NBER WORKING PAPER SERIES

DYNAMIC FACTOR MODELS OF CONSUMPTION, HOURS, AND INCOME

Joseph G. Altonji

Ana Paula Martins

Aloysius Siow

Working Paper No. 2155

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
February 1987

An earlier draft of this paper was presented at the meetings of the Econometric Society in New York, December 28th, 1985. We wish to thank Jonathan Friedman and Thomas Melito for excellent research assistance in the initial stages of the study. We also thank John Ham, Joe Hotz, John Kennan, participants in seminars at McMaster University, Princeton University, University of Toronto, University of Virginia, and participants at the conference of intertemporal choice organized by the Econometric Society and NORC for helpful comments. Altonji and Siow gratefully acknowledge research support from the National Science Foundation. The research reported here is part of the NBER's research program in Labor Studies. Any opinions expressed are those of the authors and not those of the National Bureau of Economic Research.

NBER Working Paper #2155
February 1987

Dynamic Factor Models of Consumption, Hours and Income

ABSTRACT

This paper addresses two questions. First, what are the key factors that affect a consumer's lifetime budget constraint and how do they evolve over the lifecycle? Second, how do consumers respond to changes in these factors? We examine the permanent income hypothesis and the Keynesian consumption model using a dynamic factor model of consumption, hours, wages, unemployment, and income. We show that a quarterly dynamic factor model with restrictions on the lag structure may be used with annual panel data to account for the fact that in many micro panel data sets the variables relevant to a study are measured at different time intervals and/or are aggregates for the calendar year. By using several income indicators we are able to extend the panel data studies of Hall and Mishkin and Bernanke to allow for measurement error. We are also able to study the response of income and consumption to some of the factors which determine them. In addition, we study a dynamic factor representation of a joint lifecycle model of consumption and labor supply. We provide estimates of the effect of wages, unemployment, and other income determinants on the marginal utility of income as well as estimates of the substitution effects of wage change on labor supply and consumption.

Joseph G. Altonji
Department of Economics
Northwestern University
Evanston, IL 60201

Ana Paula Martins
Department of Economics
Columbia University
New York, NY 10027

Aloysius Siow
Department of Economics
Columbia University
New York, NY 10027

INTRODUCTION

This paper addresses two longstanding questions in the economics of intertemporal choice. First, what are the key factors that affect a consumer's lifetime budget constraint and how do they evolve over the lifecycle? Second, how do consumers respond to changes in these factors?

These questions are closely related. First, the lifecycle model of consumer behavior treats work hours, which are a key determinant of income, as an endogenous variable. Consequently, as Ghez and Becker (1975) have emphasized, the model of consumer behavior is part of the income model. Second, even if one views the determinants of income as exogenous to the consumer, as in most empirical research using Friedman's (1957) permanent income model, the response of consumption to a change in the factors which drive income should depend upon consumer beliefs about the size and persistence of the changes.[1] The application of the rational expectations hypothesis to consumer behavior allows the econometrician to quantify consumer expectations after specifying an income model. The estimation of a dynamic model of income and its economic factors permits one to study the responses of consumers to expected and unexpected changes in these factors.

Despite these connections, substantial research on lifecycle models of consumption, income and labor supply has been conducted without explicitly modelling the behavior of wages, prices, and income.[2] However some questions cannot be answered without modelling the factors that determine the budget constraint facing the individual. If we want to estimate the response of consumption and labor supply to changes in the marginal utility of income induced by a typical wage, price or unemployment shock within the lifecycle context, we need to model these processes. Little empirical research on these consumption and labor supply responses has been conducted.

A few studies of the rational expectations-permanent income model have estimated a joint model of consumption and income. In a path-breaking paper, Sargent (1978) use aggregate time series data to estimate a rational expectations permanent income model. The innovative panel data studies of Hall and Mishkin (1982) and Bernanke (1984) also estimated income and consumption jointly. In order to identify the response of consumption to permanent and transitory income changes, they had to impose tight restrictions on the form of the income process. In particular, they had to assume that income is measured without error. The assumption of no measurement error is strong, as Hall and Mishkin recognized, since many of the variables in panel data are widely believed to contain substantial measurement error.[3] Unfortunately, inferences about consumer responses to income innovations are likely to be sensitive to misspecification of the income process.

In this paper, we examine the permanent income hypothesis using a richer model of the income process. Many micro data sets contain some measures of income determinants, such as wage rates, hours worked, and hours of unemployment. These determinants provide leverage in estimating models of consumption and income while allowing for measurement error in income.[4] Furthermore, use of indicators of the determinants of income makes it possible to identify some of the economic factors that drive income.[5] Our analysis of the income process builds upon earlier work and is of independent interest.[6]

In addition, we estimate a lifecycle model of consumption and labor supply. We focus on estimating the effects of wages, unemployment, and other income determinants on the marginal utility of income. We also provide new estimates of the intertemporal substitution effects of wage changes on labor supply.

Our econometric models are vector moving average representations of the consumption, hours, wages, unemployment, and income processes. The theoretical models place restrictions on the autocovariances and cross covariances of these variables. We estimate a model's parameters by fitting the theoretical covariances of the model to sample covariances that are estimated from data using minimum distance estimators (Chamberlain (1984), Hansen (1982)). The data are from the Panel Study of Income Dynamics (PSID).

In conducting the empirical analysis, we pay special attention to four econometric issues concerning model specification. First, we experiment with different assumptions about measurement error. Second, we also provide tests of a number of the restrictions embodied in our models.

Third, we attempt to account for the fact that in many micro panel data sets, including the PSID, the variables relevant to a study are measured at different time intervals and/or are aggregates for the calendar year. For example, in the PSID, individuals are interviewed at yearly intervals. The consumption measure and the hourly wage measure refer to the time of the survey (typically in March) while family income and hours unemployed refer to the calendar year which precedes the survey date. This non-syncronization and time aggregation of the relevant variables is an important problem for estimating and testing the permanent income and lifecycle models. We show how quarterly dynamic factor models can be restricted with polynomial distributed lag structures to cope with this problem.

A fourth set of issues arises because the conventional Chi-square tests largely reject the hypothesis that the data are covariance stationary. That is, the tests reject the hypothesis that the covariances are the same for each year. This finding is typical of previous studies of income (see, for example, Hause (1980), Kearl (1985), Abowd and Card (1986)). The finding poses a potential problem because the structural models may be unidentified if the non-stationarity cannot be easily parameterized. For our sample, when we allowed for simple parameterizations of non-stationarity of the data or when we used dummy variables for specific moments to control for the strongest departure from stationarity, we obtained estimates of the structural parameters which do not differ much from those where we made no allowance for non-stationarity. We also provide evidence that the rejection of stationarity may be due partly to imprecision in our estimate of the fourth moment matrix of the data, which is used for both inference and efficient estimation.

Our main substantive findings are the following.

1. Changes in consumption, hours, income, wages, and unemployment are not normally distributed. Inference based on the assumption of normality, which is imposed in a number of previous studies, is likely to overstate the precision of the estimates. Even with our sample size, 1051 individuals, it is difficult to obtain precise estimates of structural dynamic factor models using the PSID data.

2. In general, the zero restrictions implied by the permanent income model on the covariance structure of the data are not rejected. There is some evidence, although quantitatively small, that lagged unemployment and income factors affect the change in consumption when we estimate the model without transforming the data. After transforming the data into logs, there is no evidence that lagged factors affect the change in consumption[7]. We interpret this lack of robustness and the quantitative magnitudes involved as supportive of the permanent income hypothesis.

3. There is substantial measurement error in measured income in all our models (45% - 75% of the variance of the change in measured income). The lower estimates are based on models that account for non-syncronization in the data. We are less successful in obtaining precise estimates of measurement

error in measured wages and work hours. A number of our point estimates are negative. We find only weak evidence against the hypothesis that measurement error is white noise.

4. After accounting for measurement error in measured income, innovations in the wage, unemployment and work hours explain surprisingly little of the remaining variance in the change in family income. This lack of explanatory power is consistent with results which we obtain using regression techniques to describe the data. However the result still suggests misspecification of the income model. When we account for non-syncronization in the data, the explanatory power of the economic variables determining income improves.

5. We could not get a precise estimate of the discount factor used by consumers to discount their projected income flows. Estimates range from -.04 to 1.6. The more reasonable point estimates are obtained after accounting for non-sycronization in the data. The imprecision may be attributed to the lack of precision in our estimates of the consumption response to unemployment and work hours innovations, and in our estimates of the response of income to lagged innovations in wages and income, and possible misspecification of the income process. We obtained estimates of the marginal propensity to consume food out of permanent income in the range of .036 to .067. We had similar difficulties getting a precise estimate of the discount factor with the Hall and Mishkin model.

6. The Keynesian model was consistently rejected by the data.

7. We show that it is feasible to estimate quarterly models of intertemporal choice with non-syncronized annual panel data by restricting the quarterly lag structures to polynomial functions.

8. We find that the zero restrictions implied by the lifecycle model are not rejected. However, we obtain a small and imprecise negative estimate of the intertemporal labor supply elasticity. We also obtain a small and imprecise negative estimate of the cross substitution elasticity. This suggests that consumption and leisure are complements. However, the null hypothesis of intra period separability of consumption and leisure cannot be rejected.

9. We provide an estimate of the total variance of the innovation in the marginal utility of income. Wage and unemployment innovations together explain over 40% of the total variance. Wage innovations are responsible for most of this variance.

The paper proceeds as follows. Section 1 provides an overview of the dynamic factor models studied in the paper. Section 2 discusses our specification of the permanent income model and the Keynesian model. Section 3 presents a methodology for taking account of time aggregation and nonsynchronization in estimating such models. Section 4 discusses estimation methods and the data. In Section 5 we discuss the estimates of the covariance stationary model, the properties of the income process, and estimates of the permanent income and the Keynesian consumption models. Sections 6 and 7 present a dynamic factor specification of the lifecycle model and a set of results. We provide a research agenda in Section 8.

1. DYNAMIC FACTOR MODELS OF CONSUMPTION, INCOME AND HOURS: AN OVERVIEW

This paper estimates various dynamic factor models of consumption, income and hours. We use the real wage and unemployment as additional indicators of factors which drive these variables.[8] Throughout the paper, Δ is the first difference operator, C_t is consumption at t, Y_t is real family income at t, W_t is the real wage at t, Z_t is annual hours of unemployment at t for the head of household, and N_t is the head's annual work hours at t. For notational convenience, subscripts for individuals are left implicit. For X=C,W,Y,Z, and N, X^*_t is the measure of X_t at t. We estimate models using first differences of the levels of the variables and models using first differences of the logs of the variables (we note one exception to this when the case arises). In analyzing the RE-lifecycle model, we replace Y_t with labor earnings of the head of household Y^n_t. For convenience, when it does not cause confusion, we refer to the first difference of the variable as the variable itself.

We analyse consumption, hours and income using various dynamic factor models that are nested in the following general model:

A General Dynamic Factor Model of Consumption, Income and Hours

General Consumption Model (ΔC^*_t):

(1.1a) $$\Delta C^*_t = \beta_{cw0}u_{wt} + \beta_{cw1}u_{wt-1} + \beta_{cw2}u_{wt-2} + \beta_{cz0}u_{zt} + \beta_{cz1}u_{zt-1} + \beta_{cz2}u_{zt-2} + \beta_{cn0}u_{nt} + \beta_{cn1}u_{nt-1} + \beta_{cn2}u_{nt-2} + \beta_{cy0}u_{yt} + \beta_{cy1}u_{yt-1} + \beta_{cy2}u_{yt-2} + \beta_{cc0}u_{ct} + \beta_{cc1}u_{ct-1} + \beta_{cc2}u_{ct-2}$$

General Income Model

Income Equation (ΔY^*_t):

(1.1b) $$\Delta Y^*_t = \beta_{yw0}u_{wt} + \beta_{yw1}u_{wt-1} + \beta_{yw2}u_{wt-2} + \beta_{yz0}u_{zt} + \beta_{yz1}u_{zt-1} + \beta_{yz2}u_{zt-2} + \beta_{yn0}u_{nt} + \beta_{yn1}u_{nt-1} + \beta_{yn2}u_{nt-2} + \beta_{yy0}u_{yt} + \beta_{yy1}u_{yt-1} + \beta_{yy2}u_{yt-2} + \Delta\varepsilon_{yt}$$

Annual Work Hours Equation (ΔN^*_t):

(1.1c) $$\Delta N^*_t = \beta_{nw0}u_{wt} + \beta_{nw1}u_{wt-1} + \beta_{nw2}u_{wt-2} + \beta_{nz0}u_{zt} + \beta_{nz1}u_{zt-1} + \beta_{nz2}u_{zt-2} + \beta_{nn0}u_{nt} + \beta_{nn1}u_{nt-1} + \beta_{nn2}u_{nt-2} + \beta_{ny0}u_{yt} + \beta_{ny1}u_{yt-1} + \beta_{ny2}u_{yt-2} + \Delta\varepsilon_{nt}$$

Wage Equation (ΔW^*_t):

(1.1d) $\Delta W^*_t = \beta_{ww0}u_{wt} + \beta_{ww1}u_{wt-1} + \beta_{ww2}u_{wt-2} + \Delta\varepsilon_{wt}$

Unemployment Equation (ΔZ^*_t):

(1.1e) $\Delta Z^*_t = \beta_{zz0}u_{zt} + \beta_{zz1}u_{zt-1} + \beta_{zz2}u_{zt-2}$

The factors u_{ct}, u_{wt}, u_{zt}, u_{nt}, and u_{yt} are assumed to have the following properties:

$\mathrm{Var}(u_{it}) = 1$ $i=c,y,w,z,n$ (Normalization of the variances to 1)

$\mathrm{Cov}(u_{it},u_{it-k}) = 0$, $i=c,y,w,z,n$; $k \neq 0$ (No serial correlation)

$\mathrm{Cov}(u_{it},u_{jt-k}) = 0$, $i \neq j$; for all k (factors have 0 cross covariances)

The measurement error (ME) components have the properties.

$\mathrm{Var}(\varepsilon_{it}) = \sigma_i^2$ $i=y,w,n$

$\mathrm{Cov}(\varepsilon_{it},\varepsilon_{it-k}) = 0$ $i=y,w,n$; $k \neq 0$ (No serial correlation in ME)

$\mathrm{Cov}(\varepsilon_{it},\varepsilon_{jt}) = 0$ $i \neq j$, (ME are unrelated)

$\mathrm{Cov}(\varepsilon_{it},u_{jt-k}) = 0$ for all i,j,k. (ME are unrelated to true variables)

The β_{ijk} are the response coefficients or "factor loading" relating the variable i to factor j lagged k periods. For example, β_{yw1} is the response of income to the wage factor u_{wt-1}. We restrict the analysis to second order vector moving average (MA) models because autocovariances and cross covariances among the variables are very small after two lags. We work with a dynamic factor framework rather than a VAR regression model for ΔC^*_t, ΔY^*_t, ΔW^*_t, ΔZ^*_t and ΔN^*_t in part because it is very difficult to accomodate measurement error in the latter framework.

Equations (1.1d) and (1.1e) specify that wages ΔW^*_t and unemployment ΔZ^*_t are autonomous processes that are driven only by their own factors. The zero correlation between wages and unemployment implied by this assumption is tested below. We use the same equations for wages and unemployment in all of our empirical models.

Equation (1.1a) specifies that consumption ΔC^*_t depends on the current and lagged wage, unemployment, hours of work, and income factors. We also include current and lagged values of an independent consumption factor u_{ct} that captures consumption shocks unrelated to the rest of the model and also measurement error in consumption. Equations (1.1b) and (1.1c)) specify that income ΔY^*_t and hours ΔN^*_t depend on the current and lagged wage, unemployment, hours, and income factors. Different economic models of consumption, income and hours imply different restrictions on the factor loadings in the consumption, income and hours equations.

The general model also allows for serially uncorrelated measurement errors ε_{yt}, ε_{wt}, and ε_{nt} in the measures Y^*_t, W^*_t and N^*_t of the variables Y_t, W_t, and N_t. In specific cases, we also experiment with models in which ε_{yt}, ε_{wt} and ε_{nt} are first order moving average measurement errors.

The above model cannot be estimated with our data. Instead we consider smaller models whose restrictions are implied by various economic models of consumption and hours. For each economic model, we first test the zero restrictions implied by the theory against a model which imposes only covariance stationarity on the data. Then we estimate the economic model, test the overidentifying restrictions against larger factor models and also models which only impose covariance stationarity, and evaluate the parameter estimates. Without futher ado we turn to the permanent income and the Keynesian models.

2. THE RATIONAL EXPECTATIONS-PERMANENT INCOME AND KEYNESIAN MODELS

The starting point for the rational expectations permanent income (RE-PI) model is the consumption change equation:

$$(2.1)\quad \Delta C_t \equiv C_t - C_{t-1} = \Delta y^p{}_t \equiv (1 - \rho) \sum_{i=0}^{\infty} \rho^i (E_t - E_{t-1}) Y_{t+i}$$

$C_t \equiv$ consumption at time t

$\rho \equiv$ constant discount factor = $(1 + \text{interest rate})^{-1}$

$E_t \equiv$ expectation operator conditional on information available at t

$Y_t \equiv$ income of individual at t

$y^p{}_t \equiv$ permanent income conditional on information at t

Equation (2.1) states that the change in consumption of an individual is directly proportional to the change in permanent income. This equation can be derived rigorously from utility maximization (Hall (1978), Hall and Mishkin (1982)) only under very strong assumptions about the utility function, the behavior of unobserved preference shifters over time, and uncertainty about wages, nonlabor income, and interest rates. We prefer to interpret equation (2.1) as an approximation or as a basic assumption about behavior (as in Sargent (1978) and Flavin (1981)). Equation (2.1) is invalid if substitution effects of wage changes and interest rate movements are important for consumption.

For empirical work, equation (2.1) must be modified in two ways. The first modification is needed because the principal consumption measure in our data set is family expenditure on food. The marginal propensity to consume food out of permanent income is not unity. The second modification is to allow for preference related transitory consumption changes and measurement error in the consumption data, which we assume to follow a moving average process. (In this paper, measurement error in consumption is not identified separately from transitory consumption.) We also assume that the measurement error in consumption is uncorrelated with the other variables used in our study. With these two modifications, measured consumption is related to permanent income by:

(2.2) $C_t^* = \alpha(1-\rho)y^P_t + u_{ct} + \lambda u_{ct-1}$

$\alpha \equiv$ marginal propensity for food consumption

$u_{ct} \equiv$ transitory consumption and measurement error.

Substitution of equation (2.1) into (2.2) yields:

(2.3) $\Delta C^*_t = \alpha(1-\rho)\sum_{i=0}^{\infty}\rho^i\,(E_t - E_{t-1})Y_{t+i} + u_{ct} + (\lambda-1)u_{ct-1} - \lambda u_{ct-2}$

Equation (2.3) cannot be estimated directly because the revision in expected wealth is unobserved. Therefore the RE-PI model can be estimated only by adding a model for income.

Within both the RE-PI model and the Keynesian model, labor supply and family income are determined independently of consumption. Consequently, to analyze these models, we restrict the hours equation of the general income model in (1.1c) as follows

<u>Exogenous Work Hours Equation</u> (ΔN^*_t):

(1.1c') $\Delta N^*_t = \beta_{nn0}u_{nt} + \beta_{nn1}u_{nt-1} + \beta_{nn2}u_{nt-2} + \beta_{nz0}u_{zt} + \beta_{nz1}u_{zt-1}$
$+ \beta_{nz2}u_{zt-2} + \Delta\varepsilon_{nt}$

We will refer to the income model consisting of equation (1.1c') for hours and equations (1.1b, 1.1d, 1.1e) for income, wages and unemployment as the "income model with exogenous hours". The only difference between the above income model and the general income model is that the current and lagged values of the wage factor u_{wt} and the income factor u_{yt} are not included in the hours equation (1.1c'). These zero restrictions will be tested.

Given the above income model, the RE-PI consumption model implies two sets of restrictions on the general consumption equation (1.1a). First, it implies that the change in consumption only depends on the contemporaneous factors affecting income: u_{wt}, u_{zt}, u_{nt}, and u_{yt}. This implies the following consumption equation:

RE-PI Consumption Equation (ΔC^*_t):

$$\Delta C^*_t = \beta_{cw0}u_{wt} + \beta_{cz0}u_{zt} + \beta_{cn0}u_{nt} + \beta_{cy0}u_{yt} + \beta_{cc0}u_{ct} + \beta_{cc1}u_{ct-1} + \beta_{cc2}u_{ct-2} \tag{2.4}$$

The second set of restrictions involve the factor loadings β_{cw0}, β_{cz0}, β_{cn0}, and β_{cy0}. Equation (2.3), which defines the optimal consumption response, and equation (1.b) for the income process imply that β_{cw0}, β_{cz0}, β_{cn0}, and β_{cy0} must satisfy

$$\beta_{cj0} = \alpha\ (\beta_{yj0} + \rho\beta_{yj1} + \rho^2\beta_{yj2}) \qquad j=w,z,n,y \tag{2.5}$$

The marginal propensity to consume, α, and the discount rate, ρ, are determined by the four equations in (2.5) and are overidentified.

An advantage of using dynamic factor models of income with multiple indicators is that various factors are allowed to have different effects on income, and consequently should have different effects on consumption. For example, if the estimates of the equations of the income process indicates that unemployment has only a temporary effect on income, then the RE-PI model implies that unemployment has only a small effect on consumption. Since the parameters α and ρ are overidentified, one may test whether the response of consumption to particular factors affecting income is consistent with the permanent income model. It is also clear that one can only hope to get valid estimates α and ρ if the income model is correctly specified. Here again, the use of multiple indicators is an advantage because some of the factors determining income are now identified with observable quantities (e.g. the wage factor), and we can use apriori information to judge how reasonable the estimated income model is.

An alternative to the RE-PI model is the Keynesian model of consumption. We can use the same income process as specified in (1.1b). The consumption change equation must be respecified as:

$$(2.6) \qquad \Delta C^*_t = \alpha \Delta Y_t + \text{transitory consumption}$$

The dynamic factor specification for the Keynesian consumption function is

$$(2.4') \qquad \Delta C^*_t = \alpha \; (\beta_{yw0}u_{wt} + \beta_{yw1}u_{wt-1} + \beta_{yw2}u_{wt-2} + \beta_{yz0}u_{zt} + \beta_{yz1}u_{zt-1} + \beta_{yz2}u_{zt-2} + \beta_{yn0}u_{nt} + \beta_{yn1}u_{nt-1} + \beta_{yn2}u_{nt-2} + \beta_{yy0}u_{yt} + \beta_{yy1}u_{yt-1} + \beta_{yy2}u_{yt-2}) + \beta_{cc0}u_{ct} + \beta_{cc1}u_{ct-1} + \beta_{cc2}u_{ct-2}$$

where u_{ct} and its lags reflect both variation in consumption preferences and measurement error in consumption. The Keynesian model also implies strong restrictions on the covariances between consumption and the other variables in the model. While the Keynesian model and the RE-PI model are not nested models, they are both nested in the model consisting of the general consumption model (1.1a) and the income model with exogenous hours (1.1b, 1.1c', 1.1d, 1.1e).

We estimate the general consumption equation, the RE-PI equation, and the Keynesian equation using the first differences of the levels (actual values) of the variables. To facilitate comparison to our analysis of the lifecycle consumption and labor supply model below, we also estimate the general consumption equation and the Keynesian equation using the changes in the logs of the variables. Unfortunately, the RE-PI restrictions on the response of consumption to the innovations in the log linear income process are extremely complicated and involve family wealth. Consequently, it does not appear to be feasible to estimate the RE-PI model with a loglinear income process.

3. TIME AGGREGATION AND NONSYNCHRONOUS MEASUREMENTS: THE QUARTERLY DYNAMIC FACTOR MODEL

In many micro panel data sets, the variables relevant to a study may be measured at different time intervals. For example, in the PSID, individuals are interviewed at yearly intervals. The consumption measure and the hourly wage measure refer to the time of the survey (typically in March or April) while family income and hours unemployed refer to the calendar year which precedes the survey date. This poses a problem because the inconsistency of the timing may weaken the relationship between the change in family income and the change in the wage. Futhermore, the differences in the timing of the consumption, wage, income, and unemployment variables may affect the estimates of the relative response of consumption to the various factors which drive income, particularly since consumption should not respond to lagged income innovations if the RE-PI is correct. Since the consumption change is measured a few months after the income change measure, part of u_{yt} may be past information. Consequently, estimates of the response of consumption to the income factor u_{yt} may be understated. (Many tests of the RE-PI model hinge on the issue of timing of information about income. See the surveys by Hayashi (1985a) and King(1985)). In addition, the use of annual values rather then the unavailable quarterly values may cause problems.

Hall and Mishkin (1982) recognized the problem of nonsynchronization in their data and they made adjustments within the annual framework of their model to deal with the problem. However their approach is difficult to generalize to other models. First, the adjustments that should be made to a particular annual model may not be obvious. Second, modifications of an annual model may imply unreasonable restrictions on the underlying quarterly model.[9]

We treat the problems of nonsynchronous timing and time aggregation by specifying quarterly dynamic factor series models for the determinants of consumption and income, and aggregating where this is appropriate. Given the inherent data limitations, we impose Almon (1962) polynomial distributed lag structures on the coefficients of the quarterly dynamic factor models.

Our model is as follows. Let

$$
\begin{aligned}
(3.1)\quad W_{t.i} - W_{t.i-1} &= \textstyle\sum_{j=0}^{7} \beta_{wwj} u_{wt.i-j} \\
Z_{t.i} - Z_{t.i-1} &= \textstyle\sum_{j=0}^{7} \beta_{zzj} u_{zt.i-j} \\
N_{t.i} - N_{t.i-1} &= \textstyle\sum_{j=0}^{7} (\beta_{nzj} u_{zt.i-j} + \beta_{nnj} u_{nt.i-j}) \\
Y_{t.i} - Y_{t.i-1} &= \textstyle\sum_{j=0}^{7} (\beta_{ywj} u_{wt.i-j} + \beta_{yzj} u_{zt.i-j} + \beta_{ynj} u_{nt.i-j} + b_{yyj} u_{yt.i-j}) \\
C_{t.i} - C_{t.i-1} &= \beta_{cw0} u_{wt.i} + \beta_{cz0} u_{zt.i} + \beta_{cn0} u_{nt.i} + \beta_{cy0} u_{yt.i}
\end{aligned}
$$

where

$W_{t.i} \equiv$ Wage rate in the i'th quarter of year t

$Z_{t.i} \equiv$ Hours of unemployment in the i'th quarter of year t

$N_{t.i} \equiv$ Work Hours in the i'th quarter of year t

$Y_{t.i} \equiv$ Income in the i'th quarter of year t

$C_{t.i} \equiv$ Food consumption in the i'th quarter of year t.

In the model above, the data are generated at a quarterly rate (i runs from 1 to 4). For example, the difference of Z in the i'th quarter of year t from Z in the i-1'st quarter of year t is a seventh order moving average process (a two year process). At the risk of some confusion, the time subscript t.i-j refers to the observation j quarters prior to the i'th quarter of year t. Thus, t-1.i and t.i-4 both refer to the i'th quarter of year t-1.

The RE-PI model, using (2.3) and (3.1), implies

(3.2) $\beta_{ck0} = \alpha\sum_{j=0}^{7} \rho_q{}^j\beta_{ykj}$; k=w,z,n,y

$\rho_q \equiv$ quarterly discount factor.

Note that our specification of the quarterly RE-PI consumption equation and the associated income model is analogous to our annual specification. If quarterly data are available to the econometrician, then the model in (3.1) can be estimated directly. However the data are only available at annual intervals, and Z^*_t, N^*_t and

Y^*_t are annual averages:

(3.3)
$$W^*_t - W^*_{t-1} \equiv W_{t.1} - W_{t-1.1} + \Delta\varepsilon_{wt}$$
$$Z^*_t - Z^*_{t-1} \equiv \sum_{i=1}^{4}(Z_{t-1.i} - Z_{t-2.i})$$
$$N^*_t - N^*_{t-1} \equiv \sum_{i=1}^{4}(N_{t-1.i} - N_{t-2.i}) + \Delta\varepsilon_{nt}$$
$$Y^*_t - Y^*_{t-1} \equiv \sum_{i=1}^{4}(Y_{t-1.i} - Y_{t-2.i}) + \Delta\varepsilon_{yt}$$
$$C^*_t - C^*_{t-1} \equiv C_{t.1} - C_{t-1.1} + \beta_{cc0}u_{ct} + \beta_{cc1}u_{ct-1} + \beta_{cc2}u_{ct-2}$$

For the PSID data, W^*_t is the reported wage rate at the time of the survey (typically March or April), which we approximate as the first quarter wage. Z^*_t is the reported total hours of unemployment in the calendar year preceding the survey date. N^*_t is total work hours on the main job in the calendar year preceding the survey. Y^*_t is reported total annual income in the calendar year preceding the survey date. C^*_t is the annual rate of food consumption reported in the week of the survey, which we interpret as the rate of consumption for the first quarter.

Given the available data (i.e. data as defined in (3.3)), we cannot hope to recover all the parameters of the model in (3.1). Our strategy is to restrict the lag structures in (3.1) to polynomial functions. In particular we impose:

(3.4) $$\beta_{ijk} = a_{0ij} + a_{1ij}k + a_{2ij}k^2$$

ij=ww,zz,nz,nn,yw,yz,yy; k=0,1,2,3,4,5,6,7

We have reduced the number of free parameters, 8, in each of the quarterly moving averages to 3 parameters. If we have three years of consecutive data as defined in (3.3), then the model of (3.1) as restricted by (3.2) and (3.4) can be estimated. The differences in timing and aggregation of the different variables help identify the quarterly lag structure from annual observations. The model implies that several of covariances at 3 year lags will be nonzero, and so we add the relevant moments to the set of sample moments used in estimation.

4. DATA AND ECONOMETRIC METHODOLOGY

The structural parameters of the models are estimated by fitting the theoretical auto-covariances and cross-covariances implied by the models to the corresponding sample moments of the variables. Chamberlain (1984) contains a comprehensive discussion of these estimators.[10]

The estimation procedure minimizes a quadratic form

$$(S-\Sigma(\Pi))'\Omega(S-\Sigma(\Pi))$$

where S is the vector of distinct sample covariance elements, $\Sigma(\Pi)$ is the vector of predicted covariance elements, considered as a function of the vector of parameters Π (e.g. β_{ijk}'s and σ_i's in (1.2)). Ω is the identity matrix in the case of unweighted least squares estimates, and a consistent estimate of the inverse of the fourth moment matrix of the underlying data in the case of optimal minimum distance estimates (OMD). In practice, we follow a number of previous studies and use the inverse of the empirical fourth moment matrix of the underlying data, V, when computing OMD estimates. The unweighted least squares case amounts to running a nonlinear regression of the individual sample covariances in S against the elements of $\Sigma(\Pi)$. The optimal minimum distance estimator (OMD) is analogous to fitting this relationship by generalized least squares.

We use the OMD estimator rather than maximum likelihood under the assumption of normality, which was used by Hall and Mishkin and Bernanke. We do so because our preliminary data analysis, for both levels and logs, indicated that the data are non-normal. Specifically, we calculated the Kolmogorov-Smirnov test statistic for the null hypothesis of normality for each variable in each year (e.g. ΔC_{1979}). The null hypothesis was rejected in every case at a marginal significance level less than .01. We also found that the empirical fourth moment of a given variable, x_t, varies from 1.5 to 10 times larger than $3*(var(x_t))^2$ even though these quantitites should be approximately equal if x_t is normally distributed.

Unfortunately, there are also drawbacks to the OMD estimator. In particular, we will present evidence that, for our problem, the sample estimate V of the fourth moment matrix is imprecise. Furthermore, sampling error in the fourth moments is likely to be correlated with sampling error in the second moments. If this is true, it may be preferable to use a simpler weighting scheme to estimate the models than the full GLS transformation used in the OMD case. For this reason, we also estimate our models with the diagonal elements of Ω set to the inverse of the average of the diagonal elements of V corresponding to a given type of covariance (e.g., the variance of the income change, the covariance of the wage change with the consumption change, etc.).[11] In this case all off diagonal elements of Ω are set to 0. This amounts to fitting the model by a form of weighted least squares, which hereafter we will refer to as WLS. The average of the estimated fourth moments for the various years corresponding to each of the moments in equation (2.9) is used as the weight for the particular moments.

Chamberlain shows how tests of parameter restrictions can be conducted when the OMD estimator is used. Let $E(S) = \Sigma(\Pi)$, where the vector Π has dimension K. Suppose restrictions on $\Sigma(\Pi)$ imply $E(S) = G(\ell)$ where the vector ℓ has dimension $L < K$. Then if the restrictions hold, $d_1 - d_2 \dashrightarrow \chi^2(K-L)$, where

$$d_2 = m(S - \Sigma(\Pi))'A(S - \Sigma(\Pi))$$

$$d_1 = m(S - G(\ell))'A(S - G(\ell))$$

m is the number of observations,

where A is set to V^{-1}. Newey (1985) provides a goodness of fit test which is valid when WLS rather than OMD is used.

The least restricted model that can be estimated is the non-stationary model in which each moment in S is given its own parameter. In this case $\Sigma(\Pi)$ and S have the same dimension. All covariance stationary models which we experimented with are overwhelmingly rejected against this model.

As a second bench mark, and to provide a convenient data summary, we also use the covariance stationary model

Covariance Stationary Model

(4.1) $\quad \text{Cov}\ (\Delta I^*_t, \Delta M^*_{t+j}) = \theta_{IMj} \qquad I,M = C,Y,W,Z,N; \quad j=-2,-1,0,1,2.$

We use the covariance stationary model as a second bench mark against which to judge the fit of the structural models, for two related reasons. First, tests based upon the test statistic above using the empirical fourth moment matrix to form the χ^2 statistic indicate that the data are non-stationary in the covariances. Therefore our various economic models will be rejected just due to the fact that they are stationary models. Second, there are indications that the fourth moment matrix may be too imprecisely estimated to permit reliable tests of the restricted models against the nonstationary model using the test procedure discussed above. We conducted the following experiment to get a sense of whether the imprecision in our estimate of the fourth moments may have an effect on tests of stationarity.

For the data in the levels, we randomly divided our sample of 1051 individuals into two subsamples, A and B. Consequently, the sample moments for the two subsamples have the same distribution. For the two subsamples, we calculated two separate fourth moment matrices, V_A and V_B, for use as an estimate of the variance of the second moments for the subsample. We used them to test the hypothesis that the expectations of the second moments of our subsamples are equal, without imposing stationarity across years. The test statistic indicated rejection of this hypothesis, which is true by construction, at the .003 level. In contrast, when we used the fourth moment matrix from the full sample to form the V matrix for both subsamples, the hypothesis that the subsamples have the same second moments easily passes.

Furthermore, when we used the common V matrix estimated from the full sample to compute OMD estimates of separate stationary models from the moments in the two subsamples, the χ^2 statistic with 314 degrees of freedom to test stationarity is 440.3. When we use V_A and V_B, the corresponding χ^2 statistic is 570.9. We conclude that the estimates of the fourth moments may have a substantial effect on the test statistic for stationarity. The results for the data in logs were similar although the discrepancies were less dramatic. Of course, these findings do not provide a clear indication of whether the problems which arise when the same sample of 526 observations is used to compute both the second moments and V carry over to a sample of 1051. But in view of these results, it seems sensible to also judge the performance of our structural models against the covariance stationary model.

Our use of stationary structural models in the face of evidence of nonstationarity raises the possibility of inconsistency in the estimates of the parameters of income and consumption equations. We checked this in several ways. First, we estimated models in which the variance of u_{ct}, u_{yt}, u_{nt}, u_{zt}, and u_{wt} were permitted to depend on a common year specific scalar. This typically resulted in a significant improvement in the fit of the models (although the modified models were also overwhelmingly rejected against the unrestricted nonstationary model). However, the response coefficients of the income equations and the consumption equation did not change very much. We experimented with other ways of introducing nonstationarity into the dynamic factor models, with little change in the estimates of the income and consumption equations despite improvements in the fit of the model.

Second, we introduced dummy variables for the moments for which there was a significant departure (at the .05 level) from stationarity. This is analogous to excluding these moments from the analysis. We identified these moments using a step-wise regression procedure to estimate the stationary model. The procedure resulted in the introduction of dummy variables for about 6 percent of the moments. The fit of the dynamic factor models generally improved to the point where they cannot be rejected against the unrestricted nonstationary model. More importantly, the parameters of the consumption and income equation are basically similar to those which we report below. Our findings are consistent with those of Kearl (1985) and Hause (1980), who found that relaxing stationarity improved the fit of their models of labor earnings but had little effect on key parameters.

Consequently, we have evidence that our inferences about the form of the income process and the consumption equation are valid despite the fact that the stationary dynamic factor models are rejected against the nonstationary model.

Our reported standard errors of the parameter estimates are based on a modification of the formula provided in Chamberlain (1984). Chamberlain's formula is valid under the assumption that the discrepancy between the fitted covariances and the sample covariances arise only from sampling error in the covariances. Since the χ^2 goodness of fit tests discussed below indicate model misspecification, it seemed appropriate to scale the standard errors up by a factor equal to the square root of the mean square error of the estimated residuals of the models. The formula in Chamberlain assumes that the mean square error of the estimated residuals for the OMD estimator is one. It leads to standard error estimates for the model parameters which typically are about one third smaller than the ones we report. To make our standard error estimates comparable to those of other studies (e.g., Abowd and Card (1985, 1986), one may divide them by the square root of the mean square error reported in the Tables. We are, of course, on shaky ground in performing statistical inference in the presence of model misspecification. This is one reason to prefer the conservative standard errors which we report.

Data

For most of the analysis the data are from the 1976-1981 Panel Study of Income Dynamics individuals tape (See Survey Research Center (1982)). Consequently, in first differences, data are available for five years. For a given year, the sample contains male heads of household who were between the ages 18-60 inclusive, who had not retired, and who were employed. temporarily laid off or unemployed at the time of the survey. We have limited the analysis to these years because the wage measure is unavailable for salaried workers prior to 1976. In the balanced sample, an individual is included only if he has complete observations on all the variables for all the years. The sample contains 1051 individuals. Because the wage measure is collected only if the individual is employed or on temporary layoff at the time of survey, the balanced sample is likely to consist of individuals with more stable employment histories than the sample at large. We experiment with unbalanced samples for 1976-1981 and for 1969-1981 as well.

A few of the variables require discussion. C^*_t is the sum of the family's food expenditures at home and outside of the home, deflated by the food component of the consumer price index. This is the consumption measure used in Hall and Mishkin (1982), Altonji (1986), Altonji and Siow (1986), and other recent studies of lifecycle models based on the PSID. There appears to be considerable measurement error in the variable. We account for it with the error component u_{ct}.

The variable ΔW^*_t is the change in the straight time wage at the time of the survey. Given our assumptions about measurement error, it is important to note that for both hourly workers and salary workers this wage variable is based upon survey questions which are independent of those used to construct ΔY^*_t, family income. For salaried workers measurement error in ΔW^*_t may be correlated with the true change in work hours, since the variable is usually imputed from information on salary per week, per month, or per year using a standard number of work hours (such as 40 hours per week). We ignore this potential problem.

As noted earlier, the consumption measure and the hourly wage measure refer to the time of the survey (typically in March) while family income and hours of unemployment, Z^*_t, refer to the calendar year which precedes the survey date.

For computational convenience, we followed Hall and Mishkin (1982) and Hayashi (1985b) and removed the effects of economy wide disturbances and a variety of demographic characteristics from the variables used in the analysis of the dynamic factor models. We do so by first regressing the change in consumption, the change in income, and the income determinants against a set of year dummies, age, age^2, age^3, education, the change in a dummy variable for marital status, current and lagged values of dummy variables for 8 Census regions, residence in an SMSA, and residence in a city with more than 500,000 people, as well as variables for the level and squared value of the change of family size, the change in the number of children in the family unit, and the change in the number of children under age 6. The residuals from these regressions form the basis for the analysis below. Given the large samples which were used to form the residuals, the fact that the estimation was performed in two stages is of little consequence.

When analyzing the models using changes in the levels (as opposed to the changes in logs) of consumption and income, we followed Bernanke (1984) in attempting a correction for the fact that the variances of the changes in the level of income and consumption are strongly related to the level of income. We split our sample into 13 income classes based upon the 6 year average of annual income for each family. We then divided the change in the income levels, the change in the consumption level, and the change in the wage level by the mean of the averages for the families in a given class. Essentially, this imposes the assumption that the variances of all of the factors except those of unemployment and work hours are proportional to the square of the mean income level in the income class. Note that the effect of changes in work hours or unemployment on the change in the family income level should depend on the wage. To allow for this, we did not deflate the hours change or the unemployment variable by the mean income level, under the assumption that the mean wage level of individuals in the income class is proportional to the mean family income level.

Finally, we have eliminated some outliers from the analysis.[12]

5. RESULTS FOR THE PERMANENT INCOME AND KEYNESIAN MODELS

In Section 5.1 we begin with the estimates of the stat onary model (4.1) in levels and logs and tests of the 0 restrictions on the stationary model that are implied by the income model and by the RE-PI consumption equation. In Section 5.2 we report estimates of the income equations of the dynamic factor model, the PIH and Keynesian consumption equations. In Section 5.3 we discuss a number of extentions, including the use of weighted least squares, experiments with alternative assumptions about measurement error, and estimates obtained when we extended the sample to years prior to 1976 and to individuals who are missing data for some years. In Section 5.4, we present estimates of the quarterly dynamic factor models. Estimates of the Hall and Mishkin Model are in Section 5.5.

5.1 Estimates and Tests of the Stationary Model and the Unrestricted Dynamic Factor Models

This section presents OMD estimates of the stationary model (4.1) in levels and logs and tests of the 0 restrictions on the stationary model which are implied by the income model and by the RE-PI consumption equation. Table 1a presents the OMD estimates of the stationary model (4.1) when the data are in levels. It consists of the covariances among the variables ΔC^*_t, ΔY^*_t, ΔW^*_t, ΔZ^*_t and ΔN^*_t at 0, 1, and 2 lags. The model contains parameters for 65 distinct covariances which we estimate from 250 second moments. The signs of the contemporaneous covariances seem reasonable. One distinguishing feature is that the covariances at the second lags are small for almost all of the variables. Out of 25 such covariances, only $\mathrm{Cov}(\Delta Y^*_t, \Delta Y^*_{t-2})$ is statistically significant. Furthermore, the estimates of the covariances are somewhat imprecise despite the fact that data on 1,051 individuals and between 3 and 5 sample moments are used to estimate them.[13] Furthermore, the covariances of hours, wage, and unemployment with income are small at second order lags. The small values for these covariances and the imprecision in the estimates of the moments causes problems for estimation of the restricted models. Identification in these models utilizes the covariances at the second lags.

Table 2a presents χ^2 statistics, degrees of freedom, and p-values (marginal significance levels) of a series of restrictions on the sample moments. The row labels indicate the restrictions imposed under the null hypothesis of the test. The column labels indicate the restrictions maintained under the alternative hypothesis. The first column tests the stationary models against the unrestricted nonstationary model (which fits the sample moments perfectly). The χ^2 statistic for the stationary model with no further restrictions is 307.7 with 185 degrees of freedom, which is large enough to reject stationarity with a p-value of less than .0001 We also tested separately for stationarity of the autocovariances of each of the five variables. For levels, we reject stationarity for work hours, wages and unemployment. For logs, we reject stationarity for all variables except for work hours. As we noted earlier, stationarity of the data is also strongly rejected for all models estimated using OMD in this paper (except in two cases discussed in Section 5.5). For reasons discussed in Section 4, we use the stationary model as a yardstick to assess the restricted models.

Because the income model with exogenous hours excludes the wage factor from the hours and unemployment equations, it implies the following zero restrictions on the stationary model.

- -

0 Restrictions on Cov. Stationary Model Implied by Income Equations 1.c', 1.d, 1.e

(5.1) $\quad \text{Cov}\,(\Delta W^*_t, \Delta Z^*_{t+j}) = 0 \qquad j = -2,-1,0,1,2$

(5.2) $\quad \text{Cov}\,(\Delta W^*_t, \Delta N^*_{t+j}) = 0 \qquad j = -2,-1,0,1,2$

- -

We report tests of these restrictions in the second row of the table. The p-value is .029 when the data are in levels. Inspection of the individual sample moments indicates that none of the covariances among the wage and unemployment are significant, but the hours change has a significant negative covariance with the wage change and a positive covariance with the lagged wage change. Note that the lifecycle model of consumption and labor supply implies that wages and hours should vary together.

In addition, since the RE-PI model implies that past information does not cause a change in permanent income, it implies the following restrictions on the stationary model.

- -

Zero Restrictions on Cov. Stationary Model Implied by RE-PI Consumption Equation

(5.3) $\quad \text{Cov}\ (\Delta C^*_t, \Delta I^*_{t-j}) = 0 \qquad I = Y,W,Z,N;\ j=1,2$

- -

The third row of the table tests these restrictions. They pass easily when stationarity is maintained.

The fourth row tests the zero restrictions on the income process and the 0 restrictions implied by RE-PI for consumption. We obtained a p-value of .038 for these restrictions when testing them against the unrestricted stationarity model. This rejection at conventional significance levels is due to the restrictions on the income process.

Finally, the table reports a test against the unrestricted stationary model (4.1) of the factor model consisting of the unrestricted consumption equation (1.1a) and the income model with exogenous hours. The p-value to reject is .057, and so there is only weak evidence against the factor structure once stationarity is maintained. The p-value for this dynamic factor model is .334 when tested against the stationary model including 0 restrictions on the income process.

In summary, we find overwhelming evidence against stationarity, weaker evidence against the assumption that unemployment and hours do not vary with the wage change, little evidence against the RE-PI zero restrictions on the relationship between consumption and lagged income determinants, and little evidence against the dynamic factor representation of the data.

Table 1b reports estimates of the unrestricted stationary model when the data are in logs. Note that for this specification ΔZ^*_t is the log of (2,000 + Hours of unemployment) and is not in first differences. (Using first differences did not change the results in the cases we checked.) For the log results the standard errors are usually smaller relative to the parameter estimates than for the level results. Once again, most of the covariances at the second lag are small relative to the covariances between the same variables at lags 0 and 1. (Only 3 out of 25 are significant at the 5% level.)

Table 2b reports a series of χ^2 tests of the restrictions on the stationary model against various alternatives. Column 1 of the Table shows that stationarity is overwhelmingly rejected. However, once stationarity is imposed, the restriction that wages do not vary with hours or unemployment passes at the .127 level. The 0 restrictions implied by the RE-PI model also pass easily. The p-value for the dynamic factor model consisting of the income model with exogenous hours and the unrestricted consumption equation is .097 in a test against the unrestricted stationary model. The p-value is .199 against the stationary model including 0 restrictions on the relationship between wages and hours.

In summary, once stationarity is imposed, the log results provide weak evidence against the income specification, but little evidence against the RE-PI 0 restrictions or against the dynamic factor representation of the data.

5.2 Estimates of the Dynamic Factor Models with Exogenous Income

We now discuss estimates of the dynamic factor models with exogenous income and hours, and various consumption equations. We begin with the equations of the income model (1.1b, 1.1c', 1.1d, 1.1e). We then turn to the consumption equations. In estimating these models we have excluded the covariances between hours and wages and between unemployment and wages from the sample, because the income model implies these are 0.

In Table 3 we present estimates of the equations of the income model with exogenous hours which are obtained when they are estimated jointly with the unrestricted consumption equation (1.2). The estimates of the family income, wage, hours, and unemployment equations reported in the table are representative of the results which we obtained for the income equations when the restrictions associated with RE-PI or the Keynesian model were imposed, although the precision of the coefficients on the income factor u_{yt}, u_{yt-1}, and u_{yt-2} is higher in the latter cases. The long run effect of a one standard deviation innovation in one of the factors may be estimated by summing the factor loadings on that factor.

The results for both logs and levels indicate that most of the response of income to a wage innovation occurs in the initial period, and that most of the effect is permanent. Because the data in levels have been deflated by the mean income values in each of 13 income classes (see section 4), the estimates for logs are somewhat easier to interpret. The log results indicate that a one standard deviation increase in the wage factor, which is equal to .20 (β_{ww0}), leads to a permanent increase in family income of about 2%. This seems small given that a one standard deviation shock to the wage raises the wage level by about 7 % in the long run, and the evidence presented earlier indicates that the relationship between wages and work hours is weak. Inconsistency in the timing of wages and income is a possible explanation for the small response of family income to wages. We investigate this possibility below. It is also worth mentioning that the standard error on the wage measurement error variance σ^2_w is large relative to the total variance in the wage change, and that the point estimate is actually negative (although not significant).

The estimate of -.0169 for β_{yz0} in the log equation is the short run effect on the income change of a one standard deviation increase in the unemployment factor u_{zt}. This factor drives the log of (2000 + hours of unemployment) and the change in the log of annual hours. The effect on annual work hours is -.037, while the effect on the unemployment variable is .0296. These results suggest that unemployment leads to a more than proportional reduction in work hours in the short run, perhaps through shorter work days, and to a less than proportional reduction in family income. The long run effect of unemployment on family income is near 0 for the log model. It is about half of the short run effect when levels are used.

The short run effect of the work hours factor u_{nt} on the log of family income is only about 1/4 of its effect on work hours. The log model implies that more than 3/4 of the effect on income is permanent, while the level results imply that slightly more than half of the positive short run effect is permanent. We obtain a small positive estimate of the variance of the measurement error component in hours, σ^2_n, when logs are used, and a small negative estimate when levels are used. These estimates come as a surprise, because Duncan and Hill (1984), Altonji (1986) and Altonji and Paxson (1986) report strong evidence of substantial measurement error in the change in the log of annual hours. Below we obtain larger measurement error estimates when we use WLS and when we account for non-syncronization in the data.

The income factor u_{yt} has a strong effect on income. In all of the models that we estimated, it was the most important factor in the income model (after measurement error). The estimates of the log model imply that measurement error is responsible for 70.8 % of the variance of ΔY^*_t. Of the remaining 29.2%, 82.9% is due to u_{yt}, 8.6% is due to u_{nt}, 5.0% is due to u_{zt}, and 3.4% is due to u_{wt}. The model in levels implies that measurement error is responsible for 73.3% of the variance of income and u_{yt} is responsible for 94.5% of the rest of the variance. In the various models that we estimated, the contribution of the variances of wage, hours of work and unemployment innovations to the variance of the first difference of log income after correcting for measurement error was always less than 30%. It seems implausible to us that variations in bonuses or overtime premia and in nonlabor income and spouse's earnings are large enough to explain the importance of u_{yt}.

In Table 4 we provide some evidence that these results reflect basic characteristics of the data rather than gross model misspecification or problems with the estimation procedures. In column 1 we present a regression of ΔY^*_t against ΔY^*_{t-1} and ΔY^*_{t-2}. The data are in logs. The R^2 is .115. In column 2 we add current and lagged wage, hours and unemployment changes. The R^2 rises by .067 to .182. In column (3) we add the current value and two lags of ΔNS^*_t, which is the change in the log of 1370 plus annual work hours of the spouse to the equation. We also add ZS^*_t and its lags, where ZS^*_t is the log of 1370 plus wife's hours of unemployment. The value 1370 is the mean of wife's work hours for wives who work positive hours. (We transformed the work hours and unemployment variables to reduce the influence of large percentage changes in hours worked by women working few hours on the log variables and to handle the fact that our sample includes unmarried men and men whose wives do not work in some years). These variables lead to an R^2 of .297. We view these results as consistent with substantial measurement error in family income. They also suggest a relatively small role for variation in husband's work hours, unemployment, and wages in the variance of measured income. The results in Altonji and Siow (1986) for a similar sample of men suggest that adding the change in work hours lost due to illness and interactions between wage changes and quits, layoffs, and promotions would result in only a small improvement in explanatory power. In light of the substantial explanatory power of wife's work hours and unemployment, it may be useful in future work to expand the dyanamic factor model to include these variables.

The Consumption Equations: Results for Levels

Table 5 reports a series of consumption equations. The χ^2 statistic and the degrees of freedom reported at the bottom of each equation are for a test of the consumption equation and the associated equations for the income determinants against a stationary model (Model B in Table 2a).

Column 1 of Table 5 reports the estimates of the unrestricted consumption equation (1.1a). β_{cw0}, the response of the consumption to u_{wt}, is estimated at 12.9 with a t-value of 1.6. The coefficients on u_{nt} is positive, and the coefficient on u_{zt} is negative, but neither is statistically significant. The variable u_{yt} has a strong positive effect on consumption (β_{cy0} is 61.3). An interesting finding is that the coefficients of lagged unemployment and lagged income both have fairly large coefficients with t values of 2.07 and 1.75 respectively. This is evidence against the implication of the RE-PI model that lagged income and unemployment factors should not affect current consumption. It comes as a surprise in view of our finding in the previous section that the 0 covariance restriction between consumption and lagged income determinants are satisfied.

In column 2 we report the consumption function when the consumption coefficients on the lagged income determinants are set to 0. Interestingly, the p-value to reject the model against the stationary model (model B) is more than .10. However, when we maintain the factor model for income and only test the consumption restrictions against the unrestricted consumption function in column 1, they are rejected at the .025 level. The coefficients on all of the income components have the right sign, but only the wage and income factors are statistically significant. The coefficient β_{cw0} is 14.5, which is 2/5 the size of β_{cy0}. From the perspective of the RE-PI model, this estimate of β_{cw} seems a bit large given that the estimates of the income model estimated jointly with column (2) imply that the long run effect on income of a one standard deviation shock to u_{wt} is only 1/4 as large as a one standard deviation shock to u_{yt}.

Column 3 in Table 5 presents estimates of the five variable restricted RE-PI model. The restrictions, when tested against the stationarity model, are not rejected at the .10. However, they are rejected at the 5% level when tested against the model with the unrestricted consumption equation in model 1. The estimate of α, the marginal propensity to consume food out of permanent income, is .0672 with a standard error of .0215. Unfortunately, the estimate for the discount factor, ρ, is -.044 with a standard error of .398. Given the large standard error, a reasonable discount factor cannot be rejected. With other specifications of the model in levels (allowing for different variables and measurement errors), we still could not pin down the estimate of the discount factor. Often we obtained discount factors slightly larger than 1 with large standard errors. Part of the problem is that only the wage and income innovations are significant in determining consumption. The other problem is that the lags of the innovations of wages and income on the income process are not determined precisely.

Column 4, Table 5 contains an estimate of the Keynesian model. The marginal propensity to consume out of current income, α, was estimated at .0291 with a standard error of .010. The estimates of the equations of the income model (not shown) and the coefficients on u_{ct}, u_{ct-1}, and u_{ct-2} are similar to those for the RE-PI models. However the Keynesian model, when tested against the stationarity model, is rejected with a p-value of .01. It is rejected at the .005 level when tested against the factor model with the unrestricted consumption equation. All variants of the Keynesian model with which we experimented performed worse than the equivalent RE-PI model.

Columns 5, 6, and 7 report estimates of some dynamic factor models that exclude hours of work from both the income process and consumption function. Although the hours decision within the RE-PI framework is viewed as exogenous, it is interesting to explore the possibility that the endogeneity of hours is adversely affecting the analysis. In column 5 we impose the restriction that lag innovations of u_{wt}, u_{yt}, and u_{zt} do not affect ΔC^*_t. A comparison of the estimates of β_{cw0} and β_{cy0} with the coefficients of the income model corresponding to column 5 indicates that the estimate of β_{cw0}, the effect of wage innovations on consumption, is still too large relative to the estimate of β_{cy0}, the effect of u_{yt} on consumption, when viewed within the RE-PI model. The effect of u_{zt} on consumption is not significantly different from 0. The model is not rejected against the four variable stationarity model at the .10 significance level.

In column 7 we estimate the restricted RE-PI model. The restrictions pass. The estimate of the discount factor ρ is 1.66 with a standard error of .598. The Keynesian model in column (7) is rejected against the stationary model at the .05 level.

Dynamic Factor Models with Exogenous Income using Logs.

Column 8 of Table 5 presents the unrestricted log linear consumption equation. In contrast to the results for levels, none of the coefficients on lagged income determinants are significantly different from 0.

Since the relationship between the consumption change and innovations in the determinants of the log of income is very complicated, we could only impose the zero restrictions implied by the RE-PI model on the loglinear model. Column 9 of Table 5 reports results for the loglinear consumption equation with coefficients on lagged income determinants set to 0. The qualitative results largely follow those found in the levels. This consumption equation and the associated income equations easily passes tests against the stationarity model and against the model with the unrestricted consumption equation. Unemployment and hours of work innovations have small, statistically insignificant, effects on consumption. Wages again have a more persistent effect on income than unemployment. However, when compared to the parameters of the income equation, β_{cw0} seems large relative to β_{cy0}. Inconsistency of timing of the variables or a substitution effect of the wage on consumption are among possible explanations for this.

Column 10 in Table 5 presents estimates for the five variables loglinear model with the Keynesian consumption function. The Keynesian model is overwhelmingly rejected, although the estimates of the income process and the other processes do not differ much from those of the PI models. However, it should be mentioned that the estimates do not satisfy the standard convergence criterion.[14]

The results for this section may be summarized as follows. First, many of the coefficients of the consumption and income model are imprecisely estimated, leading to imprecise estimates of the discount factor. Second, when the data are in levels, we find evidence that consumption is affected by lagged determinants of income. We do not find evidence of this when the data are in logs. Third, the response of consumption to u_{wt} seems large and the response to u_{yt} seems small relative to the long run effects of these variables on consumption. Fourth, the Keynesian model is rejected.

As for the family income process, the estimates are disappointing in terms of the fraction of the variance explained by the wage, unemployment and hours factors relative to the variance explained by the income factor u_{yt}. The regression analysis in Table 4 suggests that this finding reflects basic characteristics of our data. Inconsistency in the timing and time aggregation of some of the variables may also play a role. We turn to this issue below. A second explanation is that our assumptions about the properties of the measurement errors are invalid, leading to a misspecified income equation.

5.3 Extensions

Alternative Assumptions about Measurement Error

We experimented with two alternative specifications of measurement error. First, we also estimated most of our models assuming that the measurement error was zero for all equations except consumption. In all cases, these restricted models were handily rejected against their counterparts with measurement error. For example, the χ^2 statistics, with 3 degrees of freedom, for the models with no measurement error that corresponded to col. 2, 3, and 9 of Table 5 were 17.9, 12.2 and 13 respectively. Second, we also allowed for first order moving average measurement errors (i.e. $\varepsilon_{it} = \xi_{it} + \tau_i \xi_{it-1}$ for $i = y,n,w$). We cannot reject the null hypothesis that τ_i is zero for all cases at the 5% significance level.[15] Finally, we briefly experimented with cross-correlated measurement errors. However we were unsuccessful in our attempts to estimate these models.

Weighted Least Squares

We report a set of weighted least squares (WLS) estimates of the stationary models, the RE-PI and Keynesian models, in the Appendix (Table A1a, A1b, A2, A3). The reported standard errors for the levels results are calculated as if WLS is efficient. (We experienced computational problems in correcting the standard errors when the data are in levels. We will provide them in a later draft. We also will also report goodness of fit statistics for the factor models at that time.)

Based on Newey's goodness of fit test, stationarity is still overwhelmingly rejected. The parameter estimates for all models, especially for data in the levels, are larger in absolute values than those obtained with OMD. We are somewhat puzzled by this phenomena. The standard errors of the estimates are also larger as expected because WLS is inefficient relative to OMD. The deterioration in precision of the level estimates is particularly troubling.

The WLS estimates of the factor models in Table A2 and A3 are qualitatively similar to those obtained by OMD. Measurement error explains a larger portion of the variance of the change in measured work hours. It is still insignificant or has the wrong sign for measured wages. The estimates of ρ are still very imprecise. The main difference between Tables A2 and A3 and the OMD Tables 3 and 5 is that the absolute values of the factor loadings are typically larger when WLS is used.

Unbalanced Data

In trying to get more precision for our estimation procedures, we estimated the model on two larger samples. Both larger samples were unbalanced (i.e. each sample covariance was not necessarily calculated with the same number of observations). In one sample, using the same years 1976-1981, we also include individuals who did not have complete data on all variables for all the years. After this addition, between 1699 to 2877 observations are available to calculate each sample covariance. The point estimates as well as their standard errors obtained with this larger sample, using the OMD estimator, are larger than before.[16] We again could not pin down an estimate of ρ. The additional data does not improve the precision of our estimates because the sample covariances for those individuals with missing data are substantially larger than those of individuals with complete data. That is, the two sets of individuals faced different income processes. For example, for data in logs, the sample variances of income, wages and hours of work are about 3 times larger than for the balanced sample. The variance of unemployment was 10 times larger. This is not surprising given that the wage measure is a available in a given year only for persons who are employed or on temporary layoff at the time of the survey. As a result, the balanced sample is weighted toward individuals with relatively stable employment. We experimented with estimating the income process for each group of individuals separately while constraining the estimates of α and ρ to be the same for the two groups. The results are inconclusive.

In the second sample, we also included data from before 1976 back to 1968. We extended the sample temporally in an attempt to improve precision. This led to an increase in the number of second moments used in estimation from 212 to 583.[17] We used the WLS estimator with this sample because it became computationally intractable to invert the full empirical fourth moment matrix. The estimates of the covariances of the stationary model were substantially larger than those obtained for the balanced sample. The parameters of the factor models also increased in absolute value, although the relative values are basically similar to those reported.[18] The variances of the innovations again appear to be higher for those individuals who are missing data for some years, as one would expect. Our estimates of α and ρ were not very precise, as an increase in the mean square error of the stationary model and the various factor models approximately offset the increase in the sample size.

5.4: Time Aggregation and Nonsynchronous Measurements: Estimates of the Quarterly Dynamic Factor Models

Table 6 presents estimates of the quarterly dynamic factor model. (See equation (3.4)). Columns 1a and 1b report estimates and standard errors when the data are in levels and annual hours are excluded from the analysis. In this model the response of consumption to the current wage, income, and unemployment innovations are unrestricted, while the model in column 2a and 2b parameterizes these responses in terms of the marginal propensity to consume out of wealth and the quarterly discount factor ρ_q. In column 3a and b we report estimates and standard errors of the quarterly dynamic factor model when the data are in logs. We ignore the problem that the log of annual income is not equal to the sum of the logs of quarterly income.

The parameters of the income, wage and unemployment equations (the a_{kij}) are the parameters of the polynomial distributed lag specifications in equation (3.4). In Figure 1 we plot the time pattern of the response of income Y^*_t (as opposed to ΔY^*_t), the wage W^*_t, and unemployment Z^*_t to a one standard deviation innovations in u_{yt}, u_{wt} and u_{zt} when the levels of the variables are used. The effect after 7 periods is the long run response of Y^*_t, etc, to the various shocks. The plots are based on the estimates of the a_{kj} in column 1. In Figure 2 we report the corresponding information for the log model using the estimates in column 3.

We focus our discussion on the results for the log models. Y^*_t initially increases by .028 in response to a wage innovation of .058. It rises above this level in the next period, declines almost to 0, before rising again. The long run response is .028, so most of the wage effect is permanent, while the long run effect of a wage innovation on the wage level is about .038. Since the mean of labor earnings is equal to about two thirds of the mean of family income, the size of the response of income to the wage factor is basically sensible. These results are a substantial improvement over the results obtained using the annual model. However, the shape of the response is not entirely plausible and may be an artifact of the quadratic polynomial imposed on the moving average coefficients used in estimation. The pattern and size of the response of income to unemployment seems sensible.

Wages and unemployment explain 22.8% and 7.5% of the true variance in the quarterly change in income, while the income factor explains 69.6 %. Wages and unemployment explain 15.3% and 1.8% of the variance of change in the annual average of income, while the income factor explains 83.2%. The importance of measurement error in the annual average falls to 46.7%. When the data are in levels rather than logs, the wage, unemployment, and income factors explain 10.6%, 3.7%, and 86.7% of the true variance in the change in the annual average of family income. Measurement error accounts for 49.5% of the variance. The increase in the explanatory power of the wage in the quarterly models relative to the annual models suggests that treatment of timing is useful.

In column 2a, the estimate of the quarterly discount factor ρ_q is .974. This implies an annual discount factor of about .9. This point estimate is favorable to the RE-PI model but is subject to a large standard error.

We now turn to the consumption coefficients based on the loglinear specification in column 3a. The β_{cw0} is .0118 and β_{cy0} is .0114, which implies that the consumption response to a one standard deviation wage innovation and a one standard deviation income innovation are approximately equal. The response of consumption to the wage innovation seems large relative to the response to the income innovation. The long run response of income to the wage innovation (.028) is only 4/7th's as large as the response of income to the income innovation (.048). On the other hand, the small response of consumption to unemployment is consistent with the fact that the income parameters imply the long run response of income to a one standard deviation innovation in unemployment is only .001.

Table 7 presents a set of estimates of the quarterly models with annual hours included. Col. 1 presents the levels results for the model with a consumption equation in which the responses to the current wage, income, hours, and unemployment innovations are unrestricted. Col. 2 presents the RE-PI model. Col. 3 presents the unrestricted log results. The time patterns of responses of various variables to one standard deviation innovations in the various factors implied by the estimates in Col. 1 and Col. 3 are presented in Figures 3 and 4 respectively.

The results in Figures 3 and 4 are qualitatively similar to that in Figures 1 and 2. Concentrating on the log results (Figure 4), in the long run, hours rise by about 1% in response to a one standard deviation innovation in the hours factor. The long run impact on income is slightly more than 1%. The income response seems a little large although basically sensible. The long run response of hours to unemployment innovations is basically zero, consistent with that of income. Measurement error explains about 25% of the variance in the change in measured hours of work. Measurement error now explains 53% of the variance of the change in measured income. Wages, hours of work, unemployment and income innovations explain 12%, 5%, 4%, and 79% of the variance of the change in true family income respectively. It is surprising that adding hours of work reduces the variance explained by wages and unemployment relative to that explained by the income factor. When the data are in levels, wages, hours of work, unemployment and income innovations explain 6%, 3%, 2% and 89% of the variance of the change in true income. Measurement error accounts for 21% of the variance of the change in measured income. Again, adding hours of work seems to add to the explanatory power of the income factor.

Turning to the RE-PI model in Col. 2, ρ_q is estimated as 1.03 with a standard error of .077. The estimate of α is .03 with a standard error of .01. So the restricted estimates are basically consistent with that obtained in the model which excludes hours of work.

In summary, accounting for non-syncronization in the data reduces the explanatory power of measurement error in measured income. The explanatory power of the income factor is also reduced in favor of the wage factor in explaining the variance of the change in true income. Measurement error now explains a substantial portion of the variance in the change in work hours, consistent with the evidence in the literature. Finally, the point estimates of the discount rate are more reasonable.

5.5: The Hall and Mishkin Model

Given our difficulties in getting a precise estimate of ρ and also for purposes of comparison, we present estimates of the Hall and Mishkin model using the optimal minimum distance estimator. As argued earlier, we do not use maximimum likelihood because the data are not normally distributed. We estimate the model with two sets of data. The first data set are simply the consumption and income moments from our balanced sample. The second data set consists of the consumption and income moments for individuals that have complete consumption and income data. An individual with incomplete wage data will not be in the first data set but will be in the second. The larger data set has over twice the number of observations, 2324. Since we correct for heteroscedasticity and we also use different measurement units than Hall and Mishkin use, our estimated variances are not quantitatively comparable to theirs.

Col. 1 of Table 8 reproduces the Hall and Mishkin results from their Table 1 (notation in Table 8 is theirs). Their estimated β, together with their estimates of the moving average parameters of transitory income imply an infinite horizon discount factor ρ of .77. Col. 2 presents our OMD estimates of their model using the first data set. The p-value for rejecting the model against the non-stationary alternative is .013. This p-value is much larger than that obtained by any of our models. It says that the consumption and income moments alone may be close to stationarity. The p-value for the model against the stationary model is .01. The t-statistics associated with the point estimates are much smaller than that in col. 1. The point estimate of ρ seems reasonable. Col. 3 presents the results using the second and larger data set. The p-values against the non-stationary model and the stationary model are .08 and .10 respectively. Again the t-statistics are smaller than those in Col.1. However the point estimate for ρ this time is .17. Given the large standard error, a reasonable ρ cannot be rejected. The differences in point estimates across Col. 1, 2 and 3 do suggest that imprecision in the estimation of ρ also plagues the Hall and Mishkin model. We note that the qualitative features of our estimates do not differ much from theirs, especially in view of our more conservative standard errors. Unfortunately the point estimates of ρ are quite sensitive to small differences in the point estimates of the income process. Given our standard errors, these small differences are to be expected when we switch samples. The relatively smaller standard errors that they obtained are due to their assumption of normality and their subsequent choice of the maximum likelihood estimator.

6. A DYNAMIC FACTOR MODEL OF CONSUMPTION AND LABOR SUPPLY

The "permanent income" specification of the lifecycle hypothesis embodied in equation (2.1) has been used in many studies and is very convenient for empirical work. But it imposes many restrictions upon behavior that are not essential to the basic idea of the lifecycle model of consumer behavior and limit the empirical questions which it may be used to ask. First, the relationship between consumption and lifetime resources does not reduce to the simple permanent income formulation except in a very special case, even if preferences are additively separable in consumption and leisure within and across time periods. Second, there is no natural way to integrate labor supply into the RE-PI analysis. Third, if preferences are not additively separable within the period, then both anticipated and unanticipated changes in the wage rate will have pure substitution effects on consumption expenditures. It would be desirable to separate out the intertemporal substitution and within period substitution effects of the wage rate on consumption and labor supply from the "income effect" of this variable.

The lifecycle model of consumption and labor supply may explain some of our earlier empirical results. The weak evidence, for data in the levels, against the exogeneity of wages and hours can be reconciled with endogenous labor supply. The relatively large response of consumption to the wage factor may be explained by substitution of consumption and leisure in a lifecycle model (e.g. Ghez and Becker (1975)).

The RE-lifecycle Model

We use a standard lifecycle model of consumer behavior under uncertainty that incorporate intertemporal separability of preferences (See footnote 1 for references)[19]. Using loglinear approximations to the marginal of utility of income constant (λ-constant) demand equations for hours and consumption and the intertemporal optimality condition for expected utility maximization, one obtains the following model for the first difference equations for hours and consumption.

(6.1) $\ln\lambda_t \approx \ln\lambda_{t-1} - \ln r_{t-1,1} + \eta_t$

(6.2) $\Delta N_t^* = \text{constant} + B_n(\Delta W_t) + (B_n + B_{nc})\Delta P_t - (B_n + B_{nc})r_{t-1,1} +$
$(B_n + B_{nc})\eta_t + \beta_{nz0}u_{zt} + \beta_{nz1}u_{zt-1} + \beta_{nz2}u_{zt-2}$
$+ \beta_{nn0}u_{nt} + \beta_{nn1}u_{nt-1} + \beta_{nn2}u_{nt-2} + \Delta\varepsilon_{nt}$

(6.3) $\Delta C_t^* = \text{constant} + B_{cn}\Delta W_t + (B_c + B_{cn})\Delta P_t - (B_c + B_{cn})r_{t-1,1} +$
$(B_c + B_{cn})\eta_t + \beta_{cc0}u_{ct} + \beta_{cc1}u_{ct-1} + \beta_{cc2}u_{ct-2}$

λ_t : marginal utility of income at date t.

r_t : nominal interest rate at date t.

η_t : innovation in the log of the marginal utility of income.

N_t^* : log of measured labor supply at date t.

C_t^* : log of measured consumption at date t.

W_t : log of the Real Wage at date t.

P_t : log of the price level at date t.

ε_{nt} : serially uncorrelated measurement error.

Equation (6.2) is a labor supply equation in first differences that is conditional on the innovation in the marginal utility of income, η_t. Equation (6.3) is a consumption equation in first differences also conditional on η_t. With intertemporal separability of preferences, ΔN_t and ΔC_t depend upon current assets and the distribution of future wage and prices only through changes in $\ln\lambda_t$. Equation (6.1) shows the evolution of the marginal utility of income, λ_t. Under rational expectations, η_t is uncorrelated with information known to the consumer in t-1. The variables u_{nt} and u_{ct} are taste shifters. Measurement error in consumption is also incorporated in u_{ct}. In estimation, we assume that u_{nt} and u_{ct} are uncorrelated. This implies a zero correlation between the changes in labor supply and consumption preferences that are not captured by the demographics variables we control for. The variable u_{zt} is the factor driving unemployment. It may reflect changes in labor supply preferences and/or constraints on hours of work.[20]

The parameter B_n is the intertemporal labor supply elasticity. The parameters $B_n + B_{nc}$ and $B_c + B_{cn}$ are the intertemporal substitution effects of changes in the nominal interest rate on labor supply and consumption (respectively). Strict concavity of preferences and the assumption that consumption and leisure are normal goods imply $B_n + B_{nc} > 0$ and $B_c + B_{cn} < 0$ (See Heckman (1974).). Symmetry of the λ constant cross-substitution effects implies that the elasticity B_{cn} is approximately equal to $B_{nc}(N_tW_t/C_t)$. Under the assumption of intraperiod separability, $B_{cn} = B_{nc} = 0$.

The "income" effects on consumption and labor supply of shocks to budget parameters such as the wage rate and shocks to preferences arise through the effects of these shocks on λ_t. The expected value of the marginal utility of income, λ_t, is implicitly defined by the parameters of the utility function, current and the individual's wealth level and expectations about the distribution of current and future values of wages, interest rates, prices, and the preference shifters. Since an analytical solution for λ_t does not exist in the case of uncertainty and time varying preferences, there is little hope of obtaining an analytical solution for the relationship between the innovation η_t in $\ln\lambda_t$ and innovations in the exogenous factors entering the lifetime budget constraint. As a basis for empirical work, we simply specify η_t as an unrestricted linear function of unanticipated changes in exogenous (with respect to preferences) factors affecting income (such as wage rates) and unanticipated changes in preferences.

Given the "exogenous" equations (1.1d, 1.1e), that is wages and unemployment, let η_t depend upon the innovations in these variables plus the error component $u_{\eta t}$ which captures the effects of factors which have been omitted from the model:

$$(6.5)\quad \eta_t = \beta_{\eta w0}u_{wt} + \beta_{\eta z0}u_{zt} + \beta_{\eta y0}u_{yt} + u_{\eta t}.$$

where u_{wt} is the wage innovation and u_{zt} is the unemployment innovation, and u_{yt} is the innovation in components of earnings not directly related to changes in the wage rate or work hours, and $u_{\eta t}$ is a residual factor with variance $\sigma_{\eta t}^2$. In anticipation of the empirical specifications used below, in (6.5) we impose the assumptions that u_{ct} and u_{nt} do not affect η_t. This will be true only if consumers have perfect foresight about consumption and labor supply preferences (We have not been successful in attempts to estimate models which relax this assumption.). The exclusion of lagged values u_{wt}, u_{zt} and u_{yt} from (6.5) is implied by the assumption of RE, which implies that η_t is uncorrelated with information known in t-1.[21]

Substitute (6.5) for η_t, and (1.1d) for ΔW_t, in the first differenced consumption and labor supply equations (6.2) and (6.3). After surpressing constant terms this leads to

$$(6.6)\ \Delta C_t^* = B_{cn}(\beta_{ww0}u_{wt} + \beta_{ww1}u_{wt-1} + \beta_{ww2}u_{wt-2})$$
$$+ (B_c + B_{cn})(\beta_{\eta w0}u_{wt} + \beta_{\eta z0}u_{zt} + \beta_{\eta y0}u_{yt})$$
$$+ (B_c + B_{cn})(u_{\eta t} - r_{t-1,1} + \Delta P_t) + \beta_{cc0}u_{ct} + \beta_{cc1}u_{ct-1} + \beta_{cc2}u_{ct-2}$$

$$(6.7)\ \Delta N_t^* = B_n(\beta_{ww0}u_{wt} + \beta_{ww1}u_{wt-1} + \beta_{ww2}u_{wt-2})$$
$$+ (B_n + B_{nc})(\beta_{\eta w0}u_{wt} + \beta_{\eta z0}u_{zt} + \beta_{\eta y0}u_{yt})$$
$$+ (B_n + B_{nc})(u_{\eta t} - r_{t-1,1} + \Delta P_t) + \beta_{nz0}u_{zt} + \beta_{nz1}u_{zt-1}$$
$$+ \beta_{nz2}u_{zt-2} + \beta_{nn0}u_{nt} + \beta_{nn1}u_{nt-1} + \beta_{nn2}u_{nt-2} + \Delta\varepsilon_{nt}$$

We estimate versions of (6.6) and (6.7) along with the wage and unemployment equations (1.1d and 1.1e). Unfortunately, the parameters $\beta_{\eta w0}$, $\beta_{\eta z0}$, and $\beta_{\eta y0}$, σ_η^2, B_c and the parameter B_{nc} are not identified unless one imposes the symmetry restriction $B_{cn} = B_{nc}(N_t\ W_t)/C_t$. We provide one set of estimates with this restriction imposed and $N_t\ W_t/C_t = 4$. We also estimate the model with intraperiod nonseparability between food consumption and labor supply imposed ($B_{cn} = B_{nc} = 0$.)

Finally, one may make use of the fact that a measure of the change in labor earnings ΔY^{n*}_t is available that is measured independently of ΔN_t and ΔW_t by combining (6.7) and (1.1d) to form the equation

$$(6.8)\ \Delta Y^{n*}_t = (1 + B_n)(\beta_{ww0}u_{wt} + \beta_{ww1}u_{wt-1} + \beta_{ww2}u_{wt-2})$$
$$+ (B_n + B_{nc})(\beta_{\eta w0}u_{wt} + \beta_{\eta z0}u_{zt} + \beta_{\eta y0}u_{yt})$$
$$+ (B_n + B_{nc})(u_{\eta t} - r_{t-1,1} + \Delta P_t) + \beta_{nz0}u_{zt} + \beta_{nz1}u_{zt-1}$$
$$+ \beta_{nz2}u_{zt-2} + \beta_{nn0}u_{nt} + \beta_{nn1}u_{nt-1} + \beta_{nn2}u_{nt-2}$$
$$+ \beta_{yy0}u_{yt} + \beta_{yy1}u_{yt-1} + \beta_{yy2}u_{yt-2} + \Delta\varepsilon_{yt}.$$

It worth mentioning at this point that in our empirical work to date we have found that the restrictions in (6.8) are not satisfied by the data. Consequently, we report estimates of labor earnings without restricting ΔY^{n*}_t, using a specification which is analogous to equation (1.1b) for family income. The equation is

$$(6.9)\quad \Delta Y^{n*}_t = \beta_{yw0}u_{wt} + \beta_{yw1}u_{wt-1} + \beta_{yw2}u_{wt-2} + \beta_{yz0}u_{zt} + \beta_{yz1}u_{zt-1} + \beta_{yz2}u_{zt-2} + \beta_{yn0}u_{nt} + \beta_{yn1}u_{nt-1} + \beta_{yn2}u_{nt-2} + \beta_{yy0}u_{yt} + \beta_{yy1}u_{yt-1} + \beta_{yy2}u_{yt-2} + \Delta\varepsilon_{yt}$$

The effects of the interest rate and the price change will be removed using year dummies, with cross sectional variation in the after tax interest rate ignored.

From estimating the system consisting of (6.6, 6.7, 1.1d, 1.1e, and 6.8 or 6.9), we can get estimates of B_n, B_c, B_{cn} and B_{nc}. We also focus attention on the responses of ΔC^*_t and ΔN^*_t to the shocks u_{wt}, u_{zt}, and u_{yt} which arise from the effects that these variables have on η_t, the innovation in the marginal utility of income[22]. We expect that permanent shocks to these variables have larger affects on η_t than transitory ones, just as persistent shocks to income induce larger changes in permanent income (Δy^p_t) than do transitory shocks.

6. RESULTS FOR THE LIFECYCLE CONSUMPTION-LABOR SUPPLY MODEL

Column 1 in Table 9 presents estimates of the dynamic factor model that only imposes the 0 restrictions implied by (6.6, 6.7 and 6.8) on the general model (1.1). The p-value to reject the model against the covariance stationary alternative is .05. The covariance stationary model is analogous to (4.1), but is estimated using ΔY^{*n}_t in place of ΔY^*_t. Measurement error explains about 3/4 of the variance of ΔY^{n*}. The estimates of measurement error in wages and hours of work are imprecise. Variation in wage, hours of work, and unemployment innovations explain about 2/3 of the variation of ΔY^{n*} after correcting for measurement error and about 1/6th of the total variance in ΔY^{n*}. The shortfall seems large even though labor earnings may contain bonuses, overtime wages or wages on second jobs, and these are not be captured by our wage and hours variables. The regressions for labor earnings in Table 4 indicate that the marginal contribution to R^2 of current and lagged wages, hours and unemployment is .237. The variable ΔC^*_t responds only to current innovations in the wage and earnings which suggests that $B_{cn}=B_{nc}=0$. Unemployment is more transitory than wages in affecting the earnings process. An interesting finding is that innovations due to the income factor affect hours of work.

In Column 2 we report estimates of a restricted labor supply model. B_{cn}, B_{nc}, and $\beta_{\eta y}$ are restricted to be zero. Measurement error in nonlabor income is absorbed in u_{yt}. We do not impose restrictions on the earnings process to guard against misspecification of the earnings equation (in view of the results in Column 1 and the results for family income in Section 4). The strategy here is to use the unrestricted earnings process as an additional indicator to aid identification of the factor loadings in the other equations. The estimate of the intertemporal labor supply elasticity B_n is -.117 with a standard error of .131. From equations (6.7) and (1.1d), we see that B_n can be identified from $Cov(\Delta N_t, \Delta W_{t-2})/Cov(\Delta W_t, \Delta W_{t-2})$. From the point estimates in Table 1b, one can see that the sign of the estimate of B_n is partially due to the insignificant and small negative estimate of $Cov(\Delta N_t,$ $\Delta W_{t-2})$. The negative estimate has the wrong sign but is not significantly different from 0 or from the small positive values found in most previous micro data studies. The estimate of B_c is -.295 with a standard error of .119. The negative estimate is predicted by the theory. The estimate of $\beta_{\eta w}$, the effect of wage innovations on the marginal utility of wealth which should be negative, is -.0841 with a standard error of .0279. The estimate of $\beta_{\eta z}$, which is the effect of unemployment innovations on the marginal utility of wealth and should be positive, is .00300 with a standard error of .0168. Given the finding that unemployment innovations have smaller and more transitory effects on earnings than wage innovations , the relative and absolute magnitudes of $\beta_{\eta w}$ and $\beta_{\eta z}$ are sensible. The variance of $u_{\eta t}$ is imprecisely estimated at .00893. Wage and unemployment innovations explain 44% of the variance of the innovations in the marginal utility of income. We note that point estimates of the variances of all the measurement errors are positive. The p-value to reject the model is .02.

In Col. 3, we report estimates of the restricted labor supply model with $B_{cn} = 4B_{nc}$. $\beta_{\eta 4}$ is still restricted to be zero and the earnings process is again unrestricted. We can get an estimate of B_{cn} from $Cov(\Delta C_t, \Delta W_{t-2})/Cov(\Delta W_t, \Delta W_{t-2})$. Since the estimate of $Cov(\Delta C_t, \Delta W_{t-2})$ is so imprecise as shown in Table 1b, the estimate of B_{cn} should be treated with caution. The estimate of B_{nc} is -.019, with a large standard error of .042, suggests that consumption and leisure are weak complements. This small negative coefficient argues against explaining the excess response of consumption to the wage innovation in our permanent income estimates by appealing to the lifecycle model. The point estimate for B_n remains negative, again with a large standard error. The point estimate for σ_η^2 is now .0055 which is 1/3 smaller than the previous estimate. Wage and unemployment innovations now explain about 48% of the variance of the innovations in the marginal utility of income. Estimates of the other parameters and the associated standard errors are about the same as before. Finally, we cannot reject the hypothesis that $B_{nc} = 0$ (the χ^2 statistic for col. 2 against col. 3 is .4 with 1 degree of freedom).[23]

8. CONCLUDING REMARKS

Since we have summarized our main empirical findings in the introduction and Sections 5 and 7, we close the paper with a research agenda. First, since more precision in our estimates would be helpful, we are in the midst of analyzing an expanded balanced sample for the years 1976-1983.

Second, we are estimating a version of the lifecycle model based on a dynamic quarterly model.

Third, within the context of the permanent income model we are taking a number of approaches to investigate the possibility that the income factor u_{yt} in our model is contaminated by misspecification. At several points in the paper we have noted that the response of consumption to the income factor u_{yt} seems small relative to the response of consumption to the wage. This is true in the quarterly dynamic factor models as well as the models which ignore problems of timing and nonsyncronization. The income factor is distinguished from income measurement error only by the fact that it is not restricted to be a white noise process and that it is correlated with consumption. All factors that affect income, other than wages, unemployment and work hours, are summarized by u_{yt}. It is unlikely that the consumption response to these factors is appropriately modelled as if consumption was responding to a single factor that followed the u_{yt} process. Indeed, a motivation for our paper is the view that it is important to use more than one indicator of the factors which drive family income if one is to sort out the true income process from measurement error. One approach which we have already explored is to attempt to estimate the marginal propensity to consume and the discount rate from the wage, unemployment, and hours factors only Unfortunately, the results are very imprecise. A second approach we hope to explore is to add wife's work hours to the model as an additional indicator, although some researchers who are can to accept husband's unemployment and even hours of work as exogenous with respect to consumption may balk at using wife's hours. What is really needed is a data set which contains reliable information on additional factors which affect income. More accurate and complete information on consumption expenditures would also be very helpful.

Footnotes

1. Many recent papers use the terms permanent income model and "life cycle model" interchangeably. In this paper we restrict "permanent income model" to refer to models in which labor income is exogenous and current wealth plus the expected discounted value of current and future income is a sufficient statistic for the effect of lifetime resources on consumption.

2. The pure intertemporal substitution responses to wages, prices, and interest rates (with the marginal of utility of income held constant) can and have been estimated without a model of wage, price and interest rate behavior. (See for example, Heckman and MaCurdy (1980), MaCurdy (1981), Hansen and Singleton (1983) and Browning et al (1985), and Altonji (1986)). Furthermore, following Hall (1978), many studies have tested versions of the permanent income and lifecycle models by examining whether past information about wages, interest rates and other budget constraint determinants is related to changes in consumption. These studies, surveyed in Hayashi (1985a). do not require a detailed model of the income process either. See King (1985), Deaton (1985), Mayer (1972), and Hayashi (1985a) for discussions and references to the permanent income hypothesis. See Altonji (1986), Blundell (1986), Browning et al (1984), Ghez and Becker (1975), Heckman (1974), Heckman and MaCurdy (1980), King (1985), Killingsworth (1983), MaCurdy (1981,1983), Mankiw et al. (1985), for detailed discussions and references to the literature on lifecycle models.

3. Duncan and Hill (1984) have provided some direct evidence on the importance of measurement error by comparing the responses of employees of a single large firm with the records of the employer. They find that measurement error accounts for 16.8 percent of the variance in the earnings level. Under reasonable assumptions, these would translate into a much larger percentage of the variance in the first difference of earnings. Measurement error in nonlabor income is likely to be an even more serious problem. Mellow and Sider(1984) use matched employer/employee responses to show the existence of considerable measurement error in the survey data. Altonji (1986) provides evidence of substantial measurement error in the first difference of the log of earnings divided by hours and in hours of work. For the same data, Altonji and Siow (1986) found that the lifecycle model may be wrongly rejected if measurement error in the income variable is ignored, and found that the ordinary least squares estimate of the regression coefficient relating the change in consumption to the change in income is only one third of the estimate obtained using an instrumental variables estimator to account for measurement error. In his survey, Hayashi (1985a) concludes that measurement error is a major issue in micro panel studies of consumption and liquidity constraints.

4. Attention to reporting error problems in work on the consumption function is not new. For example, the interesting study by Bhalla(1979) makes use of an Indian panel data containing independent measures of consumption, savings, and income to study consumption behavior. However, Bhalla's analysis is not conducted in a rational expectations framework and di fers in many ways from the work presented here.

5. Holbrook and Stafford (1971) analyzed the link between the level of consumption and various components of family income using one year of consumption data and 3 years of income data for a cross section of families.

They assume that the components of income each consist a fixed trend and a transitory element. The transitory elements may be correlated across income components and may be autocorrelated for up to one period. Although Holbrook and Stafford do not work within a rational expectations framework, their analysis shows that consumption is less responsive to the elements of family income which are most transitory, and is an important precursor to the Hall Mishkin study and the present project. An early study by Mincer (1960) uses wage changes as an indicator of permanent income changes and hours changes as an indicator of transitory income changes.

6. See Lillard and Weiss (1979), Hause (1980), Kearl (1985), MaCurdy (1982 a and b), Abowd and Card (1985 and 1986) and Chowdhury and Nickell (1985).

7. Hall and Mishin (1982) found that the change in consumption responds to the lagged change in income using the PSID, and this result is frequently cited as evidence against a simple rational expectations permanent income model. The bulk of the evidence from time series data is consistent with their results (See Deaton (1985)). However, our finding that this evidence for the PSID is not robust is consistent with the results of our earlier paper (Altonji and Siow (1986)). In that paper we obtain different evidence on the effect of the lagged change in the log of income on the change in the log of consumption with different samples, although the empirical magnitude of the effect was small in all cases. Zeldes' (1985) findings on the relationship between change in the log of consumption and the lagged value of the log of income are also sensitive to the details of the specification and sample.

8. We also experimented with hours of illness, but it did not contribute much to explaining the variables of interest.

9. While it may not be what they had in mind, the permanent income quarterly model specified below aggregates up to the restrictions Hall and Mishkin impose on the covariance annual data (see their page 472). Moreover, it is consistent with their structural intepretation of their parameters.

$$Y_{t.i} - Y_{t-1.i} = \varepsilon_{t.i} + \eta_{t.i} - (1-\beta_1)\,\eta_{t-1.i} - (\beta_1 - \beta_2)\,\eta_{t-2.i} - \beta_2\eta_{t-3.i}$$

$$C_{t.i} - C_{t.i-1} \simeq \alpha\,(\varepsilon_{t.i} + (1 - (1-\beta_1)\,\rho_q{}^4 - (\beta_1 - \beta_2)\,\rho_q{}^8 - \beta_2\rho_q{}^{12})\eta_{t.i})$$

$$Y^*_t - Y^*_{t-1} \equiv \textstyle\sum_{i=1}^4 (Y_{t-1.i} - Y_{t-2.i})$$

$$C^*_t - C^*_{t-1} \equiv C_{t.1} - C_{t-1.1} + \beta_{cc0}u_{ct} + \beta_{cc1}u_{ct-1} + \beta_{cc2}u_{ct-2}$$

The variables $\varepsilon_{t.i}$ and $\eta_{t.i}$ are quarterly innovations of the random walk component and the moving average component of the income process respectively. $Y_{t.i}$ and $C_{t.i}$ (i=1,2,3,4) are income and consumption in the i'th quarter of year t, and ρ_q is the quarterly discount factor.

10. Abowd and Card (1985, Appendix A) provide a clear exposition of the issues which are relevant to the present paper.

11. For example, consider the variance of the wage change in each of our 5 sample years. For each year the fourth moments of the wage change form the basis of our estimates of the variance of the wage variance. These fourth

moments are the elements of the diagonal of V corresponding to the estimated variances of the wage in each of the 5 years. We set the 5 elements of the diagonal of Ω corresponding to the 5 wage variances equal to the inverse of the average of the 5 fourth moments of the wage change.

12. Briefly, if the wage, hours, family income, earnings, showed an increase of 500% or a decline of 80% from the previous year, the observation was eliminated. Observations were also eliminated if the change in consumption showed an increase of 400% or a decrease of 75% from the previous year. Finally, we elminated observations with an annual hours change of more than 3,000 hours, a level of hours above 5,000, or wage measures below \$.50 per hour in 1972 dollars.

13. 3, 4 and 5 sample moments for the covariances involving second, first, and 0 lags, respectively.

14. We had difficulty getting the algorithm used to compute the optimal minimum distance estimator to converge even with various starting values.

15. The best case for serially correlated measurement error was obtained for the log consumption model in Table 5, col. 9 and the associated income model. The χ^2 statistic with 3 degrees of freedom to test the hypothesis that the moving average parameters τ_y, τ_n and τ_w are 0 is 6.4. The estimated consumption and income equations are:

$$\Delta C^*_t = \underset{(.00822)}{.0217}u_{wt} + \underset{(.00474)}{.00121}u_{zt} + \underset{(.00657)}{.00895}u_{nt} + \underset{(.0105)}{.0350}u_{yt}$$

$$+ \underset{(.00606)}{.254}u_{ct} - \underset{(.00725)}{.148}u_{ct-1} + \underset{(.01800)}{.0180}u_{ct-2}$$

$$\Delta Y^*_t = \underset{(.00878)}{.0248}u_{wt} - \underset{(.00465)}{.00191}u_{wt-1} - \underset{(.00475)}{.000692}u_{wt-2} + \underset{(.0134)}{.0425}u_{nt} - \underset{(.00708)}{.0121}u_{nt-1}$$

$$+ \underset{(.00883)}{.0008}u_{nt-2} - \underset{(.00496)}{.0170}u_{zt} + \underset{(.00631)}{.0192}u_{zt-1} + \underset{(.00602)}{.00233}u_{zt-2} + \underset{(.0288)}{.0401}u_{yt}$$

$$+ \underset{(.0398)}{.0353}u_{yt-1} + \underset{(.0358)}{.0345}u_{yt-2} + \varepsilon_{yt} - (\underset{(.0714)}{.162} - 1)\varepsilon_{yt-1} + \underset{(.0714)}{.162}\varepsilon_{yt-2}$$

16. OMD estimates of some contemporaneous covariances are presented to be compared with those in Table 1a and 1b.

	Levels		Logs	
	Estimate	SE	Estimate	SE
Cov $(\Delta C_t, \Delta C_t)$	492000.	31100.	.123	.00333
Cov $(\Delta Y_t, \Delta Y_t)$	11900000.	457000.	.104	.00342
Cov $(\Delta N_t, \Delta N_t)$	220000.	7690.	.0669	.00293
Cov $(\Delta Z_t, \Delta Z_t)$	66200.	4340.	.00772	.000471
Cov $(\Delta W_t, \Delta W_t)$	.510	.0405	.0371	.00189
Cov $(\Delta C_t, \Delta W_t)$	25.0	13.8	.00399	.00105
Cov $(\Delta C_t, \Delta Y_t)$	205000.	46600.	.00654	.00163
Cov $(\Delta C_t, \Delta N_t)$	2460.	4470.	.0000564	.00126
Cov $(\Delta C_t, \Delta Z_t)$	-2790.	2690.	-.000160	.000364
Cov $(\Delta Y_t, \Delta W_t)$	260.	46.5	.00776	.00104

Corresponding to the log model reported in Col. 9 of Table 5, the estimate of the consumption and income equations are:

$$\Delta C^*_t = \underset{(.00495)}{.0254u_{wt}} - \underset{(.00463)}{.00625u_{zt}} + \underset{(.00454)}{.00162u_{nt}} + \underset{(.00654)}{.0266u_{yt}}$$

$$+ \underset{(.00512)}{.310u_{ct}} \underset{(.00679)}{-.154u_{ct-1}} - \underset{(.00742)}{.0059u_{ct-2}}$$

$$\Delta Y^*_t = \underset{(.00495)}{.0489u_{wt}} + \underset{(.00586)}{.00145u_{wt-1}} \underset{(.00665)}{-.00725u_{wt-2}} + \underset{(.0551)}{.0402u_{nt}} + \underset{(.00573)}{.00509u_{nt-1}}$$

$$+ \underset{(.00689)}{.00876u_{nt-2}} \underset{(.00550)}{-.0421u_{zt}} + \underset{(.00662)}{.0144u_{zt-1}} + \underset{(.00608)}{.00811u_{zt-2}} + \underset{(.0499)}{.155u_{yt}}$$

$$+ \underset{(.0598)}{.0482u_{yt-1}} - \underset{(.0163)}{.0306u_{yt-2}} + \varepsilon_{yt} - \varepsilon_{yt-1}$$

$$\sigma^2_{\varepsilon y} = \underset{(.00479)}{.0342}$$

17. We restricted our investigation to models with exogenous work hours. Certain sample moments are missing because the relevant questions were not asked in those survey years. C_{1973}, W_{68}, W_{69} are missing. The wage variable is unavailable for salary workers prior to 1976.

18. WLS estimates of some contemporaneous covariances are presented to be compared with those in Table 1a and 1b. The reported standard errors are calculated as if the diagonal weighting matrix is the optimal weighting matrix.

	Levels		Logs	
	Estimate	SE	Estimate	SE
Cov $(\Delta C_t, \Delta C_t)$	624000.	29100.	.114	.00221
Cov $(\Delta Y_t, \Delta Y_t)$	13600000.	448000.	.113	.00240
Cov $(\Delta N_t, \Delta N_t)$	240000.	5530.	.0788	.00227
Cov $(\Delta Z_t, \Delta Z_t)$	67000.	2810.	.00808	.000330
Cov $(\Delta W_t, \Delta W_t)$	.733	.0586	.0361	.00146
Cov $(\Delta C_t, \Delta W_t)$	29.0	18.4	.00358	.000998
Cov $(\Delta C_t, \Delta Y_t)$	250000.	57000.	.00869	.00136
Cov $(\Delta C_t, \Delta N_t)$	9193.	4422.	.00167	.00117
Cov $(\Delta C_t, \Delta Z_t)$	-4842.	3010.	-.000563	.000387
Cov $(\Delta v_t, \Delta W_t)$	368.	71.2	.00735	.000961

Corresponding to the log model reported in Col. 9 of Table 5, the estimates of the consumption and income equations are:

$$\Delta C^*_t = \underset{(.00711)}{.0215u_{wt}} - \underset{(.00432)}{.00983u_{zt}} + \underset{(.00467)}{.00216u_{nt}} + \underset{(.00881)}{.0475u_{yt}}$$

$$+ \underset{(.00691)}{.299u_{ct}} \underset{(.00934)}{-.146u_{ct-1}} - \underset{(.00580)}{.00824u_{ct-2}}$$

$$\Delta Y^*_t = \underset{(.00981)}{.0448u_{wt}} + \underset{(.00636)}{.00975u_{wt-1}} - \underset{(.00586)}{.00730u_{wt-2}} + \underset{(.0108)}{.0451u_{nt}} + \underset{(.00531)}{.000199u_{nt-1}}$$

$$- \underset{(.00500)}{.00211u_{nt-2}} - \underset{(.00544)}{.0531u_{zt}} + \underset{(.00554)}{.0222u_{zt-1}} + \underset{(.00494)}{.0125u_{zt-2}} + \underset{(.0201)}{.151u_{yt}}$$

$$+ \underset{(.0238)}{.0723u_{yt-1}} - \underset{(.0108)}{.0386u_{yt-2}} + \varepsilon_{yt} - \varepsilon_{yt-1}$$

$$\sigma^2_{\varepsilon y} = \underset{(.00157)}{.0380}$$

19. We have not explored models which relax intertemporal separability, and our interpretation of the evidence is of course conditional on this assumption. See Hotz et al (1985), Eichenbaum et al (1984), and Blundell (1986) for some initial steps in this direction.

20. As Ham (1986) and others have discussed, the presence of hours constraints may bias the estimates of the labor supply parameters, particularly if u_{zt} is correlated with the other factors in the model. Problems may also arise if, as in the Lucas and Rapping model of unemployment, hours of unemployment are intrinsically related to labor supply decisions and vary with the wage rate. We are ignoring these considerations. Note that we cannot reject the hypothesis that covariances between the wage and unemployment are 0. The papers by Ashenfelter (1980) Browning et al (1985)) suggest that the form of the consumption, hours, and marginal utility of income equations are affected by constraints on labor supply.

21. As Chamberlain (1984) pointed out and Hayashi (1985b) observed in a similar context, the rational expectations hypothesis does not imply that the forecast error η_t is uncorrelated with past information when the distribution is taken across households rather than over time for a given household. If the effect of an aggregrate disturbance on the marginal utility of income is systematically related to determinants of Δw^*_t ΔX^*_{t-1}, ΔZ^*_{t-1}, ΔQ^*_{t-1}, and ΔQ^*_{t-1}, then these determinants will be correlated with η_t in a short panel. A similar problem would arise in Hall and Mishkin's analysis or in the work with the RE-PI model discussed above. However, we doubt if this is a serious problem here, since most of the variation in the change in the wage, hours of unemployment, hours lost due to illness and other key elements of Δw^*_{t-1}, ΔX^*_{t-1}, ΔZ^*_{t-1} and ΔQ^*_{t-1} occurs over time for a given household rather than cross-sectional, and we follow Hall and Mishkin's lead and remove the main effects of aggregate shocks through the use of time dummies.

22. To our knowledge, this paper is the first to attempt to estimate the contribution of various factors to the variance in the innovation of the marginal utility of income. Using aggregate time series data, Attfield and Browning (1985) provide estimates of the covariance of innovation of the marginal utility of income with price changes. They do so by exploiting the symmetry and homogeneity restrictions of a demand system. They do not have to impose the assumption of rational expectations.

23. In the Appendix, Table A4 presents a set of WLS estimates. The point estimates for B_n, B_{nc} are still negative. Although consistent with earlier estimates, these results are surprising because in Table A1b, we see that Cov $(\Delta N_t, \Delta W_{t-2})$/Cov $(\Delta W_t, \Delta W_{t-2})$ and Cov $(\Delta C_t, \Delta W_{t-2})$/Cov $(\Delta W_t, \Delta W_{t-2})$ are positive. The WLS results are basically similar to the OMD results.

REFERENCES

Abowd, John M. and David E. Card, "Intertemporal Substitution in the Presence of Long Term Contracts," National Bureau of Economic Research working paper No. 1831 (February 1986).

_______ and _______, "On the Covariance Structure of Hours and Earnings Changes." Unpublished paper, Princeton University, (December 1985).

Almon, Shirley, "The Distributed Lag between Capital Appropriations and Expenditures," Econometrica Vol. 30 (1962) : 407-423.

Altonji, Joseph G., "Intertemporal Substitution in Labor Supply: Evidence from Micro Data", Journal of Political Economy XCIV No. 3 Part 2 (June 1986), S176-15.

_______, and Aloysius Siow, "Testing the Response of Consumption to Income Changes with (Noisy) Panel Data", NBER Working Paper No. 2012 (September 1986, Forthcoming in Quarterly Journal of Economics).

_______, and Paxson, Christina H., "Job Characteristics and Hours of Work", NBER Working Paper No. 1895 (April 1986, Forthcoming in Research in Labor Economics).

Ashenfelter, Orley., "Unemployment as Disequilibrium in a Model of Aggregate Labor Supply," Econometrica, XLVIII (April 1980), 547-64.

Attfield, C. L. F. and M. J. Browning, "A Differential Demand System, Rational Expectations, and the Life Cycle Hypothesis", Econometrica, Vol. 53, No. 1 (January 1985): 31-48.

Bernanke, Ben, "Permanent Income, Liquidity, and Expenditure on Automobiles: Evidence from Panel Data." Quarterly Journal of Economics, XCIX (1984), 587-14.

Bhalla, Surjit S., "Measurement Errors and the Permanent Income Hypothesis: Evidence from Rural India", American Economic Review, LXIX (June 1979), 195-07.

Blundell, R. "Econometric Approaches to the Specification of Life-Cycle Labour Supply and Commodity Demand Behavior", forthcoming in Econometric Reviews, Vol. 5(1) (2986).

Browning, Martin, Angus Deaton, and Margaret Irish, "A Profitable Approach to Labor Supply and Commodity Demands over the Life-Cycle," Econometrica LIII (May 1985), 503-44.

Chamberlain, Gary. "Panel Data." in Z. Griliches and M. Intrilligator Eds., Handbook of Econometrics, (1984).

Chowdhury, Gopa and Stephen Nickell, "Hourly Earnings in the United States: Another Look at Unionization, Schooling, Sickness and Unemployment Using PSID Data". Journal of Labor Economics Vol 3(1) Part 1 (January 1985): 38-69.

Deaton, Angus, "Life-cycle Models of Consumptoin: Is the Evidence Consistent with the Theory", (July 1985).

Deaton, Angus, and John Muellbauer, Economics and Consumer Behavior, Cambridge University Press, Cambridge (1980).

Duncan, Gregory, and Daniel Hill, "An Investigation of the Extent and Consequences of Measurement Error in Labor Economic Survey Data", Survey Research Center, The University of Michigan (July 1984).

Eichenbaum, Martin S., Lars P. Hansen and Kenneth J. Singleton, "A Time Series Analysis of Representative Agent Models of Consumption and Leisure Choice under Uncertainty", unpublished paper (January 1984).

Flavin, Marjorie A., "Excess Sensitivity of Consumption to Current Income: Liquidity Constraints or Myopia?", Canadian Journal of Economics, XVIII (February 1985), 117-36.

________, "The Adjustment of Consumption to Changing Expectations about Future Income," Journal of Political Economy, LXXXIX (1981), 974-09.

Friedman, Milton, "A Theory of the Consumpton Function, Princeton: Princeton University Press, (1957).

Ghez, Gilbert and Becker, Gary S. The Allocation of Time and Goods Over the Life Cycle. NBER Columbia University Press (1975).

Hall, Robert E., "Stochastic Implications of the Life Cycle-Permanent Income Hypothesis: Theory and Evidence," Journal of Political Economy, LXXXVI (1978), 971-987.

________, and Frederick S. Mishkin, "The Sensitivity of Consumption to Transitory Income: Estimates from Panel Data on Households," Econometrica, L (March 1982), 261-81.

Ham, John C., "Testing Whether Unemployment Represents Life-Cycle Labor Supply Behavior" The Review of Economic Studies (July 1986).

Hansen, Lars P., and Singleton, Kenneth J. "Stochastic Consumption, Risk Aversion, and the Temporal Behavior of Stock Market Returns." Journal of Political Economy, 91, No. 2 (March 1983): 249-265.

Hause, John C., "The Fine Structure of Earnings and the On-The-Job Training Hypothesis," Econometrica, 48 No. 4 (May 1980):1013-1029.

Hayashi, Fumio, "Tests for Liquidity Constraints: A Critical Survey", NBER Working Paper No. 1720 (October 1985a).

--------------, "The Permanent Income Hypothesis and Consumption Durability: Analysis Based on Japanese Panel Data," Quarterly Journal of Economics, C No. 4 (November 1985b): 1083-1113.

Heckman, James J. "Life Cycle Consumption and Labor Supply: An Explanation of the Relationship between Income and Consumption over the Life Cycle." American Economic Review 64 (March 1974): 188-194.

__________, and Thomas E. MaCurdy, "A Life-Cycle Model of Female Labour Supply." Review of Economic Studies 47 (January 1980): 47-74.

Holbrook, Robert, and Stafford, Frank., "The Propensity to Consume Separate Types of Income: A Generalized Permanent Income Hypothesis," Econometrica, XXXIX (January 1971), 1-22.

Hotz, V. Joseph, Finn Kydland, and Guilherme Sedlacek, "Intertemporal Preferences and Labor Supply," Unpublished paper, Carnegie-Mellon University (December 1985).

Kearl, J. R., "The Covariance Structure of Earnings and Income, Compensatory Behavior and On-The-Job Investments", NBER Working Paper No. 1747 (October 1985).

Killingsworth, Mark R, Labor Supply, Cambridge: Cambridge University Press (1983).

King, Mervyn, "The Economics of Saving: A Survey of Recent Contributions," in K. Arrow and S. Hartiapohja, (editors), Frontiers of Economics, Oxford: Basil Blackwell (1985).

Lillard, Lee and Yoram Weiss, "Components of Variation in Panel Earnings Data: American Scientists 1960-1970", Econometrica 47 No. 2 (March 1979): 437-454.

MaCurdy, Thomas E., "A Simple Scheme for Estimating an Intertemporal Model of Labor Supply and Consumption in the Presence of Taxes and Uncertainty," International Economic Review, XXIV No. 2 (June 1983), 265-290.

________. "The Use of Time Series Processes to Model the Error Structure of Earnings in a Longitudinal Data Analysis." Journal of Econometrics, 18 (1982a): 83-114.

________., "Modeling the Dynamic Components of Hours of Work Using Multiple Time Series Analysis Applied to Panel Data" unpublished paper, Stanford University (November 1982).

________, "An Empirical Model of Labor Supply in a Life-Cycle Setting", Journal of Political Economy, LXXXIX (December 1981), 1059-85.

Mankiw, N. Greg, Julio Rotemberg, and Lawrence H. Summers, "Intertemporal Substitution in Macroeconomics," Quarterly Journal of Economics C (February 1985), 225-51.

Mayer, Thomas, Permanent Income, Wealth, and Consumption: A Critique of the Permanent Income Theory, the Life-Cycle Hypothesis, and Related Theories, Los Angeles: University of California Press, (1972) Mellow, Wesley, and Hal Sider, "Accuracy of Response in Labor Market Surveys: Evidence and Implications", Journal of Labor Economics, I No. 4, (October 1983), 331-44

Mincer, Jacob, "Consumption and Employment", Review of Economics and Statistics, XLII No. 1 (February 1960), 20-26.

Newey, Whitney K., "Generalized Method of Moments Specification Testing.", Journal of Econometrics Vol 29 (September 1985):229-256

Sargent, Thomas J., "Rational Expectations, Econometric Exogeneity and Consumption," Journal of Political Economy LXXXVI (1978), 673-700.

Survey Research Center, A Panel Study of Income Dynamics: Procedures and Tape Codes 1981 Interviewing Year, Institute for Social Research, University of Michigan, Ann Arbor Michigan. (1982).

Zeldes, Stephen, "Consumption and Liquidity Constraints: An Empirical Investigation," Working Paper No. 24-85, Wharton School, University of Pennsylvania (November 1985).

Table 1a
Optimal Minimum Distance Estimate of Covariances (Data in Levels)

	Consumption			Family Income			Work Hours			Unemployment			Wage		
	ΔC_t^*	ΔC_{t-1}^*	ΔC_{t-2}^*	ΔY_t^*	ΔY_{t-1}^*	ΔY_{t-2}^*	ΔN_t^*	ΔN_{t-1}^*	ΔN_{t-2}^*	ΔZ_t^*	ΔZ_{t-1}^*	ΔZ_{t-2}^*	ΔW_t^*	ΔW_{t-1}^*	ΔW_{t-2}^*
ΔC_t^*	223000. (14800.)	-98300. (8110.)	5770. (8660.)	56000. (27400.)	-47600. (28700.)	22200. (29800.)	1220. (2830.)	3970. (3190.)	-3970. (4390.)	32.7 (1040.)	-1170. (1050.)	465. (1510.)	14.3 (5.54)	1.42 (5.37)	-6.15 (6.86)
ΔC_{t-1}^*				22300. (29300.)			203. (3190.)			-326. (957.)			-13.6 (5.93)		
ΔC_{t-2}^*				-854. (31700.)			721. (3530.)			-6.86 (1010.)			4.30 (5.90)		
ΔY_t^*				5060000. (279000.)	-1630000. (156000.)	-340000. (137000.)	94300. (15300.)	-31300. (15700.)	-1210. (17600.)	-22000. (5560.)	12900. (5720.)	-649. (5700.)	118. (25.9)	38.8 (27.2)	-2.57 (24.8)
ΔY_{t-1}^*							-44600. (14600.)			7940. (4180.)			-70.1 (25.2)		
ΔY_{t-2}^*							-2330. (16700.)			-894. (5200.)			-13.5 (26.2)		
ΔN_t^*							101000. (6440.)	-41000. (3650.)	-649. (2860.)	-6410. (1300.)	3690. (756.)	-433. (653.)	-6.20 (3.14)	8.13 (3.91)	-2.81 (3.26)
ΔN_{t-1}^*										1580. (546.)			.333 (3.30)		
ΔN_{t-2}^*										542. (641.)			-2.87 (3.57)		
ΔZ_t^*										5540. (1340.)	-2610. (616.)	-335. (425.)	-.0127 (1.09)	-.614 (1.14)	1.67 (1.24)
ΔZ_{t-1}^*													.319 (.943)		
ΔZ_{t-2}^*													1.18 (1.13)		
ΔW_t^*													.201 (.0153)	-.057 (.00771)	.011 (.00712)

(standard errors in parentheses)

Table 1b
Optimal Minimum Distance Estimate of Covariances (Data in Logs)

	Consumption			Family Income			Work Hours			Unemployment			Wage		
	ΔC_t^*	ΔC_{t-1}^*	ΔC_{t-2}^*	ΔY_t^*	ΔY_{t-1}^*	ΔY_{t-2}^*	ΔN_t^*	ΔN_{t-1}^*	ΔN_{t-2}^*	Z_t^*	Z_{t-1}^*	Z_{t-2}^*	ΔW_t^*	ΔW_{t-1}^*	ΔW_{t-2}^*
ΔC_t^*	.0880 (.00374)	-.0395 (.00253)	.00404 (.00253)	.00214 (.00140)	-.000293 (.00149)	-.000017 (.00169)	.000186 (.000916)	.000497 (.00107)	-.00163 (.00145)	.0000607 (.000166)	.000137 (.000172)	.000193 (.000197)	.00331 (.000848)	-.000091 (.000875)	.000199 (.000945)
ΔC_{t-1}^*				.00139 (.00137)			.000986 (.000982)			.0000075 (.000147)			-.00227 (.000905)		
ΔC_{t-2}^*				.000842 (.00149)			.0000354 (.00105)			-.000216 (.000188)			.000467 (.00104)		
ΔY_t^*				.0443 (.00228)	-.0132 (.00133)	-.00253 (.00126)	.00616 (.000890)	-.00182 (.000792)	-.000155 (.000860)	-.000265 (.000136)	.000560 (.000166)	.0000648 (.000154)	.00424 (.000843)	-.000027 (.000802)	-.000237 (.000753)
ΔY_{t-1}^*							-.00250 (.000758)			.0000332 (.000159)			-.00265 (.000791)		
ΔY_{t-2}^*							.0000426 (.000850)			.000104 (.000164)			.000589 (.000802)		
ΔN_t^*							.0251 (.00201)	-.00962 (.00101)	-.000801 (.000799)	-.000759 (.000198)	.00102 (.000214)	.000151 (.000112)	-.000809 (.000534)	-.000909 (.000593)	-.000312 (.000504)
ΔN_{t-1}^*										-.000204 (.000140)			.000293 (.000505)		
ΔN_{t-2}^*										-.000096 (.000122)			-.000025 (.000583)		
Z_t^*										.00105 (.000160)	.000417 (.0000959)	.000284 (.000100)	.0000434 (.0000946)	-.000167 (.0000893)	.000067 (.0000920)
Z_{t-1}^*													.0000398 (.0000972)		
Z_{t-2}^*													-.000097 (.0000933)		
ΔW_t^*													.0172 (.00142)	-.00549 (.000819)	.00113 (.000652)

(standard errors in parentheses)

Table 2a

χ^2 Tests of Restrictions on the Covariance Structure of Consumption, Hours, Income, Wages and Unemployment. Data in Levels

$\chi^2_{(\text{degrees of freedom})}$ [p-values in brackets]

	MAINTAINED ASSUMPTIONS OF ALTERNATIVE HYPOTHESIS IN TEST.		
RESTRICTIONS IMPOSED UNDER NULL HYPOTHESIS	Unrestricted Nonstationary Model	A:Stationarity	B:Stationarity Cov(wages, hours)=0 Cov(wages, unempl)=0
A: 1. Stationarity	$307.7_{(185)}$ [.000]		
B: 1. Stationarity, 2. Cov(wages, unempl.)=0 3. Cov(wages, hours)=0	$327.7_{(195)}$ [.000]	$20.0_{(10)}$ [.029]	
C: 1. Stationarity 4. 0 Cov between cons. and lagged income determinants	$318.7_{(193)}$ [.000]	$11.0_{(8)}$ [.200]	
D: 1. Stationarity 2. Cov(wages, unempl.)=0 3. Cov(wages, hours)=0 4. Cov between cons. and lagged income determinants	$337.7_{(203)}$ [.000]	$30.0_{(18)}$ [.038]	$10.0_{(8)}$ [.264]
E: 1. Stationarity 5. Factor model, unrestricted consumption equation	$342.3_{(208)}$ [.000]	$34.6_{(23)}$ [.057]	$14.6_{(13)}$ [.334]

Table 2b

χ^2 Tests of Restrictions on the Covariance Structure of Consumption, Hours, Income, Wages and Unemployment. Data in Logs

$\chi^2_{(\text{degrees of freedom})}$ [p-values in brackets]

	MAINTAINED ASSUMPTIONS OF ALTERNATIVE HYPOTHESIS IN TEST.		
RESTRICTIONS IMPOSED UNDER NULL HYPOTHESIS	Unrestricted Nonstationary Model	A:Stationarity	B:Stationarity Cov(wages, hours)=0 Cov(wages, unempl)=0
A: 1. Stationarity	$340.5_{(185)}$ .000		
B: 1. Stationarity, 2. Cov(wages, unempl.)=0 3. Cov(wages, hours)=0	$355.6_{(185)}$ .000	$15.1_{(10)}$ [.127]	
C: 1. Stationarity 4. 0 Cov between cons. and lagged income determinants	$345.0_{(193)}$ .000	$4.6_{(8)}$ [.804]	
D: 1. Stationarity 2. Cov(wages, unempl.)=0 3. Cov(wages, hours)=0 4. Cov between cons. and lagged income determinants	$359.4_{(203)}$ .000	$18.9_{(18)}$ [.397]	$3.8_{(8)}$ [.878]
E: 1. Stationarity 5. Factor model, unrestricted consumption equation	$372.6_{(208)}$ [.000]	$32.1_{(23)}$ [.097]	$17.0_{(13)}$ [.199]

Table 3

Equations of the Income Models (OMD Estimates)*

	Data in Levels		Data in Logs	
	Estimate	S.E.	Estimate	S.E.
<u>Income</u> (ΔY^*t)				
β_{yw0}	197.	56.0	.0210	.00682
β_{yw1}	64.6	39.6	-.000808	.00392
β_{yw2}	2.81	39.2	-.00108	.00407
β_{yn0}	164.	112.	.0333	.00870
β_{yn1}	-85.6	59.5	-.00951	.00564
β_{yn2}	8.98	52.6	-.0000868	.00695
β_{yz0}	-205.	53.7	-.0169	.00495
β_{yz1}	116.	66.2	.0189	.00627
β_{yz2}	-7.36	82.4	.00236	.00609
β_{yy0}	1050.	246.	.0766	.0737
β_{yy1}	272.	311.	.0627	.103
β_{yy2}	-286.	139.	-.0292	.0326
σ^2_y	1820000.	217000.	.0156	.00218
<u>Wage</u> (ΔW^*t)				
β_{ww0}	.699	.194	.200	.0550
β_{ww1}	-.397	.195	-.125	.0541
β_{ww2}	.00117	.0120	.00357	.00365
σ^2_w	-.220	.213	-.0189	.0176
<u>Hours</u> (ΔN^*_t)				
β_{nn0}	330.	187.	.127	.030
β_{nn1}	-194.	191.	-.0575	.0306
β_{nn2}	-5.25	9.14	-.00272	.00617
β_{nz0}	-66.8	8.88	-.0374	.00604
β_{nz1}	41.9	8.17	.0318	.00563
β_{nz2}	-8.35	9.76	.00709	.00405
σ^2_n	-25400.	99000.	.00173	.00556
<u>Unemploy.</u> (ΔZ^*_t)				
β_{zz0}	69.9	7.32	.0296	.00254
β_{zz1}	-36.0	5.59	.00951	.00163
β_{zz2}	1.41	6.29	.00674	.00247

*Both income equations were estimated jointly with their respective unrestricted consumption equations. Goodness of fit statistics are reported with the consumption equations in Table 5, Columns 1 and 8 respectively.

TABLE 4

Regression Models for the Change in Log Family Income (ΔY^*_t)

		(1)		(2)		(3)	
	Variable	**Parameter Estimate**	**Standard Error**	**Parameter Estimate**	**Standard Error**	**Parameter Estimate**	**Standard Error**
	Intercept	0.00216	0.003406	0.005889	0.0036768	0.0069037	0.0034123
Fam Inc.	ΔY^*_{t-1}	-0.344889	0.015193	-0.365845	0.015195	-0.409402	0.015237
	ΔY^*_{t-2}	-0.149442	0.014164	-0.164237	0.014207	-0.180597	0.014217
Wage	ΔW^*_t			0.255408	0.021303	0.253772	0.019779
	ΔW^*_{t-1}			0.230359	0.023417	0.259038	0.021814
	ΔW^*_{t-2}			0.130852	0.022149	0.162618	0.020694
Hours	ΔN^*_t			0.175907	0.021493	0.188632	0.019968
	ΔN^*_{t-1}			0.102820	0.023286	0.134116	0.021688
	ΔN^*_{t-2}			0.079422	0.017428	0.098556	0.016283
Unempl.	Z^*_t			-0.210617	0.073056	-0.219238	0.067839
	Z^*_{t-1}			0.243431	0.075413	0.247934	0.070081
	Z^*_{t-2}			-0.015513	0.066992	-0.020714	0.062227
Wife's Hours	ΔNS^*_t					0.315563	0.012844
	ΔNS^*_{t-1}					0.174080	0.013839
	ΔNS^*_{t-2}					0.079502	0.013325
Wife's Unempl.	ZS^*_t					-0.029845	0.026945
	ZS^*_{t-1}					0.011641	0.026542
	ZS^*_{t-2}					0.022398	0.024941
	R^2	.1154		.1822		.2970	
	MSE	.0473		.0418		.0377	

TABLE 4 (continued)

Regressions Models for the Change in Log Earnings (ΔY_t^{**})

		(1)		(2)		(3)	
	Variable	Parameter Estimate	Standard Error	Parameter Estimate	Standard Error	Parameter Estimate	Standard Error
	Intercept	0.012811	0.0032534	0.019658	0.003109	0.019634	0.003111
Earnings	ΔY^*_{t-1}	-0.412299	0.015327	-0.524590	0.015191	-0.524500	0.015197
	ΔY^*_{t-2}	-0.132896	0.013809	-0.196307	0.013848	-0.196216	0.013855
Wage	ΔW^*_t			0.361598	0.017960	0.362132	0.017976
	ΔW^*_{t-1}			0.394570	0.020287	0.393079	0.020309
	ΔW^*_{t-2}			0.251440	0.019365	0.250672	0.019390
Hours	ΔN^*_t			0.371535	0.018128	0.370928	0.018155
	ΔN^*_{t-1}			0.297834	0.020333	0.297084	0.020374
	ΔN^*_{t-2}			0.154049	0.016169	0.152987	0.016193
Unempl.	Z^*_t			-0.516155	0.061596	-0.513953	0.061660
	Z^*_{t-1}			0.410682	0.063874	0.409595	0.063981
	Z^*_{t-2}			0.133424	0.057101	0.131799	0.057175
Wife's Hours	ΔNS^*_t					-0.010471	0.011673
	ΔNS^*_{t-1}					0.000374	0.011723
	ΔNS^*_{t-2}					-0.017061	0.011240
Wife's Unempl.	ZS^*_t					-0.021584	0.024489
	ZS^*_{t-1}					-0.006724	0.024121
	ZS^*_{t-2}					0.010421	0.022663
	R^2	.1506		.3871		.3877	
	MSE	.0431		.0312		.0312	

*Sample Size is 4085. All variables are residuals obtained from regressions of the original variables against a set of demographic variables and time dummies.
See page 23.

Table 5

Consumption Equations: ΔC_t*
OMD estimates: (Standard Errors)

Col.^{a}	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.
			Data in Levels						Data in Logs			
Wage factor: u_{wt}												
β_{cw0}:	12.9	14.5			17.9			.018	.0171		.0226	
	(7.95)	(7.25)			(8.56)			(.00585)	(.00597)		(.00604)	
β_{cw1}:	1.99							.00122				
	(6.97)							(.00401)				
β_{cw2}:	-8.38							.00326				
	(9.84)							(.00499)				
Unemployment factor: u_{zt}												
β_{cz0}:	-9.91	-13.0			-8.60			-0.00	.00141		.00270	
	(11.5)	(10.5)			(11.3)			(.00625)	(.00472)		(.00462)	
β_{cz1}:	-27.9							-.00101				
	(13.5)							(.00650)				
β_{cz2}:	-2.45							.00477				
	(23.2)							(.00698)				
Hours factor: u_{nt}												
β_{cn0}:	4.48	12.2						.00422	.00653			
	(9.71)	(8.89)						(.00616)	(.00535)			
β_{cn1}:	-2.95							-.00547				
	(8.81)							(.00709)				
β_{cn2}:	-20.4							-.0109				
	(16.9)							(.0122)				
Income Factor: u_{yt}												
β_{cy0}:	61.3	35.2			39.7			.0288	.0253		.0242	
	(19.6)	(11.1)			(12.3)			(.0237)	(.00655)		(.00666)	
β_{cy1}:	-48.1							-.00341				
	(27.4)							(.0400)				
β_{cy2}:	6.78							-.00476				
	(28.4)							(.0266)				

Table 5 (continued)

Col.	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.
Consumption factor: u_{ct}												
β_{cc0}:	393.	396.	396.	391.	400.	400.	397.	.254	.255	.252	.259	.256
	(14.7)	(14.3)	(14.2)	(14.4)	(15.3)	(15.2)	(15.4)	(.00621)	(.00582)	(.00606)	(.00575)	(.00628)
β_{cc1}:	-221.	-218.	-218.	-215.	-220.	-220.	-217.	-.147	-.148	-.147	-.145	-.144
	(17.4)	(15.6)	(15.6)	(15.6)	(18.0)	(17.9)	(17.8)	(.00776)	(.00717)	(.00757)	(.00737)	(.00813)
β_{cc2}:	20.4	25.3	24.6	29.1	17.1	17.7	21.0	.0171	.0177	.0187	.0169	.0186
	(22.1)	(21.8)	(21.6)	(22.1)	(23.6)	(23.4)	(23.8)	(.0105)	(.00984)	(.0105)	(.0100)	(.0112)
α:			.0672	.0291		.0504	.0324			.239		.232
			(.0215)	(.0104)		(.0223)	(.0106)			(.0609)		(.0656)
ρ			-.0437			1.66						
			(.398)			(.598)						
χ^2:	11.3	30.9	31.4	42.8	20.0	20.2	27.9	20.6	25.4	64.6	12.4	61.6
DF	13	21	23	24	14	15	16	13	21	24	14	16
MSE	1.67	1.70	1.69	1.74	1.74	1.73	1.78	1.87	1.83	2.02	1.75	2.12

[a] Col. 1 is the unrestricted levels consumption model. It is jointly estimated with the levels income model in Table 3. Col. 2 has no lagged factors. Col. 3 is the RE-PI model. Col. 4 is the Keynesian model. Col. 5 excludes lagged factors from the consumption equation and annual hours from all equations. Col. 6 is the RE-PI model without annual hours. Col. 7 is the Keynesian model without annual hours. Col. 8 is the unrestricted consumption equation in logs which is estimated with the log income model in Table 3. Col. 9 is the log model with lagged factors excluded from the consumption equation. Col. 10 is the log Keynesian model. Col. 11 excludes lagged factors from the consumption equation and annual hours from all equations. Col. 12 is the log Keynesian model without annual hours.

[b] The χ^2 statistic and degrees of freedom are for a test of the consumption equation and the associated income model against the covariance stationary model. The cross covariances between hours and wages and unemployment and wages are not used in estimation. 212 moments are used to estimate columns 1, 2, 3, 4, 8, 9, and 10. 162 sample moments are used to estimate columns 6, 7, 11, and 12, which exclude annual hours.

Table 6

Quarterly Dynamic Factor Models

	Data in Levels, Annual Hours Excluded OMD Estimates				Data in Logs, Annual Hours Excluded OMD Estimates	
Consumption Equation Parameters	1a Parameter Estimate	1b Standard Error	2a Parameter Estimate	2b Standard Error	3a Parameter Estimate	3b Standard Error
$\beta_{cw0}(u_{wt})$	8.71	4.39			.0118	.00292
$\beta_{cz0}(u_{zt})$	-7.57	5.92			.000392	.00250
$\beta_{cy0}(u_{yt})$	18.7	5.17			.0114	.00321
$\beta_{cc0}(u_{ct})$	403	14.3	402	14.3	.258	.00582
$\beta_{cc1}(u_{ct-1})$	-225	17.6	-224	17.5	-.145	.00760
$\beta_{cc2}(u_{ct-2})$	9.87	21.7	10.7	21.6	.0156	.0102
α			.0357	.0114		
ρ_q			.974	.133		
Income Equation Parameters						
$u_{wt.i}$: a_{0yw}	245	48.7	245	48.4	.0279	.00587
a_{1yw}	-190	41.9	-189	41.6	-.0227	.00510
a_{2yw}	25.8	5.91	25.7	5.87	.00313	.000716
$u_{zt.i}$: a_{0yz}	-145	37.7	-139	36.1	-.00703	.00392
a_{1yz}	112	34.0	106	32.8	.00457	.00367
a_{2yz}	-14.7	4.95	-13.9	4.80	-.000510	.000532
$u_{yt.i}$: a_{0yy}	479	474	463	469	.0172	.0421
a_{1yy}	-209	419	-196	415	.00631	.0387
a_{2yy}	18.0	56.8	16.2	56.3	-.00188	.00535
σ_y^2	1242071	670642	1267353	614696	.0103	.00464
Wage Equation Parameters						
$u_{wt.i}$: a_{0ww}	.188	.0452	.187	.0451	.0577	.0121
a_{1ww}	-.112	.0326	-.111	.0326	-.0359	.00869
a_{2ww}	.0129	.00396	.0127	.00396	.00417	.00106
σ_w^2	-.0613	.0765	-.0601	.0758	-.00608	.00636
Unemployment Equation Parameters						
$u_{zt.i}$: a_{0zz}	8.96	.865	8.94	.863	.00257	.000326
a_{1zz}	-6.16	.705	-6.16	.705	-.00113	.000247
a_{2zz}	.741	.0992	.739	.0988	.000115	.0000348
χ^{2*}	25.7		26.9		47.1	
Degrees of Freedom*	21		22		21	
MSE	1.67		1.66		1.87	

*χ^2 statistic for test of the model against the stationary model
The degrees of freedom are the degrees of freedom of the test.

Table 7

Quarterly Dynamic Factor Models
Annual Hours Included

		Data in Levels OMD Estimates				Data in Logs OMD Estimates	
		1a Parameter Estimate	1b Standard Error	2a Parameter Estimate	2b Standard Error	3a Parameter Estimate	3b Standard Error
Consumption Equation Parameters							
$\beta_{cw0}(u_{wt.i})$		7.65	3.94			.00897	.00266
$\beta_{cz0}(u_{zt.i})$		-9.64	5.76			.000609	.00240
$\beta_{cn0}(u_{nt.i})$		-2.74	4.87			.00366	.00282
$\beta_{cy0}(u_{yt.i})$		13.3	4.97			.0103	.00303
$\beta_{cc0}(u_{ct})$		389.	13.7	388.	13.7	.251	.00564
$\beta_{cc1}(u_{ct-1})$		-218.	16.3	-217.	16.1	-.145	.00720
$\beta_{cc2}(u_{ct-2})$		11.1	20.6	12.2	20.6	.0137	.00973
α				.0316	.0106		
ρ_q				1.03	.0771		
Income Equation Parameters							
u_{wt}:	a_{0yw}	220.	43.0	220.	42.6	.0216	.00501
	a_{1yw}	-172.	37.0	-172.	36.7	-.0179	.00442
	a_{2yw}	23.6	5.23	23.5	5.18	.00251	.000626
u_{zt}:	a_{0yz}	-133.	36.6	-119.	35.9	-.00102	.00356
	a_{1yz}	99.4	32.6	89.0	32.4	.00783	.00341
	a_{2yz}	-12.9	4.74	-11.5	4.73	-.000968	.000499
u_{nt}:	a_{0yn}	85.5	98.7	90.5	114.	.0147	.00382
	a_{1yn}	-104.	109.	-107.	123.	-.00944	.00303
	a_{2yn}	15.5	16.5	15.8	18.5	.00113	.000427
u_{yt}:	a_{0yy}	762.	575.	721.	557.	.0302	.0414
	a_{1yy}	-467.	487.	-433.	474.	-.00732	.0367
	a_{2yy}	53.4	64.8	49.0	63.1	.0000826	.00499
	σ_y^2	486000.	1930000.	623000.	1730000.	.0112	.00213
Wage Equation Parameters							
u_{wt}:	a_{0ww}	.202	.0472	.201	.0467	.0649	.0149
	a_{1ww}	-.124	.0342	-.123	.0339	-.0417	.0107
	a_{2ww}	.0143	.00417	.0141	.00413	.00490	.00129
	σ_w^2	-.0942	.0886	-.0916	.0868	-.0109	.00914

Table 7 (continued)

Unemployment Equation Parameters		1a	1b	2a	2b	3a	3b
u_{zt}:	a_{0zz}	7.76	.802	7.60	.811	.00252	.000243
	a_{1zz}	−5.32	.652	−5.16	.664	−.00123	.000161
	a_{2zz}	.646	.0911	.621	.0927	.000138	.0000214
Annual Hours Equation Parameters							
u_{nt}:	a_{0nn}	6.36	15.5	6.83	16.8	.0134	.00382
	a_{1nn}	−10.3	14.7	−10.5	15.7	−.00892	.00316
	a_{2nn}	1.59	2.06	1.59	2.20	.00108	.000416
	a_{0nz}	−8.84	1.14	−8.76	1.16	−.00518	.000757
	a_{1nz}	6.65	.911	6.61	.932	.00369	.000626
	a_{2nz}	−.854	.129	−.850	.132	−.000445	.0000861
	σ^2_n	27800.	26100.	28200.	27800.	.00313	.00387
	χ^{2*}	52.9		55.0		60.4	
Degrees of Freedom*		34		36		34	
MSE		1.71		1.70		1.86	

*χ^2 statistic for test of the model against the stationary model

The degrees of freedom are the degrees of freedom of the test.

Table 8
The Hall and Mishkin Model

	1. Hall and Mishkin		2. Balanced Sample		3. Larger Sample	
	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
α	.107	13.4	.0740	2.43	.0498	2.84
β	.292	3.65				
ρ	.77		.932	3.47	.169	.28
ϕ	.253	4.4	.306	.72	.407	3.72
λ_1	.215	15.4	.143	2.28	.210	5.53
λ_2	.101	5.9	.0657	.85	.0191	.41
ρ_1	.294	14.	.208	2.37	.211	3.64
ρ_2	.114	6.3	.0238	.33	.0467	1.02
σ^2_ε	1.49	13.5	1212562.	3.32	2440932.	5.33
σ^2_ν	.158	52.7	2990402.	6.28	4974909.	9.06
σ^2_η	3.41	26.2	149998.	11.06	248592.	16.0
χ^2_3			14.1		6.32	
χ^2_{33}			52.4		44.3	
M.S.E.			1.59		1.34	

χ^2_3 is to test against the covariance stationarity model.
χ^2_{33} is to test against the non-stationary model.

Table 9
Estimates of the Lifecycle Model

	(1) Estimate	SE	(2) Estimate	SE	(3) Estimate	SE
Consumption ΔC^*_t						
β_{cw0}	.0229	.00582				
β_{cw1}	.00216	.00611				
β_{cw21}	.00538	.00780				
β_{cz0}	-.000787	.00496				
β_{cn0}	-.00397	.00591				
β_{cy0}	.0245	.0127				
β_{cc0}	.254	.00580	.252	.00689	.252	.00829
β_{cc1}	-.146	.00713	-.147	.00765	-.148	.00826
β_{cc2}	.0142	.00970	.0142	.00974	.0142	.00979
Earnings ΔY^*_t [a]						
β_{yw0}	.0459	.00627	.0503	.00660	.0495	.00661
β_{yw1}	.0109	.00617	.0104	.00656	.0112	.00662
β_{yw2}	.00310	.00572	.00373	.00608	.00391	.00601
β_{yz0}	-.0285	.00654	-.0274	.00659	-.0272	.00661
β_{yz1}	.0167	.00581	.0159	.00585	.0158	.00585
β_{yz2}	.00866	.00521	.00827	.00520	.00816	.00521
β_{yn0}	.0229	.0362	.0486	.00706	.00485	.00697
β_{yn1}	-.0137	.00764	-.00416	.00547	-.00410	.00549
β_{yn2}	-.0116	.0154	-.00204	.00585	-.00199	.00587
β_{yy0}	.0158	.0172	.137	.00537	.137	.00531
β_{yy1}	.0140	.0363	-.0833	.00622	-.0834	.00623
β_{yy2}	.0450	.0340	.00479	.00677	.00461	.00677
σ_y^2	.0127	.00194				
Wage ΔW^*_t						
β_{ww0}	.117	.0137	.107	.0120	.108	.0123
β_{ww1}	-.0457	.0120	-.0377	.0106	-.0388	.0108
β_{ww2}	.00793	.00518	.00677	.00557	.00640	.00547
σ_w^2	.000879	.00216	.00233	.00172	.00214	.00178
Unemploy ΔZ^*_t						
β_{zz0}	.0284	.00250	.0282	.00250	.0282	.00250
β_{zz1}	.00817	.00170	.00809	.00172	.00809	.00172
β_{zz2}	.00507	.00226	.00491	.00231	.00496	.00232
Hours ΔN^*_t						
β_{nn0}	.178	.197	.121	.0169	.121	.0169
β_{nn1}	-.127	.209	-.0583	.0169	-.0580	.0170
β_{nn2}	-.00181	.00427	-.00337	.00573	-.00319	.00575
β_{nz0}	-.0370	.00558	-.0353	.00585	-.0354	.00574
β_{nz1}	.0288	.00533	.0272	.00539	.0272	.00540
β_{nz2}	.00394	.00386	.00336	.00386	.00338	.00386
β_{nw0}	-.00333	.00332				
β_{nw1}	.00395	.00423				
β_{nw2}	-.00440	.00429				
β_{ny0}	.0386	.0178				
σ_n^2	-.0138	.0619	.00153	.00282	.00157	.00281
B_n			-.117	.131	-.110	.125
B_c			-.295	.119	-.370	.288
B_{nc}					-.0195	.0424
$B_{\eta w}$			-.0841	.0279	-.0713	.0384
$B_{\eta z}$			.00300	.0168	.00187	.0112
σ_η^2			.00893	.0151	.00552	.0100
χ^2	31.7		43.6		43.2	
DF	20		26		25	
MSE	1.81		1.82		1.82	

[a] Y^*_t is the log of measured labor earnings. As in the other log models in the paper, ΔZ^*_t is the log(2000 + Hours of Unemployment), rather than the change in the log(2000 + Hours of Unemployment).

Figure 1

Data in Levels, Annual Hours Excluded

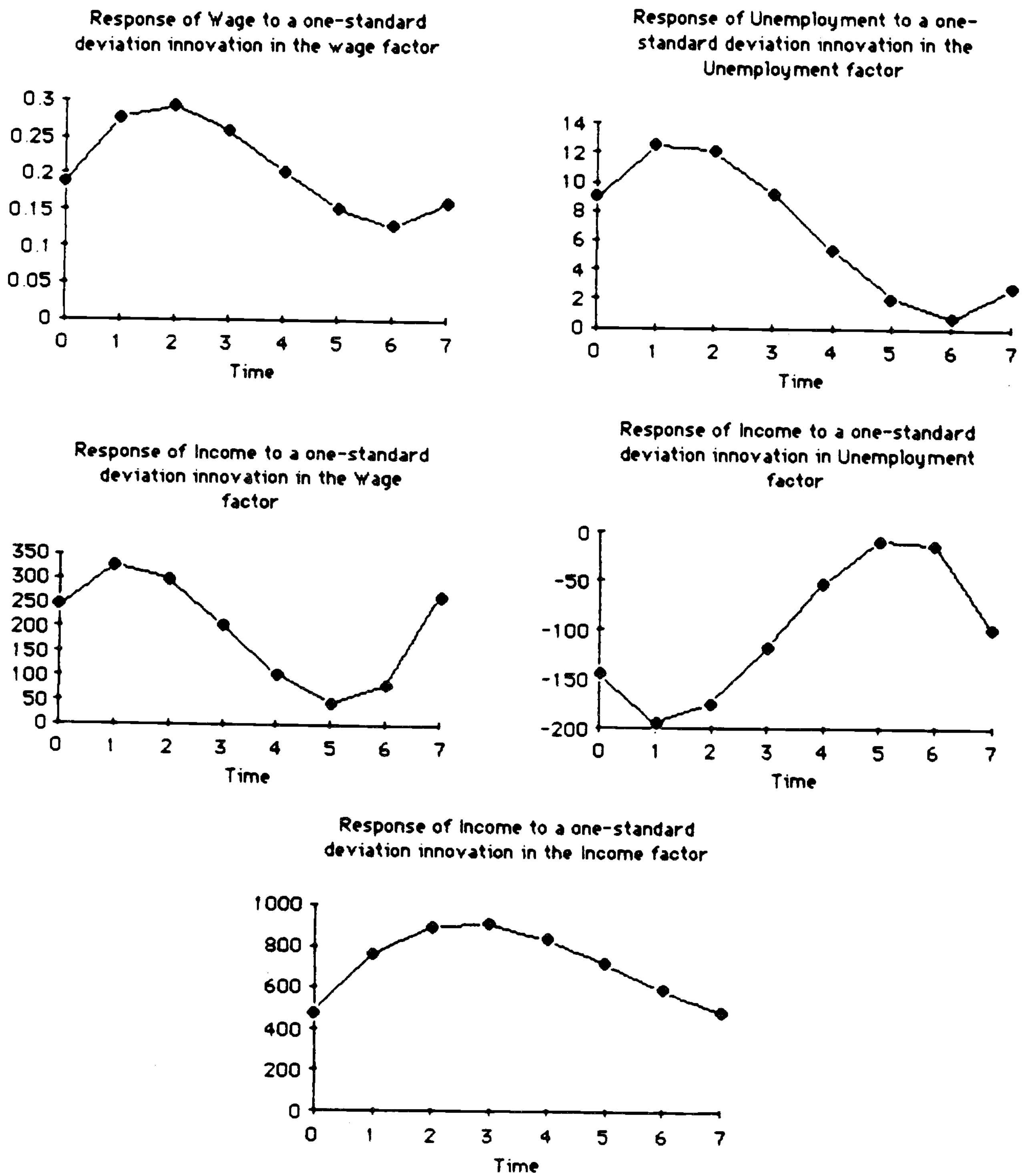


Figure 2

Data in Logs. Annual Hours Included

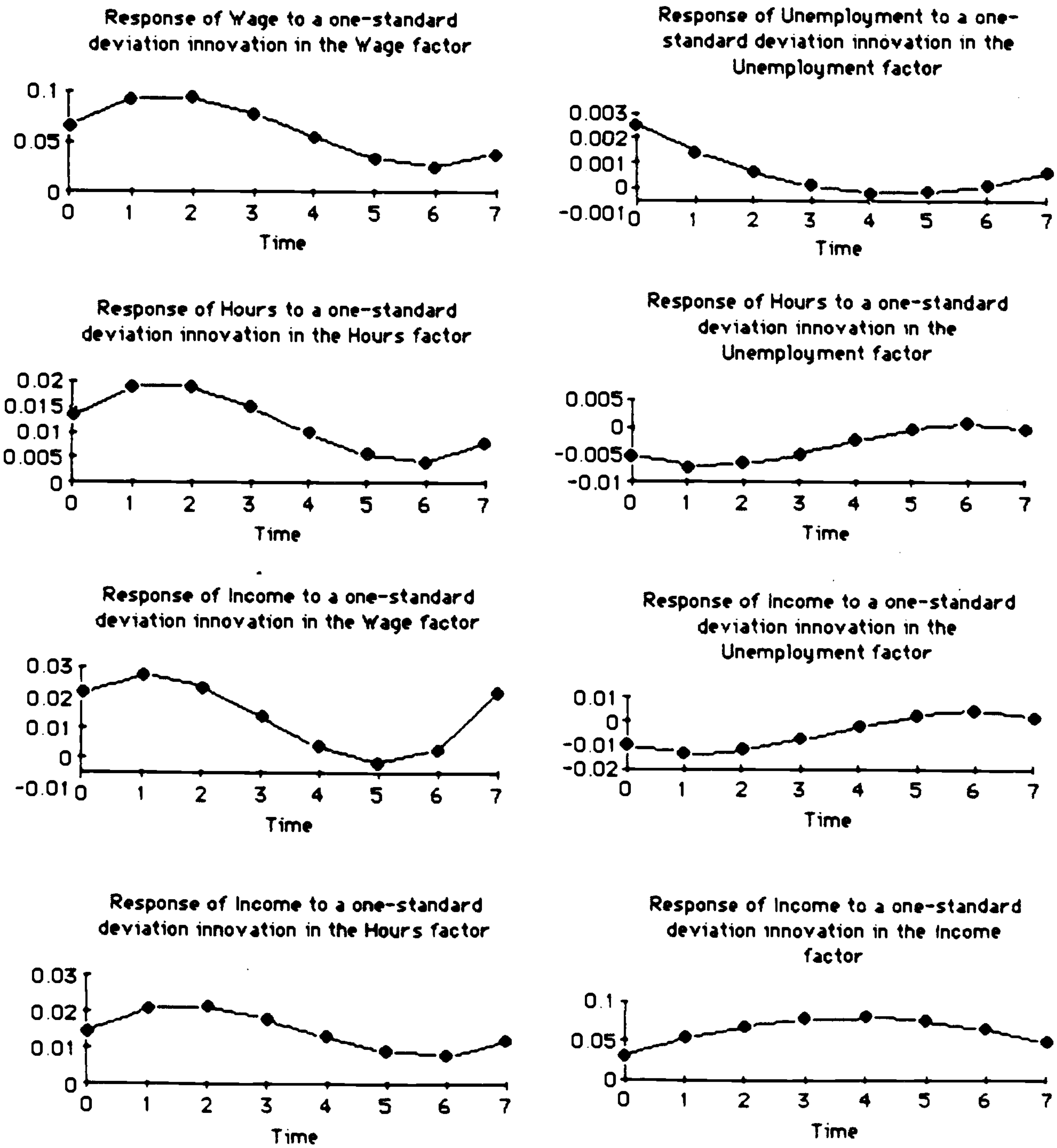


Figure 3

Data in Levels, Annual Hours Included

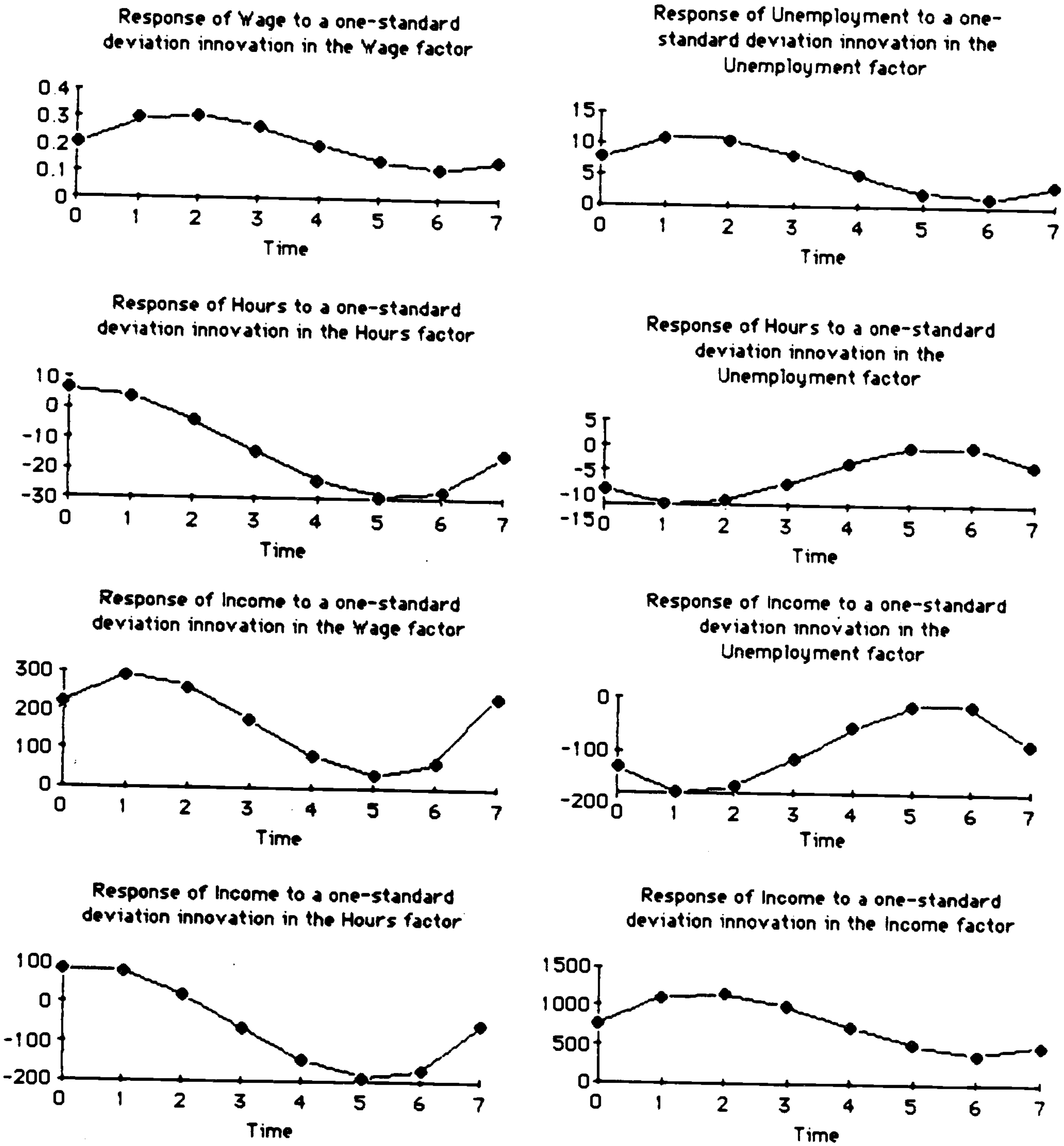
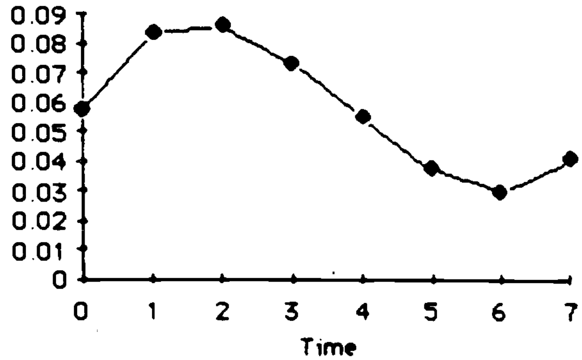


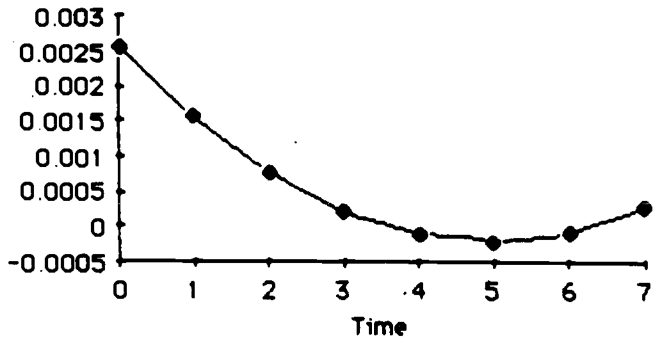
Figure 4

Data in Logs, Annual Hours Excluded

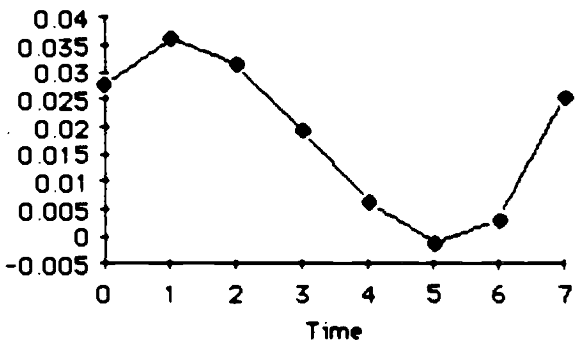
Response of Wage to a one-standard deviation innovation in the Wage factor



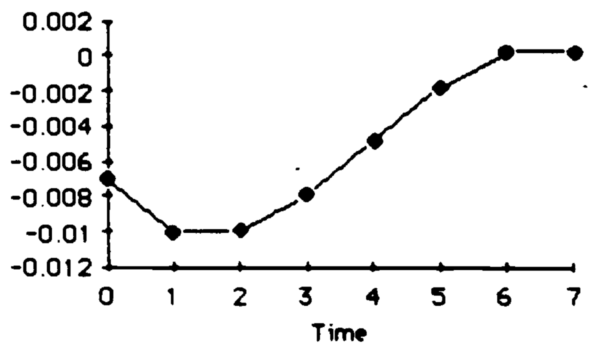
Response of Unemployment to a one-standard deviation innovation in the Unemployment factor



Response of Income to a one-standard deviation innovation in the Wage factor



Response of Income to a one-standard deviation innovation in the Unemployment factor



Response of Income to a one-standard deviation innovation in the Income factor

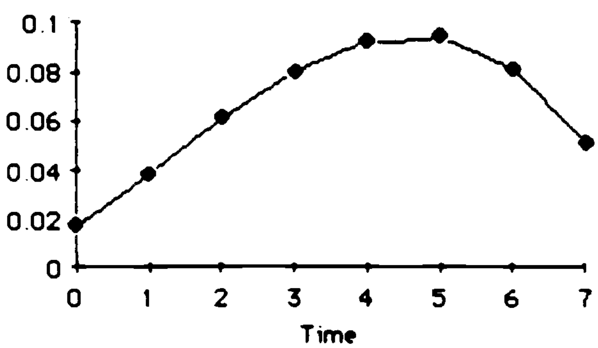


Table A1a
WLS Estimate of Covariances (Data in Levels)

	Consumption ΔC_t^*	ΔC_{t-1}^*	ΔC_{t-2}^*	Family Income ΔY_t^*	ΔY_{t-1}^*	ΔY_{t-2}^*	Work Hours ΔN_t^*	ΔN_{t-1}^*	ΔN_{t-2}^*	Unemployment ΔZ_t^*	ΔZ_{t-1}^*	ΔZ_{t-2}^*	Wages ΔW_t^*	ΔW_{t-1}^*	ΔW_{t-2}^*
ΔC_t^*	393000. (32000.)	-164000. (22300.)	-15700. (26300.)	137000. (54100.)	-110000. (56800.)	149000. (80100.)	6280. (4800.)	2200. (4780.)	-96.2 (6701.)	-3050. (2370.)	-351. (2410.)	2000. (3410.)	19.9 (15.8)	12.2 (17.1)	-4.68 (23.0)
ΔC_{t-1}^*				-9760. (51900.)			-1640. (5020.)			-416. (2270.)			-30.9 (20.0)		
ΔC_{t-2}^*				41000. (65200.)			-4940. (4920.)			1150. (2370.)			20.8 (17.7)		
ΔY_t^*				7020000. (369000.)	-2240000. (243000.)	-212000. (245000.)	135000. (20200.)	-23900. (21200.)	13000. (25600.)	-50400. (10000.)	9300. (9770.)	-2280. (10500.	239. (60.4)	86.2 (60.5)	-13.5 (61.7)
ΔY_{t-1}^*							-38700. (20400.)			10700. (8290.)			-38.9 (62.3)		
ΔY_{t-2}^*							-46600. (24900.)			19800. (11500.)			20.5 (57.5)		
ΔN_t^*							137000. (6570.)	-48300. (4920.)	-7260. (4260.)	-23000. (2350.)	5330. (1520.)	2080. (1690.)	-1.63 (5.53)	4.00 (6.48)	-8.15 (6.01)
ΔN_{t-1}^*										4940. (1430.)			4.21 (6.49)		
ΔN_{t-2}^*										3260. (1540.)			-7.16 (6.90)		
ΔZ_t^*										25500. (2550.)	-6210. (1340.)	-2450. (1100.)	-4.16 (3.33)	-1.69 (3.45)	6.70 (3.57)
ΔZ_{t-1}^*													-.173 (3.85)		
ΔZ_{t-2}^*													6.65 (6.13)		
ΔW_t^*													.431 (.0454)	-.129 (.0373)	-.0303 (.0321)

Uncorrected standard errors.

Table A1b
WLS Estimate of Covariances (Data in Logs)

	Consumption ΔC_t^*	ΔC_{t-1}^*	ΔC_{t-2}^*	Family Income ΔY_t^*	ΔY_{t-1}^*	ΔY_{t-2}^*	Work Hours ΔN_t^*	ΔN_{t-1}^*	ΔN_{t-2}^*	Unemployment Z_t^*	Z_{t-1}^*	Z_{t-2}^*	Wages ΔW_t^*	ΔW_{t-1}^*	ΔW_{t-2}^*
ΔC_t^*	.102	-.0426	-.000324	.00321	-.000521	.000569	.00132	.000655	-.00131	-.000245	.000448	.000272	.00300	.000755	-.000701
	(.00384)	(.00261)	(.00264)	(.00152)	(.00177)	(.00204)	(.00108)	(.00116)	(.00170)	(.000236)	(.000310)	(.000293)	(.000951)	(.00114)	(.00123)
ΔC_{t-1}^*				.000899			-.000327			-.0000851			-.00266		
				(.00158)			(.00118)			(.000283)			(.000987)		
ΔC_{t-2}^*				-.000471			-.00140			.000186			.00109		
				(.00168)			(.00117)			(.000363)			(.00118)		
ΔY_t^*				.0557	-.0163	-.00344	.00875	-.00150	.000503	-.00101	.00074	.000375	.00537	.00186	-.000573
				(.00258)	(.00167)	(.00143)	(.00109)	(.000952)	(.00110)	(.000242)	(.000274)	(.000329)	(.00102)	(.00105)	(.000926)
ΔY_{t-1}^*							-.00200			-.000265			-.000215		
							(.000930)			(.000210)			(.000906)		
ΔY_{t-2}^*							-.00169			.000453			.000354		
							(.00103)			(.000256)			(.000851)		
ΔN_t^*							.0401	-.0128	-.00183	-.00236	.00232	.000968	.000321	.000353	-.000821
							(.00265)	(.00129)	(.00102)	(.000392)	(.000357)	(.000341)	(.000662)	(.000786)	(.000693)
ΔN_{t-1}^*										-.000565			.000222		
										(.000248)			(.000772)		
ΔN_{t-2}^*										.0000128			-.000491		
										(.000204)			(.000710)		
Z_t^*										.00299	.00114	.000740	-.000303	-.000354	-.0000901
										(.000334)	(.000206)	(.000172)	(.000178)	(.000181)	(.000199)
Z_{t-1}^*													.000208		
													(.000163)		
Z_{t-2}^*													.000223		
													(.000163)		
W_t^*													.0281	-.00914	-.00123
													(.00211)	(.00114)	(.000845)

(Standard errors)

Table A2

Equations of the Income Models (WLS Estimates)*

	Data in Levels		Data in Logs	
	Estimate	S.E.#	Estimate	S.E.
Income (ΔY^*t)				
β_{yw0}	445.	206.	.0310	.00930
β_{yw1}	141.9	133.7	.00730	.00727
β_{yw2}	-21.4	112.	-.00366	.00623
β_{yn0}	657.	259.	.0531	.0125
β_{yn1}	-49.6	157.	-.00735	.00814
β_{yn2}	110.	188.	-.00662	.0103
β_{yz0}	-317.	67.4	-.0219	.00580
β_{yz1}	61.7	66.7	.0108	.00707
β_{yz2}	-11.4	69.8	.00682	.00758
β_{yy0}	2218.	4094.	.119	.0611
β_{yy1}	-986.	4362.	.0217	.075
β_{yy2}	-122.	259.	-.0294	.0210
σ^2_y	171000.	13400000.	.0178	.00539
Wage (ΔW^*t)				
β_{ww0}	.563	.228	.183	.0536
β_{ww1}	-.147	.184	-.0877	.0538
β_{ww2}	-.0284	.0551	-.00554	.00607
σ^2_w	.0473	.147	-.00649	.0143
Hours (ΔN^*_t)				
β_{nn0}	146.	47.7	.132	.0268
β_{nn1}	-37.8	35.9	-.0256	.0254
β_{nn2}	-57.7	24.7	-.00958	.00919
β_{nz0}	-140.	15.8	-.0534	.00871
β_{nz1}	37.4	11.0	.0359	.00680
β_{nz2}	11.7	11.2	.0181	.00737
σ^2_n	43577.	6756.	.00857	.00403
Unemploy. (ΔZ^*_t)				
β_{zz0}	152.	8.73	.0532	.00362
β_{zz1}	-43.0	8.35	.0171	.00312
β_{zz2}	-19.4	6.25	.00949	.00327

*Both income equations were estimated jointly with their respective unrestricted consumption equations. MSE statistics are reported with the consumption equations in Table A3.
#Uncorrected standard errors.

Table A3

Consumption Equations :WLS estimates (standard errors#)

	Data in Levels							Data in Logs				
Col.[a]	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.*	11.	12.*
Wage factor: u_{wt}												
β_{cw0}:	47.1	41.8			41.5			.0201	.0184		.0185	
	(33.6)	(33.6)			(32.4)			(.00755)	(.00908)		(.00826)	
β_{cw1}:	23.9							.00408				
	(34.9)							(.00678)				
β_{cw2}:	-5.57							-.00287				
	(41.9)							(.00830)				
Unemployment factor: u_{zt}												
β_{cz0}:	-16.5	-18.4			-19.7			-0.00762	-.00456		-.00414	
	(15.9)	(15.1)			(14.7)			(.00659)	(.00554)		(.00508)	
β_{cz1}:	1.77							.00663				
	(16.8)							(.00756)				
β_{cz2}:	14.3							.00508				
	(22.6)							(.00681)				
Hours factor: u_{nt}												
β_{cn0}:	42.1	33.8						.00542	.00878			
	(39.1)	(34.2)						(.00964)	(.0113)			
β_{cn1}:	16.0							.00494				
	(34.9)							(.00982)				
β_{cn2}:	17.3							-.00763				
	(49.1)							(.0158)				
Income factor: u_{yt}												
β_{cy0}:	23.5	52.2			63.1			.0212	.0196		.0218	
	(85.6)	(59.7)			(52.2)			(.0186)	(.0167)		(.0142)	
β_{cy1}:	-30.9							-.00911				
	(121.)							(.0182)				
β_{cy2}:	63.9							-.00979				
	(133.)							(.0199)				
Consumption factor: u_{ct}												
β_{cc0}:	515.	526.	526.	527.	526.	526.	528.	.279	.279	.278	.279	.277
	(109.)	(89.5)	(89.2)	(85.1)	(86.9)	(86.6)	(81.3)	(.00743)	(.00807)	(.0124)	(.00736)	(.0122)
β_{cc1}:	-339.	-331.	-331.	-327.	-331.	-331.	-327.	-.153	-.153	-.154	-.153	-.156
	(136.)	(113.)	(113.)	(109.)	(110.)	(110.)	(104.)	(.0101)	(.0111)	(.0166)	(.0101)	(.0162)
β_{cc2}:	-33.9	-29.9	-29.9	-29.4	-29.9	-29.9	-29.4	-.00141	-.00116	-.000448	-.00116	.000166
	(58.9)	(54.1)	(53.8)	(53.3)	(52.3)	(52.1)	(51.3)	(.0120)	(.0129)	(.0094)	(.0117)	(.00895)
α:			.0600	.0437		.0696	.0402			.269		.355
			(.0269)	(.0211)		(.0494)	(.0262)			(.0777)		(.0974)
ρ			1.43			1.74						
			(1.41)			(1.63)						
MSE	1.63	1.63	1.61	1.60	1.52	1.51	1.49	1.52	1.48	1.51	1.31	1.35

[a]Col. 1 is the unrestricted levels consumption model. It is jointly estimated with the levels income model in Table A2. Col. 2 has no lagged factors. Col. 3 is the RE-PI model. Col. 4 is the Keynesian model. Col. 5 excludes lagged factors from the consumption equation and annual hours from all equations. Col. 6 is the RE-PI model without annual hours. Col. 7 is the Keynesian model without annual hours. Col. 8 is the unrestricted consumption equation in logs which is estimated with the log income model in Table A2. Col. 9 is the log model with lagged factors excluded from the consumption equation. Col. 10 is the log Keynesian model. Col. 11 excludes lagged factors from the consumption equation and annual hours from all equations. Col. 12 is the log Keynesian model without annual hours.

Uncorrected standard errors.

* Estimates did not satisfy standard convergence criterion.

Table A4

Estimates of the Lifecycle Model (WLS)

	(1) Estimate	SE	(2) Estimate	SE	(3) Estimate	SE
Consumption ΔC^*_t						
β_{cw0}	.0251	.00968				
β_{cw1}	.00573	.00845				
β_{cw21}	-.00291	.00903				
β_{cz0}	-.00508	.00654				
β_{cn0}	.00398	.0263				
β_{cy0}	.00244	.0436				
β_{cc0}	.286	.0118	.267	.0807	.254	.170
β_{cc1}	-.147	.0162	-.160	.0512	-.169	.116
β_{cc2}	-.000883	.00991	-.00121	.0168	-.00138	.0185
Earnings ΔY^*_t [a]						
β_{yw0}	.0553	.0162	.0607	.0155	.0590	.0155
β_{yw1}	.0149	.00987	.0180	.0141	.0175	.0139
β_{yw2}	-.0000738	.00746	.000136	.0128	.000339	.0130
β_{yz0}	-.0424	.00853	-.0425	.0116	-.0425	.0122
β_{yz1}	.0197	.00892	.0195	.00966	.0195	.0101
β_{yz2}	.0191	.00759	.0194	.0104	.0194	.0109
β_{yn0}	.0281	.178	.0929	.0192	.0925	.0201
β_{yn1}	.00808	.722	-.0103	.0111	-.0103	.0115
β_{yn2}	.00189	.0391	.00339	.0125	.00337	.0130
β_{yy0}	.161	2.29	.165	.0176	.167	.0173
β_{yy1}	-.0292	2.46	-.0994	.0193	-.0983	.0192
β_{yy2}	.00431	.0684	.00323	.0143	.00314	.0149
σ_y^2	.0142	.458				
Wage ΔW^*_t						
β_{ww0}	.147	.0372	.136	.0350	.140	.0360
β_{ww1}	-.0504	.0281	-.0438	.0322	-.0466	.0337
β_{ww2}	-.00675	.00706	-.00703	.0103	-.00685	.0104
σ_w^2	.00208	.00646	.00370	.00599	.00311	.00635
Unemploy ΔZ^*_t						
β_{zz0}	.0534	.00308	.0533	.00503	.0533	.00525
β_{zz1}	.0170	.00250	.0170	.00428	.0170	.00447
β_{zz2}	.00925	.00234	.00921	.00426	.00921	.00444
Hours ΔN^*_t						
β_{nn0}	.160	.291	.147	.0285	.148	.0299
β_{nn1}	-.0627	.462	-.0382	.0266	-.0383	.0279
β_{nn2}	-.00499	.0120	-.00532	.0108	-.00532	.0113
β_{nz0}	-.0539	.00911	-.0527	.0133	-.0532	.0129
β_{nz1}	.0361	.0102	.0361	.00931	.0361	.00973
β_{nz2}	.0179	.00759	.0181	.0102	.0181	.0106
β_{nw0}	.00180	.00568				
β_{nw1}	.0000862	.00599				
β_{nw2}	-.00611	.00584				
β_{ny0}	.0541	.580				
σ_n^2	.00204	.0856	.00610	.00470	.00605	.00497
B_n			-.0253	.216	-.0255	.208
B_c			-.119	.427	-.384	1.37
B_{nc}					-.0376	.0738
β_{nw}			-.222	.801	-.0909	.223
β_{nz}			.0455	.175	.00995	.0304
σ_η^2			.322	3.88	.0285	.117
MSE	1.77		1.60		1.60	

[a] Y^*_t is the log of measured labor earnings. As in the other log models in the paper, ΔZ^*_t is the log(2000 + Hours of Unemployment), rather than the change in the log(2000 + Hours of Unemployment).