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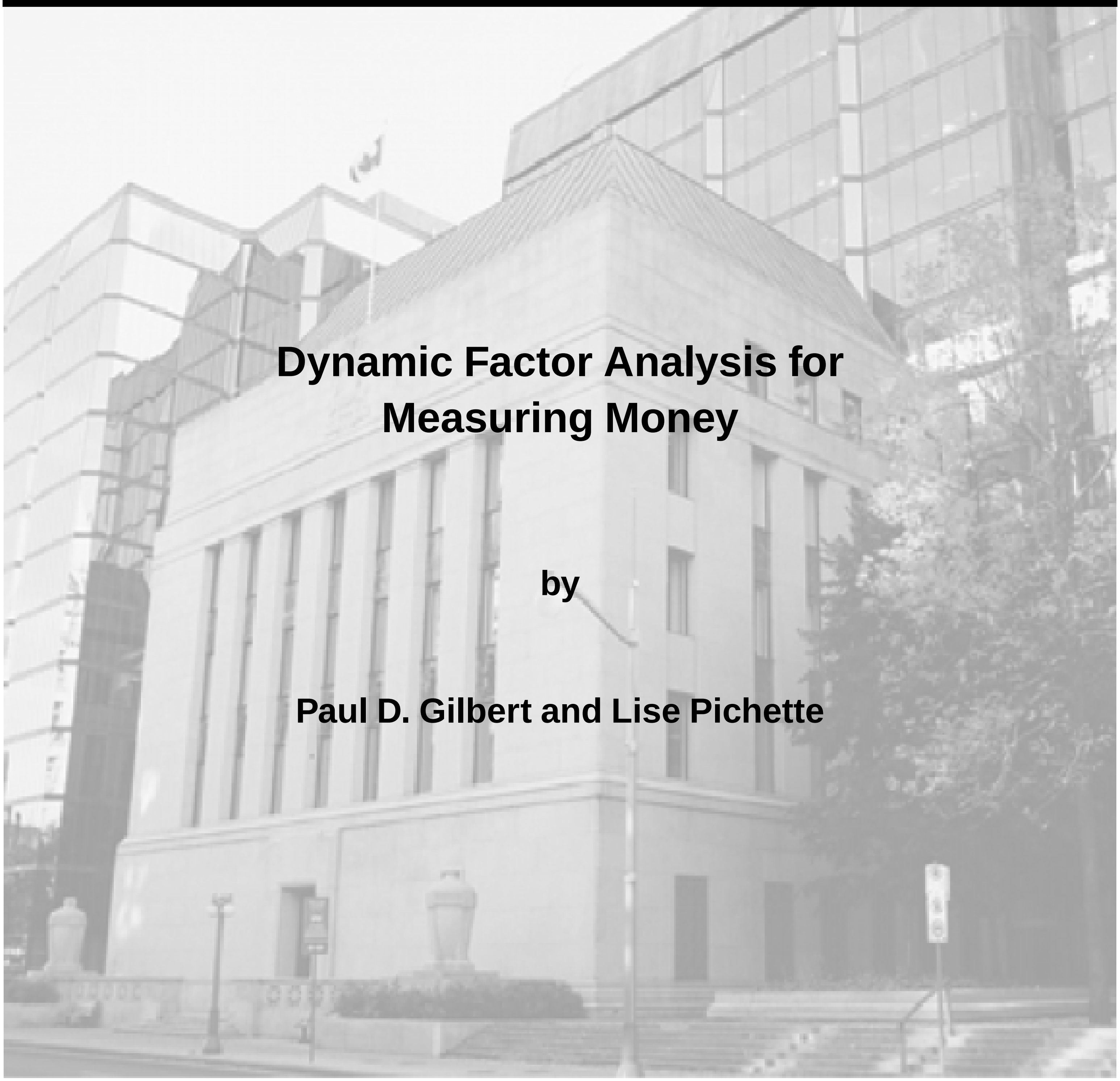

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Paul D. Gilbert and Lise Pichette

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Paul D. Gilbert and Lise Pichette

Monetary and Financial Analysis Department
Bank of Canada
Ottawa, Ontario, Canada K1A 0G9
pgilbert@bankofcanada.ca
lpichette@bankofcanada.ca

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Abstract

Technological innovations in the financial industry pose major problems for the measurement of monetary aggregates. The authors describe work on a new measure of money that has a more satisfactory means of identifying and removing the effects of financial innovations. The new method distinguishes between the measured data (currency and deposit balances) and the underlying phenomena of interest (the intended use of money for transactions and savings). Although the classification scheme used for monetary aggregates was originally designed to provide a proxy for the phenomena of interest, it is breaking down. The authors feel it is beneficial to move to an explicit attempt to measure an index of intended use.

The distinction is only a preliminary step. It provides a mechanism that allows for financial innovations to affect measured data without fundamentally altering the underlying phenomena being measured, but it does not automatically accommodate financial innovations. To achieve that step will require further work. At least intuitively, however, the focus on an explicit measurement model provides a better framework for identifying when financial innovations change the measured data. Although the work is preliminary, and there are many outstanding problems, if the approach proves successful it will result in the most fundamental reformulation in the way money is measured since the introduction of monetary aggregates half a century ago.

The authors review previous methodologies and describe a dynamic factor approach that makes an explicit distinction between the measured data and the underlying phenomena. They present some preliminary estimates using simulated and real data.

JEL classification: C43, C82, E51
Bank classification: Econometric and statistical methods; Monetary aggregates; Monetary and financial indicators

Résumé

La mesure des agrégats monétaires pose de sérieuses difficultés en raison des innovations que connaît le secteur financier. Dans leur étude, les auteurs décrivent les travaux préliminaires d'élaboration d'une nouvelle mesure de la monnaie qui permettrait de mieux isoler, et donc d'éliminer, l'incidence de ces innovations. La méthode proposée établit une distinction entre les données recueillies (concernant la monnaie hors banques et les dépôts) et les comportements en cause (détention de monnaie à des fins de transaction ou d'épargne). Conçue à l'origine pour représenter le comportement des agents économiques, la typologie des agrégats monétaires est de moins en moins adaptée à sa finalité. De l'avis des auteurs, le temps est venu de chercher à mesurer explicitement sous la forme d'un indice l'usage auquel les agents destinent leurs encaisses.

L'établissement de cette distinction représente une première étape exploratoire, qui permet de différencier l'effet des innovations financières sur les données de toute modification fondamentale du comportement sous-jacent. L'étape suivante, qui nécessitera de nouvelles recherches, consistera à prendre systématiquement en compte les innovations financières. Sur le plan strictement intuitif du moins, un modèle de mesure explicite fournit un meilleur outil pour isoler l'incidence de ces dernières sur les données. Même si les travaux sont encore embryonnaires et que de nombreux problèmes subsistent, le succès d'une telle approche révolutionnerait le mode de mesure de la monnaie, qui repose depuis un demi-siècle sur une typologie des agrégats monétaires.

Après avoir passé en revue les méthodologies antérieures, les auteurs décrivent une approche fondée sur des facteurs dynamiques qui établit une distinction explicite entre les données recueillies et le comportement sous-jacent des agents économiques. Ils présentent également certains résultats préliminaires tirés de l'estimation de données réelles et de simulations.

Classification JEL : C43, C82, E51
Classification de la Banque : Méthodes économétriques et statistiques; Agrégats monétaires; Indicateurs monétaires et financiers

1. Introduction

1.1 Overview

Monetary aggregates have been used for half a century to predict economic activity and inflation, more successfully in some periods than in others. Since the late 1970s, however, successive waves of financial innovations have made it increasingly difficult to measure the underlying growth of money. In particular, it is hard to distinguish balances used for transactions from those used for savings. It is important to have a good measure of transactions money, because theory suggests it will have the most predictive power for output and inflation. This paper presents preliminary work to develop a new measure of money that has a more satisfactory means of identifying and removing the effects of financial innovations. The proposed measure differs significantly from previous measures in that it is not an aggregate: it measures economic agents' behaviour instead of account balance items. More precisely, rather than aggregating deposit balances according to a classification scheme, indexes of intended use are established (e.g., transactions and savings). The classification scheme was designed to provide a proxy for these underlying phenomena, but it is breaking down, and we think it is beneficial to move to an explicit attempt to measure an index of intended use.

Section 1.2 explains the motivation of the larger project, for which we present some preliminary results. Section 2 surveys current methodologies and aggregates, and outlines the literature and known problems. Section 3 describes the new proposed methodology and how it might lead to an improvement over current aggregates. Section 4 presents preliminary estimates based on simulated and real data, and the results of sensitivity analysis. Section 5 concludes and proposes future research.

1.2 Motivation

Past attempts to improve Canadian monetary measures have included the development of the narrow aggregates M1+ and M1++, which include a broader range of accounts than M1, and adjusted M1, which is a model-based definition of money.[1] However, none of these is completely

1. M1+ is defined as the sum of currency held by the public and all chequable (demand and notice) deposits at chartered banks, credit unions and caisses populaires (CUCPs), and trust and mortgage loan companies (TMLs). M1++ is the sum of M1+ and all non-chequable notice deposits at chartered banks, CUCPs, and TMLs. For general background on analyzing the monetary aggregates at the Bank of Canada, see Maclean (2001).

satisfactory. M1+ and M1++ aggregates include savings balances, and adjusted M1 mutes some of the predictive power of money.

Official monetary aggregates in Canada are a simple sum of currency and various deposits, classified according to their characteristics. Narrow aggregates attempt to measure transactions money and therefore are composed of currency, demand deposits, and some other deposits traditionally associated with transactions. Broad aggregates include deposits associated with savings. Technological progress poses two major problems for the measurement of transactions money. First, transactions money is a measure of purchasing power, but this purchasing power can now be accessed in a variety of ways. Savings and transactions balances are not held in clearly defined separate accounts, but mixed together. Also, investment accounts and stock market-oriented deposits have become more popular since the late 1990s. While aimed more at savings balances, the money in these accounts is still very liquid and available for any kind of transaction. Soon, many deposits may be in accounts that are tailor-made for the habits of a person, not in accounts categorized according to historical notions. In summary, the rigid classification of account types is changing. Second, many transactions balances are held in accounts that are not included in current narrow monetary aggregates, and there are new deposit-taking institutions not included in the aggregates, such as investment dealers, life insurance companies, and near banks, which offer new types of deposits. That is, the classification of institutions is changing. Moreover, technology has changed agents' behaviour regarding their money management and, in particular, money can be moved from one account and institution to another very easily and quickly. A simple phone call or a visit through the Internet is sufficient. When this money is transferred between institutions included in the aggregates and those excluded, it produces spurious fluctuations in the aggregates that can reduce their predictive ability.

For these reasons, the old classification system is breaking down. Currently, individual problems are dealt with on a case-by-case basis when they are noticed, but this is becoming increasingly difficult. Research is needed to develop a new measure of money. These new money measures should not depend so critically on features of the different accounts, because they are becoming increasingly diverse and very difficult to classify and measure.

Dynamic factors are proposed to overcome the problems identified above. Dynamic factors focus on measuring the underlying economic activities, rather than the amounts in historical deposit classifications. We think this approach offers the best way to address the innovation problems, because it distinguishes the underlying economic activities (economic agents' intentions to transact or save) from the measured items (balances in accounts), which are affected by the above-noted financial innovations. Despite the instability in the characteristics of deposit accounts, we believe the technology revolution has not changed the fundamental uses of money for economic activities that should be measured. By instituting an explicit distinction between the measured data and the underlying phenomena, there is a clear mechanism for distinguishing financial innovation from more fundamental economic activity. This mechanism provides a way to separate measurement issues related to financial innovation from more fundamental economic issues related to agents' behaviour. It paves the way for testing structural change in the measurement process, as distinct from changes in underlying economic behaviour.

One theoretical difference between the proposed dynamic factor approach and the traditional aggregation approach is that it is no longer necessary to include all deposit-taking institutions to compute a valid measure. Aggregation is based on a census approach: all relevant institutions must report, and correct classification is required. The proposed approach is based on sampling: only a good sample of deposits is required to get a measure representative of the underlying economic activities.

2. Monetary Aggregates

2.1 Existing methodologies

Official monetary aggregates in Canada are a simple sum of currency and various deposits with weights for all components set to one. This implies that all monetary assets should be dollar-for-dollar perfect substitutes. This is not true, since some assets are clearly less liquid and give a higher yield than currency and demand deposits. Hence, the monetary aggregates constructed by a simple summation provide a good measure of the stock of nominal monetary wealth, but not underlying economic behaviour.

To account for substitutability, and for the fact that certain kinds of accounts have both a transactions and a savings nature, attempts have been made to consider weights for components. Barnett (1980) suggests the Divisia index (see also Barnett and Serletis 2000). This monetary aggregate is constructed by combining monetary theory with statistical index number theory and microeconomic aggregation theory. It measures the flow of services produced by the component assets.

The Divisia index is a time-varying weighted monetary aggregate, where the weights are expressed in terms of the contribution of each component relative to the total value of services provided by all monetary assets. This index is derived from the optimizing behaviour of economic agents. It is reputed to have better theoretical foundations than the simple-sum monetary aggregates. Also, some consider that the Divisia index is better adapted to the context of continuous financial innovations because it internalizes substitution effects. Monetary authorities, however, are reluctant to publish these monetary aggregates, because their construction requires various subjective choices that make them almost impossible to reproduce.[2]

Others have worked to measure transactions balances. Spindt (1985) suggests a weighted monetary aggregate (MQ) derived from the equation for the quantity theory of money, MV = PQ. Weights are based on each monetary asset's velocity (turnover rate). Another attempt to measure liquidity services is the currency-equivalent (CE) monetary aggregate proposed by Rotemberg, Driscoll, and Poterba (1995). This aggregate provides some improvements, but it is similar to Divisia in that it is derived from an optimization problem. Nevertheless, it has not been used, because practical issues in addition to those related to the Divisia index have emerged. For example, weights tend to be highly volatile, which complicates interpretation and empirical use.

2.2 Empirical evidence in Canada

Many studies have assessed the performance of monetary aggregates in terms of various criteria, such as their information content, money-income causality, and stability in money-demand equations. The results are mixed. For Canada, Cockerline and Murray (1981) find that Divisia aggregates contain less information on contemporaneous and future levels of income than summation aggregates. Summation aggregates also appear to be superior in causality tests. On the other hand, the study finds that Divisia indexes are more stable in money-demand equations, which is consistent with the fact that these aggregates follow more consistent time paths than their summation counterparts.

Hostland, Poloz, and Storer (1987) also look at the information content of alternative monetary aggregates. They compare summation aggregates with Fisher ideal indexes of monetary services.[3] They conclude that the information loss through simple-sum aggregation is not significant. In other words, the Fisher ideal aggregates add very little information to improve income and price forecasts. Serletis and King (1993) examine the empirical relationships between money, income, and prices, comparing summation aggregates with Divisia. They find that the growth rates of Divisia aggregates are more useful than summation aggregates for forecasting nominal income

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2. The Bank of England and the Federal Reserve Bank of St. Louis are the only institutions that publish Divisia indexes in their official statistics. For a detailed discussion on the disadvantages of Divisia indexes, see Cockerline and Murray (1981), Fisher, Hudson, and Pradhan (1993), and Longworth and Atta-Mensah (1995).
3. Like Divisia, Fisher ideal monetary aggregates are known as *superlative* indexes.

fluctuations, while the growth rate of the summation aggregate M2+ is the best leading indicator of inflation.

The results in these Canadian studies are consistent with those of other researchers using data for different countries (e.g., Bailey et al. 1982a, b; Driscoll et al. 1985; Horne and Martin 1989; and Subrahmanyam and Swami 1991). Despite the theoretical advantages of Divisia aggregates, they have not been shown to be clearly superior to summation aggregates.

2.3 Adjusted M1

In recent years, movements in M1, the traditional measure of transactions money used by the Bank of Canada, have been affected by financial innovations (Aubry and Nott 2000). This has changed the relationships between money, output, and inflation and, as a result, the M1-based models have been unstable. Since the alternative aggregates described above were not very successful, economists at the Bank of Canada created a new model-based measure of transactions balances called adjusted M1(Adam and Hendry 2000).

The objective of adjusted M1 was to correct instability in the main money-based model used at the Bank of Canada (the M1-VECM).[4] It is obtained in two steps. First, using the money-forecasting equation from an M1-VECM estimated with a sample ending in 1993 (the beginning of the second wave of innovations, according to Aubry and Nott 2000), a forecast of M1 is obtained for the period 1992Q1 to the last quarter of available data (National Accounts). This time-series is called “distortion-free” M1 and can be interpreted as an estimate of what M1 would have been if no changes in the data-generating process had occurred in the 1990s. Second, this series is regressed on the components of the monetary aggregates. This step relates the distortion-free money to the observed money data released every month. Adjusted M1 is thus a weighted sum of components’ levels.

Unfortunately, adjusted M1 is not free of problems. Some serious deficiencies are associated with each step of the procedure. In the first step, the choice of the estimation period is problematic. The year 1993 was chosen as the end of the sample under the assumption that most financial innovations occurred after that time, although M1 was probably distorted before then. To calculate “distortion-free” M1 assuming a stable model is a problem, since it implies that structural changes over the 1990s did not affect the underlying money demand and supply processes.

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4. The M1-VECM (vector-error-correction model) is developed in Hendry (1995).

Given the way adjusted M1 is constructed, it may lose valuable information as a money measure for analysis. The construction mutes some of the predictive power of money. For example, fundamental movements can be removed while attempting to remove distortions. In addition, the weights on the components are unstable and very sensitive to the choice of the sample in the second step. Some weights are also counterintuitive (e.g., the weight on currency is above 1).

Furthermore, adjusted M1 is a model-dependent money measure, which is quite dangerous. If the model is wrong, then adjusted M1 may not measure transactions money. This approach has not been as successful as hoped, which suggests that emphasis should be directed towards approaches that do not rely so fundamentally on specific economic models.

3. A New Approach to Measuring Money

3.1 Dynamic factor analysis

A factor is an index that can be used to indicate the evolution of an activity. Brillinger (1975), in introducing the technique used in this paper, quotes Bowley (1920):

> Index numbers are used to measure the change in some quantity which we cannot observe directly, which we know to have a definite influence on many other quantities which we can observe, tending to increase all, or diminish all, while this influence is concealed by the action of many causes affecting the separate quantities in various ways.

Economists have made increasing use of dynamic factor analysis (DFA—sometimes called dynamic latent variables) to estimate "underlying" processes. These processes may correspond more closely than measured data to the economic concepts economists use when building models. The techniques have been used to propose better measures of underlying inflation,[5] applied to the real side of the economy,[6] and used in arbitrage pricing theory models of financial decision-making.[7] Despite the conceptual appeal, to our knowledge no one has used these methods to measure money. One reason may be that deposit data have never been suitably organized. For instance, the money-component data used in this project needed to be adjusted for acquisitions; previously, this was done by the Bank of Canada only for the aggregates. The components had continuity breaks that made them unsuitable for econometric analysis.

5. See, for example, Bryan and Cecchetti (1993).
6. See, for example, Forni and Reichlin (1996), Geweke and Singleton (1980), Quah and Sargent (1994), and Stock and Watson (1999).
7. See, for example, Conner and Korajczyk (1988), Garcia and Renault (1999), and Roll and Ross (1980).

In DFA, the observed variables x_i ($i = 1, 2,..., p$) at each period t are expressed in terms of r factors (or latent variables), f_j, where $r < p$, and idiosyncratic terms, e_i (residuals). The measurement model is given by the equation:

$$x_t = A f_t + e_t \tag{1}$$

at each period t, where A is a $p \times r$ matrix of weights. Each deposit type is a weighting of the factors, not the other way around, as in aggregation. Also, this is distinct from aggregates in that there is an explicit idiosyncratic term that indicates amounts of the measured data not explained by the indexes. That is, there is an explicit indication of amounts in the measured data that are not considered to be part of the underlying economic phenomena.

“Factor analysis” is used here in the specific sense of equation (1), rather than in a generic sense that includes several techniques, such as principal components analysis (PCA); see, for example, Basilevsky (1994). Specifically, in our paper, the factors should result in an idiosyncratic term, e_t , with a diagonal correlation matrix. That is, in principle, the dynamic factors first explain common movements in the measurements, rather than the most variation, as in PCA. The difference is relative emphasis, since explaining as much variation as possible is also interesting. More importantly, principal components are uncorrelated (orthogonal), but factors are not necessarily uncorrelated. Transactions and savings may be correlated, so factors are more logical than principal components for our problem.[8]

The most controversial aspects of DFA are the specification of the objective function and the imposed identifying (uniqueness) constraints. These must give factor measurements that are economically interesting without imposing (potentially controversial) theory. In other words, the resulting factors should be compatible with a wide range of economic theory. This distinguishes the measurement problem considered here from the more usual econometric situation of building an interesting economic model.

The identification problem is that any invertible matrix, G, defines new factors $(G f_t)$ and weights (AG^{-1}), and the equation

$$x_t = (AG^{-1}) (G f_t) + e_t \tag{2}$$

8. PCA is sometimes suggested as a technique for estimating factors (see, for example, Johnson and Wichern 1998). This results in orthogonal factors that can be rotated to find “oblique factors.” The problem is to find the appropriate rotation. That approach is not attempted here—because it seems more natural to apply constraints and objectives in the estimation—but it may be explored in future work.

gives identical measured variables, x_t, and idiosyncratic terms, e_t, as in equation (1). Thus, these factors cannot be distinguished statistically; some otherwise-motivated constraint must be imposed. Statistical estimation criteria are based on the idiosyncratic terms, e_t. Identification involves imposing objectives or constraints that are economically motivated to give an interpretation to the factors, but statistically arbitrary since they do not affect the idiosyncratic terms, e_t.

An example would be to choose different relative scaling of the factors and weights. Since factors are an index, this scaling could be resolved by specifying that the factors have a value of 1.0 in the first period; for that reason, factors should be interpreted only in growth rates, not in levels. This does not eliminate rotations that preserve the magnitude, however, so it does not completely solve the identification problem. A second problem is that different idiosyncratic terms, e_t, may result in similar objective function values and thus cannot be distinguished in estimation. This second problem does not seem to be a serious difficulty in samples considered here, but may be more important in shorter samples.

3.2 Intuition

The new approach has some resemblance to weighted aggregates but, in fact, it is not an aggregation at all. Rather, it is an attempt to measure the common underlying (or latent) factors (of which *transactions money* and *savings money* are the two most important) that influence the use of money in different types of accounts.

A narrow aggregate is an attempt to add up currency and deposits used as transactions money. A weighted aggregate attempts to divide deposits into the portion used for transactions and the portion used for savings. The intuition of aggregation is that an exact measure will be achieved if everything is measured and allocated correctly. In contrast, factors are latent variables, which cannot be measured directly. This approach treats *transactions* and *savings* as two fundamental underlying activities in the economy. Data on currency and a wide range of deposits are used to estimate the two activities, and each measured monetary instrument (i.e., deposit type and currency) can be expressed in terms of these factors. This can be written as

$$currency = w_{\mathbf{1}}\ transactions + w_{\mathbf{2}}\ savings + e_{\mathbf{currency}}$$

$$demand = w_{\mathbf{3}}\ transactions + w_{\mathbf{4}}\ savings + e_{\mathbf{demand}}$$

$$notice = w_{\mathbf{5}}\ transactions + w_{\mathbf{6}}\ savings + e_{\mathbf{notice}}$$

$$\vdots$$

$$mutual\ funds = w_{\mathbf{n-1}}\ transactions + w_{\mathbf{n}}\ savings + e_{\mathbf{mutual\ funds}},$$

where the weights, w_i, are estimated simultaneously with the savings and transactions processes. Each type of deposit is a weighting of the two factors, not the other way around, as in aggregation. Intuitively—in the case of currency, for example—transactions activity should have the heaviest weighting and savings activity a minimal weighting. The idiosyncratic process e_{xxx} indicates amounts specific to a particular measured monetary instrument and not explained by the factors.

On the real side of the economy, there are considerably more data associated with underlying factors than on the monetary side; Stock and Watson (1999) use thousands of variables. Our application, however, has the advantage that there should be very few factors, while on the real side one expects many factors to be important. The idea is explained above in terms of savings and transactions activities, but it is possible, for example, that corporate transactions and personal transactions could be distinguished as different factors. It is even possible that financial institution transactions activity, often considered a “distortion” to the aggregates, could be a separate factor. Thus there may be more than two important factors, but it would be surprising if there were many more than that number.

In this approach, each deposit provides an additional measure of the underlying factors; there must be more monetary instruments than factors to solve the problem mathematically. More deposit types provide more measurements and thus more precision. Omitted deposit types mean fewer measurements and thus less precision. In the aggregation approach, by contrast, omitted deposit types mean that something is missing and the aggregate is not correct in an accounting sense.

As stated earlier, one result of financial innovations is that an account type may start to be used in a different way. It is a challenge to model such phenomena. In the new approach, any changes that affect many of the measured variables should result from the factors, but the idiosyncratic components mean that the measured variables can include changes that are not a result of factors. They flag anomalies (or distortions), since they should usually be small. A persistently important idiosyncratic component signals that the use of a deposit may have changed, and suggests the need to reconsider the weights used for that measured variable. Thus, weights may vary over time, but the necessity of a change in the weights is more clearly indicated.

Even though balances are shifting around, the objective of this approach is to get a transactions money measure that avoids noisy fluctuations from financial innovations that cause measurement problems due to their effect on deposit accounts. Savings money growth should also be more stable in this context. Variable weights are required to absorb the effects of shifts due to innovations. Given the large number of unknown parameters, however, it is impossible to solve the system of equations mathematically with continuously variable weights. Eventually, as a first step to address this situation, break points will be identified; that is, periods during which financial innovations modified the usage of certain accounts.[9] For example, the elimination of differential reserve requirements on business demand and notice deposits in the early 1990s removed the incentive for banks to distinguish between these two types of accounts. Before this change, notice deposits were used more as a saving account than demand deposits. Following this financial innovation, demand and notice deposits should have comparable weights on transactions and savings factors, using the new methodology.

3.3 Estimation methodology

The search for the best combination of constraints and objectives is ongoing. Results in this paper are based on an identification called "penalized anchor weights." The search is complicated by the need to simultaneously investigate estimation algorithms. This section specifies a combination of algorithms and algorithm settings that works fairly well, called the "base case" estimation methodology. Section 4 discusses sensitivity to various settings in this base case, as well as less successful earlier attempts, including some attempts with different identifying penalties. Unless otherwise identified, the data have been scaled by dividing each series by its value in the first period. Scaling will be discussed further in section 4.4.

The objective is to find the rp elements of the $r \times p$ weighting matrix A and the rT elements of the $T \times r$ factor series f that minimize the objective function $d = d_1 + a_2 d_2 + a_3 d_3$, where a_2 and a_3 are arbitrary scalars that fix the relative importance of the competing criteria; a_1 is set to 1.0 because only the relative sizes are important. Here, r is the number of dynamic factors, p the number of observed series, and T the number of time periods. The parts d_1, d_2, and d_3 of the objective function are described in more detail below. The only imposed constraint is that factors and weights are positive. In general, the solution is not at the constraint boundary (on the factors, at least). In addition, some parts of the objective function are formulated to be a penalty, or "soft constraint."

(i) d_1 is a standard least-squares-error objective, defined by

$$d_1 = \left(\sum_{j=1}^{p} \sum_{t=1}^{T} e^2{}_{jt} \right) / pT, \tag{3}$$

with $e_t = Af_t - x_t$, where x_t is the observed (measured) data at time t. The constant a_1 is set to 1.0.

9. Aubry and Nott (2000) describe the major financial innovation waves in Canada. This could be used to determine the dates of the changes.

(ii) d_2 is a roughness penalty applied by summing squared one-period differences of normalized factors:

$$d_2 = \sum_{j=1}^{r} \sum_{t=2}^{T} \frac{(\tilde{f}_{jt} - \tilde{f}_{jt-1})^2}{r(T-1)}, \tag{4}$$

where $\tilde{f}$ are factors normalized by their standard deviation, $\tilde{f}_{jt} = f_{jt}/(var(f_j))^{0.5}$, so this object does not influence the absolute size of the factors, only their volatility. A roughness penalty is suggested by Ramsay and Silverman (1997) in their theory on functional data analysis. As discussed in section 4.2, as long as the roughness penalty is not extremely large it does not have any fundamental impact on the estimated factors; it influences only the volatility.

(iii) d_3 provides identification and is the part of the penalty that is of most interest. It is based on a prior that currency is influenced mainly by the transactions factor and that measurements grouped together as “investments” are influenced mainly by the savings factor (this latter is more apparent on examining the real data in Appendix A). A penalty is imposed on factor weights different from 1.0 on these component “anchors.” Since no other scaling is imposed, this also necessitates a penalty if the sum of the two factor weights for currency differs from one, and likewise for investment. Specifically:

$$d_3 = (A_{1,1} - 1.0)^2 + (A_{6,2} - 1.0)^2 + (A_{1,1} + A_{1,2} - 1.0)^2 + (A_{6,1} + A_{6,2} - 1.0)^2. \tag{5}$$

The first squared term penalizes a transaction weight different from 1.0 for currency, the second squared term penalizes a savings weight different from 1.0 for investment, and the third and fourth squared terms, respectively, penalize weights that do not sum to 1.0 for currency and for investment. a_3 was set to 10, which gives this part of the objective a final value a few orders of magnitude smaller than d_1. This was determined by experimentation to be a size that orients the weights properly but does not force them to be exactly at these “constraint” values. (In many cases, this part of the object function becomes many orders of magnitude smaller than d_1 simply because d_3 becomes very small.) To a large extent, this objective does not conflict with the least-squares-error objective, but only enforces an identifying restriction by identifying a preferred weighting and corresponding rotation of the factors.

3.4 Monitoring data problems

The proposed methodology for measuring transactions and savings money helps solve certain kinds of measurement problems, but, more importantly, it should help to quickly pinpoint new problems so that corrections can be applied. Section 3.3 explained the intuition of how this works. This section describes data problems that can occur and what their effect would be.

It is important to distinguish between two modes in the process of collecting data following this methodology. One is the usual *operational mode,* which is the situation when new data are released but the weights in the "data measurement model" are fixed and not being estimated. The second is the *estimation mode,* which is the situation when the weights are initially estimated and occasionally re-estimated. Data problems are not corrected in operational mode, but, as explained in section 3.3, the value of the idiosyncratic terms should flag them quickly, well before they have a substantial effect on the factors. This gives some time for the analyst to investigate the problem. In this section, three types of data problems that can occur in the operational mode are described; these may signal the need for re-estimation. The estimation mode is then examined, a step where data problems actually need to be reconciled.

The first type of data problem is a shift in the use of a certain deposit classification. For example, before the introduction of ATMs, notice deposits were used mostly as a savings instrument. With the introduction of debit cards, these accounts became as liquid as demand deposits. Consequently, the weight on the transaction factor should be larger after this structural break. This change would require a re-estimation of the weights; however, there is an explicit error term that provides an automatic mechanism to partially ignore the effect of the change for some time. That is, the change affects the error term much more than it affects the factors. When there are enough periods after the break point, the weights can be re-estimated for the problematic component. By contrast, there is no simple mechanism to deal with known structural breaks in the current aggregates.

The second type of data problem is a shift among data classifications. For example, Canada Savings Bonds (CSB) decreased in popularity in the second half of the 1990s and at least part of that was a shift into mutual funds, which increased substantially in the same period. This shift had more to do with availability or marketing of different types of financial instruments than with the underlying economic phenomena of interest for monetary policy. One simple way to compensate for this problem is to omit all the affected classifications. As stated earlier, the methodology requires only samples and not a complete accounting, so omitting some classifications is a possibility. Omitting a classification, however, can lead to a wrong signal regarding the evolution of the factors if there are important amounts moving between included and omitted classifications.

For example, in this particular case, excluding mutual funds from the sample would lead to a continuous decline in savings because of the evolution of CSBs, while the underlying factor may not be decreasing. A more satisfying way to deal with this shift is to amalgamate the classifications involved; this is the approach we follow in our preliminary experiments, because of its simplicity. As a result, the shift is internal to the new classification and does not show in the data at the level of aggregation of the components that are used. Modelling the shifts among classifications would be a theoretically more satisfying solution, but it would introduce an additional level of complexity.

The third type of data problem is a shift of market share among institutions. In the current monetary aggregates, this is a problem only if it is a shift between institutions included and excluded in the aggregates. In the DFA approach, such a shift could become a problem, depending on the level of aggregation. Since more measurements provide more precision, a level of sophistication can be added by using a breakdown of each deposit category by institution. Therefore, it would be useful to model these market share shifts, as in the case of a shift from one type of deposit to another. Again, at this early stage of the project, this problem is avoided by using data aggregated across institutions.

These data problems, observed in the operational mode, would eventually lead to a re-estimation of the weights. At that time, underlying factors would have already been established for large parts of the sample, and the timing and nature of a new break point would have been identified by the monitoring of the idiosyncratic terms. During initial estimation, however, there is no established baseline for the factors, and structural break points also need to be established. There are several possibilities for dealing with the special problems at this initial stage. One is to amalgamate some problematic data classifications. Another, not yet investigated, is to begin with sample periods when structural changes appear to be less problematic. Details of the data measurement model outlined above are not provided in this paper.

Beyond data problems, estimation is a challenge because of the large number of unknown parameters. Restrictions and the carefully defined estimation objectives must be defined to obtain a unique solution. Section 4 describes issues that need to be addressed to estimate the factors.

4. Preliminary Estimation Results and Sensitivity Analysis

4.1 Estimation with simulated data

Simulation and estimation experiments were used to examine the properties of the measurement model, examine whether it produces data similar to observed data, and test estimation algorithms. Current measures for narrow money and broad money provide interesting candidates to use as “true factors” for simulation experiments. (Note that the eventual estimation with real data makes no use of these current measures.) Six series were generated using M1 and M2++ as the two factors (see Appendix A). These were first divided by population and the consumer price index (CPI) to get real per-capita factors, and then scaled so that the first period has a value of 1.0. Real per-capita factors were used to abstract from the influence of population and nominal growth; otherwise, these phenomena could emerge as the factors.[10] Factors are estimated in levels but always interpreted in growth rates, since the scale is arbitrary, so the first period is set to 1.0 for simplicity.

Artificial measurement data were generated by multiplying two assumed factors by assumed weights and adding normally distributed pseudo-random numbers with mean zero and standard deviation 0.1. These were then multiplied by scale factors of 1,000, 10,000, 10,000, 1,000, 10,000, and 100,000, respectively, for each of the generated series, so the artificial data have a magnitude similar to the real data. (Scaling will be discussed further in section 4.4.) This provides artificial data with some of the important properties of the real data.

Figure 1 shows the true factors and the factors estimated with the base-case estimation methodology. The bias is a point of concern and is being further investigated. The growth rates of the estimates appear to be fairly similar, however, and the levels of an index are not as important as the growth rates. Furthermore, the main interest is in the transactions factor, which is, at least visually, fairly good. The bias may be related to a scaling problem that is less obvious but possibly more important. These problems have been considered secondary because the research to date has concentrated on more serious difficulties.

Table 1 shows the estimated weights along with true weights used in the simulation.[11] Figure 2 shows the simulated data along with the portion explained by the estimated factors.

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10. Following estimation of the factors, the results could be reflated to reflect population and nominal growth, to provide for better interpretation.
11. Code is written in the programming language R (Ihaka and Gentleman 1996; see <http://www.r-project.org/>). Details for reproducing these results are available at <http://www.bank-banque-canada.ca/pgilbert>.

Table 1: Estimated Weights (true weights in brackets)

Component	Transaction factor 1	Savings factor 2
Series 1	1.000 (0.9)	0.000 (0.1)
Series 2	0.956 (0.8)	0.089 (0.2)
Series 3	0.523 (0.5)	0.638 (0.5)
Series 4	0.000 (0.1)	1.010 (0.9)
Series 5	0.969 (0.7)	0.229 (0.3)
Series 6	0.000 (0.1)	1.00 (0.9)

The simulated data have several of the characteristics of real data, but highlight two problems that this simple form of measurement model does not address. First, since the two factors tend to grow over time, the data generated by summing two positively weighted factors and adding random noise will also tend to grow over time. Some of the real data series do not do this as consistently. For example, personal demand deposits declined in the early 1980s when deposits shifted to personal chequing accounts, which offered chequing and better interest rates. More dramatically, CSBs dropped in the 1990s as the federal government shifted to other forms of financing and investors shifted their savings to other instruments, such as mutual funds. This type of shift cannot be reproduced by this measurement model and the phenomena need to be accommodated in some other way. This observation motivates much of the data grouping, which is discussed in Appendix A.[12]

Second, there are no serious trend breaks in the generated series, as there are in the real data. Breaks in the real data could be accommodated by changing the weights, corresponding to shifts in the use of accounts. This issue is largely ignored in the remainder of this paper, but eventually will require further study.

4.2 Sensitivity to algorithm parameters

The constant a_2 was set to 10^{-2}. This was determined after initial attempts, and adjusted so that the smoothing alters only the volatility. It scales this portion of the objective to at least an order of magnitude smaller than d_1. Figure 3 shows the result, with a_2 set to 1.0 and 0.0.

12. Investment is a grouping of several series traditionally used for longer-term savings. This is discussed in more detail in Appendix A.

The roughness penalty, d_2, is similar in some respects to a filter, but the penalty is on rapid variation of the underlying factor, rather than on the measurements themselves, as would be typical with a filter. In this regard, it is closer to a Kalman filter, but there is no attempt here to model the underlying dynamics as with a Kalman filter. Modelling the underlying dynamics may be interesting in the future, but it is an economic modelling problem and the present work is focused primarily on measurement issues. The theoretical justification for the roughness penalty is that the underlying phenomena of interest should vary less rapidly than the measured data. If it does not, the data should be measured more frequently. The disadvantage of too large a penalty is that it may obscure important rapid variations.

a_3 was set to 10.0, which gives this part of the objective a final value a few orders of magnitude smaller than d_1. This was determined by experimentation to be a size that orients the weights properly, but it does not force them to be exactly at the "constraint" values. In many cases, the weights are very close to these values, even with a much smaller value for a_3, and as a result d_3 is often many orders of magnitude smaller than d_1.

Early efforts tried to impose partial identification by setting the scale of the factors to 1.0 in the first period. This proved unsatisfactory in a few respects. It did not provide complete identification, so additional constraints or penalties were necessary. It did not determine which factor was transactions and which was savings—that had to be inferred from the estimated weights. Most importantly, the focus of the constraint on the first period did not permit adequate consideration of the fact that there should be some smoothness between the first and second periods. As a result, estimated factors often had large jumps in the second period. A large roughness penalty alleviates this somewhat, but it has other adverse effects, since the penalty must be very large because the jump is only in one period. The penalty on weights applies uniformly over the sample, so it does not produce these anomalies, and it automatically determines which factor is transactions and which is savings.

Another objective considered was that the idiosyncratic component, e_t, should have a diagonal correlation matrix (or covariance matrix), $E(e_{ti}, e_{tj}) = 0$, for i not equal to j, where i and j indicate different measured components. This is motivated by the idea that the factors should explain all the common movements, so the idiosyncratic components will be uncorrelated (see Basilevsky 1994). Experimentation suggests that adding this to the objective has little effect: the standard least-squares-error objective (i) seems to adequately ensure that the covariance matrix is nearly diagonal.

Rather than the least-squares-error objective, it would be possible to consider a likelihood-based objective. This may give similar results for the simulated data, but the assumption of the normality of the idiosyncratic component (residuals) is difficult to defend when real data are used. Experimentation to date has concentrated on the least-squares-error objective.

4.3 Initial approximation

The estimates are obtained by an iterative procedure, which can be very slow. There are a large number of parameters, since both weights and factors are estimated. The simulation experiments described above have 2 factors with 306 periods, and 6 generated measurements, giving 2 x 6 elements in the weighting matrix and 306 x 2 elements in the factor series, or 624 parameters to be simultaneously estimated. The estimation is therefore fairly difficult even if the problem is well-conditioned, and some combinations of objects or too few constraints yield ill-conditioned problems. Previous simulation/estimation experiments reported in Gilbert and Pichette (2002) used known factors and weights as the estimation starting point, and even then estimation sometimes took six to eight hours. Performance starting with known values has been improved, but using the known value as a starting point is clearly not possible with real data. Even with a good starting point, the slowness of estimation makes real applications unreasonably difficult. In addition, as with any iterative estimation algorithm, local minima pose a problem that would require tremendous amounts of time to vet. Furthermore, such slowness would inhibit the ability to study estimation objectives and constraints.

This starting-point problem has been solved using a two-step procedure. The first step is to approximate the initial factors using a two-parameter spline for each series (see, for example, Venables and Ripley 1994). In the example above, this gives four parameters for the factor series, together with the 12 entries in the weighting matrix that are optimized to get a reasonable approximation for weights and factors. This optimization typically takes a few minutes. The spline is then expanded with the optimized parameters to give the complete factor series as an initial starting point for the second step, a full optimization. With this improved starting point, the optimization step typically takes an hour or two. One could make several potential improvements to this procedure; however, it already works well enough that further improvement is not considered critical. The most serious difficulty is that the optimization of the approximating spline sometimes fails (possibly because the approximation is too flat) and the estimation must be initialized differently.

The technique improves estimation speed sufficiently to warrant considering potential problems associated with the chosen starting point and local minima. Figure 4 shows the true factors along with five estimates of the factors, using the same criteria but different starting guesses. The estimates are difficult to distinguish from each other because they are so close. The base-case estimation methodology scales the first and last components of the measured (simulated) data to use as the initial guess for the two factors (the weights make these correspond notionally to currency and investment). One of the other estimations uses the first and second components of the measured data. Three of the estimations use random numbers. Figure 5 shows the data generated by the simulation and the portion explained by these five estimates.

In experiments with different objective functions there has been one case of false convergence. This difficulty was signalled not only by the relatively poor value of the objective function, but also by the fact that many factor values are fixed at the constraint value of zero. It was also signalled by poor performance in explaining the data. It has not been determined whether this problem was due to local minima on the constraint boundary or to an insufficiently refined setting of the convergence tolerances. Other than this one case, estimates from different starting points have all converged to the same values (within reasonable tolerances), or have not converged, due to the starting approximation problem noted above. Thus, local minima problems do not appear to be a serious problem.

4.4 Preliminary estimation with real data

Appendix A provides more details of the data and the way in which they have been organized into components for estimation purposes. The sample used for the estimates was from January 1986 to April 2002. Data prior to that period is problematic for reasons described in Appendix A. Estimation was conducted using the base-case methodology and six components constructed as indicated in the left column of Table A1 in Appendix A. The measured components are scaled to a starting value of 1.0. Figure 6 shows the component data (solid line) and the portion explained by the estimated factors (dashed line). Figure 7 shows factors estimated from measured components scaled as above, as well as from measured components scaled by dividing by their mean value. Scaling by dividing by their standard deviation has an even more substantial effect. Table 2 shows the weights estimated with the base case-methodology.

Table 2: Weights Estimated with the Base-Case Methodology

Component	Factor 1	Factor 2
Currency	0.998	0.003
Personal chequing	0.898	0.000
Non-bank chequing	0.239	0.858
Non-personal demand & notice	0.000	1.008
Non-personal term	0.000	0.935
Investment	0.009	0.995

Scaling remains an important issue. On the two ends of the spectrum, currency and investment are probably both relatively accurately measured data. If no scaling is done, then investment, being orders of magnitude larger than currency, will dominate the error objective, even though currency is more important for the transactions component, which is of primary interest. On the other hand, if the data are all simply scaled to the same order of magnitude, then small but more questionable series, like non-bank chequing deposits, will have a greater influence.

While the estimates are preliminary in several ways, it is interesting to compare the results with some other measures. Figure 8 shows the same factors as Figure 7, plotted against real per-capita M1 and real per-capita M2++, both divided by their first value to put them on a similar scale to the estimated factors.

4.5 Sensitivity to sample selection and size

This section provides an initial indication of the extent to which sample size and the selection of the sample period can influence the results. This is done by estimating over some different samples and comparing the results with those in section 4.4. A more comprehensive treatment of this problem awaits resolution of the bias and scaling problems already described. By most accounts, the most recent data, starting in the mid-1990s, has been problematic because of financial innovations. The subsample from January 1999 to April 2002 was selected to indicate the way in which estimation restricted to the most recent period could affect the results. The period from January 1990 to January 1993 was selected as a smaller window that could give results similar to those reported in section 4.4, with mainly sample-size effects causing any difference. The data prior to January 1986 were initially omitted because of shifts related to the introduction of personal chequing accounts, as discussed in more detail in Appendix A; we decided to omit these data for the reasons discussed in Appendix A, prior to calculating the sample selection issues reported in this section. Thus the period from November 1981 to December 1986 provides a sample that is smaller than the previously discussed sample, and it is expected to be problematic. Finally, the full sample from November 1981 to April 2002 is considered. This full sample illustrates how the estimates are affected by a large market shift, a problem that one might conclude requires re-estimation of the weights for the structural break.

Figure 9 shows the estimated factors over these samples. The results confirm prior notions. The smaller mid-sample estimate is close to the previous results for the larger sample. The smaller sample of most recent data gives slightly different results. The early data, which were originally omitted because they were problematic, show a decline in the savings factor in the period when a market shift between account types was occurring. Most interesting is the result on the full sample, which illustrates fairly clearly the need to consider a structural break and re-estimation of the weights. Without that, the factors are heavily influenced by the market shift.

Figure 10 shows the extent to which the different estimated factors explain the component data. The result for the full sample gives a clear visual indication that the structural break was originally omitted for good reason. With the break included, the two dynamic factors do not explain the data nearly as well as in the other cases.

5. Conclusions and Suggestions for Future Research

If this approach to measuring transactions and savings money proves successful, it would be the most fundamental reformulation in the way money is measured since the introduction of monetary aggregates half a century ago. The results we have described are preliminary. The conceptual formulation is intriguing; however, numerous issues require further attention.

In particular, although we have focused on one scheme for identifying the factors—that is, penalized weights—other schemes are possible. The estimation procedure should also be refined and tested further for its sensitivity to various settings. Bias in the estimates, and the possibly related effect of data scaling, need to be better understood. An improvement in this will likely improve other results, so it seems the most pressing problem. Convergence and distribution of the estimates needs to be examined; neither theoretical nor Monte Carlo analysis has yet been done. The procedures need to be more robust. For example, the initial approximation works well most of the time, but sometimes fails. Robustness of the estimates with respect to the selected sample and sample size needs to be examined more extensively.

Although a great deal of work has been done on the data, there remain a few minor problems to address, such as a rough estimation of the term/notice split for non-banks in the first part of the sample. Extending the sample to earlier years would also require considerably more work on the component data.

To date, the weights have been considered nuisance parameters. If the distribution of the estimate of these is large, it is not too important, as long as the distribution of the estimated factors is reasonably good. However, this requires further examination.

The number of factors has been assumed here to be two, but this requires more testing and justification. Proper testing for the number of factors needs to be done.

There are lingering questions regarding whether structural breaks need to be considered, and if so, determining where they occur. There is a possibility that the number of structural breaks is so large that the measurement model is effectively time-varying. That would result in an impossibly large number of parameters, and also a theoretical construction that is not better than the current situation, so the question of the number of breaks is important.

Several operational issues need to be considered more carefully. It has been claimed that the idiosyncratic term will give a timely indication of structural shift, and also accommodate the shift for a certain period of time. This claim is only intuitive and not well-substantiated at this point. Also, the measurement model should accommodate financial innovations, but the assumption has been that it will not hide economic phenomena of interest; for example, a change in the savings rate. This needs to be examined more carefully.

Perhaps the most important question is whether the money measure contributes to our understanding and measurement of economic activity. If that seems unlikely, then there would be little reason to invest in the research and data maintenance that this approach would require.

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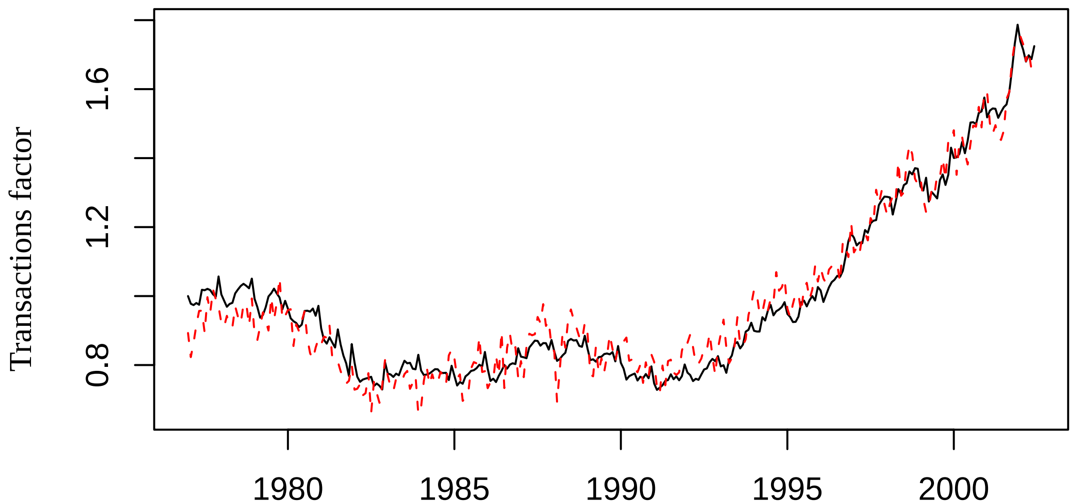
Figure 1. True Factors (solid line) and Estimated Factors (dashed line)



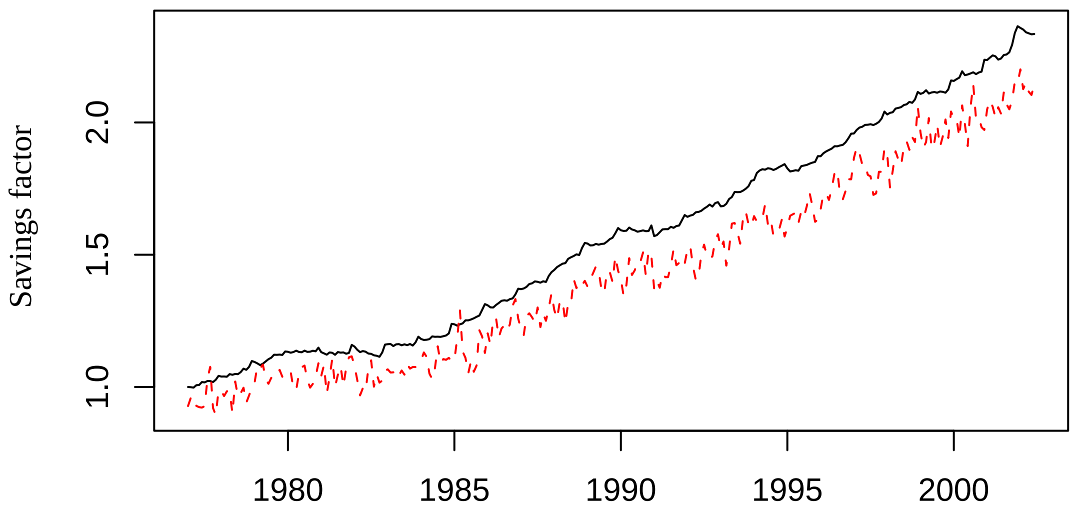
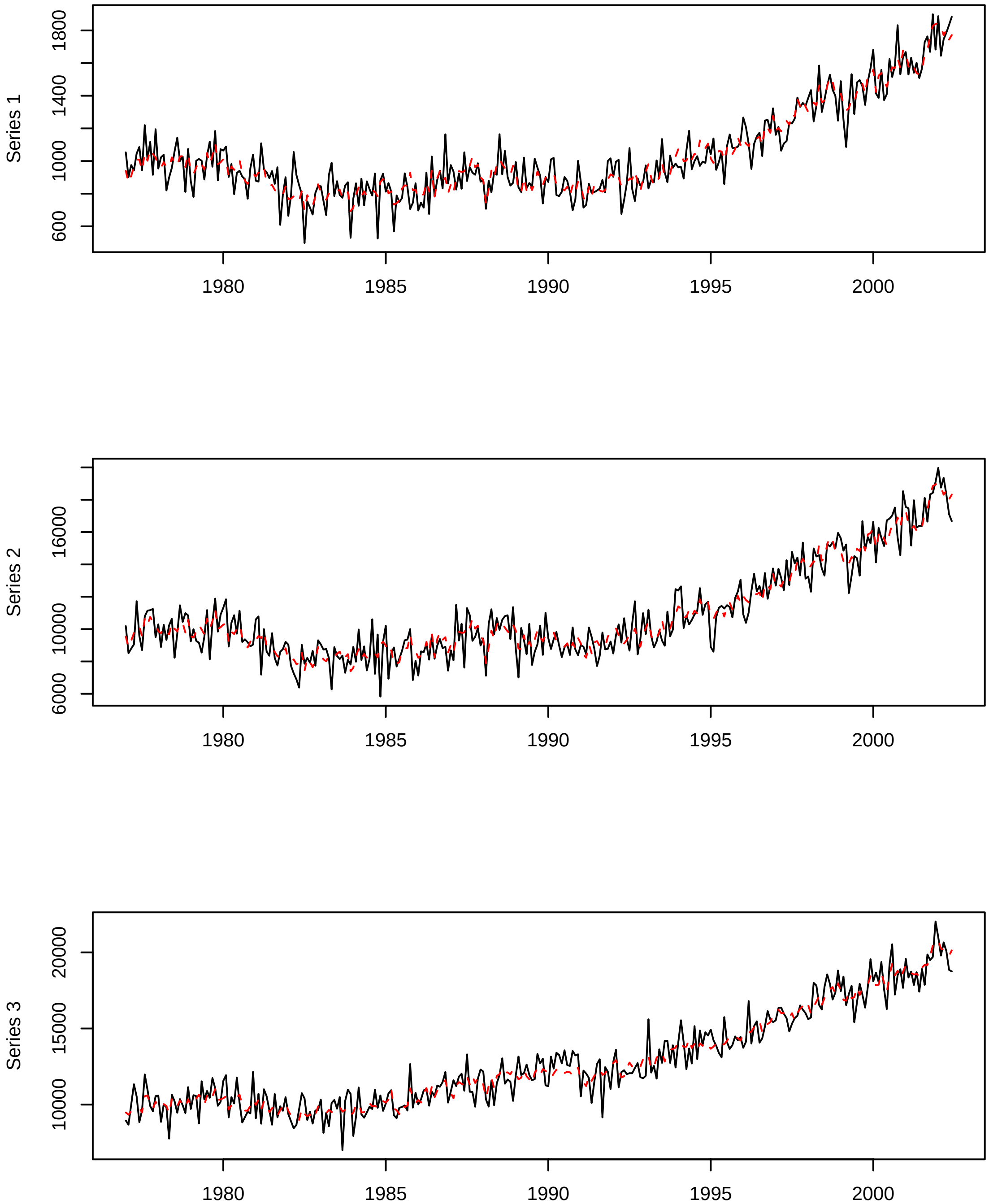


Figure 2. Simulated Data (solid line) and Explained Portion (dashed line)



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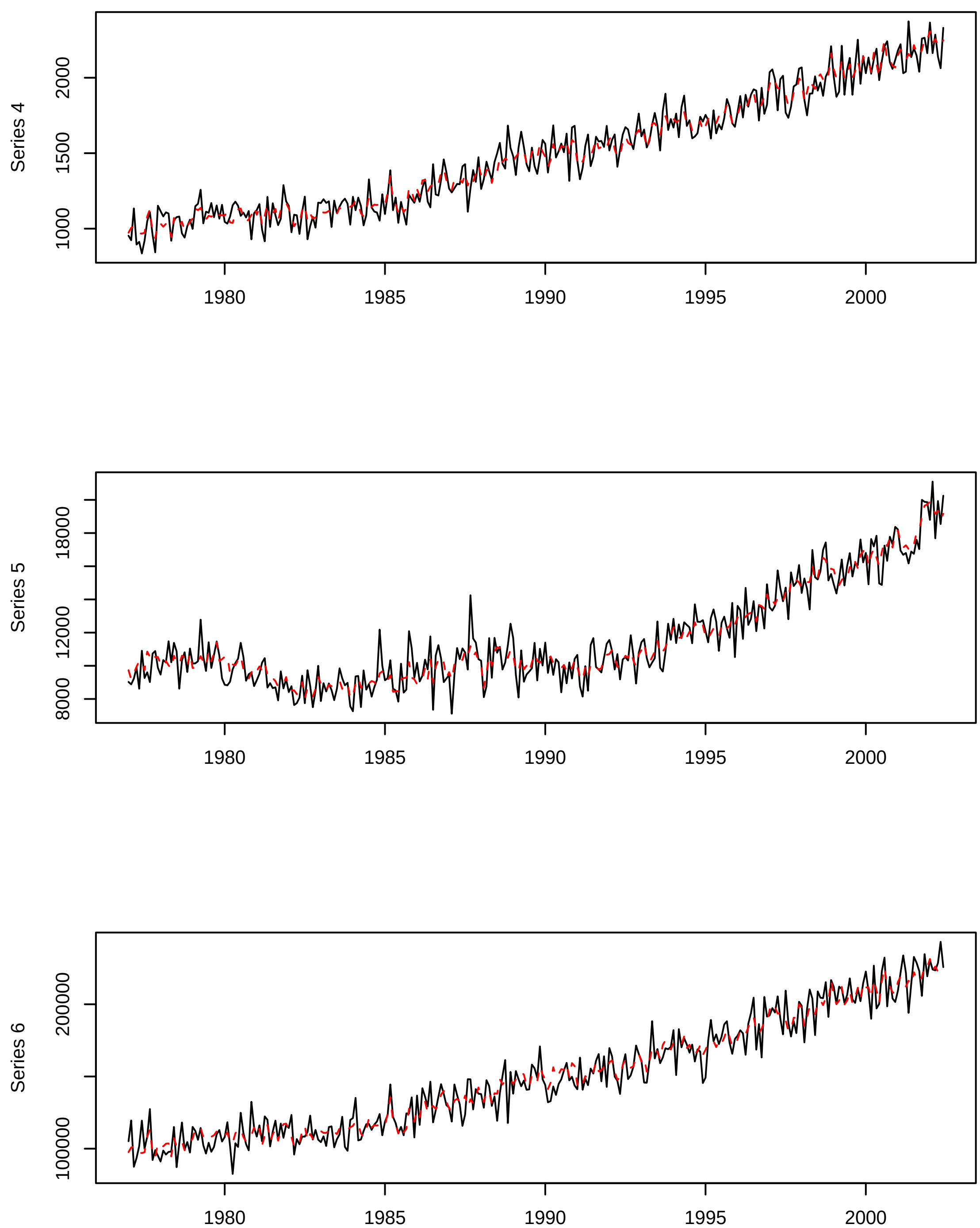
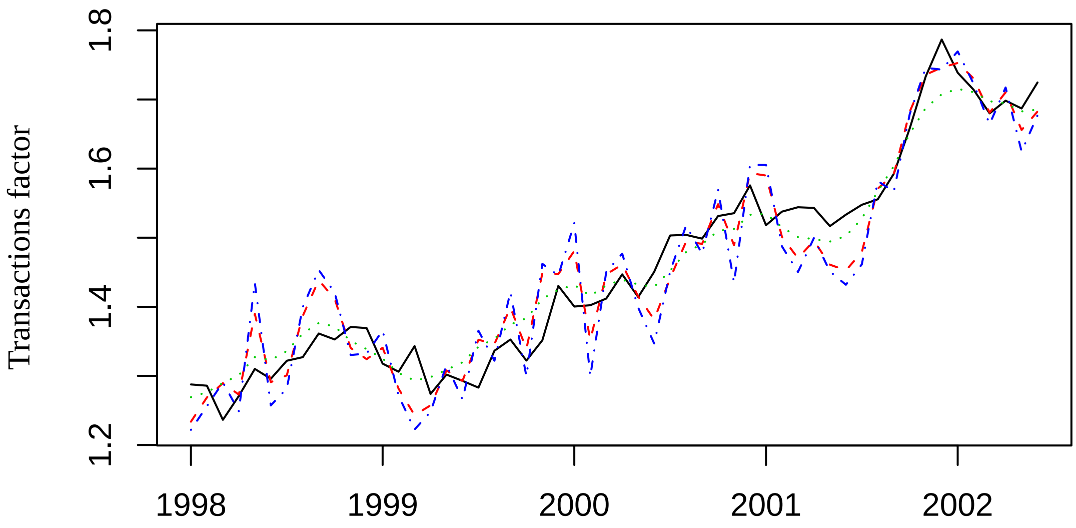


Figure 3. Base-Case Factor Estimates from Simulated Data with Larger and Smaller Roughness Penalties than the Base Case



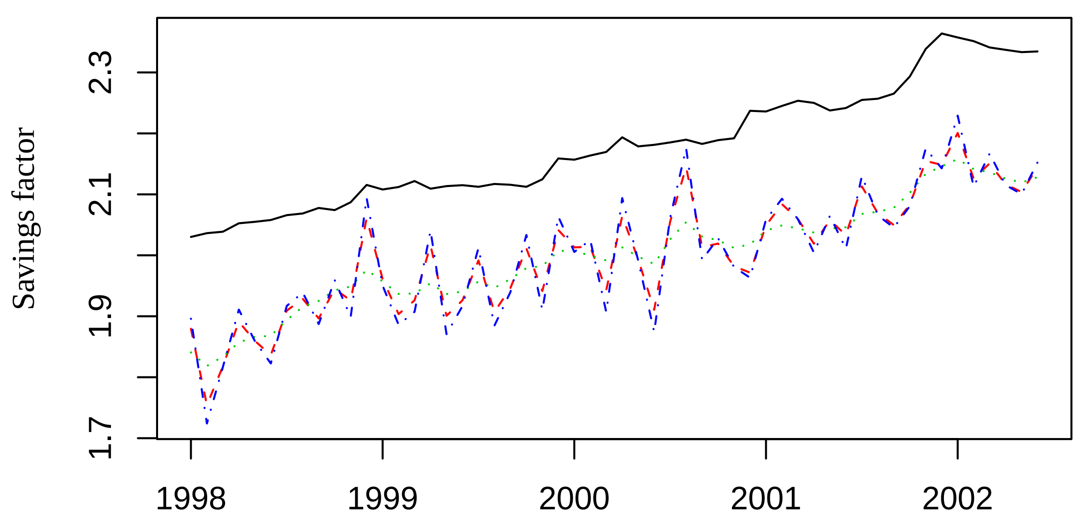
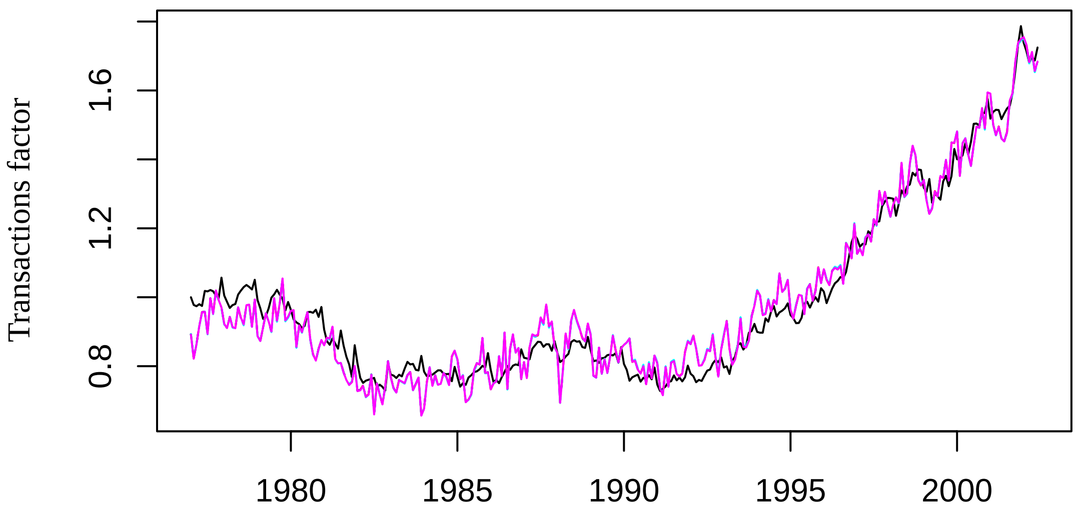


Figure 4. Factors Estimated from Different Initialization Points



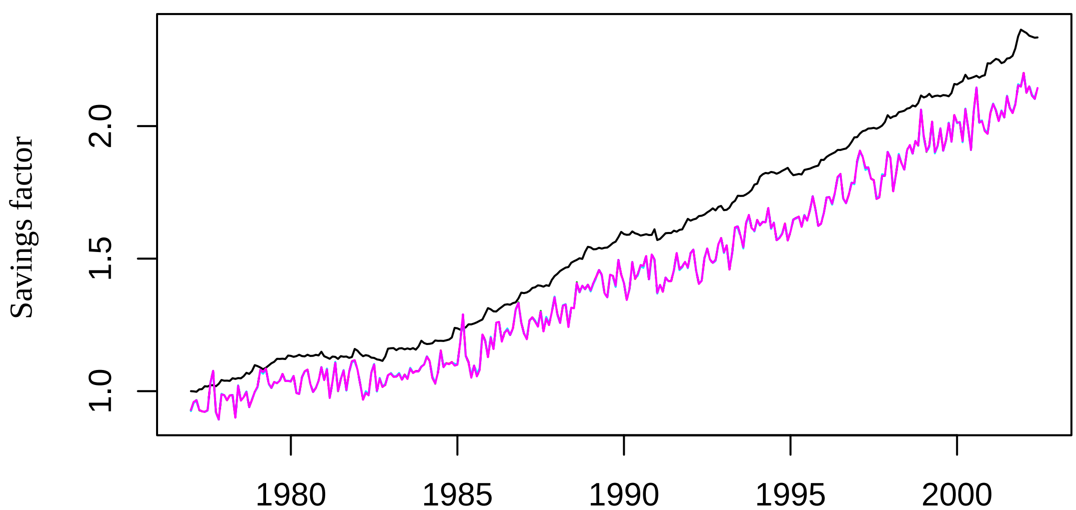
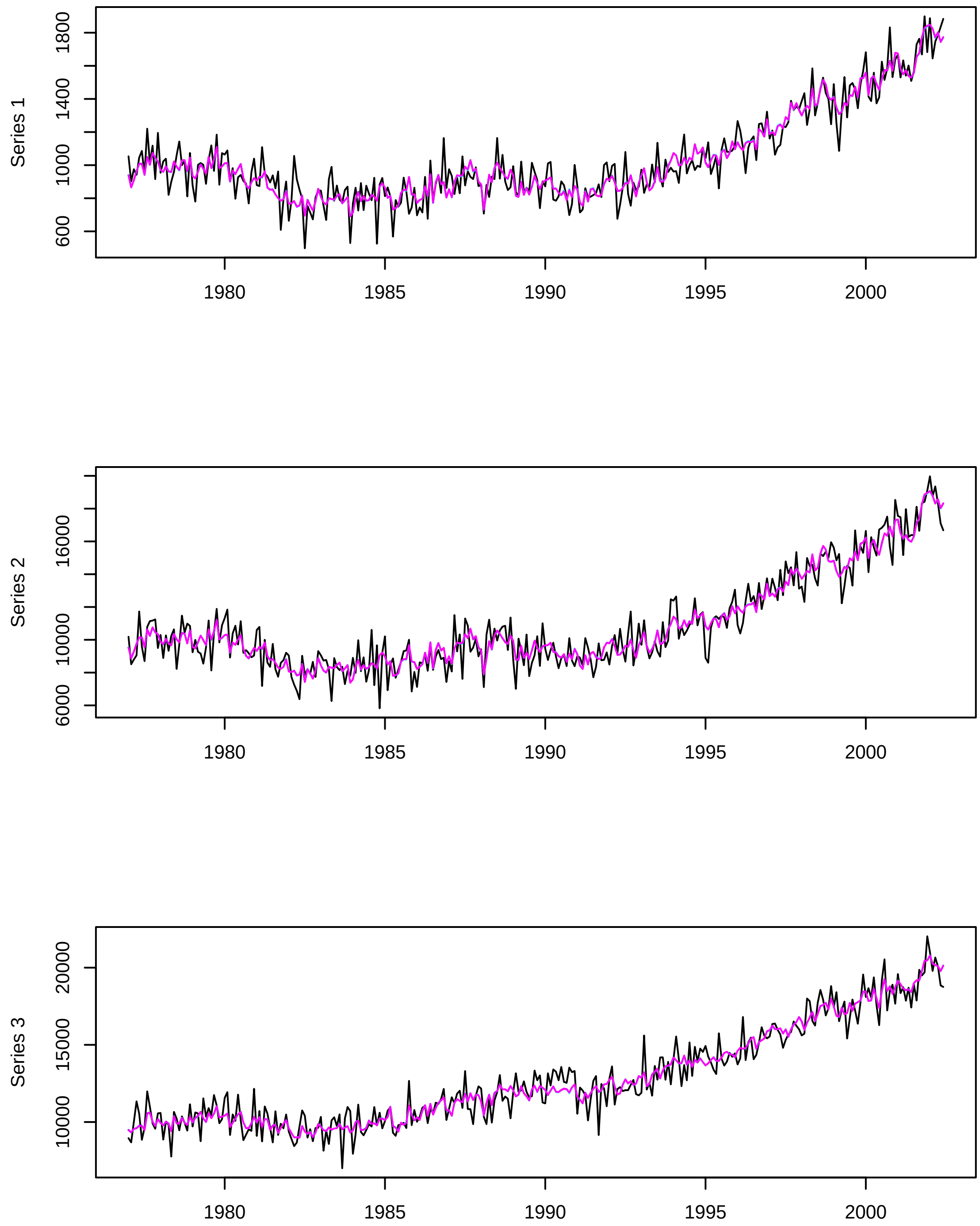


Figure 5. Simulation-Generated Data (solid line) and Portion Explained by Estimations from Different Initialization Points



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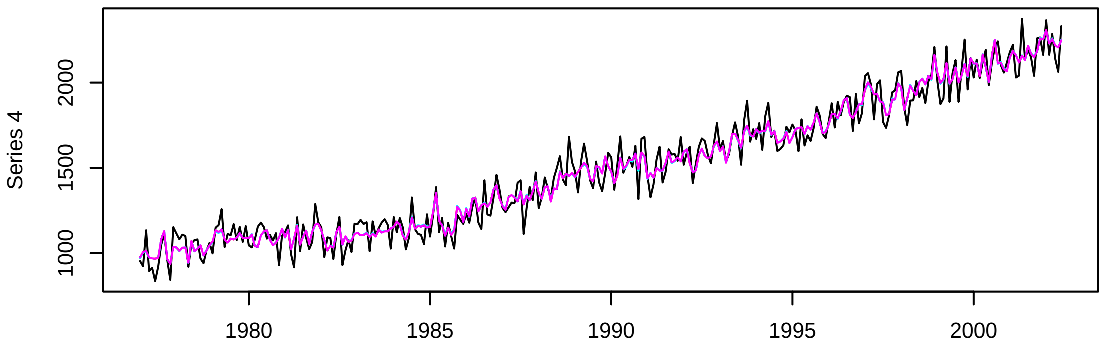
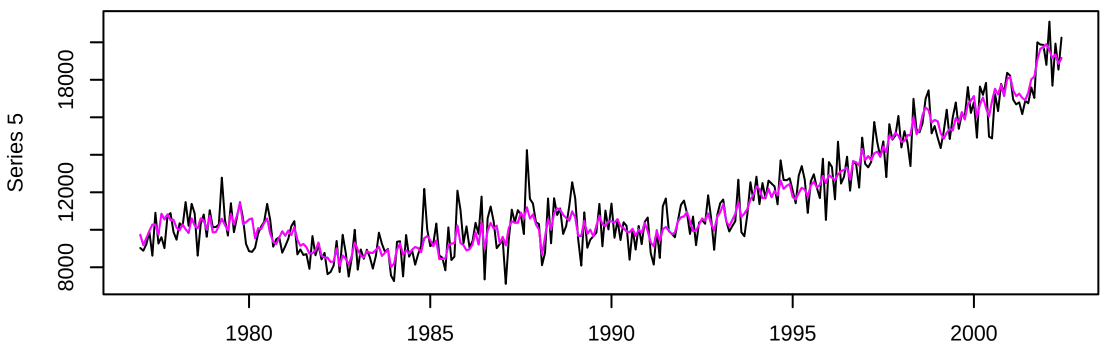




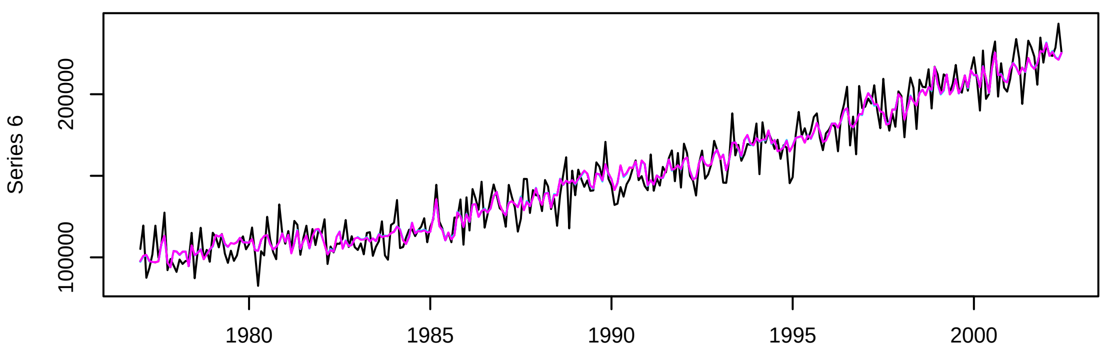
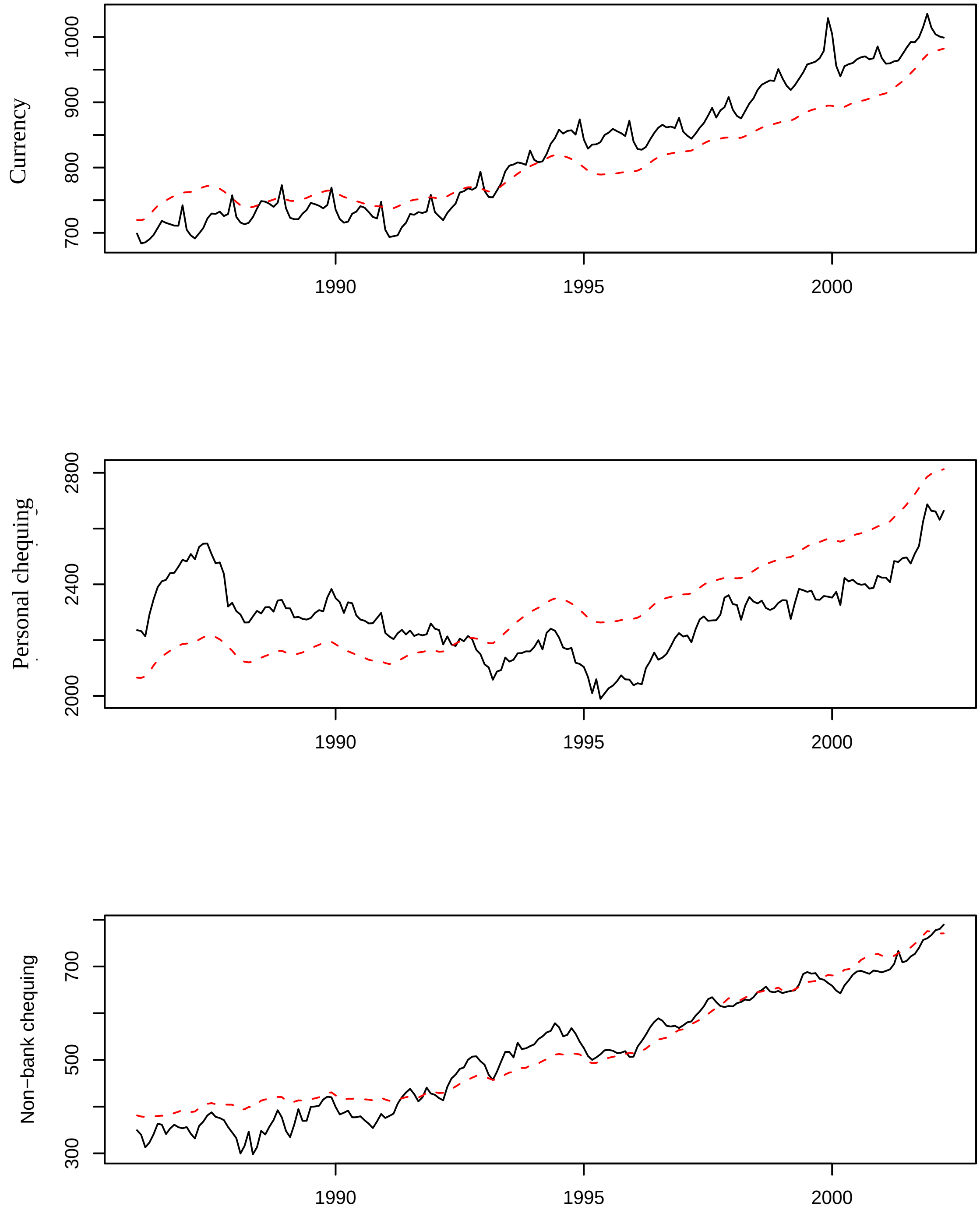


Figure 6. Component Data (solid line) and Estimates using Base-Case Methodology (dashed line)



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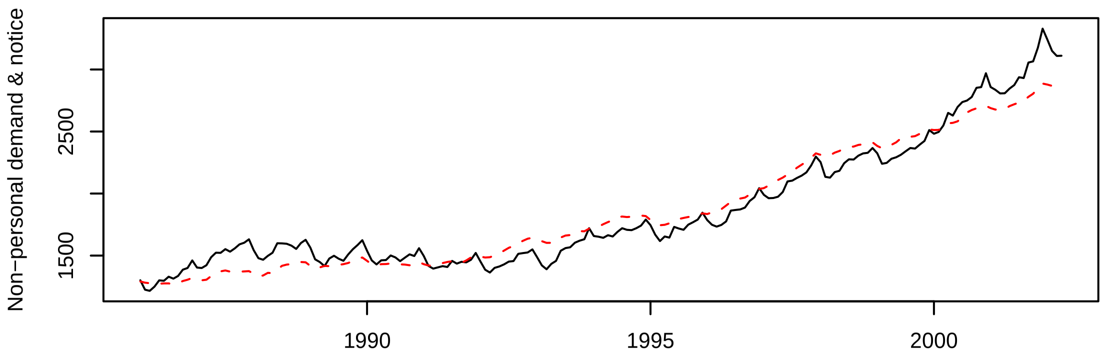
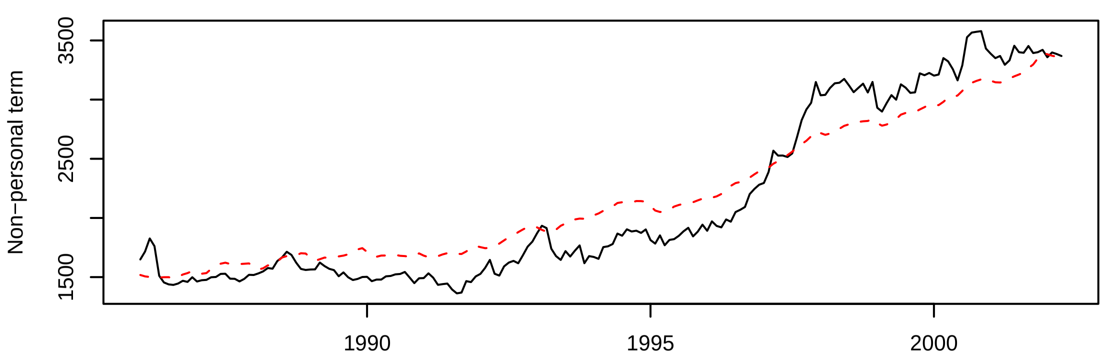




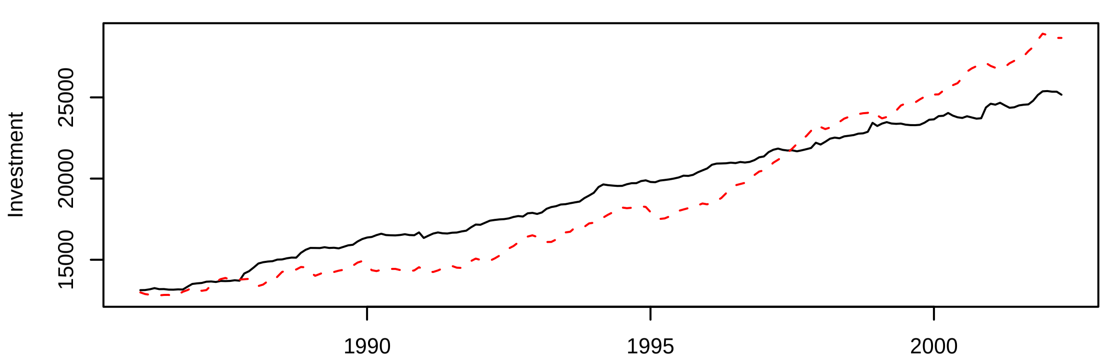
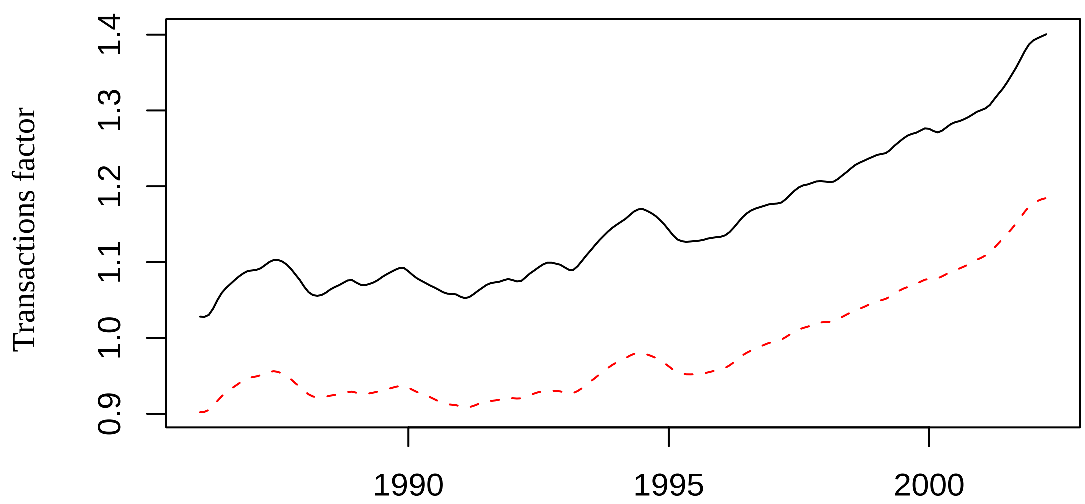


Figure 7. Estimated Factors, Scaled by First Data Point (solid line) and Scaled by Mean (dashed line)



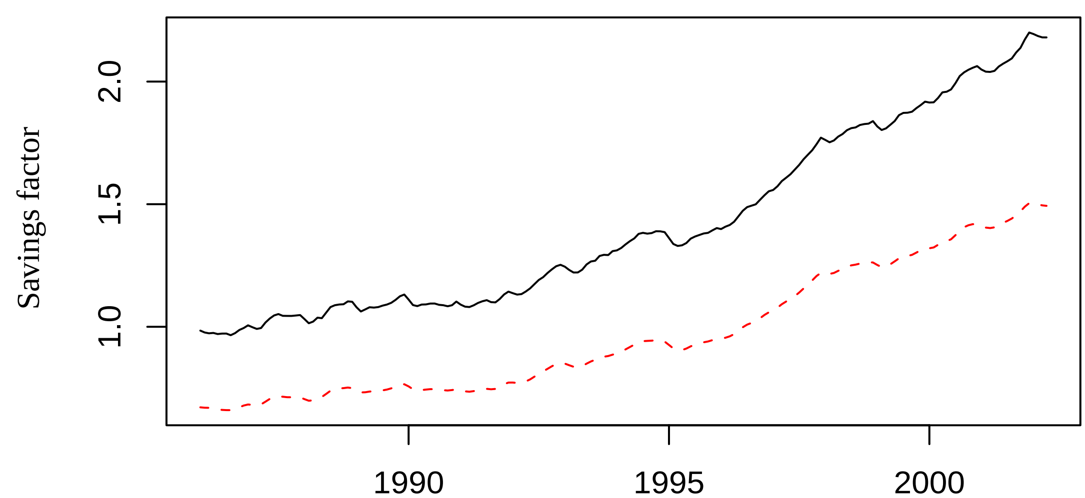


Figure 8. Real Per-Capita M1 and M2++ (normalized) and Estimated Factors

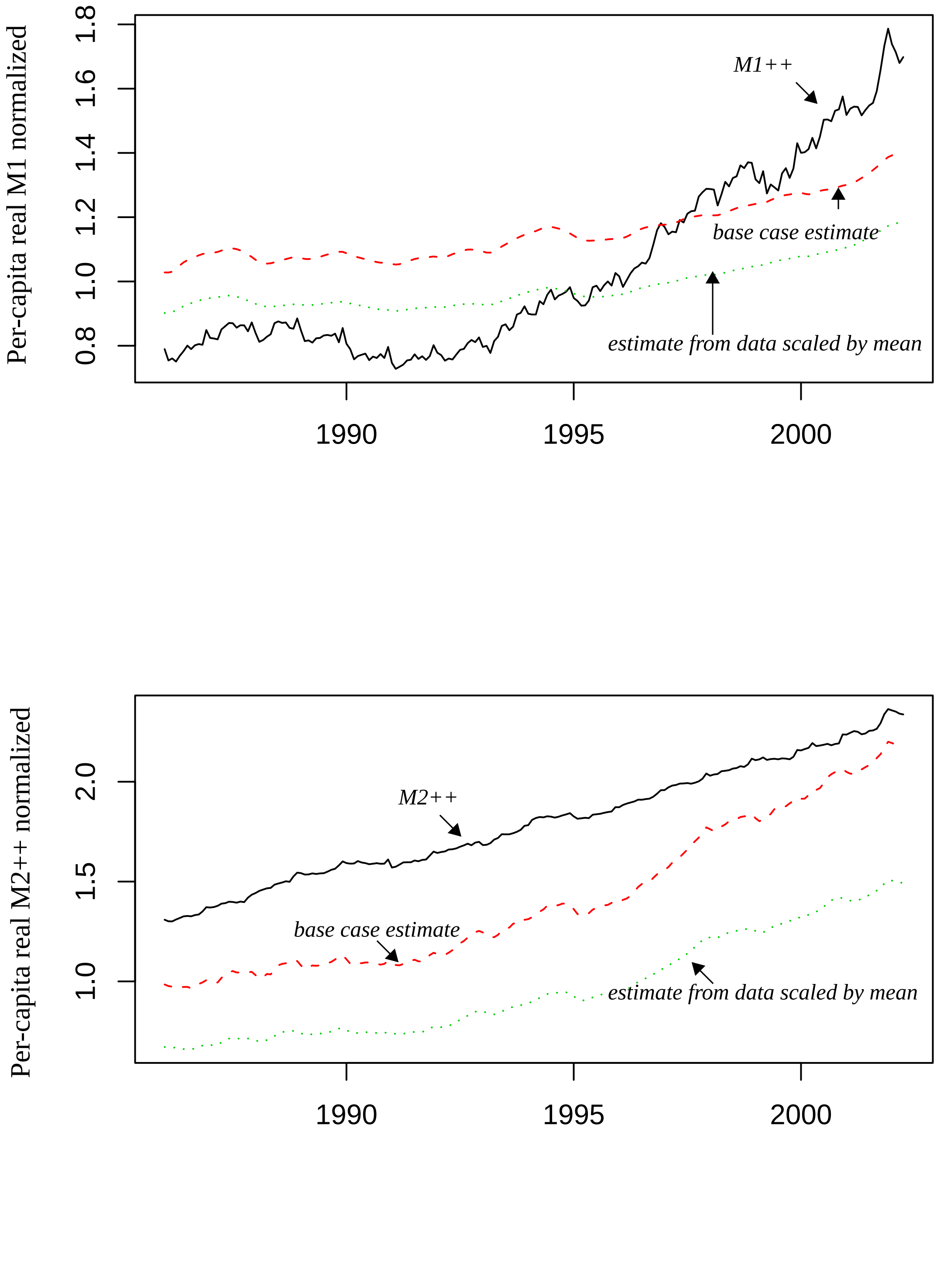


Figure 9. Factors Estimated and Different Sample Periods

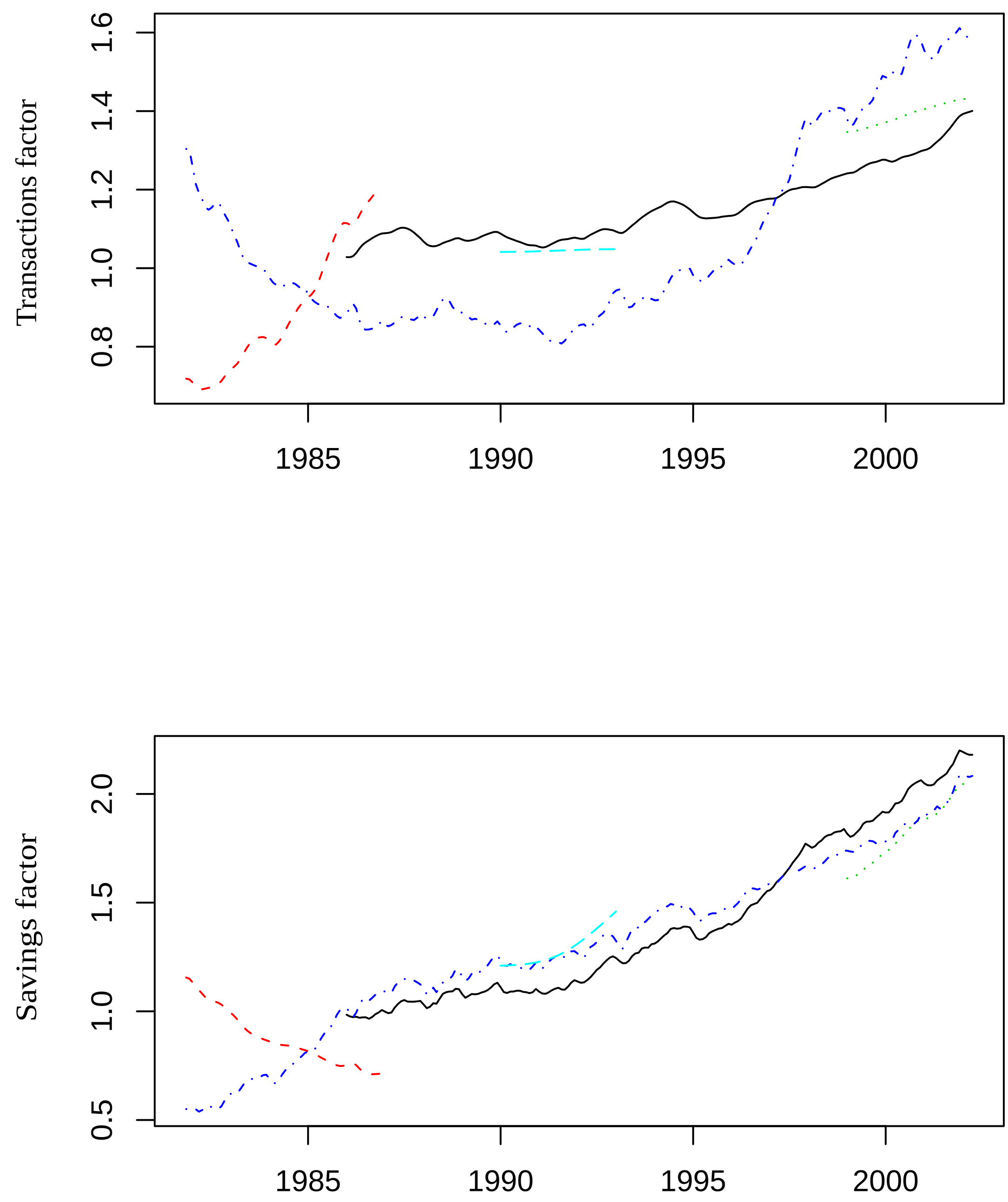
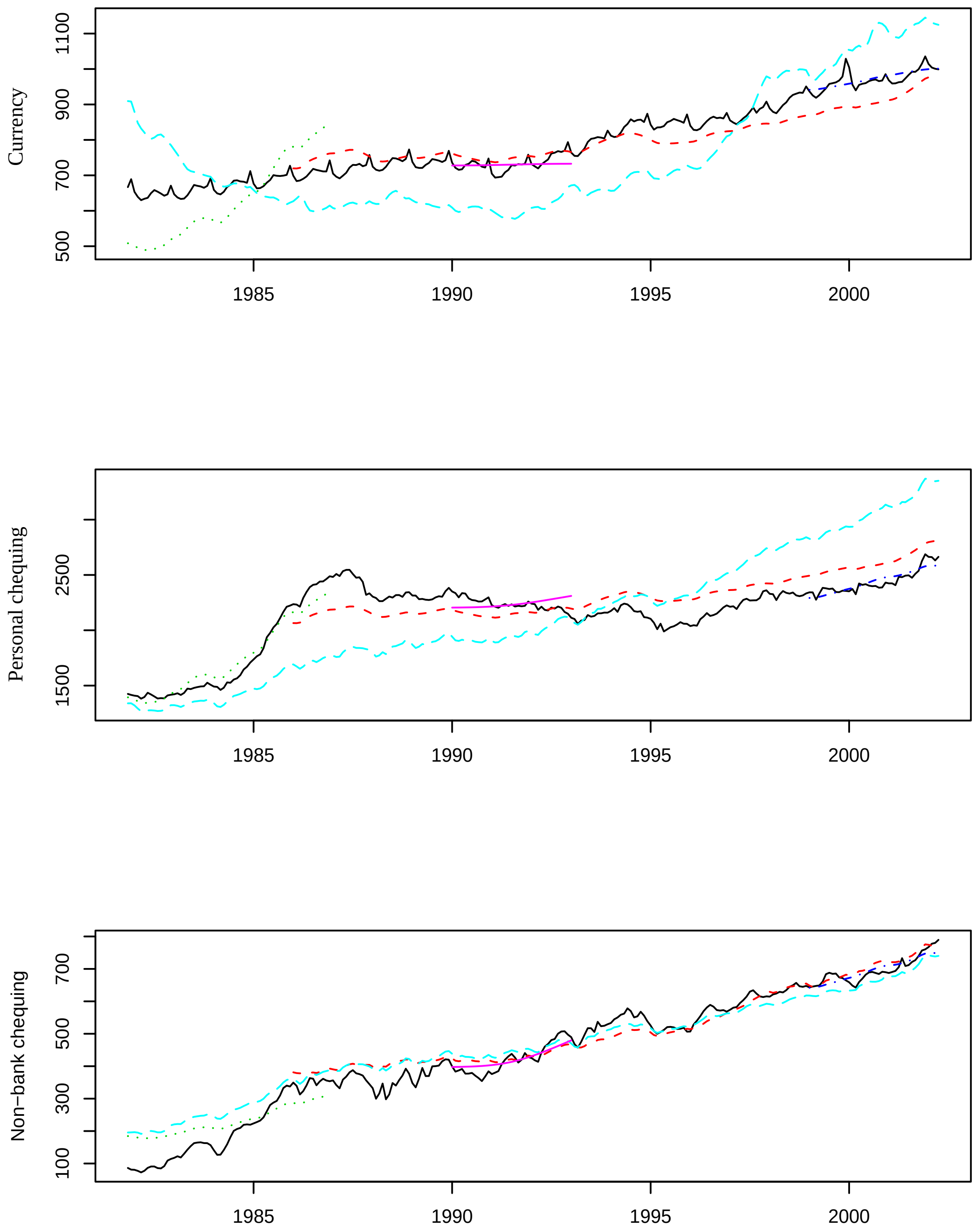
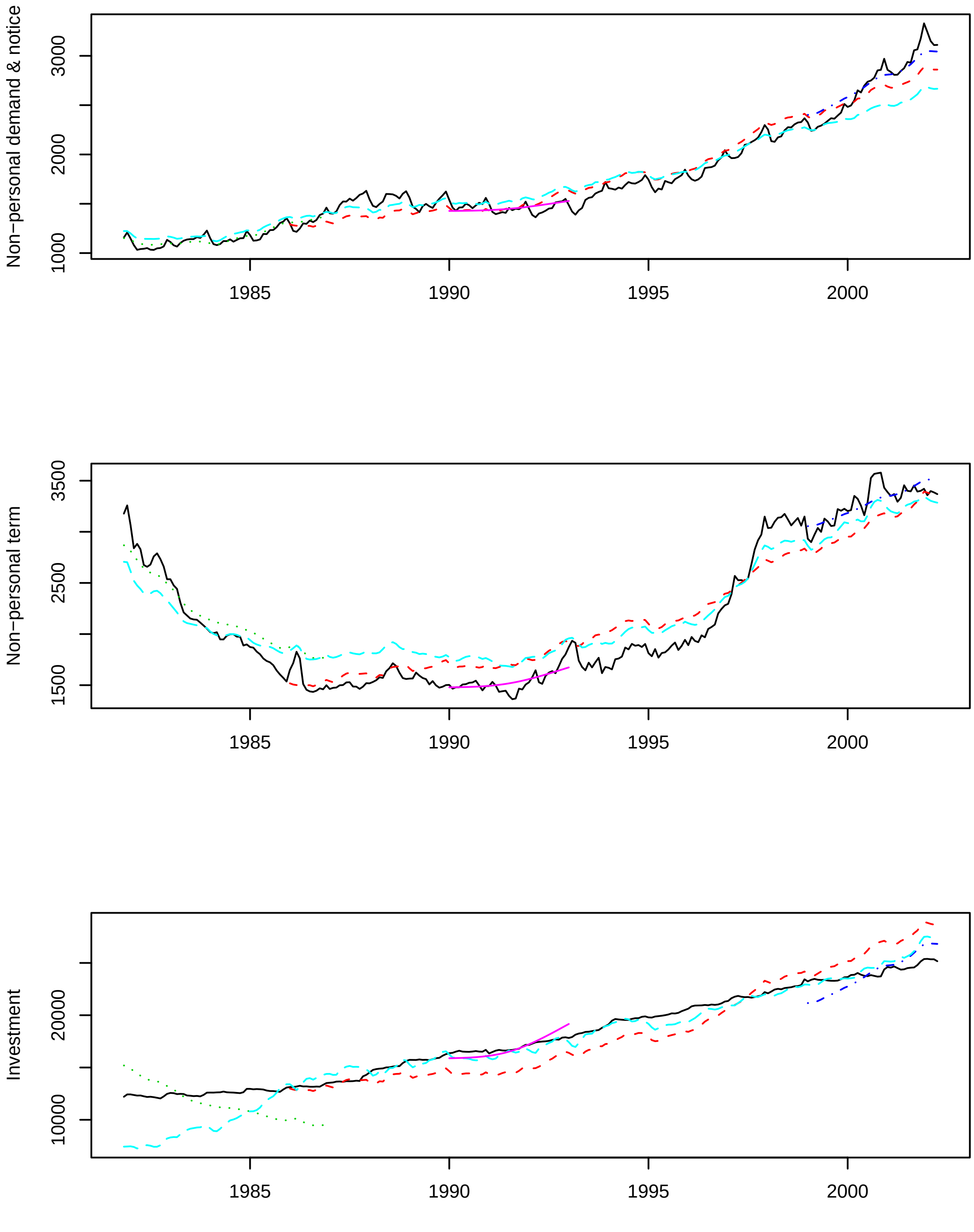


Figure 10. Component Data Explained by Factors Estimated on Different Sample Periods



(continued)

Figure 10 (concluded)



Appendix A: Money Component Data

This appendix describes the deposit classification used to construct monetary aggregates and component groupings used for extracting underlying factors. *MB* numbers are used to indicate "continuity adjusted" versions of *B* numbers published by the Bank of Canada. Historically, the monetary aggregates have been adjusted for certain institutional changes. For example, M1 uses bank data but not trust company data. When a bank took over a trust company, M1 was adjusted by adding the trust company's historical data to the bank's. Thus M1 represents history as if the bank had always owned the trust company. Aggregates would have discontinuities, making them useless for most econometric work if adjustments were not done. Adjustments are listed separately in Bank of Canada data publications, so discontinuities remain in the deposit data. To develop a new measure of money, or to do any econometric work with deposit data, it is necessary that adjustments be assigned to deposit types. These continuity-adjusted data are called *MB* numbers. They add up to the published aggregates.[1]

Table A1 lists deposit types. Column headings are monetary aggregates. An "X" indicates that the deposit type is included in an aggregate. The left-most column indicates the component with which the deposit type is grouped for the analysis in this paper. The items below the double line are not used in components, but are in some aggregates. These are all relatively small.

The grouping of deposit types resembles aggregation, but it is necessary because the measurement model does not account for substitution among asset types. For example, Canada Savings Bonds (CSBs) are now much less available than previously, and holders have shifted most of these assets into mutual funds. This is not a shift in the use of a deposit type, which can be modelled, but rather a substitution between asset types for some market reason. Component 6, called "investment," has individual deposit types that are all relatively volatile; some have grown rapidly while others have dwindled. Remarkably, the sum, shown in the last panel of Figure 6, is quite smooth (and even smoother when viewed in nominal values). This component's smooth constant growth provides some confidence that it is indeed long-term savings.

New features of some deposit types have changed their use (which can be modelled) and also attract funds from other deposit types (a substitution not modelled). Most problematic of these is the advent in the mid-1980s of attractive interest rates and low cheque charges on chequable savings accounts (MB452), and the resulting shift from non-chequable savings accounts (MB453). These deposit types are often grouped together because of this shift. More recently,

1. For more details, see Kottaras (2003). The MB data series as used in this paper are available at <www.bank-banque-canada.ca/pgilbert>.

however, MB453 has acted like an investment account while the chequing features of MB452 have made it a substitute for personal chequing accounts (PCA). A general principle in continuity adjustments has been to make the institutional and reporting structure of historical data correspond as closely as possible to the current structure. In this vein, MB452 has been grouped with PCA in component 2, while MB453 has been grouped with investment (component 6). This may lead to some problems when estimating over the mid-1980s.

In principle, more components are better. Substitution, however, is not currently modelled. One guiding observation in determining the number of components is that component data should have trend growth (total nominal, but not necessarily real per capita), because it seems certain that both the savings and transactions factors have had trend growth. In the factor-measurement model, the components are a positive sum of growing factors; thus, dwindling behaviour, as has happened to CSBs, must be due to substitution (or something else not accommodated by the measurement model). Substitution must be internalized in a component, and thus components should be organized so that none dwindle over time; this has not been difficult to obtain.

The solid line in Figure 6 shows the six component series constructed, in real per-capita terms. The data were divided by population and the CPI to abstract from the influence of population and nominal growth; otherwise, these phenomena could emerge as factors. The first series—currency—provides an anchor at the transactions end of the scale. The sixth—investment—provides an anchor at the savings end of the scale.

Table A1: Deposit Types used in Aggregates and for Constructing Components

	Short description	Identifier	**Gross M1 B2054**	**Net M1 B2033**	**M1+ B2060**	**M1++ B2061**	**M2 B2031**	**M2+ B2037**	**M2++ B2059**	**M3 B2030**
1	Currency	MB2001	X	X	X	X	X	X	X	X
2	PCA	MB486	X	X	X	X	X	X	X	X
4	CA other demand	MB487p	X	X	X	X	X	X	X	X
2	Personal chequing	MB452			X	X	X	X	X	X
6	Pers. notice, non-cheq.	MB453				X	X	X	X	X
3	N-B chequing	Non-bankCheq			X	X		X	X	
4	N-P chequable notice	MB472			X	X	X	X	X	X
4	N-P non-chequing	MB473				X	X	X	X	X
6	N-B non-chequing	NonbankNon-Cheq				X		X	X	
6	Pers savings	MB454					X	X	X	X
6	N-B Term	Nonbank-Term						X	X	
6	Life insur	MB2046						X	X	
6	Dep at gov inst	MB2047						X	X	
6	mmmf	MB2048						X	X	
6	CSB	MB2057							X	
6	Non-mmmf	MB2058							X	
5	N-P term dep	MB475								X
6	Fgn curr dep	MB482								X
	Float	MB476	+	-	+	+	-	-	-	-
	Trust co. deposits at banks	TMLinter-bank	X	X						
	Pre-1982 classif. error	MB473adj				X				
	Small pre-1982 problem	MB452adj			X					
	Adjustment for poor StatsCan estimate	CUadj				X				

Notes: Left column indicates component in which deposit type is included. “net M1” is also called “M1 total.” N-P: non-personal; N-B: non-bank; mmmf: money market mutual funds; X: included; +: float is in; -: float is out.

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