No. 48

AN ANALYSIS OF THE INFORMATION CONTENT OF ALTERNATIVE MONETARY AGGREGATES

Doug Hostland
Stephen Poloz
Paul Storer

Bank of Canada
Technical Reports

Rapports techniques
Banque du Canada

Technical Report 48

AN ANALYSIS OF THE INFORMATION CONTENT OF ALTERNATIVE MONETARY AGGREGATES

by
Doug Hostland
Stephen Poloz
Paul Storer

Presented at the XXIV Meeting of Technicians of Central Banks of the American Continent, Brasília, Brazil, October 1987. The views expressed in this report are those of the authors, and no responsibility for them should be attributed to the Bank of Canada.

ACKNOWLEDGEMENTS

A number of people in the Department of Monetary and Financial Analysis worked on various phases of this research during 1981-86, and we wish to acknowledge them specifically. An especially important contribution was made by John Murray, who co-ordinated the work during the earlier part of that period, and who saw to the construction and documentation of the superlative monetary indices data base. Important contributions were also made by John Kuszczak, Tiff Macklem, and Monica Smith. Research assistance was provided at various times by Paul Gomme, Sheila MacDonald, Rick Piotrowski, and Lee-Anne Torrens. We also are indebted to our other colleagues at the Bank, too numerous to mention individually, who commented on the work at various stages.

CONTENTS

ABSTRACT

In this study the authors compare the information content of alternative monetary aggregates with respect to total spending in the economy, using data for Canada. The analysis considers forty-six monetary measures, about half of which constitute conventional summation aggregates, while the remainder are superlative indices of monetary services based on the Fisher Ideal formula. The methodology follows a natural sequence in which the information set used to predict total spending is gradually expanded, beginning with lagged total spending itself, followed by the monetary aggregates, then other financial variables such as interest rates, exchange rates, and stock prices. Finally, the information loss due to monetary aggregation is tested by decomposing a broad and informative aggregate into its components, within a multivariate indicator model. All of the competing models are tested against one another, using the encompassing principle of Hendry and Richard (1982), and then evaluated by means of standard stability tests, one-period-ahead in-sample forecasting, and post-sample simulation.

RÉSUMÉ

Dans cette étude, les auteurs comparent l'information que différents agrégats monétaires contiennent sur l'évolution de la dépense globale. Leur analyse fondée sur des données pour le Canada vise quarante-six mesures de la masse monétaire, dont environ la moitié sont des agrégats conventionnels obtenus par addition, et l'autre moitié des agrégats "superlatifs" établis selon la formule Fisher Ideal. La méthode retenue suit un ordre naturel, en ce sens que le nombre de variables servant à prévoir l'évolution de la dépense globale est augmenté graduellement: on fait d'abord intervenir les valeurs retardées de la dépense globale elle-même, suivies d'un agrégat monétaire, puis d'autres variables financières telles que le taux d'intérêt, le taux de change et le cours boursier. Enfin, les auteurs cherchent à savoir si l'agrégation de mesures de la masse monétaire entraîne une perte d'informations; pour cela, ils décomposent un grand agrégat riche en informations et utilisent ses éléments comme indicateurs dans un modèle de prévision à plusieurs variables. Les divers modèles testés sont comparés entre eux selon le principe "englobant" de Hendry et Richard (1982); ils sont ensuite évalués sur la base de tests standard de stabilité, de prévisions récursives effectuées pour une période à l'avance et de simulations ex post.

1 INTRODUCTION

How best to measure the important concept "money" is an old and difficult question, made more complex in recent years by a variety of new ways in which liquidity can be held. The introduction of a new financial instrument which is an imperfect substitute for existing assets substantially increases the number of potentially interesting monetary aggregates. This study subjects a large number of such aggregates to a battery of tests, in order to isolate those that are economically relevant.

Economic relevance is a vague concept, which may be the most important reason for the existence and active use of a variety of monetary aggregates. Different measures of money may be useful for different analytical purposes. For this study a common yardstick is needed to provide a reasonable standard for comparison of the aggregates. In this context we consider a monetary aggregate economically relevant if it is highly correlated -- correlation being defined in various ways -- with total spending or nominal income in the economy. This definition of relevance seems reasonable from two points of view. First, in theoretical models of the macroeconomy, "money" is structurally related to "income." To the extent that these two concepts are appropriately measured, correlation between them can be viewed as support for a body of widely accepted theory. Second, "total spending" or "nominal income" is an important variable in the context of the formulation of monetary policy, and any measures of money that provide leading (or even contemporaneous, given the relative reporting lags) information on movements in that variable would be considered relevant.

In the work that follows, the information content of forty-six measures of the money supply is examined. Twenty-four of them are conventional "summation" aggregates, where various financial assets are simply added up. The remainder are superlative monetary services indices, based on the chain Fisher Ideal formula, which weight each component according to a measure of its liquidity or the monetary services it provides. For this purpose we updated the data set of Cockerline and Murray (1981), who analyzed several different methods of monetary aggregation using Canadian data.

2 DATA AND METHODOLOGY

The data are quarterly, seasonally adjusted, and are available from 1969Q1 to 1986Q4. Table 2.1 defines the forty-six monetary aggregates used. They cover the range of liquidity from currency to 3-year Government of Canada bonds, in a reasonably natural progression. Many other combinations are possible, of course, some of which were studied in preliminary work, but this array of aggregates seems most logical.[1]

The principle behind the conventional summation aggregates is well known. Broadening an aggregate serves to internalize substitution between various assets that can affect information content. Indeed, constructing a simple summation aggregate implicitly assumes that all of the components are perfectly substitutable, a condition which in fact almost never obtains. To the extent that the various components are not perfect substitutes, simple summation aggregates contain an element of aggregation bias that may reduce their economic relevance.

One alternative to summation aggregates is to construct indices of the monetary or liquidity services that each component yields. For example, since currency is perfectly liquid it yields a high level of monetary services per unit, whereas government bonds are less liquid and should receive less than unit weight in aggregation. Superlative indices weight each asset that has some "monetary characteristics" by a unique rental price that reflects its relative "moneyness." The weights are related to the rate of return that the asset in question bears, relative to some benchmark rate that is paid on a highly illiquid representative

1. Alert readers may notice the absence of the monetary aggregate M1A, which until January 1988 was published regularly in the Bank of Canada Review. This aggregate grew so strongly during 1982-1985 because of the popularity of daily interest chequable savings deposits (DICAs) that it is possible to rule it out as a useful indicator over our sample period. In its place we consider M1ALD, and allocate DICAs to the next aggregate, a procedure which implicitly assumes that DICAs are largely savings deposits, as opposed to being held principally for transactions purposes.

Table 2.1

DEFINITIONS OF MONETARY AGGREGATES

1. CURR - currency outside banks
2. BASE - currency plus chartered bank reserves (excluding required reserves on Government of Canada deposits), using a chain index to correct for changes in required reserve ratios
3. M1 - currency plus demand deposits net of float at banks
4. M1ALD - M1 plus non-personal notice deposits at banks
5. M13 - M1ALD plus daily interest chequing and personal savings deposits at banks
6. M2 - M13 plus personal fixed-term deposits at banks
7. PHMS - M2 plus non-personal fixed-term deposits at banks
8. PHMSB - PHMS plus bankers' acceptances
9. PHMSBC - PHMSB plus commercial paper
10. M3 - PHMS plus foreign currency deposits of residents booked in Canada at chartered banks
11. M3B - M3 plus bankers' acceptances
12. M3BC - M3B plus commercial paper
13. LL - M3BC plus Canada Savings Bonds, treasury bills held by the public, and 1-3 year Government of Canada bonds

14.- 24. - M1 through LL plus corresponding deposits held at trust and mortgage loan companies, credit unions, and caisses populaires -- mnemonics add a "+", for example M2+ equals M2 plus all deposits at these near-banks

25.- 46. - Fisher Ideal monetary indices corresponding to the same level of aggregation for M1 through LL and M1+ through LL+

asset. This procedure presumes that the spectrum of rates of return paid on various financial assets reflects their varying degrees of liquidity. Those assets paying the lowest rates of return are assumed to be the most liquid and receive the highest weights in the index. More details may be found in Barnett (1980), Barnett et al. (1984), and Cockerline and Murray (1981).

The superlative index used here is the chain Fisher Ideal, which is formulated as follows. The total expenditure on monetary services is equal to the product of each component's rental price (π_i) and quantity (q_i), summed over all components. The share in total expenditures on monetary services held by the ith component then is:

$$(2.1)\quad S_i = \pi_i q_i / \sum_{i=1}^{N} \pi_i q_i$$

where N components exist with monetary characteristics. The chain Fisher Ideal index of total monetary services yielded by the N assets is then:

$$(2.2)\quad Q_t = Q_{t-1} \left[\left[\sum_{i=1}^{N} S_{i,t-1} (q_{i,t} / q_{i,t-1}) \right] \Big/ \left[\sum_{i=1}^{N} S_{i,t} (q_{i,t-1} / q_{i,t}) \right] \right]^{1/2}$$

Intuitively, one can think of the growth rate of the chain Fisher Ideal index as a weighted average of the growth rates of the various components, where the weights relate to the rental prices. The latter are given by the differential between the own-rate paid on the asset in question (r_i) and the benchmark rate (r_B); algebraically, $\pi_i = (r_B - r_i)$.

Previous studies, such as that of Cockerline and Murray (1981), focussed on alternative approximations of the Divisia superlative index. As Cockerline and Murray have demonstrated, the chain Fisher Ideal index and the conventional approximation to the Divisia index behaved very similarly over the 1970s. However, the multiplicative nature of conventional approximations to the Divisia index makes them less able to incorporate the introduction of new financial instruments, compared with the additive formula of the Fisher Ideal. Because several new financial instruments were introduced during our sample period, it seemed logical to use the chain Fisher Ideal index in this study. Apart from this difference, the data used here have essentially been updated from the study of Cockerline and Murray.[2]

The tests performed with the data set follow a natural sequence in terms of sophistication. We began by calculating simple correlation coefficients between the four-quarter growth rates of the aggregates and of total spending over various sample periods. Four-quarter growth rates were used in this first stage because of their widespread use to describe significant trends in the economy. We also examined the relative stability of the velocity of each monetary aggregate about its trend, as an alternative summary statistic of the degree of association between total spending and money. These simple approaches are useful in choosing a single variable that may prove to be a reasonable guide to underlying movements in total spending, but they ignore potentially valuable leading information that may be found in lags of money and other financial variables. We therefore turned to a more formal consideration of the question of information content. Simple autoregressive models of quarterly growth rates of nominal spending and of its real and price components were specified. This detrending procedure reduces the probability of finding spurious correlations and provides a convenient benchmark against which improvements brought about by the inclusion of other variables may be measured. The first step was to introduce sequentially a number of lagged values of each of our forty-six monetary measures into these univariate models, resulting in equations of the following form:

$$(2.3)\ Y = \alpha + A^{p}(L)Y + B^{q}(L)M + \varepsilon$$

where Y represents the goal variable and M the monetary aggregate, both measured in quarterly growth rates, and ε represents a random disturbance

2. The data set is available on request from the Department of Monetary and Financial Analysis, Bank of Canada.

term. The notation $A^p(L)$ represents a polynomial in the lag operator L of order p. Thus, $A^p(L)Y = A_1Y_{-1} + A_2Y_{-2} + A_3Y_{-3} + \ldots + A_pY_{-p}$.

In constructing these bivariate models, the optimal lag lengths p and q were chosen using the Final Prediction Error criterion (FPE) of Akaike (1969). This entails minimizing the following penalty function:

$$(2.4)\quad FPE_Y(p,q) = \frac{(T + p + q + 1)}{T(T - p - q - 1)} \sum_{t=1}^{T} \hat{\varepsilon}_t^2$$

where T is the number of observations and $\hat{\varepsilon}$ is the least squares residual obtained by estimating equation (2.3). The FPE is a convenient means of specifying lag lengths. Although the FPE criterion tends not to select the correct lag length asymptotically, Monte Carlo experiments by Geweke and Meese (1981) found that the FPE performs well in small samples relative to other model selection criteria such as minimizing the standard error of the equation. Geweke and Meese showed that the FPE tends to choose too many lags and hence errs on the side of inefficiency, but we prefer this to other, asymptotically correct, criteria (such as the Schwarz (1978) Bayesian criterion, for example) which tend to choose too few lags and hence bias the estimates by imposing invalid restrictions. The FPE provides an attractive balance between parsimony and bias. Operationally, rather than fitting p x q regressions, we used p as chosen during the specification of the univariate models and then chose q according to the FPE. The FPE then became our measure of information content, and those aggregates for which (2.3) had the lowest FPEs were considered the most informative.

Having used the FPE to determine the lag lengths q for each of the forty-six aggregates, we chose a subset that appeared to be relatively informative. This subset represents a group of competing non-nested models in the form of equation (2.3). These models were compared using the encompassing principle of Hendry and Richard (1982), which enables the ranking of alternative non-nested models according to their information content. One model was chosen as "variance-dominant," which here was the model with the lowest FPE. We then constructed F-tests of the null hypothesis that the competing models cannot explain a significant proportion of the forecast error variance of the variance-dominant model. Rejection of this hypothesis would indicate that there was significant information in both the variance-dominant and competing models. Failure to reject this hypothesis would imply that the variance-dominant model encompassed the competing model. Thus, the role of the encompassing tests was to isolate significant information in the alternative models, whereas the main role of the FPE was to determine the optimal lag lengths of the models. However, we also made use of the FPE to reduce substantially the number of models involved in the encompassing tests.

Having isolated encompassing bivariate models based on autoregressive and monetary information, we next expanded the information set to include the short-term rate of interest, the exchange rate, and an index of stock prices. Lagged values of these variables were introduced into the bivariate models, Akaike's FPE was used to determine whether any of them were informative, and a set of multivariate indicator models was thereby constructed. As with the bivariate models, the multivariate model with the lowest FPE was subjected to encompassing tests against a subset of the other models with relatively low FPEs. From this emerged a second set of encompassing models for our goal variables.

Indicator models were also constructed using various components of the monetary aggregates. In this way we could test for information loss due to aggregation. In choosing components to include, we were guided by our previous results, which identified the most informative broader aggregates. To construct a model based on disaggregated monetary data, we began with the lag lengths for the goal variables based on their univariate equations and added the monetary components, using the FPE to choose their lag lengths. These component equations were used to examine aggregation assumptions implicit in the previously-specified bivariate models. Other financial variables were added to test aggregation assumptions implicit in the previously-specified multivariate models. From this exercise emerged a third set of encompassing models for our goal variables.

While this methodology ensured that the final encompassing models would have the best fit of all preceding models, we admit the possibility that they would not necessarily be the most useful in practical work. Since the approach is essentially atheoretical and consists of a good deal of searching, there is always the risk that some variables will be included for spurious or sub-sample-specific reasons. To screen for this problem, we submitted the encompassing models based on each information set to a variety of stability tests. A model which has incorporated a variable for spurious reasons is likely to be found unstable when sub-periods are compared, using a Chow test, for example. We also compared the models' ability to explain the post-sample data. This we regarded as the most useful method of discriminating among models. Our efforts on this score, however, were weak because of a shortage of post-sample data. While we were unable to point to a single preferred financial indicator model, the study succeeds in eliminating a very large number of potential models from consideration.

3. SIMPLE CORRELATIONS AND VELOCITY TRENDS

As noted in the introduction, several different measures of association between our forty-six monetary measures and total spending are used to compare their information content. In this section we consider two simple and well-known measures of association. The first is the correlation coefficient, which is given by:

$$(3.1)\quad COR(Y, M) = \frac{\Sigma(Y_i - \overline{Y})(M_i - \overline{M})}{\left[\Sigma(Y_i - \overline{Y})^2 \ \Sigma(M_i - \overline{M})^2\right]^{1/2}}$$

where a superbar indicates the mean of a series.

The second statistic used in this section is the standard deviation of the velocity of a monetary aggregate about its trend. This statistic amounts to the standard error of the following regression equation:

(3.2) $\log (Y/M) = \alpha_0 + \alpha_1 T + \varepsilon$

where T is a time trend variable. Recognizing that some monetary aggregates are interest-elastic, and therefore have velocities that vary directly with interest rates, we also compare the standard errors of the following regression equation for our various monetary aggregates:

(3.3) $\log (Y/M) = \alpha_0 + \alpha_1 T + \alpha_2 R + \mu$

where R is a 90-day money market rate of interest. This procedure prevents the variability in velocity due to interest rates (which is in some sense predictable) from affecting our comparison.

Before proceeding, it is necessary to define Y, our measure of total spending in the economy. Throughout this study nominal gross national expenditure, or GNE, is used as our goal variable. Until very recently GNE was the most-used measure of total spending in Canada; in 1986, however, Statistics Canada began to emphasize gross domestic product (GDP). GDP measures the production of all goods and services taking place within Canada, whereas GNE adds to GDP foreign investment income of Canadians and deducts domestic income of non-residents. In practice the two are very highly correlated; for example, in four-quarterly growth rates over 1971Q1-1985Q4 the correlation coefficient between GNE and GDP was 0.996.

Several other measures of total spending, in addition to GNE and GDP, might be constructed on the basis of the National Accounts, and it seemed prudent to investigate those alternative measures before proceeding with the study. Simple correlation coefficients were calculated between growth rates of seven different measures of total spending (and their real and price components) and the forty-six monetary aggregates, both contemporaneously and at lags 1-4. The seven measures of spending used were:

1. GNE
2. GDP
3. domestic demand = GDP less exports plus imports
4. final sales (GNE) = GNE less change in inventories
5. final sales (GDP) = GDP less change in inventories
6. final domestic demand = domestic demand less change in inventories
7. total transactions = GDP plus imports.

The correlations were calculated over two sample periods - 1971Q1 to 1985Q4, and 1979Q1 to 1985Q4 - resulting in some 9,000 statistics. These have been recorded in an appendix that is available on request. Here we can simply state the conclusions that emerged from this examination of the data. First, none of the goal variables appears to have a significantly closer relationship with the various measures of money than the other goal variables. Second, there is a good deal of consistency across the measures of spending in terms of which monetary aggregates have the highest correlations. In particular, the results for GNE and GDP are virtually identical. On the basis of these conclusions, it was decided to retain GNE as goal variable for the remainder of the study.

We now consider the specific correlation results relating the forty-six monetary aggregates to GNE (mnemonic YGNE) and its real (UGNE) and price (PGNE) counterparts.[3] Beginning first with the ranking of contemporaneous indicators of nominal GNE, over the full sample period the highest correlation is with M2+ (0.77); this is followed closely by M3BC (0.77) and M3+ (0.76). It is interesting that in this context the highest correlations tend to be with broad definitions of money. In the shorter sample period (1979Q1-1985Q4) the rankings change somewhat: the highest contemporaneous correlation with GNE becomes that with BASE (0.82), but M2+ is next (0.79), followed closely by PHMS+ (0.78). However, the

3. In forming these rankings we have not simply chosen the highest correlations in every case. Rather, we have exercised some judgement, choosing aggregates according to the following criteria: (a) given the longer lags in receipt of their data, we include at most one 'plus' aggregate in our top three selections; (b) we try to avoid duplication by including only one of two closely competing aggregates (for example, if the highest correlation were with M3 and the second highest with M3B, we would only include M3 in the list); and (c) simpler aggregates (narrow rather than broad, conventional rather than superlative) are preferred in the case of ties.

correlations of M3BC (0.70) and M3+ (0.76) remain high in the shorter sample as well. From these results, M2+ seems to emerge as the preferred contemporaneous indicator of nominal GNE.

Turning to contemporaneous indicators of real GNE growth, we find that over the long sample period the strongest correlation is with M1 (0.60), followed closely by CURR (0.58). Over the shorter sample period the correlation between UGNE and M1 is somewhat lower (0.48) and is exceeded by that with CURR (0.62) and that with M1ALD+ (0.52). The best contemporaneous indicator of inflation (PGNE) over the full sample is M2 (0.78); over the shorter sample this correlation is even higher (0.83), but that between PGNE and PHMSB (0.87) is higher still.

The leading indicator properties are best compared with the more sophisticated techniques of Section 4, but the simple correlation results can provide a preliminary impression of what is to come. In terms of leading indicators of nominal GNE, we find that the highest correlations tend to be with narrower aggregates such as BASE(-1, 0.80), CURR (-2, 0.77), and M1 (-2, 0.75), where the first figure in parentheses represents the lag at which the correlation is highest. For real output most leading information is in the narrower aggregates, especially M1 (-1, 0.73), FI-M1ALD (-1, 0.72), and CURR (-1, 0.60). In contrast, however, in terms of a leading indicator of inflation, the broader aggregates are selected, namely M2 (-1, 0.81) or (-2, 0.80), M3B (-1, 0.76), and PHMSBC (-1, 0.72).

Before leaving the simple correlation analysis two issues are addressed. First, it is known that the 1982-84 period was unusual in terms of the relationship between monetary aggregates and total spending. During this period there was a consolidation of balance sheets of households and firms, whereby liquid assets were used to erase debt in response to the relatively high and variable interest rates during 1980-82. One consequence of this phenomenon was a temporary breakdown of traditional relationships between total spending and certain monetary aggregates.[4] For this reason there is some danger that our choices of contemporaneous and leading indicators will be biased by inclusion of the data for this period. Hence, we recalculated the correlation statistics while excluding the 1982Q3-1984Q4 period, ten quarters in all. The results are very similar to those reported above: the best contemporaneous indicators of nominal GNE are M2+ (0.78), M3BC (0.76), and M3+ (0.76), while the best leading indicators of nominal GNE are found to be BASE (-1, 0.78) FI-M3BC (-1, 0.75) and M1 (-2, 0.72). For real GNE and the GNE deflator, the best leading indicators continue to be M1 (-1, 0.73) and M2 (-1, 0.82), respectively.

The second question concerns the use of nominal monetary aggregates to provide information on a real variable, real GNE. Suspecting that higher correlations could be obtained, and perhaps that our ranking would change, if we first deflated the monetary aggregates using the GNE deflator, we recalculated the correlations with real GNE in this way. We found that the rankings did not change significantly — the best leading indicator for real GNE was real M1 -- but that the correlation was somewhat higher: 0.83 at the first lag for the entire sample, compared with 0.73 at the same lag for nominal M1.

To sum up the results so far, M2+ seems to be the preferred contemporaneous indicator of nominal GNE. In terms of leading indicators there seem to be several contenders, and we will focus on discriminating between them more carefully in the next section. However, we have seen a tendency for leading information on nominal and real GNE to be found in narrowly defined aggregates, whereas leading information on inflation is more likely to be found in the broader aggregates. Chart 1 below illustrates the historical relationships between the growth rates of some of these variables.

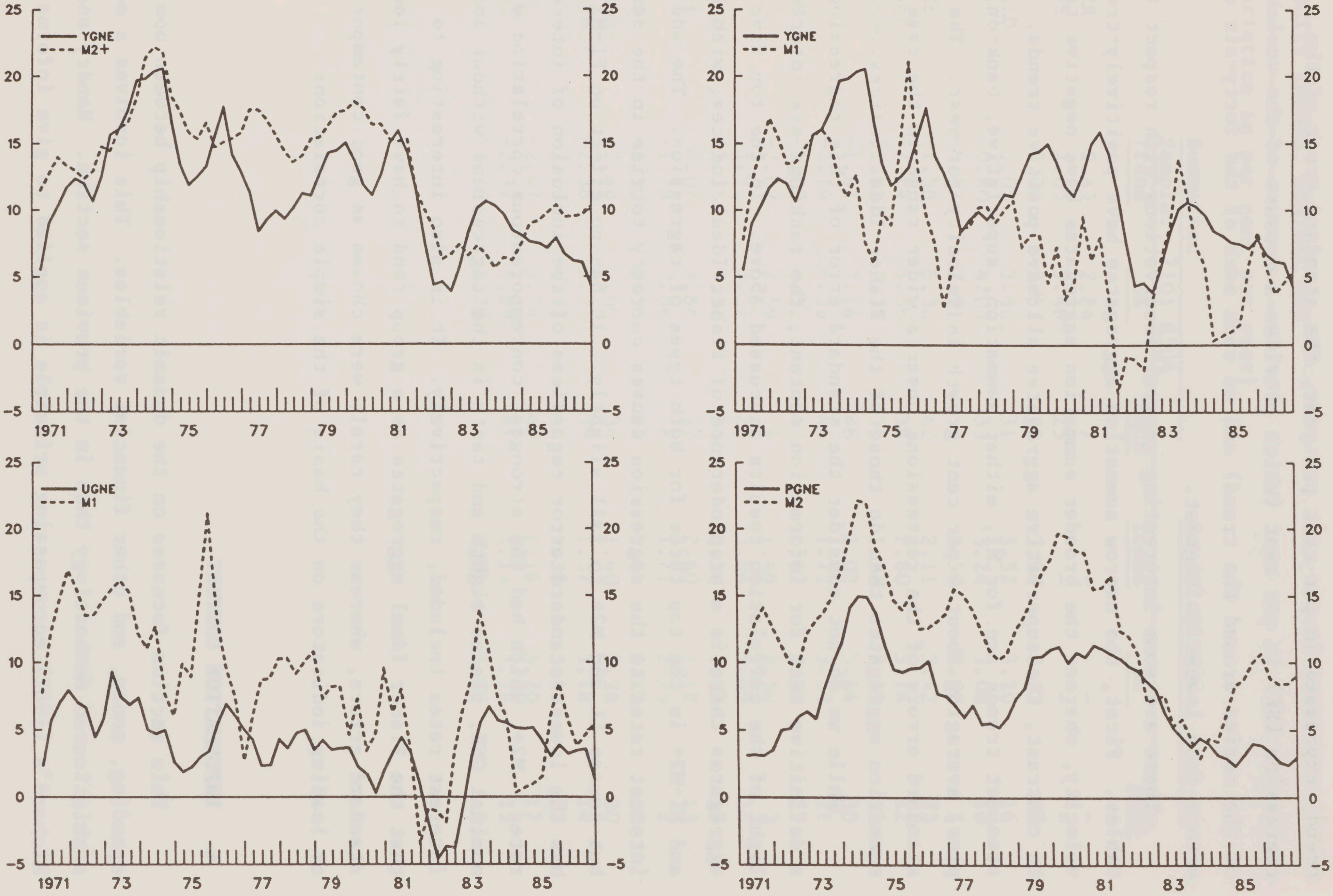
As noted above, a second crude means of measuring the degree of association between money and total spending is to examine the relative stability of the velocity of money around its trend. The results of estimating equations of the form (3.2) and (3.3) for our forty-six

---

4. See the article "Monetary Aggregates: Some recent developments" in the January 1986 issue of the Bank of Canada Review for a complete discussion of the events of this period.

CHART 1

FOUR QUARTER GROWTH RATES OF SELECTED MONETARY AGGREGATES AND GOAL VARIABLES



aggregates are given in Tables 3.1 and 3.2. We present the slope of the trend, expressed in per cent per year, the standard error of the regression (SE) in per cent (which provides a measure of the variability of the series around the trend) and we rank each of the forty-six standard errors from lowest to highest.

There are some interesting general observations with respect to these tables. First, the narrow summation aggregates have positively-trended velocity, whereas the broader summation aggregates have negative trends. In contrast, the superlative aggregates all have positive trends. The steepest trends are for M1, either summation, superlative, bank-only or plus, averaging about 4 per cent growth in velocity per year. The standard errors of the regressions cover a wider range in the case of the summation aggregates than do those of the Fisher Ideal indices.

While we do not consider the standard error of this regression to be a definitive test for information content, the rankings are interesting in light of the correlation results discussed above. In the top five aggregates there is a preponderance of Fisher Ideal indices, with FI-M2 and FI-M2+ in the top three for both types of regression. The addition of interest rates to the regression causes currency to rise in the ranking, but causes LL and M2+ to fall slightly. It has no effect on FI-M2, which has the lowest standard error regardless of the inclusion of interest rates. M2+, which had the strongest contemporaneous correlation with nominal GNE, places eighth and tenth in the regressions without and with interest rates included, respectively. It is also interesting to note that the Fisher Ideal aggregates as a group tend to have fairly low standard errors, whereas they rarely were chosen as good contemporaneous or leading indicators on the basis of the simple correlations.

4 INFORMATION CONTENT

This section focusses on the dynamic relationship between nominal spending, money, and other financial variables. This involves a more sophisticated methodology than in the previous section. Hendry and Richard's (1982) encompassing principle is applied to give information

Table 3.1

VELOCITY TRENDS, NOMINAL GNE

(statistics in per cent per year)

	Summation			Superlative		
	Sample: 71Q1 85Q4					
	Trend	SE	Rank	Trend	SE	Rank
CURR	2.43	2.84	7	-	-	-
BASE	2.05	3.46	25	-	-	-
M1	4.06	3.61	29	3.98	3.52	27
M1ALD	3.03	3.80	31	3.52	3.20	16
M13	0.80	4.03	33	3.24	3.08	10
M2	-0.97	2.91	9	2.50	2.00	1
PHMS	-1.58	6.30	42	2.11	3.42	23
PHMSB	-2.14	5.66	38	1.80	3.16	12
PHMSBC	-2.02	5.74	39	1.74	3.15	11
M3	-1.61	7.16	46	2.02	3.64	30
M3B	-2.14	6.36	44	1.72	3.33	21
M3BC	-2.03	6.52	45	1.67	3.35	22
LL	-2.62	2.59	4	1.48	2.50	3
M1+	3.92	3.57	28	3.84	3.48	26
M1ALD+	2.35	5.31	36	3.39	3.22	18
M13+	0.07	3.84	32	2.60	3.18	13
M2+	-1.79	2.86	8	1.71	2.25	2
PHMS+	-2.10	5.60	37	1.44	3.25	19
PHMSB+	-2.48	5.09	34	1.40	3.28	20
PHMSBC+	-2.38	5.21	35	1.37	3.18	14
M3+	-2.10	6.31	43	1.39	3.42	24
M3B+	-2.47	5.74	40	1.16	3.20	17
M3BC+	-2.37	5.89	41	1.13	3.19	15
LL+	-2.76	2.78	6	1.02	2.68	5

Table 3.2

VELOCITY TRENDS, NOMINAL GNE, R90 INCLUDED IN REGRESSION

(statistics in per cent per year)

	Summation			Superlative		
	Sample: 71Q1 85Q4					
	Trend	SE	Rank	Trend	SE	Rank
CURR	2.14	2.32	5	-	-	-
BASE	2.19	3.39	30	-	-	-
M1	3.89	3.51	33	3.82	3.41	31
M1ALD	2.58	2.75	12	3.25	2.64	9
M13	0.38	3.25	24	2.98	2.09	2
M2	-0.84	2.82	14	2.42	1.96	1
PHMS	-0.93	5.08	42	2.31	3.22	23
PHMSB	-1.60	4.74	39	1.97	3.04	16
PHMSBC	-1.43	4.62	37	1.94	2.96	15
M3	-0.88	5.80	46	2.27	3.37	29
M3B	-1.52	5.25	43	1.93	3.13	20
M3BC	-1.35	5.26	44	1.90	3.09	18
LL	-2.61	2.61	7	1.44	2.50	6
M1+	3.74	3.45	32	3.66	3.34	28
M1ALD+	1.68	3.64	34	3.06	2.61	8
M13+	-0.28	3.27	25	2.22	2.08	4
M2+	-1.60	2.65	10	1.61	2.20	3
PHMS+	-1.57	4.69	38	1.58	3.17	22
PHMSB+	-2.01	4.34	36	1.47	3.29	26
PHMSBC+	-1.87	4.32	35	1.46	3.16	21
M3+	-1.51	5.31	45	1.56	3.29	27
M3B+	-1.94	4.88	40	1.30	3.11	19
M3BC+	-1.80	4.92	41	1.29	3.06	17
LL+	-2.68	2.76	13	0.96	2.69	11

content a well-defined statistical meaning. This allows us to compare both nested and non-nested indicator models for our goal variables.

Most information content studies adopt a methodology which originated in information theory introduced by Shannon (1948) and later developed by Theil (1967).[5] The information theory approach has been applied in the regression framework by a number of researchers to measure the contemporaneous information in money with respect to nominal income.[6] In this framework, contemporaneous information in money (M) relative to nominal income (Y) is defined by:

$$(4.1)\ I(Y|M) = -.5 \ln (1-R^2)$$

where R^2 is the coefficient of determination from the linear regression:

$$(4.2)\ Y = a + bM + u$$

Information measured by $I(Y|M)$ in equation (4.1) is a monotonic transformation of the simple correlations examined in the previous section and, as a result, generates identical rankings.[7] We reported the rankings in terms of correlation coefficients rather than the information theory measure because simple correlations are more familiar and hence easier to interpret.

It should be emphasized that the correlation analysis in the previous section is a descriptive technique rather than a statistical measure firmly rooted in information theory. The information theory approach in the regression framework assumes that money and income are jointly normally distributed and that money is serially uncorrelated and only contemporaneously correlated with income. We find these independence assumptions inappropriate for two reasons. First, assuming growth rates of the monetary aggregates to be serially uncorrelated is inconsistent with their observed time series properties. Second, it seems unreasonable

---

5. See Tinsley et al. (1980) for a summary of information theory.

6. See Barnett and Spindt (1979, 1980), Tinsley et al. (1980), Cockerline and Murray (1981), Baily et al. (1982), and Driscoll et al. (1985b).

7. For the bivariate regression (4.2) the square root of the coefficient of determination (R^2) is equal to r, the simple correlation coefficient between Y and M, as defined above in equation (3.1).

to restrict money to be uncorrelated with past and future values of nominal income when the dynamics between money and nominal income are widely recognized in economic theory. By focussing on leading rather than contemporaneous information in money and allowing for richer dynamics, we avoid such strong independence assumptions and measure information that is more consistent with economic theory.

Information theory can be generalized to a multivariate dynamic framework using rational distributed lag specifications. This approach defines the information content of money (M) relative to nominal income (Y) in the following way:

(4.3) $I(Y|M) = -.5 \ln [SSR2/SSR1]$

where $SSR1 = \Sigma u_t^2$ and $SSR2 = \Sigma v_t^2$ are obtained from the following regressions:

(4.4) $Y = A^p(L)Y + u$

(4.5) $Y = A^p(L)Y + B^q(L)M + v$

We are interested not only in measuring information but also in determining whether the information is statistically significant. Significant information can be thought of in terms of discriminating between nested hypotheses -- M is said to be informative about Y if equation (4.5) has a significantly better fit than equation (4.4). In the regression framework, this involves testing the statistical significance of $B^q(L)$ in equation (4.5).

It is worth noting that information content tests outlined above are identical to the concept of Granger causality -- money is said to Granger cause (or be informative about) income if $B^q(L)$ is statistically significant in (4.5). Thus, information content tests are closely related to the voluminous empirical research on money, income, and causality originating in Sims (1972). However, our objective is not to uncover a structural relationship but to describe a statistical relationship between money and nominal spending. The regressions are not meant to have a structural interpretation but are used as a purely descriptive technique to measure informativeness.

Examining the relative informativeness of alternative monetary aggregates and other financial information involves comparing non-nested information sets. Information theory provides a ranking of information content, but the statistical significance of the differences in the ranking is not clearly defined. The encompassing principle can be used to make such distinctions. The encompassing methodology can be described in the context of the following general models:

(4.6) $y = E(y \mid I_1) + u_1$

(4.7) $y = E(y \mid I_2) + u_2$

where $E(y \mid I_1)$ and $E(y \mid I_2)$ refer to the expectation of y conditional on the information sets I_1, and I_2 respectively. Model (4.6) can be said to encompass model (4.7) if the following two conditions hold:

1.) $Var(u_1) < Var(u_2)$

2.) $E(u_1 \mid I_2) = 0$

The first condition establishes that model (4.6) "variance dominates" model (4.7) and the second condition determines whether the residuals in model (4.6) can be significantly explained by the information in model (4.7). In the work to follow we use Akaike's FPE criterion to rank the models and to choose that which is variance dominant. We then calculate F-statistics to see whether any of the competing models can add significant information to the variance-dominant model.

The encompassing principle is consistent with information content tests for nested information sets and extends the concept of significant information to non-nested information sets. By unifying nested and non-nested testing procedures, the encompassing principle enables us to maintain a consistent methodology across information sets. Information sets which are shown to be encompassed can be excluded from the analysis without a significant loss of forecast information. Information sets that are shown not to be encompassed can be used to provide useful forecasting information. The first step in applying encompassing tests to the data is to detrend the goal variable, nominal income.

a.) Autoregressive Models

The dangers of interpreting correlations between trended macroeconomic time series are now well known in the econometric literature.[8] Correlations between the level of nominal income and the stock of nominal money are bound to give us a misleading measure of the information content of money. For this reason, we take Nelson and Plosser's (1982) advice and apply the growth rate filter to each series to induce stationarity. Thus all regressions reported in the remainder of this paper are based on data expressed in quarterly growth rates. This detrending method is meant to reduce the probability of finding spurious correlations between money and nominal GNE.

Time series analysis was applied to nominal GNE as well as to its price and real output components over the sample period 1971Q1-1985Q4. All three series appeared to be stationary when expressed as quarterly growth rates. Estimation results reported in Table 4.1 indicate that growth rates of each series could be represented by low-order autoregressive models. A first-order autoregressive model was found to be appropriate for both YGNE and UGNE whereas PGNE was better characterized by a second-order autoregressive process. The estimated autoregressive coefficients are highly significant and there is very little evidence of serial correlation in the first four lags of the residuals from all three models. Moving-average error terms were found to be statistically insignificant when added to these autoregressive models. It is interesting to note the differences in the fit of these models -- autoregressive components explain less than 15 per cent of the variance in UGNE, about 30 per cent of the variance in YGNE, and over 50 per cent of the variance in PGNE.

The Box-Jenkins methodology of identification, estimation, and overfitting indicates that autoregressive specifications use the information in the past values of the goal variables efficiently. In this way, the low-order autoregressive specifications reported in Table 4.1 are appropriate for modelling the stochastic trend in each of the goal variables and can be considered as interesting benchmarks from which to examine the information content of money.

---

8. See Granger and Newbold (1974) and Plosser and Schwert (1978).

Table 4.1

AUTOREGRESSIVE MODELS
(SAMPLE: 1971Q1 - 1985Q4)

Model	$\bar{R}^2$	SER	FPE	Order:	Test for Serial Correlation* 1st	2nd	3rd	4th
$YGNE = \underset{(3.85)}{1.20} + \underset{(5.26)}{0.56}\ YGNE_{-1}$	0.311	0.980	0.992		0.79	0.51	0.52	0.71
$UGNE = \underset{(3.63)}{0.61} + \underset{(2.99)}{0.36}\ UGNE_{-1}$	0.118	0.973	0.978		0.66	0.63	0.52	0.69
$PGNE = \underset{(1.73)}{0.34} + \underset{(3.37)}{0.41}\ PGNE_{-1} + \underset{(3.27)}{0.40}\ PGNE_{-2}$	0.531	0.625	0.410		0.56	0.62	0.56	0.56

* The reported figures for the serial correlation tests are marginal significance levels based on the LM test suggested by Kiviet (1986) for equations with lagged dependent variables.

Note: All variables reported in the tables are expressed in terms of quarterly growth rates.

b.) Information Content of Alternative Monetary Aggregates

In this section we analyze the relative information content of alternative monetary aggregates using the encompassing principle. To determine variance dominance, we ran the following regression:

(4.6) $Y = A^p(L)Y + B^q(L)M + u$

for each of the goal variables (Y) and monetary aggregates (M).[9] Lag lengths of the goal variable (p) are taken from the autoregressive models in the previous section. Lag lengths on each monetary aggregate (q) are specified according to Akaike's FPE criterion allowing for a maximum of ten lags.[10] The FPEs from the resulting dynamic specifications were then used to rank the information content of the alternative monetary aggregates.

A number of the best specifications for each goal variable are reported in Table 4.2. M1 was found to be the most informative monetary aggregate for both nominal and real income. Eight lags of M1 has the best fit for nominal income and five lags of real M1 has the best fit for real income.[11] Five lags of FI-M1ALD and two lags of M1 have a comparable fit to these variance-dominant models for both real and nominal income.[12] Four lags of FI-M1ALD was found to be most informative for prices, with two lags of M2 and four lags of FI-M3B having comparable fit.

---

9. We did not include the "plus" aggregates in this analysis because under the current data reporting system the lag in the receipt of non-chartered bank data can be longer than that for nominal income, so that any leading information tends to be less useful.

10. Allowing for ten lags resulted in a data problem for some of the broader aggregates because foreign currency deposits are only available beginning in the first quarter of 1969. To specify the dynamics for these aggregates, we started the sample in 1972 and found that the optimal lag lengths were less than ten. We then re-estimated these dynamic specifications over the 1971Q1-1985Q4 period to make the comparisons reported in Table 4.2.

11. We found that expressing the monetary aggregates in real terms (i.e., deflating by the price level) improved their information content for real income.

12. It is important to note that variance dominance is only defined with reference to a specific model selection criterion. If we define variance dominance using the Schwarz Bayesian Information criterion instead of the FPE, for example, two lags of M1 is the variance-dominant model for nominal income and two lags of real M1 is the variance-dominant model for real income.

Given these rankings, we can now apply encompassing F-tests to isolate the aggregates having statistically significant information relative to the variance-dominant specifications. For example, to determine if there is significant information in FI-M1ALD relative to M1 we run the regresssion:

$$Y = \alpha + A^{1}(L)Y + B^{8}(L)M1 + C^{5}(L)F1\text{-}M1ALD + u$$

and test the statistical significance of $C^{5}(L)$.

Encompassing F-tests were performed on the aggregates listed in Table 4.2 using the minimum FPE specification as the variance-dominant model. The marginal significance levels reported in Table 4.3 indicate that the variance-dominant specification for each goal variable could encompass the alternatives. There is some marginal information in FI-LL relative to M1 for nominal income (at the 10 per cent significance level) and in M2 relative to FI-PHMS for prices (at the 11 per cent level). Thus if we apply the conventional 5 per cent significance level, we can restrict our attention to the leading information in two aggregates (M1 for nominal income, real M1 for real income, and FI-PHMS for prices) without overlooking any significant information from the set of monetary aggregates. At a more liberal significance level of about 10 per cent, there is additional information in FI-LL for nominal income and M2 for prices. On the basis of these tests we present the parameter estimates of a set of preferred bivariate models for the three goal variables in Table 4.4.

The distinction between contemporaneous and leading information in money seems to be important with respect to nominal spending. Broad aggregates (M2+, M3BC, M3+) were found to have the highest contemporaneous correlation with nominal income whereas narrow aggregates (M1, F1-M1ALD) were found to have the most leading information about nominal income.[13] This distinction seems to be less important for real income and prices. Real M1 is a good contemporaneous and leading indicator of real income and M2 is a good contemporaneous and leading indicator of prices. We added contemporaneous values of the monetary aggregates to the preferred

13. This is consistent with the results in Cockerline and Murray (1981).

Table 4.2

MONETARY AGGREGATES AS INFORMATION VARIABLES FOR NOMINAL INCOME, REAL INCOME AND PRICES (1971Q1 - 1985Q4)

Monetary Aggregate	Lag on M	$\bar{R}^2$	SER	FPE
(i) Nominal Income				
M1	8	0.560	0.783	0.715
FI-MIALD	5	0.519	0.819	0.749
M1	2	0.492	0.842	0.755
Currency	3	0.457	0.870	0.820
Base	3	0.450	0.875	0.830
FI-M2	2	0.432	0.890	0.845
FI-LL	2	0.429	0.892	0.849
(ii) Real Income				
M1/PGNE	5	0.420	0.789	0.696
FI-MIALD/PGNE	5	0.408	0.797	0.710
M1/PGNE	2	0.367	0.824	0.725
Currency/PGNE	2	0.275	0.882	0.830
FI-M13/PGNE	5	0.294	0.871	0.847
Base/PGNE	2	0.244	0.901	0.866
FI-M2/PGNE	2	0.226	0.911	0.886
(iii) Prices				
FI-PHMS	4	0.614	0.567	0.359
FI-M3B	4	0.611	0.569	0.362
M2	2	0.593	0.582	0.367
Base	2	0.553	0.610	0.404
M3B	2	0.548	0.614	0.408

Table 4.3

ENCOMPASSING F-TESTS FOR BIVARIATE MODELS

Test		F-Statistic	Significance Level
(A) YGNE with M1 as the variance dominant model.			
M1	BASE	F(3, 47) = 0.15	93%
M1	CURR	F(3, 47) = 0.64	59%
M1	FI-M1ALD	F(5, 45) = 0.72	61%
M1	FI-M2	F(2, 48) = 0.08	92%
M1	FI-LL	F(2, 48) = 2.43	10%
(B) UGNE with M1/P			
RM1	RBASE	F(2, 50) = 0.08	92%
RM1	RCURR	F(2, 50) = 0.07	93%
RM1	RFI-M13	F(5, 47) = 0.66	66%
RM1	RFI-M2	F(2, 50) = 0.62	54%
RM1	RFI-M1ALD	F(5, 47) = 0.47	80%
(C) PGNE with FI-PHMS			
FI-PHMS	BASE	F(2, 51) = 0.51	60%
FI-PHMS	M3B	F(2, 51) = 0.46	63%
FI-PHMS	M2	F(2, 51) = 2.27	11%
FI-PHMS	FI-M3B	F(4, 49) = 0.30	88%

Table 4.4

BIVARIATE EQUATION SPECIFICATIONS
(1971Q1 - 1985Q4)

Equation	$\bar{R}^2$	SER	FPE
A) Nominal Income			
$YGNE = \underset{(2.30)}{0.6796} + \underset{(2.94)}{0.3658}\ YGNE_{-1} + \underset{(3.40)}{0.2063}\ M1_{-1} + \underset{(2.46)}{0.1673}\ M1_{-2} - \underset{(1.24)}{0.0890}\ M1_{-3} + \underset{(1.41)}{0.0938}\ M1_{-4} + \underset{(1.12)}{0.0749}\ M1_{-5} + \underset{(0.27)}{0.0183}\ M1_{-6} - \underset{(1.23)}{0.0792}\ M1_{-7} + \underset{(2.64)}{0.1590}\ M1_{-8}$	0.560	0.783	0.715
$YGNE = \underset{(1.99)}{0.6088} + \underset{(3.28)}{0.3899}\ YGNE_{-1} + \underset{(3.44)}{0.2242}\ FI\text{-}M1ALD_{-1} + \underset{(2.60)}{0.1731}\ FI\text{-}M1ALD_{-2} - \underset{(0.80)}{0.0568}\ FI\text{-}M1ALD_{-3} + \underset{(0.66)}{0.0419}\ FI\text{-}M1ALD_{-4} + \underset{(2.03)}{0.1336}\ FI\text{-}M1ALD_{-5}$	0.519	0.819	0.749
$YGNE = \underset{(3.74)}{1.0690} + \underset{(3.48)}{0.3569}\ YGNE_{-1} + \underset{(2.90)}{0.1670}\ M1_{-1} + \underset{(3.25)}{0.2037}\ M1_{-2}$	0.492	0.842	0.755
B) Real Income			
$UGNE = \underset{(5.81)}{0.8766} - \underset{(0.07)}{0.0091}\ UGNE_{-1} + \underset{(4.30)}{0.2543}\ M1_{-1}/P_{-1} + \underset{(1.74)}{0.1070}\ M1_{-2}/P_{-2} + \underset{(0.78)}{0.0455}\ M1_{-3}/P_{-3} - \underset{(1.03)}{0.0594}\ M1_{-4}/P_{-4} + \underset{(2.78)}{0.1619}\ M1_{-5}/P_{-5}$	0.420	0.789	0.696
$UGNE = \underset{(5.51)}{0.8333} + \underset{(0.49)}{0.0603}\ UGNE_{-1} + \underset{(3.44)}{0.1877}\ M1_{-1}/P_{-1} + \underset{(2.79)}{0.1677}\ M1_{-2}/P_{-2}$	0.367	0.824	0.725
C) Prices			
$PGNE = \underset{(0.86)}{0.1761} + \underset{(4.19)}{0.5407}\ PGNE_{-1} + \underset{(1.26)}{0.1623}\ PGNE_{-2} - \underset{(1.71)}{0.1323}\ FI\text{-}PHMS_{-1} + \underset{(3.19)}{0.2157}\ FI\text{-}PHMS_{-2} - \underset{(1.89)}{0.1604}\ FI\text{-}PHMS_{-3} + \underset{(2.45)}{0.2014}\ FI\text{-}PHMS_{-4}$	0.614	0.567	0.359
$PGNE = \underset{(0.11)}{0.0232} + \underset{(2.56)}{0.3166}\ PGNE_{-1} + \underset{(2.12)}{0.2604}\ PGNE_{-2} - \underset{(0.06)}{0.0050}\ M2_{-1} + \underset{(3.00)}{0.2566}\ M2_{-2}$	0.593	0.582	0.367

bivariate equations but found the contemporaneous information to be statistically insignificant at the 5 per cent level in all the equations.[14] This supports our hypothesis that money is more informative as a leading rather than contemporaneous indicator of nominal income.

The superlative aggregates are more intuitively appealing than the broader summation aggregates, and as a consequence, might be expected to be more informative on movements in nominal spending. Information content tests by Barnett and Spindt (1979, 1980) indicate that Divisia aggregates are generally more informative than the corresponding summation aggregate in the United States. However, our encompassing tests indicate that with Canadian data, superlative aggregates add little information to the summation aggregates. We found only the broad superlative aggregates, FI-LL and FI-PHMS, to be informative relative to M1 and M2.[15] FI-LL adds some information to M1 but is not as informative as M1 with respect to nominal income. FI-PHMS is the most informative aggregate with respect to prices but the information content of FI-PHMS is not much greater than that of M2. Thus the information content tests with superlative aggregates provide little evidence that there is significant information loss involved in using summation aggregation.[16]

c.) Information Content of Other Financial Variables

In this section we examine how the bivariate relationships established in the previous section are affected when the information set is expanded to include financial variables besides money. The encompassing methodology is applied to isolate leading information in exchange rates as well as in rates on debt and equity instruments. Considering all available financial information would be excessive for

14. These inferences are invalid if money and the goal variables are simultaneously related. However, if we interpret the regressions in the broader context of measuring information, we can say that given the possible simultaneity bias involved there is not much additional information in contemporaneous movements in money.

15. The lack of information content in narrower superlative aggregates may be a result of the difficulty in measuring the user cost for transactions deposits.

16. This is consistent with results in Cockerline and Murray (1981) for Canada, Baily et al. (1982) for the United Kingdom, and Driscoll et al. (1985b) for Austria.

our purposes and would involve a considerable amount of data-mining. For these reasons, our empirical tests focus on the relative information in three representative financial variables, namely the 90-day rate on prime commercial paper, the bilateral Canada-U.S. exchange rate, and the price index of the Toronto Stock Exchange.[17] We also allow for the possibility of real output leading prices and prices leading real output.

Degrees of freedom limitations prevent us from testing down from a completely general model allowing for up to ten lags on each variable as in the previous section. Instead, we take the dynamic specifications for the variance-dominant bivariate equations from the previous sections as given and allow up to four lags on the other financial variables. Lag lengths of the financial variables are then determined sequentially by minimizing Akaike's FPE criterion.[18] Finally, we check the previously-determined lag lengths on money to see whether the information content of money is affected by these additional variables.

The resulting multivariate specifications are reported in Table 4.5. Four lags of the interest rate and one lag of the TSE price index are jointly significant at the 2 per cent level in the multivariate M1 equation for nominal income. Including financial variables shortens the optimal lag on M1 from eight to two. Note that most of the information in the bivariate M1 model is in the first two lags (see Table 4.4), which remain highly significant when financial information is added. We also specified multivariate models using two other aggregates found to be informative in the bivariate framework, FI-M1ALD and FI-LL. This resulted in identical dynamic specifications and estimates very similar to the

---

17. Preliminary work established that the bilateral Canada-U.S. exchange rate was more informative than the G10 effective exchange rate, the 90-day rate on prime commercial paper was more informative than other short-term and long-term rates, and the TSE price index was more informative than the TSE price/earnings ratio. Notice that the financial variables, like the monetary variables, are entered in the indicator equations as quarterly growth rates.

18. If we consider a general model with up to four lags on each of the three variables, minimizing the FPE from all possible combinations of lag lengths entails 125 regressions. We felt that this involved too much data mining. We instead minimized the FPE by sequentially searching over lag lengths on first the interest rate, then the exchange rate and finally the stock market price index. This search involved only 15 regressions. We did some specification searches with different orderings of the variables and generally obtained the same lag lengths.

Table 4.5

MULTIVARIATE EQUATION SPECIFICATIONS
(1971Q1 - 1985Q4)

	$\bar{R}^2$	SER	FPE
A) Nominal Income			
$YGNE = \underset{(4.28)}{1.1262} + \underset{(1.24)}{0.1310}\, YGNE_{-1} + \underset{(4.00)}{0.2349}\, M1_{-1} + \underset{(5.36)}{0.3487}\, M1_{-2} - \underset{(0.09)}{0.0008}\, R90_{-1} + \underset{(1.67)}{0.0141}\, R90_{-2} + \underset{(3.32)}{0.0275}\, R90_{-3} + \underset{(2.02)}{0.0145}\, R90_{-4} + \underset{(2.60)}{0.0328}\, TSE_{-1}$	0.643	0.705	0.572
$YGNE = \underset{(3.17)}{0.8268} + \underset{(1.10)}{0.1125}\, YGNE_{-1} + \underset{(5.08)}{0.3077}\, FI\text{-}M1ALD_{-1} + \underset{(5.56)}{0.3843}\, FI\text{-}M1ALD_{-2} + \underset{(0.28)}{0.0022}\, R90_{-1} + \underset{(2.39)}{0.0198}\, R90_{-2} + \underset{(3.92)}{0.0325}\, R90_{-3} + \underset{(2.33)}{0.0160}\, R90_{-4} + \underset{(2.79)}{0.0336}\, TSE_{-1}$	0.673	0.675	0.523
B) Real Income			
$UGNE = \underset{(7.98)}{0.8044} + \underset{(3.85)}{0.2189}\, M1_{-1}/P_{-1} + \underset{(1.95)}{0.1078}\, M1_{-2}/P_{-2} + \underset{(0.60)}{0.0306}\, M1_{-3}/P_{-3} - \underset{(0.83)}{0.0461}\, M1_{-4}/P_{-4} + \underset{(2.96)}{0.1629}\, M1_{-5}/P_{-5} + \underset{(2.45)}{0.0317}\, TSE_{-1}$	0.479	0.748	0.625
C) Prices			
$PGNE = \underset{(0.04)}{0.0009} + \underset{(2.61)}{0.3132}\, PGNE_{-1} + \underset{(2.08)}{0.2459}\, PGNE_{-2} - \underset{(0.64)}{0.0539}\, M2_{-1} + \underset{(3.58)}{0.3011}\, M2_{-2} + \underset{(1.95)}{0.0113}\, R90_{-1} + \underset{(2.10)}{0.0208}\, TSE_{-1}$	0.625	0.559	0.349
$PGNE = \underset{(0.17)}{0.0377} + \underset{(4.63)}{0.6290}\, PGNE_{-1} + \underset{(1.28)}{0.1607}\, PGNE_{-2} - \underset{(1.85)}{0.1407}\, FI\text{-}PHMS_{-1} + \underset{(2.93)}{0.2295}\, FI\text{-}PHMS_{-2} - \underset{(2.27)}{0.1927}\, FI\text{-}PHMS_{-3} + \underset{(2.53)}{0.2041}\, FI\text{-}PHMS_{-4} + \underset{(1.80)}{0.1428}\, UGNE_{-1}$	0.629	0.556	0.350

multivariate M1 equation (see Table 4.5 for a comparison of the multivariate M1 and FI-M1ALD equations). Interestingly, the final nominal income equation based on FI-M1ALD fits slightly better than that based on M1, so both are retained for further testing below. The model based on FI-LL was found to be encompassed by the M1 model.

There was less information in the other financial variables with respect to real output and prices. One lag of the TSE price index was found to be significant at the 2 per cent level when added to the bivariate real M1 equation for real output. None of the other financial variables was found to be significant when added to the bivariate FI-PHMS equation for prices, but lagged real output was significant at the 8 per cent level. We also specified a multivariate equation for prices using M2 instead of FI-PHMS. One lag of the interest rate and one lag of the stock price index were found to be jointly significant at the 5 per cent level when added to the bivariate M2 equation. The relative informative value of M2 and FI-PHMS changes when we add financial information. In the bivariate framework, FI-PHMS encompassed M2 but in the multivariate framework M2 easily encompasses FI-PHMS.

To summarize, some of the financial variables considered add significant information to the bivariate equations, but this has little effect on the information content of the monetary aggregates. The addition of the interest rate and the stock price index does shorten the optimal lag length of M1 for nominal income. Nevertheless, in this equation and all the other equations, the monetary aggregates remain highly significant. The exchange rate did not provide leading information for any of the three goal variables. On the basis of these results, five multivariate indicator models are retained for further testing in section 6: those based on M1 and FI-M1ALD for nominal GNE, that based on real M1 for real GNE, and those based on M2 and FI-PHMS for prices.

5 INFORMATION LOSS THROUGH AGGREGATION

In this section we examine whether there is a significant loss in information involved in aggregating monetary components. Evidence of this in other countries is somewhat mixed. Tinsley et al. (1980) found using U.S. data that there was more contemporaneous information about nominal income in monetary components than in the corresponding aggregates. Mills (1983) found that there was more leading information in monetary components than in the corresponding summation aggregates in the United Kingdom. In contrast, Driscoll et al. (1985b) found Divisia aggregates to be more informative with respect to nominal income than the underlying components for the Austrian data, and Driscoll et al. (1985a) found that summation aggregates had more leading information about prices than the underlying components in the United Kingdom. Information lost through aggregation will be analyzed in this paper by once again applying the encompassing principle.

The encompassing principle gives information lost through aggregation a clearly defined statistical meaning. This involves comparing the relative information content of the alternative monetary aggregates with their underlying components. It is useful to think of summation and superlative aggregates as imposing restrictions on their underlying components.[19] These restrictions can be considered valid in the context of information content if the aggregate is able to encompass its components. If the aggregate is unable to encompass its components, then by definition there is significant information being lost through aggregation.

Aggregation assumptions will be tested in both the bivariate and multivariate framework. This involves first specifying indicator equations using monetary components to determine whether bivariate component equations are encompassed by the bivariate aggregate equations

---

19. Since all variables, including the monetary components, are expressed as quarterly growth rates, the components do not sum up to the aggregates. The aggregation assumptions being analyzed involve non-linear restrictions which require non-nested hypothesis tests which may be carried out using the encompassing principle.

reported in the previous section. Financial information is then added to the component equations to determine whether multivariate component equations are encompassed by the multivariate aggregate equations.

We restrict the analysis to the components of M2 for degrees of freedom reasons and also because preliminary tests showed little information in components outside M2. It is not possible to consider all the available components of M2 because of degrees of freedom limitations. Consequently, six disaggregations are considered. These are described in Table 5.1.

We examine two parallel systems which differ according to the treatment of non-personal notice deposits (NPNDs). NPNDs are held for both transactions and store-of-value purposes and hence it is not clear if they should best be classified with transactions or savings-type deposits. We treat this as an empirical issue -- NPNDs are considered to be substitutable for savings-type deposits in the M1 system and for transactions-type deposits in the M1ALD system.

Innovation in personal sector deposits has meant that some personal sector transactions balances are now maintained in daily interest chequing accounts (DICAs). However, recent strong growth of DICAs is believed mainly to represent inflows from conventional savings accounts rather than transactions accounts. Combining DICAs and personal chequing accounts would likely vastly overcompensate for the flows out of PCAs, and so we include DICAs with other daily interest and non-daily interest savings accounts.

Within the M1 portion of M2 we test the aggregation assumptions involving currency, personal chequing accounts, and current accounts (or current accounts and non-personal notice accounts in the M1ALD system). These disaggregations are particularly interesting with respect to nominal and real income for which M1 and real M1 respectively are the most informative aggregates. We disaggregate the non-M1 portion of M2 (or non-M1ALD in the M1ALD system) into two types of savings categories: those which are deposited for a fixed period of time, and ordinary savings deposits that may be withdrawn at any time (subject, in principle, to the

Table 5.1

SIX DISAGGREGATIONS OF M2

M1 System			M1ALD System		
1	2	3	4	5	6
CUR	CUR	M1	CUR	CUR	M1ALD
PCA	NDD		PCA	NDDA	
CA			CAA		
CNCSA	CNCSA	CNCSA	CNCS	CNCS	CNCS
PFTD	PFTD	PFTD	PFTD	PFTD	PFTD

where CUR = currency
PCA = personal chequing account deposits
CA = current account deposits
NPND = non-personal notice deposits
CAA = current account deposits plus NPNDs
NDD = net demand deposits (PCA + CA)
NDDA = net demand deposits plus NPNDs (PCA + CAA)
M1 = CUR + NDD
M1ALD = M1 plus NPNDs (CUR + NDDA)
CNCS = chequable plus non-chequable savings deposits
CNCSA = CNCS plus NPNDs
PFTD = personal fixed-term deposits

requirement of notice). It will be of considerable interest to determine if the components of M2 contain more information about prices than the aggregate.

We specify bivariate component equations in a manner similar to the previous section. Beginning with the autoregressive specification for each goal variable, we add four lags of each component and determine optimal lag lengths according to the FPE criterion. Some of the most informative specifications are reported in Table 5.2.

For nominal income, we find that the most informative component equation includes two lags of M1 and one lag of personal fixed-term deposits. This model is able to encompass the alternative component specifications. For example, the second most informative specification involves disaggregating M1 into currency, current accounts, and personal chequing accounts. The optimal lag specification for these components involves two lags of currency and two lags of current accounts. Personal chequing accounts are insignificant at all lag lengths. This specification fits almost as well as the M1 equation including personal fixed-term deposits but does not add any significant information to that equation. Consequently, there is little information loss involved in aggregating currency, current accounts, and personal chequing accounts to form M1. Moreover, the M1 equation including personal fixed-term deposits is able to encompass the bivariate M1 equations reported in Table 4.4. Although the aggregation assumptions involved in using M1 are valid in the bivariate equations, the information gain in considering components of M2 comes about through personal fixed-term deposits.

The results are remarkably similar for real income. The search procedure results in exactly the same dynamic specifications as for nominal income except that all the components are more informative when expressed in real terms. The equation with two lags of real M1 and one lag of real personal fixed-term deposits is able to encompass the alternative component specifications. This implies that the aggregation assumptions involved in using M1 in the bivariate equations are valid. The bivariate equation with five lags of real M1 was able to encompass the

Table 5.2

COMPONENT EQUATION SPECIFICATIONS
(1971Q1 - 1985Q4)

Equation	$\bar{R}^2$	SER	FPE
A) Nominal Income			
$YGNE = 0.770 + 0.165\ YGNE_{-1} + 0.036\ CUR_{-1} + 0.346\ CUR_{-2} + 0.145\ CA_{-1} + 0.103\ CA_{-2} + 0.059\ PFTD_{-1}$	0.542	0.799	0.713
(2.12) (1.39) (0.17) (1.70) (3.14) (2.44) (2.39)			
$YGNE = 1.066 + 0.191\ YGNE_{-1} + 0.236\ M1_{-1} + 0.224\ M1_{-2} + 0.067\ PFTD_{-1}$	0.546	0.795	0.685
(3.94) (1.68) (3.95) (3.75) (2.78)			
B) Real Income			
$UGNE = 0.714 + 0.19\ UGNE_{-1} + 0.034\ CUR_{-1}/PGNE_{-1} + 0.248\ CUR_{-1}/PGNE_{-2} + 0.141\ CA_{-1}/PGNE_{-1}$	0.390	0.809	0.731
(4.54) (0.15) (0.22) (1.75) (3.11)			
$+ 0.093\ CA_{-2}/PGNE_{-2} + 0.043\ PFTD_{-1}/PGNE_{-1}$			
(2.14) (1.65)			
$UGNE = 0.783 + 0.002\ UGNE_{-1} + 0.234\ M1_{-1}/PGNE_{-1} + 0.180\ M1_{-2}/PGNE_{-2} + 0.040\ PFTD_{-1}/PGNE_{-1}$	0.382	0.814	0.718
(5.12) (0.02) (3.79) (3.01) (1.55)			
C) Prices			
$PGNE = 0.256 + 0.315\ PGNE_{-1} + 0.259\ PGNE_{-2} - 0.003\ CAA_{-1} + 0.063\ CAA_{-2} + 0.078\ CNCS_{-1} + 0.048\ PFTD_{-1}$	0.581	0.591	0.389
(1.10) (2.45) (1.96) (0.09) (2.33) (1.90) (2.08)			
$PGNE = 0.208 + 0.318\ PGNE_{-1} + 0.269\ PGNE_{-2} - 0.009\ M1ALD_{-1} + 0.095\ M1ALD_{-2} + 0.073\ CNCS_{-1} + 0.042\ PFTD_{-1}$	0.584	0.589	0.387
(0.84) (2.48) (2.04) (0.21) (2.44) (1.74) (1.90)			
$PGNE = 0.359 + 0.237\ PGNE_{-1} + 0.212\ PGNE_{-2} + 0.020\ M1ALD_{-1} + 0.166\ M1ALD_{-2} + 0.083\ CNCS_{-1}$	0.643	0.545	0.347
(1.44) (1.99) (1.74) (0.41) (3.31) (2.13)			
$+ 0.002\ R90_{-1} + 0.016\ R90_{-2} + 0.015\ R90_{-3} + 0.012\ R90_{-4}$			
(0.39) (2.24) (2.21) (2.08)			

component equation with two lags of real M1 and one lag of real personal fixed-term deposits. Thus the information in real personal fixed-term deposits appears to be fragile with respect to the lag length of real M1.

With respect to prices the most informative specification involves two lags of M1ALD, one lag of chequable and non-chequable savings deposits, and one lag of personal fixed-term deposits. This equation is able to encompass the alternative component equations but is itself encompassed by the bivariate equation consisting of two lags of M2. This implies that there is no significant information loss involved in aggregating the components of M2.

We added financial information to the component equations using the methodology outlined in the previous section. For nominal income, this resulted in the multivariate M1 equation reported in Table 4.5 -- adding four lags of the interest rate and one lag of the stock price index makes personal fixed-term deposits insignificant. For real income we get similar results. Real personal fixed-term deposits do not add any significant information to the multivariate real M1 equation for real output. Thus the component approach does not contribute any information with respect to nominal and real income in the multivariate setting.

We found the component approach to be informative with respect to the multivariate model of prices, however. Four lags of the interest rate are significant at the one per cent level when added to the M1ALD component equation, and this equation is able to encompass the multivariate M2 equation for prices at the 11 per cent level and the multivariate FI-PHMS equation for prices at the 44 per cent level. Thus, in the multivariate framework, there is a significant gain in information with respect to prices when M2 is disaggregated into M1ALD and chequable plus non-chequable savings deposits.

To summarize, there is little evidence to reject the aggregation assumptions underlying M1 (and M1ALD) in both the bivariate and multivariate frameworks. Personal fixed-term deposits add some information to M1 for both nominal and real output, but when we include other financial variables the information in personal fixed-term deposits becomes insignificant. For prices we find the aggregation assumptions underlying M2 to be valid in the bivariate framework but invalid in the multivariate framework.

6 EVALUATING THE VARIOUS INDICATOR MODELS

In this section we employ several methods to evaluate the indicator equations. Two criteria are used: a comparison of in-sample and post-sample forecasting performance based on root-mean-squared-errors and an analysis of the stability of the estimated relationships. The relevance of the first type of test is intuitively clear. The second is designed to help distinguish between equations that capture a truly informative relationship and those that are specific to certain periods and hence likely to represent a spurious relationship.

We subject fourteen different models to this analysis. For nominal income we examine five models. From the bivariate models we consider both the optimal FPE specification with eight lags on M1 and an alternative with just two lags. This second choice is included because of a suspicion that the long lags on money might be spurious. Light can be shed on this question by comparing the stability of the eight-lag and two-lag equations. Two lags were chosen because most of the information in M1 is restricted to these lags. The bivariate equation using FI-LL is also examined. From the multivariate models we consider two, one based on two lags of M1, and the other on two lags of FI-M1ALD (see Table 4.5).

For prices, we look at the bivariate and multivariate equations based on both M2 and FI-PHMS (four models) as well as the component multivariate prices equation (recorded in the last row of Table 5.2). For real income we look at long (five) and short (two) lag versions of the bivariate equations based on real M1 to address issues of stability, as explained above for nominal income. Finally, we examine the multivariate real income equation based on real M1 (see Table 4.5) and the bivariate component equation based on real M1 and real PFTD (row 4 of Table 5.2).

We begin this section by examining two Chow test methods for evaluating model stability. First, we search each quarter between 1975Q1 and 1982Q4 to test the hypothesis that the parameters are different in the two sub-samples on either side of this breakpoint. Conducting our tests at the 5 per cent level, we find evidence of instability during 1979, 1980, and 1981 for the nominal income multivariate equation based on FI-M1ALD in ten of the thirty-two quarters. Also, the F-statistic exceeds the 5 per cent significance level for the multivariate prices equation based on M2 for three of the thirty-two quarters. These results provide fairly strong evidence against the FI-M1ALD multivariate nominal income model and a marginally negative comment on the M2 multivariate prices equation.

The second type of Chow test employed tests the hypothesis that the four post-sample quarters of 1986 belong to the same model as the 1971-85 estimation period. For this test, we can reject stability for two models, the two multivariate nominal income equations based on FI-M1ALD and M1. The former rejection is at the 0.3 per cent significance level and the latter at the 2 per cent level. This suggests that we may wish to consider placing greater emphasis on our bivariate models for nominal income and less on the better-fitting multivariate models.

In the previous three sections we developed models by criteria which were functions of the in-sample ordinary least squares regression residuals. In this section we will look at recursive forecast errors, that is one-quarter-ahead forecast errors from an equation that has been estimated using only data prior to the quarter being forecast. The properties of these errors are determined primarily by two factors: the accuracy of the estimated in-sample relationship and the stability of this estimated relationship outside the estimation period. We will examine root-mean-squared (RMS) recursive forecast errors to summarize the one-step-ahead forecast performance of our fourteen models.

Table 6.1 shows the RMS recursive forecast errors for the various models, calculated over 1975Q1-1986Q4. For nominal income, the lowest RMS error is provided by the multivariate model using M1, a model which we found to be unstable over 1986 on the basis of the partial Chow test.

Table 6.1

RMS RECURSIVE FORECAST ERRORS (1975Q1 - 1986Q4)

(i) Nominal Income

FI-LL	$M1_{-8}$	$M1_{-2}$	M1 Multivariate	FI-M1ALD Multivariate
0.89	1.25	0.88	0.81	0.86

(ii) Real Income

$M1/P_{-5}$	$M1/P_{-2}$	Multivariate	Component
0.90	0.82	1.03	0.83

(iii) Prices

FI-PHMS	M2	M2 Multivariate	FI-PHMS Multivariate	Component
0.59	0.56	0.59	0.63	0.63

Given this problem, it is interesting that the bivariate equation using short lags on M1, which was found to be stable, provides a fairly similar RMS error. Also the bivariate equation with two lags on M1 provides a lower RMS error than the bivariate equation with eight lags on M1. This suggests that the eight-lag model is somewhat less stable since it fits better in terms of in-sample residuals. Some of this larger forecast error variance in the eight-lag model may be due to a large one-period-ahead error in 1975, however, so it may be dangerous to make broad generalizations about the relative stability of these two models.

For prices, the simple bivariate model using M2 is best. The superiority of this equation over the multivariate model using M2 and other variables indicates that the extra information in the multivariate equation does not produce more reliable forecasts one period ahead of the estimation period. The short bivariate real income model using real M1 has the lowest RMS recursive error. As in the price equation, this indicates that the simple bivariate models are likely to perform better in an operational mode because they have been relatively more stable out of the estimation period.

To this point, we have been able to make several inferences regarding our alternative models. First, we are led to prefer the bivariate nominal income models over the multivariate models because of the stability test results. Furthermore, within the bivariate models, the RMS error results indicate that the models with shorter lags, such as the FI-LL and M1 models with two lags, have superior one-period-ahead forecasting properties, with the latter yielding the lowest RMS error. Second, for real income we find the lowest RMS errors for the bivariate M1 model with two lags. Although none of the real income models fails the stability tests, one interpretation of the superior one-period-ahead fit for the short-lag M1 model is that it is relatively more stable out of sample. Finally, for prices we find that only the M2 multivariate equation cannot pass the formal stability tests. However, we again find informal support for the proposition that the bivariate M2 equation is more stable than the other specifications because in terms of RMS recursive forecast errors it dominates models that were found to fit better in sample.

To close out this section we examine equations for nominal income which are created by combining a real income and a price equation. Table 6.2 looks at this issue by calculating RMS errors for the recursive forecasts from single-equation nominal income equations and several pairs of real income and price equations (including those we prefer). We find that these combined forecasts generally perform worse than the preferred single-equation nominal income forecast which, based on the stability tests and RMS error results, is the M1 model with two lags.

The second part of this table looks at the question of encompassing tests within this combined model framework. Here we use the model evaluation procedure suggested by Chong and Hendry (1986) which involves regressing the actual growth rate of nominal income on the one-quarter-ahead forecasts from two different models. The coefficients can be interpreted as relative weights for constructing an optimal composite forecast. We can test to see if the information in a given forecast adds information to the preferred model by conducting a simple t test on the significance of its coefficient in the regression. In each case, the $\hat{\alpha}$ coefficient represents the weight to be placed on the preferred model (the two-lag bivariate M1 model) while $\hat{\beta}$ is that for the alternative model. This forecast encompassing principle enables us to evaluate forecasts from the nominal indicator equations relative to the forecasts from combined price and real income forecasts.

In these regressions we find that the following models are not encompassed by the twice-lagged M1 model: (i) the combined bivariate long-lag real M1 model for real income and the bivariate M2 price equation, (ii) the combined multivariate (real M1 for real output, M2 for prices) models, (iii) the combined component models, (iv) the FI-LL model and, as expected, (v) the M1 multivariate model. This indicates that while these models may provide higher RMS errors or have instability problems, there is still some useful information contained within them.

To conclude this section we can reflect on how these nominal income results add to the stability tests and previous RMS error tests. The stability tests and RMS error rankings led us to prefer simple bivariate

Table 6.2

RMS FORECAST ERRORS FOR COMBINED NOMINAL INCOME FORECASTS (1975Q1 - 1986Q4)

Model	RMSE	Combined Forecast Regression $\hat{\alpha}$	Combined Forecast Regression $\hat{\beta}$
(a) Combined Real Income and Prices Models			
Long Real M1 & M2	0.94	0.60 (3.02)	0.37 (2.17)
Short Real M1 & M2	0.91	0.50 (1.79)	0.45 (1.57)
Long Real M1 & FI-PHMS	1.05	0.65 (3.41)	0.28 (1.93)
Short Real M1 & FI-PHMS	0.97	0.59 (2.40)	0.32 (1.43)
Real M1 Multivariate & M2 Multivariate	1.04	0.50 (2.77)	0.37 (3.28)
Real M1 Multivariate & FI-PHMS Multivariate	1.09	0.62 (3.06)	0.25 (1.87)
Multivariate Component Model (Real M1, real PFTD & M1ALD, CNCS)	0.92	0.49 (2.12)	0.38 (2.23)
(b) Single-Equation Nominal Income Models			
Long M1	1.25	0.71 (3.79)	0.17 (1.56)
Short M1	0.88	-	-
FI-LL	0.89	0.51 (2.19)	0.44 (1.98)
M1 Multivariate	0.81	0.26 (1.03)	0.63 (2.94)

short-lag models for all three goal variables. In particular, for nominal income we chose a model with just two lags on M1. We have now also found that no combined real income and prices equations forecasts dominate this model. However, we have found five models which can add some information to the preferred specification. Hence, while it might be desirable to focus attention upon the twice-lagged M1 model, it might be useful to monitor the other non-encompassed specifications as well.

7 CONCLUSION

The purpose of this paper was to compare the information content of a comprehensive set of alternative monetary aggregates, in order to isolate a small subset that might be useful for monitoring economic developments. The sequence of tests performed has served to eliminate all but a small number of aggregates. In terms of a contemporaneous indicator of nominal spending, M2+ appears to be the most useful. In terms of leading indicators, the most useful models of nominal GNE and its real and price components are based on M1, real M1, and M2, respectively, and to some extent on FI-PHMS (for prices) and FI-M1ALD (for nominal income). In addition, significant leading information was found in short-term interest rates and an index of stock prices. Finally, the information loss due to aggregation was found to be very small for M1, but more important in M2, and significant information could be gained by using some of the components of M2.

Several secondary results are also worth highlighting. We note that the leading informativeness of money was reduced but not eliminated by the addition of other financial variables to our indicator models. This addition, however, did tend to shorten the optimal lag lengths on monetary information, which tended to be short compared with those often found in the literature. When short-lag and long-lag versions of the same model were subjected to the series of evaluations in Section 6, we found a distinct preference for the more parsimonious models. This suggests that there is a tendency to overfit models using our methodology and underlines the importance of the model evaluation step.

An interesting finding was that the superlative indices tended to perform less well in terms of information content than did the summation aggregates. It was hoped at the outset that these indices would internalize the financial innovation of the 1980s more satisfactorily than do the broader summation aggregates, but this proved not to be the case. This conclusion is consistent with that of Cockerline and Murray (1981), who found that Divisia indices were inferior to their summation counterparts as indicators of nominal income, in both contemporaneous and distributed lag models, for the 1968-1980 sample period.

Also of interest was the finding that real GNE and the GNE deflator are predicted better by different monetary aggregates, with narrower aggregates performing best for the real component and broader aggregates for prices. This suggests that users of vector autoregressive models (VARs) might benefit from including two definitions of money, rather than the usual single definition.

Further discrimination between the preferred models would require either more data or more sophisticated testing. Future research might focus on such questions as alternative filters for eliminating trends from the data, alternative loss functions to least squares for measuring the relative success of models, and further means of evaluating non-nested models.

Throughout the study we have refrained from attaching any causal or structural interpretation to our results, but of course any description of the data will contain useful clues for the structural modeller. The body of evidence presented here can perform at best a role complementary to that of a fully articulated structural model. A study parallelling this one will consider the information content of various measures of credit. It is hoped that, taken together, these two bodies of evidence will provide clues essential to an understanding of the structural interaction of money and credit and of their links to the real economy and prices.

REFERENCES

Akaike, H. "Statistical Predictor Identification." Annals of the Institute of Statistical Mathematics 21(1969):203-207.

Baily, R.W.; Driscoll, M.J.; Ford, J.L.; and Mullineux, A.W. "The Information Content of Monetary Aggregates in the U.K." Economics Letters 10(1982):61-67.

Bank of Canada. "Monetary aggregates: Some recent developments." Bank of Canada Review, January 1986.

Barnett, W. "Economic Monetary Aggregates: An Application of Index Number and Aggregation Theory." Journal of Econometrics 14(1980):11-48.

Barnett, W., and Spindt P. "The Velocity Behaviour and Information Content of Divisia Monetary Aggregates," Economics Letters 4(1979): 51-57.

Barnett, W., and Spindt P. "The Information Content of Divisia Monetary Quantity Indices." Federal Reserve Board Special Studies Paper No. 146, 1980.

Barnett, W.A.; Offenbacher, E.K.; and Spindt P.A. "The New Divisia Monetary Aggregates." Journal of Political Economy 92(1984): 104-9-85.

Chong, Y.Y. and Hendry, D.F. "Econometric Evaluation of Linear Macroeconometric Models." Review of Economic Studies LIII(1986): 671-690.

Cockerline, J.P., and Murray, J.D. "A Comparison of Alternative Methods of Monetary Aggregation: Some Preliminary Evidence." Bank of Canada Technical Report 28.

Driscoll, M.J.; Ford, J.L.; and Mullineux A.W. "The Elasticity of Prices with Respect to Monetary Components: Some Estimates for the U.K. 1948-1979." Applied Economics 17(1985):95-106.

Driscoll, M.J; Ford, J.L.; Mullineux, A.W.; and Kohler W. "Monetary Aggregates, Their Information Content and Their Aggregation Error: Some Preliminary Findings for Austria, 1965-1980." Empirical Economics 10(1985):13-25.

Geweke, J., and Meese, R. "Estimating Regression Models of Finite but Unknown Order." International Economic Review 22(1981):55-70.

Granger, C.W.J., and Newbold, P. "Spurious Regressions in Econometrics." Journal of Econometrics 2(1974):111-120.

Hendry, D.F., and Richard, J.F. "On the Formulation of Empirical Models in Dynamic Econometrics." Journal of Econometrics 20(1982):3-33.

Kiviet, J. "On the Rigour of Some Misspecification Tests for Modelling Dynamic Relationships." The Review of Economic Studies LIII(1986):241-261.

Mills, T.C. "The Information Loss Through Aggregation of the U.K. Monetary Components." Economics Letters 12(1983):305-311.

Nelson, C.R., and Plosser, C.I. "Trends and Random Walks in Macroeconomic Time Series." Journal of Monetary Economics 10(1982):139-162.

Plosser, C.I., and Schwert, G.W. "Money, Income, and Sunspots: Measuring Economic Relationships and the Effects of Differencing." Journal of Monetary Economics 4(1978):637-660.

Schwarz, G. "Estimating the Dimension of a Model." Annals of Statistics 6(1978):461-464.

Shannon, C. "A Mathematical Theory of Communication." Bell System Technical Journal 27(1948):379-452.

Sims, C.A. "Money, Income and Causality." American Economic Review 62(1972):540-555.

Theil, H. Economics and Information Theory. Amsterdam: North-Holland, 1967.

Tinsley, P.A.; Spindt, P.A.; and Friar, M.E. "Indicator and Filter Attributes of Monetary Aggregates: A Nit-Picking Case for Disaggregation." Journal of Econometrics 14(1980):61-91.

Printed in Canada Imprimé au Canada