
| **DIN does not cause PBIR** | 0.1961 | YES | D6, D5, D2 |
| Lags | 3 | | |
| **PBIR does not cause LIQMN** | **0.0099** | YES | |
| **LIQMN does not cause PBIR** | 0.9410 | YES | D6, D5, D2 |
| Lags | 4 | | |
| **PBIR does not cause LIQME** | 0.0567 | YES | |
| **LIQME does not cause PBIR** | 0.1868 | YES | D6, D5, D2 |
| Lags | 8 | | |

*Source: Own elaboration.*

## 7. CONCLUSIONS

The purpose of this paper was to provide some insights about the empirical relationship between money and output in Peru, in order to establish if there is any role of monetary aggregates for monetary policy as indicators of real activity. Thus, the main hypothesis analyzed in this paper was that narrow monetary aggregates could help forecasting real output. This conjecture is supported by some recent theoretical developments which assert that monetary aggregates can be useful for monetary policy as long they could provide relevant information about future real output.

The empirical analysis was based on an orthogonal decomposition of series by timescale obtained using wavelets, following Ramsey and Lampart (1998), and subsequent research by Chew (2001) and Gençay et al. (2002). These authors applied wavelets to analyze the short-run relationship between money and output, reaching some interesting results: (1) the link between money and real output is not unique, and (2) the direction of Granger causality depends on the timescale considered. In this paper we went

a little bit further in the empirical analysis of the money-output relationship using wavelets. In particular, it was proposed the application of wavelet filtering to analyze cointegrating relationships. Using Peruvian data it was not possible to find evidence of cointegration between money, real output and prices. However, it was found evidence of cointegration between non-stationary components of the series that includes different timescale details. This result could be considered as an alternative way to represent the existence of hidden co-integration, as proposed by Granger and Yoon (2002).

Given the existence of cointegration between non-stationary series constructed using wavelet filtering, it was found that the link between money and real output is not unique, and that the direction of Granger causality and exogeneity depends on both the time scale and the monetary aggregate considered. Furthermore, exogeneity tests reveal that narrow monetary aggregates are weakly and strongly exogenous, i.e., they are helpful to forecast movements in real output. In particular, it is found that intermediate time scale components (cyclical movements from 4 to 8 months) of money can help forecasting the same time scale components of real output. These results suggest that money has a role for monetary policy as an indicator of future real activity, thus supporting the hypothesis.

The methodology proposed in this paper —the use of wavelets and multiresolution analysis in a co-integrated context— has been useful in the evaluation of different causality relations between money and real output in the long run. Then, it could be helpful to analyze theoretical long run relationships, which have not yet found strong empirical support (i.e., the PPP theory) and empirical causality between non-stationary series that move together in the long run (real output and financial development, real output and trade, real output and fiscal spending, among others).

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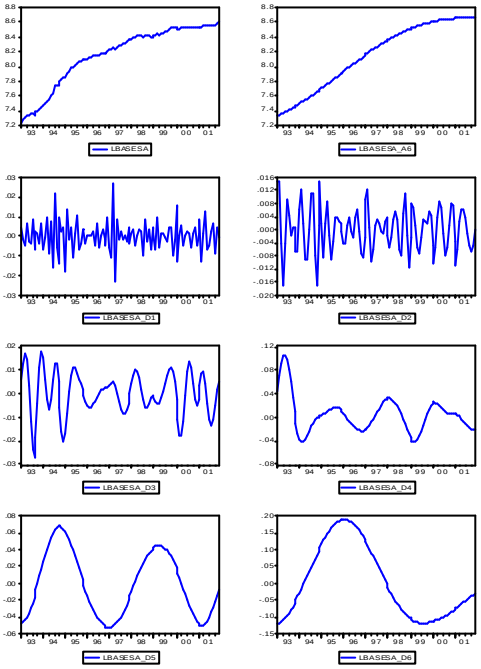
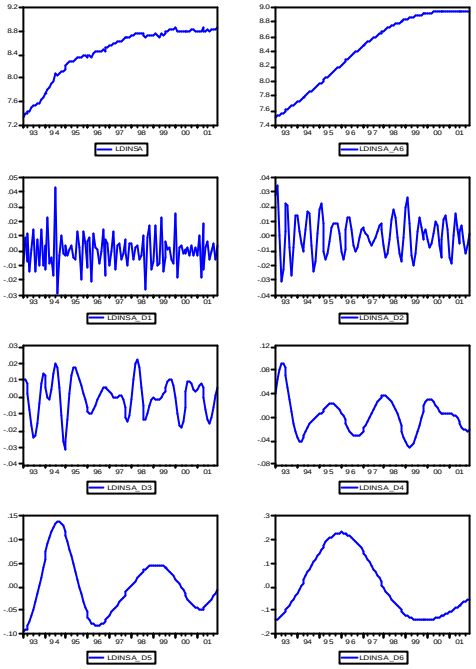
**APPENDIX**: Multiresolution analysis.

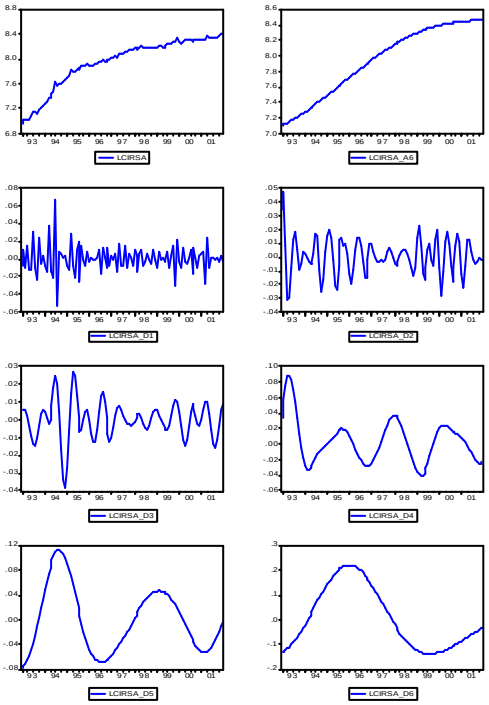
Monetary Base



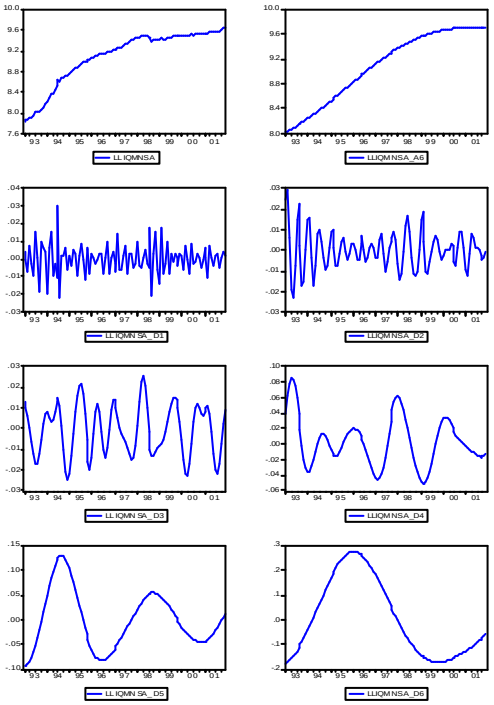

Money



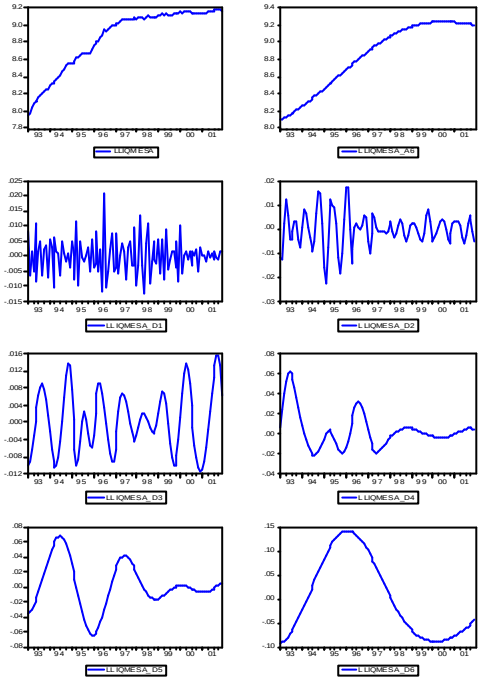

Currency



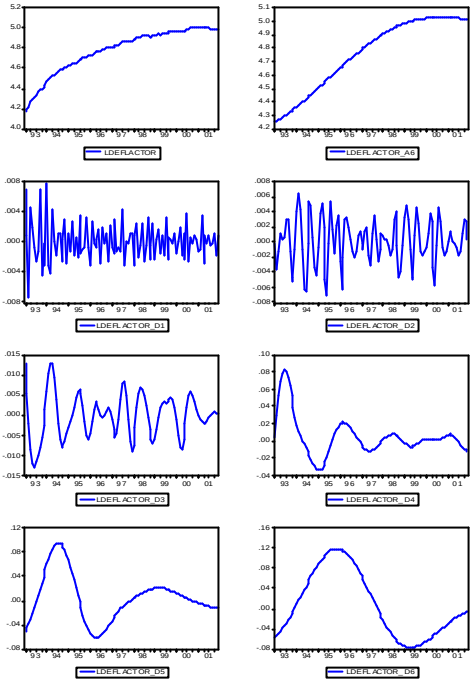

Broad money in domestic currency



## Broad Money in foreign currency




## GDP Deflator




## Real GDP