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The Spending Behavior of Wealth- and Liquidity-Constrained Consumers

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Life cycle models emphasize the distinction between wealth- and liquidity-constrained consumers. In a world with perfect capital markets, consumption can be freely spread across time subject only to a lifetime budget constraint which makes no distinction among different types of wealth. In a world with imperfect capital markets intertemporal consumption plans depend upon the composition of wealth. Human capital and pension benefits are highly illiquid, and many other types of wealth, for example, partnerships, real estate, structures, and durable goods, are not easily divisible and entail very high transaction costs.

For some people, expenditure and income flows mesh sufficiently well so that they behave pretty much as they would if capital markets were perfect. The consumption and investment plans of these wealth-constrained consumers will depend upon preferences, alternative yields and lifetime wealth. They will be unaffected by the realization of anticipated income changes and may be little affected by unanticipated income changes; they may be very sensitive to revised expectations of future income, prices and asset yields.

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For other people, capital market imperfections relating to difficulties in trading future income for current consumption are binding constraints. These liquidity-constrained consumers lack the current funds necessary to realize their optimal consumption path, and thus need not plan far into the future since changes in distant illiquid wealth are of little use. Their present behavior is largely shaped by their current period budget constraints, and their propensity to spend any new funds is very high. In addition, they will own few liquid assets, borrow heavily, and try to avoid investments which are illiquid or involve high transactions costs.

Aggregate behavior will depend upon the pervasiveness of liquidity constraints. To some extent, liquidity constraints are institutionalized reflections of bankruptcy laws, differing assessments of illiquid wealth, and different risk preferences. However, the breadth and scale of such constraints may change secularly and cyclically. There may be widespread changes in assessments of future relative to current income or spending plans which cause large numbers of consumers to become liquidity-constrained. The number of liquidity-constrained consumers is likely to be higher in recession than in boom years, and in credit crunches financial institutions will tighten loan requirements and make borrowing against future income much more difficult. There are also longer run demographic factors. For example, young families are more likely to be liquidity-constrained than retirees.

Macro models might benefit from an allowance for cyclical and secular fluctuations in liquidity constraints. However, there are no direct data on the number of liquidity-constrained households. Aggregate spending equations consequently allow for their presence only by including such proxy variables as consumer debt or the income-wealth ratio. Many have argued before us, and we agree, that the household survey data collected over the past thirty years represents a valuable source of distributional detail which might profitably be incorporated into macro models. We have followed this approach here, using selected household characteristics to partition the respondents in the annual Michigan survey data into liquidity- or wealth-constrained groups. The annual macro expenditure and asset proportions estimated from this classification are then applied to macro Flow-of-Funds data and interpolated to provide separate quarterly time series for liquidity- and wealth-constrained households. Expenditure and asset acquisition equations are then estimated for both groups.

Data and Classification Procedure

The annual surveys of Consumer Finances, conducted by the Survey Research Center at the University of Michigan from the late 1940's until the early 1970's, represent an excellent source of household data. They contain considerable demographic and economic detail but omit some preferred indicators of the presence of liquidity constraints. To correct this deficiency, we have employed the Survey of Changes in Family Finances, conducted in 1964 by Dorothy Projector for the Board of Governors of the Federal Reserve System. This survey of some 2000 households is unique in the scope and accuracy of its saving and wealth information, and we have classified each household in the sample as either wealth- or liquidity-constrained. Then, using variables common to this survey and to the Michigan data, we have constructed an alternative classification scheme which approximates our initial split of the Projector data and can be applied to the annual Michigan surveys.

In order to classify the households in the Survey of Changes in Family Finances sample the following data were examined:

Spending claims = consumption plus contractual saving;

Liquid assets = total demand deposit and savings account balances plus corporate equity holdings plus total bond holdings;

Contractual saving = saving in non-home mortgage loans, active business interest, life insurance loans, installment debt, and all medical debt;

Noncontractual saving = saving in demand deposits, all savings accounts, all types of bonds, corporate equity, home and other real estate improvements, nonactive business interests, brokerage accounts, mortgage assets, other loans held as assets, security credit, noninstallment debt, personal assets;

Net wealth = value of automobiles, demand and all savings account balances, corporate equity and all bond holdings, brokerage accounts, mortgage assets, other loans held as assets, pensions, personal trusts, and other assets, minus life insurance loans, security credit, installment and noninstallment debt.

A household is classified as wealth-constrained if any of the following conditions are met:

(a) The ratio of liquid assets to spending claims is at least 1/4, or

(b) The ratio of noncontractual saving to spending claims is at least 1/12, or

(c) The household is a net purchaser of bonds plus corporate equity, or

(d) The ratio of net wealth (excluding personal homes) to spending claims is at least 2.0.

If none of the tests are satisfied, then the household is considered liquidity-constrained.

These are rough judgmental criteria intended to identify likely characteristics of liquidity-constrained households. Condition (a) recognizes that such a household will have few liquid assets; one-fourth the size of annual spending claims is taken as the threshold for a liquid asset buffer. Similarly, condition (b) states liquidity-constrained consumers will do little voluntary saving. Condition (c) assumes that, because of transaction costs, a liquidity-constrained household will probably not increase its bond and equity holdings. Condition (d) identifies wealth-constrained households, primarily those headed by a retiree, that do not need many liquid assets.

When these criteria were applied to 1873 households in the Survey of Changes in Family Finances, only 35% of the households, owning 86% of net wealth, were found to be wealth constrained.* Table 1 displays the portfolio characteristics of these households.

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*Classifications were also computed with liquid asset thresholds of .2 and .4. Neither alternative changed the results greatly, and only the original classification was used here.

TABLE 1

Fractions of Total Owned by Wealth-Constrained Households in Projector Survey

Item	Initial Classification	Logit Function Classification
Demand deposits	.73	.85
Savings accounts	.91	.95
Treasury bills	1.00	1.00
Bonds	.94	.88
Equity	.99	.98
Home mortgages	.33	.35
Installment debt	.20	.14
Net wealth	.86	.87
Gross income	.42	.45
Number of households	.35	.34

The next step was to obtain an approximation of this classification using variables found in the Michigan surveys. Since this approximation must predict (the probability of) liquidity-constrained status, logit analysis is an appropriate estimator. The explanatory variables of this function should be variables used in the original classification or otherwise suggested by the life cycle hypothesis. Demand deposit, savings account and installment debt balances are reported for most of the Surveys of Consumer Finances samples and are closely related to the initial classification. Gross annual income* and home mortgage debt also seem reasonable indicators of liquidity-constrained status, the first related inversely and the second positively. The life cycle hypothesis also suggests age, employment status, the education level of the head of the household, and the number of household members as possible demographic indicators of liquidity-constrained status, and all of these variables

*Net income is preferable but unavailable.

are reported in both the Projector survey and in all of the Michigan samples.

The choice of the appropriate functional form is not unambiguous. The demographic variables were divided into a number of dummy variables corresponding to ranges of values or particular categories. The asset, debt, and income explanatory variables were deflated to eliminate the effects of growth as well as any possible short-term cyclical peculiarities in the data, since the logit approximation is to be used over a twenty-year period. The deflator chosen was a simple average of the household's gross income and the average gross income of all households with the same number of household members as that household. If for example a household has three members and a gross income of $5000, while the average gross income of all households in the sample with three members is $8,000, then the asset, debt, and income variables for this household are deflated by .5(5000) + .5(8000) = 6500.

The actual explanatory variables used in the logit function are defined below:

A25: dummy variable with value one if the age of the head of the household is less than 25, zero otherwise;

A35: dummy variable with value one if the age of the head is between 25 and 34, zero otherwise;

A45: dummy variable with value one if the age of the head is between 35 and 44, zero otherwise;

A55: dummy variable with value one if the age of the head is between 45 and 54, zero otherwise;

S1: dummy variable with value one if the number of household members is one, zero otherwise;

S2: dummy variable with value one if the number of household members is two, zero otherwise;

S3: equals the number of household members if that number is three, four, or five (or more), zero otherwise;

ED1: dummy variable with value one if the education of the household head is zero to eight years, zero otherwise;

ED2: dummy variable with value one if the education of the head is nine to twelve years, zero otherwise;

EM1: dummy variable with value one if the head is self-employed, zero otherwise;

EM2: dummy variable with value one if the head is retired, zero otherwise;

EM3: dummy variable with value one if the head is not employed, zero otherwise;*

INCRATO = total gross income/PINC;

ACCT = total demand deposit and savings account balances/PINC;

IDB = total installment debt outstanding/PINC;

HMR = total home mortgage outstanding/PINC;

where

PINC = .5 × total gross income + .5 × average income by household size.

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*The definition of the employment variables is restricted by the employment status variable in the Survey of Changes in Family Finances. "Not employed" includes unemployed and not in the labor force.

The average values of the explanatory variables in the Projector survey and in the Michigan surveys are shown in Table 2. _A priori_ we would expect liquidity-constrained status to be inversely related to age, education, and the first two employment variables. Liquidity-constrained status should also be inversely related to relative income and liquid assets and is probably positively related to installment and mortgage debt. The actual estimated logit function is shown in Table 3 under the heading "all variables," with asymptotic "t-ratios" in parentheses.

Recalling that this function forecasts the probability of being liquidity-constrained, only the coefficient on HMR is questionable. Otherwise the coefficients appear very reasonable; the coefficients of the variables which approximate steps in the algorithm have the correct sign and are large in absolute value, and the coefficients of the demographic dummies all move in the right direction in each category. Table 1 contains a comparison of the initial and logit classifications, when each household with an estimated probability $\geq .5$ is considered liquidity-constrained.

One other logit function was estimated, excluding the installment debt variable IDB, since the 1953 and 1954 Michigan surveys do not record installment debt. As shown in Table 2 the results seem (if anything) slightly improved and we have decided to omit IDB and retain the 1953 and 1954 samples.* On the other hand the four samples, 1961, 1964, 1966, and 1967 were omitted from the analysis because they do not record the important information on demand deposit and savings account balances.

*Every household misclassified by this function was also misclassified by the function including IDB.

This logit function can now be used to estimate the liquidity-constrained and wealth-constrained populations in each of the Survey of Consumer Finances samples (other than 1961, 1964, 1966 and 1967). The samples are first "cleaned" by making any necessary transformations, omitting observations with missing data, collapsing the 1965 to 1971 observations from car unit to household unit, and adjusting weights where possible. After computing the average incomes by size of the household, the probability of being liquidity-constrained is estimated for each household by fitting the appropriate logit function to each household's set of characteristics. If the probability is greater than or equal to to .5, the household is classified as liquidity-constrained; otherwise the household is classified as wealth-constrained. This step estimates the two populations in each sample. Then for each sample, population aggregates are computed by summing (weighted) household values in each population, and the ratio of the wealth-constrained population total to the sum of the liquidity-constrained and wealth-constrained population totals is computed for each variable corresponding to variables in the Flow-of-Funds household accounts. Table 4 displays some of the results of this classification. On the whole, the results appear quite reasonable.

According to these figures the fraction of aggregate income earned by liquidity-constrained households has varied between .50 and .60. This implies a variation in the aggregate marginal propensity to consume out of a proportionately distributed increase in income equal to one-tenth the difference between the two groups' marginal propensities to consume:

$$\frac{\partial C}{\partial Y} = \frac{\partial C}{\partial Y_L}\frac{Y_L}{Y} + \frac{\partial C}{\partial Y_W}\frac{Y_W}{Y}$$

$$= \frac{\partial C}{\partial Y_W} + \left(\frac{\partial C}{\partial Y_L} - \frac{\partial C}{\partial Y_W}\right)\frac{Y_L}{Y} .$$

If for instance the marginal propensities to consume are .1 for the wealth constrained group and 1.0 for the liquidity-constrained, then the aggregate propensity to spend out of a proportionately distributed increase in income varies between .55 and .64.

Split Quarterly Income Data

The logit function provides a liquidity-wealth constrained split for annual data in each of sixteen years. For estimating household spending and asset acquisition decisions, we would prefer quarterly data and also to fill in the gaps in the annual data.

We turned first to the income series. We interpolated and extrapolated these series by assuming that the quarterly income aggregates Y_L and Y_W depend upon total income $Y = Y_L + Y_W$, the unemployment rate U, the yield spread between treasury bills and FHA mortgages $r_{TB} - r_M$, and the expected rate of inflation π^e.

$$(1) \quad \begin{aligned} Y_L &= \theta_L + \alpha_L Y + \beta_L U + \gamma_L(r_{TB} - r_M) + \delta_L \pi^e + \varepsilon_L \\ Y_W &= \theta_W + \alpha_W Y + \beta_W U + \gamma_W(r_{TB} - r_M) + \delta_W \pi^e + \varepsilon_W \end{aligned} .$$

The θ_i are intercepts and the ε_i are the error terms. The adding up restrictions on this allocation are:

$$\theta_L + \theta_W = 0$$

$$\alpha_L + \alpha_W = 1$$

$$\beta_L + \beta_W = 0$$

$$\gamma_L + \gamma_W = 0$$

$$\delta_L + \delta_W = 0$$

$$\varepsilon_L + \varepsilon_W = 0 \ .$$

The unemployment rate is a business cycle indicator. The yield spread variable is a proxy for credit market tightness. When the treasury bill rate is high relative to the mortgage rate, credit rationing may be more prevalent. Based upon our earlier discussion, we expect that an increase in either the unemployment rate or the yield spread will make liquidity constraints more prevalent. The parameter γ_L should be positive, but β_L is somewhat uncertain since, for a given aggregate income Y, a higher unemployment rate indicates a larger number of liquidity-constrained households but also lower incomes for many of these families. Changes in the rate of inflation may have two quite different effects. First they may be redistributions of income and wealth. Second households may become liquidity-constrained as they attempt to make earlier purchases of commodities. On balance, we would expect δ_L to be positive.

The aggregation across time of the quarterly model (1) provides analogous annual equations which can be estimated using the constructed annual data on Y_L and Y_W. These estimates can then be used with quarterly observations on U, $r_{TB} - r_M$ and Y to calculate quarterly values for Y_L and Y_W. Following Chow and Lin, the constructed quarterly data is adjusted so as to be consistent with the initial annual data.

Specifically, rewriting (1) in obvious matrix notation

$$y_L = Xb_L + \varepsilon_L \qquad (2)$$
$$y_W = Xb_W + \varepsilon_W ,$$

these can be premultiplied by a matrix G consisting of zeroes and ones in the appropriate places, defined so as to transform the complete quarterly data into available annual data:

$$Gy_L = GXb_L + G\varepsilon_L \qquad (3)$$
$$Gy_W = GXb_W + G\varepsilon_W .$$

If, for example, the first annual observation was the second year of the sample period, then the first row of G would consist of four zeroes followed by four ones and then repeated zeroes. If desired, G could be divided by four, though the scale of the variables is of course only of aesthetic and perhaps computational interest.

Under the usual maintained assumptions, Chow and Lin show that the best linear unbiased estimator of the Y_i is

$$(4) \qquad \tilde{y}_i = X\hat{b}_i + VG'(GVG')^{-1}G\hat{\varepsilon}_i \; ; \quad i = L, W$$

where $V = E(\varepsilon_i \varepsilon_i')$ is the assumed covariance structure for the quarterly disturbances and $\hat{b}_i$ and $G\hat{\varepsilon}_i$ are the generalized least squares estimates obtained with the annual data (3):

$$\hat{b}_i = (X'G'(GVG')^{-1}GX)^{-1}X'G'(GVG')^{-1}Gy_i$$

(5)

$$G\hat{\varepsilon}_i = Gy_i - GX\hat{b}_i \; .$$

The correction in (4) represents the optimal adjustment of the quarterly estimates to enforce compliance with the annual data.

We assumed a first order autoregressive pattern for the quarterly disturbances, $\varepsilon_i = \rho\varepsilon_i(t-1) + U_i$ so that

$$V = \frac{\sigma_U^2}{1-\rho^2}\begin{bmatrix} 1 & \rho & \rho^2 & \cdots \\ \rho & 1 & \rho & \\ \rho^2 & \rho & 1 & \\ \vdots & & & \end{bmatrix}$$

The adding up restriction on the errors $\varepsilon_L + \varepsilon_W = 0$ implies that both σ_U^2 and the autoregressive parameter ρ are the same for both equations.

Generalized least squares can be interpreted as ordinary least squares applied to data that has been premultiplied by a non singular matrix P such that P'P is equal to the inverse of the disturbance covariance matrix. Now since G , X , and V are the same for the liquidity- and wealth-constrained data sets, we are in essence applying ordinary least squares to two equations with the same right hand side variables and with left hand variables whose sum is equal to one of the right hand variables (the transformed aggregate income). It is well known (Nicholson gives an early proof), that in this situation the separately estimated parameters will automatically add up.

Using an iterative grid search, our maximum likelihood estimate of ρ was .761. The parameter estimates at that point were

$$Y_L = \underset{(3.53)}{5.20} + \underset{(.065)}{.365Y} - \underset{(.590)}{.599U} + \underset{(1.15)}{3.80}(r_{TB} - r_M) + \underset{(1.42)}{3.34}\pi^e$$

$$Y_W = \underset{(3.53)}{-5.20} + \underset{(.065)}{.635Y} + \underset{(.590)}{.599U} - \underset{(1.15)}{3.80}(r_{TB} - r_M) - \underset{(1.42)}{3.34}\pi^e \ .$$

The unemployment rate, yield spread, inflation rate are percentages; the income figures are quarterly rates. Throughout this paper the standard errors are in parentheses.

As anticipated, the separately estimated parameters do in fact add up. The estimated coefficients of Y are plausible and highly significant. The yield spread and inflation rate coefficients are correctly signed and statistically significant. These indicate that a one percent increase in either the yield spread or the inflation rate is associated with more than three billion in quarterly income being reclassified as belonging to liquidity constrained agents. The unemployment rate has a small and statistically insignificant effect. Figure 1 displays the initial annual data on Y_L/Y and the interpolated quarterly series.

Simple Expenditure Functions

Our first test of the usefulness of the partitioned data involved the estimation of simple quarterly Keynesian consumption functions,

$$E_{ij} = a_{ij} + b_{ij}Y_j + e_{ij} \ , \quad j = L, W \tag{6}$$

where E_{ij} is the expenditure by group j on commodity i. The quarterly error terms e_{ij} are assumed to follow a first order autoregressive pattern.

Premultiplication by a matrix G to convert these quarterly equations into a form appropriate for the available annual data leads again to the estimator (5). Using partitioned annual expenditure data (1951-70, except the missing years 1960, 1963, 1965, and 1966) on nondurables (END) ,* durable goods other than housing (ED) , and housing (EH) , the following results were obtained:**

$$END_L = \underset{(.010)}{.009} + \underset{(.017)}{.831}Y_L , \quad \rho = .72$$

$$END_W = \underset{(.013)}{-.007} + \underset{(.026)}{.672}Y_W , \quad \rho = .72$$

$$ED_L = \underset{(.007)}{-.007} + \underset{(.011)}{.157}Y_L , \quad \rho = .72$$

$$ED_W = \underset{(.004)}{.001} + \underset{(.008)}{.095}Y_W , \quad \rho = .55$$

$$EH_L = \underset{(.006)}{.016} + \underset{(.010)}{.026}Y_L , \quad \rho = .65$$

$$EH_W = \underset{(.004)}{.016} + \underset{(.009)}{.009}Y_W , \quad \rho = .65$$

In the nondurables equation, there is a sizeable and statistically significant difference between the behavior of liquidity- and wealth-constrained households. For nondurables and housing, liquidity-constrained again have a higher MPC, though the differences are here small and statistically insignificant. The sum of the liquidity-constrained MPC's is close to one.

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*Nondurable expenditure data were obtained residually by subtracting other items from income.

**In the actual regressions, the variables were deflated by income to combat heteroscedasticity problems.

Equations of the type (6) also imply aggregate quarterly equations.

$$E_{iL} + E_{iW} = (\alpha_{iL} + \alpha_{iW}) + \beta_{iL}Y_L + \beta_{iW}Y_W + (e_{iL} + e_{iW})$$

which can be estimated from our interpolated and extrapolated quarterly income series. Again the variables were deflated by aggregate income and allowance made for serial correlation. For the period 1952I-1978III the results are

$$END = END_L + END_W = \alpha_N + \underset{(.052)}{.919}Y_L + \underset{(.045)}{.586}Y_W , \quad \rho = .128$$

$$ED = ED_L + ED_W = \alpha_D + \underset{(.021)}{.111}Y_L + \underset{(.018)}{.141}Y_W , \quad \rho = .278$$

$$EH = EH_L + EH_W = \alpha_H + \underset{(.011)}{.036}Y_L + \underset{(.009)}{.024}Y_W , \quad \rho = .904$$

$$END + ED = \alpha_{ND} + \underset{(.061)}{1.006}Y_L + \underset{(.053)}{.750}Y_W , \quad \rho = .045$$

$$END + ED + EH = \alpha_{NDH} + \underset{(.069)}{1.008}Y_L + \underset{(.060)}{.813}Y_W , \quad \rho = .110 .$$

Each of these equations was estimated with four seasonal dummies; their coefficients are not of primary interest and have not been reported. In the nondurables equation, there is a substantial and statistically significant difference between the propensities to spend out of liquidity- and wealth-constrained income. In the durables and housing equations, there is only a slight and statistically insignificant difference. When durables and nondurables are aggregated, the marginal propensity to consume out of liquidity-constrained income is very close to one, and again statistically significant from the marginal propensity to consume out of wealth-constrained income. For all expenditures, including housing, the difference between the marginal propensities is smaller and not quite statistically significant.

Overall, these results are very encouraging. However, the high MPC's of the wealth-constrained are somewhat disconcerting, and it is disappointing to not find even larger differences in the behavior of the two groups. One possibility is that our classification procedure was not completely successful, in that the two selected groups do not actually contain greatly dissimilar proportions of liquidity-constrained households. For example, although the results in Table 4 indicate that on average 30% of all households earned 40% of total income, census statistics report that only about 20% of all households account for this percentage of total income. It is also possible that at this rough level, the behavior of wealth- and liquidity-constrained households may actually be similar. Perhaps the wealth-constrained do not have very long horizons, or they may view most income changes as largely permanent (or as proxies for other omitted variables). In this section, we reported the separate estimates of a simple model using annual and quarterly data. In the next section, these data are merged and a richer model estimated.

Integrated Expenditure and Asset Demands

Backus and Purvis have recently estimated an aggregate model of household flow of funds allocations, purchases of commodities and financial instruments. The adoption of their integrated "pitfalls" framework and data provides a convenient basis for gauging the usefulness of pursuing the separation of liquidity- and wealth-constrained groups. Our version* of their framework is displayed in Table 5, and the variables are defined in Table 6. Their model's consistency and specific detail are appealing. The inclusion of transitory income and lagged asset stocks may be particularly helpful in ascertaining differences in wealth- and liquidity-constrained behavior. Backus-Purvis calculated expected income YE by estimating an exponential time trend on real per capita income; Y - YE is then a measure of transitory income. We here apportioned YE to the wealth- and liquidity-constrained groups according to our estimates of their share of actual income. We could have alternatively estimated separate permanent income data from the two actual income series, but this would have had the unfortunate effect of counting as transitory income fluctuations due to the movement of households between the two groups.

Separate quarterly Backus-Purvis models could not be estimated for liquidity- and wealth-constrained households since we did not have partitioned quarterly data for any of the dependent variables.** Instead we have aggregate quarterly series and partitioned annual data which can be merged to estimate the parameters jointly.

Let E_{ij} now represent a vector of quarterly data of the acquisition by group j of some item i, either a commodity or financial

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*Because of a lack of partitioned data on stocks, we have not separated consumer durables and housing from other consumer expenditures.

**To estimate the model it is necessary to construct partitioned quarterly data on lagged asset stocks. We simply applied a rough eyeball interpolation using our annual micro data, hoping that the actual changes in the stock proportions were minor relative to the flows. It would have been more elegant to use the asset demand equations themselves and a Chow-Lin procedure to iteratively construct this data. However, the resultant estimates would have been biased and difficult (or at least expensive) to calculate.

asset category. The matrix X_j consists of quarterly observations on the explanatory variables; these may differ for the two groups, but are the same for each asset acquisition by a particular group.

(7) $$\begin{bmatrix} E_{iL} \\ E_{iW} \end{bmatrix} = \begin{bmatrix} X_L & 0 \\ 0 & X_W \end{bmatrix} \begin{bmatrix} \beta_{iL} \\ \beta_{iW} \end{bmatrix} + \begin{bmatrix} \varepsilon_{iL} \\ \varepsilon_{iW} \end{bmatrix}$$

We have quarterly series on $E_{iL} + E_{iW}$ and have constructed some consistent annual data on E_{iL} and E_{iW}. The system (7) can be multiplied by an appropriate matrix G containing zeroes and ones to reflect the available data. There will then be a stacked set of equations, some quarterly of the form $E_{iL} + E_{iW} = X_L\beta_{iL} + X_W\beta_{iW} + \varepsilon_{iL} + \varepsilon_{iW}$ and some annual of the form $\overline{E}_{iL} = \overline{X}_L\beta_{iL} + \varepsilon_{iL}$ shown in (8).

$$\begin{bmatrix} E_{iL} + E_{iW} \\ \overline{E}_{iL} \end{bmatrix} = \begin{bmatrix} X_{iL} & X_{iW} \\ \overline{X}_{iL} & 0 \end{bmatrix} \begin{bmatrix} \beta_{iL} \\ \beta_{iW} \end{bmatrix} + \begin{bmatrix} \varepsilon_{iL} + \varepsilon_{iW} \\ \overline{\varepsilon}_{iL} \end{bmatrix}$$

The annual wealth-constrained data are redundant and omitted.

Since there are 107 quarterly and 15 annual observations, G will be 122 by 214. With serial correlation the structure of the transformed error covariance matrix is quite compliated and its calculation involves formidable computational difficulties. We consequently decided to simply assume a diagonal covariance structure. The omission of serial correlation can be rationalized by the elaborate list of explanatory variables. The neglect of the correlation between ε_{iL} and $\overline{\varepsilon}_{iL}$ can only be explained as a rough approximation motivated by computational simplicity.

We chose instead to be relatively aggressive in our explicit incorporation of *a priori* information about the parameters. "Pitfalls" type models have an exceptionally rich detail that is capable of explaining and predicting a wide variety of phenomena. But they also require a great deal of parametric information, more than aggregate time series data alone can provide. The Smith-Brainard and Smith papers show that such estimates tend to be very sensitive to the sample data and cannot be reliably used for out-of-sample forecasts. There is a compelling need for auxiliary information from such sources as earlier studies, theory, and practical experience.

For each acquisition category, our supplementary information is of the form

$$(9) \qquad r_{iL} = I\beta_{iL} + U_{iL}$$

The covariance matrix for the prior errors is $\sigma^2_{U_{iL}} \Omega_L$ and is assumed to differ across acquisition categories by only a scale factor. Generalized least squares can then be straightforwardly applied to (8) and (9).

Table 5 displays our prior means and the mixed estimates. Since all bonds and equities are allocated to the wealth-constrained, the bond and equity rates and lagged asset stocks are omitted from the liquidity-constrained equations. In the aggregate, our prior information is little different from Backus-Purvis. Smith had a hand in constructing these priors, and we find them very reasonable. In addition, the use of similar values facilitates comparisons of our results with theirs.

The Backus-Purvis demand equations are derived from a generalized adjustment toward desired asset stocks. The derived flow demands depend upon those variables which influence target stocks (expected income, the rate of inflation, and nominal interest rates), the actual beginning of period asset stocks, and transitory income (which influences the adjustment but not the targets). Our prior means in Table 5 reflect the crude assumptions that the liquidity- and wealth-constrained groups have the same stock adjustment parameters, but that the liquidity-constrained asset targets depend only upon expected income. This roughly depicts the idea that the liquidity-constrained are at corner solutions. The prior means of the coefficients on transitory income were adjusted so that the liquidity-constrained spend most of any increase while the wealth-constrained mostly acquire liquid assets. Overall our prior means for the two groups are consistent with the Backus-Purvis means for the entire population.

The mixed estimates are given in Table 5. Overall, our results are similar to Backus-Purvis. For the wealth-constrained, all of the own rate responses and all but one of the diagonal elements of the adjustment matrix are correctly signed. There are some peculiarities among the cross effects and the off-diagonal elements, and for the liquidity-constrained. Our wealth-constrained prior means are the same as those of Backus-Purvis for the aggregate, and if anything our mixed estimates for the wealth-constrained sector may be slightly more reasonable than the Backus-Purvis aggregate estimates. There are also some interesting specific details of our results. Like Backus-Purvis we find that, contrary to the prior means, the wealth-constrained have a higher propensity to spend out of bonds than M3 . However we do find that the liquidity-constrained have a higher propensity to spend out of M3 than do the wealth-constrained. Happily, the liquidity-constrained also have a higher propensity to spend out of transitory income than do the wealth-constrained, though both estimates are less than our prior means. There is also no evidence in the mixed estimates that interest rates influence the liquidity-constrained.

One often interesting test of an estimated model is its out-of-sample forecasting ability. Table 7 reports a comparison with Backus-Purvis. There is really not much difference in our results. Since their accuracy was impressive, this is comforting. Still we would of course have preferred to find some improvement.

Summary

Partitioned micro data were used here to separate aggregate flow of funds data into liquidity- and wealth-constrained groups. This strategy appears quite useful in the estimation of simple consumption functions. In more elaborate models, the gains if any are less clear. Perhaps we were not completely successful in our partitioning of the many variables appearing in the more detailed model. Or it may be that this aggregate detail itself picks up most of the information in the partitioned data.

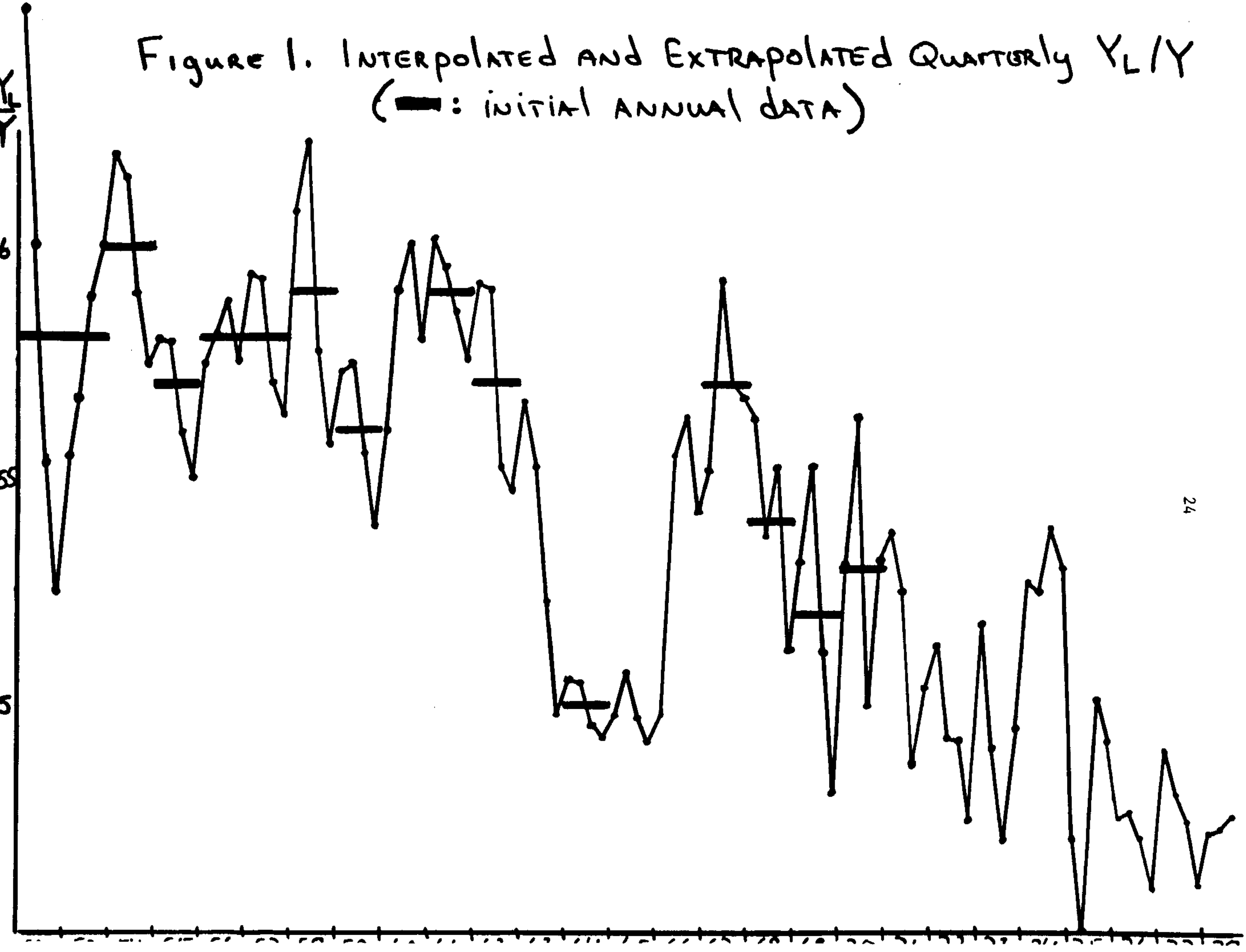

Figure 1. Interpolated and Extrapolated Quarterly Y_L/Y
(▬: initial annual data)

TABLE 2. Average Values for Logit Function Variables

Year	A25	A35	A45	A55	S1	S2	S9	ED1	ED2	EM1	EM2	EM3	INC	ACCT	IDB	HMR
1951	0.0523	0.2417	0.2393	0.2050	0.1372	0.3269	2.1360	0.4560	0.3887	0.0711	0.0821	0.0751	0.9182	0.2489	0.0330	0.0620
1952	0.1034	0.2474	0.2164	0.1821	0.2415	0.3029	1.8227	0.3973	0.4166	0.0805	0.0746	0.0807	0.9008	0.2745	----	0.1911
1953	0.0854	0.2301	0.2278	0.1809	0.2281	0.2899	1.9631	0.3848	0.4410	0.0895	0.0801	0.0954	0.8969	0.2622	----	0.2772
1954	0.0815	0.2563	0.2323	0.1760	0.2211	0.2816	2.0368	0.3517	0.4847	0.0738	0.0831	0.1359	0.8961	0.2868	0.0603	0.2781
1955	0.0933	0.2081	0.2345	0.1779	0.2278	0.3009	1.9302	0.3710	0.4424	0.0745	0.1056	0.1042	0.8925	0.2899	0.0620	0.2439
1956	0.1070	0.2263	0.2221	0.1796	0.1938	0.2932	2.0810	0.3437	0.4608	0.0726	0.0960	0.1058	0.8958	0.2642	0.0736	0.2991
1957	0.1015	0.2237	0.2395	0.1735	0.2394	0.2654	2.0696	0.3340	0.4513	0.0622	0.0848	0.1612	0.8857	0.2692	0.0681	0.2851
1958	0.0914	0.2045	0.2282	0.1785	0.2272	0.2846	1.9970	0.3413	0.4438	0.0759	0.1105	0.1339	0.9027	0.2688	0.0720	0.2918
1959	0.0808	0.2145	0.2234	0.2036	0.2172	0.2591	2.1267	0.3120	0.4549	0.0738	0.1033	0.1158	0.8963	0.3175	0.0654	0.3169
1961	0.1078	0.2122	0.2311	0.1825	0.2285	0.2490	2.2088	0.3054	0.4367	0.0586	0.1308	0.1386	0.8904	0.2964	0.0715	0.3528
1962	0.1177	0.1792	0.2094	0.1813	0.2261	0.2661	2.0853	0.2925	0.4690	0.0551	0.1317	0.1355	0.8934	0.2971	0.0770	0.3453
1964	0.0901	0.1910	0.2063	0.1946	0.1667	0.2775	2.2838	0.2928	0.3432	0.0991	0.1658	0.1216	0.8826	0.3339	0.0730	0.3456
1967	0.0654	0.1929	0.1815	0.1859	0.1826	0.2988	2.1306	0.2944	0.3373	0.0826	0.1381	0.1626	0.8937	0.1753	0.0767	0.2980
1968	0.0982	0.2058	0.1738	0.1667	0.1888	0.2940	2.1159	0.2664	0.3387	0.0662	0.1637	0.1606	0.8879	0.3308	0.0878	0.3039
1969	0.1145	0.1955	0.1915	0.1876	0.1644	0.3021	2.1688	0.2350	0.3514	0.0676	0.1204	0.1629	0.8977	0.3350	0.0737	0.3054
1970	0.0979	0.2016	0.1908	0.1869	0.1605	0.3258	2.0939	0.2573	0.3376	0.0656	0.1605	0.1419	0.9006	0.4209	0.0620	0.2897
SOFF	0.0347	0.1511	0.2173	0.2339	0.1159	0.2776	2.4965	0.2301	0.3967	0.1997	0.0833	0.0422	1.1003	0.5368	0.0542	0.4025

TABLE 3. Logit Functions

	All Variables		Without IDB	
A25	1.5644	(2.7877)	1.6649	(2.9792)
A35	1.0006	(3.8672)	1.0374	(4.0425)
A45	0.5688	(2.5092)	0.6130	(2.7291)
A55	0.2411	(1.1492)	0.2703	(1.2964)
S1	1.1611	(2.3485)	1.0841	(2.2070)
S2	0.5954	(1.2992)	0.5369	(1.1791)
S9	0.1490	(1.3968)	0.1323	(1.2487)
ED1	0.9610	(4.2822)	0.9666	(4.3290)
ED2	0.6676	(4.0190)	0.6746	(4.0928)
EM1	-0.1812	(-0.9692)	-0.2106	(-1.1337)
EM2	-0.6575	(-2.1012)	-0.7706	(-2.4692)
EM3	-0.6528	(-0.1324)	-0.1049	(-0.2620)
INCRATO	-1.0651	(-4.3000)	-1.0696	(-4.3314)
ACCT	-6.1872	(-13.822)	-6.4370	(-14.378)
IDB	2.5357	(3.4084)	----	----
HMR	-0.0399	(-0.3737)	-0.0005	(-0.0047)
CONSTANT	1.0178	(1.8463)	1.2440	(2.2760)

All Variables:
13% in-sample forecasting error
166 misclassified wealth-constrained
70 misclassified liquidity-constrained

Without IDB:
12% in-sample forecasting error
153 misclassified wealth-constrained
67 misclassified liquidity-constraine

TABLE 4. Logit Classification
% Wealth Constrained

End of Year	Households	Time and Savings Accounts	Durables Purchases	Installment Debt	Total Income
1951	29	92	37	11	42
1952	28	91	33	--	42
1953	29	90	30	--	42
1954	28	92	34	11	40
1955	31	93	32	11	43
1956	30	92	31	9	42
1957	28	92	37	11	42
1958	29	93	33	11	41
1959	32	93	36	15	44
1961	29	93	37	9	41
1962	32	93	37	13	43
1964	35	95	39	17	50
1967	33	99	32	15	43
1968	35	94	34	15	46
1969	36	94	41	16	48
1970	37	96	35	18	47

TABLE 5. Prior Means and Mixed Estimates for the Integrated Model

			1	π^e	Ln r_{M3}	Ln r_B	Ln r_E	Ln r_M	Ln r_L	$\frac{M3(-1)}{YE_i}$	$\frac{BOND(-1)}{YE_i}$	$\frac{EQ(-1)}{YE_i}$	$\frac{NM(-1)}{YE_i}$	$\frac{MORT(-1)}{YE_i}$	$\frac{LOAN(-1)}{YE_i}$	$\frac{Y_i - YE_i}{YE_i}$
$\frac{CON_i}{YE_i}$	L	Prior	None	.000	.000			.000	.000	.170			.040	.100	.150	.950
		Mixed	-.288	-.000	-.000			.000	.000	.149			.038	-.050	.019	.713
	W	Prior	None	.485	-.235	-.043	-.143	-.037	-.106	.170	.120	.090	.040	.100	.150	.400
		Mixed	.755	-.068	-.247	.036	.305	.063	.035	.066	.221	.016	.075	-.030	.162	.380
$\frac{\Delta M3_i}{YE_i}$	L	Prior	None	.000	.000			.000	.000	-.400			.050	.050	.080	.050
		Mixed	.059	-.000	.000			-.000	-.000	-.174			.038	.014	-.007	.056
	W	Prior	None	-.254	1.391	-.118	-.533	-.193	-.123	-.400	.080	.070	.050	.050	.080	.600
		Mixed	.038	.005	.152	.074	-.270	.047	-.241	-.002	.115	-.014	.059	.097	.138	.669
$\frac{\Delta BOND_i}{YE_i}$	L	Prior	None	.000	.000			.000	.000	.100			.010	.020	.020	.000
		Mixed	.031	.000	.000			-.000	-.000	.056			.027	.030	.009	-.066
	W	Prior	None	.076	-.424	.289	-.204	-.014	.010	.100	-.250	.040	.010	.020	.020	.200
		Mixed	-.298	-.015	-.102	.139	.029	-.086	.175	-.010	-.196	.016	.057	-.054	-.013	.137
$\frac{\Delta EQ_i}{YE_i}$	L	Prior	None	.000	.000			.000	.000	.060			.000	.010	.000	.000
		Mixed	1.336	-.000	-.000			.000	-.000	-.080			-.108	.011	-.024	276
	W	Prior	None	-.214	-.400	-.106	1.097	-.089	-.032	.060	.050	-.200	.000	.010	.000	.000
		Mixed	-.233	.051	.226	-.027	.251	-.101	-.041	-.074	-.260	.009	-.138	-.105	-.150	-.032
$\frac{\Delta NM_i}{YE_i}$	L	Prior	None	.000	.000			.000	.000	.000			-.100	.000	.000	.000
		Mixed	-.026	-.000	-.000			.000	-.000	.038			-.046	-.046	.017	.085
	W	Prior	None	.050	-.015	-.010	-.130	-.020	-.010	.000	.000	.000	-.100	.000	.000	.000
		Mixed	.490	-.005	-.063	-.054	-.502	.027	-.001	.022	.042	-.021	-.064	.057	.057	.098
$\frac{\Delta MORT_i}{YE_i}$	L	Prior	None	.000	.000			.000	.000	.020			.000	-.150	.000	.000
		Mixed	-.054	.000	-.000			-.000	.000	.006			.012	-.026	.053	.008
	W	Prior	None	-.096	-.098	-.010	-.054	.323	-.010	.020	.000	.000	.000	-.150	.000	.000
		Mixed	-.300	.007	-.035	-.051	.032	.127	-.001	.000	.028	-.003	.016	-.062	.042	-.013
$\frac{\Delta LOAN_i}{YE_i}$	L	Prior	None	.000	.000			.000	.000	.050			.000	-.030	-.250	.000
		Mixed	-.058	-.000	.000			.000	-.000	.005			.039	.067	-.067	-.072
	W	Prior	None	-.047	-.220	-.003	-.033	.030	.272	.050	.000	.000	.000	-.130	-.250	-.200
		Mixed	.082	.025	.069	-.117	.155	-.077	.074	-.002	.050	-.003	.002	.108	-.236	-.239

TABLE 6. Variable Definitions

CON	consumption expenditures on nondurables and services, durables and residential structures
M3	currency, demand deposits, time deposits, and savings accounts
BOND	U.S. securities except savings bonds, state and local government obligations, corporate and foreign bonds, and open market paper
EQUITY	corporate equity and investment company shares
NONMKT	"non-marketable" assets: life insurance reserves, pension fund reserves, savings bonds, and various miscellaneous assets
MORT	mortgage loans
LOAN	liabilities except mortgages (mostly consumer credit)
Y	current income, the sum of expenditures and net acquisitions of financial assets
YE	expected income, exponential trend on Y with serial correlation adjustment
r_{M3}	time deposit rate
r_B	bond rate
r_E	equity rate
r_M	mortgage rate
r_L	loan rate

TABLE 7. Mixed Estimates Root Mean Squared Errors

	In-Sample (1954-72) B-P	In-Sample (1954-72) K-S	Out-of-Sample (1973-75) B-P	Out-of-Sample (1973-75) K-S
END	2.04		6.94	
ED	1.06	3.16	5.83	32.30
EH	.59		7.14	
M3	2.61	2.41	21.66	12.34
BOND	2.27	2.11	6.52	12.26
EQ	.78	.84	1.49	1.50
NM	1.56	1.77	18.69	14.66
MORT	.62	.60	6.62	4.64
LOAN	2.06	2.30	7.77	11.97

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