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Nonlinear Relationship between Permanent and Transitory Components of Monetary Aggregates and the Economy

Richard G. Anderson Marcelle Chauvet Barry Jones*

Abstract

This paper uses several methods to study the interrelationship among Divisia monetary aggregates, prices, and income, allowing for nonstationary, nonlinearities, asymmetries, and time-varying relationships among the series. We propose a multivariate regime switching unobserved components model to obtain transitory and permanent components for each series, allowing for potential recurrent and structural changes in their dynamics. Each component follows distinct two-state Markov processes representing low or high phases. Since the lead-lag relationship between the phases can vary over time, rather than pre-imposing a structure to their linkages, the proposed flexible framework enables us to study their specific lead-lag relationship over each one of their cycles and over each U.S. recession in the last 40 years. The decomposition of the series into permanent and transitory components reveals striking results. First, we find a strong nonlinear association between the components of money and prices – all low phases of the transitory component of prices were preceded by tight transitory and permanent money phases. We also find that most recessions were preceded by tight money phases (its cyclical and permanent components) and high transitory price phases (with the exception of the 2001 and 2009-2010 recessions). In addition, all recessions were associated with a decrease in transitory and permanent income.

Keywords: Prices, Divisia Monetary Aggregates, Income, Unobserved Components, Permanent Component, Transitory Component, Turning Point Analysis, Markov-Switching.

JEL Classification: E31, C22

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1. Introduction

In the aftermath of the financial crisis in 2008, the Federal Reserve (Fed) implemented massive purchases of government bonds, referred to as the quantitative easing program (QE). With short term policy interest rates at the zero lower bound, the Fed undertook this 'unconventional monetary policy' in a first round to handle the liquidity problem that had led to a sudden reduction in the availability of credit and a resultant tightening of the conditions required to obtain loans within and outside the U.S. The second and third rounds came as a response to the slow subsequent recovery and weak labor market conditions. The policy leads to expansion of money available for banks to borrow, with the intent of injecting money in the economy.

The effect of these 'unconventional' measures can only be studied with frameworks in which money supply plays a role. However, monetary economic research has largely abstracted from the role of money in the last decade. The core consensus New-Keynesian model that is mostly used at central banks to inform monetary policy gives a major role to short-term interest rates instead, which at a zero lower bound has become a limited tool. The financial crisis and recent monetary policy influencing money supply has motivated new empirical and theoretical research to analyze the potential consequences of changes in money on prices and economic activity. New theoretical models have been developed that include credit frictions and the role of financial markets and/or monetary aggregates.[1] A recent growing empirical literature has also been resurging to study the role of money in the dynamics of prices and the economy.[2]

The goal of this paper is to investigate the nonlinear empirical dynamic linkages among money as measured by Divisia monetary aggregates, prices, and income. We propose a new model to study the relationship between the long run and short run components of times series, with potential recurrent changes in their dynamics. This multivariate three-factor Markov-switching system is applied to study how permanent and transitory changes in the quantity of

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[1] See Chauvet and Lu (2013) and Belongia and Ireland (2012a), and references therein for new theoretical models.

[2] Recent empirical related papers are, for example, Cobham and Kang (2012) and Reynard (2012). Cobham and Kang (2012) examine the implications of QE for broad money using flow of funds and find a major role for money during the recent financial crisis, and during the implementation of QE. Reynard (2012) finds a stable equilibrium relationship between money and prices across countries. It also concludes that money predicts prices, and that this relationship is stronger during high inflation periods than during low inflation periods.

money impact permanent and transitory components of income and prices during normal times and around recessions.[3]

The shift in focus of monetary economics from monetary aggregates has its roots in Bernanke and Blinder (1988, 1992) and Friedman and Kuttner (1992). Considering the turbulent 1980s, these papers find that the demand for credit had been more stable than the demand for money, and that there was a break down in the relationship between money and aggregate economic activity affecting the predictive ability of money. They also conclude that the short term interest rates had a better predictive value than money. The implication is that stabilizing monetary policy would be more effective if it targeted credit than changes in money. With Taylor's (1993) proposed new rule for monetary policy based on short term interest rates, and its incorporation in Clarida, Gali, and Gertler (1999) seminal New Keynesian model, monetary aggregates have been downplayed in monetary models.

There is a large literature that questions the instability or lack of forecasting ability of monetary aggregates with respect to the economy. The core argument in these papers is that these results are mostly derived from problems in the measurement of monetary aggregates, which are overturned when the simple sum monetary aggregates are replaced by Divisia monetary aggregates, as proposed by the seminal papers of Barnett (1978, 1980). An important theme in Barnett's research has been proper measurement of the flow of monetary services provided to households and firms by the monetary assets they hold. This, in turn, requires careful attention to measuring the user costs of those monetary assets. An increasing number of imperfect substitute short-term financial assets with time-varying relative prices have been emerging in the last decades. However, monetary aggregates generated from simple sum assume that user-cost prices of the services of individual money assets do not change over time, each asset is a perfect substitute for the others within the set of components, and the coefficients of the linear aggregator function are all the same. The implication of this measurement is that the constant user-cost prices among monetary assets are exactly equal to each other. In addition, shifts in simple sum monetary aggregates can be spurious, as those shifts do not necessarily reflect a change in the utility derived from money holdings. The disconnection between observed financial assets dynamics and the assumptions of simple sum aggregation has led to the

[3] We use interchangeably the terms 'permanent', 'trend', 'level', or 'long run' components; and the terms 'transitory', 'temporary, 'cyclical', or 'short run' components.

unreliability of the monetary assets obtained by this method. Monetary aggregates have been less influential in U.S. monetary policymaking due to these problems and potential instability in the relationships between monetary aggregates and other economic variables.

Barnett (1978) and Donovan (1978) showed that the user cost of a monetary asset is the interest income that is forgone due to holding that asset rather than a higher-yielding asset that does not provide any monetary services. Building on Diewert (1976), Barnett (1978, 1980) developed Divisia monetary aggregates to measure the aggregate flow of monetary services derived from a collection of assets. Specifically, Divisia aggregates are chain-weighted superlative index numbers constructed over the quantities and user costs of the monetary assets included in the aggregate. The proposed aggregation-theoretical monetary function correctly internalizes substitution effect constructed by using expenditure shares as the component growth-rate weights. The share weights of the index growth rate resulting from this approach are different across assets, as they depend on all of the quantities and interest rates in each share, and those weights can be time-varying at each point in time.

Barnett's Divisia monetary aggregates yield a measure of the aggregate flow of monetary services (not just the transactions services) provided by the monetary assets that are included in the aggregate. It is often argued that Divisia aggregates should be more closely related to the spending plans of households and firms than conventional simple sum monetary aggregates.[4]

Since the seminal paper by Barnett (1978, 1980) and the problems found in Bernanke and Blinder (1988, 1992) and Friedman and Kuttner (1992) with simple sum monetary aggregates, there has been a large literature comparing the performance of Divisia money measures with simple sum money measures in term of forecasting ability and stability with the economy. Belongia (1996) and Hendrickson (2011) revisit Bernanke and Blinder (1988, 1992) and Friedman and Kuttner (1992), using the same framework and sample period as in these papers, but replacing simple sum monetary aggregates with Divisia monetary aggregates (Monetary Services Indices, MSI). They find that the demand for money is stable, and that money displays a strong linkage with macroeconomic variables. More recently, Belongia and Ireland (2012b) include Divisia monetary aggregates in the structural vector autoregression model (SVAR)

[4] The earliest comparisons between Divisia monetary aggregates and simple sum aggregates are reviewed in Barnett and Serletis's survey (2000). Other overviews of published theoretical and empirical results in this literature are available in Serletis (2006). More recent papers include Schunk (2001), Belongia and Ireland (2006), Barnett, Chauvet and Tierney (2009), Barnett and Chauvet (2011), and Barnett (2012).

proposed in Leeper and Roush (2003). They find several interesting results. First, MSI is useful to predict economic variables; second, the inclusion of MSI substantially improves the fit of the SVAR model, and the "price puzzle" is reduced.[5] Finally, they find that specifications for monetary policy based on the Taylor rule are rejected in favor of specifications that consider the role of money. Serletis and Rahman (2012) use several alternative models to examine the relationship between uncertainty in the growth of monetary aggregates and overall U.S. economic activity. They find a positive relationship between uncertainty in MSI growth and real economic activity, but not when using broad measures of money based on simple sum aggregates.

The closest related papers to ours are Barnett, Chauvet and Tierney (2009) and Barnett and Chauvet (2011). Barnett, Chauvet and Tierney (2009) model and examine the differences (measurement errors) between simple sum monetary aggregates and the Divisia monetary aggregate indexes over time, across business cycle phases, and across high and low inflation and interest rate phases. They find that the largest measurement errors occur around the beginning and end of recessions, and during periods of high interest rates. Barnett and Chauvet (2011) find that recessions have been preceded by more contractionary money growth as measured by Divisia monetary aggregates than indicated by simple sum money measures. There are sub-samples differences as well. For example, during the Great Moderation period money growth was looser as measured by Divisia monetary aggregates than by simple sum money.

Following this literature, this paper aims to investigate the role of Divisia monetary aggregates and the economy. The focus of our paper is not on comparing simple sum monetary aggregate with Divisia money measure (MSI), as the differences have been established in the literature both using linear and nonlinear frameworks.[6] Instead, we use a non-structural empirical model to study the nonlinear interrelationship among trends and cycles in money, prices, and income – using Divisia monetary aggregates as the measure of money. The multivariate three-factor Markov-switching system combines in a unified framework the joint dynamics of the long run and short run components of these series. We assume that the components of each series follow distinct two-state Markov processes, representing low or high phases of the transitory (short run) and of the permanent (long run) components of Divisia monetary aggregates, income,

[5] The 'price puzzle' refers to the empirical finding that monetary tightening tends to lead to an increase rather than a fall in the price level in vector autoregressive models.
[6] Section 5 contains a brief discussion comparing results from simple sum and Divisia monetary aggregates.

and prices. The Markov state probabilities allow analysis of the interactions among the phases of each series and their components. Since the lead-lag relationship between the phases can vary over time, rather than pre-imposing a structure to their linkages, the proposed flexible framework enables us to study their specific lead-lag relationship over each one of their cycles and over each expansions and recessions that occurred in the U.S. in the last forty years.

We find substantial changes in the structure of the economy over time. In particular, the permanent components of both income and prices show a steeper slope in the early part of the sample, compared to the last two decades. However, Divisia monetary aggregates do not display structural breaks, as also found in Belongia (1996) and Hendrickson (2011). The decomposition of the series into permanent and transitory components reveals some patterns distinct from those in the total series, and some striking results. There is a strong nonlinear association among the components of Divisia monetary aggregate, income, and prices, and with business cycles. The evidence holds across different methods such as vector autoregression, average phase lead, and turning point analysis. We find that both transitory and permanent tight money phases are associated with subsequent low transitory price phases, and with low transitory and permanent income phases. Additionally, most recessions were preceded by tight permanent and transitory monetary phases and high cyclical prices.

The remainder of the paper is organized as follows: section 2 presents the multivariate unobserved component Markov switching model used in our empirical analysis. In section 3 we review the data and specification tests. Section 4 discusses the empirical results. Specifically, it discusses the findings with respect to the dynamic interrelationships of Divisia monetary aggregates, prices, and income, and their permanent and transitory components. Section 5 briefly discusses the results when simple sum monetary aggregates are used instead of Divisia money measures. Section 6 contains concluding remarks.

2. A Dynamic Three-Factor Regime Switching Model of Permanent and Transitory Components

We propose a unified nonlinear model of the long run and short run components of money, prices, and income that takes into account their dynamic interrelationships. As in the univariate unobserved-components framework of Harvey (1985) and Clark (1987) each variable is decomposed into a nonstationary trend and a stationary cycle. We extend this approach considering a multivariate framework of trend and cycle for the three series using a dynamic three-factor model with regime switching. The interactions among the components are investigated by specifying the factors as following a vector autoregressive system and through Markov switching processes representing phases of the permanent and transitory components.

We assume that the series are represented as the sum of a permanent (or trend) component and a transitory (or cyclical) component. Let $\mathbf{Y}_t = [i_t \quad p_t \quad m_t]'$ be the vector of the log nominal income, $i_t = \ln(I_t)$, log prices, $p_t = \ln(P_t)$, and log nominal money, $m_t = \ln(M_t)$, $\mathbf{P}_t$ be the vector of permanent components, $\mathbf{P}_t = [P_{it} \quad P_{pt} \quad P_{mt}]'$, and $\mathbf{C}_t$ be the of the transitory components $\mathbf{C}_t = [C_{it} \quad C_{pt} \quad C_{mt}]'$. The series are decomposed as:

$$\mathbf{Y}_t = \mathbf{P}_t + \mathbf{C}_t \tag{1}$$

where the permanent component is assumed to follow a random walk with switching drift, $\boldsymbol{\mu}_{s_t^P}$:

$$\mathbf{P}_t = \boldsymbol{\mu}_{s_t^P} + \mathbf{P}_{t-1} + \boldsymbol{\varepsilon}_t \qquad\qquad \boldsymbol{\varepsilon}_t \sim i.i.d.\, N(0, \boldsymbol{\Sigma}) \tag{2}$$

and the transitory component for each series, $\mathbf{C}_t$, follows a stationary VAR(p) process with switching intercept, $\boldsymbol{\alpha}_{s_t^C}$:

$$\mathbf{C}_t = \boldsymbol{\alpha}_{s_t^C} + \mathbf{A}_1\mathbf{C}_{t-1} + \cdots + \mathbf{A}_p\mathbf{C}_{t-p} + \boldsymbol{\eta}_t \qquad\qquad \boldsymbol{\eta}_t \sim N(0, \boldsymbol{\Theta}) \tag{3}$$

where $\mathbf{A}_r$ are the coefficient matrices, for $r = 1,..., p$, $\boldsymbol{\varepsilon}_t$ is the vector of zero mean idiosyncratic terms, $\boldsymbol{\Sigma}$ is the diagonal variance-covariance matrix of the permanent components, $\boldsymbol{\eta}_t$ is the vector of zero mean transitory errors, and $\boldsymbol{\Theta}$ is the diagonal variance-covariance matrix of the transitory components. The idiosyncratic terms $\boldsymbol{\varepsilon}_t$ are assumed to be uncorrelated with the components of $\mathbf{C}_t$ and with $\boldsymbol{\eta}_t$ at all leads and lags for identification purposes.

The model is cast in state space, which allows us to simultaneously estimate the unobservable factors as well as their intertemporal relationship. The interactions are investigated by specifying the transitory components as following a vector autoregressive system and by studying the relationships across the Markov states for the permanent and transitory components.

There is generally more than one way to represent a dynamic system in state space form. We transform the model into first differences and treat the transitory components as unobserved state variables. The state space representation of the proposed model for the series, in the special case of $p = 1$ has measurement equations:

$$\Delta \mathbf{Y}_t = \boldsymbol{\mu}_{s_t^P} + \boldsymbol{\Lambda}\boldsymbol{\xi}_t + \boldsymbol{\varepsilon}_t \qquad \boldsymbol{\varepsilon}_t \sim i.i.d.N(0,\boldsymbol{\Sigma}) \tag{4}$$

and transition equations:

$$\boldsymbol{\xi}_t = \boldsymbol{\alpha}_{s_t^c} + \boldsymbol{\Phi}\boldsymbol{\xi}_{t-1} + \mathbf{v}_t \qquad \mathbf{v}_t \sim i.i.d.N(0,\mathbf{N}) \tag{5}$$

where:

$$\begin{array}{ccccccccc} \Delta\mathbf{Y}_t & & \boldsymbol{\mu}_{s_t^P} & & \boldsymbol{\Lambda} & & \boldsymbol{\xi}_t & & \boldsymbol{\varepsilon}_t \\ \begin{bmatrix} \Delta i_t \\ \Delta p_t \\ \Delta m_t \end{bmatrix} & = & \begin{bmatrix} \mu_{is_t^P} \\ \mu_{ps_t^P} \\ \mu_{ms_t^P} \end{bmatrix} & + & \begin{bmatrix} 1 & 0 & 0 & -1 & 0 & 0 \\ 0 & 1 & 0 & 0 & -1 & 0 \\ 0 & 0 & 1 & 0 & 0 & -1 \end{bmatrix} & & \begin{bmatrix} C_{it} \\ C_{pt} \\ C_{mt} \\ C_{it-1} \\ C_{pt-1} \\ C_{mt-1} \end{bmatrix} & + & \begin{bmatrix} \varepsilon_{it} \\ \varepsilon_{pt} \\ \varepsilon_{mt} \end{bmatrix} \end{array}$$

$$\begin{array}{ccccccccc} \boldsymbol{\xi}_t & & \boldsymbol{\alpha}_{s_t^c} & & \boldsymbol{\Phi} & & \boldsymbol{\xi}_{t-1} & & \mathbf{v}_t \\ \begin{bmatrix} C_{it} \\ C_{pt} \\ C_{mt} \\ C_{it-1} \\ C_{pt-1} \\ C_{mt-1} \end{bmatrix} & = & \begin{bmatrix} \alpha_{is_t^c} \\ \alpha_{ps_t^c} \\ \alpha_{ms_t^c} \\ 0 \\ 0 \\ 0 \end{bmatrix} & + & \begin{bmatrix} \phi_{ii} & \phi_{ip} & \phi_{im} & 0 & 0 & 0 \\ \phi_{pi} & \phi_{pp} & \phi_{pm} & 0 & 0 & 0 \\ \phi_{mi} & \phi_{mp} & \phi_{mm} & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \end{bmatrix} & & \begin{bmatrix} C_{it-1} \\ C_{pt-1} \\ C_{mt-1} \\ C_{it-2} \\ C_{pt-2} \\ C_{mt-2} \end{bmatrix} & + & \begin{bmatrix} \eta_{it} \\ \eta_{pt} \\ \eta_{mt} \\ 0 \\ 0 \\ 0 \end{bmatrix} \end{array}$$

The vector $\Delta\mathbf{Y}_t$ includes the log first difference of income, Δi_t, prices, Δp_t, and monetary aggregate MSI, Δm_t, and is a function of the switching drifts, the difference of the transitory components, and the idiosyncratic terms. The state space vector then includes three unobserved factors, representing the cyclical components of the series. The coefficients of the transition matrix $\boldsymbol{\Phi}$ capture the lead-lag relationship among the latent cyclical factors.

We allow the low and high phases of the permanent and latent cyclical components of money, prices, and income to follow different two-state Markov switching processes. By allowing for potentially independent Markov processes, we do not restrict the trend and cycles of each variable to switch between phases at the same time. Specifically, the representation allows the underlying process for the permanent and transitory components of monetary aggregates to switch non-synchronously with the permanent and transitory components of prices and income.

The drifts of the permanent components, $\boldsymbol{\mu}_{s_t^P}$, and the intercepts of the latent cycles, $\boldsymbol{\alpha}_{s_t^C}$, are functions of distinct Markov switching processes, $\mathbf{S}_t^P = \{S_{it}^P, S_{pt}^P, S_{mt}^P\}$ and $\mathbf{S}_t^C = \{S_{it}^C, S_{pt}^C, S_{mt}^C\}$, respectively. For $h = i_t, p_t, m_t$ the drift of the trends switches between $\mu_{h,0}$ for low trend values $(S_{ht}^P = 0)$ and $\mu_{h,1}$ for high trend values $(S_{ht}^P = 1)$, while the intercept of the cyclical component takes the value $\alpha_{h,0}$ in low cyclical phases ($S_{ht}^C = 0$) and $\alpha_{h,1}$ in high cyclical phases ($S_{ht}^C = 1$). The switches between the two phases of the trend and the two phases of the cycle are ruled by the transition probabilities, $p_{h,kj}^P = \Pr[S_{h,t}^P = j \mid S_{h,t-1}^P = k]$ and $p_{h,gl}^C = \Pr[S_{h,t}^C = l \mid S_{h,t-1}^C = g]$, respectively, with $\sum_{j=0}^1 p_{h,kj}^P = 1,\ \ for\ k, j = 0,1$ and $\sum_{l=0}^1 p_{h,gl}^C = 1,\ \ for\ g, l = 0,1$.

The model is estimated by maximum likelihood through a nonlinear filter that combines a discrete version of the Kalman filter with Hamilton's (1989) algorithm, using an approximation proposed in Kim (1994). The nonlinear Kalman filter is initialized using the unconditional mean and unconditional covariance matrix of the state vector. In maximizing the likelihood, we employ transformations such that the resulting autoregressive processes are stationary and innovation covariance matrices are positive definite. A nonlinear optimization procedure is used to maximize the likelihood function, which is obtained as a by-product of the probabilities of the Markov states. The predictions of the unobserved factors and of the probabilities of the Markov states are obtained as a final pass of the nonlinear filter based on the maximum likelihood estimates. We estimate all parameters and factors simultaneously in one step. The joint modeling and estimation has the advantage that it does not carry out parameter estimation uncertainty associated with extracting the factors to a vector autoregressive model that specifies the dynamic relation between the factors, compared to two-step procedures.

The filter generates optimal inferences of the probabilities of low or high values for the permanent and transitory components of income, prices, and money in period t, given information set available at t, I_t, which are denominated filtered probabilities, $\Pr[S_{h,t}^P = j \mid I_t]$ and $\Pr[S_{h,t}^C = l \mid I_t]$. These probabilities can be combined with available information in the full sample, I_T, to generate smoothed probabilities of low or high value states, $\Pr[S_{h,t}^P = j \mid I_T]$ and

$\Pr[S_{h,t}^{C}=l\,|\,I_T]$. We report the smoothed probabilities and the smoothed components from the model estimation.

Related approaches that propose multivariate unobserved component models with Markov switching are Kim and Piger (2002), Kim, Piger and Startz (2007), and Senyuz (2011). Kim and Piger (2002) propose a common trend and common cycle unobserved component model for GDP, consumption, and investment. Both permanent and transitory components follow the same Markov switching process, although they exhibit different types of asymmetries. Kim, Piger, and Startz (2007) and Senyuz (2011) extend Kim and Piger (2002) by allowing the Markov switching process for the common trend and common cycle to switch non-synchronously. These models differ substantially from the one proposed in this paper as we assume an unobserved component model for each of the three series. Additionally, each component of each series follow an independent Markov switching process, which allows the cycle and the trend of money, prices, and income to switch non-synchronously. As far as we know, a multivariate unobserved component model with a vector autoregression for the components and independent Markov processes for each permanent and transitory component as proposed in this paper has not been previously seen in literature.

3. Data, Model Selection, and Specification Tests

3.1 Data

We examine the dynamic relationships between the Divisia Monetary Services Index MSI and the U.S. macro economy between 1967:01 and 2010:05. Our data are monthly nominal personal income less transfer payments obtained from the Bureau of Economic Analysis, the chain-price index for Personal Consumption Expenditure, and monthly nominal Divisia MSI-ALL, both obtained from the Federal Reserve Bank of St. Louis.[7]

[7] The earliest Divisia aggregates for the U.S. were constructed at the Federal Reserve Board through the mid 1980s by Barnett and Spindt (1982) and, later, by Farr and Johnson (1985) who introduced the descriptive label "monetary services indexes" to describe them. Anderson, Jones and Nesmith (1997) constructed monetary services indices (MSI) for the Federal Reserve Bank of St. Louis, with later revisions as described by Anderson and Buol (2005), and a comprehensive revision described in Anderson and Jones (2011). This is the version of the data used in this paper. These data can be found at the Saint Louis database FRED at http://research.stlouisfed.org/msi/. More recently, Barnett has made Divisia monetary aggregates including broader measures such as M3 and M4 (both quantity and dual user cost-aggregates) available to the public at the Center of Financial Stability at http://www.centerforfinancialstability.org/amfm.php (for an explanation of the methods underlying the data see Barnett, Liu, Mattson, and Noort 2013). An appendix providing an overview of Barnett's theory of Divisia monetary

In the analysis we consider the natural log of the series, which are denoted m_t (money), p_t (prices), and i_t (income). The series in log level and in log first difference are displayed in Figures 1 and 2, respectively. Figure 1 suggests that the series may have experienced a shift in trend during the Federal Reserve's disinflation campaign of 1979-1982 (indeed, to the extent the campaign was successful, this must be the result). Below, we formally examine each series for possible shifts in trend.

3.2 Model Selection and Specification Tests

Structural Breaks. We apply structural stability tests for potential endogenous breaks in the variance and mean of each series when the breakpoint date is not known. We implement the asymptotically optimal tests developed by Andrews (1993) and Andrews and Ploberger (1994), and the sequential procedure of Bai (1997) and Bai and Perron (1998) for multiple breaks. We test two separate hypotheses. First, we consider the possibility of a break in the variance of the series assuming that the mean has remained constant. However, the results of this test would be unreliable if there was a break in the parameters of the underlying model. In this case, evidence of a break in the volatility from this test could be due to neglected structural change in the conditional mean of the series. In order to account for this, we also test for a break in the conditional mean of the series, allowing for changing variance.[8]

The tests indicate strong evidence of several breaks in prices and income, but not in Divisia monetary aggregate. First, we find that income has a significant break in its mean in 1981:11, and prices display a mean break in 1990:01. In addition, the variance of these series displays a break in the mid-1980s, consistent with the large literature on the Great Moderation. Income volatility displays a break in 1984:04 towards increased stability, whereas the tests applied to prices find a break in its volatility in 1986:05.

We estimate an extension of model (1)-(5) that considers dummy variables representing these dates for structural breaks in mean and variance of the series. Alternatively, we also consider an extension of the model that allows for potential unknown breakpoints in the series. The model is augmented by allowing $\Delta\mathbf{Y}_t$ to follow additional independent absorbing two-state Markov processes that capture permanent structural breaks in the mean and in the variance of the

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aggregates, and an overview of the new data series constructed by Anderson and Jones (2011) is available from the authors upon requested.

[8] The details of the tests are described in an appendix available upon request.

components. For example, the Markov process for detecting structural break in the switching drift of the permanent component of variable *h* is:

$$\mu^{D_t}_{h,S^P_{ht}} = \mu^{D_t}_{h,S^P_{h0}}(1 - D^P_t) + \mu^{D_t}_{h,S^P_{h1}} D^P_t \tag{6}$$

where $D^P_t = 0$ if $t < t^*$ and $D^P_t = 1$ otherwise, and t^* is the unknown break date. The transition probabilities for the Markov process are constrained to capture the endogenous permanent break as in Chib (1998) and Kim and Nelson (1999):

$$\Pr[D^P_t = 0 \mid D^P_{t-1} = 0] = q \qquad 0 < q < 1$$

$$\Pr[D^P_t = 1 \mid D^P_{t-1} = 1] = 1.$$

The results from estimating model (1)-(6) with endogenous breaks model support the ones obtained from the structural breaks tests applied to the univariate regressions, as discussed in subsection 4.1.

Cointegration. We test for cointegration using Engle and Granger (1987) and Stock and Watson's (1988) tests, and the nonlinear nonparametric test of Bierens (1997). It is well known that cointegration tests have low power in the presence of structural breaks. We apply these tests with and without taking into account the possibility of structural breaks. The results fail to detect cointegration in the series. The null hypothesis of no cointegration and the null of no common stochastic trends cannot be rejected at the 5% level.

Markov Switching. We apply Garcia's (1998) tests for the presence of nonlinear dynamics. The test for regime switching model has the null hypothesis of one state against the alternative of two states. The test overcomes the problem of presence of nuisance parameters under the null in Markov switching models. Hansen (1992) uses empirical process theory to derive an upper bound for the asymptotic distribution of the likelihood ratio test. Garcia (1998) shows that if the transition probabilities are treated as nuisance parameters, the information matrix for the other parameters is non-singular and there are no score to the probability terms. In this case, Hansen's (1992) results can be applied to test regime switching models. Garcia (1998) proposes a simulation method for obtaining chi-square process and derives analytically the asymptotic null distribution and critical values for the likelihood ratio test in the context of regime switching models. That is, fixing the transition probabilities at a set of different values over their parameter space, and excluding the values zero or one, Garcia derives the likelihood ratio statistic as the supremum over the parameter space of likelihood ratios obtained for each of the sets of the transition probability values. The results from Garcia's test indicate that that the null hypothesis of no switching is strongly rejected at the 1% level for all series.

Specification Tests. Several different specifications of the dynamic factor Markov switching models were estimated to examine the suitability of their fit, such as alternative autoregressive processes in the transition and measurement equations.[9] The extracted switching factors are almost identical for all specifications.

Higher parameterized models were estimated, but the coefficients of higher dynamic orders were not significant at the statistical level of 5%. Hurvich-Tsai's bias-corrected version of Akaike Information Criterion, Schwarz criterion and the likelihood ratio test were used to choose between alternative specifications of the model.[10]

In order to check the adequacy of the model specification we analyze the disturbances in the observable variables. If the model is correctly specified, the estimated residuals for each observable variable are serially uncorrelated and nearly uncorrelated with each other. Thus, the residuals' sample autocorrelation should be close to zero for displacements greater than one and the errors should be white noise. The diagnostic tests indicate that the specifications selected are adequate for all equations.

Some variations were also introduced to the basic models such as allowing the factor variance and mean to switch regimes or holding the mean constant and allowing the variance of the factor to switch. We also allow for breaks in the mean, in the variance or in both.

The procedure followed was to first estimate univariate Markov switching unobserved component models for each series separately. Structural breaks and specification tests were applied to each model. Next, we estimate the multivariate unobservable model with Markov switching for the components in one step, using the parameters from the univariate models as starting values. Structural breaks tests and specification tests are applied to the multivariate framework. Based on the results of the structural break tests, we specify variants of the multivariate unobserved component model that take into account changes in the mean and variance before and after the breakpoints in addition to the switching in the parameters related to cyclical changes in the components of money, prices, and income.

[9] Here we test the null of simpler Markov switching models versus the alternative of more parameterized Markov switching models. These tests, thus, do not encounter the problem of nuisance parameters.
[10] The Akaike Information Criterion is biased toward highly parameterized models. Hurvich-Tsai's test consists of a corrected version of AIC for overfitting bias.

4. Relationship among Monetary Services Index, Income, and Prices

In this section we study the relationships among log money (m_t), log income (i_t), and log prices (p_t). Below, the variables' permanent and transitory components, respectively, will be denoted $\{i_t^P, p_t^P, m_t^P\}$ and $\{i_t^C, p_t^C, m_t^C\}$. We first report the results obtained from the likelihood estimation of the dynamic three-factor Markov switching model. This is followed by a discussion on the nonlinear relationship among money, income, and prices and their transitory and permanent components. Finally, we present a turning point analysis of the phases of each of the series and their interrelationships.

4.1 Maximum Likelihood Estimates

Table 1 reports maximum likelihood estimates of the best specification according to the tests. Interestingly, we find that once Markov switching in the drifts of the trend and cycle are taken into account, the breaks in the mean of income and prices are still significant, but not the breaks in volatility. We thus select the specification with absorbing Markov process (as in equation 6) for the drift in the permanent and cyclical components only.[11] The probabilities from the absorbing Markov processes increases to values close to one, indicating a mean break in the permanent component of income in 1981, a mean break in the permanent component of prices in 1985, and a mean break in the cyclical component of prices in 1990.

The model captures a dichotomous pattern in the series associated with high and low phases. The permanent components of money and income switch between a high and positive mean rate at state 1 (μ_{1m}, μ_{1i}) and a negative average rate (μ_{0m}, μ_{0i}) in state 0. The transition probabilities are highly significant and the probability of staying in a positive mean phase is higher than the probability of staying in a low mean phase.

The mean of the permanent income has a significant break around 1981, with values almost twice as large after the break than before the break for the positive state (state 1) and values a lot more negative after the break for the negative state (state 0). That is, when the sample includes the period between 1980 and the Great Recession, there is a larger gap between the mean at state 0 and state 1 for the permanent component of income than before the break.

[11] The results for other specifications of the model are not shown due to space consideration but are available from the authors upon request.

A different pattern is observed in the permanent component of prices before and after a break around 1985. Before the break, the mean of the permanent component of prices switches between high positive and low positive values. After the break, the mean switches between negative and positive values, reflecting a much lower price trend. We also find that there is a break in the cyclical component of prices around 1990. The mean of cycle phases after the break decreased to almost half its pre-break values, for both state 0 and state 1. This is in accord with the observation of much lower long run and short run prices during the Great Moderation period.

Although there have been several structural changes in the dynamics of the economy, this is not the case for Divisia money, as their components did not show a significant break. This supports evidence found in Belongia (1996) and Hendrickson (2011) of stability in Divisia monetary aggregates.[12]

The estimated parameters of the transition probabilities yield an assessment of the expected duration of the Markov phases.[13] Price phases are highly persistent, as extensively found in the literature on price stickiness. For example, low cyclical price phases last around 5 years ($p^{C}_{00P} = 0.984$ or 62 months) – almost twice as long as high cyclical price phases, which have an expected duration of 2.7 years ($p^{C}_{11P} = 0.969$ or 32 months). The duration of phases can be more precisely measured by the smoothed probabilities of low and high phases assuming a threshold of 50% (see Ohn, Taylor and Pagan 2004 and subsection 4.3.1). Using this metric, we find very similar average duration for low and high cyclical price phases, of 60 and 33 months, respectively. Although displaying a shorter duration, the phases of transitory and permanent money are remarkably similar to the phases of cyclical prices.

The interactions among the cyclical components are investigated by specifying the factors as following a vector autoregressive system. The autoregressive coefficients ϕ_{hf} from the transition equations (5) indicate the coefficient of the lagged variable f in the transition equation for variable h. As shown in Table 1, the cyclical components are highly persistent, with high values for the autoregressive coefficients for income, prices, and money. The signs of the coefficients

[12] As discussed in section 5, when the model (1)-(6) is applied to simple sum M2 instead, we find strong evidence of structural breaks in the components of this series. The implication is that Divisia monetary aggregate is a stable measure of money that could prove useful for monetary policy.

[13] The expected duration of phases can be inferred by the transition probabilities using the formula: $\sum_{l=1}^{\infty} l p_{00}^{l-1}(1-p_{00}) = 1/(1-p_{00})$.

are as expected. Lagged transitory money is positive correlated with transitory income ($\phi_{im} = 0.170$) and transitory prices ($\phi_{pm} = 0.010$), and the coefficients are statistically significant at any level. That is, low values of lagged transitory money are associated with low future values of transitory income and transitory prices. Additionally, high lagged transitory prices are positively associated with high future values of income ($\phi_{ip} = 0.012$), and high lagged income is associated with low future values of money ($\phi_{mi} = -0.018$).

Notice that these coefficients reflect the average relationship over the states. The lead-lag dynamics of the series is better depicted by studying the linkages between their phases. This can be directly examined within our proposed nonlinear framework that allows for distinct (but potentially dependent) Markov processes to represent prices, money, and income.

4.2 Analysis of Permanent and Transitory Components and the Business Cycle

This section studies the dynamics of the transitory and permanent components of money, prices, and income around NBER recessions as depicted by the smoothed probabilities of their high or low states. We find that the components of money, prices, and income are associated with NBER recessions. In general, transitory money is low and transitory price is high before recessions.[14] In addition, both permanent and transitory components of income show a substantial decrease during recession periods. Below we discuss these results in more detail.

Money (MSI-ALL) **-** Figure 2 shows the probabilities that the transitory and permanent components of money are in the "low" state, and NBER recessions. The probabilities of tight transitory and permanent money phases are associated with business cycles, with increases in these probabilities associated with the beginning of all recessions with the exception of the two most recent ones.

In the first half of the sample, the probabilities of tight transitory and permanent money increase one or two years before an NBER recession. From the mid-1980s to mid-1990s, the probabilities of low transitory money remain high (which is associated with a period of relative low total money growth as shown in Figure 1b). The 2001 and 2007-2009 recessions are different from all others, with no preceding increase in the probabilities of low transitory or low

[14] The NBER Business Cycle Dating Committee seeks to identify the dates of "peaks" and "troughs" in economic activity. Traditionally, "expansions" are those periods between a business cycle trough and the subsequent peak, and "recessions" those dates between a cycle peak and the subsequent trough.

permanent components of money. This suggests that the onset of these recessions was not associated with monetary components. In addition, the last three recessions (1990-1991, 2001, and 2007-2009) have instead been followed – not preceded - by increases in the probability of a low permanent component of money. That is, relatively tight permanent money persisted until well after business cycle troughs. Notice that these recessions were followed by sluggish recoveries coinciding with these tight money phases.

Prices **-** The probabilities of the transitory component of prices being in the "high" state are shown in Figure 3. These probabilities increase before recessions and remain high until after their end. This is the case for all recessions except for the 1970-1971 and the 2001 ones.[15] For the more recent case of the 2007-2009 recession, the probabilities of high cyclical prices stayed above 50% only up to the middle of this recession, decreasing sharply before its end.

The probabilities of the low state for the permanent component of prices are also shown in Figure 3. Although increases in the probabilities are somewhat clustered around recessions, there is a less clear business cycle pattern.

Income **-** The probabilities of low transitory and permanent income components are plotted in Figure 4. These probabilities increase after each business cycle peak, suggesting a strong association between recessions and a reduction in transitory and permanent income. Note that the probabilities of low transitory income component increase during recessions, but also during recoveries, and during economic slowdowns. In fact, this is the case for periods in which the U.S. economy experienced low growth phases but the NBER did not label them as recessions, as in 1976-1977, 1984-1986 (slowdown in Europe), 1994-1995 (Mexican crisis), and 1998-1999 (Russia and Brazil currency crises). That is, even though these periods are not considered more severe and widespread economic contractions as during recession phases, there is still a significant economic impact, as transitory personal income falls when the economy displays low economic growth.

4.3 Nonlinear Relationship Among the Series' Permanent and Transitory Components

In this section we study the interrelationships among the series across specific periods using the probabilities of high or low states for each series and turning point analysis. The method is

[15] The cyclical component of prices is highly correlated with inflation. As shown in Figure 1b, although rises in inflation precede these recessions, the magnitude is relatively small compared to the dynamics of inflation during other recessions.

distinct from the analysis of the vector autoregressive coefficients in subsection 4.1, as it can capture dynamics in the series that regression representations of the series' average behavior over the full sample may miss. For example, the largest errors in predicting income or prices occur around NBER-dated turning points. This suggests that economic agents may react differently to changes in economic variables, depending on their perceptions about the state of the economy. In effect, changes in the trend or cycle of monetary aggregates may have a stronger or weaker impact on prices and income depending on whether the economy is in the middle of an expansion or in a recession or whether prices is in a high or low phase.

4.3.1 Turning Point Analysis - Nonlinear Lead-Lag Relationship

While the probabilities displayed in figures 2-4 are revealing and intuitive, it is difficult to assess the tightness of the relationships between permanent and transitory components of the series at turning points without formal rules. In this section, we use probability methods to tabulate and examine nonlinear lead-lag relationships among money, price, and income and their transitory and permanent components circa their peaks and troughs. We use two methods to evaluate their nonlinear relationship: first, the phases of each series are compared using probability scores to assess their closeness for all cycles. Second, turning point classification tables are used to investigate their temporal lead-lag relationship for each of their specific cycles.

Average Probability Scores – the closeness of the probabilities of states for the series is measured by a probability counterpart of the mean squared error – the probability square deviation, which evaluates the match between the probabilities of states for each series:

$$PSD_n = \frac{1}{T}\sum_{t=1}^{T}\left\{p^i_{t-n} - p^j_t\right\}^2 \quad n = \{-48,...,-,2,-1,0,1,2,...,48\}$$

where p^i_{t-n} and p^j_t are the smoothed probabilities for the series *i* and *j*, respectively, at lead/lag *n*. The probability square deviation ranges between 0 and 1, with the maximum closeness corresponding to zero.[16]

Turning point Analysis – we tabulate specific turning point dates based on the smoothed probabilities. To do so, a formal definition is needed to convert the model's probabilities into turning-point dates. A widely used approach is to classify a turning point as occurring when the smoothed probability of a state moves from below 50% to above 50%, or vice versa. This has

[16] Notice that this measure is different from the quadratic probability score, which evaluates the closeness of probability forecasts from the realization of an event.

intuitive appeal because it separates periods when a high state is more likely from those when a low state is more likely. Formally, month *t* is a business cycle *peak* if the series was in a high state in month *t-1* and $\Pr[S_t = low\ state \mid I_T] \geq 0.5$; and month *t* is a *trough* if the series was in a low state phase and $\Pr[S_{t+1} = low\ state \mid I_T] \leq 0.5$, for the full sample information I_T. Using this rule, we date "high" and "low" phases (turning points) of the transitory and permanent components of m_t, p_t, i_t. We use the chronology obtained by this method to study the lead-lag relationship among the low and high states of money, prices, and income, as well as with NBER recessions.

The turning points from the smoothed probabilities can be used as rules to analyze the relationship between money and prices, and money and income. In particular, we can contend two hypotheses:

a. If the peak of tight money phase lagged or coincided with the onset of a low prices or low income phase, it could not have been an original cause of this phase since they did not anticipate it.
b. If the peak of tight money phase preceded low prices and low income phases, there is a possibility that they could have been a causal factor.

In the next sections we study each of the phases of money, prices, and income, as well as the average lead-lag relationship of these series across all phases.

Nonlinear Relationship between Money and Prices - The decomposition of the series uncovers some interesting relationships among the series that are not revealed when studying their total components. Figure 5 shows the probabilities of low permanent and transitory components of money, and the probabilities of low transitory prices. The probabilities of low phase for the components of money anticipate five out of the six low transitory price phases in the sample. That is, every time cyclical price entered a low phase, it was preceded by a persistent low money phase. The results confirm a strong association between low phases of money and low cyclical prices. The timing of the probabilities suggests that money phases could be one of the causal factors for cyclical price phases (hypothesis b). This evidence is also found from the vector autoregressive coefficients in subsection 4.1.

Table 2 shows the lead (minus sign) or lag (plus sign) at which the PSD of transitory and permanent components of prices and income reaches minimum values *with respect to the transitory and permanents components of money*. While the smoothed probabilities in Figure 5 depicts each temporary price and money phases in particular, the PSD gives the average dynamics for all their phases in the sample. The results confirm the assessment obtained from the smoothed probabilities, but the analysis further reveals how the components of prices are related to the components of money. We find that the lead through which transitory and permanent changes in money anticipates low cyclical prices is 12-14 months (Table 2 column 1). The results suggest that the outside lag for tight money phases to presumably cause cyclical prices to enter a low phase is about one year. By the same token, low permanent (but not transitory) changes in money anticipate high cyclical prices with a lead of 10 months (Table 2 column 2). This result might indicate that expectations of transitory increases in prices are anticipated by low permanent money phases.

In order to compare the results from the decomposition of the series with the series themselves, we fit a simple univariate AR(0) Markov switching model to the log first difference of total prices, and to the log first difference of monetary aggregates.[17] Interestingly, if we compare the probabilities of low total money growth and probabilities of low inflation, we find that low total monetary aggregates leads low inflation by a shorter outside lag of 6 months (minimum PSD between these series), compared to our results.

***Nonlinear Relationship between Money and Income* -** Figure 6 plots the probabilities of being in the low state for the permanent and transitory components of money, and the probability of low cyclical income. The probabilities of low transitory and permanent money tend to anticipate low cyclical income phases with a long lead. This pattern is particularly strong around recessions, except, again, for the 2001 and 2007-2009 ones. In these latter cases, the probabilities of low permanent and transitory money components only increased after the probabilities of low cyclical income had increased.

Notably, using the average behavior as measured by the PSD we find that the low permanent and transitory components of money anticipate low permanent income with long leads (Table 2 column 4). The conclusions are different if we examine the relationship of the total series instead of their components. Again, fitting a univariate AR(0) Markov switching model to the log first difference of income, and to the log first difference of monetary aggregates, we find that low

[17] We fitted several higher order autoregressive Markov switching specifications and find that the best model is the parsimonious AR(0) process, based on specification tests and the characterization of low and high states. This result holds across many U.S. macroeconomic and financial series and is related to potential outliers and instabilities in the series, as discussed in Chauvet and Su (2013) and references therein.

total money growth states anticipate low total income growth states with a short lead of only 3 months.

Chronology and Sequence of Turning Points - Money, Prices, Income, and Recessions - We now turn our attention to how the series' phases are related to each of their cycles and to the U.S. business cycle. Table 3 shows the chronology and sequence of turning points of the transitory and permanent components of money with respect to turning points of transitory prices and transitory income, as well as with the NBER recession peaks. The table reflects information in Figures 5 and 6.

There are seven NBER recessions and nine money, transitory prices and/or transitory income cycles in our sample. All business cycle peaks were preceded by tight phases of permanent and/or transitory monetary aggregates, with the exception of the 2001 and 2007-2009 recessions. A prominent feature is that decreases in the permanent component of money occur before decreases in its transitory component, for all cycles.

Remarkably, we find that all low cyclical price phases were anticipated by low states of cyclical money, as in the PSD analysis and in the vector autoregressive analysis in subsection 4.1, indicating a strong association between Divisia monetary aggregates and cyclical prices. Another interesting finding is that high cyclical price phases are generally anticipated by low states of money. In fact, transitory and permanent monetary aggregates fell before or at the beginning of five out of the six high cyclical price phases in the sample. The only exception is the high cyclical price phase that started in 2007 and ended in 2008.[18] We also find that five out of the seven recessions in the sample were preceded by high cyclical price phases (exceptions are the 1969-1970 and the 2001 recessions). Notice that, as in the PSD analysis, all recessions were associated with decreases in income, with low cyclical income phases coinciding or slightly lagging the beginning of recessions.

In summary, we find that both transitory and permanent tight cyclical money phases are associated with subsequent low cyclical price phases. Additionally, permanent and transitory tight money phases preemptively lead phases of high cyclical prices. Most recessions were

[18] This high cyclical price phase was mostly caused by high oil prices and other supply side factors. Given the weakening of the housing market and of some sectors of the economy, the Federal Reserve continued to decrease interest rates in 2007, which may have contributed for the fact that monetary aggregates did not enter a low phase during this period.

preceded by tight monetary phases and high cyclical prices and all recessions were accompanied by a decrease in both permanent and transitory income.

5. Monetary Services Index and Monetary Aggregate Simple Sum M2

The focus of our paper is not on comparing simple sum monetary aggregate with Divisia money measure (MSI), as the differences have been established in the literature both using linear and nonlinear frameworks. However, in this section we illustrate some further evidence of the differences when simple sum monetary aggregate M2 is decomposed into permanent and transitory components. We replace Divisia monetary aggregate by M2 in model (1)-(6). Differently from Divisia monetary aggregates, the model indicates structural breaks in the permanent component of M2 between 1980-1981 (the probabilities of the ergodic Markov process increases to values above 50% in 1980:10 and close to one in 1981:02.

Figure 7 shows the cyclical component for M2 compared to MSI, and Figure 8 compares the probability of low money phases as measured by M2 and MSI. Visual inspection confirms previous findings, with M2 and MSI showing some important differences around the beginning and end of recessions, and during some expansions. Sometimes the phases of low transitory M2 sometimes start years before the phases of low transitory MSI, other times it continues years after the phases of MSI. Other times M2 is in low cyclical phases while the MSI is in high cyclical phases, particularly between 1985 and 1990.

The most recent data show that there was a major contraction in transitory money as measured by MSI – the largest in the last 50 years. However, a much milder contraction in transitory money is shown when it is measured with simple sum aggregation. Interestingly, this decrease in transitory money coincides with an abrupt increase in total reserves on banks (by both measures, transitory money was in a low phase between 2008 and 2010). This pattern only reverts after the implementation of the 'Quantitative Easing' program in late 2010, in which the Federal Reserve committed to buy long-term government bonds to increase liquidity.

6. Conclusions

This paper examines the dynamic relationships among a new measure of the U.S. economy's money stock with aggregate income and the economy's price level. The analysis is undertaken by decomposing each series into their permanent and transitory components. In particular, we study how the nominal quantity of Divisia money affects the short-term and long-term components of nominal income and the price level. The magnitude and timing of the impact of a change in money on prices and income depend on several factors such as how inflation expectations are formed, the state of the economy, policy regimes, institutional factors, and possibly behavioral factors. We use methods that allow the mechanism through which money impacts the economy to be non-stationary and nonlinear, which allows for potentially time-varying and asymmetric size and timing of the monetary impact.

The evidence indicates structural changes in the economy over time, with nominal income and prices exhibiting a less steep slope since early 1980s. However, we find that Divisia monetary aggregates do not display structural breaks. We also generally find that the dynamics of the series during the last two recessions differ somewhat from the previous ones.

The results indicate that the effect of Divisia monetary aggregates on income and prices not only changes over time, but also differs over their cycles, and across expansions and recessions. The decomposition of the series uncovers some interesting results. Overall, there is a strong association between Divisia money and prices. All low cyclical price phases were preceded by tight permanent or transitory money phases. The potential outside lag of tight monetary phases in reducing cyclical prices is around 12-14 months on average. In addition, we find that the low permanent and transitory components of money are associated with subsequent low permanent income with longer leads of 11-18 months.

Finally, we find a clear business cycle pattern in the components of prices and money. Most NBER recessions were preceded by tight transitory and permanent monetary phases and high cyclical prices. The exceptions are the two most recent ones, which were not preceded by tight transitory and permanent components of money. This suggests that the onset of these recessions was not associated with low transitory money phases in contrast with the previous ones. With respect to income, both its permanent and transitory components are highly correlated with NBER recessions and tend to decrease just after the beginning of recessions, suggesting that recessions permanently reduce income. The most drastic decrease in both permanent and transitory income occurred during the 2007-2009 recession.

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Table 1 - Maximum Likelihood Estimates

Parameters	**Income**	***Parameters***	**Prices**	***Parameters***	**Money**
μ_{0i}	-	μ_{0p}	-	μ_{0m}	-0.07 (0.041)
μ_{1i}	-	μ_{1p}	-	μ_{1m}	0.668 (0.021)
μ_{0i} *pre-break*	-0.215 (0.022)	μ_{0p} *pre-break*	0.521 (0.024)	μ_{0m} *pre-break*	-
μ_{0i} *post-break*	-0.328 (0.083)	μ_{0p} *post-break*	-0.259 (0.101)	μ_{0m} *post-break*	-
μ_{1i} *pre-break*	0.262 (0.028)	μ_{1p} *pre-break*	1.082 (0.026)	μ_{1m} *pre-break*	
μ_{1i} *post-break*	0.481 (0.017)	μ_{1p} *post-break*	0.502(0.012)	μ_{1m} *post-break*	-
α_{0i}	-0.176 (0.069)	α_{0p}	-	α_{0m}	0.044 (0.649)
α_{1i}	0.324 (0.022)	α_{1p}	-	α_{1m}	0.609 (0.023)
α_{0i} *pre-break*	-	α_{0p} *pre-break*	0.387 (0.015)	α_{0m} *pre-break*	-
α_{0i} *post-break*	-	α_{0p} *post-break*	0.160 (0.016)	α_{0m} *post-break*	-
α_{1i} *pre-break*	-	α_{1p} *pre-break*	0.786 (0.027)	α_{1m} *pre-break*	
α_{1i} *post-break*	-	α_{1p} *post-break*	0.331 (0.037)	α_{1m} *post-break*	
ϕ_{ii}	0.812 (0.001)	ϕ_{pi}	-0.046 (0.075)	ϕ_{mi}	-0.018 (0.007)
ϕ_{ip}	0.012 (0.002)	ϕ_{pp}	0.843 (0.002)	ϕ_{mp}	-0.013 (0.002)
ϕ_{im}	0.170 (0.046)	ϕ_{pm}	0.010 (0.001)	ϕ_{mm}	0.746 (0.032)
$\sigma^2_{\varepsilon i}$	0.080 (0.005)	$\sigma^2_{\varepsilon p}$	0.033 (0.003)	$\sigma^2_{\varepsilon m}$	0.102 (0.007)
$\sigma^2_{\eta i}$	0.126 (0.009)	$\sigma^2_{\eta p}$	0.028 (0.003)	$\sigma^2_{\eta m}$	0.116 (0.008)
p^C_{00i}	0.899 (0.047)	p^C_{00p}	0.984 (0.010)	p^C_{00m}	0.886 (0.039)
p^C_{11i}	0.976 (0.011)	p^C_{11p}	0.969 (0.016)	p^C_{11m}	0.965 (0.013)
p^P_{00i}	0.858(0.073)	p^P_{00p}	0.871(0.109)	p^P_{00m}	0.888(0.028)
p^P_{11i}	0.968(0.007)	p^P_{11p}	0.954(0.005)	p^P_{11m}	0.958(0.011)
LogL	1607.66				

Asymptotic standard errors in parentheses correspond to the diagonal elements of the inverse hessian obtained through numerical calculation. The absorbing Markov processes for capturing breaks indicate that permanent income has a mean break in 1981:01 and price has a mean break in its permanent component in 1985:01 and in its cyclical component in 1990:01.

Table 2: Lead/Lag of Minimum Probability Square Deviation (PSD) of Money with respect to Prices and Income: Transitory, and Permanent Components

	Low Price Transitory	High Price Transitory	Low Income Transitory	Low Income Permanent
Low Money Transitory	-12	+1	+4	-11
Low Money Permanent	-14	-10	0	-18

(-) or (+) signs denote leads or lags, respectively, of money and its components to prices, income, and its components. E.g. The entry in row 1 column 1 indicates that low transitory money phases anticipate low transitory price phases with a 12 month lead.

Table 3: Chronology and Sequence of Turning Points of the Transitory (m_t^C) and Permanent (m_t^P) Components of Money, and of Income and Prices

Cycles	Low Permanent Money	Low Transitory Money	Low Transitory Price	Mid-Cycle Transitory Price	High Transitory Price	Recession Start	Low Income
Cycle 1	$\downarrow m_t^P \rangle$ 1968:10	$\downarrow m_t^C \rangle$ 1968:12				$Recession \rangle$ 1969:12	$\downarrow Income$ 1970:10
Cycle 2	$\downarrow m_t^P \rangle$ 1972:11	$\downarrow m_t^C \rangle$ 1973:03	$\downarrow p_t^C$ 1975:11	$\downarrow p_t^C$ 1975:03	$\uparrow p_t^C \rangle$ 1973:09	$Recession \rangle$ 1973:11	$\downarrow Income$ 1973:12
Cycle 3	$\downarrow m_t^P$ $\uparrow Inflation \rangle$	$\downarrow m_t^C \rangle$ 1978:05			$\uparrow p_t^C \rangle$ 1978:04	$\downarrow Income$ $Recession$ 1980:01	
Cycle 4	$\downarrow m_t^P \rangle$ 1980:07	$\downarrow m_t^C \rangle$ 1980:11	$\downarrow p_t^C$ 1981:10	$\downarrow p_t^C$ 1981:05		$Recession \rangle$ 1981:07	$\downarrow Income$ 1981:10
Cycle 5	$\downarrow m_t^P \rangle$ 1982:12	$\downarrow m_t^C \rangle$ 1983:04		$\downarrow p_t^C$ 1985:08	$\uparrow p_t^C$ 1984:02		
Cycle 6	$\downarrow m_t^P \rangle$ 1986:08	$\downarrow m_t^C \rangle$ 1987:01	$\downarrow p_t^C$ 1992:06	$\downarrow p_t^C$ 1991:03	$\uparrow p_t^C \rangle$ 1986:10	$\downarrow Income$ $Recession$ 1990:07	
Cycle 7						$\downarrow Income$ $Recession \rangle$ 2001:03	$\downarrow m_t^T$ 2001:09
Cycle 8	$\downarrow m_t^P \rangle$ 2002:11	$\downarrow m_t^C \rangle$ 2002:12	$\downarrow p_t^C$ 2006:04	$\downarrow p_t^C$ 2005:11	$\uparrow Inflation$ 2005:08		
Cycle 9			$\downarrow p_t^C$ 2008:09	$\downarrow p_t^C$ 2008:09	$\uparrow Inflation \rangle$ 2007:03	$Recession \rangle$ 2007:12	$\downarrow Income$ 2008:01
Cycle 10	$\downarrow m_t^P \rangle$ 2008:11	$\downarrow m_t^C \rangle$ 2009:01	$\downarrow p_t^C$ 2008:08				

Note that the high transitory price phase that starts in 1978:04 was still occurring when the new tight permanent money phase started in 1980:07.

Figure 1a – Divisia MSI-All (—), PCE Price Index (----), and Personal Income (- - -) in Log Levels (1967:t=100)

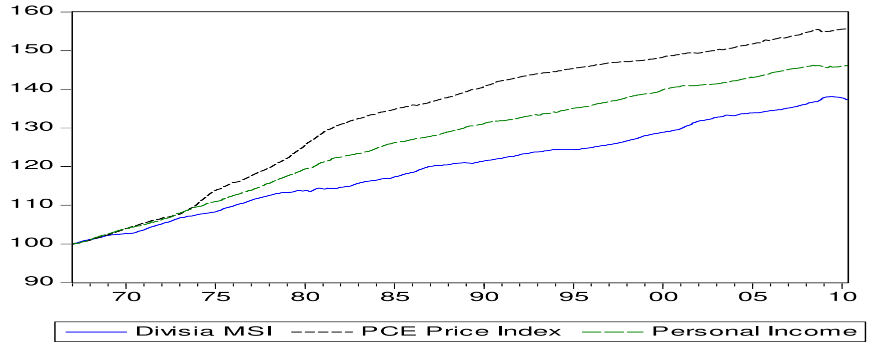

Figure 1b – Divisia MSI-All (—), PCE Price Index (----), and Personal Income (- - -) in Log First Difference (annual rate)

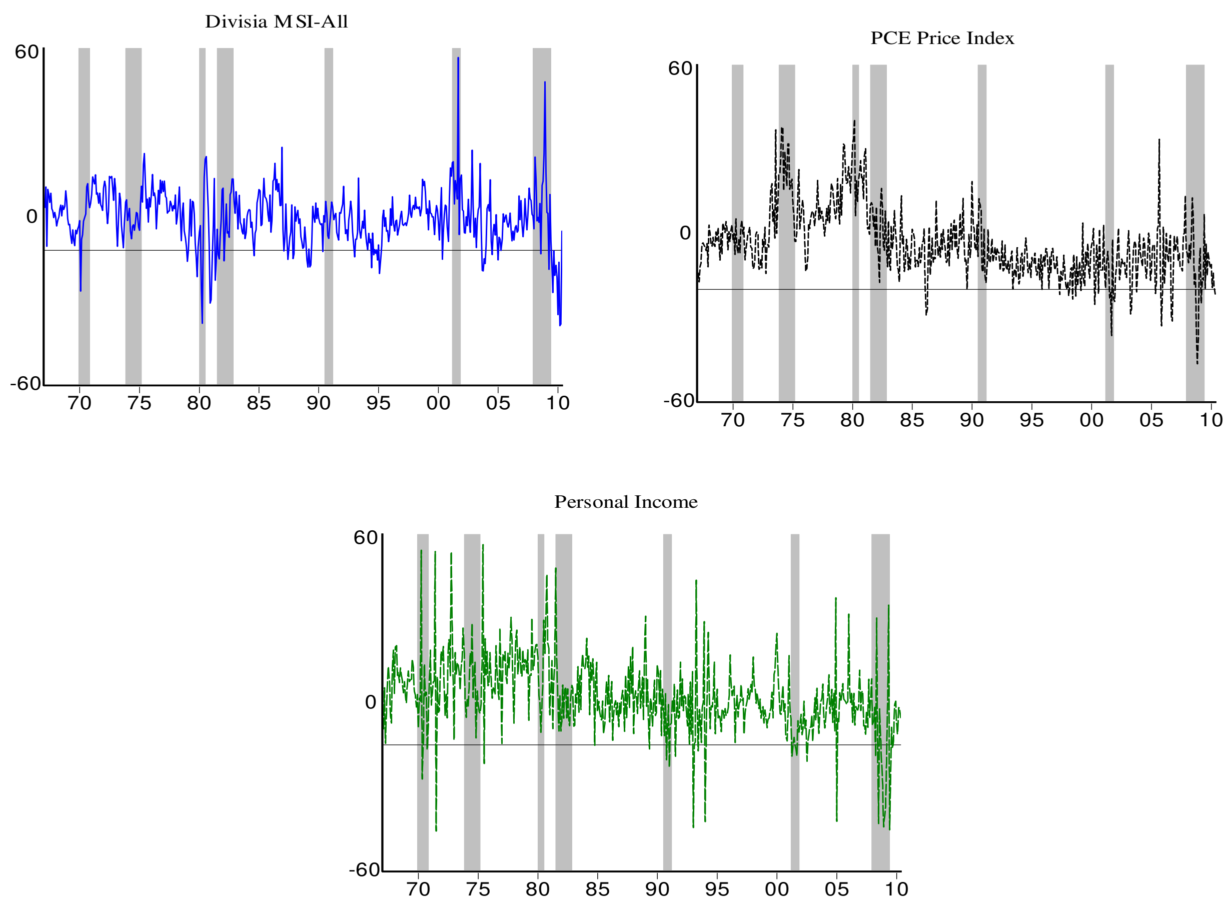

Figure 2 – Probabilities of Low Transitory (—) and Low Permanent (---) Components of Money

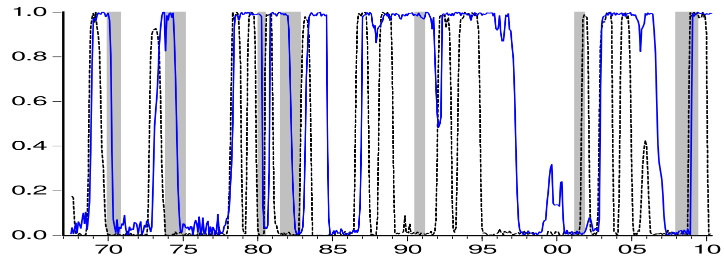

Figure 3 – Probabilities of High Transitory (—) and Low Permanent (---) Components of Prices

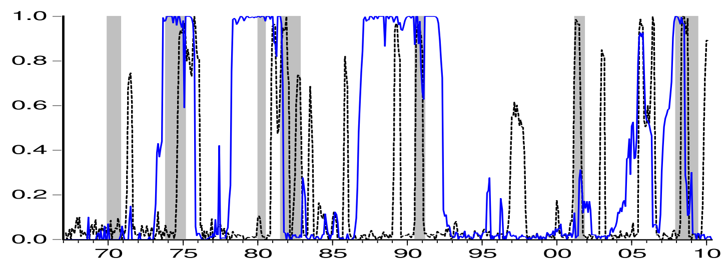

Figure 4 – Probabilities of Low Transitory (—) and Low Permanent (---) Components of Income

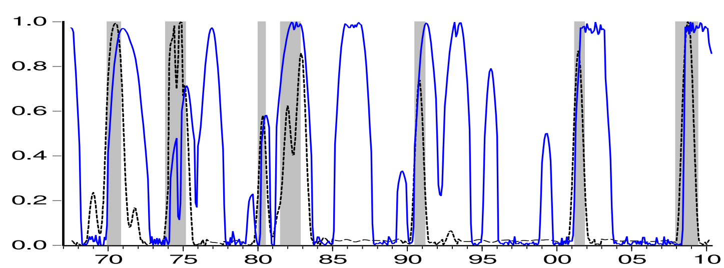

Figure 5 – Probabilities of Low Permanent Money (---) and Low Transitory Money (—) and Probabilities of Low Cyclical Prices (---)

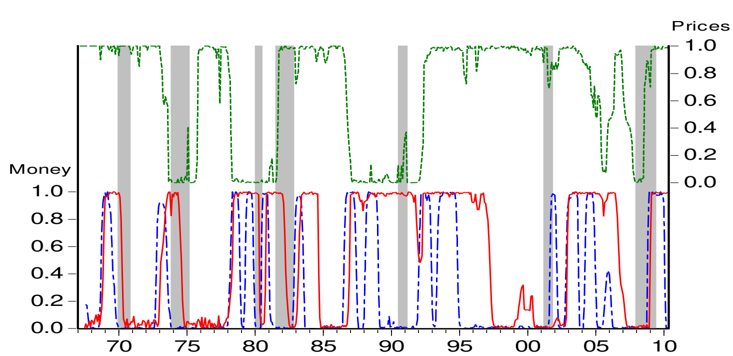

Figure 6 – Probabilities of Low Permanent Money (---) and Low Transitory Money (—) and Probabilities of Low Transitory Income (---)

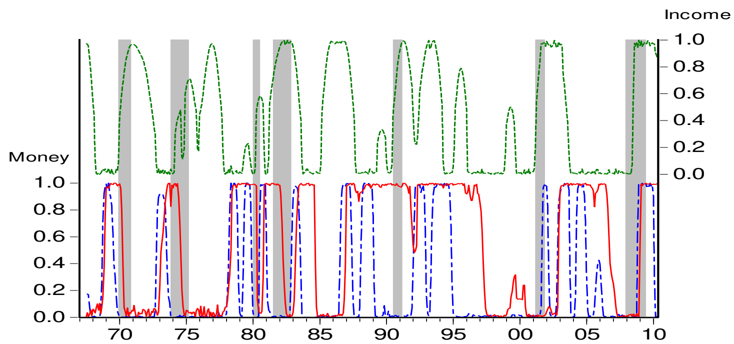

Figure 7 – Transitory Components from Monetary Services Index MSI-All (—) and Simple Sum Monetary Aggregate M2 (---)

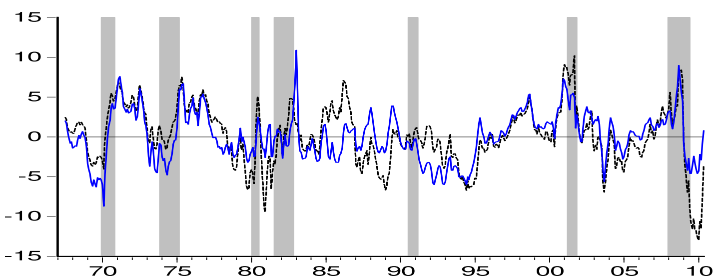

Figure 8 – Probabilities of Low Transitory Monetary Services Index MSI-All (—) and Probabilities of Low Transitory Simple Sum Monetary Aggregate M2 (---)