Financial Market Effects on Aggregate Money Demand: A Bayesian Analysis

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Article:

Empirical researchers in aggregate money demand have long been concerned with the degree of substitutability between money and other capital assets and the impact on money holdings of financial markets developments. Despite the potential importance of financial market linkages to money demand, empirical studies display substantial diversity in modeling these influences. Various econometric studies have found that money holdings may depend on short-term debt returns, bond yields, and even the term structure of interest rates. There is also evidence that stock market returns and measures of stock trading affect money holdings. Existing studies are limited in their evaluation of asset substitution patterns and other financial market effects because they look at a small subset of possible specifications.

There are several reasons for model diversity. First, parsimonious models are a practical response to the high degree of collinearity in asset returns. Second, different opinions about the asset substitution patterns lead to various model specifications. For example, Hamburger (1977, 1983) argues that the return on equity is an important variable but it is usually omitted by other researchers. Third, the instability in money demand models suggests that important transaction technology and financial market influences have been omitted from the standard money demand model.[1] The lack of consensus about the causes of instability and the financial market linkages permits considerable latitude in modeling these effects.

Many money demand studies focus on debt market relationships to the exclusion of the equity market. Aside from theoretical work to the contrary, this orientation is unfortunate for two reasons. First, Cooley and LeRoy (1981), Leamer (1978, 1982, 1985), and Leamer and Leonard (1983) have documented the problems that ad hoc model selection procedures create for interpreting and reporting results.[2] In our view, their work suggests a healthy skepticism about the reliability of existing evidence on the debt market- and equity market-money demand linkages. Second, there is considerable interest among financial economists in the connections between the stock market and aggregate economic activity (see Fischer and Merton 1984). Integration of the stock market into macroeconomic models cannot be fully realized unless various connections between the equity market and money holdings are explored more carefully.

Our principal aim is to discover the circumstances under which aggregate data can support robust inferences about financial market connections to money demand. To address this question, we incorporate various financial influences into a general empirical money demand model in section 1 and employ advances in Bayesian econometric procedures unavailable to earlier investigators [in particular, Cooley and LeRoy (1981)] in section 2, Section 3 contains our econometric results including an extensive sensitivity analysis. In section 4 we address the impact of nonstationarity on our results using a cointegration/error correction model. Section 5 provides a summary of our findings.

I. MONEY DEMAND MODELS

Based on a transactions demand model (e.g., Baumol 1952 and Tobin 1956) and a nominal adjustment mechanism where all variables are in logs, real money holdings *(M P)r* depend on current real income *(yet),* a short-term interest rate *(rs,),* and the cost of selling bonds *(rc,)* which is often assumed constant because a measure has been unavailable.[3,4]

$$(M/P)_t = \alpha_0 + \alpha_1 yc_t + \alpha_2 rs_t + \alpha_3 tc_t + \alpha_4(M_{t-1}/P_t)\ . \qquad (1)$$

The instability of (1) during a period of financial innovation and the decline in transaction costs has renewed interest in identifying and measuring the appropriate set of financial innovation and transaction cost variables. Quick and Paulus (1979) argue that relatively high interest rates and falling fixed costs of installing cash management systems contributed to a decline in effective brokerage charges during the 1970s. They suggest that previous peak interest rates capture this fall in brokerage costs. Mauskopf and Porter, (1979) and Roley (1985) generally confirm the significance of the interest rate ratchet *(rat)* for the entire post-I 973 period.

We proxy the marginal cost of transferring cash into securities with the real bid-ask spread *(spr),* defined as the difference between the bid and ask prices on Treasury bills with thirty days or less to maturity divided by the price level. The transaction model (I) is supplemented by rat_t (the previous peak value of the commercial paper rate) and spr_t replaces tc_t to form

$$(M/P)_t = \alpha_0 + \alpha_1 yc_t + \alpha_2 rs_t + \alpha_3 rat_t + \alpha_4 spr_t + \alpha_5(M_{t-1}/P_t)\ . \qquad (2)$$

The asset approach (e.g., M. Friedman 1956) regards money as one of many substitutable assets held by consumers or firms in their portfolios. This theoretical model includes several asset returns, the expected inflation rate (Π^e) and permanent income *(yp).* Using the nominal adjustment mechanism and dropping the *r* sub-script, a linear representation of this model would be

$$(M/P) = \alpha_0 + \alpha_1 yp + \alpha_2 rE + \alpha_3 rD + \alpha_4 \Pi^e + \alpha_5(M_{t-1}/P_t) \qquad (3)$$

where *rE* is the return on equity and *rD* is the return on debt.

The determinants of aggregate money holdings also have been analyzed in a multiasset model that recognizes the interrelationships among asset demands arising from the balance sheet constraint, For example, B. Friedman (1978) represents the demand for money, capital *(K),* and government debt *(B)* in a three-asset demand system:

$$\begin{bmatrix} M \\ B \\ K \end{bmatrix} = \begin{bmatrix} m_0 \\ b_0 \\ k_0 \end{bmatrix} + \begin{bmatrix} m_1\ m_2\ m_3 \\ b_1\ b_2\ b_3 \\ k_1\ k_2\ k_3 \end{bmatrix} . \begin{bmatrix} rM \\ rB \\ rK \end{bmatrix} + \begin{bmatrix} m_4 \\ b_4 \\ k_4 \end{bmatrix} yc + \begin{bmatrix} m_5 \\ b_5 \\ k_5 \end{bmatrix} W \qquad (4)$$

where *W* is wealth, *rM, rB,* and *rK* is the expected return on money, government debt and capital, and *W* = *M* + *B* + *K.* If we replace the K equation by separate private sector debt and equity equations, money demand would depend virtually on the same set of interest rates as in (3).[5]

While there are common elements in these specifications, considerable uncertainty remains about the appropriate model for testing hypotheses about the linkages between financial markets and money demand. Variables such as wealth and the return on equities, prominent in some theoretical models, often are omitted from empirical models. This specification diversity affects inferences. For example, B. Friedman contends that Hamburger's dividend-price ratio *(DPR)* is significant only because it proxies real household wealth. When Wis included, *DPR* becomes insignificant. Hamburger (1983) notes that his model's superior predictive power is probably due to the omission of short-term interest rates and the corresponding insensitivity to financial innovations. Interpretation of results varies with the researcher's priors.[6]

Other variables have been included in money demand models such as the savings and loan passbook rate *(rSL)* and Cooley and LeRoy's real value of credit card transactions (*VCC).*[7] Field (1984) finds a stock trading volume measure *(SM V)* to be statistically significant during the 1920s, but financial trading influences generally are excluded from money demand studies.[8]

We begin with the following double-log model:

$$(M/P) = \gamma_0 + \gamma_1 yc + \gamma_2 W + \gamma_3 rCP + \gamma_4 rSL + \gamma_5 rat + \gamma_6 spr + \gamma_7 rE$$
$$+ \gamma_8 SMV + \gamma_9 \Pi + \gamma_{10} VCC + \gamma_{11}(M_{t-1}/P_t) + \gamma_{12} D + \epsilon \qquad (5)$$

where *D* is an intercept dummy set to 0 for 1961/I-1974 /II and 1 thereafter, rCP is the four- to six-month commercial paper rate that proxies *rs*, *rE* is the total return on equity (dividends plus capital gains), the inflation rate (Π) in period *t* is substituted for Π^e, and all other variables are as defined earlier.[9] The advantage of (5) is that virtually any (linear) empirical model can be derived through application of appropriate coefficient restrictions (e.g., the transaction model corresponds to $\gamma_2 = \gamma_4 = \gamma_7 = \gamma_8 = \gamma_9 = \gamma_{10} = \gamma_{12} = 0$)

Since transactions demand models need not apply to the same monetary aggregate as econometric models from the asset demand approach, we specify prior distributions for M1 and M2. Our prior distributions, shown in Table 1, distinguish between M1 and M2 based on scale variable influences, adjustment speed, and asset substitution patterns as reflected in interest rate effects. Different substitution patterns among money, debt, and equities are set by specifying a prior distribution with the margin of substitution favoring either the debt or equity market. The primary difference between the debt and equity priors are the prior means on the interest rate variables. The prior mean on the *rSL* is invariant with respect to debt versus equity substitution but changes sign to reflect its status as an own-rate of return for M2. The standard errors for *rCP*, *rSL*, and *rE* are set to allow for a zero effect within two standard deviations of the prior mean.

TABLE 1

PRIOR DISTRIBUTIONS FOR M1 AND M2 SPECIFICATIONS

	M1		M2	
Variable	Debt Prior	Equity Prior	Debt Prior	Equity Prior
yc	.75/.125	.75/.125	.1/.1	.1/.1
W	0/.1	0/.1	1/.2	1/.2
rCP	−.5/.25	0/.1	−.5/.25	0/.1
rSL	−.3/.15	−.3/.15	.1/.05	.1/.05
rat	0/1	0/1	0/1	0/1
spr	.5/.25	.5/.25	.5/.25	.5/.25
rE	0/.1	−.5/.25	0/.1	−.5/.25
Π	0/1	0/1	0/1	0/1
VCC	0/1	0/1	0/1	0/1
SMV	0/.1	0/.1	0/.1	0/.1
M_{t-1}/P_t	.25/.125	.25/.125	.5/.25	.5/.25
D	0/1	0/1	0/1	0/1

NOTES: The number to the left of the slash mark is the prior mean and the number to the right is the prior standard error.

Our prior means on *yc* and *W* reflect their different theoretical roles in transaction and asset money demand models. For M1, we adopt a prior mean of .75 for *yc* and assume that W has no effect on the demand for transaction balances. For M2, we assume an unitary wealth elasticity and a prior mean of .1 for *yc* reflecting Darby's (1972) view that M2 balances might be a shock absorber for transitory income. We adopt the prediction from Baumol's model of .5 as our prior mean for *spr.* For Π, *rat*, *SMV*, and the 1974 shift variable we are less confident of any significant effect so we adopt a zero prior mean and a wide prior confidence interval. For the speed of adjustment coefficient our prior mean implies 75 percent adjustment in one quarter for MI and 50 percent adjustment for M2. The standard errors are set to encompass complete adjustment in the quarter within two standard deviations.

2. BAYESIAN ESTIMATION AND SENSITIVITY AN'ALYSIS

Extreme Bounds Analysis

Economic theory rarely provides a complete prior distribution (our view is that prior distributions are personal and subjective), but researchers often can classify variables as either free variables, which always are included in an econometric model or doubtful variables, which might be excluded. For this case, the researcher's location prior information is a combination of a prior mean of zero on the doubtful variables and diffuse prior on the free variables.[10] Chamberlain and Learner (1976) and Leamer (1978) have shown that this prior information and the sample variance-covariance matrix are sufficient to generate the minimum and maximum coefficient values from the set of all possible OLS regressions. This set of possible coefficient values is described by an ellipsoid of constrained regression estimates.

One problem with this form of sensitivity analysis is that the ellipsoid may encompass portions of the parameter space considered very unlikely, a priori, In response, the investigator might constrain the least-squares estimates to fall within an α-percent joint confidence ellipsoid based only on the sample and computed with all doubtful variables included. The idea behind this constraint is that the researcher is not willing to believe any point estimates from a constrained regression that is seriously at odds with the data. The extreme values of regression coefficients are derived from the intersection of the ellipse of constrained estimates and the sample-based confidence ellipsoid. This second set of extreme bounds, reported by Cooley and LeRoy, is useful and appropriate if the researcher's prior meets the conditions described above and if the issue is the sensitivity of free coefficients values to this prior.

There are several reasons why we do not use these extreme bounds analysis methods. First, our prior information set is larger than that used by Cooley and LeRoy and the extreme bounds methods they used are not appropriate under these circumstances. Second, the extreme bounds analysis can be compromised in several ways (see McAleer, Pagan, and Volker 1985, Learner 1985, and Cooley and LeRoy 1986). In particular, extreme bounds calculated under the confidence interval constraint reflect the effects of the location prior and the sample variance-covariance matrix but the prior variance-covariance matrix can be any positive definite or positive semidefinite matrix (of appropriate rank). Unfortunately, we have no way of knowing the characteristics of the prior variance-covariance matrix implied at every confidence level although we could probably dismiss some prior standard errors as unreasonable, In addition, severe multicollinearity inflates estimated standard errors resulting in a larger sample-based α-percent confidence ellipsoid and wider bounds than with more orthogonal regressors.[11] Adding irrelevant explanatory variables makes it more likely that the extreme bounds analysis will indicate sensitivity to prior location information because efficiency falls with extra, unnecessary regressors.

A third problem arises because the confidence level is arbitrary. For example, if the bounds cross at 90 percent (versus 75 percent) does this indicate unacceptable sensitivity? This suggests that only when bounds cross at extreme values of the data confidence will there be general consensus about sensitivity. Finally, extreme bounds are calculated from a joint confidence ellipsoid involving all elements of the parameter vector. This can be misleading if we are interested in a confidence interval involving only one element of the β vector. Using a joint confidence ellipsoid can produce wider intervals under some conditions and therefore, wider extreme bounds.

Bayes Estimator

In conjunction with our more substantial prior information set, these drawbacks render the extreme bounds analysis inappropriate. To use our prior information and evaluate the sensitivity of the resulting estimates to changes in the prior distribution, we need different methods. Our approach uses the prior means and a prior Variance-covariance matrix (which can be diagonal) and combines the prior and sample information in the following way:

$$\hat{\beta} = [\sigma_p^{-2}X_p'X_p + \sigma^{-2}X'X]^{-1} \quad [\sigma_p^{-2}X_p'X_p\beta_p + \sigma^{-2}X'X\beta_{OLS}]\,. \tag{6}$$

This Bayes estimator (actually, the mean of the posterior distribution) allows different variances from the prior and sample information where *p* indicates part of the prior, X is the sample data matrix, σ is the standard error of the estimate, and β is the coefficient vector. A useful way to view (6) is that $\hat{\beta}$ is a matrix-weighted average of β_p and β_{OLS} with weights given by $\sigma_p^{-2}X_p'X_p$ and $\sigma^{-2}X'X$. Thus, coefficient estimates are generated by combining two (presumably different) information sources and the weights determine the relative emphasis given to each information source, Different sets of weights trace out a set of coefficient estimates along what Learner calls the information contract curve, For given data and prior moment matrices, a useful starting point assumes an equal weight on the prior and sample information in (6) ($\sigma_p^2 = \sigma^2$). For given cross-product matrices, changes in the relative size of the variances lead to different weights being assigned to the two information sources and hence to different coefficient estimates. Likewise, since X′X is fixed, changes in the prior moment matrix (for a fixed σ_p^{-2}) generate a different weighting scheme and different coefficient estimates. Finally, for a set of matrix weights, changes in σ_p^{-2} lead to new coefficient estimates.

Sensitivity Analysis

The construction of β_p and the diagonal elements of $\sigma_p^2(X_p'X_p)^{-1}$ (for $\sigma_p^2 = 1$) is described in section 1, We now discuss the selection of other elements of the prior distribution and how the sensitivity analysis works. We expect our coefficient estimates to fall between —1.96 and 1.96 so we selected $\sigma_p^2 = 1$ as a first approximation (i.e., $\beta_i < 1.96\sigma$). This amounts to saying our prior covariance matrix is proportional to $(X_p'X_p)^{-1}$. To evaluate the impact of this assumption, define $\sigma_1 = \sigma_p^2/\sigma^2$. Our starting point on the contract curve corresponds to the estimates of β where $\sigma_1 = 1$. If we have less faith in the prior information, σ_p^2 rises so σ_1 increases and we move along the contract curve toward the least-squares point. In the limit, as σ_1 approaches infinity, the least-squares estimates are obtained. Conversely, as confidence increases in the prior information, σ_p^2 falls and σ_1 declines. In the limit as σ_1 approaches zero, β collapses to β_p.

Second, specifying a prior covariance matrix is quite tenuous so it is important to establish the sensitivity of matrix-weighted estimates to different prior covariance matrices.[12] Learner (1982) develops such an analysis by showing that there are bounds on the coefficient vector if the prior covariance matrix V can be bounded $V_* \leq V \leq V^*$.[13] If an interval that incorporates the researcher's prior opinions about the coefficient variances (and covariances) can be specified this prior information can be used to find upper and lower bounds on the coefficient vector. If the coefficient bounds are relatively narrow for an interval which encompasses research opinion generally, then β does not depend on the choice of the prior covariance matrix. With a diagonal prior variance-covariance matrix, V_0, based on Table 1 and an interval bounded by $V_* \leq \lambda^{-2}V_0$ and $V^* \leq \lambda^2 V_0$, an entire range of prior variance-covariance matrices can be found by varying λ.[14]

We can establish the sensitivity of our estimates by computing the extreme bounds on the matrix-weighted estimates as λ varies. For example, suppose we specify a prior mean and standard error for *yc* of .75 and .125. When λ = 1, the 95 percent prior confidence interval for *yc* ranges from .5 and 1.0 thereby encompassing both the transaction and wealth hypotheses about income elasticity, By selecting λ = 2, a 95 percent prior confidence interval for the upper bound would range from 25 to 1,25. For the lower bound, the prior confidence interval is tighter, meaning we are more certain of our prior beliefs. This case is usually of less practical interest so we do not pursue it. At λ = 4, a 95 percent prior confidence interval for the upper bound ranges from —.25 to 1.75. Given the expectation the income coefficient should be positive, no greater scaling would be sensible.[15]

3. EMPIRICAL RESULTS

Coefficient estimates and sensitivity analysis of equation (5) for M1 and M2 using our debt prior distribution are reported in Tables 2 and 3 for 1961/I-1978/ IV and 1961/I-1984/IV. Our conclusions are not changed by using the equity prior (results available on request). The Durbin *h* statistics for M1 are 0.92 and 1.44 and for M2 are 2.44 and 3.21. We experimented with adjustments for serial correlation but we could find no important impact of the autocorrelation corrections on our findings. For the 1961-1984 period Wand VCC are omitted due to the unavailability of data and D802 and D803 are included as zero-one dummy variables for the 1980 credit controls where the dummies are equal to zero except for the quarter indicated by their name.

Financial Influences on M1

For the *rCP* coefficient, the equal weight and OLS estimates (reported under the heading $\sigma_p^2/\sigma^2 = \sigma_1 = 1$ and $\sigma_1 = \infty$) are nearly the same, indicating that the *rCP* estimate is not sensitive to location on the contract curve for either time period. The precision of the estimate displays similar insensitivity. On the right-hand side of Table 2 we report a prior covariance matrix sensitivity analysis. For different values of λ, we report coefficient extreme bounds as the prior covariance matrix is varied over the interval, $\lambda^{-2}V_0 \leq V \leq \lambda^2 V_0$. For λ = 2, the scalings are relatively small but the size of the interval increases until at λ = ∞ all positive definite (or semidefinite) covariance matrices are considered.[16] For *rCP*, we find that widening the interval substantially (i.e., λ = 4) does not alter the conclusion that money demand is negatively related to the interest rate. This suggests that such findings are not exclusively the product of selective reporting.

TABLE 2

Coefficient Estimates and Sensitivity Analysis Results for M1 Equation

	Debt Prior: 1961/I–1978/IV								
	Pooled Estimate Sensitivity to Changes in σ_1					Extreme Bounds Estimates Prior Covariance Matrix Intervals: $\lambda^{-1}V_0 \leq V \leq \lambda^{1}V_0$			
	$\sigma_1 = .50$	1	2	4	∞	$\lambda = 2$	4	8	∞
rCP	−.008	−.009	−.010	−.011	−.011	−.005	.003	.014	2.78
	(2.28)	(2.76)	(3.00)	(3.08)	(3.10)	−.013	−.020	−.037	−3.29
rSL	−.163	−.034	.038	.061	.070	.135	.300	.571	41.8
	(4.63)	(.80)	(.82)	(1.31)	(1.48)	−.260	−.510	−.813	−42.1
rE	.0003	.003	−.006	−.007	−.007	.043	.111	.229	16.1
	(.02)	(.14)	(.31)	(.37)	(.39)	−.048	−.119	−.241	−16.1
spr	.003	.001	.0004	.0002	.0001	.004	.007	.013	1.20
	(2.99)	(1.14)	(.41)	(.20)	(.13)	−.0004	−.001	−.003	−.697
rat	−.008	−.010	−.011	−.012	−.012	.004	.024	.053	5.94
	(1.19)	(1.48)	(1.71)	(1.79)	(1.82)	−.023	−.045	−.081	−5.96
SMV	−.001	.003	.005	.005	.006	.006	.009	.017	2.68
	(.47)	(1.01)	(1.64)	(1.83)	(1.90)	−.002	−.012	−.029	−2.67
Π	.465	.311	.233	.210	.201	.729	1.34	2.33	144.0
	(3.08)	(1.96)	(1.45)	(1.29)	(1.24)	−.031	−.596	−1.74	−144.0
VCC	−.051	−.007	.016	.023	.026	.027	.055	.105	11.7
	(4.67)	(.60)	(1.21)	(1.76)	(1.95)	−.063	−.124	−.194	−11.7
D	−.029	−.013	−.006	−.003	−.002*	−.002	.008	.026	3.60
	(8.99)	(3.52)	(1.42)	(.81)	(.61)	−.033	−.056	−.078	−3.60
yc	.305	.085	−.030	−.067	−.081*	.373	.683	1.02	44.2
	(9.51)	(2.01)	(.63)	(1.38)	(1.63)	−.098	−.240	−.473	−43.5
W	−.054	.025	.073	.089	.096*	.176	.315	.523	30.9
	(2.42)	(.85)	(2.19)	(2.60)	(2.74)	−.157	−.331	−.525	−30.8
Lag	.621	.845	.947	.977	.988*	1.03	1.18	1.46	48.8
	(16.2)	(17.4)	(17.9)	(18.1)	(18.1)	.539	.185	−.186	−47.7
	Debt Prior: 1961/I–1984/IV								
rCP	−.019	−.015	−.013	−.013	−.13	−.011	−.007	.001	3.13
	(6.69)	(4.93)	(4.42)	(4.28)	(4.23)	−.021	−.036	−.058	−3.64
rSL	−.070	.011	.039	.046	.049	.129	.308	.569	45.5
	(2.02)	(.29)	(.97)	(1.15)	(1.21)	.161	−.473	−.825	−45.8
rE	.004	−.001	−.003	−.003	−.004	.056	.162	.313	22.4
	(.19)	(.17)	(.14)	(.11)	(.11)	−.156	−.160	−.321	−22.4
spr	.001	.001	.0003	.0003	.0003	.002	.004	.007	.983
	(1.93)	(.82)	(.48)	(.39)	(.361)	−.000	−.001	−.003	−.482
SMV	−.000	.006	.008	.008	.008	.009	.012	.020	3.05
	(0.81)	(2.15)	(2.82)	(3.00)	(3.06)	−.001	−.017	−.040	−3.04
rat	−.007	−.015	−.017	−.018	−.018	.006	.043	.083	8.57
	(1.01)	(1.99)	(2.32)	(2.42)	(2.45)	−.031	−.058	−.102	−8.59
Π	−.475	−.621	.670	−.684	−.688	−.199	.664	1.93	176.0
	(3.24)	(4.06)	(4.33)	(4.41)	(4.43)	−.946	−1.60	−2.76	−177.0
yc	.152	.069	.044	.037	.034	.159	.353	.601	22.6
	(8.63)	(3.66)	(2.25)	(1.89)	(1.77)	.037	.012	−.038	−21.8
Lag	.793	.895	.926	.935	.938	.947	1.00	1.11	31.2
	(32.9)	(34.3)	(34.7)	(34.8)	(34.9)	.772	.510	.194	−30.0
D	−.020	−.011	−.007	−.007	−.006	−.006	−.002	.007	3.77
	(6.47)	(3.23)	(2.27)	(2.02)	(1.93)	−.022	−.046	−.074	−3.78
*D*802	−.033	−.031	−.030	−.030	−.030	−.028	−.022	−.012	6.26
	(5.96)	(5.63)	(5.52)	(5.49)	(5.48)	−.035	−.044	−.055	−6.29
*D*803	.010	.014	.015	.015	.015	.017	.023	.032	6.35
	(1.81)	(2.48)	(2.68)	(2.74)	(2.76)	.008	−.005	−.021	−6.33

NOTE: The absolute value of the *t*-statistics (in parentheses) is an asymptotic approximation because it is calculated using s^2 for $\sigma_1 = 0$, regardless of the actual value of σ_1. An asterisk (*) indicates an OLS coefficient estimate significantly degraded by multicollinearity (see fn. 18). Lag = $M1_{t-1}/P_t$.

TABLE 3

COEFFICIENT ESTIMATES AND SENSITIVITY ANALYSIS RESULTS FOR M2 EQUATION

	Pooled Estimate Sensitivity to Changes in σ_1					Extreme Bounds Estimates Prior Covariance Matrix Intervals: $\lambda^{-1}V_a \le V \le \lambda^{2}V_a$			
	$\sigma_1 = .50$	1	2	4	∞	$\lambda = 2$	4	8	∞
	Debt Prior: 1961/I-1978/IV								
rCP	−.031	−.031	−.030	−.030	−.030	−.025	−.017	−.001	25.8
	(9.43)	(8.87)	(8.68)	(8.63)	(8.62)	−.036	−.048	−.075	−26.3
rSL	.131	.150	.169	.178	.182	.345	.619	1.09	355
	(6.08)	(4.46)	(3.97)	(3.86)	(3.82)	−.045	−.323	−.799	−355
rE	.014	.011	.008	.007	.006	.048	.127	.307	134
	(.85)	(.63)	(.46)	(.38)	(.35)	−.026	−.106	−.293	−134
spr	.002	.001	.001	.001	.001	.002	.004	.008	7.54
	(1.65)	(1.30)	(1.20)	(1.18)	(1.17)	.0009	.0005	−.001	−7.04
rat	−.011	−.012	−.013	−.014	−.014	.009	.042	.099	54.5
	(1.96)	(1.87)	(1.88)	(1.90)	(1.91)	−.034	−.067	−.126	−54.5
SMV	−.0008	.0004	.0009	.001	.001	.004	.011	.024	22.8
	(.29)	(.14)	(.30)	(.35)	(.37)	−.004	−.014	−.036	−22.8
Π	.012	.006	.004	.004	.003	.256	.899	2.48	1160
	(.08)	(.04)	(.03)	(.02)	(.02)	−.240	−.876	−2.45	−1160
VCC	.003	.004	.007	.008	.009	.041	.097	.201	95.2
	(.33)	(.35)	(.56)	(.66)	(.71)	−.030	−.077	−.155	−95.2
D	.001	.001	.001	.001	.001*	.004	.010	.020	17.2
	(.57)	(.45)	(.50)	(.54)	(.56)	−.002	−.006	−.015	−17.2
yc	.091	.056	.030	.018	.013*	.312	.695	1.35	479
	(2.48)	(1.10)	(.50)	(.29)	(.21)	−.191	−.555	−1.19	−479
W	.139	.113	.113	.115	.116	.244	.474	.879	265
	(5.59)	(3.78)	(3.37)	(3.30)	(3.28)	−.007	−.147	−.455	−264
Lag	.825	.866	.882	.887	.888*	.999	1.21	1.62	323
	(25.8)	(22.2)	(21.0)	(20.6)	(20.5)	.709	.436	−.024	−321
	Debt Prior: 1961/I-1984/IV								
rCP	−.028	−.027	−.026	−.026	−.026	−.024	−.018	−.006	12.8
	(9.36)	(8.61)	(8.37)	(8.30)	(8.28)	−.031	−.039	−.056	−13.4
rSL	.100	.099	.098	.097	.097	.193	.334	.581	161
	(4.77)	(3.21)	(2.69)	(2.55)	(2.50)	.049	−.135	−.382	−161
rE	.007	.007	.007	.007	.007	.030	.083	.207	78.6
	(.40)	(.37)	(.36)	(.36)	(.36)	−.016	−.069	−.195	−78.6
spr	.000	.001	.001	.001	.001	.001	.002	.004	2.83
	(.75)	(.86)	(.88)	(.89)	(.89)	−.000	−.001	−.003	−2.32
rat	−.007	−.006	−.006	−.006	−.006	.066	.025	.061	30.7
	(1.09)	(.94)	(.86)	(.83)	(.82)	−.019	−.038	−.070	−30.7
SMV	.006	.005	.005	.005	.005	.008	.013	.025	10.4
	(2.46)	(2.21)	(2.13)	(2.11)	(2.11)	.003	−.001	−.008	−10.4
Π	−.858	−.913	−.929	−.933	−.934	−.747	−.297	.792	605
	(6.22)	(6.37)	(6.39)	(6.38)	(6.38)	−1.04	−1.31	−2.05	−606
yc	.121	.114	.110	.110	.110	.195	.343	.609	166
	(3.99)	(3.08)	(2.81)	(2.74)	(2.72)	.037	−.102	−.361	−166
Lag	.875	.883	.888	.889	.889	.941	1.04	1.23	133
	(34.8)	(29.8)	(28.3)	(27.9)	(27.8)	.822	.703	.485	−132
D	−.0001	.0002	.0003	.0003	.0003	.001	.003	.007	9.73
	(.03)	(.09)	(.13)	(.13)	(.14)	−.001	−.004	−.009	−9.73
D802	−.013	−.012	−.012	−.012	−.012	−.011	−.009	−.002	22.0
	(2.38)	(2.30)	(2.28)	(2.27)	(2.27)	−.014	−.017	−.027	−22.0
D803	.004	.004	.004	.004	.004	.005	.008	.014	22.0
	(.67)	(.77)	(.81)	(.82)	(.82)	.602	−.002	−.011	−22.0

See note to Table 2. Lag = $M2_{t-1}/P_t$.

The *rSL* coefficient provides a good example of how the choice of weights on prior and sample information can be important. The equal-weight estimate is negative but the OLS estimate is positive for the 1961/I-1978/ IV period. A slight increase in the weight on prior information relative to the equal-weight estimate (σ_1 = .5) yields a large increase in the coefficient size and significance. Similar results are noted for σ_1 = .5 and 1 for the 1961/ I-1984/ IV period. Furthermore, the *rSL* coefficient displays considerable sensitivity to alternative prior covariance matrices because the bounds on this coefficient estimate cross zero when λ = 2 for the 1961-78 period.

The equity rate coefficient is negative and insignificant for both the equal and OLS information weights and the coefficient extreme bounds cross zero when λ = 2 for both periods. Thus, we find no support for an equity rate effect when we base our estimates on the more favorable equity prior distribution.[17] Similarly, the equal-weight and the OLS estimate of the bid-ask spread coefficient estimate is not significantly different from zero and the coefficient extreme bounds cross zero when λ = 2, Thus, the marginal transaction cost measure does not have any effect on money demand for either period.

We now consider other financial market variables. The size and statistical significance of the ratchet coefficient is insensitive to the information weights for both periods but the *rat* coefficient extreme bounds cross zero at λ = 2. The positive impact of stock market volume on M1 suggests Field's results for the 1920s may hold more generally. The SMV coefficient doubles in size between the equal-weight and the OLS estimate for the 1961-78 period and the *t*-score increases when greater weight is put on the OLS information, (This is not surprising given our priors for this variable,) The *SM V* coefficient is positive, significant, and less sensitive to the position on the contract curve when the 1979-84 period is included. The coefficient extreme bounds for the two time periods cross at λ = 4 and 2.

The *VCC* coefficient is insignificant and changes sign with different weights and the coefficient extreme bounds cross zero at λ = 2. The Π coefficient is insignificant and the bounds cross zero at λ = 2 for the 1961-78 period. The Π coefficient, however, is negative and significant and insensitive to its position on the contract curve for the period ending in 1984. Thus, the inflation rate is an important determinant of money holdings through the inflationary experience of the late 1970s and 1980s.

The equal-weight and OLS estimates of the 1974 shift variable are negative and statistically significant except for the OLS estimate for 1961/I-1978/IV which is seriously degraded by multicollinearity. For the extended period, the D802 coefficient is negative and significant and the D803 coefficient is positive and significant. Neither estimate is sensitive to the position on the contract curve.

Financial Influences on M2

Table 3 reports estimates of financial influences on M2 demand. The *rCP* coefficient is negative, significant, and insensitive to different information weights. The *rSL* coefficient has the correct sign and is statistically significant in both periods. The coefficient extreme bounds cross zero at λ = 2 and 4 for both sample periods. The equal-weight and OLS estimates of the *rat* coefficient are significant for 1961-78 and insignificant for 1961-84 and the extreme bounds cross zero at λ = 2 for both periods. Thus, the *rat* variable accounts for shifts in the M2 demand function during the 1970s only if the 1979-84 period is excluded.

We found no evidence that *rE, spr,* or *VCC* are significant for either sample periods. The SMV coefficient is insignificant for the 1961-78 period but positive, significant, and insensitive to the information weight for the 1961-84 period. In addition, the extreme bounds estimates cross zero at λ =4. This confirms that stock market volume increases both M1 and M2 demand when the 1979-84 period is included in the sample.

The Π coefficient is negative, significant, and insensitive to the weighting on the contract curve for the period ending in 1984, but is insignificant for the period ending in 1978. Thus, we find the inflation rate is an important determinant of both M1 and M2 holdings when 1979-84 data are added. One obvious implication is that sample period is crucial to determining the preferred adjustment mechanism using Milbourne's test. The significance of the n coefficient in the 1961-1984 period supports Milbourne's finding that the nominal adjustment mechanism is superior.

Scale Variables Effects on M1 and M2

In the OLS regressions using M1 for 1961-78, we found evidence of substantial multicollinearity affecting the *yc*, *W*, and lagged dependent variable coefficients. Perhaps as a consequence, the OLS estimates of the income and wealth coefficients are very different from the equal-weight estimates and do not seem to accord with expectations. The equal-weight estimates and *t*-scores indicate that current income is statistically significant while wealth is not (the reverse of the t-score pattern for the OLS estimates). Roley's findings (tables 1, 3, 4, and 5) indicate that income and wealth both influence M1 holdings. Given the sensitivity of point estimates to the information weights, we suspect that robust inferences about scale variable influences in M1 regressions may be hard to find unless there is very broad agreement about the nature of the prior distribution. The equal-weight estimates are quite sensitive to alternative prior covariance matrices as the income and wealth coefficients cross zero at $\lambda = 2$.

The wealth coefficient is positive, significant, and insensitive to the information weight for M2 and is positive and significant for the OLS estimate for M1. For either definition of money the wealth coefficient is sensitive to the scaling of the covariance matrix because the *W* coefficient becomes negative at $\lambda = 2$.

The *yc* coefficient is degraded by multicollinearity and is insignificant when the wealth coefficient is included.[18] The *yc* coefficient is positive and significant in the M1 and M2 equations for the 1961-84 period, but the coefficient estimate is sensitive to the weighting in the M1 equation. The sensitivity analysis indicates that the coefficient estimates do not cross zero until $\lambda = 8$ for M1 and $\lambda = 4$ for M2.

The equal-weight coefficient estimates of the M1 and M2 lagged dependent variable are high given our priors but are consistent with OLS findings.[19] Note, however, the sensitivity of the coefficient to small scalings of the prior covariance matrix.

4. ERROR CORRECTION MODELS

Until now, we have investigated the sensitivity of empirical results on financial market variables in the money demand function to different money demand specifications. In this same spirit, we now explore briefly the implications for our results of modeling the variables in our empirical models as nonstationary time series.

Many macroeconomic time series have unit roots that can generate spurious regression results unless stationarity of the time series is first achieved. Time series data is often differenced to obtain stationarity. Recent work on unit roots, cointegration, and error correction models (ECM) has questioned the strategy of differencing the data to obtain stationarity. Instead, the procedure is to specify and estimate an equilibrium (cointegrating) model, retrieve the residuals from this model, and estimate an ECM with the retrieved residuals from the equilibrium model entered as regressors. Long-term equilibrium and short-term adjustment behavior are both modeled in such an approach. The ad hoc nature of the partial adjustment mechanism is thereby overcome and the spurious regression problem avoided.

Unit root tests proposed by Fuller (1976) and Dickey and Fuller (1979) indicate that with the exception of *rE* and *spr*, the other time series were nonstationary for both sample periods. Following Engle and Granger (1987), we specified equilibrium models corresponding to the transactions and asset demand models along with closely related alternative models [see (2) and (3)]. The Durbin-Watson, Dickey-Fuller, and augmented Dickey-Fuller tests are computed for both sample periods for each model and for each normalization of the cointegration models.[20] We find evidence of cointegration for each model and each normalization using one or more of the tests2[21]

When cointegration is found, the next step is to build an ECM using the cointegrating regression to supply the lagged residuals. Unfortunately, even if there is agreement on the equilibrium (cointegrating) model, there is still uncertainty with regard to the specification of the ECM. Lag structures are quite reasonable in ECMs given the close connection between ECMs and VAR models (see Engle and Granger for further details). Lag length selection is one obvious problem in specifying an ECM. Accordingly, it seems that sensitivity analyses ought to be reported.

We experimented with various ECMs based on all the equilibrium models (for both sample periods) and found only one combination of a cointegrating regression with money holdings as the dependent variable and a corresponding ECM with sensible signs. The equilibrium model is a transaction model:

$$M1 = 4.1082 + .1985y + .0124rCP + .0185spr \qquad R^2 = .785 \qquad (7)$$
$$\quad (.148) \quad (.024) \quad (.014) \quad (.004) \qquad DW = .407$$

that provides the error term ($e_t = M1_t - \hat{M}1_t$) for the ECM:

$$\Delta M1 = .0008 + .0945e_{t-1} - 1.3711e_{t-1}^2 + .0032\Delta rSL - .0384\Delta rat$$
$$\quad (.001) \quad (.035) \quad (.997) \quad (.081) \quad (.027)$$
$$- .2002\Delta\Pi - .0026\Delta SMV + .0025\Delta re - .0102\Delta D$$
$$\quad (.168) \quad (.003) \quad (.016) \quad (.006)$$
$$+ .3101\Delta W + .0066\Delta VCC \qquad R^2 = .57 \qquad (8)$$
$$\quad (.006) \quad (.025) \qquad DW = 1.52$$

where standard errors are reported in parentheses.[22] We find support from a joint test for the hypothesis that the error correction term is negatively related to the change in money holdings. We would expect this from any well-specified error correction model. From the error correction regression, it is apparent there is no support for the hypothesis that financial market variables have an impact on money holdings. Changes in wealth appear to be important in explaining changes in money holdings, a variant of the hypothesis explored by Darby.

We were unable to find another error correction model with changes in money holdings as the dependent variable in which the lagged cointegrating regression residuals were significantly negative. This leaves us concerned about the generality of our results. In our view, there is much work yet to be done on applying the unit root/cointegration approach to money demand modeling. Perhaps most important is a unified treatment of model uncertainty in specifying and estimating error correction models. We believe the methods used in earlier sections of this paper may prove valuable in this regard.

5. SUMMARY

This paper assesses the role of a broad class of financial market effects on money demand. In particular, we evaluate the influence of M1 and M2 balances of a new proxy for marginal transaction costs, a stock market volume variable, and several stock market return measures. The Bayesian methods we employ allow us to investigate the impact of specification uncertainty on inferences from money demand models. For M1 and M2 we find clear evidence of a small, robust, negative interest rate effect working through the commercial paper rate, contrary to the Cooley-LeRoy result. Separate prior distributions that emphasize the role of substitution between either money and debt or money and equities were employed. Regardless of our prior or the money definition, we find no evidence of a significant equity coefficient, contrary to Hamburger's results.

In addition we find the ratchet variable exerts a small, negative effect on both M1 and M2 holdings, but its size and significance are sensitive to the prior distribution used. We also found evidence that narrow money demand responds to the volume of stock trading. We found little support for including a credit card variable or our marginal transaction cost variable, Work on the simultaneous equations issue and a cointegration /error-correction model represents unfinished research.

DATA APPENDIX

The basic data set we use is identical to that used in Cooley and LeRoy who were very generous in making it available to us. It is described in more detail in their paper on page 835, Table 1. We have supplemented their data set with the bid-ask spread on Treasury Bills with thirty days or less to maturity. 'This data was collected from the *Wall Street Journal* on the last Friday of the month. We computed the average spread for the issues maturing that month and deflated this measure by the GNP deflator to form the real bid-ask spread. The two equity return measures, the ratio of dividends plus capital gains to stock price and the dividend-price ratio are the month end-of-quarter observations from Ibbotson and Sinquefield (1985), Exhibits B-I and B-2, respectively. The stock market volume measure was obtained from the Citibank Economic Database computer tape and is defined as shares traded on the NYSE for the month end-of-quarter (in millions of shares).

Notes:

[1]Judd and Scadding (1982) and Roley (1985) survey these issues.

[2]The problem of simultaneous equations bias (see Cooley and LeRoy, Gordon 1984, and Roley 1985) was investigated. Using test procedures from Hausman (1978) and Wu (1973), we could not reject the null hypothesis of exogeneity in virtually all cases. The Bayesian version of these procedures (see Reynolds 1982), however, strongly indicated that an instrumental variables estimator is preferred. We believe our results using a single equation approach are interesting irrespective of the exogeneity test results.

[3]Empirical evidence favors the nominal adjustment mechanism, which does not assume immediate adjustment of money holdings to price level changes, over the real adjustment mechanism (see Hafer and Hein 1980, Milbourne 1983, and Hafer 1985). For a richer dynamic structure see Baba, Hendry, and Starr (1987) and references therein.

[4]Our data sources and description are in the data appendix, The mean of the nominal bid-ask spread declines from .45 from 1971/I-1975/IV to .26 from 1976/I-1978/IV reflecting the decline of transaction costs in the 1970s.

[5]See Backus et al, (1980) for an economy-wide model.

[6]Laumas and Spencer (1980) claimed that a Goldfeld equation with *yp* and not *yc* had appreciably lower forecast errors in the post-73 period. Hafer and Hein (1982b) show that the improvement is due to their omission of *rSL*

[7]Researchers have dropped *rSL* on the theoretically defensible grounds that it is a controlled rate. The omission of *rSL*, however, may be due to its positive coefficient when the sample period includes the late 1970s and 1980s which is an example of selective reporting criticized by Cooley and LeRoy.

[8]Lieberman (1977) investigates bank debits but he explicitly excludes debits associated with financial transactions.

[9]Lin and Oh (1984) use 1974/III while Hafer and Hein (1982a) use 1974/II as the breakpoint. Our results are not sensitive to this timing difference.

[10]See McAleer, Pagan, and Volker (1985) and Leamer (1983) for a discussion of the partition of variables into free and doubtful.

[11]We found overwhelming evidence of seriously degrading multicollinearity in the Cooley-LeRoy experiments (see footnote 18).

[12]Specifying a nondiagonal prior covariance matrix is especially difficult. We experimented with several ad hoc methods for developing the prior covariances but without much success.

[13]Mathematically. $V^* \leq V$ means $V-V^*$ is positive definite. This ordering of matrices imposes bounds on all linear combinations of the coefficients. This approach does not require diagonality of the prior covariance matrix or diagonality of all prior covariance matrices in the interval defined above.

[14]Contrary to McAleer et al. (p. 295), there is a way to evaluate this type of sensitivity analysis even though the scaling factor is arbitrary.

[15]We checked the sensitivity of each coefficient to a one-standard deviation change in any other element of β_p , but these effects were negligible.

[16]These bounds are the same as would be calculated in the Cooley-LeRoy type analysis with the confidence interval constraint set at 100 percent.

[17]We found the same results when Hamburger's dividend-price ratio is employed for the 1961/I- 1978/IV period.

[18]Belsley, Kuh, and Welsch (1989) present diagnostics to determine the extent of multicollinearity and to identify those coefficients (marked in the tables with an asterisk) whose estimates are particularly affected.

[19]Referees suggested that we evaluate the impact of more substantial dynamic structures on our inferences about financial variables. We reestimated both equations including lagged values of the three interest rates, wealth, income, and inflation, and found only one important change. In the M1 equation, the *rCP coefficient* was insignificant and changed sign but the *rSL* coefficient doubled in size and was statistically significant.

[20]See Engle and Granger (pp, 260-63) on the identification problems in cointegration models and (p. 268) for the use of these tests.

[21]Engle and Granger report critical values for these tests and recommend using the augmented Dickey-Fuller test. The critical values and small sample properties of the test statistics are at best approximations because the

test statistics have quite nonstandard distributions and appear to be sensitive to initial conditions and distributional assumptions.

[22]In unpublished work, Granger has suggested that when there is evidence of cointegration but a linear ECM is insufficient, a sensible next step is to investigate nonlinear models (i.e., a quadratic in this case).

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