Monetary Aggregates and Monetary Policy

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Introduction

Recently, economists and central bankers renewed their interest in identifying monetary policy disturbances. This involves a search for a variable, or combination of variables, to appropriately measure the stance—the looseness or tightness—of monetary policy. Over the years, many variables have been used for this purpose. For example, monetarist authors of the 1960s and 1970s, such as Friedman and Schwartz (1963), and Cagan (1972), emphasized monetary aggregates such as M1 and M2 as indicators of policy. They argued that such money measures lead output and prices, and are also positively related to changes in output (at least in the short run) and to changes in the price level (at least in the long run).

However, using monetary aggregates as indicators of policy is controversial because changes in monetary aggregates can result from factors other than changes in policy, factors such as changes in money demand or bank behaviour due to economic conditions over the business cycle. This problem with monetary aggregates as indicator variables has led many economists to consider either central bank balance-sheet measures, such as the base and various reserves measures (on the grounds that movements in these variables are dominated by changes in policy), or

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market-determined interest rates, such as the overnight rate and yield-curve spreads.

Another problem with using monetary aggregates as policy indicators is that the many studies of money's influence on the economy are based on official simple-sum money measures. Under some conditions such aggregates are appropriate, but if the relative prices of the financial components that constitute the aggregates fluctuate over time (as the evidence suggests), then simple-sum aggregation will produce theoretically unsatisfactory definitions of money. The problem is incorrectly accounting for substitution effects inherent in simple-sum aggregation, and the result is a set of monetary aggregates that do not accurately measure the actual quantities of the monetary products that optimizing economic agents select (in the aggregate).

Recently, researchers have focused on the gains that can be achieved by rigorously using microeconomic- and aggregation-theoretic foundations to construct monetary aggregates. This new approach to monetary aggregation was advocated by Barnett (1980) and has led to the construction of monetary aggregates based on Diewert's (1976) class of superlative quantity index numbers—the most recent example is Anderson, Jones, and Nesmith (1997a, 1997b). The new aggregates are Barnett's monetary services indices (also known as divisia aggregates) and Rotemberg's (1991) currency-equivalent (CE) indices—see also Rotemberg, Driscoll, and Poterba (1995). These aggregates are a viable and theoretically appropriate alternative to the simple-sum aggregates that central banks and researchers still use.

One aim of our paper is to investigate the roles of simple-sum, divisia, and CE monetary aggregates in Canadian monetary policy, using quarterly data over the 1974Q1–1998Q2 period. Our investigation used Hodrick-Prescott cyclical correlations, integration and cointegration tests, and the single-equation causality approach (with the time-series properties of the data imposed in estimation and hypothesis testing), as well as the multi-equation vector autoregression (VAR) framework, which treats all variables as part of a joint process.

The paper is organized as follows. In the next section we briefly discuss the problem of the definition (aggregation) of money, and in section 2 we describe the data. In section 3 we summarize some key facts regarding the dynamic co-movements between the different money series and real GDP, using the methodology suggested by Kydland and Prescott (1990). In section 4 we investigate the univariate time-series properties of the variables and test the existence of a long-run equilibrium relationship between money, prices, and income. In section 5 we investigate the strength of the empirical relationship connecting money to income and prices using causality tests and the single-equation approach, and in section 6 we investigate the robustness of the results of the multi-equation VAR approach. The final section is the conclusion.

1 The Many Kinds of Money

The monetary aggregates that the Bank of Canada and many central banks around the world now use are based on the simple-sum method of aggregation. The essential property of this method of monetary aggregation is that it assigns all monetary components a constant and equal (unitary) weight. This index is M in

$$M = \sum_{i=1}^{n} x_i, \tag{1}$$

where x_i is one of the n monetary components of the monetary aggregate M. This summation index assumes that the relative prices of the monetary components are constant and equal over time; this implies that component monetary assets must not only be perfect substitutes, but also dollar-for-dollar perfect substitutes. The empirical evidence shows that this is quite an unrealistic assumption—see, for example, Fleissig and Serletis (1999).

Over the years, many have attempted to properly weight monetary assets linearly within the simple-sum index. With no theory, however, any weighting scheme is questionable. The work of Diewert (1976, 1978) and Barnett (1980) was important in constructing monetary aggregates consistent with existing microeconomic and aggregation theory. These monetary aggregates are based on the so-called superlative class of quantity index numbers, among the most important of which is the discrete-time divisia index:

$$\log M_t^D - \log M_{t-1}^D = \sum_{i=1}^{n} s_{it}^{*}(\log x_{it} - \log x_{i,t-1}). \tag{2}$$

Equation (2) defines the growth rate of the money aggregate as the share-weighted average of the growth rates of the component asset quantities.

$$s_{it}^{*} = \frac{1}{2}(s_{it} + s_{i,t-1})$$

is the average of the expenditure shares from the two adjacent periods, and

$$s_{it} = \pi_{it} x_{it} / \Sigma \pi_{jt} x_{jt}$$

is the expenditure share of asset *i* during period *t*. π_{it} is the user cost of asset *i*, as derived in Barnett (1978):

$$\pi_{it} = \frac{R_t - r_{it}}{1 + R_t}, \tag{3}$$

where r_{it} is the market yield of asset *i* and R_t is the yield on the benchmark asset (theoretically the highest yield available). The benchmark asset is used only to transfer wealth from one period to another. The user cost measures the opportunity cost of the monetary services provided by asset *i* for the given period—see Barnett, Fisher, and Serletis (1992) for more details on the divisia approach to monetary aggregation.

A newer alternative index number with potential application to monetary aggregation is the Rotemberg, Driscoll, and Poterba (1995) CE index:

$$CE_t = \sum_{i=1}^{n} \frac{R_t - r_{it}}{R_t} x_{it}. \tag{4}$$

This index is basically the simple-sum index with a simple weighting mechanism added. In the event that a component monetary asset, such as currency, pays no interest, this asset will be added to the stock of monetary assets with a weight of 1. The weight applied to the individual asset will decline towards 0 as its return increases toward R_t and the asset comes to behave more like the benchmark asset (a means to transfer wealth) and less like money.

The CE and divisia indices differ in much the same way as do the simple-sum and divisia indices: The CE index under most conditions functions as a stock measure (though a different stock measure from the simple-sum index), and the divisia index functions as a flow measure. Specifically, the CE index measures the stock of monetary wealth, and the divisia index measures the flow of monetary services. However, the CE and simple-sum indices can measure the flow of monetary services if a specific set of assumptions is satisfied for each. The key difference between the CE and simple-sum indices is that the CE can measure the flow of monetary services under a less restrictive set of assumptions than the perfect and dollar-for-dollar substitutes assumption required by the simple-sum index—see Rotemberg (1991) and Barnett (1991) for more details on divisia and CE measures.

In this paper we use Canadian simple-sum, divisia, and CE monetary aggregates to investigate the relationship between money, prices, and income. The data are quarterly over the 1974Q1–1998Q2 period and are described in the following section.

2 Data

We begin with the list of monetary assets that the Bank of Canada now uses to construct five popular monetary aggregates—M1, M1+, M1++, M2, and M3. We disregard the other two monetary aggregates, M2+ and M2++, because some of the interest rate series used in these aggregates are unavailable. As shown in Table 1, M1, M1+, M1++, M2, and M3 are constructed by means of a recursive form of accounting that starts with M1 and adds blocks of items to M1 until the broadest of these aggregates, M3, is constructed.

Table 1
Bank of Canada monetary aggregates/components

Monetary aggregate	Component	CANSIM series number
	Currency outside banks	B2001
	Personal chequing accounts	B486
M1	Current accounts	B487
	Personal chequable savings deposits	B452
M1+	Non-personal chequable notice deposits	B472
	Personal non-chequable savings deposits	B453
M1++	Non-personal non-chequable notice deposits	B473
M2	Personal fixed-term savings deposits	B454
	Non-personal term deposits	B475
M3	Foreign currency deposits	B482

As we noted previously, the monetary aggregates the Bank now uses are simple-sum indices; a unitary weight is assigned to each monetary asset. In contrast, to build divisia and CE monetary aggregates we must first calculate monetary asset user costs, as defined by equation (3). To do so, we set the user cost of currency equal to 0, and to calculate user costs for demand deposits (CANSIM series B486 and B487), we use the implicit rate of return, as in Klein (1974) and Startz (1979), based on the formula

$$r_D = (1 - \kappa) r_A,$$

where r_A is the interest rate on an alternative asset and κ is an estimate of the maximum required reserve ratio. Here r_A is taken to be the interest rate on 3- to 5-year Government of Canada bonds (CANSIM B14010), and κ is constructed from both the primary and secondary reserve ratios against demand deposits over the sample period.

The interest rate on B452 is taken to be the rate on personal chequable savings deposits (CANSIM B14035) from 1974M1 to 1982M9 and the interest rate on daily-interest chequing accounts (DICA) in excess of $5,000 (DICA 5K+) from 1982M10 to 1998M6. For the interest rate on B453 we use the rate on personal non-chequable savings deposits (CANSIM B14019) from 1974M1 to 1986M12, the rate on daily-interest savings accounts (DISA) in excess of $25,000 (DISA 25K+) from 1987M1 to 1988M1, and the average of DISA 25K+ and DISA 75K+ from 1988M2 to 1998M6. Finally, we use the prime rate (CANSIM B14020) as a proxy for the interest rate on B475, the euro/US$ deposit rate (CANSIM B54415) for the interest rate on B482, the 5-year term deposit rate (CANSIM B14045) for the interest rate on B454, and the rate on 90-day personal fixed-term deposits (CANSIM B14043) for the interest rate on both B472 and B473. The 5-year term deposit rate was yield-curve adjusted to remove the premium that exists for an asset with a typically long term to maturity.

We use seasonally adjusted data and a reasonable proxy for the benchmark rate of interest (see Molik [1999] for details regarding these issues) to construct simple-sum, divisia, and CE monetary aggregates at each of the M1, M2, M3, M1+, and M1++ levels of aggregation. Figures 1 to 5 show graphical representations of these monetary aggregates. As the figures indicate, the fluctuations of the money series are different at different levels of aggregation and also across aggregation methods, reflecting the fact that monetary aggregation issues are complicated—something to be kept in mind when interpreting the results later on.

3 Some Basic Business Cycle Facts

For a description of the stylized facts we follow the current practice of detrending the data with the Hodrick-Prescott (H-P) filter—see Prescott (1986). For the logarithm of a time series X_t, for $t = 1, 2, \ldots, T$, the detrending procedure defines the trend or growth component, denoted τ_t, for $t = 1, 2, \ldots, T$, as the solution to the following minimization problem:

$$\min_{\tau_t} \quad \sum_{t=1}^{T} (X_t - \tau_t)^2 + \mu \sum_{t=2}^{T-1} [(\tau_{t+1} - \tau_t) - (\tau_t - \tau_{t-1})]^2, \qquad (5)$$

Figure 1
Sum M1, divisia M1, and CE M1 money measures

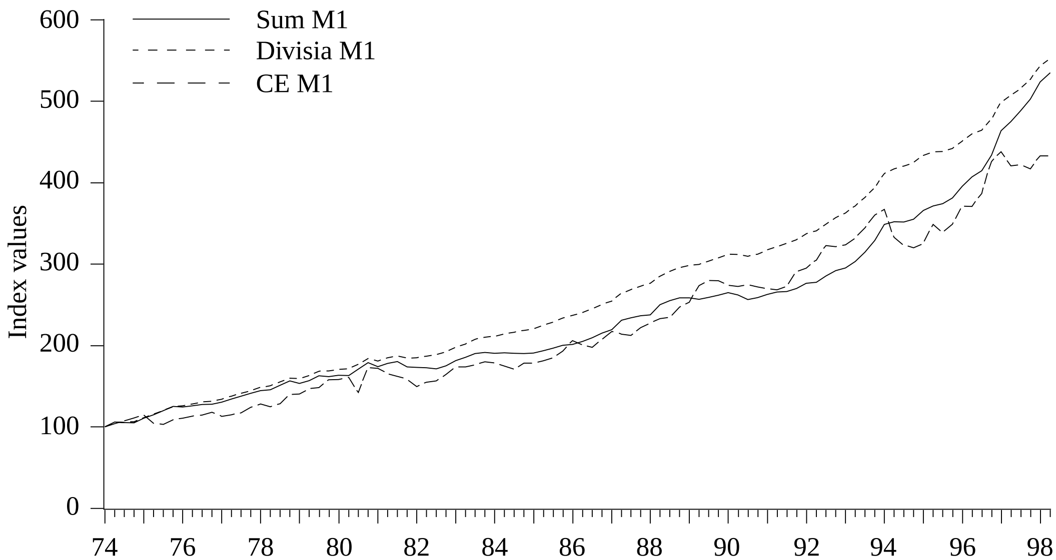


Figure 2
Sum M2, divisia M2, and CE M2 money measures

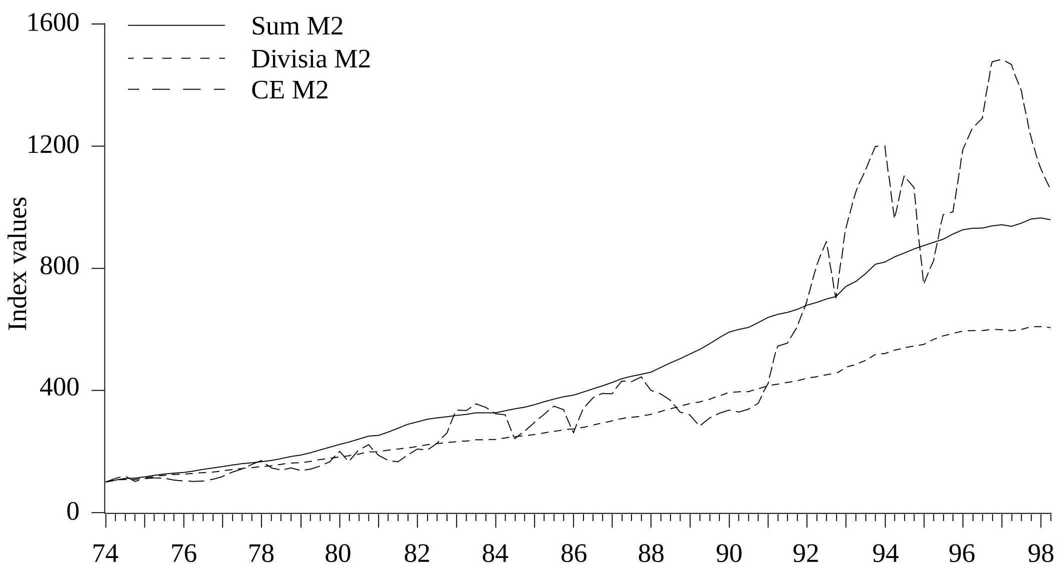


Figure 3
Sum M3, divisia M3, and CE M3 money measures

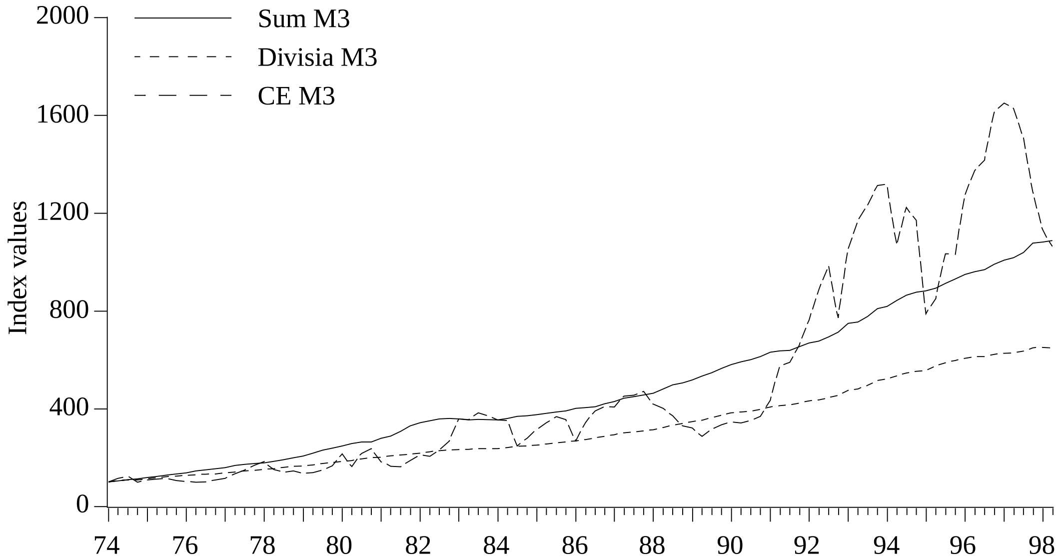


Figure 4
Sum M1+, divisia M1+, and CE M1+ money measures

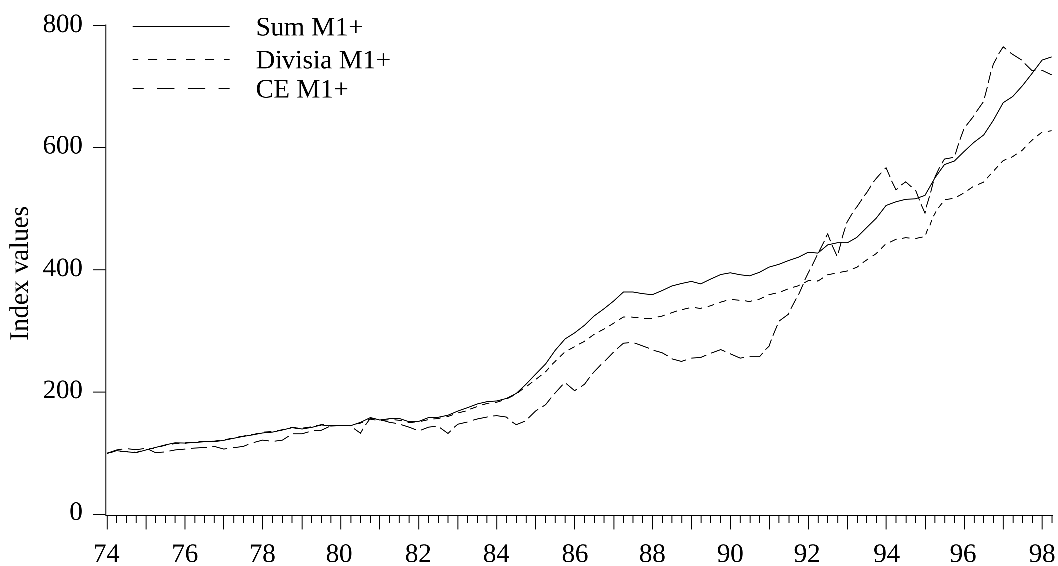
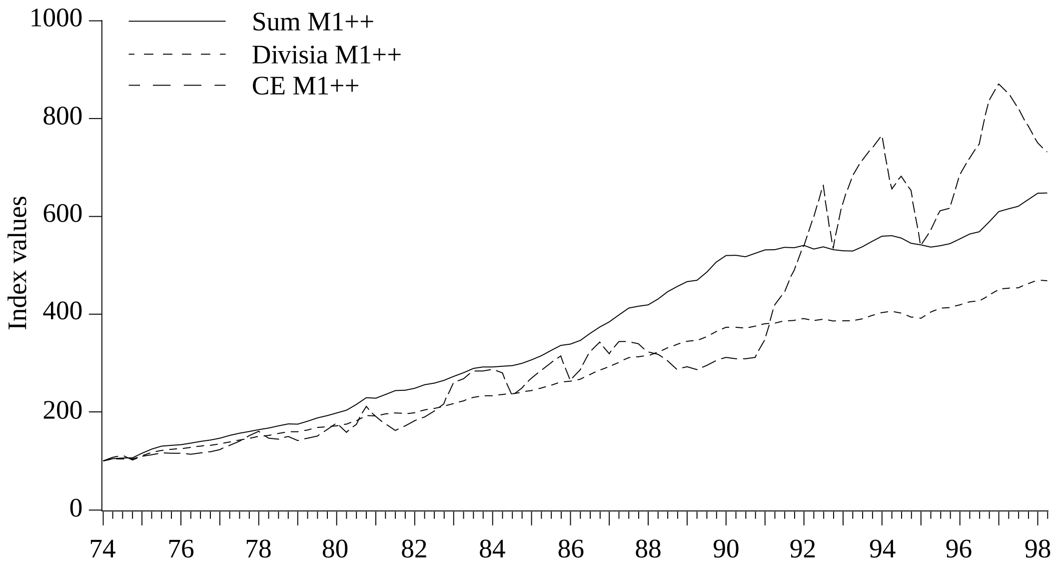


Figure 5
Sum M1++, divisia M1++, and CE M1++ money measures



so X_t divisia minus τ_t is the H-P–filtered series. The larger μ is, the smoother the trend path, and when $\mu = \infty$, a linear trend results. In our computations we set $\mu = 1,600$, as recommended by Kydland and Prescott (1990).

We measure the degree of co-movement of a money series with the cycle by the magnitude of the correlation coefficient $\rho(j),\ j \in \{0, \pm1, \pm2, \ldots\}$. The contemporaneous correlation coefficient—$\rho(0)$—gives information on the degree of contemporaneous co-movement between the series and the pertinent cyclical variable. In particular, if $\rho(0)$ is positive, zero, or negative, we say that the series is procyclical, acyclical, or countercyclical, respectively. In fact, for data samples of our size, authors such as Fiorito and Kollintzas (1994) have suggested that for $0.5 \le |\rho(0)| \le 1,\ 0.2 \le |\rho(0)| < 0.5$, and $0 \le |\rho(0)| < 0.2$, we say that the series is strongly contemporaneously correlated, weakly contemporaneously correlated, or contemporaneously uncorrelated with the cycle. Also, $\rho(j),\ j \in \{\pm1, \pm2, \ldots\}$—the cross-correlation coefficient—gives information on the phase-shift of the series relative to the cycle. If $|\rho(j)|$ is maximum for a positive, zero, or negative j, we say that the series is leading the cycle by j periods, is synchronous, or is lagging the cycle by j periods.

In Table 2 we report contemporaneous correlations as well as cross correlations between the cyclical component of money and the cyclical component of real output at lags and leads of 1, 2, 3, 4, 6, and 9 quarters. Clearly, sum M1, divisia M1, sum M1+, and divisia M1+ are procyclical

Table 2
Hodrick-Prescott cyclical correlations of money measures with real GDP
$\rho(M_t, Y_{t+j}), j = -9, -6, -4, -3, -2, -1, 0, 1, 2, 3, 4, 6, 9$

Series	$j = -9$	$j = -6$	$j = -4$	$j = -3$	$j = -2$	$j = -1$	$j = 0$	$j = 1$	$j = 2$	$j = 3$	$j = 4$	$j = 6$	$j = 9$
Sum M1	0.108	0.031	0.016	0.063	0.180	0.345	0.489	0.637	0.687	0.582	0.428	0.115	–0.236
Divisia M1	–0.120	–0.118	–0.060	0.019	0.177	0.371	0.536	0.704	0.764	0.669	0.524	0.217	–0.135
CE M1	0.154	0.133	0.025	–0.006	0.029	0.098	0.193	0.264	0.252	0.202	0.180	–0.010	–0.214
Sum M2	0.213	0.402	0.366	0.267	0.137	–0.023	–0.186	–0.304	–0.388	–0.447	–0.480	–0.479	–0.423
Divisia M2	0.054	0.381	0.364	0.247	0.139	0.053	–0.005	–0.007	–0.016	–0.063	–0.127	–0.271	–0.375
CE M2	0.033	–0.193	–0.486	–0.569	–0.622	–0.601	–0.454	0.243	–0.047	0.124	0.260	0.391	0.304
Sum M3	0.257	0.287	0.277	0.197	0.081	–0.066	–0.251	–0.398	–0.490	–0.530	–0.524	–0.390	–0.311
Divisia M3	0.104	0.404	0.390	0.266	0.156	0.062	–0.014	–0.029	–0.042	–0.085	–0.143	–0.272	–0.391
CE M3	0.028	–0.200	–0.493	–0.573	–0.623	–0.599	–0.449	–0.235	–0.042	0.123	0.259	0.385	0.289
Sum M1+	–0.134	0.234	0.282	0.275	0.297	0.350	0.414	0.492	0.522	0.484	0.425	0.324	0.296
Divisia M1+	–0.206	0.173	0.264	0.271	0.303	0.364	0.433	0.512	0.545	0.511	0.461	0.371	0.324
CE M1+	0.027	–0.048	–0.185	–0.260	–0.172	–0.083	0.057	0.169	0.240	0.287	0.315	0.320	0.293
Sum M1++	0.578	0.424	0.159	0.038	–0.031	–0.060	–0.055	–0.010	–0.007	–0.088	–0.197	–0.373	0.346
Divisia M1++	0.545	0.413	0.142	0.006	–0.042	–0.012	0.061	0.179	0.228	0.153	0.028	–0.208	–0.280
CE M1++	0.003	–0.273	–0.556	–0.640	–0.675	–0.606	–0.414	–0.185	0.002	0.148	0.257	0.342	0.328

Note: Sample period quarterly data, 1974Q1–1998Q2.

(divisia M1 is more so) and lead the cycle—recall that a monetary aggregate leads the cycle if its cross correlations with future real output are larger (in absolute value) than the contemporaneous correlation. Sum M3, CE M2, CE M3, and CE M1++ are countercyclical, and the remaining aggregates are acyclical. These results appear to support a monetary effect on real output only in the case of the sum M1, divisia M1, sum M1+, and divisia M1+ aggregates and also illustrate some differences across simple-sum, divisia, and CE monetary aggregates.

4 The Data's Integration and Cointegration Properties

4.1 Integration tests

In the single-equation approach, estimation and hypothesis testing critically depend on the variables' univariate time-series properties. Therefore, in what follows we test for unit roots using three different testing procedures to deal with anomalies that arise when the data are not very informative about whether or not there is a unit root.

In the first two columns of Table 3 we report *p* values for the augmented Dickey-Fuller (ADF) test (see Dickey and Fuller [1981]) and the nonparametric, $Z(\tau_{\hat{\alpha}})$ test of Phillips (1987) and Phillips and Perron (1988). These *p* values (calculated using time-series processor 4.5) are based on the response surface estimates given by MacKinnon (1994). For the ADF test we selected the optimal lag length according to the Akaike information criterion (AIC) plus 2—see Pantula, Gonzalez-Farias, and Fuller (1994) for details on the advantages of this rule for choosing the number of augmenting lags. The $Z(\tau_{\hat{\alpha}})$ test was done with the same Dickey-Fuller regression variables, using no augmenting lags. Based on the *p* values for the ADF and $Z(\tau_{\hat{\alpha}})$ test statistics reported in panel A of Table 3, the null hypothesis of a unit root in levels cannot generally be rejected at conventional significance levels. This is consistent with the Nelson and Plosser (1982) argument that most macroeconomic time series have stochastic trends.

In the unit root-tests that we have discussed so far, the unit root is the null hypothesis to be tested, and the way in which classical hypothesis testing is carried out ensures that the null hypothesis is accepted unless there is strong evidence against it. In fact, Kwiatkowski et al. (1992) argue that such unit-root tests fail to reject a unit root because they have low power against relevant alternatives, and they propose tests, called KPSS tests, of the hypothesis of stationarity against the alternative of a unit root. They argue that such tests should complement unit-root tests and that by testing both the unit-root hypothesis and the stationarity hypothesis, one can distinguish series that appear to be stationary, series that appear to be

Table 3
Unit-root and stationarity test results in the variables

	A. Log levels				B. First differences of log levels			
	***p* values**		**KPSS *t*-statistics**		***p* values**		**KPSS *t*-statistics**	
Series	**ADF**	$Z(t_{\hat{\alpha}})$	$\hat{\eta}_{\mu}$	$\hat{\eta}_{\tau}$	**ADF**	$Z(t_{\hat{\alpha}})$	$\hat{\eta}_{\mu}$	$\hat{\eta}_{\mu}$
Sum M1	0.949	0.958	1.227*	0.267*	0.045	0	0.287	0.205*
Divisia M1	0.13	0.265	1.289*	0.308*	0.029	0	0.192	0.159*
CE M1	0.029	0.014	1.284*	0.292*	0	0	0.034	0.025
Sum M2	0.98	0.993	1.289*	0.314*	0.06	0	1.558*	0.102
Divisia M2	0.976	0.99	1.290*	0.315*	0.009	0	1.049*	0.139
CE M2	0.061	0.111	1.093*	0.253*	0	0	0	0.041
Sum M3	0.367	0.838	1.280*	0.311*	0.032	0	1.057*	0.176*
Divisia M3	0.829	0.613	1.276*	0.322*	0.14	0	0.621*	0.175*
CE M3	0.052	0.091	1.079*	0.244*	0	0	0.048	0.041
Sum M1+	0.091	0.663	1.275*	0.246*	0.404	0	0.147	0.128
Divisia M1+	0.044	0.601	1.280*	0.249*	0.252	0	0.122	0.116
CE M1+	0.378	0.631	1.144*	0.301*	0.001	0	0.115	0.052
Sum M1++	0.98	0.976	1.324*	0.13	0.011	0	1.210*	0.061
Divisia M1++	0.949	0.977	1.330*	0.125	0	0	1.017*	0.049
CE M1++	0.072	0.097	1.182*	0.233*	0	0	0.053	0.039
Deflator	0.906	0.985	1.298*	0.308*	0	0	2.784*	0.097
Nominal GDP	0.868	0.981	1.329*	0.102	0.007	0	1.789*	0.215*
Real GDP	0.152	0.588	1.319*	0.06	0.01	0	1.685*	0.118

Notes: Sample period quarterly data, 1974Q1–1998Q2. Numbers in the ADF and $Z(t_{\hat{\alpha}})$ columns are tail areas of unit-root tests. An asterisk next to a KPSS *t*-statistic indicates significance at the 5 per cent level. The 5 per cent critical values for the KPSS $\hat{\eta}_{\mu}$ and $\hat{\eta}_{\tau}$ *t*-statistics (given in Kwiatkowski et al. [1992]) are 0.463 and 0.146 respectively.

integrated, and series that are not very informative about whether or not they are stationary or have a unit root.

KPSS tests for level and trend stationarity are presented in the KPSS columns in panel A of Table 3. As can be seen, the *t*-statistic $\hat{\eta}_{\mu}$ that tests the null hypothesis of level stationarity is large relative to the 5 per cent critical value of 0.463 given in Kwiatkowski et al. (1992). As well, the statistic $\hat{\eta}_{\tau}$ that tests the null hypothesis of trend stationarity exceeds the 5 per cent critical value of 0.146, also given in Kwiatkowski et al. (1992); the exceptions are sum M1++, divisia M1++, nominal GDP, and real GDP. Combining the results of the stationarity hypothesis tests with the results of unit-root hypothesis tests, we conclude that all the series have at least one unit root.

To test the null hypothesis of a second unit root, we test both the null hypothesis of a second unit root—using the ADF and $Z(t_{\hat{\alpha}})$ tests—and the null hypotheses of level and trend stationarity in the first differences of the series. The results are shown in panel B of Table 3. Clearly, some of the series (such as sum M1, divisia M1, sum M3, and to a larger extent, divisia M3) are not very informative about whether or not they are stationary in their first differences, since both the null hypothesis of a second unit root and the null hypothesis of trend stationarity are rejected. However, combining the results of the tests of the unit-root hypothesis and of the level and trend stationarity hypotheses, we conclude that these variables have one unit root, keeping in mind that some of the variables are not very informative about their time-series properties.

4.2 Cointegration tests

As mentioned earlier, causality tests critically depend on the data's integration and cointegration properties. In particular, if the variables are integrated but not cointegrated, ordinary least squares (OLS) yield misleading results. In fact, Phillips (1987) formally proves that without cointegration, a regression involving integrated variables is spurious. In this case the only valid relationship that can exist between the variables is in terms of their first differences. If, however, the variables are integrated and cointegrated, then the short-run dynamics can be described by an error-correction model in which the short-run dynamics of the variables in the system are influenced by the deviation from the long-run equilibrium.

To present empirical evidence on this issue, we test the null hypothesis of no cointegration (against the alternative of cointegration) between each money measure and the price level, nominal income, and real income, using the Engle and Granger (1987) two-step procedure. This involves regressing one variable against another to obtain the OLS regression residuals $\hat{e}$. A test of the null hypothesis of no cointegration (against the alternative of cointegration) is then based on testing for a unit root in the regression residuals using the ADF test and critical values, which correctly take into account the number of variables in the cointegration regression.

In Table 4 we show asymptotic *p* values, computed using the coefficient estimates in MacKinnon (1994), of the bivariate cointegration tests (in log levels). The entries are *p* values for testing the null hypothesis of no cointegration. The cointegration tests are first done with one series as the dependent variable in the cointegration regression and then with the other series as the dependent variable—we should be wary of a result indicating cointegration using one series as the dependent variable but indicating no

Table 4
Marginal significance levels of Engle-Granger cointegration tests between money and prices, nominal GDP, and real GDP

	Cointegration tests between money and the GDP deflator: Dependent variable:		Cointegration tests between money and nominal GDP: Dependent variable:		Cointegration tests between money and real GDP: Dependent variable:	
Monetary aggregate	m_t	p_t	m_t	$(py)_t$	m_t	y_t
Sum M1	0.457	0.289	0.985	0.297	0.993	0.266
Divisia M1	0.15	0.092	0.989	0.299	0.994	0.251
CE M1	0.021	0.373	0.741	0.363	0.742	0.2
Sum M2	0.148	0.355	0.585	0.285	0.732	0.253
Divisia M2	0.143	0.425	0.574	0.283	0.729	0.244
CE M2	0.829	0.989	0.76	0.272	0.949	0.477
Sum M3	0.114	0.105	0.915	0.2	0.984	0.254
Divisia M3	0.034	0.12	0.647	0.243	0.774	0.242
CE M3	0.851	0.993	0.729	0.304	0.944	0.492
Sum M1+	0.16	0.562	0.932	0.449	0.909	0.149
Divisia M1+	0.141	0.559	0.877	0.433	0.929	0.153
CE M1+	0.282	0.641	0.866	0.269	0.953	0.243
Sum M1++	0.664	0.983	0.456	0.143	0.617	0.32
Divisia M1++	0.527	0.977	0.474	0.19	0.615	0.34
CE M1++	0.644	0.982	0.664	0.324	0.733	0.595

Notes: Sample period quarterly data, 1974Q1–1998Q2. All tests use a constant and trend variable. Asymptotic p values are computed using the coefficients in MacKinnon (1994). The number of augmenting lags is determined using the AIC+2 rule.

cointegration when the other series is used as the dependent variable. The tests use constant as well as trend variables, and the number of augmenting lags is chosen using the AIC+2 rule mentioned earlier.

The results suggest that the null hypothesis of no cointegration between each monetary aggregate, the price level, nominal output, and real output cannot be rejected at the 5 per cent level. These results provide guidelines as to how Granger causality tests should be performed. In fact, because of the strong evidence that the series are nonstationary and do not cointegrate, in the next section we use the single-equation approach and test for Granger causality using I(0) variables; that is, the first differences of the variables.

5 Granger Causality Tests

In this section we investigate whether monetary aggregates provide information about recent or current economic conditions that could be useful in conducting monetary policy. In doing so, we take an “information variable” approach and test for Granger causality, using the single-equation framework in which money is treated as predetermined and the integration and cointegration properties of the data are imposed in estimation.

To test for causality, in keeping with Granger (1969) it must be assumed that the relevant information is entirely contained in the present and past values of the variables. An obvious specification is

$$\Delta z_t = \alpha_0 + \sum_{j=1}^{r} \alpha_j \Delta z_{t-j} + \sum_{j=1}^{s} \beta_j \Delta m_{t-j} + u_t, \tag{6}$$

where Δz_t is the inflation rate, the growth rate of nominal output, or the growth rate of real output, and Δm_t is the growth rate of a given money measure. To test if m_t causes z_t in the Granger (1969) sense, equation (6) is first estimated by OLS, and the unrestricted sum of squared residuals (SSR_u) is obtained. Then, by running another regression equation under the restriction that all β_js are zero, the restricted sum of squared residuals (SSR_r) is obtained. If u_t is white noise, then the statistic computed as the ratio of $(\mathrm{SSR}_r - \mathrm{SSR}_u)/s$ to $\mathrm{SSR}_u/(T-r-s-1)$ has an asymptotic F distribution with numerator degrees of freedom s and denominator degrees of freedom $(T-r-s-1)$, where T is the number of observations and 1 is subtracted out to account for the constant term in equation (6).

Before we could perform Granger causality tests we had to deal with the lengths of lags r and s in equation (6). In the literature, r and s are frequently chosen to have the same value, and lag lengths of 4, 6, or 8 are used most often with quarterly data. However, such arbitrary lag specifications can produce misleading results because they may imply misspecification of the order of the autoregressive process. For example, if r or s (or both) is too large, the estimates will be unbiased but inefficient. If r or s (or both) is too small, the estimates will be biased but have smaller variances.

Here we used the data to determine the “optimum” lag structure. In particular, the optimal r and s was determined using the AIC. We considered values from 1 to 12 for each of r and s in equation (6). By running 144 regressions for each bivariate relationship we chose the one that produced the smallest value for the AIC. From these optimal specifications we present, in Table 5, p values for Granger causality F tests in the quarterly data over the 1974Q1 to 1998Q2 period.

Table 5
Tail areas of tests of Granger causality from money to prices, nominal income, and real income

	Money to prices		Money to nominal income		Money to real income	
Money measure	**AIC lags**	***p* value**	**AIC lags**	***p* value**	**AIC lags**	***p* value**
Sum M1	(9,1)	0.45	(1,4)	0.046	(1,2)	0.063
Divisia M1	(9,1)	0.537	(1,4)	0.036	(1,2)	0.048
CE M1	(9,1)	0.681	(1,1)	0.951	(1,1)	0.415
Sum M2	(5,1)	0.342	(1,5)	0.254	(1,1)	0.686
Divisia M2	(9,1)	0.587	(1,2)	0.286	(1,1)	0.798
CE M2	(9,1)	0.682	(1,1)	0.726	(1,1)	0.603
Sum M3	(5,5)	0.265	(1,1)	0.999	(1,7)	0.199
Divisia M3	(9,3)	0.488	(1,2)	0.35	(1,1)	0.946
CE M3	(9,1)	0.692	(1,1)	0.653	(1,1)	0.551
Sum M1+	(5,5)	0.224	(1,3)	0.139	(1,2)	0.122
Divisia M1+	(9,1)	0.945	(1,3)	0.234	(1,2)	0.126
CE M1+	(9,1)	0.999	(1,1)	0.999	(1,1)	0.708
Sum M1++	(9,1)	0.675	(1,5)	0.081	(1,4)	0.222
Divisia M1++	(9,1)	0.807	(1,5)	0.074	(11,8)	0.012
CE M1++	(9,1)	0.654	(1,1)	0.604	(1,1)	0.461

Notes: Sample period quarterly data, 1974Q1–1998Q2. Numbers in parentheses indicate the optimal lag specification, based on the AIC. Low *p* values imply strong marginal predictive power.

We find that the hypothesis that money does not “Granger cause” the price level cannot be rejected with each of the monetary aggregates. The hypothesis that money does not cause nominal income is rejected only with the sum M1, divisia M1, sum M1++, and divisia M1++ aggregates—note that divisia M1 produces a smaller test tail area than do the other aggregates. Finally, the hypothesis that money does not cause real output is rejected only with the sum M1, divisia M1, and divisia M1++ aggregates. In conclusion, none of the monetary aggregates appears to be a good leading indicator of inflation, divisia M1 is apparently the best leading indicator of nominal income, and divisia M1++ is apparently the best leading indicator of real income.

To investigate the robustness of these results under alternative specifications, we applied the statistical approach Stock and Watson (1989) used in their study of U.S. money-output causality. This involves including a short-term interest rate in equation (6) and deciding whether removing the deterministic trend from the growth rate of each money measure sharpens the relationship between money and real output. We therefore considered the following specification with I(0) variables:

$$\Delta y_t = \alpha_0 + \sum_{j=1}^{r} \alpha_j \Delta y_{t-j} + \sum_{j=1}^{s} \beta_j \Delta m_{t-j} + \sum_{j=1}^{q} \gamma_j \Delta R_{t-j}, + \phi t + u_t, \tag{7}$$

where R is the 90-day treasury bill rate and t is a linear trend. The inclusion of t is equivalent to detrending each variable individually, and thus the causality tests focus on the marginal predictive power of detrended money growth. As in Stock and Watson (1989), we tested for causality with no time trend and with a linear time trend. Again, we used the AIC with values from 1 to 12 for each of r, s, and q in equation (7), and by running 1,728 regressions for each trivariate relationship we chose the one that minimizes the AIC. The results, based on these optimal lag specifications, appear in Table 6.

The results show that including the interest rate does not change the predictive power of money over the 1974Q1–1998Q2 sample period. Moreover, including the linear time trend does not seem to significantly change statistical inference regarding the strength of the empirical relationship between money and real output.

6 Evidence from VARs

The Granger causality results just reported evaluate the proposition that both anticipated and unanticipated money movements influence real output. Moreover, the single-equation approach (of the previous section) can be interpreted as a VAR in which a specific subset of coefficients is restricted to equal 0. We investigated the robustness of the Granger causality results by using the multi-equation VAR framework, in which the variables were treated as jointly determined. In doing so, we also evaluated the effects of unanticipated shocks by tracing out the implied impulse-response functions.

We considered Sims's (1992) classic 4-variable VAR, consisting of the interest rate (R), the logged money supply (M), the logged price level (P), and logged real GDP (Y), in that order. That is, we assumed that the interest rate is determined before the money supply (an interest-rate-targeting operating procedure). We used quarterly data over the 1974Q1–1998Q2 period, set the lag length equal to six quarters, and ignored low-frequency variables such as linear trends. The interesting comparison is running the different monetary aggregates through otherwise identical models.

Table 6
Tail areas of tests of Stock and Watson (1989) causality from money and interest rates to real output

	No trend			Linear trend		
Money measure	**AIC lags**	**Money**	***R***	**AIC lags**	**Money**	***R***
Sum M1	(1,2,1)	0.059	0.507	(1,2,1)	0.053	0.455
Divisia M1	(1,2,1)	0.043	0.389	(1,2,1)	0.044	0.389
CE M1	(3,1,3)	0.452	0.154	(1,2,12)	0.431	0.074
Sum M2	(1,5,3)	0.676	0.465	(1,5,3)	0.364	0.407
Divisia M2	(3,2,7)	0.221	0.071	(3,2,7)	0.3	0.062
CE M2	(3,1,3)	0.673	0.15	(3,1,3)	0.723	0.132
Sum M3	(1,7,3)	0.287	0.54	(8,8,12)	0.096	0.024
Divisia M3	(3,2,3)	0.439	0.113	(1,2,7)	0.325	0.136
CE M3	(3,1,3)	0.677	0.156	(3,1,3)	0.734	0.137
Sum M1+	(1,10,7)	0.108	0.158	(3,10,7)	0.064	0.045
Divisia M1+	(1,1,3)	0.289	0.483	(1,2,7)	0.181	0.33
CE M1+	(3,1,3)	0.981	0.159	(1,2,12)	0.868	0.079
Sum M1++	(1,5,7)	0.103	0.194	(1,5,7)	0.101	0.114
Divisia M1++	(1,2,12)	0.054	0.007	(1,2,12)	0.067	0.01
CE M1++	(3,1,3)	0.559	0.176	(3,1,3)	0.616	0.155

Notes: Sample period quarterly data, 1974Q1–1998Q2. Numbers in parentheses indicate the optimal lag specification, based on the AIC. Low p values imply strong marginal predictive power.

The marginal significance levels for Granger causality F-tests and 5-year forecast-error-variance decompositions for each of the 15 money measures appear in Table 7. The p values are for the null hypothesis of no causality from the variable in the column heading to the variable in the row heading. Clearly, the hypothesis of no causality from money to real output can be rejected at conventional significance levels only with the sum M1, divisia M1, sum M1++, and divisia M1++ monetary aggregates. The hypothesis, however, of no causality from the interest rate to real output can in general be rejected, irrespective of how money is defined.[1]

The forecast-error-variance decompositions in panel B of Table 7 show percentages of the 5-year forecast-error variance of a variable explained by its own shocks versus shocks to other variables. The forecast-error-variance decompositions show that innovations in money explain a

1. Because the VARs are run in levels and the coefficients have non-standard unit-root distributions, the marginal significance levels reported in the table are not exact. Nevertheless, they are still useful for relative comparisons between specifications employing the different money measures.

Table 7
Unrestricted VAR results for {*R*, *M*, *P*, *Y*} model

	A. Marginal significance levels for exclusion of lags				B. Forecast-error-variance decompositions (20-quarter horizon)			
Equation	***R***	***M***	***P***	***Y***	***R***	***M***	***P***	***Y***
				Sum M1				
R	0	0.135	0.243	0.116	27.596	25.267	34.341	12.795
Sum M1	0.012	0	0.128	0.854	60.324	9.044	15.678	14.952
P	0.556	0.589	0	0.894	0.605	24.667	71.219	3.508
Y	0.116	0.093	0.038	0	34.221	23.864	19.962	21.951
				Divisia M1				
R	0	0.052	0.095	0.099	26.861	17.009	44.446	11.682
Divisia M1	0.014	0	0.216	0.656	47.278	7.619	27.167	17.934
P	0.825	0.801	0	0.982	0.838	12.026	84.635	2.498
Y	0.067	0.06	0.037	0	32.16	22.59	25.862	19.385
				CE M1				
R	0	0.186	0.029	0.109	29.494	9.133	54.267	7.105
CE M1	0.249	0.001	0.142	0.158	30.286	38.483	26.693	4.536
P	0.475	0.359	0	0.935	1.775	2.919	95.166	0.138
Y	0.015	0.249	0.032	0	55.557	5.667	26.316	12.457
				Sum M2				
R	0	0.431	0.09	0.12	36.945	4.03	50.942	8.082
Sum M2	0.066	0	0.416	0.686	12.456	71.099	9.631	6.812
P	0.757	0.754	0	0.999	2.953	4.857	90.846	1.342
Y	0.01	0.11	0.015	0	53.436	10.465	24.767	11.33
				Divisia M2				
R	0	0.278	0.081	0.107	37.393	7.275	48.151	7.18
Divisia M2	0.337	0	0.345	0.524	12.957	75.533	0.873	10.634
P	0.093	0.761	0	0.991	3.903	3.804	92.036	0.254
Y	0.014	0.312	0.319	0	50.835	12.032	24.797	12.333
				CE M2				
R	0.001	0.358	0.064	0.054	30.311	2.109	58.344	9.235
CE M2	0.305	0	0.736	0.07	19.748	38.329	26.12	15.801
P	0.284	0.73	0	0.999	6.217	5.825	87.227	0.729
Y	0.025	0.468	0.038	0	49.387	1.92	32.525	16.167
				Sum M3				
R	0	0.171	0.05	0.083	27.06	7.245	58.739	6.954
Sum M3	0.176	0	0.887	0.598	12.065	72.826	14.402	0.705
P	0.634	0.573	0	0.999	3.978	0.242	95.61	0.169
Y	0.016	0.227	0.031	0	47.324	7.983	32.027	12.664
				Divisia M3				
R	0	0.426	0.084	0.104	37.379	2.389	51.709	8.521
Divisia M3	0.431	0	0.496	0.234	17.075	68.958	3.175	10.79
P	0.719	0.789	0	0.999	2.833	5.375	91.451	0.339
Y	0.015	0.376	0.03	0	52.826	7.807	26.272	13.093

(continued)

Table 7 (continued)
Unrestricted VAR results for {*R*, *M*, *P*, *Y*} model

	A. Marginal significance levels for exclusion of lags				B. Forecast-error-variance decompositions (20-quarter horizon)			
Equation	***R***	***M***	***P***	***Y***	***R***	***M***	***P***	***Y***
				CE M3				
R	0	0.246	0.068	0.042	31.601	1.929	57.384	9.083
CE M3	0.265	0	0.791	0.08	22.081	36.251	23.828	17.837
P	0.319	0.828	0	0.999	6.277	5.573	87.599	0.548
Y	0.027	0.506	0.041	0	49.605	2.133	32.31	15.95
				Sum M1+				
R	0	0.231	0.054	0.092	34.576	8.423	44.146	12.853
Sum M1+	0.172	0	0.186	0.552	41.364	27.343	26.659	4.632
P	0.748	0.303	0	0.885	2.822	7.804	86.564	2.808
Y	0.054	0.215	0.043	0	53.827	3.392	23.079	19.7
				Divisia M1+				
R	0	0.167	0.059	0.075	29.783	15.635	41.173	13.408
Divisia M1+	0.29	0	0.214	0.892	31.191	36.504	27.279	5.024
P	0.67	0.397	0	0.896	1.849	11.83	84.166	2.153
Y	0.086	0.48	0.053	0	45.326	9.691	22.472	22.508
				CE M1+				
R	0.001	0.327	0.025	0.151	22.97	7.207	63.129	6.692
CE M1+	0.187	0	0.231	0.15	2.606	33.661	58.499	5.232
P	0.488	0.352	0	0.999	1.584	0.767	96.471	1.176
Y	0.01	0.178	0.016	0	45.462	3.834	37.056	13.646
				Sum M1++				
R	0	0.146	0.057	0.067	27.113	30.332	37.208	5.346
Sum M1++	0.119	0	0.892	0.416	6.092	56.184	32.153	5.569
P	0.482	0.989	0	0.971	5.989	6.85	87.005	0.154
Y	0.01	0.057	0.025	0	26.766	52.598	9.699	10.935
				Divisia M1++				
R	0	0.087	0.427	0.066	26.361	25.791	43.201	4.645
Divisia M1++	0.317	0	0.596	0.332	24.201	57.208	12.779	5.812
P	0.544	0.988	0	0.955	5.024	3.103	91.639	0.232
Y	0.012	0.062	0.041	0	31.3	47.068	11.98	9.65
				CE M1++				
R	0	0.141	0.052	0.056	25.418	4.743	61.722	8.115
CE M1++	0.129	0	0.997	0.078	17.534	40.388	30.045	12.032
P	0.421	0.922	0	0.999	2.751	1.098	94.124	2.025
Y	0.021	0.441	0.035	0	46.327	5.717	32.682	15.273

Notes: Sample period quarterly data, 1974Q1–1998Q2. The models have been estimated with six lags. Low *p* values imply strong marginal predictive power.

very small percentage of the variance of real output except in the case of sum M1++ and divisia M1++. In fact, in the sum M1++ VAR, sum M1++ explains 52.6 per cent of the variance of real output, whereas in the divisia M1++ VAR, divisia M1++ explains 47 per cent of the variance of output. On the other hand, changes in the interest rate explain a very high percentage of the variance of output except in the case of the sum M1++ and divisia M1++ VARs. Hence, on the basis of significance levels and the variance-decomposition metric, sum M1++ and divisia M1++ perform better than the interest rate.

Solid lines in Figures 6 through 10 show the impulse-response functions over five years of each of the four variables (*R*, *M*, *P*, and *Y*) to each of the 15 measures of money. The dashed lines denote +2 and –2 standard deviation bands. The qualitative responses pictured in Figures 6 through 10 differ substantially across the simple-sum, divisia, and CE aggregation procedures, as well as across the M1, M2, M3, M1+, and M1++ aggregation levels. In Figure 6, for example, a major difference is that the responses of *P* and *Y* to shocks in sum M1 and divisia M1 are consistent with a priori expectations about the effects of monetary policy on output and the price level, but their responses to a shock in CE M1 are persistently negative. Also, changes in sum M1 and divisia M1 produce a liquidity puzzle, whereas changes in CE M1 produce negative effects on the interest rate at short horizons.

It is generally difficult, based on impulse-response functions, to identify a monetary aggregate that produces results consistent with common expectations about the qualitative effects of monetary policy. Of course, there have been many attempts to unravel the price and liquidity puzzles presented by VAR studies. For example, Eichenbaum's (1992) solution to the U.S. price puzzle is to use a non-borrowed-reserves VAR, while Sims's (1992) solution to the same puzzle is to extend his federal funds VAR by including a measure of commodity prices as a proxy for the central bank's information about inflation. In general, as more variables are introduced and the VAR specification is refined, monetary VARs produce results that capture reasonable monetary dynamics—see, for example, Christiano, Eichenbaum, and Evans (1996), Strongin (1995), and Bernanke and Mihov (1998). Resolving the liquidity and price puzzles we identified is well beyond the scope of this paper; see Koustas and Serletis (2000) for work in that direction.

Conclusion

We have looked at data consisting of the traditional simple-sum monetary aggregates and recently constructed divisia and CE monetary aggregates to

Figure 6
Impulse responses, {*R*, M1, *P*, *Y*} models

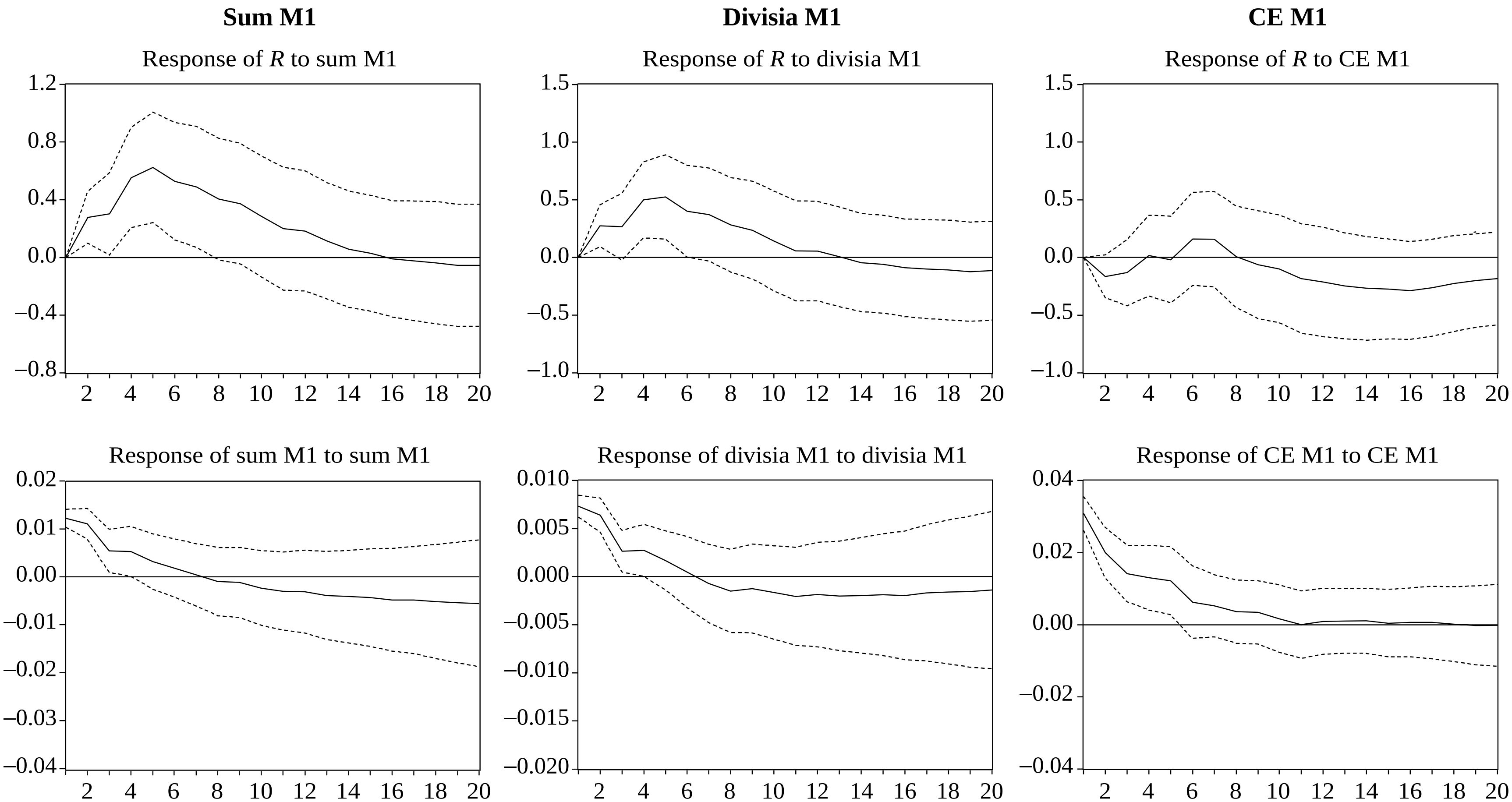


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Figure 6 (continued)
Impulse responses, {*R*, M1, *P*, *Y*} models

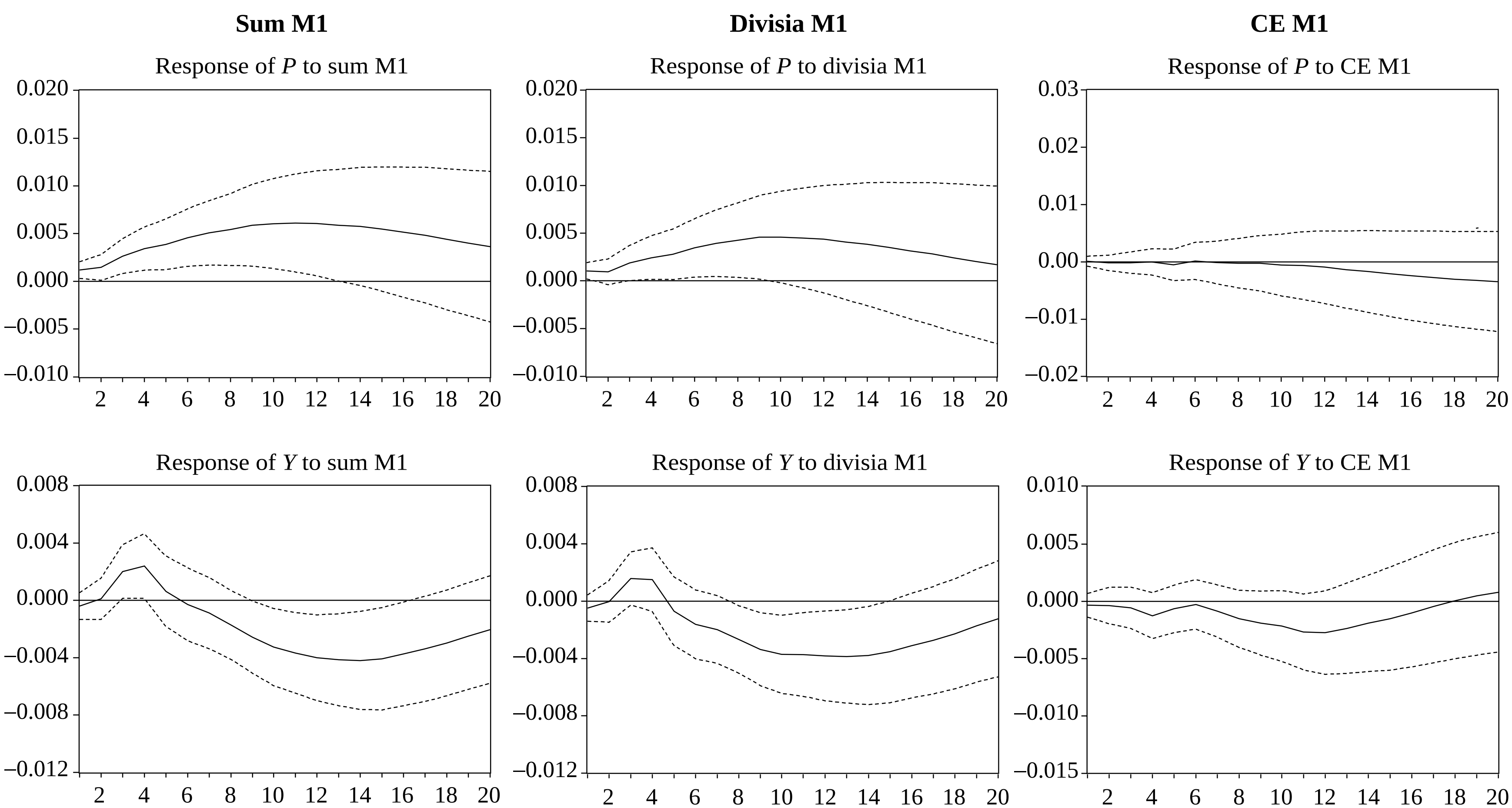

Figure 7
Impulse responses, {*R*, M2, *P*, *Y*} models

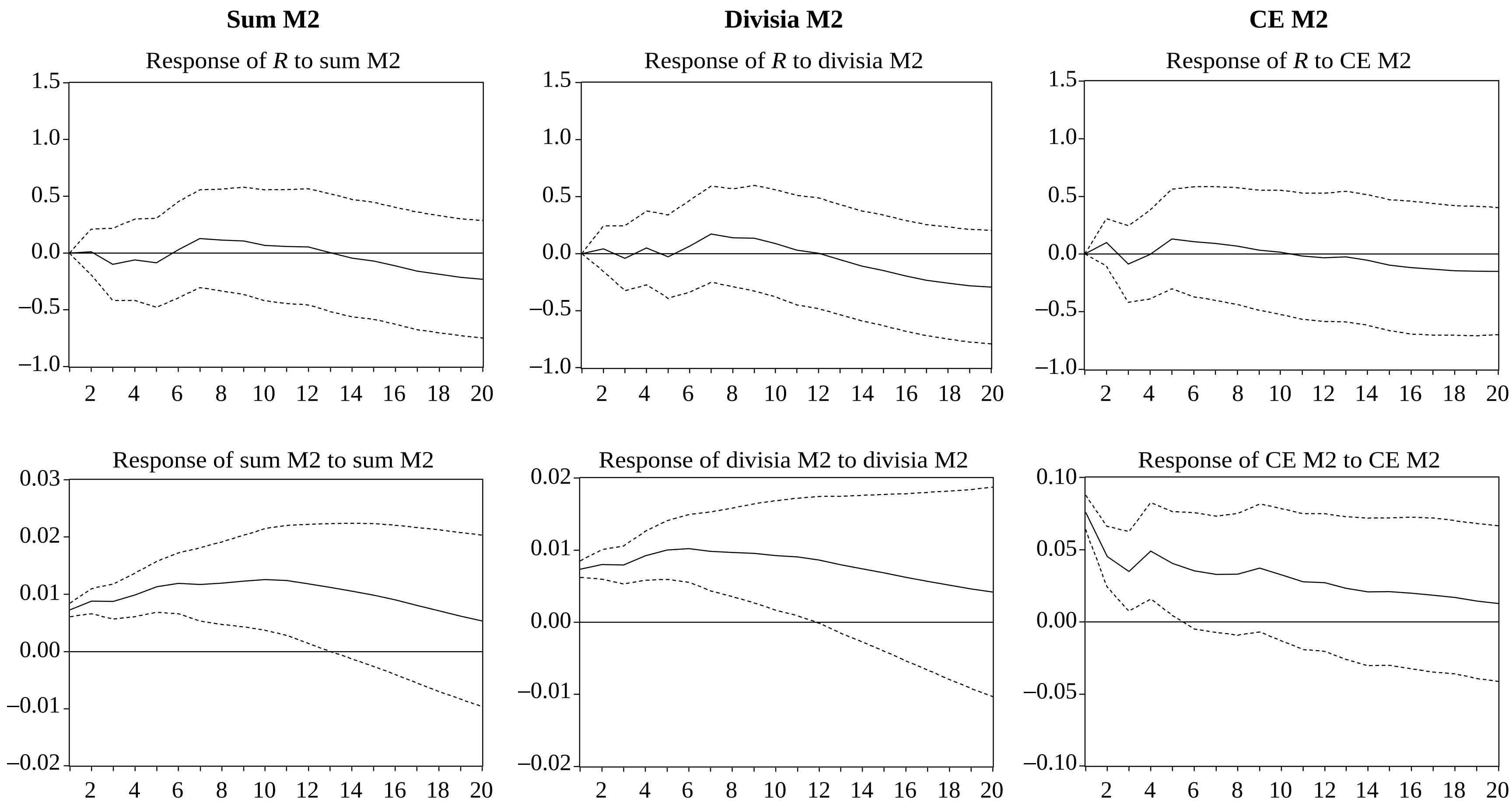

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Figure 7 (continued)
Impulse responses, {*R*, M2, *P*, *Y*} models

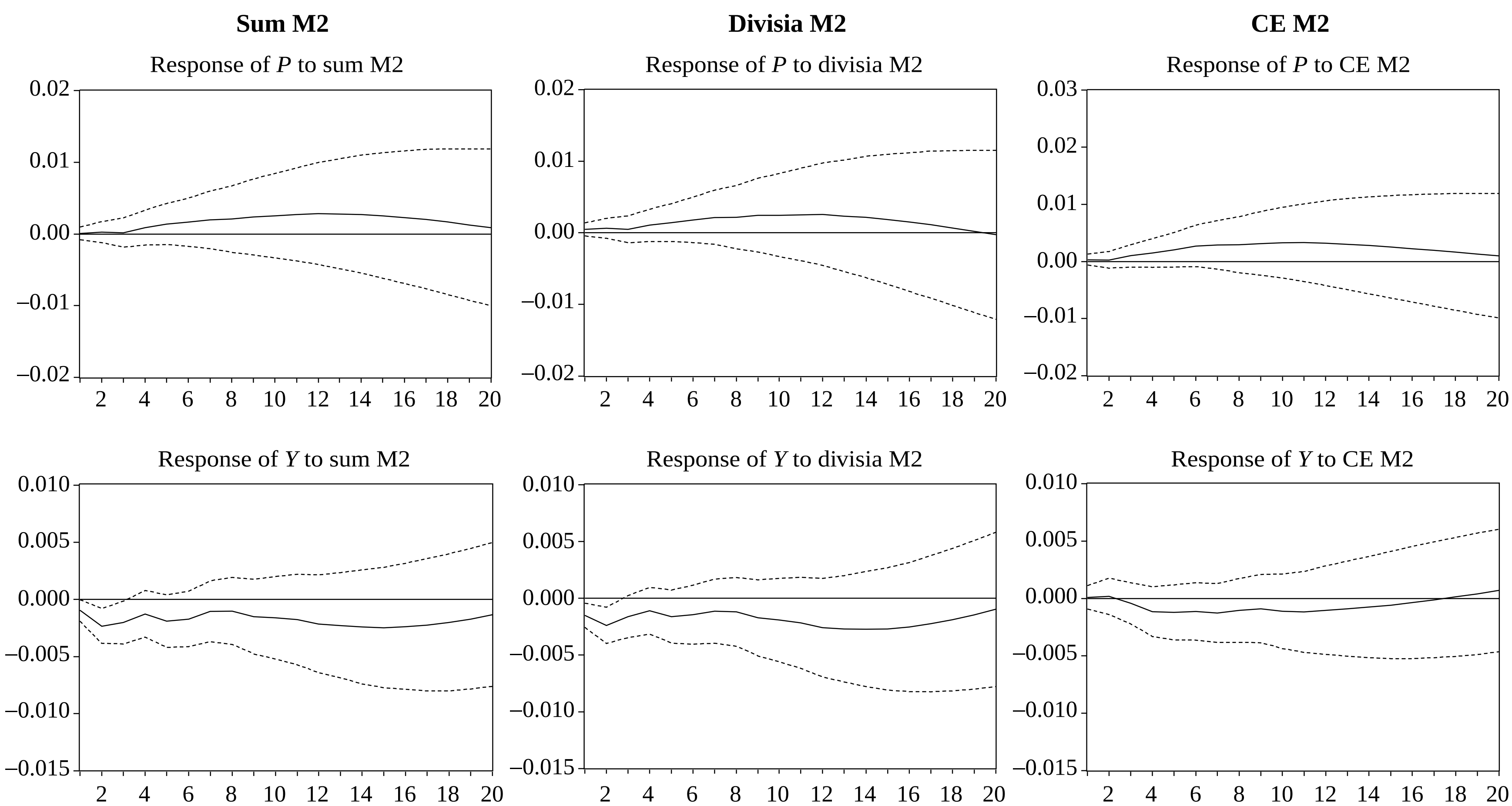

Figure 8
Impulse responses, {*R*, M3, *P*, *Y*} models

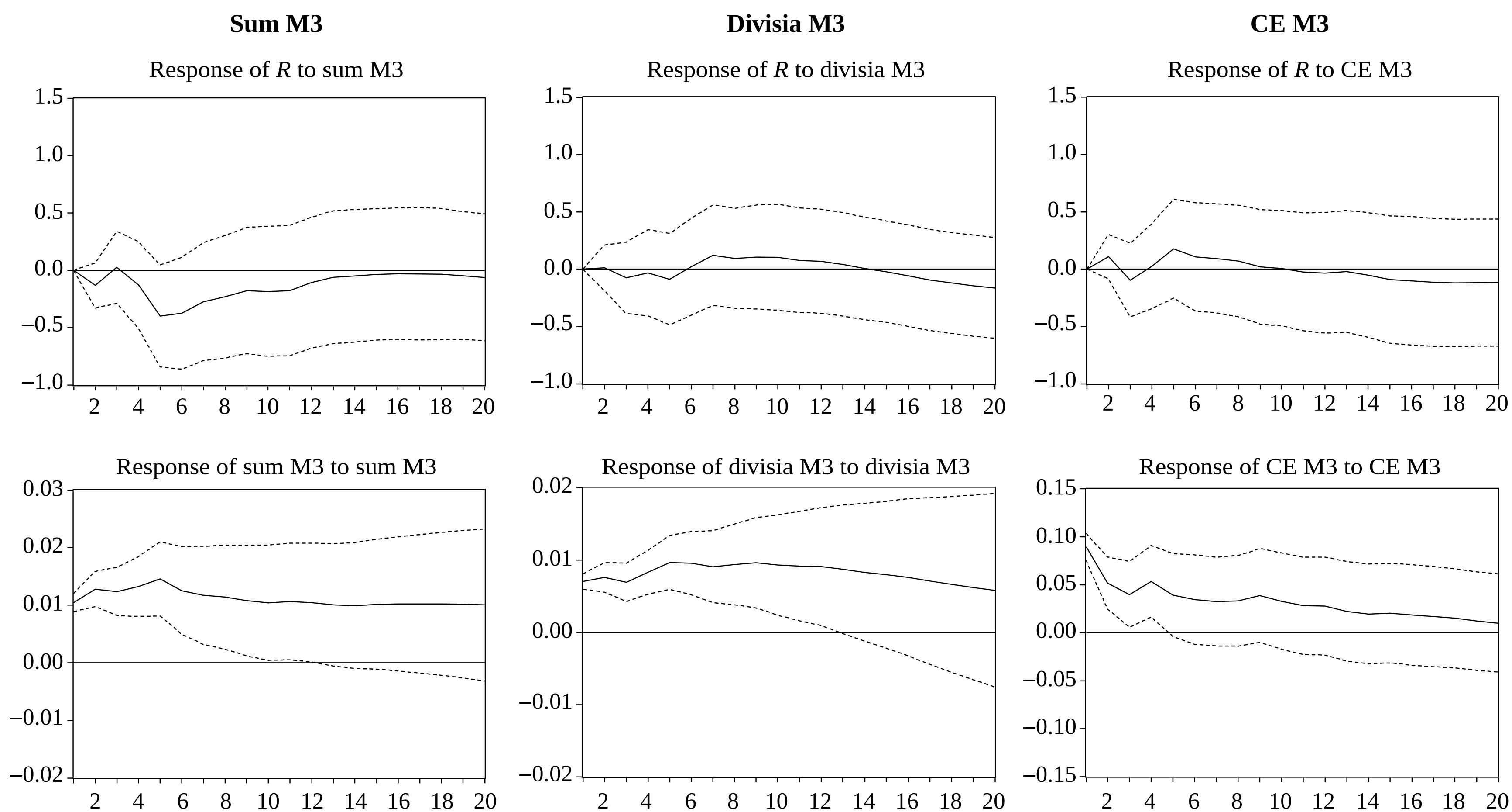

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Figure 8 (continued)
Impulse responses, {*R*, M3, *P*, *Y*} models

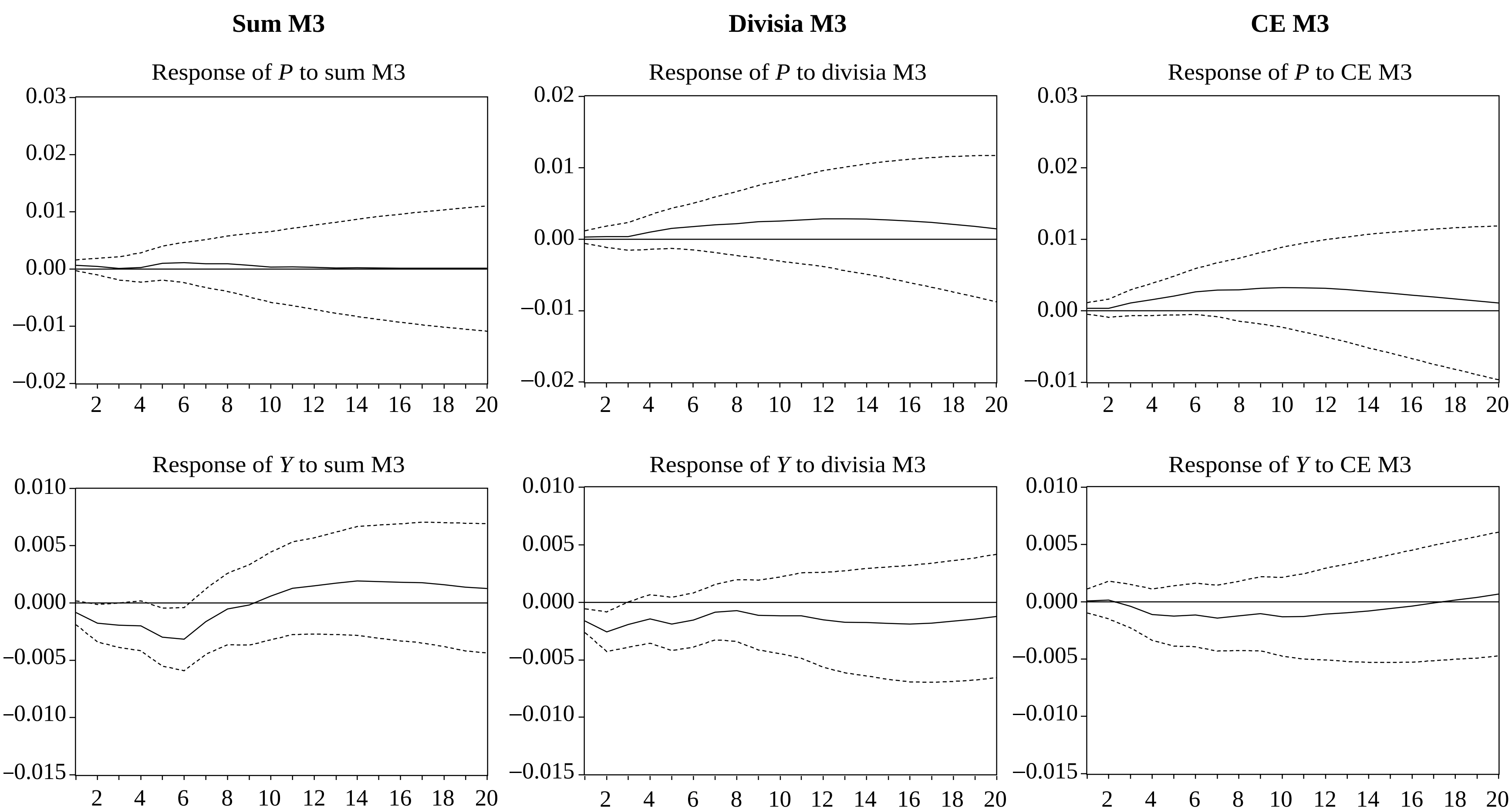

Figure 9
Impulse responses, {*R*, M1+, *P*, *Y*} models

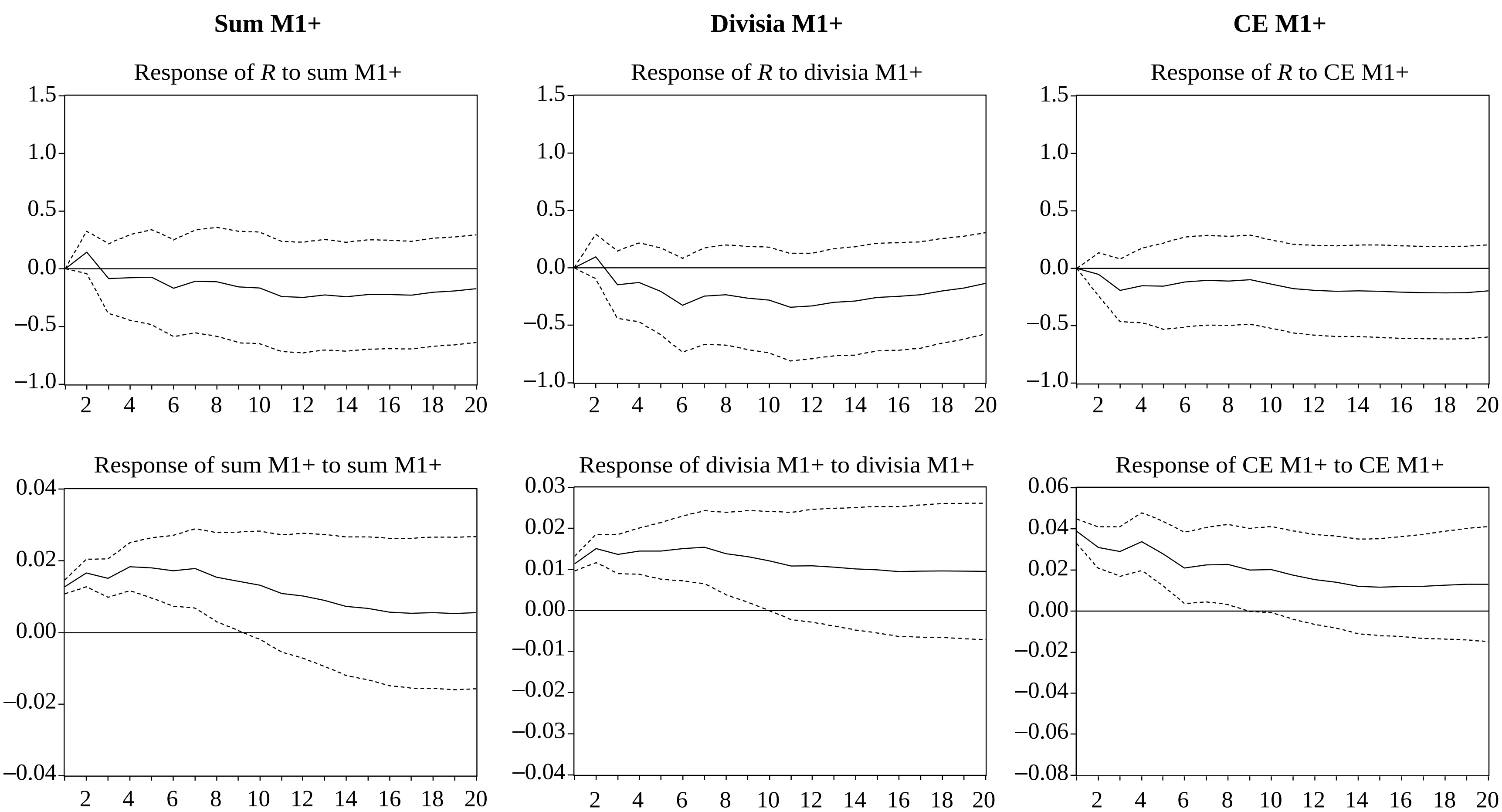

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Figure 9 (continued)
Impulse responses, {*R*, M1+, *P*, *Y*} models

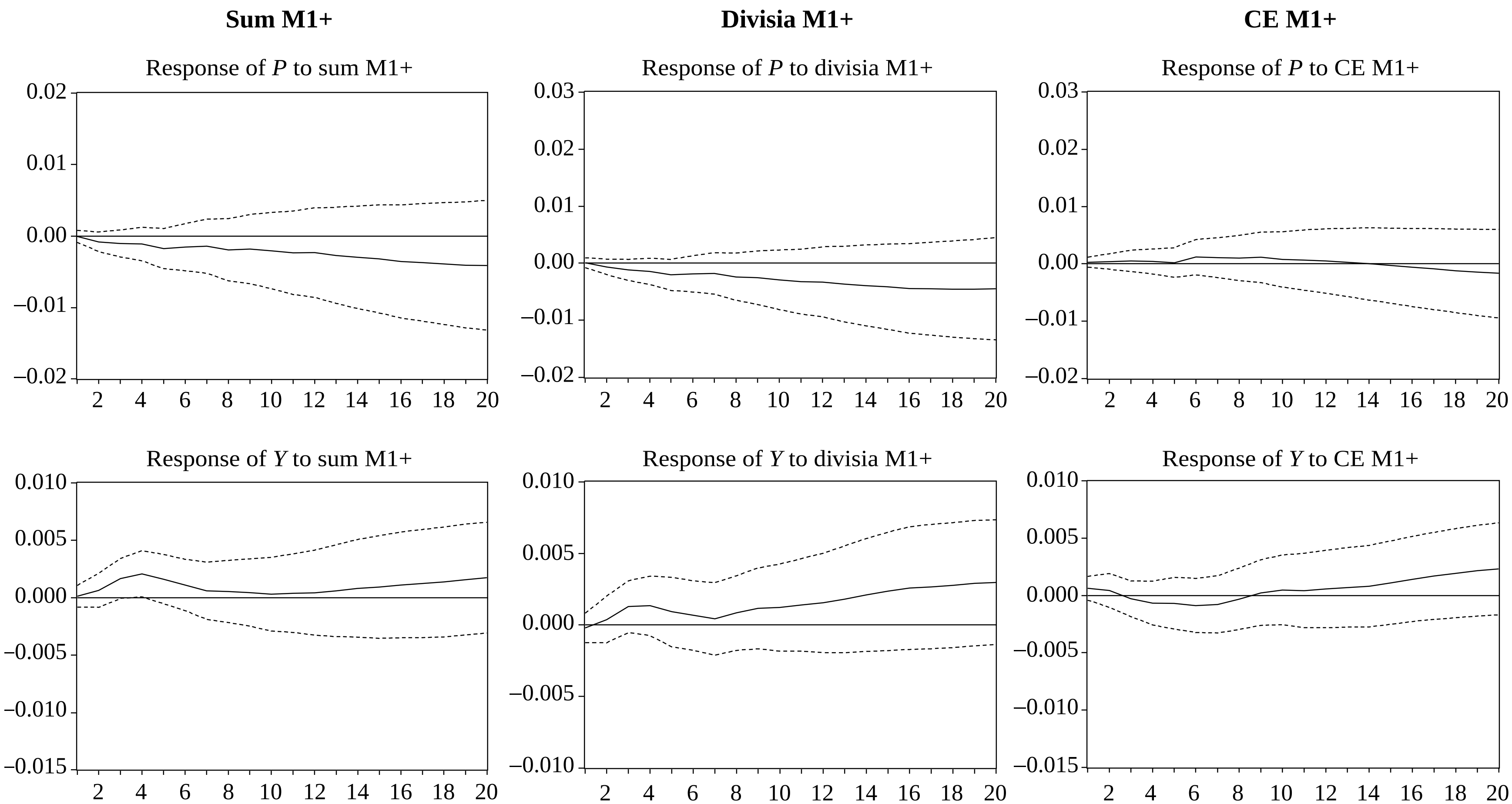

Figure 10
Impulse responses, {*R*, M1++, *P*, *Y*} models

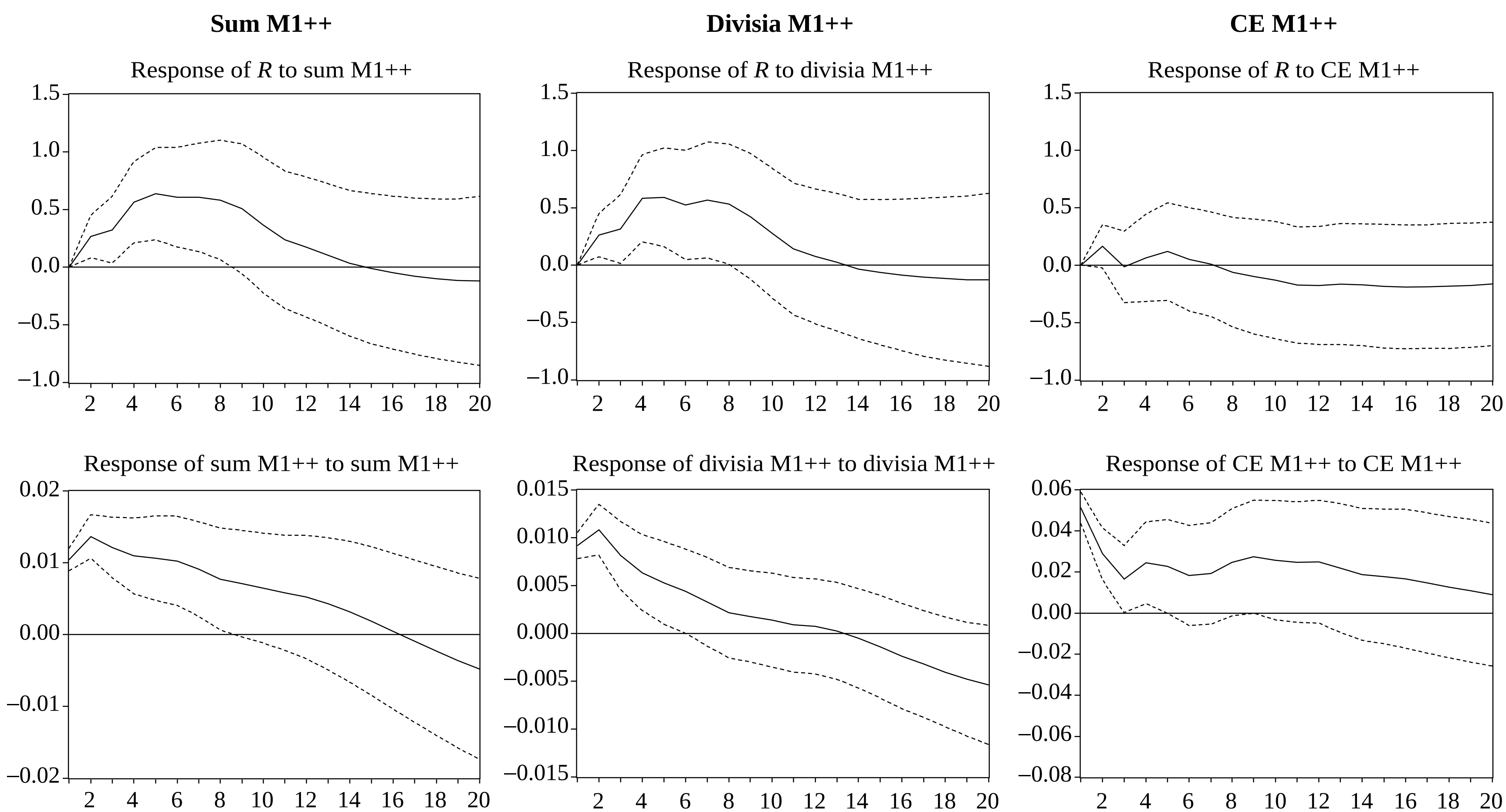

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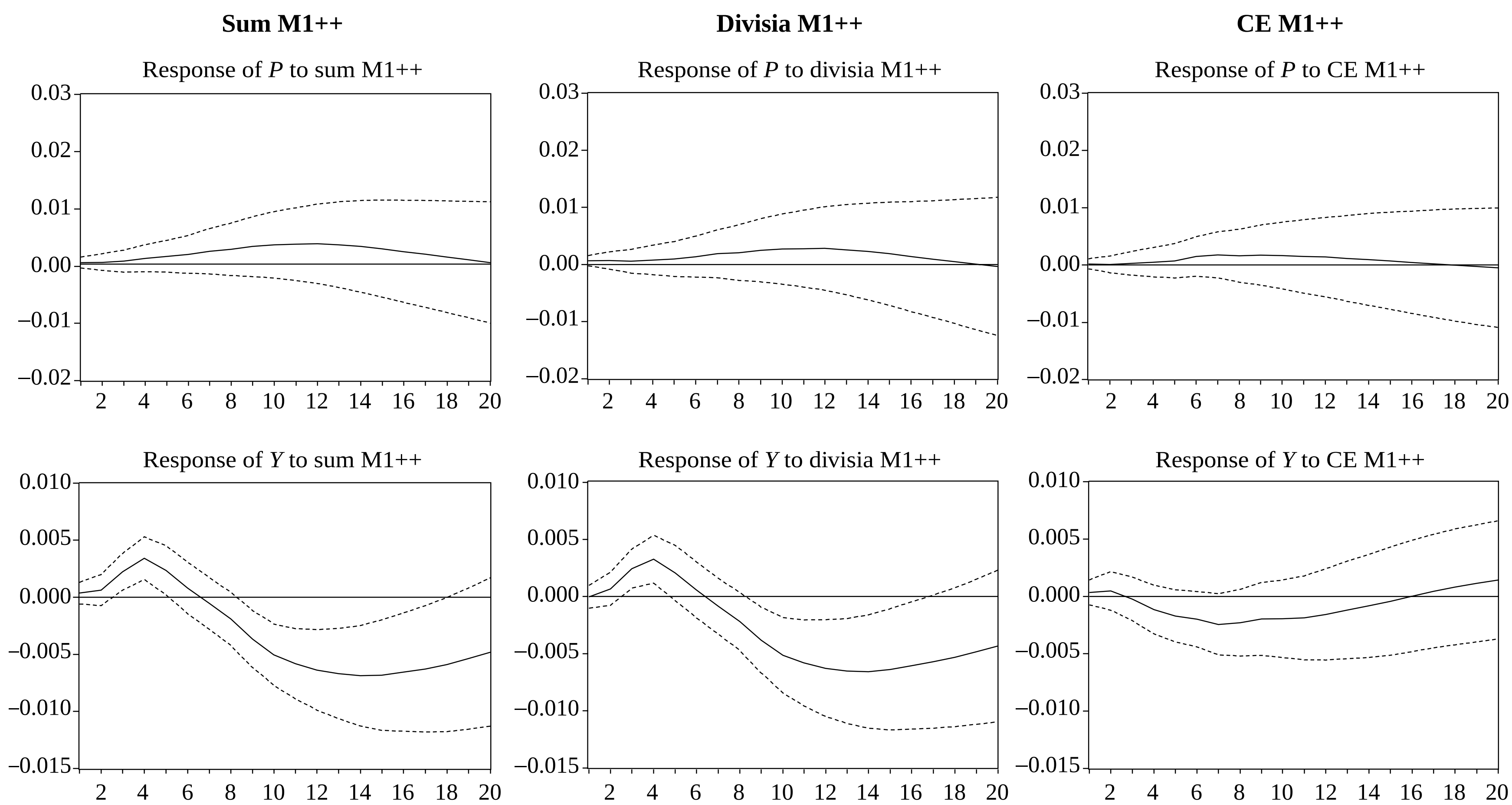
Figure 10 (continued)
Impulse responses, {*R*, M1++, *P*, *Y*} models



infer the effect of money on economic activity and to address disputes about the relative merits of different monetary aggregation procedures. We made our assessment using recent advances in the theory of integrated regressors and the single-equation approach, with the time-series properties of the data imposed in estimation and hypothesis testing. We also used the multi-equation VAR framework, which treats all variables as part of a joint process.

We find that the choice of monetary aggregation procedure is crucial when evaluating the relationship between money and economic activity. We provide evidence, consistent with that reported by Serletis and King (1993), that money, irrespective of how it is measured, does not cointegrate with prices or income. The evidence suggests that real money balances and velocity are nonstationary quantities and that monetary targeting will be problematic. However, Granger causality tests showed us that divisia M1++ is the best leading indicator of real output. Moreover, divisia M1++ causes changes in real output in VARs that include interest rates, and changes in divisia M1++ also explain a very high percentage of the forecast-error variance of output; changes in interest rates explain a smaller percentage of that variance.

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Discussion

Joseph Atta-Mensah

> It is a singular and, indeed, a significant fact that, although money was the first economic subject to attract men's thoughtful attention, and has been the focal centre of economic investigation ever since, there is at the present day not even an approximate agreement as to what ought to be designated by the word. The business world makes use of the term in several senses, while among economists there are almost as many different conceptions as there are writers upon money. (Andrew 1899, 219)

The Serletis and Molik paper renews the debate as to whether it is appropriate for central banks to use simple-sum monetary aggregates. Some monetary theorists, including Serletis and, notably, Barnett, have not been satisfied with the current computation of the monetary aggregates by central banks around the world, particularly the aggregates calculated by the summation of the monetary value of financial assets. By using a definition based on simple summation, the central banks imply that the aggregates' components all have the same degree of substitutability and liquidity. In an attempt to rectify this "anomaly," Barnett (1980) strongly advocated that central banks use statistical index number theory, such as divisia, to construct the monetary aggregates.

Serletis and Molik begin by providing a theoretical derivation of the formulas for constructing Barnett's (1980) divisia and Rotemberg, Driscoll, and Poterba's (1991) CE aggregates. Before I discuss the weaknesses inherent in these methods of constructing monetary aggregates, let me first shed light on how the divisia aggregates evolved.

Central banks initially defined money to include only financial assets used as a medium of exchange—currency and demand deposits—and started publishing data on two types of exchange media: currency outside the banking system and demand deposits at banks.[1] The sum of these two types of assets later became known as M1.

Friedman (1956, 1959), Friedman and Meiselman (1963), and Friedman and Schwartz (1969, 1970) proposed broadening the definition of money to include time deposits and savings deposits. This broader definition captured the "store of value" property of money. Friedman's main argument was that money served as a temporary abode of purchasing power and therefore bridged the gap between sales and payments.

Following these arguments the Federal Reserve System and other central banks started publishing broader monetary aggregates. However, these aggregates raise the problem of determining the degree of substitutability between the various financial assets that make up the aggregates. Although financial innovation has blurred the distinction between transactions- and savings-type assets, the assets that make up the broader aggregates do not have the same liquidity as currency. Batten and Thornton (1985, 30) argued that, "If different assets have different degrees of moneyness, we may wish to aggregate (add) them with respect to this homogeneous characteristic." However, the aggregates that the central banks now use are computed as simple summations. Thus, all assets in the aggregates are implicitly assumed to have the same degree of "moneyness." Some monetary theorists find this method of aggregation unacceptable and propose other methods.

One method, which Serletis and Molik build on, is that proposed by Barnett (1980) and much discussed in the literature. Barnett's method uses statistical index number theory to construct the monetary aggregates. He argued that this method gives true economic meaning to the aggregates. The approach uses aggregation theory to compute financial asset indices that reflect the total utility, relative to some base period, attributable to the monetary services obtained from these assets.

Consistent with Barnett's proposal, "superlative" monetary aggregates have been developed based on the index number theory.[2] This method defines money as a monetary quantity index. As Barnett noted, in this approach, aggregates are measured in terms of the flow of services that

1. See Walter (1989) for a detailed summary of the evolution of the monetary aggregates in the United States.

2. Diewert (1976, 1978) introduced these indices to the literature, suggesting that an index is superlative if it is exact for some aggregator function; in other words, if a close correspondence exists between the aggregator function and the index number formula.

constitute the output of the economy's monetary transactions technology. Two superlative indices used in the literature are the Tornquist-Theil divisia and the chain-linked Fisher ideal.[3]

As Serletis and Molik mention, theoretically the superlative monetary aggregates are a significant improvement over the summation aggregates for several reasons. First, they measure the flow of monetary services in the economy, determining the flow by weighting the quantity of each component asset with its unique rental cost. The rental cost is the difference between the rate of interest on a pure store-of-wealth asset and each asset's own rate of return. Second, superlative indices are exact for flexible functional forms. Thus they avoid the restrictive assumptions required to justify the linear form of the summation aggregate. Third, superlative aggregates attempt to internalize the substitution effects of interest rate changes. Income effects are reflected in the form of utility or monetary service changes. However, changes in interest rates would, in the case of summation aggregates, induce both substitution and income effects.

Using the theoretical derivations, Serletis and Molik construct divisia and CE aggregates. Although I commend them for their "public service" in constructing these aggregates, I would like to point out some measurement problems with divisia and CE aggregates.[4] First, posted rates on deposits at financial institutions may exaggerate the effective rate that economic agents expect on their investments. Cockerline and Murray (1981) argued that minimum-balance requirements for certain accounts, early encashment penalties on some fixed-term assets, and other service charges all tend to reduce the measured own rates of return on monetary assets. These measurement problems are complicated further by the possibility that financial institutions cross-subsidize activities, such as varying service fees or interest rates as a customer does other business with the institution.

Second, computing rental prices for the divisia aggregate could be complicated by aggregating across assets with different maturity dates. For example, if the yield curve is downward-sloping, then current short-term interest rates will be higher than long-term rates. Hence, the rental price of some of the monetary assets may be negative as their own rates rise above those of the benchmark asset, which is generally proxied by a long-term asset. Since the rental price represents a measure of liquidity, it is meaningless when it is negative.

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3. See Barnett, Fisher, and Serletis (1992) for other superlative indices and the exact formula for constructing each one.

4. Barnett (1991) showed that the CE aggregate is a special case of the divisia aggregate. Hence, my comments on the divisia aggregates also apply to the CE aggregates.

Third, the method of constructing the superlative indices assumes that economic agents hold the optimal values of assets in their portfolio and makes no allowance for portfolio adjustment costs. However, in practice, investors constantly readjust their portfolio holdings in response to changes in interest rates. Since the superlative method measures the user cost of an asset by the difference between the asset's rate of interest and that of a benchmark asset, and since the portfolio adjustment costs are not captured in the interest rates, the "true" user cost is underestimated.

Fourth, when calculating any asset's user cost, one assumes that the benchmark asset is completely illiquid. This implies that an asset traded in secondary markets does not qualify as a benchmark, because in a secondary market that asset could be readily converted into more-liquid assets that could be used for transactions. In practice such assets are difficult to come by. Also, only benchmark assets with non-negative user costs must be chosen; a negative user cost would imply that economic agents are prepared to sacrifice some of the returns on a purely non-monetary asset in order not to receive monetary services.

Fifth, the weights or rental prices used in the superlative indices are very sensitive to changes in interest rates. Higher interest rates will increase the user cost of currency and therefore lead instantaneously to a higher weight. However, as the higher interest rates cause investors to hold less cash in their portfolios, the weight for currency will fall over time. On the other hand, if the amount of currency held by economic agents grows more rapidly than the amount of interest-bearing deposits, rising interest rates will instantaneously increase the weight for currency and reduce that for interest-bearing assets, leading to an increase in the superlative index growth rate. The superlative index could therefore be a misleading information variable for monetary policy-makers. One should be cautious when interpreting empirical results derived using superlative aggregates.

I shall now turn to Serletis and Molik's empirical work. Their empirical focus is the investigation of the roles of simple-sum, divisia, and CE aggregates in Canadian monetary policy. They use H-P filters to examine the correlations between the aggregates and income and prices. They also conduct integration, cointegration, and Granger causality tests. Their main results are as follows. First, using the H-P filters the authors find that M1, M1+, and their divisia counterparts are the only aggregates that lead real GDP. Second, they find all the monetary aggregates, prices, and nominal and real GDP are integrated of order 1. Third, they find no cointegration between each of the monetary aggregates on the one hand and either the price level or nominal or real GDP on the other hand. Fourth, using the Granger causality tests they find that none of the monetary aggregates is a leading indicator of inflation, that divisia M1 is the best leading indicator of nominal income, and that divisia M1++ is the best leading indicator of real income. From these results they conclude that monetary targeting in Canada would not be appropriate.

The first issue I will take up with Serletis and Molik on their empirical work is the substitutability of the financial assets that make up each aggregate. One criticism of the current monetary aggregates is that they treat all constituent financial assets as perfect substitutes for money; however, studies have shown that few financial assets actually do appear to be good substitutes.[5] I believe this criticism applies to Serletis and Molik's paper as well, since in constructing their aggregates they fail to test whether the components of each aggregate are substitutes.

Barnett (1982) argued that it is important that all the components in an aggregate are close substitutes in order to ensure that monetary assets are separable from non-monetary goods. He argued that a monetary aggregate can exist if, and only if, there is a subset of monetary goods that is at least weakly separable from non-monetary goods. Weak separability implies that the marginal rate of substitution between any two monetary goods in a subset is independent of other goods not in the subset. Thus, as Swofford and Whitney (1991) pointed out, this condition ensures that monetary aggregates are not affected by changes in the composition of spending on non-monetary goods. In other words, the monetary aggregate depends on total income and not on the composition of expenditures.

Belongia and Chalfant (1989) and Swofford and Whitney (1992) recommended using Varian's (1982, 1983) nonparametric-revealed-preference conditions to test whether a monetary aggregate satisfies the condition of weak separability. Varian's test of weak separability has three steps. The first is to check whether the data set satisfies the consistency condition of the generalized axiom of revealed preference (GARP). The second is to check any sub-utility for consistency with GARP. The third is to verify whether the data set meets certain sufficient conditions.[6] A well-behaved utility function can serve as an aggregator function if the financial data obey the GARP axiom.

I would also like to comment on Serletis and Molik's result that money neither correlates nor leads inflation. This very puzzling finding goes against the old adage in monetary economics that inflation is a monetary phenomenon. I believe that they obtain their results because they examine the relationship between the aggregates and prices using quarterly growth rates. As we know, quarterly growth rates are more volatile, or "noisy," than are annual rates. Consequently, quarterly growth rates do not easily yield

5. See Belongia and Chalfant (1989) for a summary of some of the studies.
6. See Swofford and Whitney (1991, 1992) for the test of some of the sufficient conditions.

meaningful relationships in the data. Moreover, monetary policy actions as we know them affect prices only after a considerable lag, generally thought to be about six to eight quarters. So the correlation between money and prices can best be observed using their year-over-year growth rates.

Furthermore, the literature is filled with results that demonstrate strong relationships between various definitions of money and inflation. Here at the Bank our work shows that money is important in the price formation process. Engert and Hendry (1998) and Adam and Hendry (2000) found that an M1-based vector-error-correction model (VECM) provides considerable leading information about inflation, forecasting the 8-quarter inflation rate with relatively small errors. Also, a structural VAR analysis conducted by Kasumovich (1996) and Fung and Kasumovich (1998) shows that money plays an active role in transmitting monetary policy. In all these models a monetary policy shock disturbs the relationship between the money stock and long-run demand, leading to a long adjustment process in which prices adjust to restore monetary equilibrium. McPhail (2000) also found that broad money, in particular M2++, is a useful predictor of inflation at a horizon of one to two years. In sum, this body of work identifies a strong relationship between money and inflation; an excessive expansion of money would cause inflationary pressures to build up.

Overall I find that the empirical work in the paper does not go very far. Serletis and Molik use various econometric techniques, but their main purpose is to examine the correlations in the data, the order of integration, and the direction of causality between the variables. Since they seek to compare the empirical performance of the simple-sum monetary aggregates against those of their divisia and CE counterparts, I would have liked to see the authors also compare the aggregates' stability in money-demand equations and their ability to forecast macroeconomic variables, such as real GDP and inflation. Such analysis would compare the aggregates more completely.

If monetary aggregates are to be used effectively in conducting monetary policy, the demand function for the aggregates must be stable. Stability requires that the demand for the aggregates be a systematic function of small macroeconomic variables, such as income and interest rates; thus, changes in the aggregates are predicted in terms of changes in the variables. Stability also means that the parameter estimates of the demand functions do not change significantly when the function is re-estimated with an additional data set.

At the Bank we have been able to estimate stable long-run money-demand functions for the simple-sum narrow and broad aggregates. Using Johansen-Juselius methodology, Hendry (1995) identified a unique stable long-run money-demand function for M1. McPhail (1993, 2000) has also used the Johansen-Juselius methodology to find stable long-run demand functions for broad monetary aggregates. An interesting exercise would be for Serletis and Molik to estimate the demand functions for the divisia and CE aggregates and assess the stability of these demand functions. As well, if the estimated demand function for these aggregates is stable, the authors could compare the forecasting ability of these aggregates in VECMs to that of their simple-sum counterparts.

As I pointed out earlier, theoretically the superlative aggregates are unquestionably far superior to their simple-sum counterparts. So why do central banks, including the Bank of Canada, continue to use simple-sum aggregates? In my view this paper and proponents of the superlative aggregates have not shown enough empirical evidence to warrant abandoning simple-sum aggregates. Overall, the work at the Bank by Cockerline and Murray (1981), Hostland, Poloz, and Storer (1988), and Longworth and Atta-Mensah (1995) does indicate that, on the basis of the in-sample fit of indicator models, the out-of-sample forecasts by indicator models, the specification of money-demand functions, and the temporal stability of money-demand functions, the simple-sum aggregates are empirically superior to their divisia or Fisher ideal counterparts.

The answer to this debate may lie between the simple-sum and the superlative aggregates. However, in constructing reliable monetary aggregates, central banks must be clear as to what assets qualify as money. Unfortunately, neither the literature on monetary economics nor traditional textbooks adequately define money. Also, financial innovations have so fundamentally altered the characteristics of many monetary assets that it is very difficult to find a precise definition of money. Indeed, a universal definition may be beyond our grasp. As Friedman and Schwartz (1970, 137) noted,

> The definition of money is to be sought for not on grounds of principle but on grounds of usefulness in organizing our knowledge of economic relationships. “Money” is that to which we choose to assign a number by specified operations; it is not something in existence to be discovered, like the American continent; it is a tentative scientific construct to be invented, like “length” or “temperature” or “force” in physics.

I suggest that, in the absence of a universal definition, central banks define “money” pragmatically in a manner that will help them conduct a sound and effective monetary policy. Central banks could define money to include assets that are accepted as means of payment, liquid assets, and other types of liabilities held by financial institutions. These assets need not be tangible, but when used, should not generate debt or a repayment obligation. Such a definition excludes from the money stock all forms of credit. On the basis of this definition, monetary aggregates could be classified into transactions and savings aggregates. Furthermore, based on chosen criteria, these assets should perform well empirically.

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Discussion

Seamus Hogan

Serletis and Molik's paper is one of a number in this conference that address what is perhaps the fundamental question of empirical monetary economics: In a world in which there are many monetary assets that are not perfect substitutes, what empirical measure of money best corresponds to the simple *M* of textbook monetary theory?

An important contribution of their paper is to combine two strands of the literature dealing with this question. The first strand focuses on what assets to include in the monetary basket; that is, it addresses the binary question of whether a particular asset is money or is not. Typically this involves ranking assets according to their liquidity and then choosing where along that liquidity continuum to draw the line between what is money and what is not. The second strand, of which divisia and CE indices are examples, makes the binary question more continuous by taking a broad basket of assets but allowing the more-liquid assets to have a greater weight.

The approach to the latter strand does not encompass the approach to the former one: The weights in divisia and CE indices are derived from theory rather than being estimated and so do not allow weights of 0 and 1 as special cases. For each of these index classes, therefore, there remains the question of what to include in the basket. A strength of their paper is that they consider a simple-sum aggregate, a divisia index, and a CE index for *each one* of five different monetary aggregates. This requires a lot of work, but it enables us to discern to what extent the weighting scheme rather than the choice of basket is the source of the results.

The value of this work becomes apparent when looking at their Figures 1 to 5. For all aggregates broader than M1, the CE index behaves very differently from the other two measures, particularly in the 1990s. Perhaps it goes beyond the scope of their paper, but I would have liked to have seen more follow-up on this: What is it about CE indices and about the 1990s that causes this divergence? It would also be interesting to know whether the CE measures have more or less explanatory power in the various regressions for the 1990s in order to see whether the pattern clearly observable to the eye conveys useful information about what the best measures of money are.

The second thing I like about their paper is its empirical focus. The theory underlying the variable-weight indexes is appealing, but it depends on a number of assumptions about how well we can measure the *effective* relative prices between different monetary assets, how well individual money-demand functions aggregate, and so on. Ultimately, although theory can suggest different candidates to try, the empirical question as to what is the best real-world measure of money has to be determined empirically.

I think, however, that Serletis and Molik have taken the strictly empirical approach too far. Before going to the data to ask what is the best measure of money, we have to first ask the question: best at what? For instance, are we looking for the measure that is the best leading indicator of inflation or income, that is the best measure of the stance of monetary policy, or that meets some other criterion? The answer to this question should suggest the best way to interrogate the data and hence how to interpret the results. I would have liked to see the authors orient their paper more along these lines rather than leaving the data to speak for themselves. Serletis and Molik present their results in a purely *statistical* dimension rather than in an *economic* dimension relevant to the motivating question. For instance, some insight into which money measure is the best leading indicator of inflation is found in their Granger causality tests; however, these results are presented purely in terms of *p* values for falsely rejecting the null hypothesis of no causality. Although this provides some useful information, it does not directly address how good a leading indicator each measure of money is. It would have been interesting to see this information supplemented with the results of some out-of-sample forecasts, perhaps based on rolling samples.

Overall, their paper presents a wealth of information that raises many interesting questions. I hope that they and others will continue down the road they have started to further explore these issues.

General Discussion

In his response to the discussants, Serletis reiterated the need to look beyond simple-sum aggregates to a more general approach, which has long been advocated by authorities such as Friedman and Schwartz (1970); however, he conceded that there are complications involved in constructing and using divisia aggregates. In particular he noted that the judgment needed in the choice of own rates and user costs often makes it difficult for other researchers to replicate results. Also, institutional changes such as bank mergers and acquisitions of near-banks may lead to difficulties in constructing consistent time series.

Alain Paquet raised three concerns. First, only pair-wise cointegration is examined in Serletis and Molik's paper. He argued that you cannot conclude whether the aggregates do or do not have desirable properties based merely on results from pair-wise cointegration tests. Instead, one should use more variables in the tests, since doing so may change the results. Second, the VAR is estimated in levels. If the data are nonstationary the distribution of the Granger-causality statistics would be non-standard and the reported *p* values would be biased. Also, estimating the VAR in levels with integrated variables and a finite sample can result in significant biases for the estimated impulse responses (for example, see Phillips 1998). Therefore it may be more appropriate to estimate the VAR in differences, or alternatively, use a VECM. Third, the results may be very sensitive to the ordering used in the Choleski decomposition to identify the VAR. An alternative identification could use long-run restrictions; e.g., the neutrality of money, a concept that Serletis and Koustas (1998) support. In conclusion Paquet suggested that more work be done to test the robustness of the results.

* Prepared by Jamie Armour.

Pierre Duguay was puzzled by the asymmetric treatment of demand deposits versus other deposits regarding the own rate of return. Serletis and Molik adjusted implicit returns for services only for demand deposits and not for chequable notice deposits. Duguay also pointed out a contrast between their Figure 1 and Figure 1 in the Aubry-Nott presentation. The big shifts that occur in the simple-sum M1 in the Aubry-Nott paper are not apparent in the divisia aggregate in Serletis and Molik's paper. Duguay conjectured that this was related to the behaviour of the relative value of the calculated yields.

A theoretical question about the definition of transactions money was raised by Shamik Dhar. He noted that in the U.K., divisia indices are highly correlated with sum M4 because movements in the two series are dominated by non-bank financial institutions. The M4 aggregate largely represents "financial transactions demand" for money. If economists were more interested in "goods and services transactions demand" for money, then they might regard the assets of non-bank financial institutions as less important.

Robbie Jones was interested in how term-structure models would affect the calculated rates of return in their paper. For example, how would you interpret an inverted yield curve? Differences between the rates of return on short and long assets would usually reflect expected changes in short rates. Jones wondered if it would be possible to use an ex post return to holding long-term bonds for 90 days. Serletis replied that all the returns used in the paper are risk-adjusted and that the benchmark rate is the maximum rate over the sample.

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