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Cross-Country Evidence on the Demand for Money

by

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Abstract

This paper examines the demand for real money balances using both cross-country and panel data for 48 countries over the 1980-95 period. We utilize the cross-country data to investigate conventional money demand functions and the role that institutions, financial structure and financial development may have in the demand for money. On the basis of possible heterogeneity within the cross-country data set, we use Bayesian classification and finite mixture models to partition the data and re-examine our initial regression results. We then continue by examining the conventional money demand function through a panel data context. Our empirical modeling not only utilizes traditional panel methodology, but exploits recent state-of-the art advances in the panel unit root and panel cointegration literature. Such procedures allow us to take advantage of desirable statistical properties and obtain consistent estimates in order to test long-run hypotheses.

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Chapter 1

Introduction

The relationship between the demand for money and its determinants are underlying building blocks for most theories of macroeconomic behavior. Researchers have long been preoccupied on the subject matter because the demand for money is considered a crucial component in conducting monetary policy. Furthermore, stability in the demand for real balances has been viewed as a requirement for policy makers to utilize monetary aggregates as strategic mechanisms. In particular, the literature has focused on whether money is neutral and or superneutral, in the sense that changes in the nominal money supply and or growth rate of the nominal money supply can effect real economic variables and can be used as exploitable policy instruments. Within these various subfields of research there have been significant contributions, yet there remains unresolved issues which warrant further study and investigation.

In this paper, we have three main objectives. First, we utilize a comprehensive cross-country data set for 48 countries over the 1980-95 period. The data is comprised of not only conventional money demand variables, but of institutional, financial structure and financial development measures from Levine (2002), which allow us to systematically examine their possible role in the demand for money, at an aggregate multi-country setting. Secondly, we apply an innovative Bayesian approach to cluster the 48 countries in to distinct groups. This method of unsupervised classification based on finite mixture models, priors and statistical attributes allows us to establish whether heterogeneity in money demand exists between different classes or groups of countries within the data set. Lastly, we embark on the first preliminary investigation in the money demand literature, which exploits panel routines to investigate the long-run relationship between real balances, interest rates and real income. In this section, we exploit the conventional panel methodology as well as recently developed state-of-the art panel unit root and panel cointegration techniques in order to test diverse aggregate long-run theories of money demand and examine possible heterogeneity from an individual country perspective. As Baltagi and Kao (2000, p. 8) point out: "[T]he hope of the econometrics of nonstationary panel data is to combine the best of both worlds: the method of dealing with nonstationary data from the time series and the increased data and power from the cross-section."

The organization of this paper is as follows. Section 2 briefly sketches out the fundamental theoretical contributions that link money and modern economics. In Section 3, we discuss and review the traditional and contemporary empirical methodologies which researchers have utilized to estimate money demand functions. Section 4 outlines the econometric specification undertaken for the cross-country data, for both narrow and broad specifications. In Section 5, we describe the data and the underlying sources of collection and origin. Section 6 presents the initial cross-country econometric results. In Section 7, we introduce the Bayesian classification approach, based on finite mixture models. Section 8 presents the results of the Bayesian classification analysis. In Section 9 we partition the data according to the Bayesian classification and explore the economic significance of our clustered regression results. Section 10 outlines the panel data methodology used to estimate narrow and broad money demand functions. In Section 10, we present the estimated panel data models used to investigate the aggregate group/individual relationships between real monetary aggregates, interest rates and real gross domestic product. The final section concludes the paper and outlines the implications of our findings.

Chapter 2

Theoretical Considerations

In this section, we survey the fundamental theoretical literature which links the demand for money and modern macroeconomics. To begin, we define money as the modern medium of exchange and the customary unit in which prices and debts are expressed. Ultimately, money has three primary functions in our modern economy: medium of exchange, unit of account and store of value. The use of money as a medium of exchange fosters economic efficiency by reducing the opportunity cost of physically exchanging goods and services. Money fits the criteria required to be a medium of exchange because, first, it is easily standardized, second, it is widely accepted by the public, third, divisibility is made with ease, fourth, it is easy to carry, and lastly, it does not physically deteriorate too quickly.

Money is a unit of account since it measures value within the economy. By measuring the value of goods and services in terms of money, we can reduce transaction costs within the economy by reducing the number of prices which would otherwise need to be considered. Regarding its function as a store of value, money serves the purpose of preserving purchasing power. Other assets can act as a store of value, but such assets involve transaction costs in order to be converted into money. The liquidity of money explains why there is a willingness to hold money even if there exists more attractive assets which are also considered a store of value.

In general, the demand for money is considered the demand for real balances. Theories surrounding money demand have evolved over time and we will briefly highlight some of the most influential developments beginning from the classical tradition to the more contemporary.[1] We begin with the transaction version of the equation of exchange, pioneered by Irving Fisher (1911),

$$M^s V = PT \tag{2.1}$$

where M^s denotes the actual physical stock of money, V signifies the transactions velocity of circulation, P represents the price level in the economy and T is the volume of transactions. The equation of exchange states that the quantity of money times the average number of times that it changes hands while making transactions (velocity) must equal the number of transactions carried out over the period multiplied by the average price at which they take place. Essentially this condition states that the number of purchases must equal the value of sales. Money is simply held to assist in transactions and has no intrinsic utility.

In the literature, the equation of exchange is sightly modified and alternatively presented as the income version of the equation of exchange,

$$M^s V = PY \tag{2.2}$$

where real output, Y, replaces the volume of transactions and now income velocity replaces the transactions velocity. In this second presentation, it is assumed that real income and the volume of transactions are proportionally related. From the identity above, the quantity theory of money is developed by making certain assumptions regarding the determinants of the equation of exchange variables. In particular,

[1]In doing so, we closely follow Serletis (2001).

Fisher (1911) assumes that real activity and money are exogenously determined, velocity has a constant long-run value and that the price level is the only endogenous variable in the monetary sector. Such assumptions allow for the equation of exchange to be altered into the quantity theory of money, which can be expressed as,

$$\bar{M}^s\bar{V} = P\bar{Y} \tag{2.3}$$

where bars above M^s, V and Y indicate that these variables are determined independently. The quantity theory of money states that by treating $\bar{M}^s$ exogenous and holding $\bar{V}$and $\bar{Y}$ constant, the equilibrium price level moves in strict proportion to the quantity of money, which means that money is neutral.

In order to interpret the quantity theory of money as a theory of the demand for money, one must assume that the money market is in equilibrium. Essentially, all money must be willingly held, or alternatively, the supply of money must equal the demand for money, such that, $M^s = M^d = M$. If we solve for M^d, then equation (2.3) becomes,

$$M^d = kPY \text{ or } \frac{M^d}{P} = kY \tag{2.4}$$

where $k = 1/V$. Equation (2.4) is the long-run demand for money function, deduced from the quantity theory of money. It states that the demand for nominal (real) money is proportional to nominal (real) income.

To examine the properties of the long-run money demand function, we can linearize equation (2.4) by rewriting it in logarithmic form,

$$\log M - \log P = \alpha + \log Y \tag{2.5}$$

where $\alpha = \log k$. Equation (2.5) suggests that for given values of real income, the demand for real money balances, $\log M - \log P$, is impervious to exogenous changes in nominal money. Furthermore, equation (2.5) indicates that the price level elasticity of the demand for nominal money balances, $\eta(M, P)$, is

$$\eta(M, P) = \frac{\mathrm{d}\ \log\ M}{\mathrm{d}\ \log\ P} = 1 \tag{2.6}$$

and that the real income elasticity of the demand for real money balances, $\eta(M/P, Y)$, is

$$\eta\left(\frac{M}{P}, Y\right) = \frac{\mathrm{d}\ \log\ (M/P)}{\mathrm{d}\ \log\ Y} = 1. \tag{2.7}$$

It is also implied from equation (2.5) that the demand for money is entirely a function of income and that interest rates do not have a role in effecting the demand for money. Simply put, the nominal interest rate elasticity of the demand for real balances, $\eta(M/P, R)$, is

$$\eta\left(\frac{M}{P}, R\right) = \frac{\mathrm{d}\ \log\ (M/P)}{\mathrm{d}\ \log\ R} = 0. \tag{2.8}$$

Theories of the demand for money which highlight money's medium-of-exchange role are called *transactions theories.* One of the most prominent models in the literature is the Baumol-Tobin Model. The underlying idea behind this money demand model is the choice of when and how often agents exchange bonds for money at the margin. The two authors which this theory is accredited to is, Baumol (1952) and

Tobin (1956). Both emphasize the costs and benefits of holding money and come to analogous conclusions regarding the variables which affect transactions demand. The argument follows from the idea that the benefit of holding money is convenience and the cost associated with the convenience is the foregone interest income by not holding interest-bearing assets, such as bonds.[2]

To begin, Baumol considers an agent who plans to spend Y, in real terms, gradually over the course of one year. The agent is faced with the choice of holding his wealth in the form of money, which is non-interest-bearing, or in the form of interest-bearing bonds. The interest rate, R, is assumed to be constant over the period and is meant to reflect the opportunity cost of holding money rather than bonds. As well, the agent is faced with a *brokerage fee* or a lump-sum transaction cost b, when portfolio substitution takes place. The real value of bonds turned into money each time a transfer is made by the agent is denoted by K.

The total cost of making transactions can be expressed as,

$$\text{Total Cost} = b\frac{Y}{K} + R\frac{K}{2} \tag{2.9}$$

where $b\,(Y/K)$ represents the brokerage cost, with (Y/K) signifying the number of withdrawals and $R\,(K/2)$ denotes the forgone interest if money were held instead of bonds, with $K/2$ being the average amount of real money holdings $(= M/P)$. Evidently, the fewer the withdrawals, Y/K, the lower will be the brokerage cost and the higher the interest cost. In fact, solution to the agents problem is to chose the number of withdrawals that minimizes the total transaction cost. In particular, the agent must find the point where the increase in brokerage cost, as a result of an

[2]See Serletis (2001) for textbook treatment of the Baumol-Tobin model.

additional withdrawal, is offset by the reduction in the interest cost resulting from the withdrawal in question.

The solution to the agent's problem is easily obtained by taking the partial derivative of equation (2.9) with respect to K and setting it equal to zero and then solving for K. The corresponding value is the optimal value which minimizes total cost. Thus,

$$\frac{\partial(\text{Total Cost})}{\partial K} = -\frac{bY}{K^2} + \frac{R}{2} = 0 \tag{2.10}$$

which yields the following *square root* relationship between K and Y, b and R

$$K = \sqrt{\frac{2bY}{R}}. \tag{2.11}$$

At this value of K we can express average money holding in real terms by remembering that $K/2 = (M/P)$,

$$\frac{M}{P} = \frac{K}{2} = \frac{1}{2}\sqrt{\frac{2bY}{R}}. \tag{2.12}$$

The implication of equation (2.12), is that the demand for real (transactions) money balances is proportional to the square root of Y and inversely proportional to the square root of R. As well, further inspection of equation (2.12) shows that as $b \to 0$, $M/P \to 0$, which means that in the absence of transactions costs there would not be any demand for money. The intuition is that in such a situation the agent would synchronize cash withdrawals with their purchase of goods and services. Consequently, the demand for money emerges from the trade-off faced by the agent with respect to transaction costs and interest earnings.

An additional advantage of this approach to the demand for money is that it generates testable relationships between the demand for money and its determinants. In particular, we can linearize equation (2.12) by rewriting it in logarithmic form,

$$\log\left(\frac{M}{P}\right) = \alpha + \frac{1}{2}\log Y - \frac{1}{2}\log R \tag{2.13}$$

where $\alpha = \log\,(1/2)\sqrt{2b}$. Working with the log-linear equation (2.13), we can express the elasticity of M/P with respect to Y as,

$$\eta\left(\frac{M}{P}, Y\right) = \frac{\mathrm{d}\log\,(M/P)}{\mathrm{d}\log Y} = \frac{1}{2}. \tag{2.14}$$

The implication of equation (2.14) is that a rise in real spending leads to a less-than- proportionate increase in the average holding of real money balances. In the literature, economists typically refer to this result as *economies of scale* in money holding. In other words, agents with larger scale of spending hold less money when expressed as a ratio to their expenditures.

As well, we can express the elasticity of M/P with respect to the interest rate as

$$\eta\left(\frac{M}{P}, R\right) = \frac{\mathrm{d}\log\,(M/P)}{\mathrm{d}\log R} = -\frac{1}{2} \tag{2.15}$$

and the elasticity of nominal money, M, with respect to the price level as

$$\eta\left(\frac{M}{P}, P\right) = \frac{\mathrm{d}\log\,(M)}{\mathrm{d}\log P} = 1. \tag{2.16}$$

Evidently, the Baumol-Tobin model corresponds to a significant deviation from the classical quantity theory of money. In particular, it predicts economies of scale in the demand for money and an interest elasticity away from zero. Given the conflict between the two theories, many attempts have been made to reformulate the Baumol-Tobin model to reflect the properties found in the quantity theory of money.[3]

Within the money demand literature, there exists many more classes of money demand models. In particular, there have been notable developments put forth by Keynes (1936) and Friedman (1956). Keynesian theory defines the explict motives for holding money, transactions, precautionary and speculative motives, and then builds a theory of money demand around interest rates. Friedman on the other hand, introduces the notion of permanent income and builds his money demand theory with it at its heart.[4]

As well, there have been recent advances within the transactions theories of money demand with models known as *cash-in-advance*. These equilibrium models incorporate a specific restriction that purchases made by agents in a given period should only be paid for by currency derived from the previous period. This type of limitation is typically known as the "cash-in-advance-constraint". As well, other theorists have brought portfolio theories of money demand into the mainstream discussion. Notable models are Tobin's *Theory of Liquidity Preference* and *Overlapping Generation* models with money. These theories stress and emphasize the role of money as a store of value and predict that the demand for money depends on the return and risk offered by money and other assets. In particular, the focus is predominantly on portfolio substitution and wealth.

Although, we do not explicitly base our empirical methodology on these later

[3]See Serletis (2001 Chapter 6) pg. 69-70 for further disscusion on the attempts to reformulate the Baumol-Tobin model.

[4]The reader is urged to refer to either Goldfeld and Sichel (1990), Sriram (1999) or Serletis (2001) for a more comprehensive, in depth presentation of these two theoretical models.

models, we refer the reader to Goldfeld and Sichel (1990), Sriam (1999) and Serletis (2001) for a comprehensive survey on both the early and more contemporary theoretical literature.

Chapter 3

Empirical Contributions

In the macroeconomic literature, there exists a large body of research dedicated to estimating money demand functions. One of the major contributors of the empirical research on money demand has been the major advancements made in time series econometrics in the past couple of decades. Such innovations have inspired researchers to revisit previously built empirical models and their subsequent findings. Past estimation has primarily been confined to industrialized countries, especially the United States, United Kingdom and more recently Canada. However, there has been some interest in several industrial and developing countries alike in the current literature. With this in mind, this section provides a brief survey and overview of the empirical modeling framework and estimation techniques most commonly used in the applied money demand literature.

In general the base specification of the theoretical money demand relationship can be written as

$$\frac{M_t}{P_t} = \Phi(R_t, Y_t) \tag{3.1}$$

where M_t is nominal money balances demanded, P_t is the price index used to convert nominal balances to real balances, Y_t is the *scale* variable relating to activity in the real sector of the economy and R_t is the *opportunity cost* of holding money. The possible choices to represent the above specification vary from study to study and therefore require a brief discussion on the choice of variables.

The first issue in the empirical estimation of money demand functions is the selection of an explicit definition of money.[1] Typically transactions-based theories of the demand for money accentuate narrow definitions of money which consist of those assets readily available and transferable in everyday transactions. However, theories which highlight portfolio substitution require broad definitions of money comprised of a wide range of assets to render diverse investment opportunities for asset holders. Nevertheless, Goldfeld and Sichel (1990) claim that such definitions are somewhat arbitrary. As a result, authors such as Diewert (1976), Barnett (1980) and Rotemberg (1991) have contributed to the extensive research in properly defining monetary aggregates. Although such discussion is beyond the scope of this paper, we recommend referring to Serletis (2001) and Serletis and Afxentiou (2002) for a comprehensive survey on simple-sum, divisia and currency equivalent aggregates and their stylized empirical properties within the United States and Canada.

The scale variable in the money demand function is used to gauge transactions related to economic activity. As mentioned in the preceding section transaction theories highlight the level of income as the appropriate scale variable whereas asset theories emphasize wealth. In empirical estimation, GDP or GNP is the most widely accepted representation of the level of income. However, such measures are not without criticism since GDP and GNP do not include transactions in financial assets, transfers, sales of intermediate goods, all of which are expected to affect the demand for money. Contemporary research has focused on developing alternative scale variables based on the transaction measure. For example, Goldfeld and Sichel

[1] See Laidler (1993) for an extensive discussion on subject matter.

(1990) suggest disaggregating GNP or GDP into several scale variables to reflect the fact that all transactions are not equally money intensive. As well, Mankiw and Summers (1986) argue that consumption is the more appropriate scale variable. They contend that consumption is the natural observable proxy for the unobservable permanent income and wealth. Nevertheless, the selection of an appropriate scale variable is an empirical issue dependent on data availability.

The opportunity cost of money can be defined as the difference between the rate of return on assets alternative to money and the own rate of return. In general, researchers who embrace the transactions methodology, by using a narrow definition of money, typically make use of a short-term interest rate, such as the Treasury bill rate, commercial paper rate or the saving deposit rate. Whereas those who adopt an asset approach and exploit broader definitions of money, make use of longer-term rates of interest. Regarding the own rate on money, typically researchers implicitly assume that the explicit rate of return on most forms of money is zero. Goldfeld and Sichel (1990) point out that this is incorrect because money earns an implicit rate of return, in the form of gifts, services or through reduced transaction fees, when agents maintain a minimum level of deposits. However, measuring this implicit return is difficult and for this reason the issue has largely been ignored.

As well, there are some researchers who include additional variables that they deem relevant in determining money demand. In particular, Mulligan and Mankiw *et al.* (1992), while examining money demand across state lines in the United States, add state specific variables for population, population density, agricultural sector's share of income and regional dummies. Their results do show some significance with respect to the addition of these variables, especially for the agriculture variable. While investigating cross-country estimates of money demand, Kenny (1991) conditions on inflation, the fraction of the population who are elderly, education, agriculture, population density, and then he includes dummy variables for dictatorships and the 1970's. He also finds that most of the supplementary variables are significant. However, he does recognize that some may not be exogenous through diagnostic testing and does have to create instrumental variables.

In general, the most popular empirical money demand functions take the form of three possible specifications. The first is the long-run function expressed as

$$\log\left(\frac{M_t^*}{P_t}\right) = \alpha + \beta_1 \log Y_t + \beta_2 \log R_t + \varepsilon_t \tag{3.2}$$

where, M^* denotes the desired stock of nominal money, P is the price index used to convert nominal balances to real balances, Y denotes the scale variable and R is the opportunity cost variable. The money market is assumed to be in equilibrium initially. Prices and interest rates are assumed to be perfectly flexible and agents are assumed to have perfect foresight so they are continually adjusting their current money holdings to the desired long-run level. However, specification error is typically discovered through diagnostic testing for this empirical model. For example, Serletis (2001) exploits (3.2) and makes comparisons between narrow and broad simple-sum, Divisia and CE monetary aggregates (of M1, M2, M3, and MZM) from the MSI database, for the United States. Upon estimation, the test statistics indicate significant residual serial correlation, parameter non-constancy and model mispecification.

The current methodology utilized by researchers, which is now the most widely accepted, involves modeling trends and investigating cointegrating properties of the aggregate money demand function through error correction models (ECM). The

ECM representation captures the long-run equilibrium relationship between money and its determinants while embedding the short-run dynamics defined by the data generating process. Granger (1983, 1986) and Engle and Granger (1987) have shown that the concept of stable long-term equilibrium is the statistical equivalence of cointegration. Simply put, when cointegration holds and if there is any shock which causes disequilibrium in the money market, there exists a properly defined short-term dynamic adjustment process such as the error-correction mechanism that pushes the system back toward the long-run equilibrium.

The basic idea behind cointegration is to search for a linear combination of individually integrated time series that is itself stationary.[2] We can rewrite equation (3.2) as,

$$(m-p)_t = \beta_0 + \beta_1 y_t + \beta_2 r_t + \varepsilon_t, \tag{3.3}$$

where m, p, y and r denote the logs of nominal money, the price level, aggregate real income and the nominal interest rate. The behavior assumptions require that $\beta_1 > 0$, $\beta_2 < 0$ and that the sequence ε_t is stationary, such that any divergence from the long run money market equilibrium is simply transitory. Consequently, for this system, it is required that there exists a combination of the nonstationary variables $(m-p)_t$, y_t and r_t,

$$\varepsilon_t = (m-p)_t - \beta_0 - \beta_1 y_t - \beta_2 r_t, \tag{3.4}$$

that is stationary. If ε_t is found to be stationary in levels, then (3.3) can be considered

[2]See Campbell and Perron (1991), Kwaiatkowski *et al.* (1992), Stock (1994) for selective surveys and Enders (2004) for textbook treatment of testing for unit roots and stationarity in individual time series.

a credible long-run relationship with short-run dynamics incorporated in ε_t, which is frequently referred to in the literature as the equilibrium error.

Alternatively in matrix notation, an equilibrium money demand model requires that,

$$\varepsilon_t = \beta_t^T \mathbf{X}_t = \begin{bmatrix} 1 & -\beta_0 & -\beta_1 & -\beta_2 \end{bmatrix} \begin{bmatrix} (m-p)_t \\ 1 \\ y_t \\ r_t \end{bmatrix} \tag{3.5}$$

be stationary. If found stationary, or integrated of order zero, I(0), in the Engle Granger sense, the vector $\beta = \begin{bmatrix} 1 & -\beta_0 & -\beta_1 & -\beta_2 \end{bmatrix}$ can be called the cointegrating vector for the nonstationary stochastic process $\mathbf{X}_t$, corresponding to $\begin{bmatrix} (m-p)_t & 1 & y_t & r_t \end{bmatrix}'$. The error correction representation relating current and lagged first differences of $(m-p)_t$, y_t and r_t, and at least one lagged value of $\hat{\varepsilon}_t$ can be written as,

$$\Delta(m-p)_t = \alpha_1 + \alpha_{(m-p)}\hat{\varepsilon}_{t-1} + \sum_{j=1}^{r} \alpha_2(j)\Delta(m-p)_{t-1} + \sum_{j=1}^{s} \alpha_3(j)\Delta y_{t-1} + \sum_{j=1}^{w} \alpha_4(j)\Delta r_{t-1} + \varepsilon_{(m-p)_t} \tag{3.6}$$

where $\alpha_1, \alpha_2, \alpha_3, \alpha_4$, and $\alpha_{(m-p)}$ are all parameters, $\varepsilon_{(m-p)_t}$ is a white noise disturbance and $\hat{\varepsilon}_{t-1}$ estimates the deviation from long run equilibrium in period $t-1$. r, s, and w denote the number of lags chosen for each of the variables through lag selection procedures. $\alpha_{(m-p)}$ can be interpreted as a speed of adjustment parameter, where larger values imply a greater response of $(m-p)_t$ to the previous period's deviation from long-run equilibrium.

However, it must be noted that if the variables are integrated of different orders, they cannot be cointegrated. As well if $\mathbf{X}_t$ contains two components, there can only exist at most one independent cointegrating relationship. But if $\mathbf{X}_t$ contains n variables then there may exist as many as n-1 independent cointegrating vectors.[3]

There have been various methodologies proposed in the literature to test for cointegration. For a statistical survey on cointegrated systems, see Gonzalo (1994) and Watson (1994) and for textbook treatment see Enders (2004). The most popular approaches are the Engle and Granger (1987) and Johansen (1988) methods. The Engle and Granger (1987) technique is a two-stage estimator, whereas the Johansen (1988) procedure involves maximum likelihood estimation.[4] There have also been recent advances by Pesaran *et al.* (1999) who, through their bounds testing approach, do not require the researcher to take a stand on the order of integration of the variables under consideration.

Sriram (1999) provides a comprehensive summary of money demand studies involving cointegration/error-correction modeling for selected industrial and developing countries. Most of the findings suggest a cointegrating relationship between the chosen monetary aggregates and the chosen scale and opportunity cost variables. Serletis and Koustas (1998) contribute to the literature by drawing on recent advances in long-run neutrality tests in bivariate vector autoregressive models, put forth by Fisher and Seater (1993) and King and Watson (1992). In particular, their results show that the data are generally supportive of the quantity-theoretic proposition that money is neutral in the long-run, for the ten countries they consider in their

[3]See Enders (2004) for a comprehensive discussion on the subject matter.
[4]See Enders (2004) and Serletis (2001) for a comprehensive overview of both procedures.

study. However, they do discover that superneutrality is violated for Italy, with the violation being on the negative side: a permanent increase in the growth of money is linked to a permanent decrease in the level of output.

Chapter 4

Cross-Country Specification

We begin our econometric analysis by first outlining the cross-country specification. Cross-country data is characterized as observations on an assortment of economic variables, for multiple countries, averaged over periods of time. Simply put, for each country there exists one observation for each of the variables examined by the researcher.[1] This type of data is typically exploited within the growth literature. For instance, Mankiw *et al.* (1992) exploit this type of data while investigating the Solow model across different groups of countries, Levine (2002) draws on this methodology to investigate the link between growth, banks, markets and financial development across 48 countries, where as Beck and Levine (2004) contribute by investigating the relationship between stock markets, banks and economic growth.[2] This approach has also been experimented within the money demand literature by Kenny (1991), where he studied the linkage between real money balances, GDP and an assortment of other possible determinants, over both the 1960's and 1970's, across 88 countries. Given that the cross country approach is widely accepted, we adapt the methodology to suit our goals and objectives.

In general, standard conventional money demand models and their surrounding econometric specifications try to capture a real monetary aggregate as a function of a scale or transaction variable along with an opportunity cost variable. Universally,

[1]Alternatively, this data can be characterized as cross-section.

[2]These are but a few of the many studies which utlize cross-country data. See Levine (2002) along with Beck and Levine (2004) for further surveys on past contributions.

real GDP represents the transaction variable and an interest rate represents the opportunity cost variable.[3] Consider the following cross-country money demand regression equations,

$$m_i = \mathbf{a}'\mathbf{X} + \varepsilon_1 \tag{4.1}$$

$$m_i = \mathbf{a}'\mathbf{X} + \mathbf{b}'\mathbf{I} + \varepsilon_2 \tag{4.2}$$

$$m_i = \mathbf{a}'\mathbf{X} + cS + \varepsilon_3 \tag{4.3}$$

$$m_i = \mathbf{a}'\mathbf{X} + dF + \varepsilon_4 \tag{4.4}$$

where m is the natural logarithm of the real money stock defined by either a narrow or broad definition, with $i \in \{1,2\}$ and X being the standard set of conditioning information, ie., the natural logarithm of real GDP and a short term interest rate. **I** represents a vector of institutional variables that measure macroeconomic stability, openness to international trade and political stability. S gauges financial structure. Larger values of S suggest a more market-based economy, whereas smaller values imply a bank-based economy. F measures the degree of financial development. Larger measures imply an increased development of securities markets, banks, and non-banks. Such measures can also be interpreted as a proxy for financial services. ε_i, with $i \in \{1, ..., 4\}$, is the corresponding error term for each of the four equations, respectively. **a**, **b**, c and d are estimated coefficients (with bold letters signifying vectors of coefficients). **I**, S and F are the same variables that Levine (2002) considers as possible growth determinants.

[3]See Sriram (1999) for an extensive review of the past literature on empirical estimation of money demand. Also see Goldfeld and Sichel (1990).

Regarding money demand, similar analysis with respect to the degree that institutions, financial structure and development affect the money market can be tested as they are in the growth literature. However, this requires different assumptions regarding the implied values and signs of the parameters in regressions (4.1)-(4.4) than those made in the growth literature.

The idea is that countries with greater institutional stability should exhibit less uncertainty and therefore display a reduced demand for money. Specifically, the sign of b' will depend on each of the institutional variables under consideration. For example, a higher level of average schooling years over the population implies a stronger knowledge of the mechanics of the economy and the money market; which in turn suggests that the demand for money should be reduced as the educational index rises. Large black market premium values indicate that the transaction costs incurred while purchasing goods and services are also large, which in turn requires agents to hold more liquid money. There is also a possible relationship between government expenditure and money demand. Theory asserts that private spending and public spending maybe perfect substitutes or complements.[4] If perfect substitutes, then the expenditure on goods and services by the government will reduce expenditure by agents, requiring them to hold less money, ceteris paribus. If complements, then providing additional services will require agents to purchase these services and compel them to retain additional funds, ceteris paribus.

The trade variable attempts to proxy the degree of openness. With enhanced trade comes exposure to different markets, where agents must now consider foreign

[4]See Barro (1997, Chapter 12) for further explanation into the theoretical role of government in the economy.

interest rates and balance of payment issues. As a result, agents will have to divide their monetary holdings between domestic and foreign accounts. Higher degrees of openness would suggest that there would be lower demand for domestic money. Measures of civil liberties, revolutions and coups and political assassinations can be thought of as proxies for political stability. With domestic political instability comes capital flight. The theory is that as the future of the financial system becomes dismal, faith in a paper promise declines and faith in other assets such as gold and tangible goods useful for bartering increases. Kenny (1991) considers a similar approach by trying to control for the type of government by including a dummy variable for dictatorships. Our interpretation differs given that the three political stability variables are not mutually exclusive to dictatorships or democracies. As well, Kenny (1991) emphasizes precautionary motives for his interpretation but neglects speculative motives, which have increasingly dominated financial markets during our sample period.

Bureaucratic efficiency measures the extent of autonomy from political pressures and strength to govern. This is important because it signals a degree of competence within key governmental departments such as finance and the central bank. Given that autonomy and expertise indicate certainty and provide faith in the monetary and political system, the implication is that as the quality of the bureaucracy rises, the demand for money should decline. As with the black market premium measure, corruption can also accordingly be considered a source of raising transaction costs. It is not unreasonable to assume that an increase in corruption would be followed by bribery and possibly influence peddling. Therefore, as we observe an increase in corruption we should also observe an increase in the demand for money.

The addition of financial structure measures allows for investigation into the possible heterogeneity in money demand under diverse financial systems. Specifically, a better understanding of whether money demand is higher or lower in a bank-based or market-based system can be explored. Such analysis and its insights may be useful in formulating monetary policy to remedy a financial crisis or to restructure a command style economy to a more capital driven one, from a policy perspective. Given that, the hypothesis is that under market-based systems firms can easily raise funds in the open market for financing and investment through capital markets, which in turn would broaden loan possibilities. Boot and Thakor (1997) along with Allen and Gale (1999) articulate that competitive capital markets contribute positively in aggregating dispersed information signals and efficiently relay such information to investors, with favorable implications for firm level financing.[5] In comparison, under a bank-based system, funds would have to be raised through banks, therefore limiting financing possibilities. Bhide (1993) along with Boot and Thakor (1997) argue that banks act as a coordinated coalition of investors which can monitor firms more efficiently to diminish post lending moral hazard issues and a myopic investor climate. Thus, given the possibility of easily attainable funds under a market based system and the possible impediments under a bank-based system, we should observe the demand for money to be lower in economies where there are market-based characteristics and higher in economies where bank-based characteristics are observed. Hence, we should observe $c < 0$.

Financial Services, whether provided by banks or capital markets, can also give broad insight into transaction costs. The idea is that financial arrangements such

[5]Refer to Levine 2002 pg.3 for a further explanation and other references on the subject matter.

as contracts, markets and intermediaries alleviate market imperfections. Merton and Bodie (1995) and Levine (1997) stress that this view curtails the significance of the bank-based and market-based discussion. The argument Levine (2002) makes is that financial arrangements (such as contracts, markets and intermediaries) highlight prospective investment opportunities, promote corporate responsibility, contribute to risk management, develop liquidity and reduce savings mobilization. With regards to money demand, the issue is whether such arrangements assist in lowering transaction costs or aid in increasing them. Standard economics textbooks describe financial innovations having a negative effect on the demand for real money balances.[6] However, there is not a definitive hypothesis given that reductions in market imperfections come at a price. Ambiguity arises because the derived benefits from financial services may not outweigh the costs and vice versa. As a result, the data will have to dictate which case is more likely. If the benefits offset the costs, transaction costs decline and the implied sign is $d < 0$. Whereas, if the costs overshadow the benefits, transaction costs could rise and the implied sign is $d > 0$. Kenny (1991) presents a similar idea by using population density as a surrogate for bank proximity and their corresponding services [7]

[6]See Barro (1997, Chapters 4-5) for current theoretical insights into money demand and transaction costs.

[7]See Kenny (1991 pgs.698 and 703). He also predicts an ambiguous relationship between services and the monetary aggregates. Although our explanations differ, we both arrive at the same conclusion.

Chapter 5

The Data

In order to analyze the possible relationships between different real monetary aggregates, short term interest rates, real GDP and different institutional, financial structure and financial development measures, we adopt the common broad cross-country approach. The study involves pure cross-sectional analyses with one observation for each variable under consideration, per country, for 48 countries over the 1980-1995 period. Many of the variables used in this study are derived from census and privately collected data and simply are not available on an annual basis. The countries we consider are the same as those investigated in Levine (2002) and are listed in Table 1. As Levine (2002 p.405) points out, "[o]ne advantage of the broad cross-country approach is that it permits a consistent treatment of financial system structures across countries and thereby facilitates international comparisons". However, we are aware of the potential pitfalls of such analyses. First, we cannot exploit the time series dimension of the data. Issues often raised in the money demand literature typically try to address serial correlation of the error term, non-stationarity and cointegration.[1] Thus by opting for the cross-country approach, we try to overcome these potential issues by assuming that there are geographical similarities in money demand and that money demand is stable.[2] Secondly, there are possible issues regarding simultaneity. These concerns can be overcome by estimating the same

[1] See Serletis and Koustas (1998) for recent estimation techniques which exploit time series properties while investigating the neutrality and superneutrality of money in a multi-country setting.

[2] Mulligan, Mankiw, et.al (1992) adopt a similar approach to avoid such issues.

group of countries within a panel framework. This is the approach we opt for as a comparison to the cross-country methodology.

The narrow definition of money chosen is what we shall refer to as M1. The International Monetary Fund (IMF) and standard monetary textbooks define such a narrow measure as, transferable deposits (demand deposits) and currency outside of banks. The broad definition of money chosen is what we shall refer to as M2. This broad measure is identified as M1 plus quasi money (time, savings and foreign currency deposits). For the 48 countries included in the study, annual data pertaining to both measures were collected over the 1980-1995 period from the International Financial Statistics (IFS), World Development Indicators (WDI) and various central banks in local currency units (LCU). The data were then converted to USA dollars by using the USA dollar per LCU 1995 average exchange rate and then averaged to obtain a single data point for each nominal measure of money, over each country.[3]

To analyze the monetary aggregates described above in real terms, we then collected data from the WDI on the consumer price index (CPI) for each country with a base year of 1995. The average was then taken to obtain a single observation for each country.[4] Each of the cross-country monetary aggregates was then deflated by the average consumer price index for each of the 48 countries to obtain a real measure. Although the GDP deflator would have been the ideal price index to use, it was not exploited due to data availability and base year issues. However, for those countries for which we found both, a comparison was made and differences between the two indices were minor if not nill. At any rate, the CPI is the most publicly reported

[3]For both M1 and M2, Greece is missing a data point for 1995. For only M2, UK is missing data points for 1980-81.

[4]Tunisia is missing CPI data for 1980-1982.

price index. Constant 1995 USA dollar GDP data were also collected from the WDI for each country.

With regards to short term interest rate data, there were some data availability issues. We could not find a uniformly defined interest rate series for all 48 countries. As a result, data were first collected for countries for which there existed a 90 day treasury bill rate or the local equivalent. Subsequently, data were collected for those countries for which there existed a money market rate. For those countries which neither existed, a deposit rate was collected.[5] Collecting interest rate data from Latin and South American countries in some cases was quite tedious.

The institutional, financial structure and financial development variables are taken from Levine (2002). We consider nine institutional variables in this study. The first, the logarithm of the initial workforce education, is measured as the average schooling years in the total population over 25 in 1980. The second is the logarithm of one plus the average black market premium and is averaged over the 1980-92 period. The third is the logarithm of government size as a share of GDP and is averaged over the 1980-95 period. The fourth is the logarithm of international trade (real exports and imports) as a share of GDP and is also averaged over the 1980-95 period. The fifth is an indicator of civil liberties averaged over the 1980's. This indicator is scaled from 1 (most freedom) to 7 (least freedom). The sixth is an index of revolutions and coups averaged over the 1980's. The seventh is political assassinations. This measures the average number of assassinations per thousand inhabitants, over the 1980's. The eighth is bureaucratic quality, which is scaled from

[5]Ecuador is missing data for 1980-1982. Honduras is missing data from 1980-81. Israel is missing data from 1980-83. Panama is missing data for 1980-1985. Tunisia is missing a data point for 1980.

0 to 6 and averaged over 1982-1995. High scores indicate autonomy from political pressures, strengths and expertise to govern without drastic changes in policy or interruptions in government services. Lastly, the level of corruption within a given country is indexed through a scale over the 1982-95 period. This index is scaled from 0 (high level of corruption) to 10 (low level of corruption). Levine's inflation variable is left out to avoid any possible simultaneity, given that both measures of money and GDP are in real terms.[6]

Levine constructs and employs a set of five variables to capture comparative differences in financial structure between the 48 countries. The purpose of these variables is to proxy whether financing in a country is comparatively bank-based or market-based. Structure-Activity, Structure-Size and Structure-Efficiency measure the activity, size, and efficiency of equity markets relative to banks in each country. Levine then forms a comprehensive measure (highest joint R-squared) of the previous three variables called Structure-Aggregate. Low values of the Activity, Size, Efficiency and Aggregate measures indicate that an economy is bank-based, whereas high values indicate that an economy is market-based. The fifth variable, Structure-Regulatory, is created to capture the degree of commercial bank restrictions, with smaller values signifying a lower degree of restrictions on commercial banking activities.[7]

In order to observe relative differences in financial development between the 48 countries, Levine also constructed and utilized four measures of financial development. Finance-Activity, Finance-Size and Finance-Efficiency quantify financial de-

[6]See Levine (2002) for further details regarding the sources of his data collection.

[7]See Levine (2002 p.405-411) for an extensive discussion on the construction of each of the variables.

velopment based on the activity, size and efficiency of the financial sector within each country. Finance-Aggregate is another comprehensive measure of the three previous variables and is constructed in a similar fashion as the Structure-Aggregate variable. Lower values of these indicators imply underdeveloped financial sectors, whereas higher values imply thriving financial sectors. In his construction of these measures, Levine exploits equity markets as a proxy for capital markets due to data availability in the bond markets.[8] These measures in our view can also be interpreted as a proxy for transaction costs as previously discussed.

[8]See Levine (2002 p.411-414) for further details on these variables.

Chapter 6

Cross-Country Results

We begin by displaying the cross-country summary statistics in Table 2. It can be seen that there is some variation within most of the variables. However, there is less variability in for example our assassination and revolutions and coups variables. Table 3 presents the initial conventional money demand results using ordinary least squares (OLS) estimation with heteroskedasticity-consistent standard errors. The top panel displays the results for M1 as the dependent variable using the simple information set. The bottom panel displays the results for M2 as the dependent variable. A common sample is used the whole time, so that there are 48 observations for each of the regressands and regressors. For both real monetary aggregates, the estimated real income elasticity of the demand for real balances is highly significant and is in accordance with the quantity theory demand for money. For both aggregates we also test the null hypothesis that the income coefficient is equal to one, and cannot reject the null at the 95% level. The estimated interest elasticities of the demand for real balances are negative and both significant at the 95% level. Although the interest elasticity estimates are not zero for both aggregates, as predicted by the quantity theory demand for money, they are quite low and statistically different than the implied value of the Baumol-Tobin transaction theory.

Table 4 presents the institution results for M1 and M2, respectively. The estimation procedure we opt for is to control sequentially for each institutional variable conditioned on the simple information set. The reasoning stems from issues regarding simultaneity and mutual exclusiveness. In particular, we are concerned with high correlations between the bureaucracy and corruption indexes and the small variance of the political indexes. As well, we are also apprehensive about the validity and consistency of OLS once multiple indexes measured by scale are included concurrently and when degrees of freedom are lost from including multiple explanatory variables in our small sample. Although Kenny (1991) and Levine (2002) do not take the same approach, Beck and Levine (2004) do take a similar approach when investigating associations between stock market and bank development with economic growth. As a result, we are simply interested in the influential direction each of the explanatory variables has on the monetary aggregates and caution on interpreting the results as exploitable elasticities. In order to present a large number of regressions, the results are only reported for each of the institutional variables.

The results in the top panel of Table 4 imply that only the educational variable is significantly related to money demand when considering a narrow measure. The sign of the coefficient also theoretically conforms because increases in the level of workforce education impacts money demand negatively from a narrow perspective. This result is also consistent with Kenny (1991) where he also finds a negative relationship between literacy and M1. None of the other institutional indicators enter the narrow money demand regressions at the 10% level. With regards to the broader aggregate, Table 4 shows that the black market premium and assassination variables enter significantly. However, the sign of the black market premium coefficient is incorrect from the theoretical expectation. The assassination variable is significant at the 10% level. The negative sign corresponds to our prediction that domestic turmoil would lead to a substitution out of money and into other tangible assets. However, given that it narrowly makes the 10% level we are still aware of potentially making a Type II error. None of the other institutional indicators enter the broad money demand regressions at the 10% level.

The implication of both the narrow and broad money regressions is that conditioning on institutions may not be so informative and unnecessary when investigating money demand issues. This follows from only one out of the nine institutional variables entering the narrow specification significantly and only two out of the nine being significant in the broad specification. As a result, it would be suspect to add any of the institutional variables to the information set. One interpretation may be that the demand for both aggregates could be stable irrespective of most institutional differences. In both specifications the elasticities with respect to income and the interest rate remain statistically similar to those in Table 3.

Table 5 presents the results for M1 and M2 when controlling for financial structure. The same estimation methods were used as in the institutional specification. The top panel displays the results for M1 as the dependent variable using the simple information set. The bottom panel displays the results for M2 as the dependent variable. Three of the structure measures enter the narrow specification significantly at the 10% level. In particular, the activity, size and aggregate coefficients are all negative and of similar statistical magnitude, with size having the largest effect. The implication is that some measures of financial structure indicate that money demand is negatively related to market-based economies. This result corresponds to the economic theory outlined in the specification section. However, it also shows that there is some measurement sensitivity to such a conclusion. On the other hand, only the size variable is significant at the 10% level in the broad specification. This result suggests that measures of financial structure are for the most part statistically trivial when investigating money demand from a broad perspective. Again, the elasticities with respect to income and the interest rate remain statistically similar to those in Table 3.

Table 6 presents the results for M1 and M2 when conditioning on the simple information set and controlling for financial development. The elasticities with respect to income and the interest rate again remain statistically similar to those in Table 3 for both aggregates. Using the same estimation method as the previous specification for financial structure, the results indicate that measures of financial development do not bring forth additional information regarding narrow money demand. None of the financial variables enter significantly at the 10% level. Conversely, in the broad specification there are intuitive results. All of the four measures of financial development enter significantly at the 10% level or higher. The sign on all of the coefficients is positive. Recall that the implied sign may be positive or negative. Given the consistent positive sign, we argue that this may suggest possible evidence that although greater financial development would bring forth additional services through financial arrangements, the benefits of such services may be outweighed by the costs and may actually raise transaction costs on a cross country scale. Kenny (1991) also finds a significantly positive estimate on the bank proximity variable in his M2 specification.[1] Such results warrant further analysis before a definitive conclusion can be made

[1]See Kenny (1991 pgs. 701 and 703) for his estimate and interpretation of his population density variable in his M2 specification.

Chapter 7

Bayesian Classification Theory

In the previous cross country analysis we, following Kenny (1991), Levine (2002) and Beck and Levine (2004), treated the 48 countries as a homogeneous unit by using the same aggregate econometric specification for all of the countries. In order to explore the possibility of heterogeneity within our dataset, we provide a unique approach to investigate such a query. The methodology we deem to be the most appropriate for such analysis, is utilized within an automatic classification program, Autoclass, developed by the Bayes Group at the Ames Research Center. This Bayesian approach is based on finite mixture models, which searches for the most probable number of classes (clusters), conditioned on the attributes of the data set in question and prior expectations of the researcher. Classification analysis is generally conducted in either a supervised or unsupervised manner. The Bayesian approach under consideration is a branch of the unsupervised form.

By opting for an unsupervised approach, we can avoid many of the drawbacks and shortcomings found within traditional supervised cluster analysis. In particular, we can sidestep creating predetermined classes, which identify membership on the basis of maximizing both in-class similarities and out-of-class differences.[1] In contrast, Bayesian inference exploits the data to produce "natural" classes by determining a probability of class membership. This is also known as "fuzzy" classification. Specifically, Cheeseman and Stutz (1996), through Autoclass, implement the conditional

[1]See Dillion and Goldstein (1984) for further discussion on such clustering.

binary probability of observing an attribute, and Gaussian probability if the attribute is actually observed, in order to aid in the selection of the most suitable model class. By utilizing not only the associated priors, but the data itself and the Expectation Maximization (EM) algorithm, maximum a posteriori (MAP) values can be estimated. Through repeated iteration, convergence in the MAP parameters can be obtained and then the posterior probabilities for each model class are evaluated to determine the optimal class setting. Furthermore, such a procedure also allows the researcher to rank class and alternative class membership.

However, the Bayesian approach is also not without its criticisms. As with the traditional classification approaches, there is some sensitivity to the selection of attributes used to describe the underlying objects. Nevertheless, the Bayesian approach does make progress with respect to the biasedness found in the traditional methodology by generating class quantity and membership through the data (conditioned on descriptive attributes), rather than relying on capricious decisions made by the researcher. We also acknowledge that the discovery of critical structure (classes) in data is not a one-shot process of dumping a database into Autoclass (or a similar program) and obtaining insightful results. Rather, we agree with Cheeseman and Stutz that the discovery of important class structure is part of a research process of uncovering clusters, deciphering the results, revisiting the data and then repeating the sequence. In other words, the procedure we described above, is an illustration of the hypothesize-and-test cycle of normal economic scientific discovery. Since Autoclass can examine huge amounts of data in search of multi-dimensional structures with speed and accuracy that a researcher could never match, and while the researcher has domain knowledge to model and interpret, which the program lacks, both are required for the interactive process of making structural inferences.

Before we proceed with the implementation of Autoclass on our data set, we will give a quick description of the theory regarding how Autoclass operates and how it implements unsupervised classifications.[2] As indicated earlier, Autoclass utilizes the classic mixture model developed by Everitt and Hand (1981) and Titterington *et al.* (1985). The mixture model can be expressed in Bayesian form by addressing the priors of the parameters. Let $\mathbf{y} = \{\mathbf{y}_1, ..., \mathbf{y}_I\}$ denote the data set, where $i = 1, ..., I$ indexes the number of cases or instances. Additionally, each $\mathbf{y}_i$ includes a number of attributes which are indexed by k, where $k = 1, ..., K$, such that each $\mathbf{y}_i$ is a $(1 \times K)$ dimensional vector of observable attribute values denoted as $\{y_{i1}, ...y_{i1}\}$, and where the data set is an $(I \times K)$ matrix of data. As well, it is implicit that $\mathbf{y}$ is sampled within a heterogeneous population and the classes, C, are indexed by j, where $j = 1, ..., J$ denotes the optimal number of classes. Now to be explicit, our purpose is to discover the most probable classification, which means to cluster the I instances into the optimal number of representative classes.

In order to identify each of the classes we let $\Upsilon = \Upsilon_1, ..., \Upsilon_J$ signify the mathematical form of the probability distribution function associated with the corresponding J components and $\phi = \phi_1, ..., \phi_J$ be the parameter set for each of the analogous J distributions. Which means that, in order for each class to be identified there must exist a distribution function for the attributes, Υ_j, with parameters ϕ_j, for the data sampled from a population with J subgroups or classes, with J unknown.

Let T represent the inter-class mixture model. Υ_j is then assumed to be weighted by the mixture model T, i.e. the probability distribution that any $\mathbf{y}_i$ is a mem-

[2]This section draws heavily upon the reference material provided with the Autoclass program.

ber of class j, C_j, despite its attributes. The parameters of T, q, can then be defined as such. Letting q $=q_1, ..., q_j$, with $\sum_{j=1}^{J} q_j = 1$, be the parameters of T representing the proportion of the population which comes from C_j, which means, $q_j = P(y_i \in C_j \mid \mathrm{q}, T)$, allows us to express the likelihood of observation y_i as,

$$
\begin{aligned}
P(\mathrm{y}_i \mid \phi, \mathrm{q}) &= q_1 P(\mathrm{y}_i \mid \phi_1, \Upsilon_1) + ... q_j P(\mathrm{y}_i \mid \phi_j, \Upsilon_j) \\
&= \sum_{j=1}^{J} q_j P(\mathrm{y}_i \mid \mathrm{y}_i \in C_j, \phi_J, \Upsilon_J).
\end{aligned}
$$

Let $\tau = (\phi, \mathrm{q})$ be the set of parameters encompassed in the complete model and $M = (\Upsilon, T)$, with $M \in S$, where S is the space of possible mixture models. Then the likelihood function pertaining to the entire sample, y, can be expressed as,

$$
P(\mathrm{y} \mid \tau, M) = \prod_{i} \sum_{j=1} q_j P(\mathrm{y}_i \mid \mathrm{y}_i \in C_j, \phi_j, \Upsilon_j).
$$

Accordingly, the joint distribution of the data set and the parameters can be expressed as the prior probability distribution for the parameters times the likelihood of the sample,

$$
\begin{aligned}
P(\mathrm{y}, \tau \mid M) &= P(\tau \mid M) P(\mathrm{y} \mid \tau, M) \\
&= P(\tau \mid M) \prod_{i} \sum_{j=1} q_j P(\mathrm{y}_i \mid \mathrm{y}_i \in C_j, \phi_j, \Upsilon_j). \qquad (7.1)
\end{aligned}
$$

The prior probability distribution, which incorporates all prior information and where q and T are independent, can be expressed as $P(\tau \mid M) = P(\mathrm{q} \mid \mathrm{T}) P(\phi \mid \Upsilon)$.

Now, the goal is to find the posterior distribution of the parameters and the MAP parameter values. The posterior distribution is,

$$P(\tau \mid \mathrm{y},M) = \frac{P(\mathrm{y},\tau \mid M)}{P(\mathrm{y} \mid M)} = \frac{P(\mathrm{y},\tau \mid M)}{\int P(\mathrm{y},\tau \mid M)\, d\tau}.$$

In order to allow for comparisons between alternative classifications, we can also calculate the posterior probability of the model given the data. The posterior distribution of the model given the data is,

$$\begin{aligned} P(M \mid \mathrm{y}) &= \frac{P(M \mid \mathrm{y})}{P(\mathrm{y})} = \frac{\int P(\mathrm{y},\tau \mid M)\, P(M)\, d\tau}{P(\mathrm{y})} \\ &\propto \int P(\mathrm{y},\tau \mid M)\, d\tau = P(\mathrm{y} \mid M). \end{aligned} \tag{7.2}$$

Now, the proportionality holds only when we make the assumption that the prior probability, $P(M)$, is uniform. Such an assumption is warranted, given that we do not have a reason to prefer on model over another.

When finding the MAP parameter values, the technique of direct optimization is not so constructive. However, if we refer to the underlying mixture assumption that each observation is a member of only one class, we can write $P(\mathrm{y}_i \mid \mathrm{y}_i \in C_j, \phi_j, \Upsilon_j) = 0$ whenever $\mathrm{y}_i \notin C_j$. This reference then allows us to express joint distribution of the data as,

$$P(\mathrm{y},\tau \mid M) = P(\tau \mid M) \prod_j \prod_{\mathrm{y}_i \in C_j} q_j P(\mathrm{y}_i \mid \phi_j, \Upsilon_j). \tag{7.3}$$

Notice, maximization of (7.3) is straightforward for the case of a supervised classification, i.e. when J is known. However in the situation when J is unknown, i.e. an unsupervised classification, searching for every single partitioning of the data and proceeding with maximization of (7.3) is not reasonable for large data sets. For such cases, we can then refer to the EM algorithm of Titterington *et al.* (1985) and Dempster *et al.* (1977). Given the set of class distributions, Υ_j, and the current MAP estimates of the values of τ, the expectation step of the algorithm yields weighted class assignments, w_{ij}. These assignments can alternatively be expressed as the probability that case i belongs to class j. The weighted class assignments can be written as,

$$w_{ij} = P\left(\mathrm{y}_i \in C_j \mid \tau, M\right) \propto p_j P\left(\mathrm{y}_i \mid \mathrm{y}_i \in C_j, \phi_j, \Upsilon_j\right).$$

These weights described above, permit the construction of statistics which can be used in the maximization of (7.3) in order to obtain MAP estimates of the values of τ converging to a stable local maximum. Now as one may suspect, there are many such local maxima. As a result, the Autoclass software searches and accumulates such local maxima. Next, $P\left(\mathrm{y} \mid M\right)$ is computed for each local maxima and these are then used to approximate $P\left(M \mid \mathrm{y}\right)$ and then the models are ranked according to their largest log probability $P\left(M \mid \mathrm{y}\right)$.

Given that our cross-country data contain real valued attributes, these assignments give us our weighted class number, mean and variance due to the log-Gaussian model,

$$w_j \sum_i w_{ij}, \beta_{jk} = w_j^{-1} \sum_i w_{ij} y_{ik}, \sigma_{jk}^2 = w_j^{-1} \sum_i w_{ij}^{-1} \left(y_{ik} - \beta_{jk}\right)^2.$$

The statistics above, are used to reestimate (7.3) and the corresponding probabilities. The EM algorithm is reiterated until the MAP parameters converge to a maximum stationary point.

Chapter 8

Bayesian Cluster Inference

As previously mentioned, the classifications and cluster analysis preformed by Autoclass are sensitive to the choice of sorting characteristics chosen a priori. To overcome this potential pitfall, we conduct ten different sorts in order to build power, robust results and to determine if heterogeneity exists among the 48 countries. Initially we paired real GDP per capita in USA dollars and the average price level over the 1980-1995 time period as the sorting characteristics.[1] The rationale behind this sort is to determine whether a cluster can be formed based on development and inflation. In this case we define high inflationary countries as those with average price levels, over the 1980-95 period, which are far away from the 1995 base level. This sort grouped the data into two clusters based on the highest probability of class association. Table 7 presents the results with class 1 having 27 countries and class 2 having 21 countries. Furthermore, the probability of class membership for each of the 48 countries is quite pronounced by fluctuating from 0.814 to 1.

We then proceeded by considering real GDP per capita in USA dollars along with schooling and each of Levine's (2002) financial structure and development variables. Although none of these nine sorts yielded the exact same classification as the initial pairing, they did come close. In particular, six of the financial structure and development sorts produced consistent class associations amongst each other and the

[1]The data for real GDP per capita in 1995 USA dollars was collected from the WDI and the Taiwan central bank over the 1980-95 period.

schooling sort was also nearly the same as the price sort. However, the probability of class association was very weak in some cases. Specifically, Cyprus, Greece, Israel, Portugal and Taiwan frequently bounced between classes and had low probabilities of class association ranging from 0.532 to the low 0.7's. Further inspection of the data revealed that these five countries consistently ranked either at the top echelon for one of the variables and at the bottom for the other variable in the pairing or persistently in the middle, which makes it difficult for Autoclass to distinguish them from either class.

Given the circumstances, we abandon the assumption that all the countries can be treated as a homogeneous unit and split the sample into two sub-samples with each reflecting the three nearly identical classifications. Then for each sub-sample we estimate the money demand specifications outlined in the previous section to investigate whether the heterogenous specification results are sensitive to the five questionable countries. Estimation of the three different possible class structures generated nearly identical results. As a result, we use the high probability of class association in the price sort as a selection criteria and prefer using the cluster results in Table 6, which seem to fit the data quite well. This also allows us to loosely identify the sample created by class 1 as "developing-high inflation countries" and the sample created by class 2 as "developed-low inflation countries".

However, we acknowledge that such labeling is contentious, especially for Greece, Israel and Portugal. Although each of these countries do have average or above average per capita real GDP in USA dollars and are also ranked in the upper end on the United Nation's 2004 Human Development Report, their corresponding price levels are far from the 1995 base level. It is for such reasons that we would then consider them as being at the very upper end of the "developing-high inflation countries". With regards to the "developed-low inflation countries", 19 of the 21 members represent the top 21 spots on the United Nations 2004 Human Development index.[2]. The aim of such branding is to allow for heuristic inferences rather than corresponding to a precise taxonomy. This criteria is met by reflecting the Bayesian viewpoint that membership in one class differentiates membership in the other class through diversity in country characteristics.

[2]Cyprus ranks 30 and Taiwan is not listed because it is grouped in with mainland China.

Chapter 9

Cluster Results

Following the sequence of presentation provided in the cross-country results section, we first consider the results from conventional money demand estimation, which are then followed by those from the institutional, financial structure and development specifications. With the intent of investigating any possible heterogeneity, we jointly present the results for developing-high inflation countries and developed-low inflation countries.

Table 8 presents the initial results for the conventional money demand specification for both classes and both monetary aggregates. When the narrow measure of money is considered, the estimated real income elasticity of the demand for real balances is highly significant for both the developing-high inflation countries and developed-low inflation countries. As before, we test if the coefficient is equal to one and cannot reject the hypothesis for either class. These results are again in accordance with the quantity theory demand for money. The estimated interest elasticity of the demand for real balances is almost identical to the result found in Table 2 for the developing-high inflation class. However, for the developed-low inflation class the coefficient is not significant at any conventional level. This finding also conforms with the quantity theory demand for money. When the simple information set is regressed on the broad monetary aggregate, the estimated real income elasticity of the demand for real balances is statistically different from one for the developing-high inflation class, but not for the developed-low inflation class. The estimated interest elasticity of the demand for real balances remains stable and virtually unchanged for the developing-high inflation class. Regarding the developed-low inflation class, the estimated interest elasticity moves toward the Baumol-Tobin prediction but is barely significant at the 10% level. As a result, we are cautious in our interpretation at the risk of making a Type II error. In comparison to the homogenous sample, the conventional demand for real balances seems to be relatively consistent and fairly stable under both sub-samples.

The institutional parameter estimates for the two classes are presented in Tables 9 and 10. Table 9 corresponds the estimates for M1 as the dependent variable and Table 10 displays the estimates for M2 as the dependent variable. The schooling variable is highly significant for the developing-high inflation class but not for the developed-low inflation class. The estimated coefficient is also larger in magnitude than the previous estimate indicating that it may have previously been biased downwards. The assassination measure is also highly significant for the developing-high inflation class but not the developed-low inflation class. The sign of the coefficient is consistent with the prediction made earlier in the specification section. None of the other variables enter significantly in the developed-low inflation sample. However, the black market premium, trade openness and civil rights measures do significantly enter the developed-low inflation sample. In particular, they all theoretically conform. A higher black market premium raises the cost of transacting and positively affects the demand for real balances. Additional exposure to the global trading system and decreases in freedom negatively impact the demand for real balances.[1] In particular, these two findings may help shed some light into recent economic developments

[1]The index of civil liberties is scaled from 1 (most freedom) to 7 (least freedom).

surrounding the United States, with regards to their large trade deficit and the legislative passage of the Patriot Act. However, such analysis is beyond the scope of this paper.

In the broad specification, the estimated black market premium coefficient is significant for the developing-high inflation class. The coefficient is of similar magnitude to the one estimated in the homogeneous sample but has the wrong sign again. The estimated government expenditure, trade openness and assassination coefficients are also highly significant. The positive sign on the government expenditure estimate implies that public and private spending are compliments. This seems reasonable given that developing countries expend large amounts on infrastructure and capital projects. We also test if the government expenditure coefficient is equal to one and weakly accept the null hypothesis of private spending and public spending being perfect compliments. However, the estimated trade coefficient does not follow the prediction previously made, given that it is positive. An increase in the number of assassinations decreases the demand for real balances as predicted. Regarding the developed-low inflation sample, only the trade openness coefficient enters significantly. It is again negative, as in the narrow regression and of similar magnitude. However, the RESET statistic indicates that there may an unmodelled component missing in this estimation, so we must interpret with caution.

For both monetary aggregates, the institutional results clearly display some degree of heterogeneity with regards to institutional effects between the developed-low inflation countries and the developing-high inflation countries. The estimated real income and interest elasticities remain similar to those in Table 8 for the developing-high inflation cluster. Regarding the developed-low inflation sample, the real income and interest elasticities also remain similar to those presented in Table 8, when we consider M1 as the dependent variable. But, when we consider the broad aggregate, the high interest elasticity in Table 8 does become highly significant for some cases and is of similar magnitude. Therefore, we conclude that the interest elasticity of M2 in developed-low inflation countries is likely to be statistically different then the interest elasticity found in the developing-high inflation cluster. We attribute the small sample of 21 observations and lack of degrees of freedom to be the source of bias in the conventional money demand estimation. The real income elasticity does however remain stable in the M2 specification.

The financial structure estimates are reported in Table 11. With respect to the narrow aggregate, none of the financial structure measures enter the developing-high inflation class significantly at conventional levels. Only the size measure enters significantly at the 10% level for the developed-low inflation sample. In the M2 specification, only the size measure enters significantly at the 10% level for the developing-high inflation sample. None of the financial structure measures are significant for the developed-low inflation class. In the cross-country results, size is also significant for both M1 and M2 and of similar magnitude to the coefficients estimated in each of the cluster sub-samples. Since only one of the five measures is consistent within both the cross-country and cluster regressions, we interpret that the demand for real balances is relatively stable irrespective of structural financing. The real income elasticity and the interest elasticity of the demand for real balances remain similar to what we discussed in the previous paragraph for both classes.

Table 12 presents the financial development parameter estimates for the two classes. Not one of the four measures enter the narrow specification for either class significantly. This result was also found in the cross country results. When we treat M2 as the dependent variable, all four measures of financial development are highly significant for the developing-high inflation class. The estimated coefficients are positive and of similar statistical magnitude to those in Table 5. When we consider the developed-low inflation countries in the broad specification, none of the four measures of financial development enter significantly. Given the results in Table 12, we conclude that the developing-high inflation countries are driving the cross-country results in Table 5. In particular, the persistent positive sign on all of the measures, allows us to infer that the benefits brought forth by financial services in developing-high inflation countries are outweighed by the costs of utilizing them and actually raise transaction costs. One explanation could be that in the early stages of financial development economies of scale have not yet been captured to bring transaction costs down, or to a constant state where money demand would not be affected, as it appears in the developed-low inflation class. The real income elasticity and the interest elasticity of the demand for real balances remain similar to what was discussed in the prior paragraphs.

Given the results of the cluster estimation, there is some evidence of heterogeneity across countries. The implication of such heterogeneity has important implications to the way monetary policy is to be conducted by central banks across the world. If ignored, the heterogeneity will bias the monetary authority's ability to effectively conduct policy.

Chapter 10

Panel Specification

Panel data refers to data for N different entities observed at T different time periods. A panel data set is advantageous because it allows us to sort out economic effects that may not be distinguishable with the use of either cross-section or time series data alone. In this section, we apply traditional and more recently developed, state-of-the-art, panel data methodology to estimate conventional money demand functions for narrow and broad specifications. Although we would have liked to include the institutional, financial services and financial development variables presented in the cross-country section, we again point out that many of these variables are derived from census and privately collected data and simply are not available on an annual basis. As such, we are unable at the present time to explore their role in the money demand function due to data availability and collection issues.[1] Nevertheless, we believe that this study is the first preliminary investigation, in the money demand literature, which exploits panel routines to investigate the long-run relationship between real balances, interest rates and real income.

The use of panel data has a number of advantages. First, since in our case panel data relates to countries overtime, we can enhance our econometric modeling and hypothesis testing to capture the heterogeneity within these units. The techniques of panel data estimation can take such heterogeneity into account by allowing for

[1] As previously mentioned, most of the institutional variables are only collected periodically by private organizations and are typically averaged over time periods.

country-specific variables, as we will show shortly. Secondly, panel data analysis minimizes the bias that might result if we aggregate countries into a broad homogeneous unit. Lastly, by combining the time series of cross-sectional observations, panel data gives us more informative data, more variability, less collinearity among variables, more degrees of freedom and more efficiency.[2]

As previously mentioned, not all of the countries in our study have the same number of time series observations, hence we are dealing with an unbalanced panel.[3] Initially we begin our study by estimating the three most common estimators: pooled ordinary least squares (OLS), and the estimators for fixed and random effects models (FEM and REM, respectively). The assumptions of these estimators are rather restrictive. The pooled model can be expressed as,

$$m^i_{c,t} = \beta_1 + \beta_2 R_{c,t} + \beta_3 Y_{c,t} + \varepsilon_{c,t} \tag{10.1}$$

where i signifies the definition of money with $i = 1, 2$, c represents the country with $c = 1, ..., 48$ and t denotes time with $t = 1, ..., 15$. R and Y denote the natural logarithm of the opportunity cost and transactions variables, respectively. We estimate (10.1) for each monetary aggregate separately, but we drop the index i for notational convenience hereafter. For the pooled model it is assumed that $\mathrm{E}(\varepsilon_{c,t}) = 0$, for all c and t, $\mathrm{E}(\varepsilon^2_{c,t}) = \sigma^2$ and $\mathrm{E}(\varepsilon_{c,t},\ \varepsilon_{j,s}) = 0$, for all $s \neq t$ or all $c \neq j$. This set of assumptions makes the pooled model nearly identical to the cross-sectional data analyses made previously. Nevertheless, both procedures ignore heterogeneity across countries with respect to unobservable characteristics, either for lack of variation

[2]See Gujarati (2003, Chapter 16) for an extensive discussion.

[3]We listed those countries for which we could not locate data in the Data section.

or as a deliberate modeling choice. Hsaio (1986) points out that either reason may cause the pooled estimator to be biased.[4] Hence, we use it as a base specification to make comparisons against. A total of $NT-3$ degrees of freedom would be involved for this estimator.

In general, the most common procedures to account for heterogeneity in panel data are the FEM and REM estimators. Between the two estimators, they can account for heterogeneity across units, by means of decomposing the effects of unobservable factors into effects specific to cross-sectional units, to time-periods, and to both cross-sectional units and time-periods.[5] The fixed effects model which we are interested in can be expressed as,

$$\begin{aligned} m_{c,t} &= \beta_1 + \alpha_1 D_{2c} + \alpha_2 D_{3c} + \ldots + \alpha_{47} D_{47c} + \beta_2 R_{c,t} + \beta_3 Y_{c,t} + \gamma_1 (D_{2c} R_{c,t}) + \gamma_2 (D_{2c} Y_{c,t}) \\ &\quad + \gamma_3 (D_{3c} R_{c,t}) + \gamma_4 (D_{3c} Y_{c,t}) + \ldots + \gamma_{93} (D_{47c} R_{c,t}) + \gamma_{94} (D_{47c} Y_{c,t}) + \varepsilon_{c,t} \qquad (10.2) \end{aligned}$$

where the α's are the differential intercept coefficients and the γ's are the differential slope coefficients; both represent a time-invariant group specific attribute. The D's represent country specific dummy variables. Recall, the quantity theory demand for money equations; i.e. equations (2.4) and (2.5). By allowing the intercept to vary, we can investigate whether or not country specific attributes shift the money demand function. As well, if one or more of the γ coefficients are statistically significant, it will indicate to us that one or more of the elasticities are statistically different

[4]Hsiao (1986, pp. 6-7) demonstrates the occurrence of heterogeneity bias in slope coefficients, when group-specific intercepts are omitted to account for heterogeneous cross-sectional units in panel data sets. In simple cross-section analysis, the problem arising from unspecified heterogeneity is similar. The source of the problem is heterogeneity across units with respect to some relevant but unmeasured characteristic that is correlated with the included explanatory variables.

[5]See Hsiao (1986, p.97) for an introduction and comprehensive discussion of the two estimators.

from the base group. This is imperative given that it is likely that in some countries the demand for real balances may (not) be more responsive to interest rates and real output than other countries. However, as a group we should observe a long-run money demand theory, such as the quantity theory demand for money, to hold.

It must be noted that the inclusion of dummies does not directly identify the sources which may cause the intercept and interest and income elasticities to shift over countries. However, the cross-country estimates which we obtained earlier, can give some kind of idea and intuition to which institution, financial development and financial service variables may be useful for future panel modeling, once data availability and collection issues are overcome. In addition, another pitfall of the FEM is that a substantial number of degrees of freedom are lost with the addition of so many coefficients. For example, in our case where we allow both the constant and slopes to vary, there would be 47 dummy differential intercept coefficients, 94 additional differential slope coefficients and 3 other standard coefficients for the base case country. Clearly specification tests will have to be conducted to determine which of the three models is preferred.

Since the inclusion of differential intercept and slope dummies represents some lack of knowledge about the model, it is accepted to alternatively describe this lack of knowledge through the disturbance term. The REM model does so by using a pooled cross-section and time series model in which error terms may be correlated across time and individual units. The REM model can be expressed as,

$$\begin{aligned} m_{c,t} &= \beta_1 + \beta_2 R_{c,t} + \beta_3 Y_{c,t} + \varepsilon_{c,t} && (10.3) \\ \varepsilon_{c,t} &= u_c + v_t + w_{c,t}, && (10.4) \end{aligned}$$

where $u_c \sim N(0, \sigma_u^2)$ represents the cross-section error component, $v_t \sim (0, \sigma_v^2)$ signifies the time series component and $w_{c,t} \sim (0, \sigma_w^2)$ denotes the combined error component. It is assumed that individual error components are uncorrelated with each other and are not autocorrelated across both cross-section and time series. At the same time the error term would consist of three components and would have variance

$$\text{Var } (\varepsilon_{c,t}) = \sigma_u^2 + \sigma_v^2 + \sigma_w^2. \qquad (10.5)$$

If both σ_u^2 and σ_v^2 are 0, the error term consists of a single combined white noise disturbance and the pooled model is preferred. When the combined error component σ_w^2 equals zero, then the fixed effects model is preferred. The REM is estimated as two-stage generalized least-squares regression. Typically the REM is considered an intermediate model which lies between the extreme of a zero combined error component (FEM) and an infinitely large combined component (pooled model).

More recently, there have been supplementary procedures developed in order to further the panel data methodology. In particular, the literature on panel unit root testing has grown impressively and has been a successful area of study since the initial application to real exchange rates by Abuaf and Jorion (1990). Methodological developments by Levin and Lin (1992, 1993), Levin, Lin and Chu (2002), Im, Pesaran and Shin (1997, 2003), Maddala and Wu (1997, 1999), Sarno and Taylor (1998), Breitung (2000) Choi (2001) and Hadri (1999) have stimulated the application of panel unit root tests to study, among others, purchasing power parity, real GDP, R&D spillovers, and growth convergence. One motivation of such testing is to account for autocorrelation and benefit from increased power over that of single equation tests. As well, the emphasis of the literature on unit roots has lead to advances in testing for the existence of cointegration within panel data. Such developments by McCoskey and Kao (1998), Kao (1999) and Pedroni (1997a, 1997b, 2000, 2004) have allowed researchers to directly test long-run equilibrium relationships, which is exactly what we are investigating. As Banerjee (1999) puts it, "...as in other instances where a new literature comes to be seen to be significant, the aggregate has turned out to be greater than the sum of its parts and the theory and practice of integrated series in panel data have given rise to a set of interesting and surprising results which are uniquely its own."

The panel unit root tests which we consider are from the Levin-Lin-Chu (LLC), Breitung, Im-Pesaran-Shin (IPS), Maddala-Wu-Choi (MWC) and Hadri methodology. Regarding cointegration, we will exploit Pedroni's developments.[6] Although the panel unit root tests are similar, they are not identical and as such, we begin by briefly outlining the various tests through the following AR(1) process for panel data,

$$y_{i,t} = \rho_i y_{i,t-1} + X_{it}\delta_i + \varepsilon_{i,t}, \tag{10.6}$$

where as before, $i = 1, 2, ..., N$ cross-section units, that are observed over periods $t = 1, 2, ...T$. The exogenous variables in the model, which may include any fixed

[6] Although we would have liked to include Sarno and Taylor's MADF, based on SUR, we could not because we are dealing with an unbalanced panel. In order to apply their methodology a balanced panel is required.

effects or individual trends, are represented by X_{it}, the autoregressive coefficients are denoted by ρ_i, and the errors, $\varepsilon_{i,t}$, are assumed to be mutually i.i.d. If $|\rho_i| < 1$, then y_i is said to be weakly (trend-) stationary. However, if $|\rho_i| = 1$ then y_i has a unit root. With regards to testing, two assumptions can be made about ρ_i. Tests which are considered first generation tests, assume that the persistence parameters are common across cross-sections, so that $\rho_i = \rho$ for all i. The LLC, Breitung and Hadri tests make this assumption. Alternatively, second generation tests allow ρ_i to vary freely across the cross-section units. The IPS and MWC tests are of this form.

LLC and Breitung both consider the following basic ADF specification:

$$\Delta y_{i,t} = \alpha y_{i,t-1} + \sum_{j=1}^{p_i} \beta_{ij} \Delta y_{i,t-j} + X_{it}^{'} \delta + \varepsilon_{i,t} \tag{10.7}$$

where a common $\alpha = \rho - 1$ is assumed, but the lag order for the difference terms, p_i, is allowed to vary across the units. Under the null hypothesis, $H_0 : \alpha = 0$, there is a unit root for all series, whereas under the alternative, $H_A : \alpha < 0$, none of the series contain a unit root.

The methodology described in Levin, Lin and Chu (2002) develops estimates of α from proxies for $\Delta y_{i,t}$ and $y_{i,t}$, which are standardized and free of autocorrelations and deterministic components. For a given set of lag orders supplied by the researcher, the LLC algorithm begins by estimating two additional sets of equations. First, both $\Delta y_{i,t}$ and $y_{i,t-1}$ are regressed on the lag terms $\Delta y_{i,t-j}$ (for $j = 1, 2, ..., p_i$) and then on the exogenous variables X_{it}. The estimated coefficients from these two regressions can be denoted as $(\hat{\beta}, \hat{\delta})$ and $(\dot{\beta}, \dot{\delta})$, respectively. Then the autocorrelations and deterministic components are removed from both auxiliary estimates of $\Delta y_{i,t}$ and

$y_{i,t-1}$, allowing for $\Delta\bar{y}_{i,t}$ and $\bar{y}_{i,t-1}$ to be defined as,

$$\Delta\bar{y}_{i,t} = \Delta y_{i,t} + \sum_{j=1}^{p_i} \hat{\beta}_{ij}\Delta y_{i,t-j} - X_{it}'\hat{\delta} \tag{10.8}$$

and

$$\bar{y}_{i,t-1} = y_{i,t-1} + \sum_{j=1}^{p_i} \dot{\beta}_{ij}\Delta y_{i,t-j} - X_{it}'\dot{\delta}. \tag{10.9}$$

Next, the proxies are obtained by standardizing both $\Delta\bar{y}_{i,t}$and $\bar{y}_{i,t-1}$ by the regression standard error, s_i, estimated from estimating each ADF in equation (10.7). The proxies can be denoted as,

$$\Delta\tilde{y}_{i,t} = (\Delta\bar{y}_{i,t}/s_i)$$

and

$$\tilde{y}_{i,t-1} = (\bar{y}_{i,t-1}/s_i). \tag{10.10}$$

Lastly, an estimate of the coefficient α can be obtained from the pooled proxy equation:

$$\Delta\tilde{y}_{i,t} = \alpha\tilde{y}_{i,t-1} + \eta_{i,t}. \tag{10.11}$$

Levin, Lin and Chu (2002) show that under the null, a modified t-statistic for the resulting $\hat{\alpha}$ is asymptotically normally distributed,

$$t_{\alpha}* = \frac{t_{\alpha} - \left(N\tilde{T}\right) S_N \hat{\sigma}^{-2} se(\hat{\alpha}) \mu_{m\tilde{T}}*}{\sigma_{m\tilde{T}}*} \sim N(0,1) \tag{10.12}$$

where t_α is the standard t-statistic for $\hat{\alpha} = 0$, $\hat{\sigma}^2$ is the estimated error term η, $se(\hat{\alpha})$ is the standard error of $\hat{\alpha}$ and $\tilde{T} = T - (\sum_i p_i/N) - 1$. The remaining terms involve complicated moment calculations. S_N is defined as the mean of ratios of the long-run standard deviation to the innovation standard deviation for each individual. Kernel-based procedures are required to derive its estimate. $\mu_{m\tilde{T}}*$ and $\sigma_{m\tilde{T}}*$ are adjustment terms for the mean and standard deviation.

The Breitung method differs from LLC in two ways. First, only the autoregressive portion is removed when constructing the standardized proxies. Second, the proxies are transformed and detrended. As such, the Breitung algorithm does not require kernel computations.[7]

The Hadri panel unit root test is akin to the KPSS stationarity test and has the null hypothesis of no unit root in any of the series in the panel. As with the KPSS test, the Hadri test is based on the residuals from the individual OLS regressions of $y_{i,t}$ on a constant or constant and a trend. Such a regression can be defined as

$$y_{i,t} = \delta_i + \eta_i t + \varepsilon_{i,t}. \tag{10.13}$$

In particular, an LM statistic can be constructed from the residuals, $\hat{\varepsilon}$, estimated from the individual regressions,

$$LM = \frac{1}{N}\left(\sum\nolimits_{i=1}^{N}(\sum_t S_i(t)^2/T^2)/\bar{f}_0\right), \tag{10.14}$$

where $S_i(t)$ are the cumulative sums of the residuals, $S_i(t) = \sum_{s=1}^{t} \hat{\varepsilon}_{i,t}$, and $\bar{f}_0$ is the average of the individual estimators of the residual spectrum at frequency zero,

[7]See Breitung (2000) for the differences in the proxies.

$\bar{f}_0 = \sum_{i=1}^{N} f_{i0}$. Hadri then demonstrates, with mild assumptions, that

$$Z = \frac{\sqrt{N}(LM - \xi)}{\zeta} \sim N(0,1), \tag{10.15}$$

where $\xi = 1/6$ and $\zeta = 1/45$, if the model includes constants and $\xi = 1/15$ and $\zeta = 1/6300$, otherwise. Such a stationarity test can be considered a viable alternative to the above unit root tests because it allows the researcher to investigate the autoregressive nature of the panel in a diverse way in comparison to the ADF methodology. As such, it helps builds power to the conclusions made with respect to the panel members individually and as a group.

In contrast to the three tests described above, the IPS and MWC methodology allow for cross-sectional heterogeneity in the value of ρ_i. These second generation tests are in a class of their own because of the way they combine individual unit root tests to derive a panel specific result. Im, Pesaran and Shin (2003) also begin by utilizing (10.7) as a separate ADF specification for each of the cross-sectional units. The null and alternative hypotheses are then defined as, $H_0 : \rho_i = 0$ for all i and $H_A : \rho_i < 0$, $i = 1, 2, ..., N_1$, $\rho_i = 0$, $i = N_1 + 1, N_1 + 2, ...N$. Since the ρ_i's are not restricted to be identical under the null hypothesis, the alternative hypothesis is "not all members of the panel contain a unit root". Once the separate individual ADF regressions have been estimated, the average of the t-statistics for α_i is then adjusted to arrive at the desired test statistics. This can be expressed as

$$\bar{t}_{NT} = \left(\sum_{i=1}^{N} t_{iT_i}(p_i) \right) / N. \tag{10.16}$$

Im, Pesaran and Shin (2003) provide simulated critical values for $\bar{t}_{NT}$ for different numbers of cross section units and series lengths, when the lag order is always zero. In the general case where the lag order is non-zero for some of the cross-sectional units, Im, Pesaran and Shin (2003) illustrate that a properly standardized $\bar{t}_{NT}$ has an asymptotic standard normal distribution,

$$W_{\bar{t}_{NT}} = \frac{\sqrt{N}\left(\bar{t}_{NT} - N^{-1}\sum_{i=1}^{N} E(t_{iT_i}(p_i))\right)}{\sqrt{N^{-1}\sum_{i=1}^{N} Var(t_{iT_i}(p_i))}} \sim N(0,1). \tag{10.17}$$

Where $E(t_{iT_i}(p_i))$ is the expected mean, and $Var(t_{iT_i}(p_i))$ is the variance of the ADF regression t-statistics and are provided by IPS for various values of T and p.

Maddala and Wu (1999) and Choi (2001) propose an alternative approach to panel unit root tests. In particular, they propose using Fisher's (1932) results to derive tests which combine the p-values from individual unit root tests. They illustrate that if π_i is defined as the p-value from any individual unit root test for the cross sectional unit i, then under the null hypothesis of unit root for all N units, an asymptotic result can be derived in the form of,

$$-2\sum_{i=1}^{N} \log(\pi_i) \sim \chi^2_{2,N}. \tag{10.18}$$

Additionally, Choi (2001) establishes that,

$$Z = \frac{1}{\sqrt{N}}\sum_{i=1}^{N} \Phi^{-1}(\pi_i) \sim N(0,1) \tag{10.19}$$

where Φ^{-1} is the inverse of the standard normal cumulative distribution function. When the Fisher tests are based on ADF test statistics, the number of lags used in each cross-section ADF regression must be specified. For the Phillips-Perron (PP) form of the test, a kernel for estimating the frequency zero spectrum, f_0, must be specified by the researcher.

However, some caveats must be noted with all five unit root tests. Breuer *et al.* (2002) point out, the alternative hypothesis in the first generation tests is rather restrictive in the sense that with as few as one stationary member in the panel, the rejection rate rises above the nominal size of the test, and increases with the number stationary series in the panel. In such a case, the null could be correctly rejected, but the alternative of "no unit roots" is also false in mixed panels. In contrast, the second generation tests admit that there may be a mixture of stationarity and nonstationarity contained within the panel under the alternative. However, rejection of the null in these second generation tests does not does not provide the researcher with information regarding the exact mix of series in the panel.

If unit roots are verified in multiple variables, who theoretically have a long-run relationship, then cointegration can be explored. In particular, the Pedroni (1997a, 1997b, 1999, 2000, 2004) cointegration methodology proposes methods which can accommodate for considerable heterogeneity across individual members of the panel. The advantage of this approach is that it allows one to pool the long run information contained in the panel, while permitting the short run dynamics and fixed effects to be heterogeneous among different members of the panel. In general, the following regression equation can be drawn upon to help summarize a cointegration test,

$$y_{i,t} = \alpha_i + \delta_i t + \beta_i X_{i,t} + e_{i,t}. \tag{10.20}$$

$y_{i,t}$ and $X_{i,t}$ are both a time series panel of observable variables, where $X_{i,t}$ is an m-dimensional column vector for each i and β_i is an m-dimensional row vector for each i. The variables assumed to be integrated of order one, I(1), for each member of the panel. Inherently, testing for cointegration amounts to a unit root test in the panel residuals.

The null hypothesis can be defined as, H_0 : "all of the individuals of the panel are not cointegrated.". If the null can not be rejected, then $e_{i,t}$ is also $I(1)$. With regards to the alternative hypothesis, the researcher must first make an assumption about the underlying data generating process (DGP). If the underlying DGP is assumed to require that all individuals of the panel be either uniformly cointegrated or uniformly not cointegrated, then the alternative hypothesis can be expressed as, H_A : "all of the individuals are cointegrated". This would mean that e is $I(0)$ for all panel members. In contrast, if the underlying DGP is assumed to permit individual members of the panel to differ in whether or not they are cointegrated, then the alternative hypothesis can be expressed as, H_A : "a significant portion of the individuals are cointegrated. This can be interpreted as most of the $e_{i,t}$ are $I(0)$. This follows from the parameters α_i and δ_i and β_i being permitted to vary across individual, which allows for the cointegrating vectors to possibly be heterogeneous across panel members.

In particular, Pedroni (1999, 2004) constructs two classes of cointegration tests. The first class is composed of four tests based on pooling the data across the within dimension of the panel.[8] The "panel-rho" statistic is comparable to the semiparametric "rho" statistic studied in Phillips and Perron (1988) and Phillips and Ouliaris (1990) for the conventional time series application. Similarly, the "panel-t" statistic

[8]Within-subject information is reflected in the changes within subjects (time-series). In contrast, the between-subject information is reflected in the changes between subjects (cross-sectional).

and the "panel-v" statistics are also akin to the semiparametric t-statistic and long run variance ratio statistic, each of which was also investigated in Phillips and Ouliaris (1990). The "panel-ADF" statistic is constructed in a familiar fashion as the LLC and IPS panel unit root tests described previously. In contrast, the second class of statistics are constructed by pooling the data along the between dimension of the panel. Therefore, these statistics in effect compute the group mean of the individual conventional time series statistics. Pedroni presents three statistics within this class: the "group-rho", "group-t" and the "group ADF".

All test statistics within both classes are asymptotically normally distributed. The usage of these statistics is the same as for the single series case. Large positive values of the panel-v statistics indicate rejections of the null, whereas large negative values of panel-rho, panel-t and panel-ADF the indicate rejections.[9] We urge the reader to refer to Pedroni (1999, 2004), where the construction and asymptotics of the tests are thoughly outlined and beyond the scope of this paper.

Pedroni (2000) also proposes FMOLS methods for estimating and testing hypotheses for cointegrating vectors in dynamic time series panels. Pedroni argues that the advantage of this estimator lies within its small sample properties of producing asymptotically unbiased estimators and nuisance parameter free standard normal distributions.[10] The case is also made that, through FMOLS, inferences can be made regarding common long-run relationships, which are asymptotically invariant to the degree of short-run heterogeneity in the dynamics typically associated with panels composed of aggregate national data. Pedroni (2000) then proceeds by thoroughly

[9]The same can be said for the "group" statistics.
[10]See Pedroni (1999 pg.94) for an indepth discussion.

outlining the underlying algorithm used to test hypotheses about common cointegrating vectors. He then also demonstrates, through monte carlo simulations, that FMOLS estimation in heterogeneous cointegrated panels has superior small sample properties and is asymptotically powerful and superconsistent.[11] Pedroni (2001) also points out that another advantage of this approach is that the point estimates have more useful interpretation in the event that the true cointegrating vectors are heterogeneous. As such, the FMOLS approach is appealing because it allows us to directly test the condition on the cointegrating vector that is required for long-run money demand propositions, such as the quantity theory demand for money or the Baumol-Tobin theory, to prevail.

Thus, we can consider the following regression

$$y_{i,t} = \alpha_i + \beta_i \mathrm{X}_{i,t} + \varepsilon_{i,t} \tag{10.21}$$

where $y_{i,t}$ is a logged monetary aggregate, $\mathrm{X}_{i,t}$ is a vector of explanatory variables (i.e. logged interest rate and logged real output) and $y_{i,t}$ and $\mathrm{X}_{i,t}$ are cointegrated with slopes β_i which may or may not be homogeneous across i. Let $\xi_{i,t} = (\hat{\varepsilon}_{i,t}, \triangle \mathrm{X}_{i,t})'$ be a stationary vector consisting of the estimated residuals from the cointegrating regression and the differences in the explanatory variables, and let $\Omega_i \equiv \lim_{T\to\infty} E\left[T^{-1}(\sum_{t=1}^{T} \xi_{i,t})(\sum_{t=1}^{T} \xi'_{i,t}\right]$ be the long-run covariance for this vector process. Pedroni (2001) notes that the long-run covariance matrix is typically estimated using any one of a number of HAC estimators, such as the Newey-West estimator. It can be decomposed as $\Omega_i = \Omega_i^o + \Gamma_i + \Gamma_i^T$, where Ω_i^o is the contemporaneous covariance and Γ_i is a weighted sum of autocovariances.

[11]The monte carlo simulation results are found in Pedroni (2000 pg. 107-114).

Continuing, it can be shown that the expression for the between-dimension, group-mean panel FMOLS estimator is given as

$$\hat{\beta}^*_{GFM} = N^{-1}\sum_{i=1}^{N}\left(\sum_{i=1}^{T}(\mathrm{X}_{i,t}-\bar{\mathrm{X}}_i)^2\right)^{-1}\times\left(\sum_{i=1}^{T}(\mathrm{X}_{i,t}-\bar{\mathrm{X}}_i)\right)y^*_{i,t}-T\hat{\gamma}_i \qquad (10.22)$$

where

$$\begin{aligned} y^*_{i,t} &= (y_{i,t}-y_i)-\frac{\hat{\Omega}_{21i}}{\hat{\Omega}_{22i}}\triangle\,\mathrm{X}_{i,t}, \\ \hat{\gamma}_i &\equiv \hat{\Gamma}_{21i}+\hat{\Omega}^o_{21i}-\frac{\hat{\Omega}_{21i}}{\hat{\Omega}_{22i}}(\hat{\Gamma}_{22i}+\hat{\Omega}^o_{22i}). \end{aligned}$$

Since the expression following the summation over the i units is the same as the conventional time series estimator, it can be seen that the between-dimension estimator can be constructed as $\hat{\beta}^*_{GFM} = N^{-1}\sum_{i=1}^{N}\hat{\beta}^*_{FM,i}$, where $\hat{\beta}^*_{FM,i}$ is the conventional FMOLS estimator, applied to the ith unit of the panel. Similarly the corresponding t-statistic for the between-dimension estimator can be constructed as

$$t_{\hat{\beta}^*_{GFM}} = N^{-1/2}\sum_{i=1}^{N}t_{\hat{\beta}^*_{FM,i}} \qquad (10.23)$$

where

$$t_{\hat{\beta}^*_{FM,i}} = (\hat{\beta}^*_{FM,i}-\beta_0)\left(\hat{\Omega}^{-1}_{11i}\sum_{i=1}^{T}(\mathrm{X}_{i,t}-\bar{\mathrm{X}}_i)^2\right)^{-1/2}.$$

We strongly urge the reader to refer to Pedroni (2000, 2001), where the construction and asymptotics of the tests are thoughly outlined and beyond the scope of this paper. We also recommend that the reader refer to Banerjee (1999) and Baltagi and Kao (2000), two surveys of unit root and cointegration testing in panel data, in order to become familiar with and fully understand how the statistics for each test are derived and how they differ.

Chapter 11

Panel Results

In order to obtain our estimates of the panel models described in the previous section, we utilize EViews 5 quantitative micro software. To begin, Table 13 presents the panel descriptive statistics for the conventional money demand variables. There is a wide variation of logged real money supplies, logged interest rates and logged real output across the panel. Table 14 displays the results for the pooled OLS, FEM and REM estimators, for both narrow and broad specifications. Not surprisingly the results for the pooled estimator are almost, if not, identical to the conventional money demand results we initially found for the cross-country data. Once again we can not reject the null hypothesis that the real income elasticity of the demand for real balances is equal to one, for both aggregates. The next four columns show the two versions of the fixed effects model we experimented with. In the first specification, we only allowed the constant to vary and in the second, we allowed both the constant and slope to vary among countries. The last two columns report the results for the REM.

In general, all three models are either in accordance with the quantity theory demand for money, or come close. However, although we do not report the country specific results, both versions of the FEM displayed some heterogeneity in the constant and in the income elasticity of the demand for real balances. For example, in the second FEM we report the country specific interest and income elasticities for Canada. The Canadian income elasticity, for the narrow aggregate, is much higher than that predicted by both the quantity theory demand for money and Baumol-Tobin models. However, it is close to the classical quantity theory demand for money prediction when we experiment with M2 as the dependent variable. In comparison, the other 47 countries ranged from -4.276, for Sweden, to 3.630 for Denmark, when we considered the narrow aggregate. When we considered the broad aggregate, the country specific income elaticities ranged from -1.529, for Argentina, to 4.620 for Brazil.

As well, the constant also exhibited some heterogeneity. For instance, in the first FEM specification the country specific constants varied from -2.129, for Belgium, to 1.232 for Japan, when we treated M1 as the dependent variable. When we treated M2 as the dependent variable, the country specific constants varied from -2.291, for Belgium, to 1.326 for Cyprus. In the second FEM with a narrow aggregate as the dependent variable, the constant ranged from -67.450, for Norway, to 135.29 for Sweden. When we treated the broad aggregate as the dependent variable, the constant varied from -90.076, for Brazil, to 75.069 for Argentina.

In contrast to the fixed effects estimates, the random effects estimates are more supportive of the quantity theory demand for money. The interest elasticity is not significant at conventional levels for either aggregate. The income elasticity varies from 0.94 for M1 and 1.17 for M2.

In order to make selection between the models we experimented with, we conducted a variety of specification tests. The Likelihood Ratio test statistic (LR) is highly significant in all four cases. This allows us to reject the null hypothesis of the pooled model over the each of the two fixed effects variants, for each monetary aggregate. The Hausman test statistic is also highly significant, indicating that the fixed effects model is preferred over the random effects model.[1] In summary, these standard panel specification tests show that the fixed effects model is to be preferred over the pooled cross-section and the random effects models. However, inspection of the Durbin-Watson (DW) statistic indicates significant residual serial correlation and specification errors. The DW statistic is very low for all of the models we experimented with. Therefore, we conclude that these estimators are biased and may not be consistent and further hypothesis testing within these models would be spurious. As such, we apply the new state-of-the-art developments in panel data in order to further our analysis of investigating money demand from a panel context. We commence this process by first testing for unit roots within the panel.

Table 15 reports the LLC, Breitung, IPS, Fisher and Hadri panel unit root statistics preformed on the four variables of interest. The top panel displays the results for the variables in log levels and the bottom reports results for the variables in first differences. The optimal lag lengths was taken to be the order selected by the Akaike Information Criterion (AIC) plus 2, with a max lag of 2. Setting the max lag at 2, is common practice in the purchasing power parity and real GDP literature when dealing with annual panel data.[2] For both monetary aggregates, the null hypothesis of a unit root in levels cannot, in general, be rejected at conventional levels. Regarding the Hadri statistic, we can reject the null hypothesis that there are no unit roots in any of the level series in the panel. Now, some ambiguity does arise when we preform the panel unit root tests on the interest rate.

[1]The Swamy and Arora algorithm requires that the number of cross-sectional units excced the number of estimated parameters in order to estimate a REM. Hence we could not preform a Hausman comparing a second REM and FEM #2.

[2]See Pedroni (2004) and Rapach (2002).

When we investigate the order of integration of the interest rate variable, we find that both the Breitung and Fisher PP tests do not reject the null of a unit root, where as the LLC, IPS and Fisher ADF do reject the null of a unit root. Alternatively, the Hardi test does reject the null hypothesis of no unit root. The interpretation of these mixed results leads us to the conclusion that not all panel members likely contain a unit root. This could be due the fact that some countries conduct monetary policy via an interest rate rule rather than a money supply rule. Inspection of the raw data reveals that this is likely the case for Cyprus and Egypt.[3] With the exception of the outliers, we conclude that the interest rate panel series can best be described as difference stationary. We also find support for a unit root across the panel in real output. Rapach (2002) also finds such evidence that real GDP levels are nonstationary within a panel data framework. From our perspective, the panel unit roots tests lend support to the Nelson and Plosser (1982) argument that most macroeconomic time series have a stochastic trend and are I(1). Furthermore, we interpret these results as evidence of the real business cycle theory of economic fluctuations.

Given that we have established evidence supportive of unit roots in the variables within the panel, we then proceed by testing for a cointegrating relationship between the variables of interest The cointegration tests are conducted for each monetary aggregate as the dependent variable, along with both the opportunity cost and scale variables as explanatory regressors. In particular, we interpret such cointegration tests as an investigation of whether or not a long-run relationships between each

[3]For both Cyprus and Egypt the interest rate series remains constant for most of the 1980-95 period, with minor changes after long periods of time.

of the monetary aggregates and explanatory variables exist. To obtain the desired test statistics we utilized RATS 6.02 and Pedroni's PANCOINT source file, which is available from www.estima.com. We did consider and experiment with a couple of variants of the cointegration tests. In particular, we considered subtracting out common time effects and including heterogeneous member specific trends.[4] Neither of these options affected the sensitivity of the conclusions drawn from each of the hypothesis tests.

Table 16 presents the results for the panel-stats and group-stats for both monetary aggregates. The panel-stats are listed in the upper portion and the group-stats are listed in the lower portion of the table. For the panel and group mean statistics we report results both for the raw data and for data that has been demeaned with respect to common time effects to accommodate some forms of cross-sectional dependency. The ADF and t-statistic indicate that we can reject the null hypothesis of no cointegration for all members of the panel. However, the panel-v, panel-rho and group-rho are always too small to reject the null hypothesis. Between all of the tests which we considered, we are left with mixed results which are typically found in the time series literature. One explanation can be that even though all of the statistics are asymptotically consistent, they converge at different rates depending on the DGP. In particular, Pedroni (2004) shows that with a fixed number of cross-section units and a with time dimension increasing, that the panel-v, panel-rho and group-rho converge from below, indicating that they are somewhat undersized.[5] As a result, we proceed as if most of the countries are cointegrated and there exists long-

[4]Although the cointegration test results with the heterogeneous member specific trends are not reported, they are availiable upon request from the author.

[5]See Pedroni (2004 pg.609).

run equilibrium relationships which link narrow and broad real monetary aggregates to interest rates and real output.

Previously in the initial panel estimation, we determined that there was heterogeneity within the estimated elaticities through diagnostic tests, which indicated that the fixed effects model was preferred to the other models which we considered. This finding, along with evidence of cointegration, allows us to test for the cointegrating vector using Pedroni's FMOLS procedure, which is designed explicitly for heterogeneous cointegrated panels. This source file, PANELFM, is also available on the Estima website. In particular, we can directly test whether the condition on the cointegrating vector that is required for either the classical quantity theory demand for money or the Baumol-Tobin transactions theory to hold. In the case for the quantity theory demand for money to hold, we require under the null hypothesis that interest and real output coefficients equal zero and unity, whereas under the Baumol-Tobin theory they should equal -1/2 and 1/2, respectively. Our approach is similar to the approach taken by Pedroni in the Purchasing Power Parity(PPP) literature, where he experiments within a bivariate framework which links the logged bilateral U.S. nominal exchange rate and logged aggregate price ratio between the two countries. After establishing that cointegration exists between his variables in his 1995 paper, he then uses FMOLS in his 2001 paper to test the condition on the cointegrating vector such that the price ratio coefficient is unity. Such a test can be interpreted as a test of strong PPP.

The FMOLS results are displayed in Table 17. We report only the group FMOLS estimates and t-statistics for each definition of real balances under the null hypotheses, $H_0 : \beta_1 = 0$ (nominal interest elasticity) and $H_0 : \beta_2 = 1$ (real income elasticity).

In addition to the raw data, we again display results for data that has been time demeaned. The raw coefficient estimates and corresponding t-statistics for both aggregates are presented in the upper portion of the table. The time demeaned results are presented in the bottom portion of the table.

The results of the raw specification when we consider the narrow aggregate as the dependent variable, indicate that we can not reject the null that the cointegrating vector contains unity but can reject the null that it contains zero. Given the estimated interest elasticity, this finding is nearly supportive of the quantity theory demand for money and challenges the Baumol-Tobin theory. However, under the time demeaned specification, the estimated income elasticity coefficient is slightly larger and the null of unity is rejected, along with the null of the interest elasticity being significantly different from zero. Our interpretation of both specifications is that the group cointegrating vector is likely to be near, but not exact, to the hypothesized classical prediction for the countries under investigation.

With regards to the broad cointegrating vector, the results of the raw specification reject both of our null hypotheses at conventional levels. The estimated real income elasticity of the demand for real broad balances is also much higher than either of the narrow estimates. The results of the time demeaned specification also reject the null hypothesis of the real income elasticity equalling unity. However, we can not reject the null hypothesis placed on the nominal interest elasticity of the demand for real narrow balances. Surprisingly, the estimated coefficient is right at zero. Again, we conclude that the cointegrating vector is close to, but not exact, to the hypothesized classical prediction.

From the FMOLS results, we conclude that both the real income and nominal interest elasticity coefficients are heterogeneous across aggregates, with the real income elasticity being more responsive in the broad money measure. As such, we interpret these results as an indication that the cointegrating vector is heterogeneous across different definitions of money, even in the aggregate.[6]

[6]We do not report the individual tests because the theories we are testing are considered long-run propositions which should theoretically hold in the aggregate. However, the individual results did display a great deal of heterogeniety in the estimated coefficients, indicating heterogeneous cointegrating vectors. The results are availiable upon request.

Chapter 12

Conclusions

In this study, we have used cross-country and panel data to investigate the long-run relationship between both narrow and broad monetary aggregates and interest rates, real GDP, institutions, financial structure and financial development for 48 countries over the 1980-95 period. In particular, with the cross-country data we have shown that the interest and income elasticities for real balances is fairly stable and conforms to the theoretical prediction of the quantity theory demand for money. As well, we have found that institutions, financial structure and development do play a role in the demand for money in an aggregate setting; abeit a limited role.

However, we have shown that the assumption of all of the countries being homogeneous can cause systematic distortions. Specifically, we utilized unsupervised Bayesian methods based on finite mixture models, priors and mathematical properties, which clustered the data set into 2 distinct clusters. Regressions based on each of the partitioned data sets displayed heterogeneity with respect to the influence institutions, financial structure and financial development have on money demand, for each of the two groups. In particular, we found that our developing-high inflation class somewhat dominated the data set and distorted some of the developed-low inflation class results.

Regarding the panel data, we considered and evaluated a variety of models. Our selection criteria and regression diagnostics indicated that the fixed effects specification, which allowed for the most heterogeniety within the 48 countries, was the ideal model among the others, but that there did exist some serial correlation. Rather than ignoring the possible specification error, we applied new innovative unit root tests and found evidence that our conventional money demand variables within the panel were for the most part all I(1). As a result, this outcome then allowed us to apply panel cointegration tests. The results from these tests, in our opinion, showed evidence of a long-run relationship between different monetary aggregates, interest rates and real GDP. Furthermore, the application of direct panel cointegrating vector tests indicated that, as a group, the quantity theory demand for money does come close holding. However, the cointegrating vector is heterogeneous not only for each individual country but for each monetary aggregate.

Appendix A

Tables

Table A.1: Countries

TABLE 1

COUNTRIES

Argentina	Kenya
Australia	Malaysia
Austria	Mexico
Belgium	Netherlands
Brazil	New Zealand
Canada	Norway
Chile	Pakistan
Colombia	Panama
Cyprus	Peru
Denmark	Philippines
Ecuador	Portugal
Egypt	South Africa
Finland	Spain
France	Sri Lanka
Germany	Sweden
Ghana	Switzerland
Greece	Taiwan, China
Honduras	Thailand
India	Trinidad and Tobago
Ireland	Turkey
Israel	Tunisia
Italy	United Kingdom
Jamaica	United States
Japan	Zimbabwe

Table A.2: Cross Country Data Descriptive Statistics: 1980-1995

TABLE 2
CROSS COUNTRY DATA DESCRIPTIVE STATISTICS: 1980-1995

	Mean	Minimum	Maximum	Std. dev.	Observations
Ln M1	18.660	15.307	23.298	1.980	48
Ln M2	19.884	16.097	24.557	2.029	48
Ln R	2.885	1.600	13.448	1.848	48
Ln Y	25.246	21.874	29.419	1.856	48
Ln School80	1.668	0.553	2.479	0.531	48
Ln BMP	0.129	0.004	1.791	0.278	48
Ln GOV	2.695	1.998	3.393	0.317	48
Ln Trade	3.982	2.746	4.921	0.503	48
Civil	2.491	1.000	7.000	1.691	48
REVC	0.129	0.000	1.500	0.250	48
ASSASS	0.333	0.000	2.200	0.565	48
Bureau	4.242	1.107	6.000	1.476	48
Corrupt	4.068	1.750	6.000	1.383	48
Structure-Activity	-2.004	-5.166	0.588	1.159	48
Structure-Size	-0.635	-2.456	1.342	0.761	48
Structure-Efficiency	-6.476	-9.984	-3.032	1.419	48
Structure-Aggregate	5.073	-2.753	1.857	1.000	48
Structure-Regulatory	9.020	4.000	14.000	2.496	48
Finance-Activity	-3.839	-9.069	0.549	2.073	48
Finance-Size	4.213	2.727	5.514	0.719	48
Finance-Efficiency	0.367	-2.710	4.431	1.799	48
Finance-Aggregate	-7.838	-2.196	1.875	1.000	48

Table A.3: Conventional Money Demand

TABLE 3
CONVENTIONAL MONEY DEMAND
(DEPENDENT VARIABLE: (LOGGED) MONETARY AGGREGATE, 1980-1995)

Explanatory Variable	Coefficient	Standard error	t-statistic	p-value	$\bar{R}^2$	RESET F
			M1			
Constant	-6.575	0.943	-6.969	0.000	0.897	1.099
Ln R	-0.108	0.037	-2.899	0.006		
Ln Y	1.012	0.040	25.240	0.000		
			M2			
Constant	-6.615	0.787	-8.396	0.000	0.940	0.110
Ln R	-0.102	0.024	-4.165	0.000		
Ln Y	1.061	0.032	32.468	0.000		

Note: The reported explanatory variables are all included in each of the regressions. The simple information set only includes the logarithm of short term interest rates and the logarithm of real GDP in USA dollars.

Table A.4: Institutions, Political, Macroeconomic Stability and Money Demand

TABLE 4
INSTITUTIONS, POLITICAL, MACROECONOMIC STABILITY AND MONEY DEMAND
(DEPENDENT VARIABLE: (LOGGED) MONETARY AGGREGATE, 1980-1995)

Explanatory Variable	Coefficient	Standard error	t-statistic	p-value	$\bar{R}^2$	RESET F
			M1			
Ln School80	-0.395	0.161	-2.452	0.018	0.904	1.003
Ln BMP	0.095	0.136	0.698	0.489	0.895	1.027
Ln GOV	-0.086	0.310	-0.279	0.781	0.895	1.093
Ln Trade	-0.422	0.309	-1.363	0.180	0.902	0.289
Civil	0.034	0.058	0.593	0.556	0.895	1.205
REVC	-0.257	0.219	-1.174	0.247	0.896	1.105
ASSASS	-0.081	0.128	-0.632	0.530	0.895	0.892
Bureau	-0.051	0.095	-0.543	0.590	0.895	1.067
Corrupt	-0.045	0.087	-0.512	0.611	0.895	0.934
			M2			
Ln School80	0.056	0.132	0.424	0.673	0.939	0.107
Ln BMP	-0.531	0.131	-4.059	0.000	0.943	0.096
Ln GOV	0.274	0.183	1.490	0.143	0.941	0.151
Ln Trade	-0.046	0.319	-0.145	0.885	0.939	0.169
Civil	0.002	0.036	0.071	0.943	0.939	0.104
REVC	-0.228	0.163	-1.400	0.168	0.940	0.148
ASSASS	-0.178	0.103	-1.724	0.092	0.942	0.354
Bureau	0.028	0.068	0.416	0.679	0.939	0.090
Corrupt	0.061	0.054	1.130	0.264	0.940	0.020

Note: The reported explanatory variables are included one-by-one in each of the regressions. The simple information set only includes the logarithm of short term interest rates and the logarithm of real GDP in USA dollars.

Table A.5: Financial Structure and Money Demand

TABLE 5
FINANCIAL STRUCTURE AND MONEY DEMAND
(DEPENDENT VARIABLE: (LOGGED) MONETARY AGGREGATE, 1980-1995)

Explanatory Variable	Coefficient	Standard error	t-statistic	p-value	$\bar{R}^2$	RESET F
		M1				
Structure-Activity	-0.170	0.091	-1.854	0.070	0.902	1.038
Structure-Size	-0.204	0.107	-1.900	0.064	0.901	1.920
Structure-Efficiency	-0.110	0.094	-1.168	0.249	0.899	1.157
Structure-Aggregate	-0.194	0.105	-1.839	0.073	0.903	1.377
Structure-Regulatory	0.014	0.031	0.461	0.647	0.895	0.929
		M2				
Structure-Activity	-0.002	0.066	-0.031	0.975	0.939	0.113
Structure-Size	-0.132	0.070	-1.872	0.068	0.942	0.117
Structure-Efficiency	0.071	0.075	0.951	0.347	0.941	0.064
Structure-Aggregate	-0.009	0.074	-0.121	0.904	0.939	0.116
Structure-Regulatory	-0.002	0.027	-0.108	0.914	0.939	0.102

Note: The reported explanatory variables are included one-by-one in each of the regressions. The simple information set only includes the logarithm of short term interest rates and the logarithm of real GDP in USA dollars.

Table A.6: Financial Development and Money Demand

TABLE 6
FINANCIAL DEVELOPMENT AND MONEY DEMAND
(DEPENDENT VARIABLE: (LOGGED) MONETARY AGGREGATE, 1980-1995)

Explanatory Variable	Coefficient	Standard error	t-statistic	p-value	$\bar{R}^2$	RESET F
		M1				
Finance-Activity	-0.044	0.073	-0.609	0.545	0.896	0.946
Finance-Size	0.033	0.173	0.194	0.847	0.895	1.080
Finance-Efficiency	-0.069	0.064	-1.072	0.289	0.897	0.785
Finance-Aggregate	-0.074	0.143	-0.514	0.609	0.895	0.974
		M2				
Finance-Activity	0.143	0.060	2.356	0.023	0.949	0.009
Finance-Size	0.447	0.127	3.522	0.001	0.952	0.089
Finance-Efficiency	0.110	0.057	1.917	0.062	0.944	0.022
Finance-Aggregate	0.304	0.113	2.679	0.010	0.950	0.006

Note: The reported explanatory variables are included one-by-one in each of the regressions.The simple information set only includes the logarithm of short term interest rates and the logarithm of real GDP in USA.

Table A.7: Bayesian Cluster Inference

TABLE 7
BAYESIAN CLUSTER INFERENCE

Class 1	Class 2
Argentina	Australia
Brazil	Austria
Chile	Belgium
Colombia	Canada
Ecuador	Cyprus
Egypt	Denmark
Ghana	Finland
Greece	France
Honduras	Germany
India	Ireland
Israel	Italy
Jamaica	Japan
Kenya	Netherlands
Malaysia	New Zealand
Mexico	Norway
Pakistan	Spain
Panama	Sweden
Peru	Switzerland
Philippines	Taiwan, China
Portugal	United Kingdom
South Africa	United States
Sri Lanka	
Thailand	
Trinidad and Tobago	
Tunisia	
Turkey	
Zimbabwe	

Table A.8: Bayesian Clustered Data: Conventional Money Demand

TABLE 8
CONVENTIONAL MONEY DEMAND
(DEPENDENT VARIABLE: (LOGGED) MONETARY AGGREGATE, 1980-1995)

Explanatory Variable	Coefficient	Standard error	t-statistic	p-value	$\bar{R}^2$	RESET F
			M1			
	Class 1 (Developing-High Inflation Countries)					
Constant	-5.818	1.041	-5.586	0.000	0.913	0.182
Ln R	-0.103	0.041	-2.495	0.020		
Ln Y	0.981	0.045	21.358	0.000		
	Class 2 (Developed-Low Inflation Countries)					
Constant	-7.673	2.432	-3.153	0.005	0.792	0.447
Ln R	-0.326	0.476	-0.685	0.502		
Ln Y	1.070	0.069	15.375	0.000		
			M2			
	Class 1 (Developing-High Inflation Countries)					
Constant	-7.749	1.169	-6.628	0.000	0.940	0.500
Ln R	-0.108	0.025	-4.354	0.000		
Ln Y	1.108	0.050	21.932	0.000		
	Class 2 (Developed-Low Inflation Countries)					
Constant	-3.832	1.156	-3.312	0.004	0.870	0.215
Ln R	-0.523	0.300	-1.742	0.098		
Ln Y	0.991	0.044	22.340	0.000		

Note: The reported explanatory variables are all included in each of the regressions. The simple information set only includes the logarithm of short term interest rates and the logarithm of real GDP in USA dollars.

Table A.9: Bayesian Clustered Data: Institutions, Political, Macroeconomic Stability and Money Demand (M1)

TABLE 9
INSTITUTIONS, POLITICAL, MACROECONOMIC STABILITY AND MONEY DEMAND (M1)
(DEPENDENT VARIABLE: (LOGGED) MONETARY AGGREGATE, 1980-1995)

Explanatory Variable	Coefficient	Standard error	t-statistic	p-value	$\bar{R}^2$	RESET F
			M1			
		Class 1 (Developing-High Inflation Countries)				
Ln School80	-0.504	0.139	-3.609	0.001	0.937	2.461
Ln BMP	-0.039	0.154	-0.257	0.799	0.909	0.150
Ln GOV	0.268	0.357	0.751	0.460	0.913	0.035
Ln Trade	0.037	0.219	0.172	0.864	0.909	0.153
Civil	0.072	0.053	1.363	0.186	0.916	0.016
REVC	-0.192	0.153	-1.252	0.223	0.911	0.378
ASSASS	-0.252	0.099	-2.536	0.018	0.923	0.858
Bureau	0.109	0.083	1.311	0.203	0.914	0.419
Corrupt	0.033	0.118	0.279	0.782	0.909	0.143
		Class 2 (Developed-Low Inflation Countries)				
Ln School80	-0.684	0.563	-1.213	0.241	0.788	0.594
Ln BMP	19.114	9.278	2.059	0.055	0.791	0.072
Ln GOV	-0.878	0.984	-0.892	0.384	0.789	0.414
Ln Trade	-1.173	0.616	-1.902	0.074	0.832	0.858
Civil	-0.166	0.089	-1.855	0.081	0.786	0.306
REVC	-2.188	1.646	-1.329	0.201	0.795	0.487
ASSASS	0.547	0.371	1.473	0.159	0.791	0.386
Bureau	-0.357	0.285	-1.249	0.228	0.796	0.294
Corrupt	-0.080	0.236	-0.337	0.740	0.781	0.386

Note: The reported explanatory variables are included one-by-one in each of the regressions. The simple information set only includes the logarithm of short term interest rates and the logarithm of real GDP in USA dollars.

Table A.10: Bayesian Clustered Data: Institutions, Political, Macroeconomic Stability and Money Demand (M2)

TABLE 10
INSTITUTIONS, POLITICAL, MACROECONOMIC STABILITY AND MONEY DEMAND (M2)
(DEPENDENT VARIABLE: (LOGGED) MONETARY AGGREGATE, 1980-1995)

Explanatory Variable	Coefficient	Standard error	t-statistic	p-value	$\bar{R}^2$	RESET F
			M2			
		Class 1 (Developing-High Inflation Countries)				
Ln School80	0.078	0.172	0.456	0.652	0.938	0.384
Ln BMP	-0.503	0.125	-4.024	0.001	0.948	0.001
Ln GOV	0.696	0.182	3.813	0.001	0.957	0.019
Ln Trade	0.505	0.178	2.831	0.009	0.954	0.028
Civil	0.013	0.043	0.318	0.753	0.938	0.398
REVC	-0.226	0.133	-1.696	0.103	0.940	1.186
ASSASS	-0.309	0.092	-3.329	0.003	0.954	2.149
Bureau	0.095	0.080	1.191	0.245	0.941	0.559
Corrupt	0.129	0.087	1.474	0.154	0.943	0.214
		Class 2 (Developed-Low Inflation Countries)				
Ln School80	-0.092	0.279	-0.331	0.744	0.863	0.212
Ln BMP	11.429	7.480	1.527	0.145	0.867	0.019
Ln GOV	-0.152	0.651	-0.234	0.817	0.863	0.212
Ln Trade	-1.141	0.559	-2.040	0.057	0.924	4.581
Civil	-0.033	0.060	-0.554	0.587	0.863	0.181
REVC	0.093	0.968	0.096	0.924	0.862	0.199
ASSASS	0.370	0.219	1.690	0.109	0.869	0.166
Bureau	-0.189	0.165	-1.146	0.267	0.868	0.108
Corrupt	-0.007	0.086	-0.087	0.931	0.862	0.227

Note: The reported explanatory variables are included one-by-one in each of the regressions. The simple information set only includes the logarithm of short term interest rates and the logarithm of real GDP in USA dollars.

Table A.11: Bayesian Clustered Data: Financial Structure and Money Demand

TABLE 11
FINANCIAL STRUCTURE AND MONEY DEMAND
(DEPENDENT VARIABLE: (LOGGED) MONETARY AGGREGATE, 1980-1995)

Explanatory Variable	Coefficient	Standard error	t-statistic	p-value	$\bar{R}^2$	RESET F
		M1				
	Class 1 (Developing-High Inflation Countries)					
Structure-Activity	-0.129	0.112	-1.151	0.262	0.919	0.141
Structure-Size	-0.070	0.112	-0.624	0.538	0.911	0.031
Structure-Efficiency	-0.124	0.096	-1.289	0.210	0.920	0.114
Structure-Aggregate	-0.131	0.122	-1.068	0.296	0.918	0.089
Structure-Regulatory	0.040	0.043	0.926	0.364	0.912	0.520
	Class 2 (Developed-Low Inflation Countries)					
Structure-Activity	-0.221	0.161	-1.367	0.189	0.794	0.288
Structure-Size	-0.485	0.262	-1.851	0.082	0.814	0.925
Structure-Efficiency	-0.112	0.197	-0.571	0.575	0.784	0.274
Structure-Aggregate	-0.314	0.197	-1.597	0.129	0.800	0.306
Structure-Regulatory	-0.027	0.071	-0.382	0.706	0.781	0.654
		M2				
	Class 1 (Developing-High Inflation Countries)					
Structure-Activity	-0.060	0.084	-0.717	0.480	0.939	0.275
Structure-Size	-0.143	0.074	-1.934	0.065	0.944	0.171
Structure-Efficiency	0.005	0.089	0.058	0.954	0.938	0.525
Structure-Aggregate	-0.069	0.091	-0.762	0.453	0.940	0.255
Structure-Regulatory	0.032	0.041	0.774	0.446	0.939	0.599
	Class 2 (Developed-Low Inflation Countries)					
Structure-Activity	0.041	0.124	0.334	0.742	0.863	0.289
Structure-Size	-0.089	0.148	-0.604	0.554	0.864	0.233
Structure-Efficiency	0.126	0.148	0.851	0.406	0.869	0.653
Structure-Aggregate	0.053	0.131	0.411	0.686	0.863	0.271
Structure-Regulatory	-0.017	0.049	-0.363	0.721	0.863	0.321

Note: The reported explanatory variables are included one-by-one in each of the regressions. The simple information set only includes the logarithm of short term interest rates and the logarithm of real GDP in USA dollars.

Table A.12: Bayesian Clustered Data: Financial Development and Money Demand

TABLE 12
FINANCIAL DEVELOPMENT AND MONEY DEMAND
(DEPENDENT VARIABLE: (LOGGED) MONETARY AGGREGATE, 1980-1995)

Explanatory Variable	Coefficient	Standard error	t-statistic	p-value	$\bar{R}^2$	RESET F
		M1				
	Class 1 (Developing-High Inflation Countries)					
Finance-Activity	-0.030	0.066	-0.455	0.653	0.910	0.155
Finance-Size	0.097	0.140	0.692	0.495	0.911	0.101
Finance-Efficiency	-0.018	0.079	-0.228	0.821	0.909	0.170
Finance-Aggregate	0.007	0.134	0.005	0.996	0.909	0.175
	Class 2 (Developed-Low Inflation Countries)					
Finance-Activity	-0.063	0.236	-0.266	0.793	0.781	0.334
Finance-Size	-0.085	1.080	-0.079	0.938	0.780	0.417
Finance-Efficiency	-0.097	0.135	-0.720	0.481	0.785	0.312
Finance-Aggregate	-0.172	0.465	-0.370	0.716	0.783	0.327
		M2				
	Class 1 (Developing-High Inflation Countries)					
Finance-Activity	0.133	0.065	2.056	0.051	0.953	0.557
Finance-Size	0.370	0.128	2.892	0.008	0.957	0.661
Finance-Efficiency	0.160	0.067	2.384	0.026	0.952	0.562
Finance-Aggregate	0.313	0.118	2.648	0.014	0.957	0.628
	Class 2 (Developed-Low Inflation Countries)					
Finance-Activity	0.163	0.189	0.863	0.400	0.876	1.070
Finance-Size	1.022	0.724	1.410	0.176	0.896	0.590
Finance-Efficiency	0.049	0.107	0.459	0.652	0.864	0.375
Finance-Aggregate	0.311	0.369	0.844	0.410	0.874	0.828

Note: The reported explanatory variables are included one-by-one in each of the regressions.The simple information set only includes the logarithm of short term interest rates and the logarithm of real GDP in USA.

Table A.13: Panel Descriptive Statistics: 1980-1995

TABLE 13
PANEL DESCRIPTIVE STATISTICS: 1980-1995

	Mean	Minimum	Maximum	Std. dev.	Cross Sections	Observations
Ln M1	18.620	14.828	23.632	1.991	48	764
Ln M2	19.787	15.046	0.190	21.685	48	762
Ln R	2.617	24.795	16.087	29.624	48	752
Ln Y	25.229	2.046	1.184	1.849	48	768

Table A.14: Money Demand: Conventional Panel Data Estimators

TABLE 14
MONEY DEMAND: CONVENTIONAL PANEL DATA ESTIMATORS

Regressors	Model							
	Pooled OLS		Fixed Effects #1		Fixed Effects #2[b]		Random Effects	
	Dependent Variable[a]							
	M1	M2	M1	M2	M1	M2	M1	M2
Constant	-6.559**	-6.617**	-3.506**	-12.655**	-5.507**	-14.747**	-5.096**	-9.811**
	(0.332)	(0.272)	(1.151)	(0.966)	(1.875)	(1.618)	(0.846)	(0.685)
Ln R	-0.114**	-0.145**	-0.015	0.031**	-0.091	-0.073	-0.016	-0.024*
	(0.020)	(0.016)	(0.011)	(0.009)	(0.164)	(0.141)	(0.011)	(0.009)
Ln Y	1.009**	1.061**	0.878**	1.282**	1.860**	1.105**	0.941**	1.170**
	(0.012)	(0.010)	(0.045)	(0.038)	(0.462)	(0.398)	(0.033)	(0.026)
R^2	0.891	0.931	0.986	0.991	0.993	0.995	0.499	0.705
F	3081.598**	5087.678**	1118.926**	1687.204**	754.474**	1077.832**	374.292**	893.549**
DW	0.051	0.084	0.322	0.417	0.739	0.942	0.300	0.373
LR[c]			1609.660**	1567.211**	374.373**	343.445**		
Hausman[d]							6.978*	30.197**

Note:

[a] Both aggregates are in real terms and logged. Standard errors are given in parentheses, and * and ** indicate significance at the 5 and 1% level, respectively. The Swamy and Arora algorithm is used to estimate the component variances for the REM.

[b] The first FEM only allows the constant to vary, whereas the second FEM allows both the constant and slope to vary. In the second FEM, the slope parameters reported correspond to Canada. The other estimated coefficients of the group-specific effects are omitted.

[c]The LR statistic refers to a test of the null hypothesis of the pooled cross-section model against the fixed effects model. The statistic has a χ^2 distribution with $(N-1)$ degrees of freedom, where N is the number of cross-section units. Note that the estimates of the FEM include coefficients for group-specific effects.

[d] The Hausman test is a test of the null hypothesis of the random effects model against the fixed effects model. The statistic has a χ^2 distribution with 2 degrees of freedom. The Swamy and Arora algorithm requires that the number of cross-sectional units excced the number of estimated parameters in order to estimate a REM. Hence we could not preform a Hausman comparing a second REM and FEM #2.

Table A.15: Raw Panel Unit Root Test Results in the Variables

TABLE 15
RAW PANEL UNIT ROOT TEST RESULTS IN THE VARIABLES

Series	LLC t^{*b}	Breitung t-stat	IPS W-stat	Fisher ADF[c]	Fisher PP	Hadri Z-stat[d]
	A. Log Levels					
M1[a]	1.347	-0.540	4.459	63.997	53.054	15.199**
M2	-1.537	1.792	2.443	87.732	98.591	15.844**
R	-12.247**	-1.089	-5.591**	185.345**	115.439	3.841**
Y	-0.092	-0.647	6.799	44.630	48.467	16.557**
	B. First Differences of Log Levels					
M1	-23.573**	-6.955**	-15.450**	377.259**	421.669**	1.164
M2	-14.535**	-8.199**	-11.554**	313.431**	344.449**	3.513**
R	-15.389**	-6.528**	-12.800**	333.678**	342.167**	4.256**
Y	-17.337**	-7.200**	-11.946**	295.082**	272.224**	1.812*

Note:
[a] Both aggregates are in real terms and logged. Standard errors are given in parentheses, and * and ** indicate significance at the 5 and 1% level, respectively.
[b] Automatic selection of lags based on AIC: 0 to 2 and a country specific constant is added to all tests.
[c] Probabilities for Fisher tests are computed using an asympotic χ^2 distribution. All other tests assume asymptotic normality
[d] Newey-West bandwidth selection using Bartlett kernel.

Table A.16: Panel and Group Cointegration Tests

TABLE 16
PANEL AND GROUP COINTEGRATION TESTS
IN THE MONEY DEMAND FUNCTION

Monetary Aggregate	v-stat	ρ-stat	t-stat	ADF-stat[b]
		Standard Panel-stats[c]		
M1[a]	0.987	-0.607	-5.455**	-6.070**
M2	1.045	0.961	-2.447**	-4.003**
		Time Demeaned Panel-stats[d]		
M1	-0.364	0.340	-3.149**	-3.239**
M2	0.720	0.151	-3.385**	-3.888**
		Standard Group-stats		
M1	——	2.008	-6.223**	-6.357**
M2	——	3.558	-2.919**	-4.946**
		Time Demeaned Group-stats		
M1	——	2.772	-3.333**	-3.386**
M2	——	3.007	-3.390**	-4.366**

Note:
[a] Both aggregates are in real terms and logged. * and ** indicate significance at the 5 and 1% level, respectively. All tests assume asymptotic normality. The critical values for the left hand 10%, 5% and 1% levels are -1.282, -1.645 and -2.326, respectively.
[b] The ADF tests use a max lag of 2.
[c] Panel stats are weighted by long run variances
[d] The time demeaned specification to subtracts out the common time effect.

Table A.17: FMOLS Cointegrating Vector Tests

TABLE 17
FMOLS COINTEGRATING
VECTOR TESTS

	Coefficient	t-stat
	M1 Group Results	
Ln R	-0.09	-13.81**
Ln Y	1.09	-3.97
	M2 Group Results	
Ln R	-0.03	-3.89**
Ln Y	1.45	19.49**
	M1 Group Results-Time Demeaned	
Ln R	-0.11	-12.69**
Ln Y	1.15	3.30**
	M2 Group Results-Time Demeaned	
Ln R	-0.00	0.27
Ln Y	1.26	6.52**

Note: Both aggregates are in real terms and logged * and ** indicate significance at the 5 and 1% level respectively. All tests assume assume asymptotic normality. The critical values for the right hand 10%, 5% and 1% levels are 1.282, -1.645 and -2.326, respectively. The critical values for the two-sided 10%, 5% and 1% levels are 1.282, -1.645 and -2.326, respectively.

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