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Monetary aggregation and policy decisions : an empirical evaluation across currency-equivalent, divisia, and simple sum aggregates

Hamzeh Ahmed Khaleefeh Jaradat

To the Graduate Council:

I am submitting herewith a dissertation written by Hamzeh Ahmed Khaleefeh Jaradat entitled "Monetary aggregation and policy decisions : an empirical evaluation across currency-equivalent, divisia, and simple sum aggregates." I have examined the final electronic copy of this dissertation for form and content and recommend that it be accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy, with a major in Economics.

Jean Gauger, Major Professor

We have read this dissertation and recommend its acceptance:

Charles Garrison, Hui Change, Ronald Shrieves

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(Original signatures are on file with official student records.)

To The Graduate Council:

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MONETARY AGGREGATION AND POLICY DECISIONS: AN EMPIRICAL EVALUATION ACROSS CURRENCY-EQUIVALENT, DIVISIA, AND SIMPLE SUM AGGREGATES

A Dissertation

Presented for the

Doctor of Philosophy

Degree

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Hamzeh Ahmed Khaleefeh Jaradat

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DEDICATION

This Dissertation is dedicated to

my parents, my wife, and my children

who have sacrificed a lot of their time and effort to

support me through the course of my study

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ABSTRACT

This study evaluates the relative empirical performance of two weighted monetary aggregation methods and the simple sum method. In particular, the performance of monetary aggregates constructed by currency equivalent (CE) and Divisia (D) indices is compared relative to each other and relative to their simple sum (SS) counterparts. The empirical performance is measured by the ability of these aggregates to explain fluctuations in real output, nominal output, and prices. Further, their ability to predict changes in output and prices is evaluated and compared to the predictions of the standard macroeconomic theory. This is the first study to comprehensively evaluate all the aggregation methods across the conventional four levels of monetary aggregation (M1 through L).

Multivariate time series techniques, in particular vector autoregression (VAR) and vector error correction (VEC) models are used. Several VAR and VEC models are constructed and estimated to provide evidence on the empirical differences between CE, D, and SS aggregates. Dynamic simulations of the systems (using impulse response functions, IRFs, and forecast error variance decompositions, FEVDs) suggest that there are important differences between the performance of CE, D, and SS monetary aggregates in empirical applications. At the M1 level of monetary aggregation, results here indicate that the behavior of CE, D, and SS aggregates is similar and consistently weak. At broader levels of monetary aggregation, the empirical differences between CE, D, and SS aggregates are more pronounced, in

particular between CE and D aggregates. Evidence from IRFs and FEVDs indicates that currency equivalent aggregates are notably less informative about changes in either real or nominal economic activity, relative to Divisia aggregates. This evidence suggests that CE aggregates are less useful in applied work as a measure of money, and therefore a less useful policy tool than D aggregates. Similar conclusion is drawn when comparing currency equivalent aggregates against simple sum counterparts. Furthermore, the empirical evidence presented in this study shows a close similarity in the behavior of D and SS aggregates in predicting real and nominal economic activity.

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CHAPTER ONE

INTRODUCTION

1.1 Background

Money plays a key role in most macroeconomic and monetary models. Debates on the nature of this role dominate much of the macroeconomic literature. Macroeconomists try to understand the impact of money on economic activity measures such as output and inflation. In this literature, a key assumption is that there is a stable money demand function and a predictable velocity of money. Based on this assumption, many empirical models were developed to evaluate the usefulness of money as an indicator of economic activity. These models use the official simple sum monetary aggregates. Until 20 years ago, these aggregates were a viable monetary tool to monetary authorities, in terms of their ability to meet the desired monetary targets.

In the past two decades, the fast pace of financial innovation and market deregulation has led to the introduction of a wide range of monetary assets. These assets have a mixture of transactions and a store of value attributes and, therefore, have different 'moneyness'. Simple sum aggregation method, which assigns equal weights of one to each monetary asset being aggregated regardless of its degree of liquidity, is unable to capture the correct monetary services provided by these new less liquid assets. The result was a breakdown and instability of the empirical monetary relationships. Therefore, simple sum monetary aggregates lost their role as a viable policy tool to moderate business cycles and predict changes in the economic activity (see for example De Long and Summers, 1988; Friedman and Kuttner, 1992, 1993). Thus, many developed economies' central banks abandoned using money as an indicator or intermediate target. For example, in the United States (U.S), the Federal Reserve System (Fed) has stopped all targets based on monetary aggregates as of July 1993 (Belongia, 1996a). In the United Kingdom (U.K), the Bank of England abandoned targeting money in 1985 (Chrystal and MacDonald, 1994, p.80).

Economists have long recognized the flaw and the inconsistency of the simple sum aggregation scheme. Irving Fisher (1922) considers the simple sum indices as "the very worst of index numbers [p.24]...[and they] should not be used under any circumstance [p.361]". On a theoretical basis this approach, which gives equal weight of one to each component asset, is valid only if the component assets included are perfect substitutes. This means that notes and coins are assumed to provide the same transactions or liquidity services as interest-bearing deposits such as time deposits or savings deposits within the broad monetary aggregates. Notes and coins are non-interest-bearing assets and can be considered as pure media of exchange, whereas interest-bearing components possess a mixture of transactions and a store of value characteristics varying from asset to asset and over time. It is evident that the different components included in the broad monetary aggregates are, in general, imperfect substitutes, and differ in their transaction services or 'moneyness', respectively. Simple sum index, which implicitly assumes that all assets are perfect substitutes, becomes less valid measure of money the more heterogeneous are the assets being aggregated. Therefore, the need arises to consider more appropriate measures of money when having this heterogeneity across assets.

To derive optimal monetary aggregates, which could, in principle, capture the transactions services yielded by a wide range of financial assets, each asset to be included in the aggregate should be weighted according to the degree of monetary services it provides. The seminal work by Barnett (1980) initiated a series of studies using weighted aggregation methods in constructing monetary aggregates. Two weighted monetary aggregation methods are of particular importance in this research: the Divisia (D) index suggested by Barnett (1980), and the Currency-Equivalent (CE) index derived by Rotemberg, Driscoll, and Poterba (1995). The theoretical derivation and the specific properties of these indices will be discussed in the literature review chapter. Both of these aggregation methods suggest using a theoretical approach to aggregation based on microeconomic theory and index number theory. In these methods, optimal weights for different component assets are assigned according to the degree of their transactions or liquidity services. This is in contrast to simple sum aggregates, which assign equal weights to all assets, implicitly treating all assets as perfect substitutes. The weights depend jointly on the quantities and prices (user costs) of the assets included in the aggregate. The resulting weighted monetary aggregates should provide a more valid measure of monetary services in the economy. Further, they should be more closely related to the final spending in the economy than are the conventional monetary aggregates.

At this point it is worth mentioning that there are two basic differences between CE and D index numbers in monetary aggregation. First, the Divisia index measures the flow of monetary services provided during a certain period of time, while CE measures the stock of currency that yields the same transactions services as the entire constellation of monetary assets. The second difference is that the weighting schemes of component assets included are different for each index. Therefore, the monetary aggregates constructed by using these indexes are different from each other and from the traditional simple sum monetary aggregates.

Theoretically, the superiority of weighted monetary aggregates to measure the economy's quantity of money over simple sum aggregates has been established (see, for example, Barnett, 1980; Barnett, Fisher, and Serletis, 1992; Rotemberg, Driscoll, and Poterba, 1995). These monetary aggregates are admissible aggregates on index-theoretic grounds, while simple sum aggregates are not. However, no general agreement on the empirical superiority (which could be evaluated by different performance criteria such as the information content, and the power to predict movement in economic activity) has been reached yet. This provides one explanation for the continued use of simple sum aggregates in empirical research and policy discussions. Another reason is the difficulty obtaining the data required to construct weighted monetary aggregates. Constructing weighted aggregates requires getting data on both asset quantities and user costs. These data are usually not accessible by non-central bankers in most countries.

The next section presents the main objectives and contributions of the proposed research.

1.2 Objectives of the Research

The main focus of this research is to empirically evaluate the relative performance of the weighted monetary aggregates (currency equivalent, denoted CE and Divisia, denoted D) and simple sum (SS) monetary aggregates in explaining economic activity. The evaluation is conducted across the four levels of monetary aggregation (M1 through L). The relative empirical performance of CE aggregates against D and SS aggregates would be of particular importance because empirical evidence on this is lacking in current literature. To accomplish this objective, multivariate time series techniques are used to determine the viability of using any monetary aggregate as a monetary policy variable.

The theoretical justification for the use of weighted monetary aggregates (D and CE) has been rigorously established. But the empirical evidence on their performance against the SS aggregates is inconclusive (see, for example, Rotemberg, Driscoll, and Poterba, 1995, and Chrystal and MacDonald, 1994). In the last 20 years, many empirical studies have been conducted to evaluate the empirical performance of weighted monetary aggregates against simple sum aggregates. The third section of chapter two will discuss further the available empirical evidence. Most of these studies evaluate Divisia aggregates against their SS counterparts. In contrast, few studies exist that evaluate the empirical performance of CE aggregates relative to the simple sum or

Divisia aggregates. Further, these studies do not evaluate the CE aggregates at the four levels of aggregation (from narrow M1 asset groupings to the broad L aggregate) that are consistent with the standard simple sum aggregation levels. A major contribution from the proposed research is to provide much needed empirical evidence on the relative performance of weighted monetary aggregates, particularly CE aggregates versus D aggregates, at the four levels of monetary aggregation. The evaluation will be conducted under various performance criteria. Evaluating these aggregates, at the four levels of aggregation, gives us the opportunity to compare the strength of the relationship between the respective aggregates and economic activity. Such information will be valuable both to policy makers and researchers interested in the monetary-macro relationships in the economy.

Furthermore, multivariate time series techniques have not been fully utilized in the previous studies. Many studies provided evidence from Granger-causality tests, but do not provide any evidence from tools such as impulse response functions and forecast error variance decompositions within the frameworks of Vector Autoregression (VAR) and Vector Error Correction (VEC) models. These techniques provide a suitable means to evaluate the relative performance of monetary aggregates (measured by CE, D, and SS schemes) in terms of their impacts on the economic activity and to determine if any of these monetary aggregates could be used as a viable monetary indicator or intermediate target. On the other hand, Granger causality tests do not provide such means.

Multivariate time series procedures will be used to assess the empirical usefulness of the different monetary aggregates using innovation accounting method. Two main tools are used to analyze innovation accounting: impulse response functions (IRFs), and forecast error variance decompositions (FEVDs). The first describes the over time response of a variable (e.g., real GNP) in the system to a one time shock in another variable (money). The second tool measures the ability of a variable to explain the movements in another variable in the system at different time horizons. These tools provide a vehicle to compare the magnitude and the strength of the impact of money on the economic activity. For example, IRFs can show whether money has a temporary or permanent effect on output. The FEVDs can be used to compare the ability of money, measured by the different aggregation methods, to explain future changes in output.

The remainder of this research proceeds as follows. Chapter Two provides the theoretical foundation of the different measures of money (that is, the CE, D, and SS) and surveys a sample of the available empirical evidence on the performance of the weighted monetary aggregates relative simple sum aggregates. Chapter Three contains a description of the econometric methods and a thorough analysis of the data included in the study. The integration properties, as well as cointegration tests, are provided in the chapter. Chapter Four gives a complete analysis of the models and the empirical results. The last chapter presents summary and general conclusions.

CHAPTER TWO

LITERATURE REVIEW

In the last two decades, different theoretic aggregation methods have been suggested to construct monetary aggregates. These methods are based on microeconomic and index number foundations. This research focuses on two of these aggregation methods: Divisia (D) and currency equivalent (CE). In this chapter the relevant literature on three areas of interest for this research will be discussed. The first section presents an overview of the theoretical construction of the D and CE aggregation methods in addition to the simple sum (SS) method. Section two compares the specific properties of D and CE aggregates. The last section surveys a sample of the existing empirical investigations of the performance of weighted monetary aggregates versus simple sum aggregates.

2.1 Monetary Aggregation Methods

Currently, most monetary authorities around the world use simple sum aggregation method to prepare their monetary aggregates. Unfortunately, this method, as long has been recognized, is theoretically inconsistent with microeconomic theory and index number theory. The simple sum method is unable to capture the degree of moneyness provided by a wide range of financial assets. Weighted aggregation methods have been suggested to construct monetary aggregates. These methods assign different weights to each monetary asset according to the transactions services it provides and, therefore, solve the problem inherent in the simple sum method.

In a seminal paper, William A. Barnett (1980) initiated formal theoretical modeling of monetary aggregation based on microeconomic theory and index number theory. Two monetary aggregation methods, D and CE, are the focus of this research. A review of these methods is provided next in addition to the SS aggregation method.

2.1.1 Simple Sum Aggregation

In this method, monetary aggregates are constructed by the simple summation of their various component assets. That is, if we have the stock of n monetary assets $(m_1, \ldots, m_n)$, the nominal stock of the simple sum aggregate (SSM_j) is given by the following index:

$$SSM_j = \sum_{i=1}^{n} m_i \qquad \ldots (2.1)$$

The SS aggregation method is consistent with the quantity theory of money where money was narrowly defined and its main function is for transaction purposes. Empirical measures of money stock have tried to include those assets which can be used directly in transactions (currency and demand deposits) and what could not be used directly to facilitate transactions was excluded. The problem of our time is that there is a whole range of monetary assets which can be used for transactions also yield an interest rate and could, thus, be chosen as a store of wealth as well.

In the SS aggregation method, the monetary aggregates are obtained by adding dollar-for-dollar quantities of various monetary assets. As indicated previously, this implicitly assumes that those assets are regarded perfect substitutes (infinite elasticities of substitution). If the monetary assets are perfect substitutes, then the optimizing agent should be observed choosing a corner solution and hold only one monetary asset in equilibrium: the asset with the lowest user cost (price). This asset holding behavior is both counterintuitive and counterfactual.

At the narrowest level of aggregation, where monetary assets are homogenous (such as currency and demand deposits) SS aggregation method may be an appropriate empirical measure of money. However, given the asset heterogeneity in broader aggregates, the SS method clearly is not appropriate. At broad levels of aggregation, the heterogeneous component assets do not have the same degree of substitutability and liquidity, some are clearly less liquid than currency and demand deposits. Therefore, the perfect substitutability condition is more seriously violated. Simple sum aggregates become increasingly distorted at broad levels of aggregation. From a micro-foundation perspective, only perfect substitutes can be combined as a single commodity. According to Chrystal and MacDonald (1994, p.75), there is an overwhelming body of evidence showing that monetary assets are not perfect substitutes and that there is a low degree of substitutability between some of these assets (see for example: Gauger, 1992). Hence, the simple summation of various asset components of the aggregates does not accord with microeconomic theory or statistical index number theory.

To overcome the deficiency of the simple sum aggregation method, weighted monetary aggregation methods have been suggested. These methods utilize microeconomic theory and index number theory to construct monetary aggregates. Two such methods (D and CE) are examined below.

2.1.2 Weighted Aggregation Methods

Consistent with Barnett's (1980) proposal, superlative[1] (see: Diewert, 1976,1978) monetary aggregation methods have been developed that are consistent with index number theory and microeconomic theory (see: Barnett, 1981, 1990 and Belongia, 1995). Monetary aggregates constructed using these methods should, in principle, capture the transaction services provided by a wide range of financial assets to be included in the aggregate. These aggregation methods define money as a monetary quantity index. As noted by Barnett, under this approach, aggregates are measured in terms of the flow of monetary services provided by their component assets. This flow of monetary services is determined by weighting the quantity of each component asset with its unique user cost, which depends on its degree of liquidity.

Two indices will be the focus of this research: the (Tornqvist-Theil) Divisia index advocated by Barnett (1980), and the Currency-Equivalent index proposed by Rotemberg, Driscoll, and Poterba (1995).[2] The attraction of both of these indices in

[1] An index is said to be superlative if it is exact to a second order approximation for some unknown aggregator function. In other words, it tracks the aggregator function, evaluated at optimum, without error.

[2] Divisia index is exact in continuous times; Tornqvist-Theil (hereafter referred to as Divisia) is the discrete-time approximation to Divisia.

constructing monetary aggregates is that they internalize the substitution effects between components of a potential monetary aggregate and, thus, solve the problem of composition changes (i.e., movement of deposits from non-interest bearing to interest bearing deposits). However, these indices do not themselves guarantee the weak separability of any chosen monetary aggregate from non-monetary assets in the utility function, but they do approximate optimal aggregator functions for those collections of monetary assets which have been found "admissible" on separability grounds (Belongia and Chalfant, 1989).[3]

The theoretical case for weighted monetary aggregates is overwhelming, given the strong foundation in microeconomic and index number theory. However, the empirical performance is less clear cut. The weighted aggregates do not show a clear superiority over the flawed simple sum aggregates in empirical applications. Section three below will provide a survey of the existing empirical evidence on the performance of the weighted monetary aggregates.

Divisia Index

The Divisia (D) aggregation method treats money as a durable commodity held for the flow of utility it generates in the form of monetary services. The aim of the Divisia monetary index is to construct a quantity index number of monetary services, which could capture the transactions services yielded by the different financial assets.

[3] The construction of CE and D monetary aggregates assumes that monetary assets are separable from other goods in the utility function. This assumption is discussed further in the next section.

Each financial asset included is assigned a unique weight depending on its degree of liquidity.

Barnett (1980) illustrates the microeconomic derivation of the Divisia index monetary aggregates. He utilizes the principles of microeconomic theory and index number theory to derive monetary aggregates that are consistent with an economic agent's utility maximization problem. Barnett assumes that, in each period, the representative consumer maximizes an intertemporal utility function over a finite planning horizon of T periods. The consumer's intertemporal utility function in any period, t, is:

$$u_t(\boldsymbol{m}_t, \dots, \boldsymbol{m}_{t+T}; \boldsymbol{q}_t, \dots, \boldsymbol{q}_{t+T}; A_{t+T}) \qquad \dots(2.2)$$

where for all periods $\{t, t+1, \dots, t+T\}$,

$\boldsymbol{m}_t = (m_{1t}, \dots, m_{nt})$ is a vector of real stock of n monetary assets,

$\boldsymbol{q}_t = (q_{1t}, \dots, q_{kt})$ is a vector of quantities of k non-monetary goods and services, and

A_{t+T} is the real stock of a benchmark financial asset, held in the final period of the planning horizon, at date $t+T$.

Barnett assumes that the intertemporal utility function, u_t is weakly separable in current period's consumption of goods and monetary assets.[4] For a given period, this assumption allows the utility function to be expressed in the following form:

$$u_t[f(\boldsymbol{m}_t), \boldsymbol{m}_{t+1}, \dots, \boldsymbol{m}_{t+T}; \boldsymbol{q}_t, \dots, \boldsymbol{q}_{t+T}; A_{t+T}] \qquad \dots(2.3)$$

[4] The weak separability condition of the utility function is required by aggregation theory. "Without the appropriate [weak] separability conditions, any aggregate is inherently arbitrary and spurious and does not define an economic variable" (Barnett, 1980, p.13).

The function $f(m_t)$, called a category subutility function, is the monetary services aggregator function. It measures the amount of current monetary services that the consumer receives from holding the monetary assets, $m_1, m_2, ..., m_n$. Note that only current-period monetary assets are included in the subutility function $f(m_t)$. The weak separability assumption in the group of current period monetary assets implies that the marginal rate of substitution between any two monetary assets is independent of the quantity of any non-monetary good.[5]

The weak separability of the utility function allows formulating the consumer's decision as a two-stage budgeting problem. In the first stage, the consumer chooses the optimal total expenditures for the broad categories, monetary assets (m_t), and non-monetary goods and services (q_t). In the second stage, the consumer determines specific holdings within each broad category based on the individual opportunity costs (prices) conditional on the total outlay selected in the first stage. For monetary assets, the consumer maximizes the subutility or aggregator function $f(m_t)$ and chooses the optimal quantities of the individual current-period monetary assets. These optimal quantities of the current-period monetary assets are the solution to the following maximization problem:

$$Max\, f(m_t)$$

$$\text{subject to } \sum_{i=1}^{n} m_{it}\pi_{it} = y_t \qquad \ldots(2.4)$$

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[5] For the utility function u_t, the weak separability condition implies that $\dfrac{\partial\left(\dfrac{\partial u_t / \partial m_i}{\partial u_t / \partial m_j} \right)}{\partial q_k} = 0$ for

where π_{it} is the current period nominal user cost of the i^{th} monetary asset [6] (see: Barnett, 1978, and Donovan, 1978), y_t is the total optimal expenditures on monetary assets implied by the solution to the first stage optimization, and $f(m_t)$ is the monetary services aggregator or what Barnett et al. (1992, p.2095) call it "economic (or functional) monetary index". Let $m_1^*, \ldots, m_n^*$ denote the optimal quantities of current period monetary assets chosen by the consumer. The aggregator function $f(m_t^*)$ can be regarded as defining a monetary aggregate M_t, via the following relationship:

$$M_t = f(m_1^*, \ldots, m_n^*) \qquad \ldots (2.5)$$

The major difficulty with this function is that the specific form is usually unknown. However, Diewert (1976) and Barnett (1980) have established that an aggregator function evaluated at the optimal quantities may be approximated by a superlative statistical index number. Continuous time Divisia quantity index M_t^D provides such an index.[7] It is given by the following differential equation:

$$\frac{d\log(M_t^D)}{dt} = \sum_{i=1}^{n} w_{it} \frac{d\log(m_{it}^*)}{dt} \qquad \ldots (2.6)$$

where, for $i=1,\ldots,n$

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monetay assets m_i and m_j and q_k non-monetary good.

[6] The current period nominal user cost π_{it} is given by: $\pi_{it} = p^*\left(\frac{r_{bt} - r_{it}}{1 + r_{bt}}\right)$, where p^* is a true cost of living index, r_{bt} is the nominal holding period yield on the benchmark asset, and r_{it} is the nominal holding period yield on the i^{th} monetary asset.

[7] For a discussion of Divisia index numbers, see Hulten, 1973.

$$w_{it} = \frac{m_{it}^{*}\pi_{it}}{\sum_{j=1}^{n} m_{jt}^{*}\pi_{jt}}$$

represents expenditure share for the i^{th} monetary asset.

Equation (2.6) above expresses the growth rate of the continuous-time Divisia quantity index. It is equal to the share-weighted average of the growth rates of the monetary component quantities. In continuous-time, the Divisia quantity index is exact for the unknown monetary quantity aggregate, M_t in equation (2.5).[8] The exact tracking ability of the Divisia is an implication of the economic theory, not an approximation. As expressed in equation (2.6), the Divisia index (unlike the unknown aggregator function M_t) is specification and estimation free function. Only quantities and user costs of the monetary assets are required to its calculation.

In discrete time, there is no statistical index number that is exact for an arbitrary aggregator function. However, Diewert (1976) shows that there exists a class of statistical index numbers, which he called superlative, that are exact for second-order approximations to unknown economic aggregator functions. One of the most important superlative index numbers is the Tornqvist-Theil discrete-time approximation to Divisia continuous-time quantity index. For monetary aggregation, the Tornqvist-Theil monetary quantity index, which hereafter is referred to as Divisia index, is defined as follows:

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[8] An index number is said to be exact if it exactly equal to an unknown aggregator function evaluated at optimum.

$$M^D{}_t = M^D{}_{t-1} \prod_{i=1}^{n} \left(\frac{m_{i,t}{}^{*}}{m_{i,t-1}{}^{*}} \right)^{\frac{1}{2}(w_{i,t}+w_{i,t-1})} \qquad \ldots(2.7)$$

The discrete time Divisia monetary aggregate defined by equation (2.7) is consistent with index number theory and is superlative. Diewert (1976) demonstrates that this index is exact for the translog flexible functional form. Furthermore, this index provides a second-order approximation to the unknown subutility function $f(m_t)$ obtained from the microeconomic optimization.

Other possible valid index numbers include Fisher Ideal, Laspeyres, and Paasche. Barnett advocates the use of Tornqvist-Theil Divisia index due to its straightforward interpretation. This can be seen by taking the logarithms of equation (2.7), which yields:

$$Log\,M_t^D - Log\,M_{t-1}^D = \sum_{i=1}^{n} \overline{w}_{it}(Log\,m_{it} - Log\,m_{i,t-1}) \qquad \ldots(2.8)$$

where $\overline{w}_{it} = \frac{1}{2}(w_{it} + w_{i,t-1})$. Equation (2.8) clearly indicates that the growth rate of the Divisia index is simply a weighted average of the growth rates of component monetary assets.

Currency-Equivalent Index

The currency equivalent (CE) index was proposed, but not analyzed in depth, by Hutt (1963) and Rotemberg (1991). Rotemberg, Driscoll, and Poterba (1995) provided a complete theoretical derivation and analysis of the CE index. In the case of monetary aggregation, the CE index is derived from preferences, assuming that they satisfy the separability assumption. A representative consumer is assumed to maximize his expected lifetime utility in period t of the form:

$$U_t = E_t \sum_{i=0}^{\infty} \beta^i u(C_{t+i}, M_{t+i}) \qquad \ldots(2.9)$$

where,

E_t takes expectations at time t,

β is an intertemporal discount factor,

C_t is consumption of goods and services,

M_t is the aggregate of monetary (liquidity) services, and

u is the instantaneous utility, and it is assumed to be concave in both arguments.

The aggregate of liquidity services M_t is given by:

$$M_t = f(m_{1,t}, m_{2,t}, \ldots, m_{n,t}, \alpha_t) \qquad \ldots (2.10)$$

where $m_{1,t}$ denotes the amount of currency held at time t, $m_{i,t}$ (for $i=2,\ldots, n$) is the amount of monetary asset i held at time t, and α_t is a time-varying parameter to capture changes in the financial environment, and the changing characteristics and liquidity services provided by monetary assets. This parameter would change and thereby change the function f if, for example, there is a change in the number of checks that can be written on saving accounts.

Rotemberg et al. (1995) consider three major assumptions imposed on the aggregator function f to recover the monetary aggregate M_t. First, they assume that for every value of α, f is homogeneous of degree one in all its monetary arguments.[9] Second, they assume that f is additively separable in currency ($m_{1,t}$) and other monetary assets. Thus, f could be rewritten as:

$$f(m_{1,t}, m_{2,t}, \ldots, m_{n,t}, \alpha_t) = g(m_{1,t}) + h(m_{2,t}, \ldots, m_{n,t}, \alpha_t) \qquad \ldots(2.11)$$

This assumption gives a central role to currency because it is possible to obtain any level of liquidity services by holding sufficient currency. Although the inessentiality of other monetary assets might be controversial, it is consistent with the fact that circulating media of exchange appear to predate the introduction of other liquid assets. Finally, they assume that there is a benchmark asset that does not provide monetary services and its return between time t and $t+1$ is risk free. Even if all actual assets without liquidity had stochastic returns, the analysis would apply. The return on the benchmark asset is r_{bt} and has the following standard property:

$$u_c(C_t, M_t) = (1 + r_{bt}) E_t \frac{P_t \beta u_c(C_{t+1}, M_{t+1})}{P_{t+1}} \qquad \ldots(2.12)$$

where u_c is the utility from consumption, P_t measures the price of a unit of consumption in terms of currency at date t. Equation (2.12) says that consumers are indifferent between their current optimal consumption and higher future consumption when they increase their holdings of the benchmark asset by reducing current consumption and use the proceeds to increase future consumption.

[9] If M_t is not homogeneous of degree one in its arguments, the distance function $d(m_{1,t}, m_{2,t}, \ldots, m_{n,t}, M_t)$ can be used. By construction, this function is homogeneous of degree one in monetary assets (for a discussion, see: Caves, Christensen, and Diewert, 1982).

Monetary assets do not have this property of the benchmark asset because increasing their stock raises the level of liquidity services they provide. Therefore, the loss in utility from lowering current consumption is offset by both additional future consumption and by an increase in liquidity services.

The issue at this point is whether optimizing consumers will actually choose to hold positive amounts of currency and other monetary assets, or whether they will set either currency or the other monetary assets (in equation 2.11 above) equal to zero. This issue arises because equation (2.11) is linear in these two quantities.[10] This implies that, unless the relative prices ensure that the user costs of currency and the other monetary assets are equal, the consumer will set one of these to zero. Thus the following analysis considers the condition on relative prices that leads consumers to hold both currency and other monetary assets in their portfolios. In other words, what is the condition required for obtaining an interior solution.

An interior solution can be obtained if the opportunity cost in terms of foregone consumption of getting one more unit of h other monetary assets is the same as the opportunity cost of getting one unit of currency. The cost of getting one unit of h is the result of minimizing:

$$Min \sum_{i=1}^{n} \frac{r_{bt} - r_{it}}{1 + r_{bt}} m_t \qquad \ldots(2.13)$$

with respect to m_i subject to the constraint that h is equal to one. The solution to this

[10] In microeconomic theory, maximizing a linear function leads to a corner solution (i.e., one of the quantities will be set to zero) unless prices of these quantities are equal.

minimization problem would be interior only if the minimized value of (2.13) is equal to the cost of holding one unit of currency; namely, $r_{bt}/(1+r_{bt})$. For this equality to be satisfied, interest rate differentials would have to change if tastes change (as would occur if the liquidity services of all monetary assets other than currency increase). If the interest rate differentials do not change, such a change in tastes would lead individuals to choose a corner solution in which either currency or the other monetary assets would be absent from their portfolios. The linear structure of the liquidity aggregator function implies that the interiority assumption is satisfied only if interest rates do respond to changes in tastes.

Given the assumption of linear homogeneity of the aggregator function M_t (which implies that $M_t = \sum_{i=1}^{n} f_{it} m_{it}$, where f_{it} is the partial derivative of f with respect to the i^{th} monetary asset), Rotemberg et al. (1995) show that the level of the liquidity aggregate M_t satisfies:

$$M_t = \sum_{i=1}^{n} \frac{r_{bt} - r_{i,t}}{r_{bt}} m_{i,t}^{*} \equiv CE_t \qquad \text{... (2.14)}$$

where r_{bt} is the return on the benchmark asset, r_{it} is the return on asset i, and m_{it}^{*} is the optimal quantity of asset i. The expression in equation (2.14) defines the CE aggregate. The CE aggregate can be interpreted as the stock of currency that yields the same transactions services as the entire constellation of monetary assets. Note that the weight on each asset being aggregated by the CE index is given by $(r_{bt} - r_{i,t})/r_{bt}$. This compares to the Divisia weight, which is given by expenditures on asset i relative to expenditures on all monetary assets: $\frac{m_{it}^{*}\pi_{it}}{\sum_{j=1}^{n} m_{jt}^{*}\pi_{jt}}$.

The derivation of the CE focuses on the level of liquidity held by an individual. Because (2.14) is linear in individual asset holdings, the sum of the M_t held by all individuals is simply (2.14) applied to aggregate asset holdings. Thus, CE provides an accurate measure of the sum of the individual M_t even if the aggregator function f differs for different individuals.

Barnett (1991) developed an interesting interpretation of the CE aggregate. He showed that, under the assumption of static expectations, CE equals the discounted present value of expenditures on the services of the monetary assets. These expenditures can be measured using the Divisia index. The user-cost evaluated nominal expenditures on the services of the n component monetary assets in period t equal to $\sum_{i=1}^{n} \pi_{it} m_{it}$. Under static expectations assumption, Barnett shows that the present value of these expenditures equal to what he calls "Economic Stock of Money", which equals the CE aggregate.

2.2 Properties of Currency-Equivalent and Divisia Aggregation Methods

The CE aggregates have the attractive property that monetary assets that do not pay interest, such as currency, are added together with weights of unity. Other interest-yielding monetary assets are added with weights between zero and one, with higher yield assets receiving lower weights. This makes intuitive sense, because these monetary assets with higher returns typically provide smaller liquidity services.

The CE index requires stronger assumptions than the Divisia on the aggregator function *f*. For the Divisia index, *f* is assumed to be weakly separable and homogeneous of degree one for a constant α. The CE requires an additional assumption on *f*, namely, that currency be separable from other assets (as in equation 2.11 above). In part, because of this stronger assumption, the CE aggregates can overtly account for the changes in the financial environment and the liquidity characteristics of assets (α). To see the effect of changes in α, totally differentiate equation (2.10) and obtain:

$$dM_t = \sum_{i=1}^{n} f_{it} dm_{it} + f_{\alpha t} d\alpha_t \qquad \ldots(2.15)$$

where f_{it} and $f_{\alpha t}$ are the partial derivative of f with respect to monetary asset i and α respectively. Equation (2.15) implies that:

$$\frac{dM_t}{M_t} = \sum_{i=1}^{n} \frac{(r_{bt} - r_{it})m_{it}}{\sum_{j=1}^{n}(r_{bt} - r_{jt})m_{jt}} \frac{dm_{it}}{m_{it}} + f_{\alpha t} \frac{d\alpha_t}{M_t} \qquad \ldots(2.16)$$

The first term on the right hand side of equation (2.16) is the Divisia index, which, obviously, equals the change in M_t only in periods when α does not change. By contrast, the CE aggregate incorporates changes in α when they occur.

These changes in the financial environment and the liquidity characteristics of monetary assets, which are captured by α, constitute one of the most important challenges of the monetary aggregation, because the characteristics of available monetary assets change constantly. For example, when charges on checks written on NOW accounts were eliminated, their liquidity properties changed, and therefore their respective f_i, changed. Divisia aggregates assume that, as long as asset holdings do not change, the utility provided by asset remains immutable. The CE aggregate deals with changes in asset characteristics by incorporating the idea that for asset holdings not to change, $(r_{bt} - r_{it})/r_{bt}$ must rise as much as f_i. The CE aggregate interprets increases in $(r_{bt} - r_{it})/r_{bt}$ with an unchanged asset stock as an increase in the assets' liquidity services. As a consequence, these changes in interest rates imply that CE changes even when asset holdings do not change.[11]

The ability of the CE to deal with changes in α also facilitates comparisons of money holdings across individuals, states, and countries. Different countries have different financial institutions. Therefore their monetary aggregates surely are different in terms of their liquidity characteristics, which CE can capture.

Another advantage of the CE is that monetary aggregates can, in principle, be calculated with observations at single point in time since CE measures levels, as does SS. By contrast, Divisia aggregates measure changes, and thus require the use of the discrete observations that are available to approximate the time derivatives of asset holdings. The quality of this approximation depends on the frequency of asset measurement.

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[11] This is not to suggest that the Divisia index is totally unable to deal with changes in the aggregator function f. It is shown that the discrete time Tornqvist-Theil approximation to Divisia has some desirable properties. For more discussion: see Caves, Christensen, and Diewert (1982).

A final advantage of the CE index over the Divisia index is that, as an index measured in levels, it can handle the introduction of new financial assets and changes to the characteristics of the existing financial assets in the index. The change in the Divisia index, however, is based on the changes in the logarithms of its components. Because the logarithm of zero is minus infinity, the formula for computing the Divisia index implies that the growth rate of the Divisia aggregate equals infinity when a new asset is introduced. Lately, this has been an important issue, given the fast pace of financial innovation and the introduction of new monetary assets.

Despite the above-mentioned advantages, the CE index has not gotten the same attention as Divisia index. One reason is the more recent presentation of a complete theoretical derivation and analysis of the CE index in comparison to Divisia index. The CE index was analyzed in depth in 1995 by Rotemberg, Driscoll, and Poterba, while discussion of the Divisia monetary index was initiated by Barnett more than a decade earlier (see Barnett, 1980). Another reason is the more volatile behavior of the CE aggregates relative to the Divisia aggregates.[12] The last issue will be discussed further in chapter three.

2.3 Empirical Evidence on Weighted Monetary Aggregates

In the past two decades, several empirical studies have been conducted to investigate the relative performance of weighted monetary aggregates and simple sum

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[12] Belongia (1996 b) considers CE aggregates so volatile and, therefore, he did not examine it in his study.

aggregates in terms of their information content, money-income causality, and the stability in money demand equations. A relevant sample of these studies will be surveyed here.

To test money-income causality, the most commonly used method is Granger-causality test (Granger, 1969). This test is equivalent to testing the null hypothesis that $\beta_i=0$ for all $i=1,\ldots,p$ in the following autoregressive process:

$$y_t = c + \sum_{i=1}^{p} \alpha_i y_{t-i} + \sum_{i=1}^{p} \beta_i M_{t-i} + \varepsilon_t \qquad \ldots(2.17)$$

where y_t is some measure of economic activity, M_t is a monetary aggregate.

Barnett, Offenbacher, and Spindt (1984) use U.S. quarterly data for the period 1959:1-1982:4 to test Granger-causality running from alternative money measures to nominal GNP. Eight lags are used for each variable in the autoregression specification in equation (2.17) above. The results are presented in Table 2.1. The null hypothesis that money does not Granger-cause GNP is rejected at lower significance levels (p-values) for the Divisia aggregates than for the corresponding simple sum aggregates, at all levels of aggregation. These p-values comparisons favor the Divisia aggregates. Further, using a conventional 0.05 significance level, the majority of simple sum aggregates tests fail to reject the hypothesis that simple sum money does not Granger cause GNP (SSM2 is an exception). Divisia results stand in contrast to this.

Serletis (1988) tests for Granger-causality between the growth rates of money, growth rate of real GNP, and inflation measured by the consumer price index (CPI).

Table 2.1
Granger Causality Tests
Barnett, Offenbacher, and Spindt (1984) Study

Monetary aggregate	M to Nominal GNP
SSM1	.074
DM1	.056
SSM2	.005
DM2	.001
SSM3	.090
DM3	.021
SSL	.079
DL	.002

Notes: 1) Table reports p-values at which the null hypothesis of no Granger causality could be rejected.
2) U.S. quarterly data, 1959:1-1982:4.

Two arbitrary lag lengths were used in addition to an optimal lag structure determined by Akaike's final prediction error (FPE) criterion. The tests are performed with and without detrending. Results of Granger-causality when the lag length is chosen according to the FPE criterion and trend free autoregressive process are reported in Table 2.2.

The results reveal that, with the exception of M1, the Divisia aggregates perform better than simple sum aggregates in both money-inflation and money-income relationships. The p-values of the Divisia aggregates are smaller than their simple sum counterparts at aggregation levels higher than M1.

Table 2.2
Granger Causality Tests
Serletis (1988) Study

Growth in M	M to Real GNP growth	M to Inflation
SSM1	.017	.000
DM1	.017	.000
SSM2	.007	.053
DM2	.000	.000
SSM3	.014	.000
DM3	.006	.000
SSL	.028	.045
DL	.003	.000

Notes: 1) The entries are p-values at which the null hypothesis of no Granger causality could be rejected.
2) Divisia aggregates were actually produced by the Fisher Ideal Index.
3) U.S. quarterly data, 1970:1-1985:1

Serletis and King (1993) use Canadian quarterly data for the period 1968:1-1989:3 to examine the causality between money growth and economic activity (nominal GDP growth, real GDP growth, and inflation). Schwarz's (1978) criterion was used to choose the optimal lag length. Results are summarized in Table 2.3.

Based on the criterion of the significance levels (p-values), the tests do not prove clear dominance of Divisia aggregates over simple sum aggregates, particularly in money-inflation causality. Note that, out of twelve possible comparisons of Divisia versus simple sum aggregates (4 aggregation levels x 3 columns), in six cases the absence of test results prevent comparisons across aggregates.

The following two studies are of particular importance. They are the only studies found investigating the empirical performance of CE, Divisia, and simple sum

Table 2.3
Granger Causality Tests
Serletis & King (1993) Study

M	M to Inflation	M to nominal GDP	M to real GDP
SSM1	.092	.000	.000
DM1	.085	.000	.000
SSM2	.010	*	*
DM2	.041	.001	.039
SSM3	.145	.219	.646
DM3	*	.002	*
SSLL	.170	.423	.608
DLL	*	.002	*

Notes: 1) Entries are p-values of rejecting the null hypothesis of no Granger causality.
2) *: indicate aggregates not tested because the optimal lag length found to be zero.
3) Divisia monetary aggregates were actually produced by the Fisher Ideal Index.
4) Canadian quarterly data, 1968:1-1989:3.

aggregates. The first, by Rotemberg, Driscoll, and Poterba (1995), uses U.S monthly data for the period 1960:01-1989:06 to test the causality between money, industrial production, unemployment rate for married men, and prices. Granger-causality tests are conducted using the following autoregressive process:

$$\Delta \ln y_t = \alpha + \gamma t + \sum_{i=1}^{12} \beta_i \Delta \ln y_{t-i} + \sum_{i=1}^{12} \delta_i \Delta \ln M_{t-i} + \varepsilon_t \qquad \ldots(2.18)$$

where y_t represents either the industrial production (IP) or the price level (P), and M_t is a monetary aggregate. When they study the behavior of the unemployment rate (U), they use its level, not the first difference because the unemployment rate is more likely to be stationary. Results appear in Table 2.4.

Table 2.4
Granger Causality Tests
Rotemberg, Driscoll & Poterba (1995) Study

M	M to IP	M to U	M to P
SSM1	.205	.019	.241
DM1	*	*	*
SSM2	.003	.005	.394
DM2	.013	.093	.802
SSM3	.160	.068	.693
DM3	.025	.580	.640
CE	.031	.721	.046

Notes: 1) Entries are p-values of rejecting the null hypothesis of no Granger causality.
2)*: indicates the aggregate is not considered.
3) L aggregates were not tested.
4) U.S monthly data, 1960:01-1989:06.

As the causality test results indicate, none of the monetary aggregation methods dominates, in particular the weighted aggregation methods. On the contrary, simple sum M2 proves to be the leading indicator to explain the real variables, IP and U, while for money-price causality, CE is the best indicator. It is the only aggregate found to be significant at conventional levels for M to P causality.

Note that in this study, the CE aggregate does not correspond to any of the M1, M2, M3 or L aggregates. Rotemberg et al. (1995) use the following eight monetary assets to construct their CE aggregate: currency, travelers' checks, demand deposits, other checkable deposits, savings accounts at thrift institutions, saving accounts at commercial banks, money-market accounts at commercial banks, and money-market accounts at thrift institutions. They include these assets in the CE aggregate "because they comprise the set of assets that have been traditionally considered to be monetary (i.e., those that are included in the broadest conventional definition of money, L) and that have a rate of return less than that of the benchmark rate" (Rotemberg et al., 1995, p. 72). The CE aggregate constructed in this study does not parallel any of the conventional monetary aggregates, which complicates across aggregate comparisons. The research here establishes much needed consistency in the evaluation of CE aggregates. This study assesses the empirical performance of CE and Divisia aggregates that correspond to M1, M2, M3, and L simple sum aggregates.

Chrystal and MacDonald (1994) investigate the empirical performance of the weighted monetary aggregates versus simple sum aggregates in terms of their information content to explain nominal economic activity. They use data from seven countries, including the U.S.[13] The St. Louis Equation was used to compare the empirical performance of the various monetary aggregates, which is given by:

$$\Delta \log y_t = \alpha + \sum_{i=1}^{p} \beta_i \Delta \log M_{t-i} + \sum_{i=1}^{p} \gamma_i \Delta \log X_{t-i} + \varepsilon_t \qquad \ldots (2.19)$$

where y_t is the nominal GDP or GNP, M_t is a monetary aggregate, and X_t is nominal government spending. The statistical tests Chrystal and MacDonald use are Akaike Information Criteria (AIC), J-test, and JA-test.[14] For the U.S, the first difference of T-bill rate was included in the St. Louis equation because it is found to add explanatory

[13] These countries are: U.S., U.K, Australia, Germany, Switzerland, Canada, and Japan. Only for the U.S. CE aggregates were examined.

[14] The AIC is the difference between two values of the likelihood function of the estimated model. It indicates the direction of the informational advantage. The J and JA tests are t-statistics for the rejection of one model over the other.

power. Data are quarterly for the period 1960:1-1992:4. Table 2.5 summarizes the results of these tests using the equation (2.19) specification of St. Louis equation.[15]

Only the narrowest level of aggregation do these tests favor simple sum over Divisia aggregates. At all levels of aggregation broader than M1, these tests favor Divisia indices over their simple sum counterparts, in particular DM2 and DM3. Thus, in the pairwise simple sum versus Divisia comparisons, results favor Divisia

Table 2.5
United States Results of the St. Louis Equation
Chrystal & MacDonald (1994) Study

SSM1 vs DM1			**SSM1 vs CE**	
AIC	favors SSM1		AIC	favors CE
J-test	favors SSM1		J-test	Inconclusive
JA-test	favors SSM1		JA-test	Indeterminate
SSM2 vs DM2			**SSM2 vs CE**	
AIC	favors DM2		AIC	favors SSM2
J-test	favors DM2		J-test	Inconclusive
JA-test	favors DM2		JA-test	favors SSM2
SSM3 vs DM3			**SSM3 vs CE**	
AIC	favors DM3		AIC	favors SSM3
J-test	favors DM3		J-test	Inconclusive
JA-test	favors DM3		JA-test	Inconclusive
SSL vs DL			**SSL vs CE**	
AIC	favors DL		AIC	favors SSL
J-test	Inconclusive		J-test	Inconclusive
JA-test	Inconclusive		JA-test	Inconclusive

Notes: 1) Inconclusive: both are significant; 2) Indeterminate: neither significant; 3) U.S. quarterly data, 1960:1-1992:4.

[15] Tests are calculated for two specifications of the model. The first does not include lagged dependent variable in the autoregression; and the second includes lagged dependent variable. They found that the inclusion or the exclusion of the lagged dependent variable does not change the general picture.

aggregates at broad levels of aggregation (broader than M1). In CE against SS comparison, results are less conclusive. The CE is favored against simple sum only at the M1 level and only by the AIC test. In all other cases, simple sum performs as well or better than the CE aggregates. In other countries, for example, in the U.K, there are fewer aggregates to choose from. The only choice using official aggregates is between M0 (the monetary base) and M4 (the main broad monetary aggregate).[16] The results indicate that Divisia M4 clearly dominates its simple sum equivalent. In Canada, Divisia aggregates dominate simple sum at broad levels of aggregation. As in the U.S. evidence, only simple sum M1 performs marginally better than its Divisia counterpart. No CE aggregates have been constructed and tested for the non-U.S. nations.

Note that this study only evaluates the empirical performance of the weighted monetary aggregates (CE and D) against their simple sum counterparts. It does not explicitly evaluate CE against D aggregates. Chrystal and MacDonald conclude that CE aggregates lose "out to the broader simple sum aggregates, *however,* and also to the broader-based Divisia measures (the latter result is implied but not shown)" (Chrystal and MacDonald, 1994, p. 77). The research here explicitly compares the empirical performance of CE versus D and SS aggregates.

Two points could be concluded from the above surveyed studies. First, the evidence on the superiority of the empirical performance of weighted monetary aggregates against simple sum aggregates is mixed. However, many of these studies

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[16] The Bank of England stopped reporting M1 and M3 in 1989 because it considered the data too distorted by financial innovation (Chrystal and MacDonald, 1994, p.80).

favor the Divisia aggregates over simple sum, particularly at broad levels of aggregation. Second, most of these studies do not evaluate the empirical performance *across* different weighted monetary aggregates (i.e., D and CE). Therefore, a major contribution of the proposed research is to provide empirical evidence on the performance of different weighted monetary aggregates. This project will evaluate the empirical performance of the CE aggregates versus Divisia and simple sum aggregates, across the conventional four levels of aggregation.

For the first time, unrestricted VAR and VEC models will be used to accomplish this objective. In these models no restrictions are imposed on the endogeneity or exogeneity of any variable. They are perfectly suited for analyzing macroeconomic and monetary data where no variable is obviously exogenous or endogenous. Further, these models provide a more complete picture of the dynamic differences between CE, D, and SS monetary aggregates relative to single equation Granger causality tests.

The next chapter provides further discussion of the econometric techniques used to compare the empirical performance of CE, D, and SS monetary aggregates, as well as a thorough analysis of the data series used in the research.

CHAPTER THREE

ECONOMETRIC METHODS AND DATA ANALYSIS

A major objective of this research is to empirically investigate the ability of different monetary aggregates to explain movements in both nominal and real economic activity. This objective will be accomplished by using Vector Autoregression (VAR) and Vector Error Correction (VEC) models. These models are appropriate for analyzing monetary and macroeconomic data and provide a comprehensive picture of the dynamic relationships between the variables included in the systems. The next section further discusses these models. The set of monetary aggregates that will be examined are currency equivalent (CE), Divisia (D), and simple sum (SS), measured at the conventional four levels of aggregation (M1 through L). The previous chapter summarizes the CE and D aggregation methods. A thorough analysis and the construction of the CE and D aggregates are provided in Anderson, Jones, and Nesmith (1997a, 1997b, and 1997c). As a measure of economic activity, researchers typically use real GDP, real GNP or industrial production.[17] The GNP deflator, GDP deflator, or consumer price index (CPI) is usually used to measure the effect of money on prices.[18] In this research, both real GNP and nominal GNP will be

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[17] Serletis (1988) uses real GNP; Serletis and King (1993) use real GDP; Rotemberg, Driscoll, and Poterba (1995) use industrial production.
[18] Serletis (1988) and Serletis and King (1993) use CPI and GDP deflator respectively. Friedman and Kuttner (1992) use GNP deflator.

employed in measuring the effect of money on economic activity. The GNP deflator will be used to measure the effect of money on prices.

In the empirical literature, an interest rate variable (90-day Treasury bill rate and commercial paper rate are examples) is usually included in the VAR analysis. This practice has been standard since Sims (1980a) findings. He concluded that the ability of money to explain output declines sharply when an interest rate variable is included in the VAR models. However, preliminary investigation shows, when VAR (or VEC) models have been estimated with an interest rate variable (90-day Treasury bill rate), the effect of money when measured by CE on output is magnified. This result is not surprising, since an interest rate variable is already included in the weighting scheme of CE index. When money is measured by D index or SS index, preliminary results show that the inclusion or exclusion of the 90-day Treasury bill rate does not essentially change the results. Therefore, interest rate variable will not be included in the VAR or VEC analysis here.

Two model specifications will be constructed and estimated. The first specification is a three variable (money measured by CE, D, and SS, real GNP, and prices) unrestricted VAR (or VEC) models. This model specification allows us to separate out real impacts from price impacts, which is of interest to both macroeconomists and policy makers. The second model specification is a two variable (money and nominal GNP) VAR (or VEC) models. Using these models allows comparison with existing studies in literature. These studies assess SS versus D.

Adding CE results (in same model specification) will fill out the available set of evidence in the literature. A total of twenty-four models will be estimated: 2 model specifications x 3 aggregation methods x 4 levels of monetary aggregation.

All the data series included in this study are seasonally adjusted quarterly data from the first quarter 1960 to the third quarter of 1998, available from the Federal Reserve Bank of St. Louis' web site.[19]

The next section provides a discussion of the econometric techniques used to evaluate the relative empirical performance of the different monetary aggregation schemes. Section 3.2 analyzes the integration properties of the data series included in this study. The relative levels and growth rates of the monetary aggregates constructed by CE, D, and SS methods, are compared and analyzed. Also, unit root tests and cointegration tests are conducted. The last section discusses the relevance of some of the VAR models criticisms.

3.1 Econometric Methods

This section describes the econometric methods used to evaluate the relative empirical performance across CE, D, and SS aggregation methods. Unrestricted reduced form VAR or VEC models are used. The rationale behind using these models is presented next. In addition, the tools (impulse response functions, IRFs, and forecast

[19] The St. Louis web site address is www.stls.frb.org/.

error variance decomposition, FEVDs) used within the context of VAR or VEC models are described.

3.1.1 Vector Autoregression and Vector Error Correction Models

Traditionally, macroeconometric hypothesis tests and forecasts were conducted using large-scale macroeconomic models. Usually, a complete set of structural equations was estimated, one equation at a time. Then all equations were aggregated in order to form overall macroeconomic models and forecasts. In the process of building these models, a set of ad hoc behavioral restrictions are imposed on them. Sims (1980b, p.3) considers such multi-equation models and argues that:

> ...what "economic theory" tells us about them is mainly that any variable that appears on the right-hand side of one of these equations belongs in principle on the right-hand side of all of them. To the extent that models end up with very different sets of variables on the right-hand side of these equations, they do so not by invoking economic theory, but (in the case of demand equations) by invoking an intuitive econometrician's version of psychological and sociological theory, since constraining utility functions are what is involved here. Furthermore, unless these sets of equations are considered as a system in the process of specification, the behavioral implications of the restrictions on all equations taken together may be much less reasonable than on any one equation taken by itself.

Furthermore, Sims (1980b) strongly support the use of unrestricted reduced form models. He criticizes the traditional macroeconometric models and states that: (pp. 14-15)

> Because existing large models contain too many incredible restrictions, empirical research aimed at testing competing macroeconomic theories too often proceeds in a single- or few- equation framework. For this reason alone, it appears worthwhile to investigate the possibility of building large models in a style which does not tend to accumulate restrictions so haphazardly... It should be feasible to estimate large-scale macromodels as unrestricted reduced forms, treating all variables as endogenous.

Therefore, unrestricted reduced form VAR models, which impose no restrictions regarding the exogeneity or endogeneity of any variable will be used. In these models, all variables are treated symmetrically. This approach is perfectly suited for analyzing macroeconomic and monetary data, where no variable is clearly exogenous or endogenous.

One straight application of an unrestricted VAR model is for forecasting. A VAR forecaster does not worry about the economic theory underlying his or her VAR model, and more importantly, does not need to make any assumptions about the values of exogenous variables in the forecasting period. This is in contrast with the traditional econometric forecasting, where forecasts have to be conditioned upon knowledge of exogenous variables.

In an attempt to make the interpretation of policy analysis in a VAR model more straightforward, it has become common practice to transform the model into one having "orthogonal innovations;" that is, to transform the model so that the error terms are no longer contemporaneously correlated. An approach common in the applied VAR literature is the Choleski decomposition. The idea behind making the error terms orthogonal to each other is to enable the equation to be used separately for policy analysis. In this context, policy analysis refers to the impact of a known shock or "orthogonal innovation" on the system. The next section develops these ideas in more details. One problem with such analysis is that the results may be sensitive to the ordering of the VAR equations. In practice, it may be possible to decide on the ordering of the equations following the application of a series of causality tests.

Using matrix notation, the general form of a multivariate vector autoregression of order p, VAR (P) is:

$$y_t = c + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \ldots + \phi_p y_{t-p} + \varepsilon_t \qquad \ldots(3.1)$$

where,

y_t denotes an (nx1) vector containing values of n variables at date t,

c is an (nx1) vector of intercepts,

$\phi_1, \ldots, \phi_p$, are (nxn) matrices of autoregression coefficients, and

$\varepsilon_t \sim i.i.d\, N(0, \Omega)$, such that Ω is an (nxn) matrix of the variance-covariance of the VAR residuals.

The VAR representation in equation (3.1) may be extended to include other optional deterministic or exogenous variables. In this specification, no restrictions are imposed on the nature of lagged dynamics of the model. Therefore, this representation is referred to an unrestricted reduced form.

In the VAR models, a researcher has to determine the lag structure of the autoregressive model, i.e., p in equation (3.1). Two methods have been used in the literature. The first is to use an arbitrary lag length (usually 4 or 8 lags when quarterly data are used; see for example, Friedman and Kuttner, 1992 and Barnett, Offenbacher, and Spindt, 1984. When monthly data are employed, 12 lags are common, as in Rotemberg et al., 1995). The alternative method uses specific statistical criteria to determine the optimal lag length. Several lag length selection criteria have been developed. Two well-known criteria are the Akaike's (1970) information criterion (AIC), and the Schwarz's (1978) criterion (SC). Of the two criteria, the SC has superior large sample properties and is asymptotically consistent, whereas the AIC is biased toward selecting an over parameterized model. Therefore, SC will be employed. The algebraic expression of this criterion is:

$$SC = T\,Log\,|\,\Sigma\,| + N\,Log\,(T) \qquad ...(3.2)$$

where $|\,\Sigma\,|$ is the determinant of the variance-covariance matrix of the residuals, N is total number of parameters estimated in all equations, and T is the sample size. According to this criterion, the model (here, lag length) with the lowest SC should be selected.

Since the VAR models involve only lagged variables on their right hand side, and since these by definition are not correlated with the error term, equation by equation ordinary least squares (OLS) provide a consistent estimate of these models. The estimation of these models is straightforward if the individual time series data are stationary. In this case standard VAR models in levels should be estimated. On the other hand, if the data are nonstationary, two possibilities arise. The first, if the data are nonstationary and there exist no cointegrating vectors between the variables included in the model, VAR models should be estimated after differencing the data enough times to be stationary. The second, VEC models have to be estimated if the variables are nonstationary and cointegrated. The general form of VEC model is:

$$\Delta y_t = \pi_0 + \pi y_{t-1} + \pi_1 \Delta y_{t-1} + \pi_2 \Delta y_{t-2} + \ldots + \pi_p \Delta y_{t-p} + \varepsilon_t \qquad \ldots(3.3)$$

where,

π_0 is an $(n \times 1)$ vector of intercept terms,

π_i is $(n \times n)$ coefficient matrices,

π is a matrix with elements π_{jk} such that one or more of the $\pi_{jk} \neq 0$, and

ε_t is $n \times 1$ vector of error terms.

VEC models should be estimated because estimating a standard VAR model using only first differences is inappropriate and entails a misspecification error by omitting an error-correction representation (Engle and Granger, 1987). Granger's representation theorem states that for any set of integrated variables of order one (I(1)), error correction and cointegration models are equivalent representations (see Enders, 1995). Section 3.2 provides a detailed analysis of the integration properties of the data series included in this study.

Within the context of VAR and VEC models, the main method used to analyze the dynamic simulations of the systems is "innovation accounting". This method is described next.

3.1.2 Innovation Accounting

One of the key questions that can be addressed within VAR (or VEC) frameworks is how to trace out the time path of various shocks (innovations) on the variables contained in the system. This is referred to as innovation accounting. Two tools are used to analyze innovation accounting: impulse response functions (IRFs) and forecast error variance decompositions (FEVDs). Both of them are used in this research.

Impulse Response Functions (IRFs)

IRFs are one way of characterizing the dynamic behavior of a simulation model. They describe the response of a variable y_{it} at time *t, t+1, t+2, etc.*, to a one-time impulse (shock) in another variable y_{jt} at time t with all other variables dated t or earlier held constant. These functions are derived by taking the partial derivative of the moving average representation of the VAR or VEC models with respect to the shocked variable. IRF is given by:

$$\frac{\partial y_{i,t+s}}{\partial \varepsilon_{jt}} \quad \text{for } s=0,1,2,\ldots \qquad \ldots(3.4)$$

where ε_{jt} is the innovation in variable y_{jt}, and s is the horizon.

These functions can be used directly for tracking dynamic responses of particular variable to a single unitary shock in another. To calculate the impulse response function, the model should be in a state of equilibrium when a one-period shock to one of the endogenous variables is introduced (say one standard deviation at time t). The shock is maintained for only one period and hence is an "impulse". A shock to any endogenous variable will filter through the model, affecting all other endogenous variables. In later periods, it may even have a greater effect on the original endogenous variable than it did initially, because of feedback effects through the other variables. Plotting the IRFs is a practical way to represent the behavior of y_{it} series response to the shock in the y_{jt} series.

Impulse response functions will be employed to trace out the effects of one unit shock in money on the time paths of real GNP, prices and nominal GNP, and to compare the estimated dynamics to those predicted by the standard macroeconomic models. For example, the IRFs can show whether the estimated real and nominal responses to money innovations are temporary or permanent. These responses provide evidence whether money is neutral or non-neutral, in the short or the long run. Long run neutrality implies a zero effect at long horizons. Furthermore, inferences could be drawn about the relative strengths of the relationship between money (as measured by CE, D, and SS at the four levels of aggregation) and economic activity (as measured by real GNP, prices and nominal GNP).

Forecast Error Variance Decompositions (FEVDs)

FEVD is another way of characterizing the dynamic behavior of the VAR (or VEC) models. It breaks down the variance of the forecast error for each variable into components that can be attributed to each of the endogenous variables. If ε_{jt} shocks explain none of the forecast error variance of y_{it} series at all forecast horizons, we can say that the y_{it} series is exogenous. In such a circumstance, the y_{it} series would evolve independently of the ε_{jt} shocks and y_{jt} series. At the other extreme, ε_{jt} shocks could explain all the forecast error variance in the y_{it} series at all forecast horizons, so that the y_{it} series would be entirely endogenous. In applied research, it is typical for a variable to explain almost all of its forecast error variance at short horizons and smaller proportions at longer horizons. We would expect this pattern if ε_{jt} shocks had little contemporaneous effect on y_{it}, but acted to affect the y_{it} series with a lag. This tool will be used to compare the portion of the forecast error variance of our goal variables that is explained by money innovations, for each of the different monetary aggregates (CE, D, and SS). At each level of aggregation, we can check which of the aggregates (CE, D, or SS) innovations can better explain the error variance of our economic activity measures. Conclusions can be compared at different forecast horizons.

These tools enable researchers to empirically evaluate the performance of the monetary aggregates across the different aggregation methods (CE, D, and SS) in terms of their ability to affect economic activity. They provide the means to choose which of the monetary aggregates or aggregation method could be used as a viable policy tool. This is of particular importance to both macroeconomists and policy makers.

The next section provides a detailed analysis of the integration properties of the data series included in this study.

3.2 Integration Properties of the Data

Three areas of interest are discussed in this section. The first provides a graphical analysis of the monetary aggregates series, both in levels and in growth rates. The second subsection provides unit roots tests for all data series included in this research. The last subsection tests for cointegration between the variables included in each model estimated. The pre-estimation assessment of data properties is needed for model construction. These properties of data will dictate whether to use standard VAR models or VEC models.

3.2.1 Analysis of Data

Relative Levels

Figures 3.1-3.4 provide graphical representation of the measures of money under the CE, D, and SS aggregation methods. All the series are quarterly index numbers with 1960:1=100. Figure 3.1 plots the narrowest monetary aggregates and shows a trend similarity of all aggregates in particular DM1 and SSM1 until early 1970s, when they began to diverge. The divergence is primarily due to financial innovations of early 1970s in the form of new financial assets such as interest bearing checkable accounts (ATS and NOW accounts).

At broader levels of monetary aggregation, shown in Figures 3.2-3.4, the divergence between currency equivalent, Divisia, and simple sum aggregates is more extreme. It is evident early in the period and increases over the span of the study

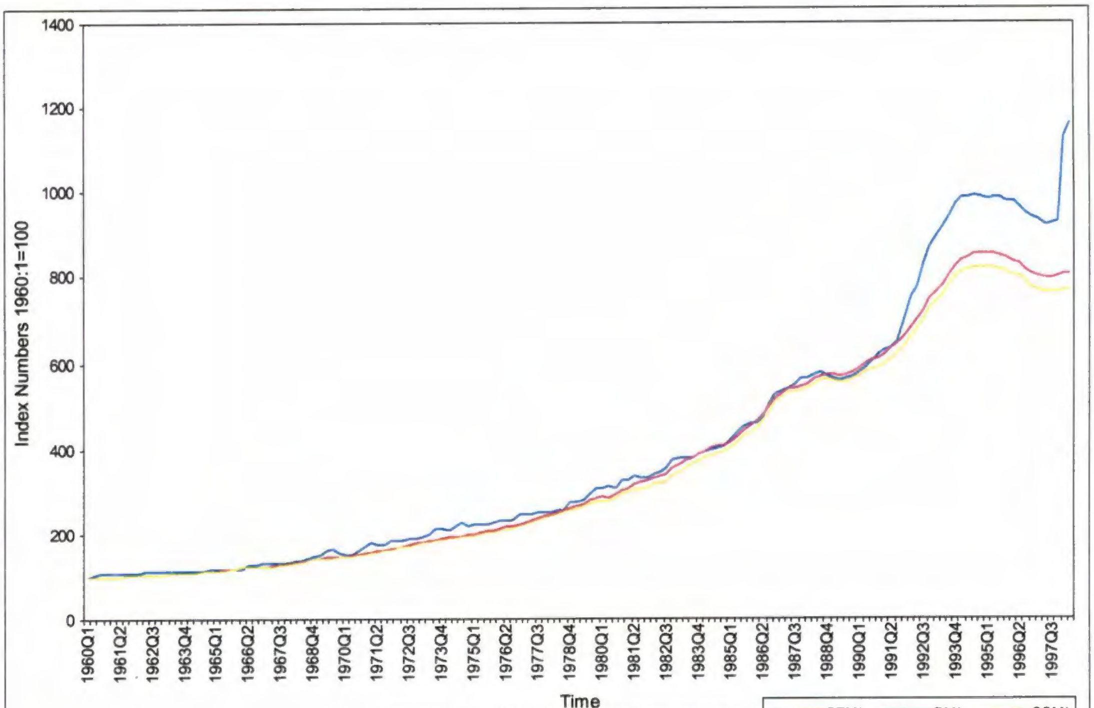

Figure 3.1: M1 Monetary Aggregates

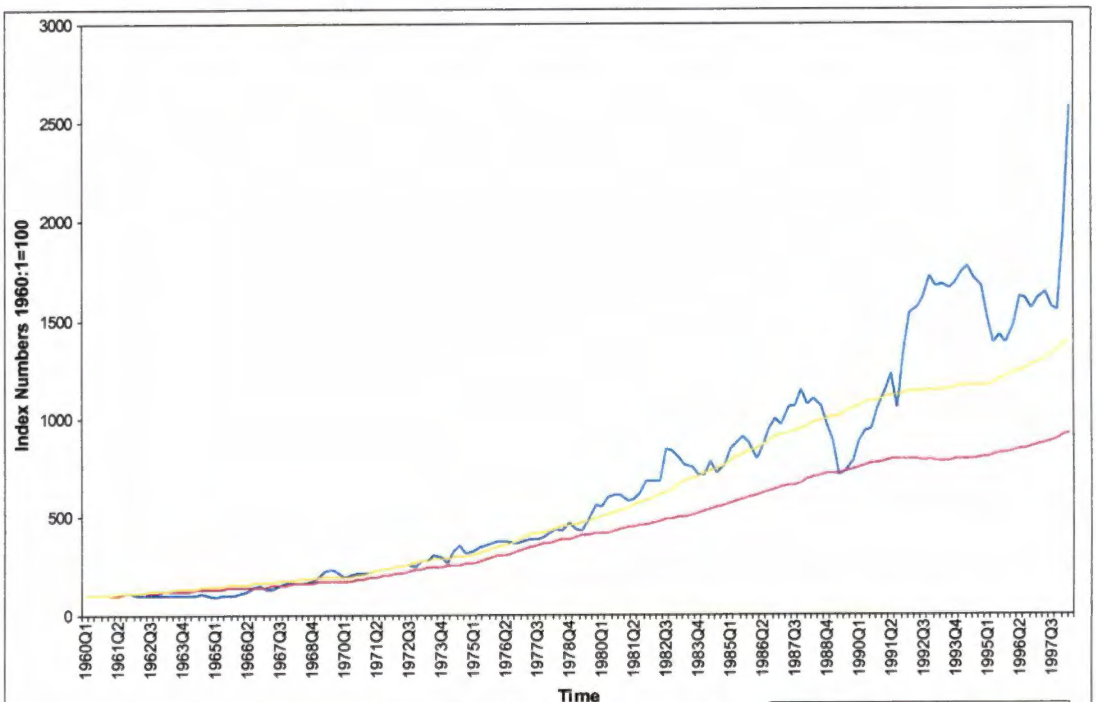

Figure 3.2: M2 Monetary Aggregates

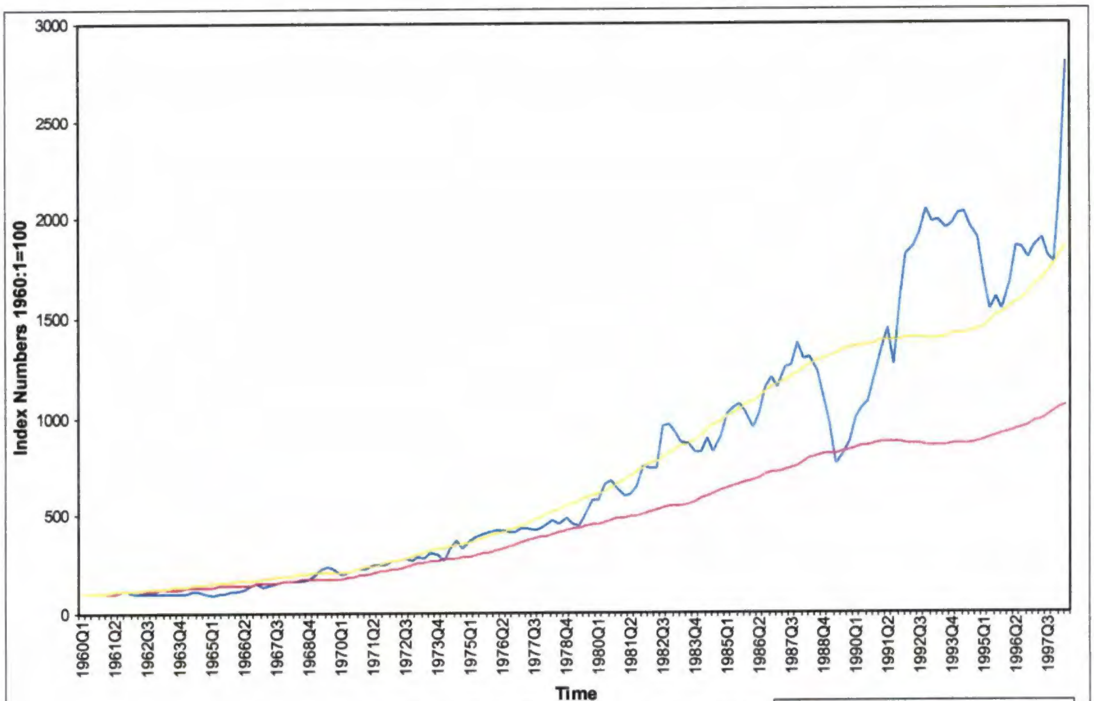

Figure 3.3: M3 Monetary Aggregates

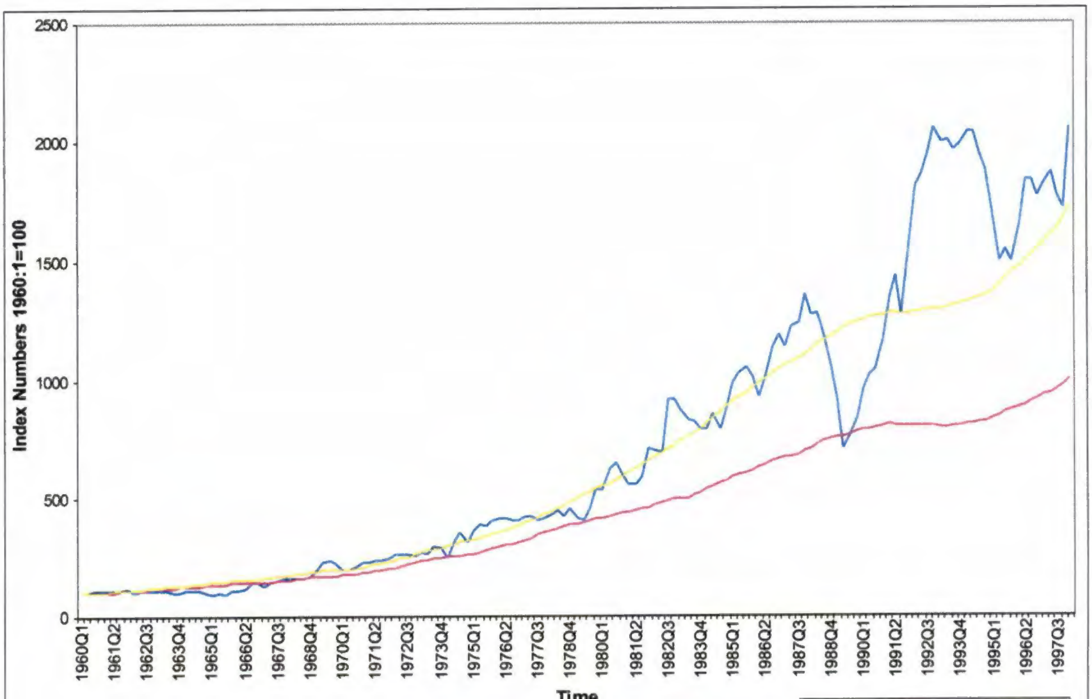

Figure 3.4: L Monetary Aggregates

period. The divergence is more pronounced for the years since 1978, when the financial innovations and market deregulations were well in place.

Also evident from Figures 3.1-3.4 is the greater volatility of the currency equivalent aggregates relative to their Divisia and simple sum counterparts over the period of study, particularly for broader levels of aggregation (higher than M1). Much of the volatility is driven by interest rates changes, since the CE weighting scheme is particularly sensitive to interest rate movements. From equation (2.14), which defines the currency equivalent index, it is clearly evident that any change in the benchmark interest rate, r_{bt} or the i^{th} monetary asset interest rate, r_{it} will change the CE aggregates, even if no change occurs in the quantities of the monetary assets being aggregated. On the other hand, Divisia aggregates are less sensitive to interest rate changes because the weights on assets are combinations of asset prices and quantities (i.e., expenditure shares).

Relative Growth Rates

Figures 3.5 through 3.8 display the quarter-to-quarter growth rates of the CE, D, and SS monetary aggregates at the four levels of monetary aggregation. The CE volatility, suggested in the previous figures (3.1-3.4), is even more evident when growth rates are examined. For the M1 level, Figure 3.5 and Table 3.1 show that the growth rate of CEM1 has higher volatility and low correlation with DM1 and SSM1. The correlation coefficients between CEM1 growth rate and the growth rates of both DM1 and SSM1 are 0.334 and 0.336 respectively (Table 3.1). The standard deviation

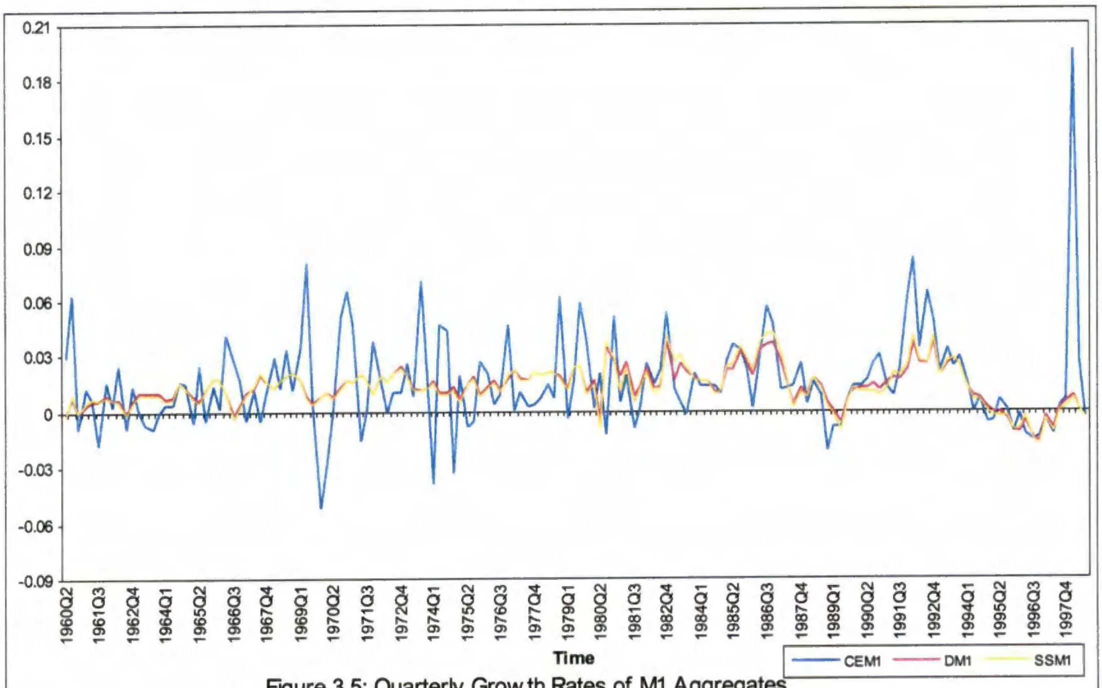

Figure 3.5: Quarterly Growth Rates of M1 Aggregates

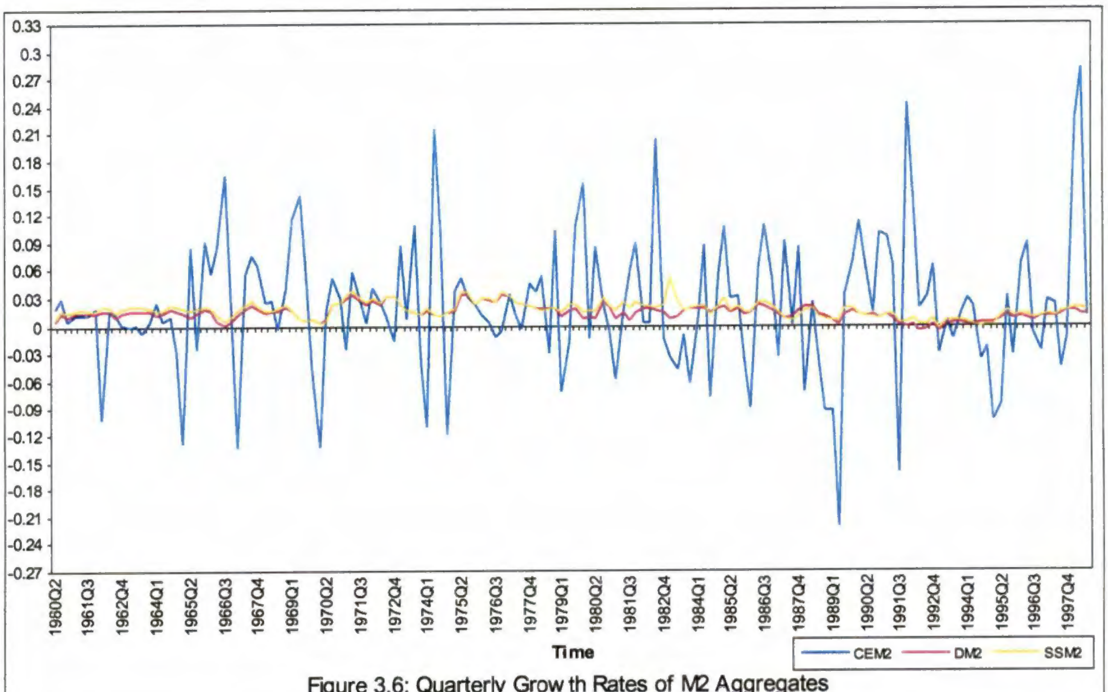

Figure 3.6: Quarterly Growth Rates of M2 Aggregates

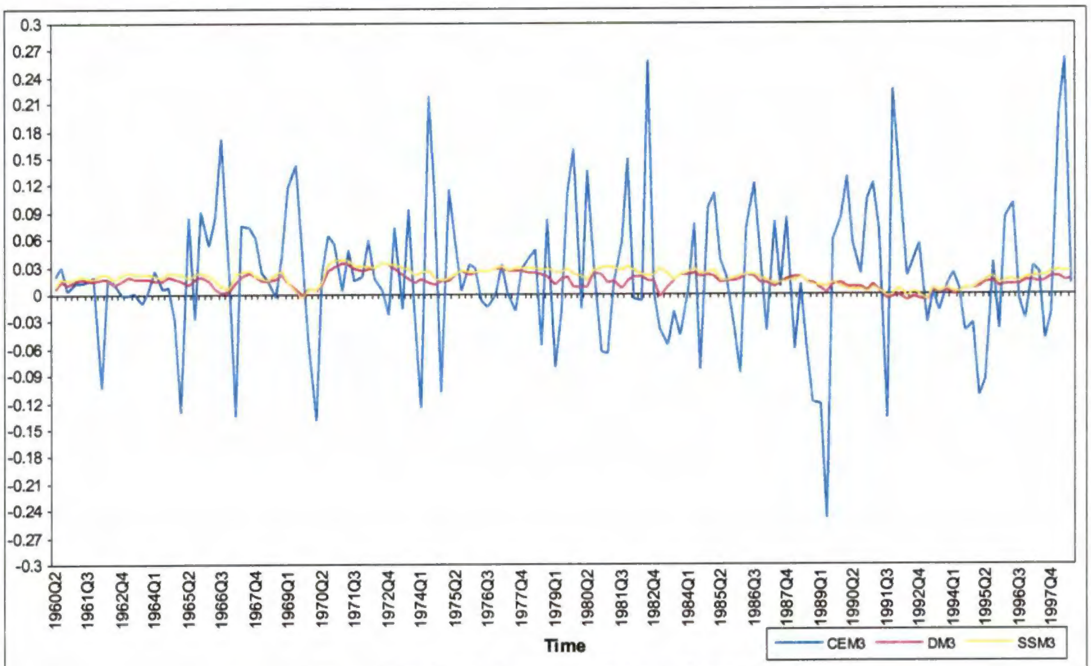

Figure 3.7: Quarterly Grow th Rates of M3 Aggregates

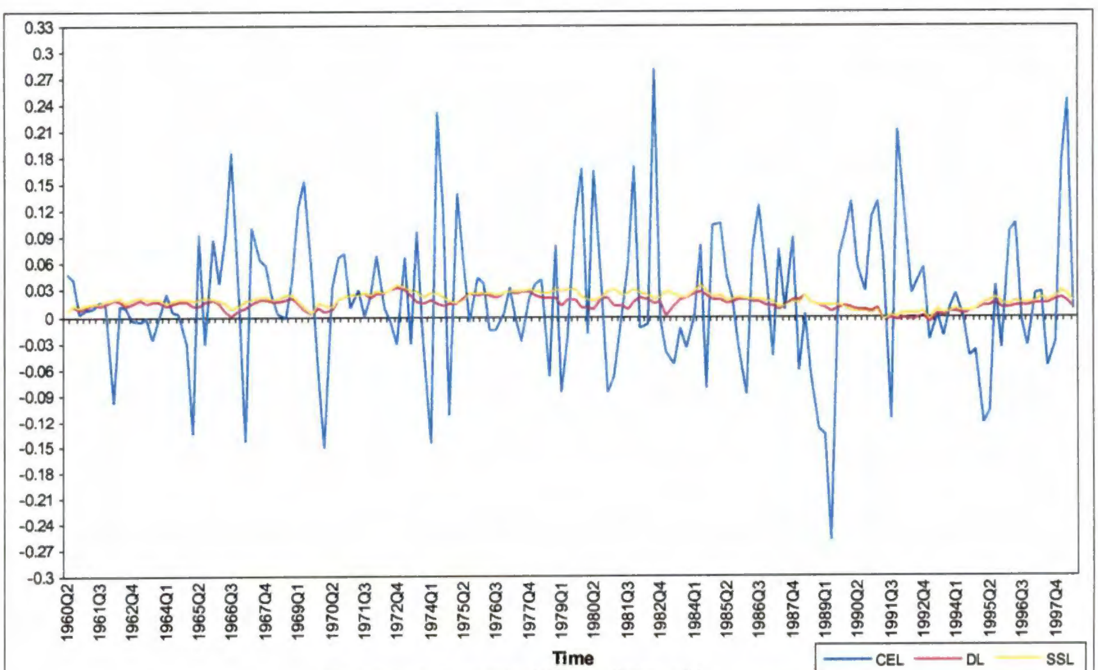

Figure 3.8: Quarterly Grow th Rates of L Aggregates

Table 3.1
The Correlation Coefficients of CE, D, and SS Monetary Aggregates Quarterly Growth Rates

M1 Level	CEM1	DM1	SSM1
CEM1	1.00		
DM1	0.334	1.00	
SSM1	0.336	0.987	1.00
M2 Level	CEM2	DM2	SSM2
CEM2	1.00		
DM2	0.057	1.00	
SSM2	0.080	0.855	1.00
M3 Level	CEM3	DM3	SSM3
CEM3	1.00		
DM3	0.026	1.00	
SSM3	0.050	0.878	1.00
L Level	CEL	DL	SSL
CEL	1.00		
DL	-.045	1.00	
SSL	-.045	0.855	1.00

of CEM1 growth rate is 2.68%, which is twice the standard deviation of DM1 and SSM1 growth rates (look at Table 3.2).

At broader monetary aggregates, as depicted in Figures 3.6-3.8 and Tables 3.1-3.2, the growth rates of CE aggregates are more volatile than CEM1 and their D and SS equivalents. The CE correlation with D and SS counterparts is even lower than that found for the M1 level. For example, at the M2 level of monetary aggregation, the correlation coefficients between CEM2 and both DM2 and SSM2 are 0.057 and 0.080 respectively (Table 3.1). This stands in contrast to the 0.855 correlation between DM2 and SSM2. The standard deviation of CEM2 is 7.42%; it is seven times higher than

Table 3.2
Mean and Standard Deviation of Monetary Aggregates Growth Rates
(All entries are %)

CE Aggregates			SS Aggregates			D Aggregates		
	Mean	St.Dev		Mean	St.Dev		Mean	St.De
CEM1	1.60	2.68	SSM	1.33	1.13	DM1	1.37	1.02
CEM2	2.13	7.42	SSM	1.72	.87	DM2	1.46	.82
CEM3	2.18	7.85	SSM	1.91	.94	DM3	1.54	.87
CEL	1.99	8.07	SSL	1.87	.83	DL	1.52	.78

DM2 and SSM2 aggregates (Table 3.2). Similar behavior of CE aggregates appears at M3 and L levels of monetary aggregation (Figures 3.7-3.8 and Tables 3.1-3.2).

The high fluctuations of CE aggregates reflect the high sensitivity of these aggregates to interest rate fluctuations. From the weighing scheme of CE aggregates (defined as $(r_{bt} - r_{it})/r_{bt}$), any change in the benchmark rate and the individual monetary asset rates will cause CE aggregate to change. These fluctuations are more pronounced at higher levels of monetary aggregations. This should not be surprising since monetary assets in the broader aggregates are more heterogeneous and differ in their liquidity attributes and interest rate yields. This causes these aggregates to be more sensitive to interest rate changes than the narrow M1 level of aggregation. In M1, most of the monetary assets included are homogeneous and have the same liquidity characteristics and do not yield any explicit interest rate. This makes this aggregate less volatile to changes in interest rates.

The sensitivity of the CE aggregates to interest rate changes raises some questions. It is hard to believe that the liquidity characteristics of existing assets change by as much as do the ratios $(r_{bt} - r_{it})/r_{bt}$. Rather, what happens is that many interest rates on monetary assets are kept relatively stable, whereas the benchmark interest rate is more variable. If people readjust their portfolio holdings continually in response to interest rate changes, the CE formula will still be valid. But, because agents do not do so, the effect of changes in $(r_{bt} - r_{it})/r_{bt}$ on actual liquidity, and thus the CE measures, is exaggerated. The Divisia aggregates do not show the same volatility as the CE aggregates because the weights on assets in the Divisia aggregates are combinations of asset prices and quantities (i.e., expenditure shares).

These high fluctuations in CE raise the question of whether CE, D and traditional aggregates have different stationarity properties. Therefore, the stationarity of these aggregates is investigated by means of unit root tests in the next subsection.

Note from the previous figures and tables that Divisia and simple sum aggregates show relatively strong correlation. At the M1 level, the growth rates of DM1 and SSM1 move almost perfectly together, with a correlation coefficient equal to 0.987. Both of the two aggregates show less variation until the early 1980s when the growth rate of NOW accounts began to accelerate. As noted in Thornton and Yue (1992), the nationwide introduction of NOW accounts in 1981 tends to increase the growth rate SSM1 relative to DM1 because these accounts have a smaller weight in the Divisia aggregation index. Thus, across the relatively homogenous M1 asset set, SS and D show similar movement and strong correlation, particularly pre-1980.

At higher monetary aggregation levels, the differences between the growth rates of Divisia and SS aggregates are wider. All of the aggregates show similar growth rates until late 1970s. The average growth rates of SS aggregates are relatively higher than the Divisia growth rates. This should be expected since interest yielding assets are assigned smaller weights in Divisia index. Table 3.2 reports the mean and standard deviation of quarter-to-quarter growth rates of both Divisia and SS monetary aggregates as well as CE aggregates. Furthermore, as reported in Table 3.1, the correlation between the growth rates of Divisia aggregates and their SS equivalents are smaller at aggregation levels above the narrow M1 aggregate.

Discussion now turns to the stationarity properties of the CE, D and SS aggregates.

3.2.2 Univariate Unit Root Tests

Two goals necessary to the VAR modeling will be achieved in this subsection. The first is the assessment of the stationarity properties of the CE aggregates compared to the D and SS aggregates. The second is to determine the order of integration (the number of unit roots) for the individual time series entering in the VAR models. This is the first stage in investigating empirical relationships between money, income and prices.

There have been a variety of proposed methods for implementing univariate unit roots tests (for example, Dickey and Fuller, 1979, Phillips and Perron, 1988, Park and Choi, 1988) and each has been used in the applied macroeconomics literature. Since, however, there is now a growing consensus that the earliest unit root test (due to Dickey and Fuller, 1979) has superior small sample properties compared to its competitors (see: Campell and Perron, 1991 for a discussion), the Augmented Dickey-Fuller (ADF) test is used. This test is equivalent to testing whether $\gamma=0$ in the following equation:

$$\Delta M_t = \alpha + \gamma M_{t-1} + \sum_{i=1}^{p} \beta_i \Delta M_{t-i} + \varepsilon_t \qquad \ldots(3.5)$$

where M_t is a monetary aggregate. Following the procedure recommended by Stock (1994), the optimal lag length, p, is chosen through Schwarz's (1978) criterion (SC).

Table 3.3 reports the t-ratio results for the estimated coefficient γ in equation (3.5) for the (log) levels and the first difference of the (log) levels of each monetary aggregate included in the study. Also reported in the table are tests for the economic activity measures (real GNP, nominal GNP, and prices).

The ADF test statistics show that all of the CE aggregates, as well as D and SS aggregates are nonstationary in levels. The null hypothesis of a unit root can not be rejected for any series in (log) levels at the conventional significance levels (5% or 10%). The unit root tests for the first difference of the (log) levels are rejected at 5% significance level (or lower) except for DM2 and SSL (where the significance levels are 9.2% and 6.8% respectively). Therefore, we conclude that CE aggregates, at the four levels of aggregation, show similar stationarity patterns as D and SS aggregates. All of the aggregates are integrated of order one, I(1).

Table 3.3
Augmented Dickey Fuller Tests for Unit Roots

Aggregate	Log Levels			First Difference of Log Levels		
	ADF test	P-values	Lags	ADF test	P-values	Lags
CEM1	0.842	0.992	3	-6.196	0.000	2
CEM2	-0.089	0.950	4	-5.799	0.000	3
CEM3	-0.272	0.929	4	-6.133	0.000	3
CEL	-0.292	0.927	4	-6.245	0.000	3
DM1	-0.897	0.789	10	-3.101	0.027	9
DM2	-1.660	0.452	7	-2.605	0.092	6
DM3	-1.651	0.456	3	-3.572	0.006	2
DL	-1.624	0.471	3	-3.537	0.007	2
SSM1	-0.792	0.821	10	-3.271	0.016	9
SSM2	-1.587	0.490	10	-3.419	0.010	3
SSM3	-1.303	0.628	3	-2.996	0.035	2
SSL	-1.341	0.610	3	-2.734	0.068	2
NGNP[1]	-2.014	0.280	4	-4.462	0.0002	3
RGNP[2]	-0.786	0.823	4	-4.795	0.000	3
Price	-1.656	0.454	5	-1.883	0.340	4

Notes: 1) NGNP: denotes nominal GNP. 2) RGNP: denotes real GNP.

The unit root tests for the economic activity measures show that both nominal GNP and real GNP are I (1) processes, while the price level, measured by GNP deflator, is an I (2) process (inflation is I(1)). These results are consistent with evidence elsewhere in the literature (see for example: King, Plosser, Stock, and Watson, 1991, and Nelson and Plosser, 1982).

The unit root tests presented above are important for the VAR modeling. They determine whether to use data in levels or in differences. In addition, these tests are the first step for cointegration analysis. If the data series are integrated (as found in the presented results) cointegration tests have to be conducted. The next subsection explains the importance of cointegration tests to VAR modeling and carries out these tests for the variables included in each VAR system.

3.2.3 Cointegration Tests

Since a stochastic trend (unit root) has been confirmed for each of the series, the question is whether there exists some long-run equilibrium relationship between the level of money and the level of income and prices.[20] That is, whether these variables are cointegrated. A set of individually integrated series is said to be cointegrated if there exists a linear combination of the series that is stationary. Such a relationship is important for two reasons. The first, which is beyond the scope of this research, concerns the potential importance of this long-run relationship in the conduct of monetary policy, particularly in a multiyear context. The second reason deals with the VAR models that are used in this research. A major concern arises when dealing with VAR models if the variables are integrated (as found in the previous results) and possibly cointegrated. As mentioned previously, estimating a standard VAR model using only first differences is inappropriate and entails a misspecification error by omitting an error-correction representation (Engle and Granger, 1987). Granger's representation theorem states that for any set of integrated variables of order one, I(1), error correction and cointegration models are equivalent representations (see Enders, 1995). The previous section's unit root tests show that all of the variables

[20] See Blanchard (1990) for the state of art regarding the relationship between money and income or prices.

included in this study are nonstationary and generally I(1). Therefore, investigation of long-run equilibrium relationships is appropriate. If these long run relationships exist (that is, if the variables in the VAR model are cointegrated) vector error-correction (VEC) models should be estimated. These models, besides accounting for cointegration, can improve the efficiency of estimation and forecasting.

Several methods have been proposed in the literature to estimate cointegration vectors (long-run equilibrium relationships). Engle and Yoo (1989) and Gonzalo (1989) provide a survey and comparison across methods. Here the Johansen's (1988) maximum likelihood method is used (see also: Johansen, 1991, and Johansen and Juselius, 1990). This method is appropriate when using VAR models since the foundation of the Johansen technique is a reduced form VAR.

Johansen Cointegration Test

The Johansen (1988, 1991) cointegration test uses the maximum likelihood approach to the estimation of the number of linearly independent cointegrating vectors for a vector autoregressive process, y_t of order p. The cointegration test is appropriate when the variables entering the VAR model are I (1). Therefore, the order of integration of any I (2), or higher, variable has to be reduced to I (1) by differencing such variable. Using the information from the unit root tests, only the price level - which is I (2)- has to be differenced. Thus, the change in the price level (or inflation, since the price level is transformed logarithmically) enters in the VAR models. The Johansen test involves i) regressing Δy_t on $\Delta y_{t-1}, \Delta y_{t-2}, \ldots, \Delta y_{t-p+1}$, ii) regressing

y_{t-p} on the same regressors, and iii) performing a canonical correlation analysis on the residuals of these regressions (see, for example, Dickey, Jensen and Thornton, 1991).

Table 3.4 reports the results of the cointegration tests for the two VAR model specifications discussed previously. The first specification includes real GNP, prices, and money (measured by the three aggregation schemes, CE, D, and SS at the four conventional levels of aggregation). The second specification of the VAR models uses nominal GNP and the respective money measures.

Table 3.4
Maximum Eigenvalue Coinegration Tests Between Money, Income, and Prices [a]

Aggregate	Cointegration Tests between Money, Real GNP, and Prices				Cointegration Tests between Money, and Nominal GNP		
	VAR order	Test Statistic	# of C.V[b]		VAR order	Test Statistic	# of C.V[b]
CEM1	4	29.48	0		3	14.84	0
CEM2	4	31.98*	1		3	19.24*	1
CEM3	4	30.69*	1		4	22.76**	1
CEL	4	30.53*	1		4	22.86**	1
DM1	9	24.96	0		4	23.64**	1
DM2	4	31.15*	1		4	13.10	0
DM3	3	30.68*	1		4	14.29	0
DL	4	30.76*	1		4	14.10	0
SSM1	9	22.42	0		7	21.33**	1
SSM2	4	37.19**	1		4	9.29	0
SSM3	3	32.94*	1		3	10.97	0
SSL	4	31.05*	1		3	10.16	0

Notes: a) Sample period: quarterly data, 1960:1-1998:3.
b) C.V denotes cointegrating vectors.
**: Significant at 1% level. *: Significant at 5% level. The critical values for 1% and 5% significance levels are 35.65 and 29.68 respectively for the model including money, real GNP, and prices, and 20.04 and 15.41 for the model including money and nominal GNP.

Tests reported are the maximum eigenvalue tests of the null hypothesis that there are r cointegrating vectors, against the alternative that there are $r+1$ cointegrating vectors. The test statistics is given by:

$$Max\ Eigenvalue\ Test = TR_r - TR_{r+1} \qquad ...(3.6)$$

where TR_r is the trace value of the cointegrating vectors which is defined as:

$$TR_r = -T\sum_{i=r+1}^{p} Ln(1-\hat{\rho}_i^2) \qquad ...(3.7)$$

where T is the number of observations, and $\hat{\rho}^2$ is the squares of the canonical correlation of the residuals obtained from regressing Δy_t on $\Delta y_{t-1}, \Delta y_{t-2}, \ldots, \Delta y_{t-p+1}$, and regressing y_{t-p} on the same regressors.

The lag structure p of the VAR system was determined by minimizing the Schwarz's (1978) criterion. The results suggest that, for all aggregation methods, there is clear evidence of one unique cointegrating vector for all monetary aggregates broader than M1 when the VAR models include money, real output, and prices (model specification one). As for the long-run equilibrium relationship between money and nominal output (model specification two), all the CE aggregates (except at the narrowest level) are significantly cointegrated with nominal output. In contrast, only the very narrow D and SS aggregates (DM1 and SSM1) are significantly cointegrated with nominal output.

Based on these results, an error-correction term has to be included in the VAR system where there exists a long-run relationship (cointegration) between the variables in that system. That is, VEC models have to be estimated. On the other hand, if there is no long-run relationship between the variables included in these models, VAR models in the first difference have to be estimated. This is because all the data series included in these models are found to I(1).

The next section provides a discussion of the relevance of some criticisms of the VAR models.

3.3 Criticisms of VAR Models

The effectiveness of VAR models for forecasting is established and leaves little room for criticism. But the ability to test theories or to determine the effect variables have on one another within the VAR model is subject to much criticism. The critics take one of two forms. The first form is that VAR models appeal to fewer theoretic assumptions; they do not allow for exact measurements or differentiation between competing theories. The fact that this form of criticism is partially true would not under cut the appropriate use of VAR models for the research question here. The goal is to see whether money, measured by CE, D, and SS, has different effects on the economic activity (measured by real and nominal GNP, and prices). It is not to distinguish whether monetary policy affects the economy, for example, as monetarists or new Keynesians would suggest. VAR models are perfectly suited to purpose here. It should be noted, however, that although VAR models can not be used to test explicitly any particular theory, the results obtained from these models can often be used to support one of two contradictory theories. For example, if this research suggests that money lead movements in GNP, then it will indirectly lend support to monetarism or new Keynesian economics over real business cycle theory.

The second form of criticism is based on the fact that VAR results are not robust. For example, parameter estimates and innovation accounting results could change if changes are made to the model. Most of those who criticize VAR models on the grounds that they are not robust use Sims' (1980a) paper as a base. Authors who have done this include Runkle (1987), Spencer (1989), and Todd (1990). These authors focus on Sims' result that shows that when an interest rate variable is included in the VAR model money explains only 4 percent of the forecast error variance decomposition of industrial production at 48-month forecast horizon in the postwar period. The subsequent studies make some changes in Sims' model and report different results. The biggest difference in findings is that money accounts for a larger portion of the unanticipated fluctuations in industrial production (from 4 percent found by Sims to around 20 or 30 percent). Some of the changes made include adding a trend as an exogenous variable, using different data frequency and changing the specific series used to represent other variables (e.g., replacing producer price index with consumer price index to measure inflation). Changes such as these would most likely lead to significant effects on the results from any statistical procedure. Valid criticisms, which are specific to VAR models, that can at times significantly change the results, include different triangularizations of the system to allow for a reordering of the recursive entrance of the contemporaneous errors and changes in the lag length of the variables.

Therefore, it is important to properly determine the optimal lag length of the VAR models using specific statistical criterion (SC as mentioned earlier is used). Also various ordering of the model's variables will be considered throughout estimation. If reordering a system's variables changes the implied dynamic behavior, it would suggest that VAR models are not appropriate tools for such analysis. On the other hand, if the estimates are robust through different changes, this lends further support to the results.

The next chapter presents the empirical findings of the study. Several VAR and VEC models are estimated to evaluate the performance of monetary aggregates (at the four conventional levels of aggregation) across CE, D, and SS aggregation methods.

CHAPTER FOUR

EMPIRICAL RESULTS

This chapter reports the empirical findings of the performance of money measured by currency equivalent (CE), Divisia (D), and simple sum (SS). Attention focuses on the ability of the respective aggregates to explain variability of output and prices within the frameworks of Vector Autoregression (VAR) and Vector Error Correction (VEC) models. Two model specifications are estimated. The first specification includes money, real GNP, and prices. This specification allows us to disentangle real impact from inflation impacts, which is of interest to macro modelers and policy makers. The second specification, which matches that in several previous studies (see for example Serletis and King, 1993, Friedman and Kuttner, 1992, and Barnett, Offenbacher, and Spindt, 1984), allows comparison with existing studies in the literature that assess SS versus D. The addition of CE results (in the same model specification) will fill out the available evidence in the literature. The variables included in the second specification are nominal GNP and money. In each specification, a total of twelve models are estimated: 3 aggregation methods x 4 levels of monetary aggregation. Previous studies do not provide such a comprehensive assessment of weighted monetary aggregates at the four levels of aggregation. Results here allow for rich comparison across different monetary measures and across the spectrum of aggregation levels.

The lag structure of each VAR system is determined by Schwarz's (1978) criterion (SC), where the model with the lowest SC value is selected. Furthermore, cointegration tests, which are presented in chapter three, are used to determine whether to include an error-correction term in the VAR models. If there exists any cointegrating vector between the set of the integrated variables (i.e., I (1) variables) included in the VAR system, then an error-correction term has to be added to the system. In other words, a VEC model should be estimated. Estimating a standard VAR model using first difference would be inappropriate and entails a misspecification error by omitting an error correction representation (see: Engle and Granger, 1987). On the other hand, if no evidence of cointegration exists, standard VAR models are estimated using the first difference of the data. Appendix A (Tables A.1 and A2) reports the variables included in each model specification, the optimal lag structure, and the number of cointegration vectors in each model specification.

In empirical applications, the main tools that are used in the analysis of the dynamic simulation of VAR or VEC models are impulse response functions (IRFs), forecast error variance decomposition (FEVDs), and Granger causality tests. This study uses the first two tools, which provide an effective and convenient means to assess the dynamic relationships between the variables in the estimated systems.[21]

This chapter is divided into two sections. The first section presents the empirical results from IRFs and FEVDs for the first model specification, that is the models that

[21] IRFs and FEVDs tools enable us to directly compare the effect of the respective monetary aggregates measured by the different aggregation methods on the economic activity. Granger causality tests do not allow us to make such comparisons.

include money, real GNP, and prices. Section 4.2 presents similar results for the second model specification, which includes money and nominal GNP.

4.1 Model Specification One: Real GNP, Money, and Prices

In this specification, three variables are included in each VAR or VEC system: money (as measured by CE, D, and SS aggregation methods), real GNP, and prices.[22] These models are similar to Sims (1980a), except that no interest rate variable is included. For the D or SS aggregation schemes, including or excluding an interest rate variable (90-day Treasury bill rate) in the VAR or VEC system did not change the basic dynamic relationships between money and output. As mentioned previously, the CE aggregation method already includes an interest rate variable in the construction of the aggregates. When an interest rate variable (90-day Treasury bill rate) is included in the CE systems, this magnifies the effect of money on output. The ordering of the variables in each system is the same as that of Sims' (1980a). This ordering is money, prices, and real GNP. However, changing the ordering of the variables in each system did not change the general pattern of the results.

A full characterization of each model, using for example impulse response functions, would require presenting 108 (3^2 x 12) individual representations. This study focuses on comparing the empirical performance of different monetary aggregates in predicting variation in output and prices. It does not examine the

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[22] Prices are measured by the change in the quarterly GNP deflator (inflation rate) since the GNP deflator is found to be I (2).

empirical evidence in support of a certain macroeconomic theory, but rather focuses on the respective aggregates' performance. Therefore, the following sections present empirical evidence from IRFs and FEVDs that are directly related to the comparisons of monetary aggregates as measured by CE, D, and SS aggregation methods.

4.1.1 Empirical Evidence from Impulse Response Functions

An impulse response function traces the effect of a one-unit shock to innovations in one of the variables upon current and future values of the endogenous variables. The IRFs presented in this subsection are real GNP and inflation rate responses following a positive one standard deviation shock to money, as measured by currency equivalent, Divisia, and simple sum aggregation methods at the four levels of monetary aggregation.

Figures 4.1 through 4.4 display the IRFs for these money, real output impacts. The real output response to M1 shocks (across all aggregation methods) is markedly different from patterns for broader aggregates. This is consistent with evidence found in other studies (see for example Schunk, 1999). Results indicate that a positive shock to M1 increases real GNP (one year for CEM1; and for two years for both DM1 and SSM1) before it turns persistently negative for all aggregates. The positive impact of DM1 and SSM1 is stronger and lasts longer than CEM1. However, the most notable feature in the M1 results is their stark contrast to results for all broader aggregates. These findings are consistent with evidence elsewhere of the lack of a reliable link

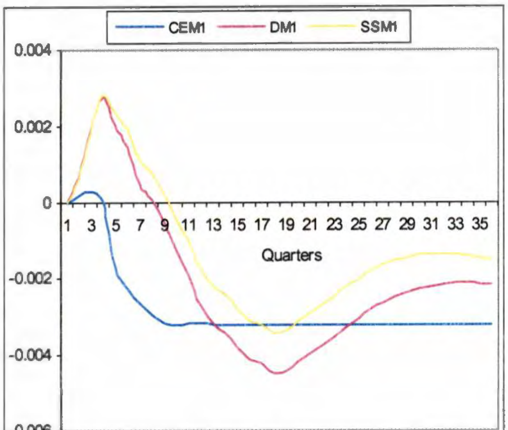

Figure 4.1: Real GNP Response to M1 shock

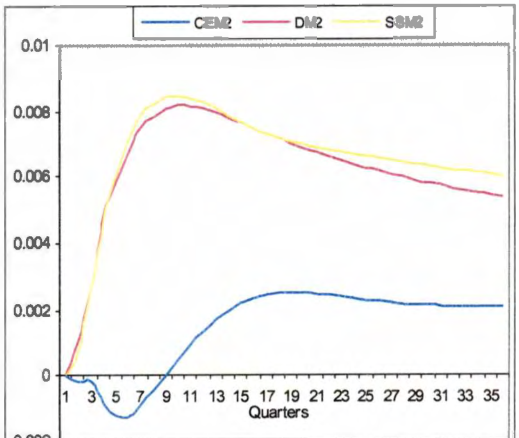

Figure 4.2: Real GNP Response to M2 shock

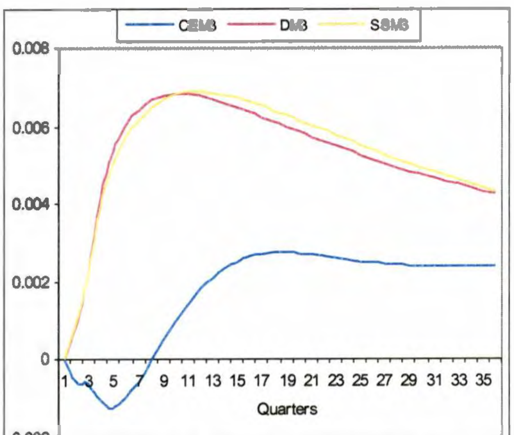

Figure 4.3: Real GNP Response to M3 shock

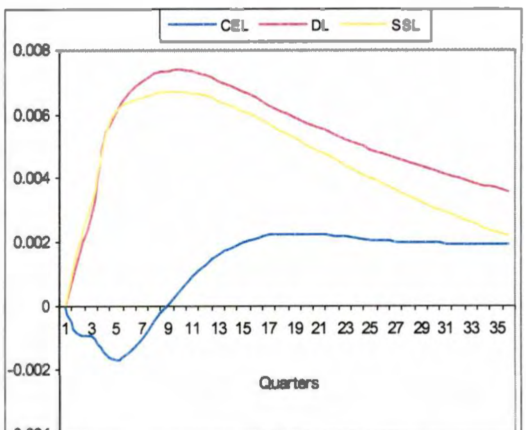

Figure 4.4: Real GNP Response to L shock

between M1 and real output. Results here add to the body of evidence indicating that M1 does not provide useful information to policy makers.

At broader levels of monetary aggregation, the most noticeable result of this analysis is the response of real output to a positive impulse in the currency equivalent aggregates. Across all levels of aggregation, the CE impacts are distinct from the other aggregation methods. The real output response to CE shocks does not correspond to the predictions of the standard macroeconomic models, which predict that an increase in money leads to an increase in output in the short run but not in the long run. In general, the CE results for IRFs (above) seem unusual.

The IRF results indicate that a positive shock to CE initially reduces real output followed by more persistent positive impacts, though weaker than D and SS impacts. Consider the response of real GNP to a shock in CEM2. An increase in CEM2 reduces real output for the first seven quarters reaching a minimum (at –0.00125) after five quarters. Two years later, the impact of money on real output is reversed. From the eighth quarter onwards, real output increases and reaches a maximum (at around 0.00253) after eighteen quarters. After eight years, the positive effect of CEM2 shock on real GNP persists and there is no evidence of decay. Thus, CE results point to non-neutral monetary impacts in the long run. Similar results of real output responses to shocks in currency equivalent aggregates emerge at M3 and L levels of monetary aggregation. Shocks to D and SS aggregates, which are discussed further below, do not indicate the initial negative impact suggested by the CE aggregates. These impacts are positive but subsiding in the long run.

As noted, the CE results consistently show unusual patterns. However, a close look at the sources of the positive shock in the currency equivalent monetary aggregates could explain the pattern shown for real GNP responses to these shocks. From the CE equation ($CE_t = \sum_{i=1}^{n} \frac{r_{bt} - r_{i,t}}{r_{bt}} m_{i,t}^*$), two sources could potentially cause currency equivalent aggregates to increase. The first is an increase in the quantities of the monetary assets ($m_{i,t}$), and the second is an increase in the weights of the monetary assets included in these aggregates $(r_{bt}-r_{i,t})/ r_{bt}$. For example, the average growth rate of currency equivalent M2 is 2.13% during the study period, while that for SSM2 is 1.72%.[23] This means that 0.41% of the growth rate in CEM2 aggregate comes from the increases in the weights of the assets included in this aggregate. These increases in the weights and consequently CE aggregates "are largely associated with increases in interest rates" (Rotemberg et al., 1995, p.79).

The above-mentioned sources of increases in CE aggregates have offsetting effects on real output. An increase in the quantities of the monetary assets has a positive effect on real output, as is evident from the response of real GNP to shocks in simple sum aggregates (which are driven purely by asset quantity changes in the aggregates). But, as theory and empirical evidence suggest, the response of real output is negative to increases in interest rates (for an empirical evidence, see: Sims, 1980a, and Rotemberg, Driscoll, and Poterba, 1995).

[23] The average growth rates of CEM3, SSM3, CEL, and SSL are 2.18%, 1.91%, 1.99%, and 1.87% respectively.

The real GNP impulse response functions presented in figures 4.1-4.4 suggest that the effect of the interest rate component in the CE monetary aggregates on real output may be stronger than the effect of assets' quantities component in these aggregates for the first two years. Therefore, a positive shock to CE aggregates decreases output for the first seven quarters before it turns persistently positive afterwards.

For comparison purposes, the same figures display the impulse response of real GNP to shocks in Divisia and simple sum monetary aggregates. A positive shock to either Divisia or simple sum M2, M3 or L do correspond to the predictions of macroeconomics models such that it appears both simple sum and Divisia shocks are non-neutral in the short run while they tend to be neutral in the long run. The effects of Divisia and simple sum shocks stand in contrast to CE results. Real output results for D and SS are more similar to each other than to CE patterns, particularly at M2 and M3 levels of monetary aggregation. Both of these aggregation methods indicate that a monetary stimulus positively affects real output initially and reaches a peak and then decay slowly over time.

Among the weighted monetary aggregation methods, CE and D, it is clearly evident that, even though both of them are theoretically valid indices, their empirical performance is different. A positive shock to any of the Divisia aggregates has a positive and stronger impact on real GNP than CE aggregates in the short run. Impacts revealed by the Divisia aggregates appear to be neutral in the long run. Evidence from CE monetary aggregates indicates more persistent, though weaker, effect than Divisia monetary aggregates. The same pattern of results appears when comparing CE aggregates to their simple sum counterparts. In interpreting results here, it is useful to keep in mind the extreme volatility of the CE aggregates reported in section 3.2 summary statistics. The unusual CE results here in the IRFs should not be surprising, given this earlier evidence on CE movements.

Figures 4.5 through 4.8 present the impulse response functions of the inflation rate following a positive shock to money measured by CE, D, and SS aggregation methods. At the narrowest level of monetary aggregation (M1) all the three aggregates indicate similar effects on inflation rate, but again M1 results do not match patterns for broader aggregates. Results suggest that an increase in M1 leads to a seemingly permanent increase in inflation with an initial sharp response, then some moderation over time. The currency equivalent effect reaches a peak (at 0.0006) after seven quarters before it declines to around 0.0002 and persist at that level, while both Divisia and simple sum effects reach a maximum (at 0.0009) after three years. CEM1 results indicate weaker inflation impacts from a monetary shock than do DM1 and SSM1.

At broader levels of monetary aggregation, the response of the inflation rate to shocks in CE, D, and SS aggregates are quite different than M1 level. As found with real output, the CE results are different than D and SS impacts. Shocks to Divisia and simple sum aggregates show an initial negative impact on the inflation rate. These impacts turn positive after 5 quarters, and show some persistent over time. After 8 years, inflation impacts are still positive after a positive monetary shock. Shocks to CE

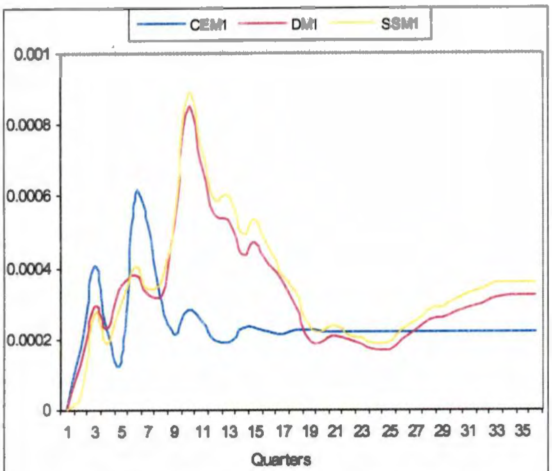

Figure 4.5: Inflation Response to M1 shock

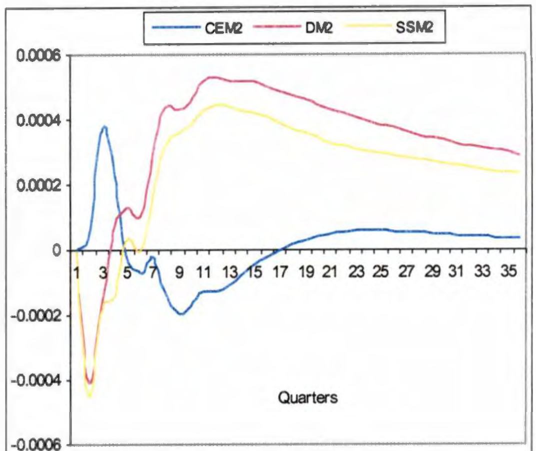

Figure 4.6: Inflation Response to M2 shock

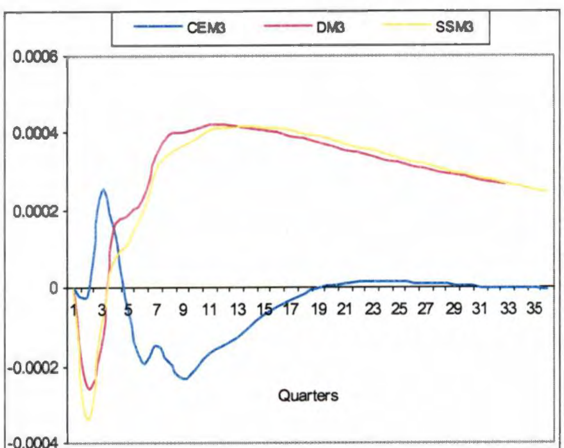

Figure 4.7: Inflation Response to M3 shock

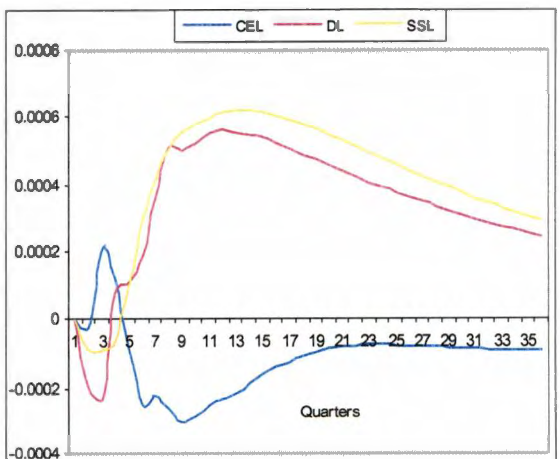

Figure 4.8: Inflation Response to L shock

aggregates indicate that the inflation rate initially increases then decreases and becomes negative for about two years. After 15 quarters, these impacts settle towards zero.

Consider the response of inflation to a shock in M2. CE results indicate that a positive monetary shock increases the inflation rate for the first 3 quarters, while a positive shock to DM2 and SSM2 reduces the inflation rate during the same period. After five quarters the effect of DM2 and SSM2 shocks are positive and tend to decay slowly after reaching a maximum after three years. These impacts appear be stronger and last longer that CEM2 impacts. On the other hand, CEM2 results indicate that the impacts on the inflation rate are fluctuating during the first 4 years and then converging to zero after that. The CE results suggest weaker monetary impacts on inflation compared to the DM2 and SSM2 evidence. As is evident in Figures 4.7 and 4.8 similar patterns emerge for broader aggregates and inflation impacts.

Divisia and SS results suggest consistent inflation responses to a monetary stimulus. For the M2 level, DM2 shock has a relatively stronger effect on the inflation rate and seems to last longer that the effect of SSM2 shock, while SSL shock has a stronger effect and lasts longer than DL.

The previous analysis of impulse response functions for real GNP and prices show that the impulse response functions for currency equivalent aggregates are quite different than their Divisia and simple sum counterparts. Shocks to currency equivalent aggregates indicate relatively weak but persistent effects on both real and nominal economic activity. The Divisia and simple sum results show patterns that are more consistent with predictions of theory and empirical evidence elsewhere.

The next subsection presents further empirical evidence on the performance of CE, D, and SS monetary aggregates. The performance of these aggregates is compared in terms of their relative ability to explain future variations in real and nominal economic activity. The tool used to accomplish this goal is the forecast error variance decomposition (FEVD) within the frameworks of VAR and VEC models.

4.1.2 Empirical Evidence from Forecast Error Variance Decompositions

FEVD gives the percentage of the forecast error variance of a variable y_{it} that could be attributed to each of the endogenous variables at different forecasting horizons. This tool will be used to compare the ability of money (defined by CE, D, and SS at the four levels of monetary aggregation) to explain the variations in output and prices at different forecasting periods. The results provide evidence on which of these aggregation methods (CE, D, or SS) and/or levels of monetary aggregation (M1 through L) can better explain the forecast error variance of real output and prices. Furthermore, FEVDs will be used to provide evidence on the endogeneity of money by presenting the percentage of money variation explained by its own innovations.

Tables 4.1 through 4.4 present the forecast error variance decomposition for real GNP using money as measured by CE, D, and SS at the four conventional levels of monetary aggregation. Results indicate that CE aggregates are dominated by both D and SS aggregates explanatory power, particularly at levels of aggregation broader

Table 4.1
Forecast Error Variance Decomposition of Real GNP for M1 [a]

Forecast Horizon (Qtr)	Innovations By		
	CEM1	DM1	SSM1
2	0.10	3.17	3.05
4	0.71	4.46	4.83
6	2.02	2.92	3.52
8	3.10	2.00	2.44
10	3.77	1.94	1.94
12	4.14	2.70	2.05
14	4.40	3.76	2.49
16	4.60	5.00	3.13
18	4.74	6.15	3.77
20	4.86	6.81	4.10
22	4.95	7.09	4.19
24	5.03	7.12	4.13

a) All entries are percentages.

Table 4.2
Forecast Error Variance Decomposition of Real GNP for M2 [a]

Forecast Horizon (Qtr)	Innovations By		
	CEM2	DM2	SSM2
2	0.03	7.17	6.88
4	0.58	21.31	22.13
6	0.66	30.09	32.07
8	0.49	34.88	37.11
10	0.47	37.07	39.34
12	0.72	37.82	40.02
14	1.14	37.74	39.84
16	1.62	37.20	39.23
18	2.08	36.41	38.40
20	2.46	35.47	37.47
22	2.76	34.46	36.49
24	3.00	33.42	35.50

a) All entries are percentages.

Table 4.3
Forecast Error Variance Decomposition of Real GNP for M3[a]

Forecast Horizon (Qtr)	Innovations By		
	CEM3	DM3	SSM3
2	0.48	5.25	5.24
4	0.80	17.28	15.60
6	0.63	23.82	21.44
8	0.48	26.83	24.43
10	0.62	27.92	25.70
12	1.05	27.96	25.96
14	1.63	27.43	25.64
16	2.23	26.59	24.99
18	2.77	25.58	24.15
20	3.22	24.50	23.20
22	3.58	23.40	22.22
24	3.85	22.3	21.22

a) All entries are percentages.

Table 4.4
Forecast Error Variance Decomposition of Real GNP for L[a]

Forecast Horizon (Qtr)	Innovations By		
	CEL	DL	SSL
2	1.10	9.18	11.98
4	1.57	24.08	24.90
6	1.32	30.94	29.65
8	0.96	33.39	31.09
10	0.84	33.97	31.15
12	1.01	33.57	30.40
14	1.32	32.62	29.23
16	1.70	31.38	27.84
18	2.05	30.00	26.35
20	2.35	28.58	24.85
22	2.58	27.15	23.38
24	2.76	25.77	21.96

a) All entries are percentages.

than M1. At the M1 level of aggregation, none of the aggregates is clearly dominant in explaining real GNP variations. Divisia M1 aggregate is marginally better than CEM1 and SSM1 at long forecasting horizons. For example, after twenty-four quarters, the share of real GNP variance accounted for by DM1 is 7.12% in comparison to 5.03% and 4.13% accounted by CEM1and SSM1 respectively. These results suggest that M1 level is unsuccessful in explaining future output movements, regardless of aggregation method. This is consistent with previous results showing weak performance at the M1 level.

At broader levels of monetary aggregation, the results are quite different. The ability of the Divisia monetary aggregates to explain the forecast error variance of real GNP clearly dominates the CE aggregates at all levels of aggregation and all forecasting horizons. For example, at the M2 level, innovations in money as measured by CE explain less than 3% of real output future variations at all forecasting horizons. On the other hand, DM2 explains 30-38% of real GNP forecast error variance after six quarters. The same pattern arises for M3 and L levels of monetary aggregation.

In results here, the FEVDs of Divisia and simple sum aggregates are very similar. At the M2 level, SSM2 and DM2 results are very similar. After six quarters SSM2 explains 32-40% of the real GNP variations, and DM2 explains 32-38%. At the M3 and L levels of monetary aggregation, Divisia aggregates are marginally better than simple sum aggregates. For example, an innovation in DL explains 30-34% of the forecast error variance of real GNP after six quarters, while SSL explains 29-32% after the same forecasting period. These results differ from results found elsewhere using similar techniques. For example, Schunk (1999) study finds that Divisia aggregates always perform better than simple sum aggregates in explaining the forecast error variance of real output. These differences might be attributed to the different econometric modeling used in Schunk's study. He uses Structural Vector Autoregression (SVAR) models, where a set of theoretical restrictions are imposed on the reduced form VAR, to evaluate the performance of Divisia aggregates against their simple sum counterparts. Further, the set of variables used in Schunk's study is different than those used in this study. He uses a set of five variable models (real output, unemployment, prices, wages and money) as opposed to three variable models (real output, inflation, and money) used here.

Tables 4.5 through 4.8 present similar results for the quarterly inflation rate.[24] They provide the forecast error variance decomposition of the inflation rate attributed to innovation in money, as measured by CE, D, and SS aggregation procedures at the four levels of aggregation.

At all levels of monetary aggregation, it is clearly evident that CE aggregates explanatory power is lower than Divisia and simple sum aggregates in explaining the forecast error variance of the inflation rate. CEM1 is the best aggregate among the CE aggregates, but it is still inferior to its Divisia and simple sum counterparts. For example, after 10 quarters CEM1 explains 4.06% of the variations in the inflation rate, while DM1 and SSM1 explain 9.52% and 10.41% respectively. At broader levels of monetary aggregation, the ability of CE aggregates to explain the forecast error

[24] The inflation rate is considered because the price level is found I (2) process.

Table 4.5
Forecast Error Variance Decomposition of the Inflation Rate for M1 [a]

Forecast Horizon (Qtr)	Innovations By		
	CEM1	DM1	SSM1
2	2.22	1.40	1.04
4	2.17	2.98	2.16
6	4.84	3.95	3.64
8	4.42	5.31	5.42
10	4.06	9.52	10.41
12	3.68	10.31	11.60
14	3.46	10.68	12.28
16	3.27	10.83	12.47
18	3.13	10.51	12.13
20	3.00	10.12	11.69
22	2.90	9.70	11.18
24	2.82	9.23	10.63

a) All entries are percentages.

Table 4.6
Forecast Error Variance Decomposition of the Inflation Rate for M2 [a]

Forecast Horizon (Qtr)	Innovations By		
	CEM2	DM2	SSM2
2	1.64	2.11	2.58
4	1.63	1.71	2.05
6	1.11	1.74	1.55
8	1.07	3.18	2.31
10	0.99	4.64	3.26
12	0.90	6.11	4.31
14	0.79	7.32	5.14
16	0.70	8.29	5.77
18	0.62	9.05	6.22
20	0.58	9.65	6.57
22	0.54	10.13	6.84
24	0.51	10.53	7.06

a) All entries are percentages.

Table 4.7
Forecast Error Variance Decomposition of the Inflation Rate for M3 [a]

Forecast Horizon (Qtr)	Innovations By		
	CEM3	DM3	SSM3
2	0.73	0.91	1.32
4	0.76	1.12	1.12
6	0.80	1.89	1.66
8	0.97	3.27	2.80
10	1.00	4.50	4.02
12	0.94	5.57	5.21
14	0.84	6.46	6.27
16	0.75	7.20	7.20
18	0.67	7.81	8.00
20	0.61	8.31	8.67
22	0.56	8.73	9.25
24	0.52	9.08	9.74

a) All entries are percentages.

Table 4.8
Forecast Error Variance Decomposition of the Inflation Rate for L [a]

Forecast Horizon (Qtr)	Innovations By		
	CEL	DL	SSL
2	0.52	1.05	0.17
4	0.56	0.93	0.25
6	0.98	1.65	1.75
8	1.41	3.94	4.52
10	1.59	5.98	7.21
12	1.59	7.88	9.85
14	1.51	9.43	12.18
16	1.40	10.67	14.21
18	1.29	11.66	15.92
20	1.20	12.44	17.35
22	1.11	13.07	18.54
24	1.05	13.57	19.52

a) All entries are percentages.

variance of the inflation rate deteriorates, even relative to CEM1's weak results, and CE results are notably weaker than Divisia and simple sum counterparts. Consider the M2 level of monetary aggregation. CEM2 explains less than 2% of the inflation rate future variations at forecasting horizons shorter than 10 quarters and less than 1% for longer forecasting periods. On the other hand, DM2 and SSM2 explain 10.53% and 7.06% of the inflation rate forecast error variance decomposition after 24 quarters. Similar results emerge at M3 and L levels of monetary aggregation.

As for the performance of Divisia versus simple sum aggregates, neither aggregate clearly dominates at all aggregation levels and all forecasting horizons in explaining the variations in the inflation rate. For the frequently examined M2 aggregation level, D aggregate performs slightly better than SS for all forecasts beyond 4 quarters. At the broadest level of aggregation (L), simple sum aggregate performs better than Divisia aggregate. After two years, 4-20% of the inflation rate variation is attributed to innovation in the SSL aggregate, while the DL aggregate explains 3-14% of the inflation rate variation.[25]

The empirical evidence presented above suggests that the ability of CE aggregates to explain the FEVD of real output and inflation is notably weaker than that of Divisia and simple sum counterparts. At all levels of aggregation and all forecasting horizons, CE aggregates performance is always dominated by D and SS aggregates. The weak explanatory power of CE aggregates (as shown in FEVD)

[25] Schunk's (1999) study suggests that simple sum aggregates always perform better than Divisia aggregates in explaining the FEVD of prices particularly at levels of aggregation broader than M1.

suggest that they are less useful in applied work as a measure of money than the alternative measures (D and SS). Furthermore, CE aggregates are less useful intermediate policy targets than D and SS aggregates to predicting real output and prices.

Another goal that could be accomplished by using FEVDs is to provide empirical evidence on the endogeneity of money hypothesis. If a high percentage of the forecast error variance of money is explained by innovations in other variables (real output and inflation rate) in the system at all forecasting horizons, then a strong argument could be made to support the endogeneity hypothesis. On the other hand, if shocks in money explain most the forecast error variance of money, a strong case could be established against the endogeneity hypothesis.

Tables 4.9 through 4.12 give the percentage of the forecast error variance of money (defined by the different aggregation methods) attributed to its own innovations. Results indicate that for all the monetary aggregates, regardless of the aggregation method or the aggregation level, a high percentage of the variability in money is explained by money shocks at all forecasting horizons. For all aggregation methods and levels, at least 89% of the movements in money during the first four quarters are explained by own shocks. That means that shocks to other variables in the system have only a small impact on the evolution of money. These results are consistent with money being exogenous.

Table 4.9
Forecast Error Variance Decomposition of M1 [a]

Forecast Horizon (Qtr)	Innovations By		
	CEM1	DM1	SSM1
2	99.37	97.01	96.00
4	98.54	93.00	89.59
6	98.15	86.51	80.78
8	97.23	80.07	73.40
10	96.70	76.46	69.47
12	96.35	73.99	66.89
14	96.13	72.01	64.84
16	95.96	70.77	63.52
18	95.83	70.00	62.68
20	95.72	69.62	62.26
22	95.63	69.54	62.13
24	95.56	69.56	62.11

a) All entries are percentages.

Table 4.10
Forecast Error Variance Decomposition of M2 [a]

Forecast Horizon (Qtr)	Innovations By		
	CEM2	DM2	SSM2
2	99.41	99.01	98.98
4	94.28	98.58	98.15
6	93.86	99.09	98.47
8	92.92	99.39	98.90
10	91.51	99.16	98.73
12	88.07	98.33	97.51
14	82.63	96.97	95.14
16	76.35	95.26	91.88
18	70.22	93.33	88.10
20	64.83	91.32	84.16
22	60.32	89.31	80.29
24	56.62	87.36	76.59

a) All entries are percentages.

Table 4.11
Forecast Error Variance Decomposition of M3 [a]

Forecast Horizon (Qtr)	Innovations By		
	CEM3	DM3	SSM3
2	99.23	99.58	99.40
4	93.05	99.08	98.71
6	92.06	98.97	98.58
8	91.21	99.16	98.81
10	90.77	99.38	99.07
12	88.87	99.51	99.26
14	85.01	99.54	99.34
16	79.92	99.45	99.29
18	74.54	99.26	99.13
20	69.57	98.98	98.87
22	65.29	98.63	98.52
24	61.69	98.23	98.12

a) All entries are percentages.

Table 4.12
Forecast Error Variance Decomposition of L [a]

Forecast Horizon (Qtr)	Innovations By		
	CEL	DL	SSL
2	99.07	99.61	99.19
4	91.75	98.59	97.29
6	89.54	97.85	96.73
8	87.76	97.44	96.63
10	87.22	97.14	96.56
12	85.94	96.78	96.45
14	83.28	96.34	96.28
16	79.50	95.82	96.06
18	75.26	95.24	95.80
20	71.14	94.62	95.51
22	67.46	93.98	95.20
24	64.28	93.33	94.88

a) All entries are percentages.

Several studies in the literature evaluate the monetary aggregates within a two variable (money and nominal output) model. To allow comparisons with these previous studies, the next section presents empirical evidence on the relative performance of the monetary aggregates (CE, D, and SS) within the context of two variable VAR or VEC models. As before, IRFs and FEVDs evidence is provided.

4.2 Model Specification Two: Money and Nominal GNP

The VAR or VEC models in this specification include only two variables: nominal GNP and money. The models in this specification are similar to those used by Serletis and King (1993), Friedman and Kuttner (1992), and Barnett, Offenbacher, and Spindt (1984). As mentioned previously, they allows comparison with existing studies in the literature, which assess SS versus D. The addition of CE results (in same model specification) will fill out the available set of evidence in the literature. Also, these models provide further evidence on the relative empirical performance of the different aggregates.

As before, money is measured successively by CE, D, and SS aggregation methods at the four levels of aggregation. Therefore, a total of 12 two-variable VAR or VEC models are estimated (3 monetary aggregation methods x 4 levels of aggregation). Appendix A, Table A.2 provides a detailed description of these models.

Following the same argument provided in the previous section, no interest rate variable is included in these models. The ordering of the variables in each VAR or

VEC model is money and nominal GNP. However, changing the order of the variables in each model did not change the general pattern of the results.

The following subsections present empirical evidence on the ability of innovations in the respective monetary aggregates to explain changes in nominal GNP. This evidence is from impulse response functions and forecast error variance decompositions. As before, the performance of CE, D, and SS aggregates is assessed at the four levels of monetary aggregation.

4.2.1 Empirical Evidence from Impulse Response Functions

Figures 4.9 through 4.12 display the impulse response functions for nominal GNP resulting from a positive shock to money, as measured by currency equivalent, Divisia, and simple sum aggregation methods. These functions are generated by a series of two variable VAR or VEC models.

Across all the aggregation methods and at all levels of monetary aggregation except M1, the responses of nominal output to a positive shock in money do accord with the predictions of the standard macroeconomic models: A positive shock to money increases nominal GNP.

Among the weighted monetary aggregates (CE and D), Divisia shocks have a stronger and a more persistent impact on nominal GNP at all levels of monetary aggregation. For example, at the M2 level, the impact of a DM2 shock on nominal output is nearly double the magnitude of the CEM2 shock. Consistent with the results above, the effects of a monetary stimulus upon nominal GNP are similar for D and SS

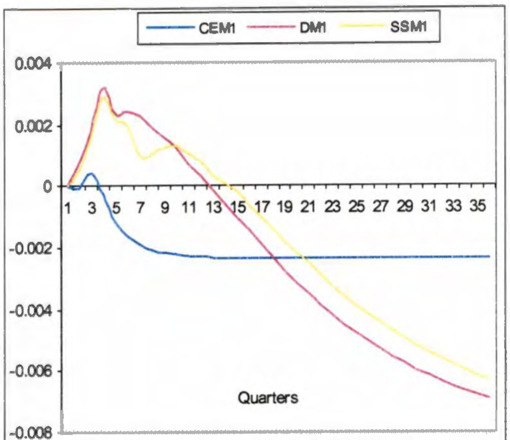

Figure 4.9: Nominal GNP Response to M1 shock

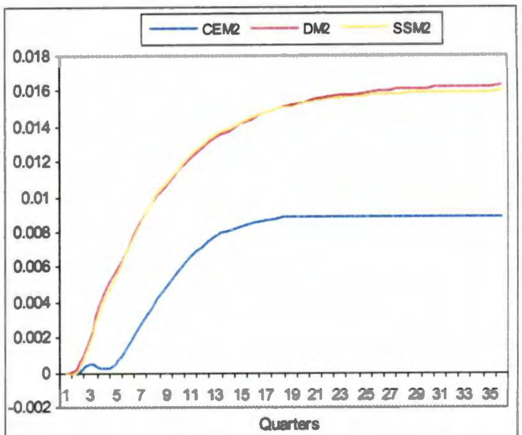

Figure 4.10: Nominal GNP Response to M2 shock

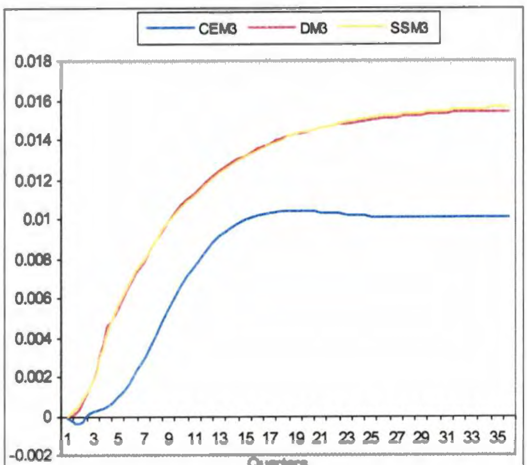

Figure 4.11: Nominal GNP Response to M3 shock

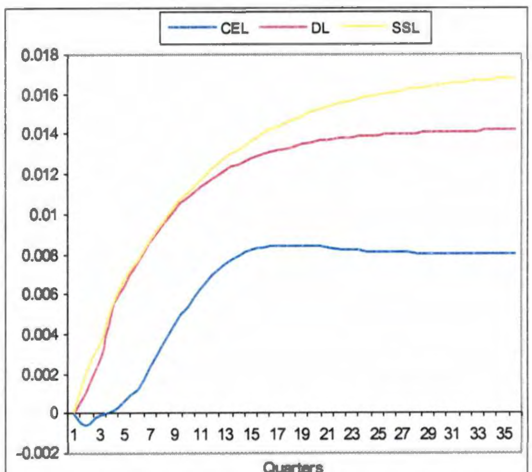

Figure 4.12: Nominal GNP Response to L shock

aggregates, across all levels of aggregation. Both D and SS shocks show notably stronger effects than their CE counterparts. All aggregates seem to have a permanent effect on nominal output. After eight years, none of the impacts shows decay. It is worth mentioning that, when use nominal output, CE impacts do not show the starkly contrasting patterns found earlier in the real output, inflation assessment.

These impulse response function results correspond with those found in the first models' specification. The response of nominal GNP to money shocks is expected to be a composite of real GNP response and prices response to the same shocks. Considering the CE results, for the broader aggregates (above M1) in the first models' specifications, results indicate that in the short run real GNP responds negatively to a positive CE shock (see Figures 4.1-4.4), while the inflation rate responds positively (see Figures 4.5-4.8). Results here showing a positive response of nominal GNP to CE shocks, which indicate that the positive inflation response is stronger than the negative real GNP response in the short run. In the long run both real GNP and inflation responses to CE shocks are positive. For simple sum and Divisia aggregates, the situation is the opposite. Short run inflation impacts were negative after a Divisia or simple sum positive shock (Figures 4.5-4.8) while real output impacts were positive and stronger than the inflation response (Figures 4.1-4.4). As results here indicate the net effect on nominal GNP is positive in the short and the long run.

4.2.2 Empirical Evidence from Forecast Error Variance Decompositions

Tables 4.13 through 4.16 report the forecast error variance decomposition for nominal output at different forecasting horizons. These decompositions are generated by a series of two variable (money and nominal GNP) vector autoregression and vector error correction models.

At the M1 level of monetary aggregation, the behavior of CE, D, and SS aggregates is similar and consistently weak. This is consistent with earlier evidence showing poor performance at the M1 level, across all aggregation methods. Shocks to CEM1, DM1, and SSM1 always explain less than 5% of the forecast error variance decomposition of nominal GNP. The explanatory power of all monetary aggregates improves at broader levels of monetary aggregation. Further, the differences in the respective aggregates (CE, D, and SS) explanatory powers become more evident. All the CE aggregates explanatory power is lower than that of D and SS counterparts. For example, at the M2 level of aggregation, it is clearly evident that DM2 dominates its CE counterpart at all forecasting horizons. After three years, DM2 explains 43% of the forecast error variance of nominal GNP while CEM2 only explains 11%. As before, D and SS results are similar. For example, DM2 is marginally better than SSM2 at short forecasting horizons (less than10 quarters), and SSM2 is marginally better than DM2 at forecasting horizons longer than 10 quarters.

Table 4.13
Forecast Error Variance Decomposition of Nominal GNP for M1 [a]

Forecast Horizon, Qtr	Innovation By		
	CEM1	DM1	SSM1
2	0.13	2.44	1.69
4	0.31	4.63	3.65
6	0.78	4.27	2.74
8	1.13	3.47	2.17
10	1.36	2.68	1.81
12	1.52	2.04	1.43
14	1.63	1.65	1.13
16	1.70	1.50	0.96
18	1.76	1.55	0.92
20	1.81	1.74	1.00
22	1.85	2.03	1.17
24	1.88	2.38	1.41

a) All entries are percentages

Table 4.14
Forecast Error Variance Decomposition of Nominal GNP for M2 [a]

Forecast Horizon, Qtr	Innovation By		
	CEM2	DM2	SSM2
2	0.17	2.39	1.96
4	0.15	14.54	12.84
6	1.23	24.73	23.66
8	3.80	33.03	32.94
10	7.36	39.05	39.91
12	11.02	43.39	45.07
14	14.27	46.59	48.92
16	16.94	49.01	51.83
18	19.07	50.88	54.07
20	20.76	52.36	55.84
22	22.11	53.54	57.25
24	23.20	54.51	58.39

a) All entries are percentages.

Table 4.15
Forecast Error Variance Decomposition of Nominal GNP for M3 [a]

Forecast Horizon, Qtr	Innovation By		
	CEM3	DM3	SSM3
2	0.10	2.02	2.17
4	0.31	12.16	11.70
6	1.55	20.49	20.40
8	4.86	27.56	27.78
10	9.47	33.02	33.73
12	14.30	37.13	38.47
14	18.51	40.28	42.25
16	21.82	42.72	45.27
18	24.30	44.64	47.72
20	26.13	46.18	49.72
22	27.48	47.43	51.37
24	28.52	48.46	52.76

a) All entries are percentages.

Table 4.16
Forecast Error Variance Decomposition of Nominal GNP for L [a]

Forecast Horizon, Qtr	Innovation By		
	CEL	DL	SSL
2	0.18	5.00	9.24
4	0.17	17.57	19.74
6	0.92	25.36	27.46
8	3.05	30.68	33.64
10	6.08	34.45	38.54
12	9.31	37.16	42.46
14	12.19	39.18	45.61
16	14.50	40.72	48.17
18	16.24	41.92	50.27
20	17.53	42.87	52.01
22	18.49	43.63	53.48
24	19.21	44.26	54.71

a) All entries are percentages.

Similar pattern of results emerges when comparing CE, D, and SS aggregates at M3 and L levels of monetary aggregation. CE aggregates forecasting ability is always notably weaker than D and SS aggregates at all forecasting horizons. On the other hand, the ability of SS aggregates to explain variation in nominal GNP is marginally better than the Divisia aggregates, particularly at long forecasting horizons and at the L level of monetary aggregation.

The general pattern of results found in this model specification is consistent with the evidence from the first models' specification based upon real GNP, prices and money. The ability of money, measured by CE, to explain variations in nominal GNP is always dominated by the Divisia and simple sum aggregates at all levels of monetary aggregation.

In results here, although both of the CE and D aggregation methods are theoretically valid, the empirical performance of these two theoretic monetary aggregates is notably different. The empirical evidence on the performance of D and CE aggregates conclusively indicates that CE aggregates explanatory power is weaker relative to D aggregates, and weaker than the atheoretic SS aggregates in predicting economic activity (real GNP, nominal GNP, and inflation). The explanatory power (using FEVD) of the Divisia aggregates is always higher than that of CE aggregates in explaining real GNP, inflation, and nominal GNP. This holds across all levels of monetary aggregation (M1 through L). From these results, it is clearly evident that, even though CE is theoretic, its empirical performance is poor and not informative for empirical work and monetary policy considerations

Furthermore, the CE results suggest some very unusual patterns. The results from IRFs do not accord with those for the other aggregates or predictions of standard theory. The real GNP response to shocks in CE aggregates is notably different than real GNP patterns found using the D and SS aggregates. Results here indicate that a positive shock to CE aggregates reduces real output in the short run, while a positive shock to both D and SS aggregates increases real output. In the long run CE shocks have a more persistent positive, though weaker, impact on real output than the seemingly temporary impact of D and SS shocks.

Comparing the empirical performance of D and SS aggregates, results here indicate that the evidence on the superiority of Divisia monetary aggregates against the simple sum aggregates is not conclusive. The results found here suggest that their empirical performance is similar in most cases.

CHAPTER FIVE

SUMMARY AND CONCLUSIONS

In the past two decades, monetary aggregation methods have become an important issue in empirical macroeconomics and monetary models. The simple sum (SS) monetary aggregation method, which has been used by monetary authorities around the world to prepare monetary aggregates, has long been recognized as theoretically flawed and inconsistent with economic aggregation theory, and index number theory. The problems inherent in this method have become more pronounced since the late 1970s. The fast pace of financial innovation and market deregulation has led to the introduction of a wide range of monetary assets with a mixture of transactions and a store of value characteristics. The simple sum method, which implicitly assumes that all assets are perfect substitutes, is unable to capture the transactions services (degree of liquidity) provided by these new assets. The implicit assumption of perfect substitutability is more likely to be violated the more heterogeneous are the assets being aggregated. Therefore, simple sum monetary aggregates have become less valid as a measure of the quantity of money in the economy. The outcome was a breakdown and instability of the empirical monetary relationships. Simple sum monetary aggregates lost their role as a viable policy tool to predict changes in the economic activity.

As an alternative, weighted monetary aggregation methods have been suggested to overcome the problems inherent in the simple sum method. These methods are theoretically consistent with both aggregation theory and index number theory. In the weighted aggregation methods, an optimal weight is assigned to each monetary asset in the aggregate that could, in principle, capture the transaction services yielded by that individual asset. These weights depend jointly on the quantities and prices of the assets included in the aggregate. The resulting weighted monetary aggregates should provide a more valid measure of monetary services in the economy. Furthermore, they should be more closely related to the final spending in the economy than are the simple sum aggregates.

One of the earliest weighted monetary aggregation methods was advocated and supported by Barnett (1980). In particular, he advocated the use of the Divisia (D) index to construct weighted monetary aggregates. Since then, several empirical studies have been conducted to evaluate the performance of Divisia aggregates against their simple sum counterparts, using different performance criteria. Although aggregation theory strongly favors Divisia aggregates over the simple sum aggregates as a measure of money, the empirical evidence obtained in many of these studies does not show clear dominance of Divisia over simple sum aggregates.

Another weighted aggregation method is the currency-equivalent (CE) index. This index was proposed previously by Hutt (1963) and Rotemberg (1991), but has not been analyzed in depth until recently by Rotemberg, Driscoll, and Poterba in 1995. Rotemberg et al. (1995) provide a complete theoretical derivation and analysis of this index. Few studies exist that evaluate the empirical performance of CE aggregates relative to simple sum or Divisia aggregates. Further, these studies do not evaluate the

CE aggregates at the four levels of monetary aggregation (M1 through L) that are consistent with the standard simple sum aggregation levels. Therefore, a major contribution from this study is providing much needed empirical evidence on the relative performance of weighted monetary aggregates, particularly CE aggregates, at the four levels of monetary aggregation.

In this study, multivariate time series techniques are used to empirically evaluate the relative performance of the different monetary aggregates. In particular, vector autoregression (VAR) and vector error correction (VEC) models are employed to provide evidence on the empirical differences between currency equivalent, Divisia, and simple sum aggregates, in terms of their performance as indicators or predictors of economic activity. These models impose no restrictions regarding the exogeneity or endogeneity of any variable. They are perfectly suited for analyzing macroeconomic and monetary data where no variable is clearly exogenous or endogenous. Further, these models provide a more complete picture of the differences between CE, D, and SS money relative to single equation tests. For the first time, the evaluation is carried across the three aggregation methods and at the four conventional levels of monetary aggregation. This gives us the opportunity to compare the strength of the relationship between the respective aggregates and the economic activity. Such information will be valuable both to policy makers and researchers interested in the monetary-macro relationships in the economy.

Two model specifications have been constructed. The first specification is a three variable (money, real GNP, and inflation) VAR or VEC model, while the second is two variable (money and nominal GNP) VAR or VEC model. This specification allows comparison with previous studies. In each specification, twelve models have been estimated using currency equivalent, Divisia and simple sum aggregation methods at four levels of monetary aggregation. Dynamic simulations of the systems (using impulse response functions, IRFs, and forecast error variance decompositions, FEVDs) suggest that there are important differences between the performance of currency equivalent, Divisia and simple sum monetary aggregates in empirical applications. These differences are particularly larger at levels of aggregation higher than M1.

At the M1 level of monetary aggregation, results here indicate that the behavior of CE, D, and SS aggregates is consistently weak. These findings indicate a lack of a reliable link between the M1 measure of money and the economic activity, regardless of the aggregation method. Results here add to the widely held belief that narrow measures of money do not provide useful information to policy makers about the role of money as a predictor or indicator of economic activity.

At broader levels of monetary aggregation, the empirical differences between CE, D, and SS aggregates are more pronounced, in particular between CE and D aggregates. Although both of the CE and D aggregation methods are theoretically consistent, their empirical behavior is clearly different. Evidence from IRFs and FEVDs indicates that CE aggregates are notably less informative about changes in either real or nominal economic activity, relative to D aggregates. This evidence suggests that CE aggregates are less useful in applied work as a measure of money, and therefore a less useful policy tool than are Divisia aggregates. The same conclusion is drawn when comparing CE aggregates against SS counterparts.

On the other hand, the empirical evidence presented in this study shows a close similarity in the behavior of D and SS aggregates in predicting real and nominal economic activity. Although aggregation theory strongly favors Divisia index over the simple sum index as a measure of money, the empirical evidence presented here does not show consistent superior performance in empirical applications. The results found in this study are consistent with other studies' findings: In some cases D aggregates perform better than SS in predicting the economic activity, in others SS aggregates perform better.

In sum, the empirical evidence obtained here suggests that among the theoretically valid monetary aggregation indices, CE and D, CE index is less favorable as a measure of money than the Divisia index. Also CE aggregates are less favorable than SS aggregates. Based on this evidence a strong case could be made to support the use of Divisia index over CE index as valid measure of money that performs well in applied research. However, the empirical evidence presented in here is not sufficiently robust to assert a clear choice of the theoretic Divisia aggregation method over the atheoretical simple sum method.

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APPENDICES

APPENDIX A

Table A.1
Model Specification One: Real GNP, Money, and Prices
Quarterly Data, 1960:1-1998:3

Model No.	Variables (CEM_i, DM_i, SSM_i, INF, RGNP) [a]	Optimal Lag, SC [b]	Number of Co – integrating Equations	Model Estimated
M1 SYSTEMS				
1	CEM1 INF RGNP	4	0	VAR, D [c]
2	DM1 INF RGNP	9	0	VAR, D
3	SSM1 INF RGNP	9	0	VAR, D
M2 SYSTEMS				
4	CEM2 INF RGNP	4	1	VEC [d]
5	DM2 INF RGNP	4	1	VEC
6	SSM2 INF RGNP	4	1	VEC
M3 SYSTEMS				
7	CEM3 INF RGNP	4	1	VEC
8	DM3 INF RGNP	3	1	VEC
9	SSM3 INF RGNP	3	1	VEC
L SYSTEMS				
10	CEL INF RGNP	4	1	VEC
11	DL INF RGNP	4	1	VEC
12	SSL INF RGNP	4	1	VEC

Notes: a) CEM_i: denotes Currency Equivalent aggregate for i=1,2,3,L. DM_i: denotes Divisia aggregate for i=1,2,3,L. SSM_i: denotes Simple Sum aggregate for i=1,2,3, L. RGNP: is Real GNP at constant 1992 prices. INF: is the Inflation rate as measured by the GNP deflator, 1992=100.
b) SC: denotes Schwartz's (1978) Criterion.
c) VAR, D: is Vector Autoregression estimated in first difference.
d) VEC: is Vector Error Correction model.

Table A.2
Model Specification Two: Nominal GNP and Money
Quarterly Data, 1960:1-1998:3

Model No.	Variables (CEM_i, DM_i, SSM_i, GNP) [a]	Optimal Lag, SC [b]	Number of Co – integrating Equations	Model Estimated
		M1 SYSTEMS		
1	CEM1 GNP	3	0	VAR, D [c]
2	DM1 GNP	4	1	VEC [d]
3	SSM1 GNP	7	1	VEC
		M2 SYSTEMS		
4	CEM2 GNP	3	1	VEC
5	DM2 GNP	4	0	VAR, D
6	SSM2 GNP	4	0	VAR, D
		M3 SYSTEMS		
7	CEM3 GNP	4	1	VEC
8	DM3 GNP	4	0	VAR, D
9	SSM3 GNP	3	0	VAR, D
		L SYSTEMS		
10	CEL GNP	4	1	VEC
11	DL GNP	4	0	VAR, D
12	SSL GNP	3	0	VAR, D

Notes: a) CEM_i: denotes Currency Equivalent aggregate for i=1,2,3,L. DM_i: denotes Divisia aggregate for i=1,2,3,L. SSM_i: denotes Simple Sum aggregate for i=1,2,3, L. GNP: is nominal GNP at current prices.

b) SC: denotes Schwartz's (1978) Criterion.

c) VAR, D: is Vector Autoregression estimated in first difference.

d) VEC: is Vector Error Correction model.

APPENDIX B

Table B.1
Forecast Error Variance Decomposition of Currency-Equivalent Aggregates
(All entries are percentages)

CEM1 Aggregation Level			
Forecast Horizon (Qtr)	CEM1	Inflation	Real GNP
2	99.37	0.28	0.35
4	98.54	1.19	0.27
6	98.15	0.95	0.90
8	97.23	0.86	1.90
10	96.70	0.72	2.57
12	96.35	0.65	2.99
CEM2 Aggregation Level			
	CEM2	Inflation	Real GNP
2	99.41	0.58	0.00
4	94.28	5.59	0.12
6	93.86	6.03	0.11
8	92.92	6.91	0.16
10	91.51	7.12	1.36
12	88.07	7.27	4.65
CEM3 Aggregation Level			
	CEM3	Inflation	Real GNP
2	99.23	0.70	0.06
4	93.05	6.45	0.48
6	92.06	6.96	0.98
8	91.21	7.62	1.16
10	90.77	7.83	1.39
12	88.87	8.01	3.11
CEL Aggregation Level			
	CEL	Inflation	Real GNP
2	99.07	0.81	0.12
4	91.75	7.18	1.06
6	89.54	7.93	2.52
8	87.76	8.89	3.34
10	87.22	9.49	3.28
12	85.94	10.20	3.85

Table B.2
Forecast Error Variance Decomposition of Divisia Aggregates
(All entries are percentages)

DM1 Aggregation Level			
Forecast Horizon (Qtr)	DM1	Inflation	Real GNP
2	97.01	0.33	2.64
4	93.00	0.82	6.17
6	86.51	1.90	11.58
8	80.07	2.74	17.17
10	76.46	2.98	20.55
12	73.99	3.01	23.00
DM2 Aggregation Level			
	DM2	Inflation	Real GNP
2	99.01	0.54	0.44
4	98.58	1.05	0.35
6	99.09	0.74	0.16
8	99.39	0.46	0.14
10	99.16	0.60	0.23
12	98.33	1.21	0.45
DM3 Aggregation Level			
	DM3	Inflation	Real GNP
2	99.58	0.26	0.15
4	99.08	0.87	0.04
6	98.97	0.99	0.03
8	99.16	0.80	0.03
10	99.38	0.58	0.03
12	99.51	0.43	0.05
DL Aggregation Level			
	DL	Inflation	Real GNP
2	99.61	0.39	0.00
4	98.59	1.13	0.27
6	97.85	1.04	1.09
8	97.44	0.75	1.79
10	97.14	0.51	2.34
12	96.78	0.39	2.82

Table B.3
Forecast Error Variance Decomposition of Simple Sum Aggregates
(All entries are percentages)

SSM1 Aggregation Level			
Forecast Horizon (Qtr)	SSM1	Inflation	Real GNP
2	96.00	0.62	3.37
4	89.59	2.20	8.21
6	80.78	4.54	14.66
8	73.40	5.90	20.69
10	69.47	6.57	23.96
12	66.89	6.80	26.30
SSM2 Aggregation Level			
	SSM2	Inflation	Real GNP
2	98.98	0.74	0.28
4	98.15	1.64	0.20
6	98.47	1.40	0.13
8	98.90	0.93	0.16
10	98.73	1.11	0.16
12	97.51	2.36	0.12
SSM3 Aggregation Level			
	SSM3	Inflation	Real GNP
2	99.40	0.53	0.06
4	98.71	1.21	0.07
6	98.58	1.30	0.11
8	98.81	1.06	0.12
10	99.07	0.78	0.15
12	99.26	0.55	0.17
SSL Aggregation Level			
	SSL	Inflation	Real GNP
2	99.19	0.64	0.16
4	97.29	1.28	1.42
6	96.73	1.02	2.24
8	96.63	0.76	2.60
10	96.56	0.52	2.91
12	96.45	0.36	3.18

Table B.4
Forecast Error Variance Decomposition of Real GNP Using Currency-Equivalent Monetary Aggregates
(All entries are percentages)

CEM1 Aggregation Level			
Forecast Horizon (Qtr)	CEM1	Inflation	Real GNP
2	0.10	0.97	98.93
4	0.71	2.51	96.77
6	2.02	3.07	94.89
8	3.10	3.29	93.59
10	3.77	3.41	92.81
12	4.14	3.49	92.36
CEM2 Aggregation Level			
	CEM2	Inflation	Real GNP
2	0.03	0.43	99.53
4	0.58	1.42	97.99
6	0.66	1.72	97.61
8	0.49	2.03	97.47
10	0.47	2.36	97.15
12	0.72	2.72	96.55
CEM3 Aggregation Level			
	CEM3	Inflation	Real GNP
2	0.48	0.45	99.06
4	0.80	1.56	97.63
6	0.63	1.98	97.38
8	0.48	2.47	97.04
10	0.62	2.97	96.40
12	1.05	3.46	95.48
CEL Aggregation Level			
	CEL	Inflation	Real GNP
2	1.10	0.44	98.44
4	1.57	1.53	96.89
6	1.32	1.90	96.77
8	0.96	2.29	96.75
10	0.84	2.66	96.48
12	1.01	3.03	95.95

Table B.5
Forecast Error Variance Decomposition of Real GNP Using Divisia Monetary Aggregates
(All entries are percentages)

DM1 Aggregation Level			
Forecast Horizon (Qtr)	DM1	Inflation	Real GNP
2	3.17	1.14	95.68
4	4.46	3.75	91.78
6	2.92	6.35	90.72
8	2.00	9.02	88.97
10	1.94	11.35	86.70
12	2.70	11.80	85.49
DM2 Aggregation Level			
	DM2	Inflation	Real GNP
2	7.17	1.02	91.80
4	21.31	4.49	74.19
6	30.09	9.09	60.81
8	34.88	14.05	51.06
10	37.07	18.62	44.30
12	37.82	22.78	39.39
DM3 Aggregation Level			
	DM3	Inflation	Real GNP
2	5.25	1.96	92.78
4	17.28	7.90	74.81
6	23.82	14.87	61.30
8	26.83	20.92	52.25
10	27.92	26.16	45.91
12	27.96	30.79	41.24
DL Aggregation Level			
	DL	Inflation	Real GNP
2	9.18	1.36	89.45
4	24.08	6.13	69.79
6	30.94	11.76	57.29
8	33.39	17.17	49.43
10	33.97	22.04	43.97
12	33.57	26.58	39.84

Table B.6
Forecast Error Variance Decomposition of Real GNP Using Simple Sum Monetary Aggregates
(All entries are percentages)

SSM1 Aggregation Level			
Forecast Horizon (Qtr)	SSM1	Inflation	Real GNP
2	3.05	1.15	95.78
4	4.83	3.74	91.42
6	3.52	6.27	90.19
8	2.44	8.75	88.81
10	1.94	10.87	87.18
12	2.05	11.22	86.72
SSM2 Aggregation Level			
	SSM2	Inflation	Real GNP
2	6.88	0.64	92.47
4	22.13	3.13	74.73
6	32.07	7.38	60.55
8	37.11	12.72	50.16
10	39.34	17.63	43.02
12	40.02	22.08	37.89
SSM3 Aggregation Level			
	SSM3	Inflation	Real GNP
2	5.24	1.83	92.92
4	15.60	7.99	76.40
6	21.44	15.46	63.09
8	24.43	21.86	53.70
10	25.70	27.32	46.97
12	25.96	32.03	42.00
SSL Aggregation Level			
	SSL	Inflation	Real GNP
2	11.98	1.41	86.60
4	24.90	6.70	68.38
6	29.65	12.80	57.53
8	31.09	18.89	50.01
10	31.15	24.54	44.31
12	30.40	29.71	39.88

Table B.7
Forecast Error Variance Decomposition of Inflation Rate Using Currency-Equivalent Monetary Aggregates
(All entries are percentages)

CEM1 Aggregation Level			
Forecast Horizon (Qtr)	CEM1	Inflation	Real GNP
2	2.22	97.66	0.11
4	2.17	95.38	2.45
6	4.84	84.08	11.07
8	4.42	78.53	17.05
10	4.06	75.07	20.86
12	3.68	72.81	23.49
CEM2 Aggregation Level			
	CEM2	Inflation	Real GNP
2	1.64	98.29	0.06
4	1.63	96.27	2.09
6	1.11	88.45	10.43
8	1.07	83.03	15.89
10	0.99	78.56	20.43
12	0.90	75.63	23.46
CEM3 Aggregation Level			
	CEM3	Inflation	Real GNP
2	0.73	99.13	.13
4	0.76	96.91	2.32
6	0.80	88.22	10.97
8	0.98	82.40	16.62
10	1.0	77.67	21.33
12	0.93	74.62	24.43
CEL Aggregation Level			
	CEL	Inflation	Real GNP
2	0.52	99.33	0.14
4	0.56	97.10	2.33
6	0.98	88.08	10.93
8	1.41	81.89	16.69
10	1.59	76.83	21.58
12	1.59	73.54	24.86

Table B.8
Forecast Error Variance Decomposition of Inflation Rate Using Divisia Monetary Aggregates
(All entries are percentages)

DM1 Aggregation Level			
Forecast Horizon (Qtr)	DM1	Inflation	Real GNP
2	1.40	98.59	0.00
4	2.98	95.58	1.43
6	3.95	86.21	9.83
8	5.31	72.75	21.94
10	9.52	60.18	30.29
12	10.31	51.84	37.84
DM2 Aggregation Level			
	DM2	Inflation	Real GNP
2	2.11	97.88	0.00
4	1.71	97.33	0.94
6	1.74	92.19	6.07
8	3.18	88.63	8.18
10	4.64	85.70	9.65
12	6.11	83.33	10.55
DM3 Aggregation Level			
	DM3	Inflation	Real GNP
2	0.91	99.05	0.04
4	1.12	97.65	1.21
6	1.89	96.11	1.99
8	3.27	94.42	2.31
10	4.50	93.02	2.47
12	5.57	91.86	2.56
DL Aggregation Level			
	DL	Inflation	Real GNP
2	1.05	98.94	0.00
4	0.93	98.50	0.57
6	1.65	94.18	4.16
8	3.94	90.51	5.54
10	5.98	87.39	6.62
12	7.88	84.69	7.42

Table B.9
Forecast Error Variance Decomposition of Inflation Rate Using Simple Sum Monetary Aggregates
(All entries are percentages)

SSM1 Aggregation Level			
Forecast Horizon (Qtr)	SSM1	Inflation	Real GNP
2	1.04	98.95	0.00
4	2.16	96.49	1.33
6	3.64	87.49	8.86
8	5.42	74.38	20.19
10	10.41	61.36	28.22
12	11.60	52.55	35.84
SSM2 Aggregation Level			
	SSM2	Inflation	Real GNP
2	2.58	97.40	0.01
4	2.05	96.73	1.21
6	1.55	91.98	6.46
8	2.31	89.10	8.58
10	3.26	86.59	10.14
12	4.31	84.62	11.06
SSM3 Aggregation Level			
	SSM3	Inflation	Real GNP
2	1.32	98.63	0.04
4	1.12	97.65	1.22
6	1.66	96.37	1.96
8	2.80	94.88	2.30
10	4.02	93.45	2.52
12	5.21	92.13	2.65
SSL Aggregation Level			
	SSL	Inflation	Real GNP
2	0.17	99.82	0.00
4	0.25	99.30	0.44
6	1.75	94.59	3.64
8	4.52	90.58	4.90
10	7.21	86.85	5.93
12	9.85	83.58	6.56

Table B.10
Forecast Error Variance Decomposition at 12-Quarter Forecasting Horizon: Three Variable Model (Money, Inflation, and Real GNP)
(All entries are percentages)

Panel A: Currency-Equivalent M2 (CEM2)

Variable Explained	**Innovations in**		
	CEM2	Inflation	Real GNP
CEM2	88.07	7.27	4.65
Inflation	0.90	75.64	23.46
Real GNP	0.72	2.72	96.56

Panel B: Divisia M2 (DM2)

Variable Explained	**Innovations in**		
	DM2	Inflation	Real GNP
DM2	98.33	1.21	0.45
Inflation	6.11	83.33	10.56
Real GNP	37.82	22.78	39.39

Panel C: Simple Sum M2 (SSM2)

Variable Explained	**Innovations in**		
	SSM2	Inflation	Real GNP
SSM2	97.50	2.36	0.13
Inflation	4.31	84.62	11.06
Real GNP	40.02	22.08	37.89

APPENDIX C

Table C
Definitions and Sources of Data [a]
Study Period, 1960:1-1998:3

Variable	Definition	Source	Frequency
CEM_i, i=1,2,3,L	Currency Equivalent monetary aggregates, seasonally adjusted	FRED	Quarterly
DM_i, i=1,2,3,L	Divisia monetary aggregates, seasonally adjusted	FRED	Quarterly
SSM_i, i=1,2,3,L	Simple Sum monetary aggregates, seasonally adjusted	FRED	Quarterly
GNP	Gross National Product at current prices, seasonally adjusted	FRED	Quarterly
RGNP	Gross National Product at constant 1992 prices, seasonally adjusted	FRED	Quarterly
GNP Deflator [b]	Gross National Product Deflator, 1992=100	FRED	Quarterly
3MTB	3 Month Treasury bill	FRED	Monthly [c]

Notes: a) All the data series used in the study were transformed logarithmically.
b) GNP deflator is used in log first difference since it is found I (2).
c) Three months Treasury bill rate is available monthly from the FRED web site. The data was converted to quarterly by averaging the monthly data for each quarter.

VITA

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