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Source: *Econometrica*, Jul., 1995, Vol. 63, No. 4 (Jul., 1995), pp. 805-840
Published by: The Econometric Society
Stable URL: https://www.jstor.org/stable/2171801

Econometrica, Vol. 63, No. 4 (July, 1995), 805–840

INDIVIDUAL INCOME, INCOMPLETE INFORMATION, AND AGGREGATE CONSUMPTION

BY JÖRN-STEFFEN PISCHKE[1]

Individual income is much more variable than aggregate per capita income. I argue that aggregate information is therefore not very important for individual consumption decisions and study models of life-cycle consumption in which individuals react optimally to their own income process but have incomplete or no information on economy-wide variables. Since individual income is less persistent than aggregate income consumers will react too little to aggregate income variation. Aggregate consumption will be excessively smooth. Since aggregate information is slowly incorporated into consumption, aggregate consumption will be autocorrelated and correlated with lagged income. On the other hand, the model has the same prediction for micro data as the standard permanent income model. The second part of the paper provides empirical evidence on individual and aggregate income processes. Different models for individual income are fit to quarterly data from the Survey of Income and Program Participation making various adjustments for measurement error. Calibrating the consumption model using the estimated parameters for the income process yields predictions which qualitatively correspond to the empirical findings for aggregate consumption but do not match them well in magnitude.

KEYWORDS: Consumption, income, aggregation, incomplete information, measurement error, Survey of Income and Program Participation (SIPP).

1. INTRODUCTION

CONTRARY TO THE PREDICTIONS of the modern version of the permanent income hypothesis (Hall (1978)), aggregate consumption changes in the U.S. are correlated with lagged income changes (see Flavin (1981)). Moreover, Deaton (1987) and Campbell and Deaton (1989) demonstrated that consumption is smoother than predicted by the model if income follows a highly persistent process. In individual data, on the other hand, the orthogonality condition implied by the permanent income model is much harder to reject as a multitude of recent studies show.[2] If it is true that the model holds for individual data but not for aggregate data[3] then some type of aggregation bias should explain the differences.

A variety of possible biases have been explored. Finite lifetimes will introduce a dependence of consumption on cohort characteristics at the aggregate level and the martingale result found by Hall will not hold. Galí (1990) has developed this point in a recent paper and has shown that it is not important enough empirically to explain aggregate consumption data. Attanasio and Weber (1993)

[1] I thank Charlie Bean, Martin Browning, John Campbell, David Card, Steve Davis, Angus Deaton, François Laisney, Ron Miller, Whitney Newey, Danny Quah, and Steve Zeldes for very useful discussions, a co-editor and three anonymous referees for their patience and constructive suggestions, and seminar participants at many universities and conferences for helpful comments. All remaining errors are mine.

[2] See Deaton (1992) for a recent survey of the literature.

[3] The inability to reject the model in micro data may of course also stem from problems related to measurement error, inexact variable definitions, etc. that make these tests less powerful.

have stressed nonlinearities as a possible reason for excess sensitivity at the aggregate level. Finally, a recent paper by Goodfriend (1992) suggests that agents may lack contemporaneous information on aggregate variables which invalidates the martingale property of the model at the aggregate level. In this paper I explore the theoretical and empirical implications of this type of incomplete information.

It is not unlikely that aggregate information plays little role in household decisions since the economic environment in which individuals operate differs sharply from the economy as it is described by aggregate data. Most importantly, individual income is much more variable than aggregate income: Below, I estimate that the standard deviation of quarterly household level income changes is about forty times larger than that for aggregate per household income. While some of this variation will be attributable to measurement problems, a large part should reflect idiosyncratic income shocks. Therefore, individuals may make little effort to gather information on the behavior of the economy, but rather watch only their own prospective fortunes. Furthermore, individual income processes are much less persistent than aggregate income. The optimal consumption response calculated on the basis of individual income processes differs substantially from the predictions of a representative agent model calibrated with aggregate data. Using these facts, I construct a simple model in which agents react optimally to their individual income innovations but do not incorporate information on economy wide variables. The model correctly predicts what we observe in aggregate data: the correlation of consumption changes with lagged income and excess smoothness.

A simple example makes clear how the model works. Suppose a worker gets laid off from his job; he does not know immediately whether this is due to specific conditions at his firm or because of the onset of a general recession. If the layoff is due to highly individual factors then it will be easy for the worker to find new employment and the income reduction associated with the unemployment spell does not call for a major revision in consumption expenditures. Should the unemployment be due to aggregate factors, employment will be depressed at other firms as well and lead to a much longer expected unemployment spell. The necessary revision in consumption will be much larger than in the former case. The worker adjusts consumption in a way that will be correct on average given his overall experience with unemployment.

Looking at aggregate data, an econometrician will find *ex post* that everybody revised consumption downward too little at the onset of a recession. Subsequently, there will be further revisions once workers learn about the true scope and persistence of the shock. Consumption will appear correlated with lagged income and will appear smoother than predicted by a model where agents know the cause and length of their unemployment spell immediately.

There are a number of well known applications of the idea that individual agents may have incomplete aggregate information. Phelps (1970) and Lucas (1973) suggested a model in which workers/suppliers confuse aggregate and relative price movements. This yields an observable Phillips curve relationship in aggregate data which is not predicted by a full information representative agent model. Altonji and Ashenfelter (1980) use the same feature in a life-cycle model of labor supply to generate an intertemporal substitution effect. If the aggregate wage follows a random walk and agents have full information, there is no room for intertemporal substitution. If workers only know the lagged aggregate wage and their own wage, consisting of an individual and an aggregate component, then the model yields aggregate employment fluctuations even if the aggregate wage is a random walk. Froot and Perold (1990) have recently suggested a model where securities market specialists observe only information on their own stock contemporaneously but not aggregate information. Their model yields correlated aggregate stock returns.

In all of these models agents observe the aggregate variable with a one period lag. An analogous model in which agents learn about aggregate income with a one quarter delay has been suggested for consumption behavior by Goodfriend (1992). His model yields an MA(1) process for consumption changes. Therefore, no variable lagged at least twice should be able to predict consumption changes. The hypothesis of lagged information on income has been considered informally by Holden and Peel (1985). They reject this model on U.K. data by regressing consumption changes on income and consumption lagged twice. Campbell and Mankiw (1989) use information variables lagged at least two periods and find the same result for the U.S. and other countries.

Models with lagged aggregate information are usually motivated by the fact that aggregate variables like GNP only become public with a lag of about a quarter. Appealing to a publication lag alone is unattractive in Goodfriend's model, however. Prices will aggregate the information of individuals perfectly in a rational expectations model where every individual costlessly receives a small piece of the total information (Grossman (1981)). In the standard permanent income-consumption model this information would be transmitted in the price of the one asset traded in the economy. Thus, agents would only need to observe their own income as well as the interest rate. On the other hand, good arguments could be made why the conditions for a fully revealing rational expectations equilibrium do not hold and asset prices at best serve as noisy signals for aggregate income.

I prefer a slightly different interpretation of the incomplete aggregate information models that I will present: agents may simply not care enough about aggregate information because ignoring it is not very costly for (most) households. Therefore in this paper I examine Goodfriend's model with lagged information on aggregate income as well as a version where agents know only their own income processes but never observe the aggregate component in their income. The latter feature has also been used by Deaton (1991) in a model of precautionary savings and liquidity constraints. To avoid convoluting information aggregation with other issues, I use Flavin's (1981) model with quadratic instantaneous utility as a tool for this analysis. This allows explicit solutions for the consumption process. Given the joint behavior of income and consumption it is then possible to calculate the regression coefficient of consumption changes on lagged income changes and the ratio of the variability in consumption to the variability in the income innovation. These predictions are easily compared to the sample statistics for aggregate data.

To calibrate the model it is necessary to have information on aggregate and individual income processes. While some estimates for individual earnings are available in the literature they are not well suited for the present purpose. In particular, no estimates are available that utilize quarterly income information comparable to the sampling frequency of aggregate data. I use the 1984 Panel of the Survey of Income and Program Participation which contains monthly information on family income to construct the appropriate quarterly micro data. I also present alternative estimates using the monthly data directly. This allows me to make adjustments for measurement error using various forms of respondent behavior.

With these results at hand, I find that the model yields predictions that are in the correct direction and deviate substantially from the full information case. Quantitatively, they do not match the results for U.S. aggregate data well. The model generally tends to predict too high a correlation of consumption with lagged income but not smooth enough consumption. Notice, however, that this procedure, using actual micro parameters to calibrate the model, subjects the model to a much more stringent test than is usually adopted in the macro consumption literature. I also show that rational consumers are unlikely to concern themselves with acquiring aggregate information as maintained by Goodfriend because the gain amounts to less than two dollars every quarter.

The paper is organized as follows. In the next section, I start by reviewing the basic full information model and the empirical failures it has generated. Using a simple income process as an example, I then analyze the model with no observability of aggregate income and describe its implications. This is contrasted with the model of Goodfriend where aggregate information becomes available with a one period lag. The model implications of more general income processes close the section. Section 3 is devoted to the estimation of individual income processes while the following section presents aggregate estimates; Section 4 also summarizes the empirical facts on the consumption puzzles. Section 5 uses the estimates on the income processes to predict features of aggregate consumption and compares the results to the findings in the previous section. Section 6 concludes.

2. THE MODEL

2.1. *Complete Aggregate Information*

In this section I will review a simple example where agents have individual specific income processes that differ from the time series structure of aggregate income. However, each micro agent has full contemporaneous information on aggregate income. At the aggregate level, this model is equivalent to a representative agent model.

The infinitely lived consumer solves a standard life-cycle maximization problem with intertemporally separable utility. The instantaneous utility function is quadratic. Every period non-interest income y_t is paid and consumption c_t takes place before interest accrues on wealth. Consumers can borrow and lend freely at a constant interest rate r which is equal to the discount rate.

If income follows a linear univariate time series process known to the consumer, then the changes in consumption can be expressed in terms of the innovations to the income process (Flavin (1981)). Let income be a process that is stationary in first differences so that it has a Wold representation $\Delta y_t = A(L)\varepsilon_t$. For this process the change in consumption is given by

$$(1) \qquad \Delta c_t = A\left(\frac{1}{1+r}\right)\varepsilon_t.$$

I will consider models where all individuals have identical income *processes* while each agent faces different realizations of this process. To fix ideas, consider a simple example where income consists of a random walk with innovations that are common to all individuals and a white noise component with shocks that are uncorrelated across individuals. In first differences this process takes the form

$$(2) \qquad \Delta y_{it} = \varepsilon_t + u_{it} - u_{it-1}.$$

Subscripts i denote individual variables while no subscripts refer to aggregate variables. ε_t is the aggregate income innovation, and u_{it} is the individual income shock. The innovations are assumed to be uncorrelated.

Every period agents observe their own income y_{it} as well as aggregate income y_t. Given that they also know the complete history of these variables they can infer the fundamental shocks ε_t and u_{it}. What is relevant to the consumer is how much each process contributes to permanent income. Given (1), the optimal rule is to adjust consumption fully to the permanent (aggregate) shock and by the annuity value $r/(1+r)$ to the transitory (individual) shock, i.e.

$$(3) \qquad \Delta c_{it} = \varepsilon_t + \frac{r}{1+r}u_{it}.$$

The change in average per capita consumption is found by summing over individuals. Because the individual shocks are mutually uncorrelated they will sum to zero in a large population so that we obtain

$$(4) \qquad \Delta c_t = \frac{1}{n}\sum \Delta c_{it} = \varepsilon_t.$$

Aggregate consumption is a random walk and the consumption change is just the aggregate income innovation. Hence this model yields the same predictions as a representative agent model where the representative agent faces the aggregate income process $\Delta y_t = \varepsilon_t$. In particular, consumption changes are uncorrelated with lagged aggregate variables, like lagged consumption or income changes. This martingale property has been tested by Hall (1978) by regressing consumption changes on lags of consumption, income, and stock prices. Hall found little explanatory power for income but rejected nonpredictability for stock prices. I will call this rejection of the full information model the *orthogonality failure*.

Hall's test only exploits the information contained in the Euler equation. Combined with the budget constraint the model has the additional implication that the variance of consumption changes should depend on the structure of the income process as pointed out by Deaton (1987). Taking variances in (1) and applying the formula to the representative agent model with random walk income yields

$$(5) \qquad \frac{\sigma_{\Delta c}}{\sigma_{\varepsilon}} = A\left(\frac{1}{1+r}\right) = 1$$

since $A(z) = 1$ for the random walk. The ratio of the standard deviation of consumption changes to the standard deviation of income innovations should equal the consumption response predicted by the model, one in this case. Deaton found that the empirical equivalent of this variance ratio is actually much too low based on an AR(1) for the first differences in aggregate income. Thus consumption exhibits *excess smoothness*.[4]

Notice how Quah (1990) has used a representative agent model with an income process as in (2) to generate excess smoothness. Agents behave just as in (3) but both shocks ε_t and u_t are common across individuals. The econometrician only observes the compound income process and calculates the magnitude of the optimal consumption change based on this (misspecified) model. Quah demonstrates that the econometrician's model implies a more variable consumption series than the true series and therefore apparent excess smoothness. However, since consumption in (3) is uncorrelated with any lags of income this cannot account for the orthogonality failure also present in the data.[5]

Using the simple example above, I will now address how incomplete information of agents on aggregate income can lead to both the orthogonality failure and excess smoothness at the aggregate level. A more general treatment will follow.

[4] Campbell (1987) provides a joint test of the orthogonality and smoothness conditions of the model using vector autoregressions. For the full information example it implies that a VAR of aggregate income changes and aggregate savings has the following form:

$$\begin{bmatrix} \Delta y_t \\ s_t \end{bmatrix} = \begin{bmatrix} 0 & 0 \\ 0 & (1+r) \end{bmatrix} \begin{bmatrix} \Delta y_{t-1} \\ s_{t-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_t \\ 0 \end{bmatrix}.$$

In the general case, the restrictions on the VAR are equality of the coefficients in the first column of the coefficient matrix and the difference of the coefficients in the second column being $(1+r)$.

[5] Campbell's (1987) test is robust to the type of superior information by consumers as envisioned by Quah. However, this test also rejects the model with U.S. aggregate data.

2.2. *Unobservable Aggregate Shocks*

Consider the income process in (2) again but now assume that individuals can only observe y_{it}. If the individual cannot distinguish the aggregate and the individual component, then this process to her looks just like an MA(1) process for the first differences in income. The income process the individual observes can thus be written as

$$\Delta y_{it} = \eta_{it} - \theta\eta_{it-1}. \tag{6}$$

The random variable η_{it} will contain information on current and lagged aggregate and individual income innovations. Note that $\{\eta_{it}\}$, though not a fundamental driving process of the model, is an innovation sequence with respect to the history of individual income changes. The MA parameter θ in (6) depends on the relative variances of the aggregate and individual income shocks.[6]

Equation (1) still holds so that changes in individual consumption follow

$$\Delta c_{it} = \left(1 - \frac{\theta}{1+r}\right)\eta_{it} = \frac{1+r-\theta}{1+r}\eta_{it} \equiv A\eta_{it} = A\frac{\Delta y_{it}}{1-\theta L}. \tag{7}$$

Individual consumption changes are a martingale with respect to the history of individual consumption and income. A researcher doing Hall's (1978) analysis on panel data for individuals should not reject the permanent income model.[7] This type of testing procedure has been carried out, for example, by Altonji and Siow (1987) who do not reject the model. Estimating a structural model as in Hall and Mishkin (1982) would not be correct because their model assumes that consumers know the income components in (2).[8] The correct structural model would use the income process in (6) instead. This has been pointed out by Speight (no date) who finds support for the model with incomplete information on Austrian panel data while the Hall and Mishkin model is rejected.

I want to focus here on the aggregate implications of the incomplete information case. To find the change in average per capita consumption use the last equality in (7) and equation (2) and sum over individuals:

$$\frac{1}{n}\sum\Delta c_{it} = \frac{A}{n}\sum\frac{\Delta y_{it}}{1-\theta L} = \frac{A}{n}\sum\frac{\varepsilon_t + u_{it} - u_{it-1}}{1-\theta L}. \tag{8}$$

[6] Define the first order autocorrelation coefficient in (2) $\rho = -\sigma_u^2/(\sigma_\varepsilon^2 + 2\sigma_u^2)$. Then $\theta = -(1-\sqrt{1-4\rho^2})/2\rho$.

[7] The martingale property only holds with respect to variables that are in individuals' information sets. Many researchers using panel data control for macroeconomic shocks. Goodfriend (1992) pointed out that such controls also invalidate the Hall procedure. I show below that the variance of individual income innovations is far larger than the variance of the aggregate component; this will therefore not be very important in practice.

[8] This is not literally true. Hall and Mishkin (1982) only distinguish a permanent and a transitory income component. These are not identified with aggregate and individual income processes as in the example in the text. Furthermore, Hall and Mishkin find nonzero correlations between consumption changes and lagged income changes or lagged consumption changes in their data. Apart from the appropriateness of the structural income process it is these correlations that lead to a rejection of the model in their sample.

Individual shocks will sum to zero again so that we obtain

$$\frac{1}{n}\sum \Delta c_{it} = \Delta c_t = A\frac{\varepsilon_t}{1-\theta L},$$

$$\Delta c_t = \theta \Delta c_{t-1} + A\varepsilon_t. \tag{9}$$

Equation (9) has a number of interesting implications. Unlike individual consumption, the per capita series of consumption is not a random walk as the representative agent model predicts. Consumption now follows an AR(1) in first differences. The intuition for this is rather simple. Suppose a positive aggregate shock hits the economy. All the individual consumers see their income increasing but they assume that part of the shock is idiosyncratic and therefore transitory. They will raise their consumption but not by as much as the permanence of the shock calls for. Because the shock is persistent, in the following period they will be surprised again that their income is higher than expected. Hence, they will increase their consumption further, and so on.

All this implies that an econometrician working with the representative agent model will find both the orthogonality failure and the smoothness result in aggregate data. Suppose the econometrician estimates the following model:

$$\Delta c_t = \alpha + \beta\,\Delta y_{t-1} + e_t. \tag{10}$$

If the data were generated by (9) the expected value of $\hat{\beta}$ would be

$$\hat{\beta} = \frac{\operatorname{cov}(\Delta c_t, \Delta y_{t-1})}{\operatorname{var}(\Delta y_{t-1})} \tag{11}$$

$$= \frac{E\left\{A\left(\frac{\varepsilon_t}{1-\theta L}\right)\varepsilon_{t-1}\right\}}{\sigma_\varepsilon^2} = \frac{A\theta\sigma_\varepsilon^2}{\sigma_\varepsilon^2} = A\theta.$$

Because individuals do not recognize an aggregate shock to be permanent they will not adjust their consumption by as much as they would if it were the only type of shock to occur. This will lead to more smoothness in aggregate data than predicted by the full information model where the variance of consumption changes equals the variance of aggregate income innovations. For the model with heterogeneous agents and incomplete information we get instead from (9)

$$\frac{\sigma_{\Delta c}}{\sigma_\varepsilon} = \frac{A}{\sqrt{1-\theta^2}}. \tag{12}$$

If idiosyncratic shocks are present and the interest rate is small enough the ratio of the standard deviations of the change in consumption and the aggregate income innovation will always be less than one. To see this more clearly, consider the case where $r \to 0$. In this case $A = 1 - \theta$ and (12) can be expressed as

$$(13) \qquad \lim_{r \to 0} \frac{\sigma_{\Delta c}}{\sigma_{\varepsilon}} = \sqrt{\frac{1-\theta}{1+\theta}}.$$

This will be less than one if $\theta > 0$.[9]

It is easy to see which features of the example drive the result. The representative agent model would hold for aggregate data if the aggregate and the individual income processes had the same persistence properties so that consumers would want to react in the same way to each type of shock. In this example, consumers do not want to increase consumption enough in response to an aggregate shock because they confuse it with the individual income innovation which is less persistent. The results also hinge on the assumption that individuals cannot or do not find it profitable to distinguish aggregate and idiosyncratic shocks. Otherwise they would react differently according to the persistence properties of the specific shock observed. Goodfriend (1992) originally proposed such a model, where information on aggregate income becomes available with a one period lag. For comparison, I will present the implications of this model with lagged information on aggregate income in the following subsection.

2.3. *Lagged Information about Aggregate Shocks*

Suppose aggregate data are published with a one period lag. In period t individual i will observe y_{it} and the aggregate shock ε_{t-1}. Also assume again that the consumer has access to the infinite history of shocks and can therefore infer u_{it-1} as well once the aggregate shock is known. Write the income process (2) for the individual as

$$(14) \qquad \Delta y_{it} = \nu_{it} - u_{it-1} \qquad \text{where} \qquad \nu_{it} = \varepsilon_t + u_{it}.$$

We can decompose the information the consumer gets every period into two parts. The first part is ν_{it}, the current period innovation which is contained in current individual income y_{it}. The consumer does not know how the innovation in a particular period is composed of the permanent (aggregate) component and the transitory (individual) component. She will therefore attribute part of the current period innovation to each component given the relative variances. For

[9] The simple example of the no information model implies that Campbell's (1987) VAR representation of income changes and savings has the form

$$\begin{bmatrix} \Delta y_t \\ s_t \end{bmatrix} = \begin{bmatrix} 0 & 0 \\ C(L) & (1+r) \end{bmatrix} \begin{bmatrix} \Delta y_{t-1} \\ s_{t-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_t \\ (1-A)\varepsilon_t \end{bmatrix}$$

with the lag polynomial $C(L) = -\theta A(1-\theta L)^{-1}$. Thus, it is the restriction of equality of the first column of the coefficient matrix rather than the second which is violated. This qualitatively reflects Campbell's findings.

every particular innovation there will be errors, of course. Secondly, the consumer gets information from the lagged aggregate shock. Once this information arrives she will be able to correct the error made last period in attributing the innovation to its components.

The optimal consumption response will have two parts corresponding to the two pieces of information: a response to the new innovation and a term that corrects for the error made in the previous period. The first part of the consumption response, the reaction to the current period innovation, can be written as

$$\omega v_{it} + (1-\omega)\frac{r}{1+r} v_{it} = \frac{\omega + r}{1+r} v_{it} \tag{15}$$

where $\omega = \sigma_\varepsilon^2/(\sigma_\varepsilon^2 + \sigma_u^2)$ is the relative variance of the aggregate shock.[10] The first term is the proportion of the new innovation expected to be permanent; the consumption response to that part is one. The second term is the part expected to be transitory; the response is $r/(1+r)$.

Consider the correction for errors made last period. Define the negative of the error in the aggregate component as

$$\xi_{it-1} = \varepsilon_{t-1} - \omega v_{it-1} = \varepsilon_{t-1} - \omega(\varepsilon_{t-1} + u_{it-1}) = (1-\omega)\varepsilon_{t-1} - \omega u_{it-1}. \tag{16}$$

The errors in the individual component and in the aggregate component have to sum to zero since the signal extraction problem the individual solved in $t-1$ yielded unbiased predictors of the two components. The response of consumption in period t to errors made in $t-1$ is therefore

$$(1+r)\left[\xi_{it-1} + \frac{r}{1+r}(-\xi_{it-1})\right] = \xi_{it-1}. \tag{17}$$

The first term in the square bracket is the correction of the error in the aggregate component, the second term the correction for the error in the individual component. Notice that interest accrued on the portions of the shocks that had not been consumed in the last period.

Putting together the two parts of the total consumption response from (15), and (17), and using (16), we obtain

$$\Delta c_{it} = \frac{\omega + r}{1+r} v_{it} + (1-\omega)\varepsilon_{t-1} - \omega u_{it-1}. \tag{18}$$

As in the model of the previous section, individual consumption changes still follow a martingale with respect to the history of individual income and consumption.[11] This can easily be seen by calculating the autocovariance $\mathrm{cov}(\Delta c_{it}, \Delta c_{it-1})$. It will be proportional to $(1-\omega)\sigma_\varepsilon^2 - \omega\sigma_u^2$ which is zero from the definition of ω. The lagged income innovations in (18) arise from the fact that errors are corrected after one period. However, optimal choice of the

[10] Note that $\omega = (1+2\rho)/(1+\rho) = (1-\theta)^2/(1-\theta+\theta^2)$. It is much more convenient to work with ω here.

[11] I thank Steve Zeldes for pointing out an error in a previous draft.

weight ω implies that these errors contain no information correlated with lagged income or consumption changes.

Sum the individual consumption responses in (18) for a large population to get the per capita consumption response

$$\Delta c_t = \frac{1}{n}\sum \Delta c_{it} = \frac{\omega + r}{1+r}\varepsilon_t + (1-\omega)\varepsilon_{t-1}. \tag{19}$$

The change in aggregate consumption follows an MA(1) process. Notice that the impact response to an aggregate shock is smaller in the lagged information model than in the no information model because $(\omega + r)/(1+r) < A = (1-\theta + r)/(1+r)$.[12] This is because the relevant innovations that the consumer responds to differ in the two models. ν_{it} in the lagged information model only contains information on contemporaneous aggregate and individual shocks. η_{it} in the no information model also contains new information on lagged shocks.

Both the orthogonality failure and the smoothness result will still arise in the lagged information model, but their quantitative importance will differ.[13] Consider the regression of the change in consumption on the lagged income change in (10) again. The coefficient on lagged income will be

$$\begin{aligned} \hat{\beta} &= \frac{\operatorname{cov}(\Delta c_t, \Delta y_{t-1})}{\operatorname{var}(\Delta y_{t-1})} \\ &= \frac{E\left\{\left[\dfrac{\omega + r}{1+r} + \varepsilon_t(1-\omega)\varepsilon_{t-1}\right]\varepsilon_{t-1}\right\}}{\sigma_\varepsilon^2} = 1-\omega \end{aligned} \tag{20}$$

which is positive. Taking variances in (19) yields

$$\frac{\sigma_{\Delta c}}{\sigma_\varepsilon} = \sqrt{\left(\frac{\omega + r}{1+r}\right)^2 + (1-\omega)^2}, \tag{21}$$

which is less than one for small values of r.[14]

2.4. *More General Income Processes*

It is straightforward to extend the examples in the previous subsections to more general processes for income. First return to the version of the model with no information. Let the first differences in individual income be stationary. This

[12] This follows from $\theta > 0$ and the relationship between θ and ω.

[13] The test carried out by Campbell and Mankiw (1989) should not reject the model since their test only relies on instruments lagged at least two periods. Their rejection therefore is inconsistent with the model with lagged information.

[14] The implied VAR representation of the model is

$$\begin{bmatrix} \Delta y_t \\ s_t \end{bmatrix} = \begin{bmatrix} 0 & 0 \\ -(1-\omega) & (1+r) \end{bmatrix} \begin{bmatrix} \Delta y_{t-1} \\ s_{t-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_t \\ (1-k)\varepsilon_t \end{bmatrix}$$

where $k = (\omega + r)/(1+r)$, fitting the qualitative results of Campbell (1987).

is a fairly general framework since it allows for stationarity in the levels as well; in this case the first differenced process has an MA unit root. Income consists of an aggregate and an individual component given by their respective Wold representations:

$$\Delta y_{it} = \phi(L)\varepsilon_t + \theta(L)u_{it} \tag{22}$$

where

$$\phi(z) = \sum_{i=0}^{\infty} \phi_i z^i,$$

$$\theta(z) = \sum_{i=0}^{\infty} \theta_i z^i.$$

Average per capita income is then given by

$$\Delta y_t = \phi(L)\varepsilon_t. \tag{23}$$

Given stationarity, the process for individual income changes has a Wold representation

$$\Delta y_{it} = A(L)\eta_{it}. \tag{24}$$

Individual consumption will follow

$$\Delta c_{it} = A\left(\frac{1}{1+r}\right)\eta_{it}. \tag{25}$$

Define $\overline{\eta}_t$ as the mean of η_{it}. Equating (22) and (24) and summing over individuals yields

$$A(L)\overline{\eta}_t = \phi(L)\varepsilon_t. \tag{26}$$

If $A(L)$ has no unit root (i.e. at least one of the two component processes is integrated of order one in levels)[15] we can invert it to obtain

$$\Delta c_t = A\left(\frac{1}{1+r}\right)\overline{\eta}_t = A\left(\frac{1}{1+r}\right)A^{-1}(L)\phi(L)\varepsilon_t. \tag{27}$$

Under what conditions does (27) imply excess smoothness in a representative agent model for aggregate consumption? For small interest rates, a necessary and sufficient condition for excess smoothness is given by

$$\frac{1}{2\pi}\frac{f_A(0)}{f_\phi(0)}\int_{-\pi}^{\pi}\frac{f_\phi(\omega)}{f_A(\omega)}\,d\omega < 1 \tag{28}$$

where $f_x(\omega)$ is the normalized spectral density at frequency ω for process x. A derivation is given in Appendix A. Condition (28) shows that relative persistence of the component processes is important: the higher is the spectral density at frequency zero of aggregate income compared to the compound process (and

[15] The analysis proceeds analogously for stationary processes in levels after canceling the common unit root in $\phi(L)$ and $A(L)$.

thus compared to individual income) the more likely is the model to yield excess smoothness. But a second component is present in (28) indicating that the entire spectral shape of the processes also matters. This is the case because individuals use current period income changes to extract not only information on current income innovations but on the entire history as well. The relative dynamics of aggregate and individual income determine how agents evaluate an observed movement in income. Excess volatility of consumption can arise even if aggregate shocks are more permanent if certain spectral densities are not well represented in individual income.[16] Therefore, the intuition on the simple examples in the previous subsections does not completely carry over to the general case.

The examples above demonstrated the orthogonality failure through the correlation at the first lag. For specific income processes, this correlation can be recovered from (27). However, there is no obvious way to parameterize the occurrence of the orthogonality failure in general. Since Galí (1991) has shown that either excess smoothness or excess volatility has to imply the orthogonality failure I will not pursue this issue separately here and refer the reader to Galí for details.

Now turn to the model with lagged information. Rewrite (22) as

$$\Delta y_{it} = \varepsilon_t + u_{it} + \bar{\phi}(L)\varepsilon_{t-1} + \bar{\theta}(L)u_{it-1} \tag{29}$$

where

$$\bar{\phi}(z) = \sum_{i=1}^{\infty} \phi_i z^i,$$

$$\bar{\theta}(z) = \sum_{i=1}^{\infty} \theta_i z^i.$$

Define ν_{it} again as the contemporaneous innovation. Since all the previous values of the aggregate shocks can be observed and all the previous values of the individual shocks can be inferred we can again think of information consisting of the innovation ν_{it} and the correction for the error made before. Equation (16) still defines the error made last period in attributing parts of the innovation to the aggregate and the individual processes. Analogously to equation (18) we obtain for the change in individual consumption

$$\Delta c_{it} = \left\{\phi\left(\frac{1}{1+r}\right)\omega + \theta\left(\frac{1}{1+r}\right)(1-\omega)\right\}\nu_{it} + (1+r)\left\{\phi\left(\frac{1}{1+r}\right) - \theta\left(\frac{1}{1+r}\right)\right\}\xi_{it-1}. \tag{30}$$

[16] An example of such a case is an aggregate MA(1) in first differences with a coefficient of 0.3 combined with an individual MA(2) in first differences with coefficients 0.6 and -0.4 and an innovation variance ten times that of the aggregate income process. Aggregate income is more persistent, as measured by the spectral density at frequency zero. Nevertheless, aggregate consumption is more volatile than in the representative agent model.

Aggregating yields[17]

$$\Delta c_t = \left\{ \phi\left(\frac{1}{1+r}\right)\omega + \theta\left(\frac{1}{1+r}\right)(1-\omega)\right\}\varepsilon_t + (1+r)\left\{\phi\left(\frac{1}{1+r}\right) - \theta\left(\frac{1}{1+r}\right)\right\}(1-\omega)\varepsilon_{it-1}. \tag{31}$$

The regression coefficient of consumption changes on lagged income changes is given by

$$\hat{\beta} = \frac{(1+r)\left\{\phi\left(\frac{1}{1+r}\right) - \theta\left(\frac{1}{1+r}\right)\right\}(1-\omega)}{\sum_{i=0}^{\infty} \phi_i^2}. \tag{32}$$

As in the previous section, the orthogonality condition holds at all further lags because agents incorporate all aggregate information after one period. It is obvious that for small interest rates the condition $\phi(1) > \theta(1)$ is necessary and sufficient for a positive regression coefficient in (32). It turns out that the same condition together with invertibility of $\theta(z)$ is also sufficient for excess smoothness. A demonstration of this fact is given in Appendix A.

In contrast to the no information model the specific form of income dynamics does not play a role here. Only the relative persistence of aggregate and individual shocks as measured by $\phi(1)$ and $\theta(1)$ matter. This is because households can separate new information ν_{it} from lagged information which is not the case for the no information model.

3. EMPIRICAL RESULTS ON MICRO INCOME PROCESSES

The remainder of the paper explores whether the data bear out the implications of the models studied above. The strategy I pursue is to estimate simple models for the micro and macro income processes first. Using these estimates I calculate the implied values of the excess smoothness ratio and the regression coefficient for the orthogonality test at the aggregate level. The results are then easily compared to the aggregate sample values of these statistics.

I start in this section by presenting results on individual income processes. Previous studies in this area reveal that income innovations for individuals are less persistent than shocks to aggregate income and that individual income variation is far more important. MaCurdy (1982) and Abowd and Card (1989) have analyzed the time series structure of earnings and Hall and Mishkin (1982) estimate processes for family income. These studies find that earnings and income changes are well described by an MA(2). Both MA coefficients are negative, with the first one between -0.25 and -0.4 and the second one closer to zero. The standard deviations of log earnings changes range from about 0.25

[17] Equations (30) and (31) correspond to equations (11) and (12) in Goodfriend (1992).

to 0.45. This means that a one standard deviation change in earnings is 25 percent to 45 percent of the previous level. Individual income risk is clearly the main source of income uncertainty individuals face.

None of these results are directly suited for the present purpose because they use annual data while the stylized facts on aggregate consumption have all been established on quarterly series. In order to have analogous results for individual income I estimated models for monthly and quarterly data that I constructed from the 1984 Survey of Income and Program Participation (SIPP). This panel survey was conducted three times a year from late 1983 to the beginning of 1986 in about 20,000 households and collected monthly income information. In each interview, separate information was collected on each of the past four months. The SIPP uses a rotation group design, where one fourth of the sample is interviewed in every calendar month. I take two alternative approaches to estimate income processes from the data, using the data in two different ways. The first is to construct a panel of quarterly income from the fourth quarter of 1983 to the first quarter of 1986, the longest span for which information on the entire sample is available. These data are used to estimate parsimonious but otherwise unrestricted income processes. This conforms most to the approach taken in previous studies. Unfortunately, much of the measured variance and dynamics in these data may be due to measurement error. To account at least for some of the error I also estimate a simple structural income process for the monthly data jointly with a model of misreporting behavior. Under certain assumptions, I can identify some of the response error. The implied quarterly income process net of measurement error is then derived by time aggregating the results.

Consumption decisions are most likely made at the family level. I therefore selected families that can be followed continuously throughout the sample period and did not change head or spouse. Most likely, events that change household composition in a major way will also lead to large income changes. The sample selection will therefore tend to understate the variance of income changes. Furthermore, I limited the sample to households whose head did not go to school in any part of the sample period. School leavers may have large movements in income which are anticipated by the individuals but would appear as random elements in the estimation. For example, an individual just finishing school will have a large increase in income. But this jump will have been foreseen and has therefore, according to the model, already been incorporated in previous consumption decisions. I also eliminated nonfamily households (for example, unrelated housemates) since I cannot judge whether they make joint or individual consumption decisions. Finally, I limited the sample to families with heads between the ages of 16 and 70 during the survey period. Appendix B contains further details on the construction of the sample.

The correct income concept is net family income from all sources excluding capital income. Variables on total family income and income from capital are provided on the SIPP user tapes; these are aggregated from an array of detailed questions on various income categories for each family member. I use the

TABLE I

BASIC SAMPLE STATISTICS

	SIPP Sample		CPS Sample	
	Mean	Std. Dev.	Mean	Std. Dev.
Age	43.9	12.9	42.5	13.4
Years of Schooling	12.6	3.25	12.5	3.22
Non-White	0.12	0.32	0.13	0.34
Male	0.77	0.42	0.73	0.44
Never Married	0.09	0.29	0.14	0.35
Family Size	3.04	1.54	2.82	1.56
Family Income 1984 (quarterly amounts)	6,878	5,180	6,416	4,870
Sample Size	8,174		25,033	

aggregate family level variables although there are some problems associated with them. First, tax information is only collected annually and cannot be apportioned to single months. I therefore have to use gross income which will have a higher variance and (in a progressive tax system) exhibit more transitory fluctuations than net income. Furthermore, the individual variables that make up family income can have imputations. Since the imputations occur at the disaggregated level it would be rather arbitrary to decide which observations to delete because of the imputations. I decided to use all the data. Imputations raise the variance of income changes, presumably largely at the cost of the transitory income component.[18] Finally, all disaggregated income items are topcoded at $8,333 per month. It is impossible to decide from the aggregated income items which variables have been topcoded. Therefore, all observations subject to topcoding are kept in the sample at the topcoded amounts. The topcoding should only affect a small portion of the sample and will reduce the estimated income variance.[19]

I provide some basic characteristics of the sample in Table I which also presents results from the March 1985 Current Population Survey (CPS). In most respects the SIPP sample matches the general population very closely.

I turn next to the description of the two estimation strategies used to identify the variance and dynamics of income at a quarterly frequency. Each strategy has

[18] Coder (1992) finds that imputations lower the cross-sectional variance of the levels of income while Jabine, King, and Petroni (1990) report that imputations exaggerate changes.

[19] About 2 percent of the households in each wave report total income of $8,333 or more. This is an upper bound for the incidence of topcoding since it may result by summing various components that may each be below the cutoff. To gauge the influence of topcoding on the later estimates I conducted a small Monte Carlo study with a log-normal distribution of the level of initial income and an income process consisting of a random walk plus white noise. The innovations were drawn from a normal distribution with individual specific variances that were distributed chi-squared. Variances were chosen to mimic the incidence of top coding in the sample. In all cases I examined, the variance of income changes and the first autocovariance were underestimated to the same degree thus reflecting income dynamics correctly. The degree to which estimated variances were too low depended on specific parameter values but was typically moderate.

its own shortcomings. The combination of the two should allow some assessment of the robustness of the results.

The Dynamics of Measured Quarterly Income

I start by deflating monthly income by the consumer price index for urban consumers (base 1982–84) and aggregating measured family income into calendar quarterly amounts. The estimation of the quarterly income process proceeds in three further stages. In a first step, I regressed changes in family income on a constant, changes in total family size, changes in the number of children, and age of the head to eliminate deterministic components of income dynamics; these regressors are similar to the ones used by Hall and Mishkin (1982). Separate regressions were run for each quarter. Thus the data will be purged of all common seasonal and aggregate components as well. None of the regressors explains income changes very well; as is usual in such regressions the R^2s range from only 0.002 to 0.008! Adding lagged labor market indicators, like number of earners in the household, weeks worked by the head, weekly hours, occupation, and industry as additional regressors hardly changes the results.

The second step was to estimate the unrestricted covariance matrix of residual income changes. Table II displays this 9×9 matrix. The standard deviations of quarterly family income changes range from \$2,796 to \$3,192. The mean level of family income is \$6,929. The standard deviations are between 40 and 46 percent of the income level, somewhat higher than MaCurdy's (1982) and Abowd and Card's (1989) findings on annual data.

TABLE II

COVARIANCE MATRIX[a] OF INCOME CHANGES[b]

(Standard Errors in Parentheses)

	84:1	84:2	84:3	84:4	85:1	85:2	85:3	85:4	86:1
84:1	10.030	−0.255	−0.128	−0.101	0.047	−0.039	−0.026	0.006	0.044
	(0.744)								
84:2	−2.317	8.242	−0.292	−0.168	−0.001	0.040	0.013	−0.040	−0.023
	(0.350)	(0.487)							
84:3	−1.173	−2.428	8.368	−0.234	−0.195	0.001	0.036	−0.064	−0.002
	(0.329)	(0.386)	(0.585)						
84:4	−0.972	−1.457	−2.051	9.163	−0.354	−0.144	−0.080	0.103	−0.026
	(0.311)	(0.312)	(0.333)	(0.629)					
85:1	0.479	−0.008	−1.803	−3.424	10.189	−0.309	−0.132	−0.037	0.058
	(0.311)	(0.284)	(0.267)	(0.505)	(0.654)				
85:2	−0.349	0.318	0.010	−1.215	−2.759	7.818	−0.243	−0.188	−0.013
	(0.212)	(0.220)	(0.198)	(0.200)	(0.319)	(0.410)			
85:3	−0.226	0.103	0.293	−0.674	−1.174	−1.902	7.825	−0.260	−0.171
	(0.197)	(0.184)	(0.210)	(0.196)	(0.222)	(0.251)	(0.404)		
85:4	0.059	−0.346	−0.560	0.947	−0.355	−1.591	−2.201	9.144	−0.325
	(0.220)	(0.181)	(0.189)	(0.215)	(0.254)	(0.212)	(0.256)	(0.542)	
86:1	0.426	−0.202	0.017	−0.240	0.563	−0.115	−1.460	−2.995	9.279
	(0.240)	(0.193)	(0.244)	(0.218)	(0.249)	(0.223)	(0.209)	(0.425)	(0.611)

[a] Covariances below the diagonal, correlations above the diagonal.
[b] Income/1000.

TABLE III

STATIONARY PROCESSES FOR INCOME CHANGES
(Asymptotic Standard Errors in Parentheses)

Coefficient	Stationary Process	MA(3)	MA(2)
Standard	2812	2762	2755
Deviation	(43.3)	(42.1)	(42.2)
1st	−0.275	−0.272	−0.272
Autocorrelation	(0.009)	(0.009)	(0.009)
2nd	−0.169	−0.162	−0.183
Autocorrelation	(0.012)	(0.012)	(0.010)
3rd	−0.042	−0.026	—
Autocorrelation	(0.012)	(0.010)	
4th	0.058	—	—
Autocorrelation	(0.013)		
5th	−0.021	—	—
Autocorrelation	(0.012)		
6th	−0.031	—	—
Autocorrelation	(0.014)		
7th	−0.004	—	—
Autocorrelation	(0.017)		
8th	0.048	—	—
Autocorrelation	(0.027)		
Specification test			
χ^2-statistic [dof]	55.1 [36]	78.9 [41]	86.5 [42]
p-value	0.022	0.000	0.000
Test for Stationarity			
χ^2-statistic [dof]	—	34.1 [26]	27.6 [21]
p-value		0.134	0.152

The first column in Table III presents minimum distance estimates restricting the diagonals of the above covariance matrix to have constant elements.[20] The first two autocorrelations are large in absolute value and comparable to the estimates for annual earnings in the literature. Since time aggregation of ARMA processes does not have this feature, measurement error may be responsible for this finding. Beyond the second lag, the autocorrelations are closer to zero but some are still significant. The positive values at the fourth and eighth lag stick out. These may indicate that there are seasonal components at the individual level in these data. A look at Table II shows that the fourth order autocorrelation is particularly large for the fourth calendar quarter. Differing seasonal employment patterns in the last quarter, e.g. in construction and retail trade, may be an explanation. However, including lagged industry and occupation dummies in the first stage regressions changes these results little.

The specification test at the bottom of Table III also reveals that the data are not very happy with the stationarity restrictions imposed (these are the only restrictions in this case); there are significant differences in the variances and autocorrelations over time. Income changes are less variable in summer as can be seen in Table II. These findings are indicative of possible deterministic components in household income changes, i.e. changes that occur with some

[20] I initially estimated covariances. The standard errors on the reported autocorrelations are obtained by the delta method.

regularity but not in the same direction for every household. Compared to the short term dynamics in income changes, as captured in the first two autocorrelations these regularities do not seem overly large. Lacking any identifying information on deterministic income changes and for reasons of tractability I will work with a stationary MA(2) model for income changes. Little is gained by using an MA(3) and the test in the last row of Table III indicates that stationarity is not a big problem once higher order autocorrelations are restricted to zero.

Adjusting for Measurement Error

Absent any validation information, the true income process can generally not be recovered from covariance estimates of survey income reports if arbitrary measurement error is present in the data.[21] The main measurement problem in the SIPP seems to be related to the timing of changes. As a referee pointed out, family income in the SIPP has the feature that it is constant over a period of time and only changes at infrequent intervals. This constancy of income in the SIPP is mainly a feature of the interview structure. Recall that information is collected retrospectively by asking respondents separately about each of the past four months. 47 percent of the families in the sample report no change in income from one month to the next if the information was collected in the *same interview*. Only 9 percent report constant income in two adjacent months if these reports come from *different interviews*. A large fraction, 27 percent, of respondents reports constant income within the entire interview.

This pattern is typically referred to as "seam bias" and is observed for most variables in the SIPP. Despite considerable research efforts at the Census Bureau the nature of the seam bias is not fully understood (see Jabine, King, and Petroni (1990)). There seems to be some consensus that most respondents tend to report roughly correct transitions (into and out of program participation, of income recipiency, and of amounts) but fail to identify the exact timing of transitions or changes. Changes during the four months of an interview seem to be underreported while too many changes are reported at the seams between interviews.

Similar patterns were found by Goudreau, Oberheu, and Vaughan (1984) in a study using data from the Income Survey Development Program (ISDP), a pilot study for the SIPP. They compare interview reports of AFDC receipts for each of the past three months with administrative records. They find that more than half the respondents reported accurate amounts. However, the vast majority of these respondents received constant amounts. Half of the remaining respondents reported accurate amounts for some months. 27 percent of them reported the most recent payment for an earlier month (a behavior called telescoping)

[21] As far as I know, the only validation study of this type that looks explicitly at income is the exact match between federal tax records and the SIPP undertaken by the Census Bureau. Coder (1992) compares the tax records with annual survey income (adding up 12 monthly reports) from the 1990 SIPP and finds that respondents tend to understate their true income except in the lowest two income deciles. His findings indicate that there must be a substantial negative correlation between survey income and the measurement error when treating the tax records as true income.

and 24 percent missed the timing of a change by one month. The remaining respondents reported incorrect amounts for all months; 62 percent of them reported a multiple or fraction of the truth.

The Goudreau, Oberheu, and Vaughan (1984) findings are consistent with various behavioral models. I will allow for four possible types of respondent behavior and let the data decide which of these is important. In order to do this I will have to model income processes and respondent behavior directly at the monthly level. Assume that true monthly income consists of a random walk component ε_{jt} plus a white noise component u_{jt}, where j denotes interviews, t months in the interview (so that $t = 1, \ldots, 4$), and household subscripts are suppressed. If the interview was in May and refers to January through April, then t will be 1 for January, 2 for February, and so forth. In differences, $t = 1$ will involve an across seam change.

Reported income for every household has a classical, additive measurement error μ_j which is constant for the four months of an interview and serially uncorrelated across interviews. Having all households make this error is a necessary but inconsequential normalization. Define $\xi_j = \mu_j - \mu_{j-1}$. I distinguish the following types of household behavior:

1. *Truthful reporting of income*. Respondents report their income correctly except for the classical measurement error. This implies

$$(33) \qquad \Delta y_{jt} = \begin{cases} \varepsilon_{j1} + u_{j1} - u_{j-1,4} + \xi_j, & t = 1, \\ \varepsilon_{jt} + u_{jt} - u_{j,t-1}, & t = 2,3,4. \end{cases}$$

2. *Telescoping of all income*, i.e. respondents report the income received in the final month for all months of the interview. Notice that this pattern of behavior still lets us observe all permanent changes in income while eliminating all information on transitory receipts during the first three months of the interview. A fraction λ_1 of the sample households behave according to this pattern. For them

$$(34) \qquad \Delta y_{jt} = \begin{cases} \varepsilon_{j1} + \varepsilon_{j2} + \varepsilon_{j3} + \varepsilon_{j4} + u_{j4} - u_{j-1,4} + \xi_j, & t = 1, \\ 0, & t = 2,3,4. \end{cases}$$

3. *Telescoping of permanent income*, i.e. respondents report changes in permanent income only at the seam while they still report transitory income in the month it was actually received. A fraction λ_2 of the sample households behave according to this pattern. This means

$$(35) \qquad \Delta y_{jt} = \begin{cases} \varepsilon_{j1} + \varepsilon_{j2} + \varepsilon_{j3} + \varepsilon_{j4} + u_{j1} - u_{j-1,4} + \xi_j, & t = 1, \\ u_{jt} - u_{jt-1}, & t = 2,3,4. \end{cases}$$

4. *Heaping of transitory income on the last month* is the analogue to the previous pattern. Respondents report all permanent changes correctly but move all transitory income received during the interview to the last month. A fraction

λ_3 of the sample households behave according to this pattern. This implies

$$(36) \qquad \Delta y_{jt} = \begin{cases} \varepsilon_{j1} - u_{j-1,4} - u_{j-1,3} - u_{j-1,2} - u_{j-1,1} + \xi_j, & t=1, \\ \varepsilon_{jt}, & t=2,3, \\ \varepsilon_{j4} + u_{j4} + u_{j3} + u_{j2} + u_{j1}, & t=4. \end{cases}$$

Obviously, these behavioral patterns are rather stylized but they convey the flavor of research findings on response behavior in retrospective panels. The possibility of accurate reports is captured in the first pattern. The additive measurement error for this group is not restrictive. If some households do not make this error, then this will be reflected in my estimate of σ_μ, a nuisance parameter, but will not influence the autocovariance structure. The parameters for the income process will therefore be estimated correctly. The telescoping found by Goudreau, Oberheu, and Vaughan (1984) is reflected in the second pattern of behavior. Since life-cycle households ought to be concerned with distinguishing between permanent and temporary income changes, misreporting may also differ along this dimension. This is captured in the last two patterns of behavior. Which of these patterns are ultimately important in the SIPP is not obvious a priori; the answer is therefore best left to the data.

In the estimation below, the fractions of households behaving according to each pattern are restricted to add to one, so that a fraction $1-\lambda_1-\lambda_2-\lambda_3$ of households follows (33). This restriction is useful in making the variance parameters directly interpretable. It does not necessarily imply that it cannot be the same respondents who, for example, telescope permanent income and heap transitory income. Which households are involved in what type of behavior is irrelevant (and not identified from covariances alone) as long as some households behave according to (33). Finally, note that the specification implies that telescoping of permanent and heaping of transitory income together is not the same as telescoping of all income. Nevertheless, all four types of behavior together are not identified from the data and I will therefore only present selected combinations (i.e. set certain values of λ_k to zero).

To estimate these models, the data have to be arranged differently from the estimates above for quarterly income dynamics. Since the measurement errors occur in the reported income amounts it is not possible to deflate income or make any prior adjustments for demographics. The latter will make little difference since these first stage regressions had very low R^2s anyway. Secondly, the data have to be arranged according to the timing of SIPP interviews rather than according to calendar time. Recall that the SIPP has a rotation group design with each rotation group being interviewed in a different calendar month. In pooling the data across rotation groups according to the timing of SIPP interviews I ignore calendar time effects (like seasonality). I use only waves one to eight in the estimation because only two rotation groups were interviewed for nine waves.

I present two sets of estimates. The first set is for monthly income changes; these estimates refer directly to the representations in equations (33) to (36).

One way of tackling estimation would be corresponding to the quarterly income changes above by estimating the full 32×32 covariance matrix first. However, this matrix has 528 distinct elements so that calculation of the weighting matrix would involve inversion of a 528×528 matrix. Since I calculate standard errors by boot-strapping below, this is computationally not feasible. Most of the 528 elements in the covariance matrix will be restricted to be zero or constant across periods. To reduce the size of the estimation problem I pool the data by treating each household-wave as a separate observation. Separate values for the variance and for the first four autocovariances are estimated depending on the interview month t the data come from (since the model above implies different values for these moments depending on time in the interview). All higher order autocovariances are zero in these models and are therefore not considered. I stack the data in such a way that samples of the same size are used in the estimation of all the moments. I also estimate the corresponding fourth moments. See Appendix B for details.

The second set of estimates is obtained from income differences four months apart. In this case, the differences will be formed by subtracting income from the same interview month in the last interview. The corresponding behavioral models should yield the same estimates as from the one month differenced data if the models are specified correctly (see, for example, Griliches and Hausman (1986)). Thus, these additional results yield an added check on the validity of the models presented. In the case of the four month differences, the data are pooled in a slightly different way. This is necessary because the model involves nonzero covariances up to lag seven for the four months differenced representation. See again Appendix B.

Table IV presents estimates of the underlying variance and share parameters using various combinations of the four types of response error described above. These were again obtained from the variances and autocovariances by optimal minimum distance.[22] Some parameter estimates for σ_μ and λ_1 in Table IV are zero. Standard asymptotic distribution theory does not apply in the case where a parameter is estimated to be on the boundary of the parameter space. I obtained the standard errors in Table IV from 500 bootstrap replications.[23] The parameters on the boundary were also estimated to be zero in all the replications. This probably is a reflection of the large number of observations and might indicate that the models are not specified quite correctly.

The models also do not fit very well according to the standard χ^2-specification test but it should be pointed out that they describe the basic features of the

[22] The estimates are not fully efficient because the stacking of various waves of the panel introduces some serial dependence across observations and this is not taken into account in calculating the weighting matrix. But with the large sample sizes estimates are relatively insensitive to the particular weighting matrix chosen: unweighted estimates were very similar. Test statistics will be affected by using a nonoptimal weighting matrix, however.

[23] Resamples of entire income records for a household were drawn from the set of households before stacking various waves since only these individual records are independent. The sampling variances were computed from the B resamples as $B^{-1}\Sigma(\theta_b^* - \bar{\theta}^*)^2$ where θ_b^* is the estimate of a coefficient in resample b and $\bar{\theta}^* = B^{-1}\Sigma\theta_b^*$.

TABLE IV

STRUCTURAL MODELS WITH MEASUREMENT ERROR FOR MONTHLY INCOME
(Bootstrap Standard Errors in Parentheses[a])

	Monthly Differences			Four Month Differences		
Parameter	(1)	(2)	(3)	(1)	(2)	(3)
σ_ε	0.400	0.395	0.421	0.231	0.234	0.234
	(0.015)	(0.015)	(0.013)	(0.010)	(0.011)	(0.010)
σ_u	0.925	0.940	0.713	0.675	0.717	0.717
	(0.022)	(0.022)	(0.025)	(0.022)	(0.027)	(0.027)
σ_μ	0.000	0.000	0.587	0.763	0.762	0.762
	(0.000)	(0.000)	(0.019)	(0.014)	(0.014)	(0.014)
λ_1	0.471	0.460	—	0.000	0.000	—
	(0.020)	(0.020)		(0.000)	(0.000)	
λ_2	—	—	0.640	—	—	0.000
			(0.044)			(0.000)
λ_3	—	0.056	0.116	—	0.147	0.147
		(0.020)	(0.039)		(0.046)	(0.045)
Specification test	56.7	47.7	30.7	82.4	63.3	63.3
χ^2-statistic [dof]	[16]	[15]	[15]	[28]	[27]	[27]
p-value	0.000	0.000	0.010	0.000	0.000	0.000
Quarterly	2859	2875	2532	1936	2030	2030
Std. dev.	(51.3)	(49.6)	(61.7)	(47.6)	(60.2)	(56.8)
Quarterly	−0.235	−0.246	−0.127	−0.307	−0.321	−0.321
Autocorrelation	(0.016)	(0.017)	(0.016)	(0.017)	(0.016)	(0.017)

[a] Based on 500 replications with uniform resampling.

estimated variances and covariances very well. Given the large number of observations the rejection may not be surprising. Another more serious sign that these models do not fully capture reported household income processes are the differences of the estimates for monthly and four month differences. In either case, the model found to be most consistent with the data is given in column (3) and combines the additive measurement error with telescoping of permanent income and heaping of transitory income. Telescoping of permanent income is found to be important for the estimates from one month differences ($\lambda_2 = 0.64$) while this behavior is estimated to be absent for the four month differences. Further discrepancies are that in the four month differences a larger part of the income fluctuations is attributed to the additive measurement error and less to the permanent income component.

The implied quarterly income process corresponding to the structural model is an IMA(1, 1).[24] The variance for quarterly income is given by $19\sigma_\varepsilon^2 + 6\sigma_u^2$ and the first autocovariance by $4\sigma_\varepsilon^2 - 3\sigma_u^2$. The corresponding standard deviation and autocorrelation are reported on the bottom of Table IV. The results differ somewhat from the estimates in Table III. The standard deviations of true

[24] I proceed by time aggregating income and assuming that consumption decisions are made at the quarterly frequency. This seems somewhat unnatural, but recall that only quarterly aggregate data is available. Since I want to study the empirical content of the imperfect information model in isolation, I do not consider implications of time aggregation on the life-cycle consumption model simultaneously. These issues have been investigated by Christiano, Eichenbaum, and Marshall (1991) and Heaton (1993).

income changes are now lower but still substantial. Furthermore, the implied results from the one month and four month differences also differ moderately; the four month differences imply lower variance but more mean reversion. It turns out that these disparities actually make little difference for the predictions from the consumption model reported below.

Remember that these results refer to nominal income. Before proceeding, I adjust the standard deviations obtained from the structural models by the average of the CPI for urban consumers (base 1982–84) over the sample period (which is 105.3). This yields \$2,404 for the estimates from monthly differences, and \$1,928 for the four month differences.

4. AGGREGATE STYLIZED FACTS ON INCOME AND CONSUMPTION

In this section I report the stylized facts pertaining to income and consumption processes in aggregate data. This has two purposes. First, I will try to establish some simple time series model for the aggregate income process. Together with the results of the previous section this will allow me to calculate predictions from the model with heterogeneous agents for aggregate consumption. Secondly, I will also report results on consumption here to compare them to the predictions in the following section.

In order to replicate the results often cited in the literature I make the same adjustments to the NIPA data as Blinder and Deaton (1985) did.[25] However, since the micro level estimates in the previous section are for households rather than individuals, all macro series used are also on a per household basis rather than on a per capita basis.[26] My sample ranges from the first quarter of 1954 to the fourth quarter of 1990; the data are taken from the 1991 Citibase tape. All variables are in levels, not in logs.[27] A detailed description of the adjustments I make is given in Appendix B.

Table V presents results on the income process. The income series refers to "labor" income, i.e. disposable income excluding capital income. There is a slight conceptual difference to the micro estimates since the aggregate income series excludes taxes. However, whether taxes are excluded or not makes little difference for the aggregate estimates. I therefore use the series commonly used in the literature. As for individual income I will use an MA(2) model for the first differences of aggregate income but I also present results for an AR(1). The MA coefficients are estimated by conditional least squares;[28] the AR model

[25] Unlike Blinder and Deaton (1985) I did not adjust income and consumption for nontax payments to state and local governments since the series on Citibase is only available starting in 1958. For the post-1958 sample the difference is completely inconsequential.

[26] Since no quarterly series of the number of households is available for the sample period I linearly interpolated annual estimates of average household size.

[27] Typically logs of variables are preferred to levels on the grounds that the level variables exhibit growing variances over time. Regressing squared changes of the variables or squared residuals from the models in Tables V and VI on a linear trend I found no evidence of this in these data.

[28] This ignores the fact that initial values are assumed rather than derived from data when filtering the process for the MA innovations.

TABLE V
AGGREGATE STYLIZED FACTS ON FIRST DIFFERENCES OF INCOME
(Standard Errors in Parentheses)

Sample Period	AR(1)	MA(2) First Coefficient	MA(2) Second Coefficient	Std. Dev. of Income Innovations
1954–1984	0.346	0.375	0.013	47.8
	(0.085)	(0.090)	(0.090)	(3.03)
1954–1990	0.288	0.299	0.010	49.0
	(0.080)	(0.083)	(0.083)	(2.85)

TABLE VI
AGGREGATE STYLIZED FACTS ON FIRST DIFFERENCE OF CONSUMPTION
(Standard Errors in Parentheses)

Sample Period	Coef. of Consumption Changes on Income Lag	AR(1) Coefficient	MA(1) Coefficient	Excess Smoothness Ratio
1954–1984	0.121	0.210	0.197	0.601
	(0.049)	(0.088)	(0.088)	(0.064)
1954–1990	0.110	0.200	0.206	0.578
	(0.045)	(0.082)	(0.081)	(0.055)

is estimated by OLS. I report results for two different sample periods. 1954 to 1984 is the period of the Blinder and Deaton (1985) data set that has been used extensively by various researchers. Notice that extending the sample to 1990 reduces the autocorrelation in the income changes slightly. Both the AR(1) and the MA(2) fit the data well. The quarterly standard deviation for aggregate per household income changes is only around $50, compared to the $2,000 or more I found for the individual income component above!

Table VI reports some results on aggregate consumption for similar sample periods as the previous table. It has been customary in the macro literature to use consumer expenditure on nondurables and services as consumption measure. Like Blinder and Deaton I eliminated expenditures on clothing and shoes from the nondurable consumption series. To make units comparable to total income I multiplied these expenditures by the sample average of the ratio of total expenditures to expenditures on nondurables and services.

The table reports the regression coefficient of consumption changes on lagged income changes which is in the order of 0.11 and significant. Consumption changes are positively autocorrelated as measured by an AR(1) or MA(1) parameter. The last column gives the excess smoothness ratio of about 0.6. All these estimates are in line with previous findings in the literature.

5. PREDICTIONS FROM THE MODEL

I am now ready to present predictions from the models using the empirical estimates for the individual and aggregate parts of the income process. Since the estimates vary for different sample periods and for the different micro income models I will present a number of results. This will also serve as a robustness check.

I assume that both the individual income process and the aggregate income process are described by an MA(2) in first differences.

$$\begin{aligned}(37)\qquad \Delta y_{it} &= \left(1+\phi_1 L+\phi_2 L^2\right)\varepsilon_t+\left(1-\alpha_1 L-\alpha_2 L^2\right)u_{it}\\ &= \left(1-\theta_1 L-\theta_2 L^2\right)\eta_{it}.\end{aligned}$$

The consumption processes for the no information and the lagged information models are given in (27) and (31), respectively. In the case of the no information model aggregate consumption follows an ARIMA(2, 1, 2) process. For the lagged information model, consumption changes are an MA(1). Appendix A presents the formula for $\hat{\beta}$, the coefficient for a regression of consumption changes on lagged income changes, for the no information model and the excess smoothness ratio $\sigma_{\Delta c}/\sigma_{\varepsilon}$.

Predictions for these parameters are shown in Table VII and compared to the aggregate stylized facts about consumption from Table VI. The base case uses the quarterly estimates for the individual income process, unadjusted for measurement error, and the 1954–1990 results for aggregate income. From the results in Section 3, the standard deviation of individual income changes is \$2,755 in this case, the first order autocorrelation is -0.27 and the second order autocorrelation is -0.18. In terms of an MA-process this translates into a standard deviation of the innovation of \$2,470, and MA coefficients of -0.44 and -0.23. The full information representative agent model implies a $\hat{\beta}$ of zero and $\sigma_{\Delta c}/\sigma_{\varepsilon}$ of 1.31. Both the no information model and the lagged information model predict parameters which are very different from this benchmark and which are qualitatively in the direction of the actual aggregate estimates. The results for the no information model are superior to the lagged information

TABLE VII

COMPARISON OF MODEL PREDICTIONS AND AGGREGATE ESTIMATES

	Aggregate Estimates		No Information Model		Lagged Information Model		Utility Loss
Case	$\hat{\beta}$	$\sigma_{\Delta c}/\sigma_{\varepsilon}$	$\hat{\beta}$	$\sigma_{\Delta c}/\sigma_{\varepsilon}$	$\hat{\beta}$	$\sigma_{\Delta c}/\sigma_{\varepsilon}$	[\$/quarter]
1[a]	0.110	0.578	0.287	0.515	0.892	1.032	1.498
2[b]	0.121	0.601	0.314	0.539	0.921	1.105	1.649
3[c]	0.110	0.578	0.359	0.951	0.403	0.976	0.139
4[d]	0.110	0.578	0.286	1.036	0.294	1.040	0.077
5[e]	0.110	0.578	0.434	0.788	0.617	0.929	0.363
6[f]	0.110	0.578	0.402	0.884	0.490	0.944	0.209

[a] Base case: σ_u = \$2,470, $\alpha_1 = 0.438$, $\alpha_2 = 0.228$, σ_{ε} = \$49.0, $\phi_1 = 0.300$, $\phi_2 = 0.010$; interest rate = 0.01, mean income = \$6,929, coef. of rel. risk aversion = 2.

[b] Case 2: As base case but σ_{ε} = \$47.8, $\phi_1 = 0.375$, $\phi_2 = 0.013$.

[c] Case 3: As base case but σ_u = \$2,384, $\alpha_1 = 0.129$, $\alpha_2 = 0$.

[d] Case 4: As base case but σ_u = \$2,099, $\alpha_1 = 0.011$, $\alpha_2 = 0$.

[e] Case 5: As base case but σ_u = \$1,811, $\alpha_1 = 0.364$, $\alpha_2 = 0$.

[f] Case 6: As base case but σ_u = \$1,487, $\alpha_1 = 0.225$, $\alpha_2 = 0$.

model in the base case. Still, both models considerably overpredict $\hat{\beta}$ and the lagged information model overpredicts $\sigma_{\Delta c}/\sigma_{\varepsilon}$ by about a factor of two.

The last column presents the utility loss for a household that uses no aggregate information compared to the full information case.[29] The loss is expressed in dollars per quarter and household and is calculated for a coefficient of relative risk aversion of two. It amounts to 1.50 dollars or 0.02 percent of total utility. This is similar to the findings by Cochrane (1989) who estimated the utility loss for a representative consumer exhibiting excess sensitivity. The loss for higher risk aversion is easily obtained by dividing by two and multiplying by the new coefficient. Even for a risk aversion coefficient of 10 the loss would still be minor. This provides some evidence that the assumptions of the no information model seem to be quite reasonable: it does not pay to collect aggregate information to improve consumption decisions.

The next rows present variations on the base case. Case 2 uses the aggregate estimates for the 1954–1984 period; the results are very similar. Case 3 presents calculations using the structural estimates for the micro income process from one month differences. In this model most of the transitory variation is removed from the micro income estimates. The results in this case are much less favorable to the no information model while the lagged information model improves. Both $\hat{\beta}$ and $\sigma_{\Delta c}/\sigma_{\varepsilon}$ are too large now. The utility loss is much less in this case because the dynamics of the micro income process are much closer to those of aggregate income. Case 4 is a variation on the previous case. The structural model underlying these estimates is able to account for interview specific measurement error as well as for telescoping of income reports. In addition, some of the transitory month to month income fluctuations may also be due to measurement error. Case 4 therefore halves the variance of the transitory monthly income component. This reduces the quarterly innovation variance as well as the importance of mean reversion. This does not change the results much compared to case 3 but makes the no information model and the lagged information model even more indistinguishable. Case 5 refers to the structural estimates from four month differences. Again, the results are not fundamentally different from those for the one month differences. Finally, case 6 again halves the transitory variance from the four month differenced estimates with little change in the predictions.

Further calculations, which are not reported, showed that removing the MA(2) term from micro income is responsible for the differences between the base case and cases 3 to 6. This does not mean that the size of the coefficient α_1 does not affect the predictions of the model at all but the predictions are relatively insensitive to the range implied for this parameter in cases 3 to 6. Changing the micro variance alone has basically no effect on the results unless the variance is reduced to a magnitude close to the aggregate variance.

[29] Instead of comparing the model with no information to the Goodfriend model I use a model with full contemporaneous information on aggregate variables as benchmark. Utility for this model is calculated much more easily than for the lagged information model. The utility differences I present are therefore upper bounds for the differences between the two models in the paper.

The results illustrate various things. Adjusting the micro income estimates for (some of the) measurement error yields results rather different from using the raw micro data. The exact estimates for the structural income models, on the other hand, make very little difference for the final results. This seems to indicate that these estimates might be useful despite the fact that individual income dynamics in the SIPP is certainly more complicated. The magnitudes for the implied coefficients in tests of the life-cycle model with aggregate data, in particular $\hat{\beta}$ is striking. They illustrate how ignoring small pieces of information at the micro level can have substantial implications at the aggregate level. Since these predictions only pertain to the most simple minded version of a life-cycle consumption model it is not surprising that they do not match the data more closely.

6. CONCLUDING COMMENTS

In this paper I have analyzed the implications of heterogeneity in income and incomplete information on the source of income shocks for the form of the aggregate consumption process and its relation to observed income. The failures of the full information life-cycle consumption model usually found in aggregate data clearly arise if individual consumers adjust their consumption correctly to individual income innovations but do not care to distinguish aggregate and idiosyncratic income variation. Using estimated parameter values for individual and aggregate income processes, the model gives predictions that deviate substantially from the full information benchmark. However, the results indicate too much correlation of consumption changes with lagged income but not smooth enough consumption. Nevertheless, heterogeneity in income and incomplete information seem to account for a large portion of the deviations from the full information case.

Rational expectations models with incomplete aggregate information have mostly used the assumption that aggregate information arrives with a one period lag. In the present context, the no information model seems to yield slightly better results than the lagged information model but does not clearly dominate it. Some combination of the two models seem more reasonable as a description of reality. Consumers may not deliberately collect aggregate information. But their interaction with many other individuals will reveal a lot to them about the nature of their own income process. Formalizing models in which aggregate information arrives more slowly than in the lagged information model should be an area that deserves more attention.

The feature that drives the results in this paper is that the model yields an autocorrelated process for aggregate consumption changes. Galí (1991) has shown that excess smoothness of consumption can be characterized in the frequency domain with less restrictive assumptions than in Deaton (1987) or Campbell and Deaton (1989). Essentially, his results stem from the autocorrelation in consumption changes and are therefore consistent with the predictions from the no information model.

A number of other models have been suggested that lead to autocorrelated consumption. A simple model of habit formation (Deaton (1987)) or slow adjustment of consumers to income shocks (Attfield, Demery, and Duck (1992)) also leads to an AR(1) for consumption changes. Unlike for the models studied here, the micro parameters are generally not estimable in these cases so the models cannot be subjected to the same stringent test. Furthermore, these models imply that consumption should have the same autocorrelation structure in micro and in aggregate data. This seems to be at odds with the empirical findings.

Although in this paper I have focussed on implications of the no information model for aggregate data the model is roughly consistent with previous findings on micro data for consumption. It predicts correctly that the orthogonality conditions should not be rejected in panel data. The approach taken by Altonji and Siow (1987), Zeldes (1989), and Runkle (1991) is consistent with the model presented here. These studies find little evidence against the permanent income model with food consumption data from the PSID. The exception is Zeldes (1989), who finds some evidence for such correlations for low wealth consumers in the PSID, interpreting them as liquidity constraints.

It seems quite reasonable a priori that part of the population is liquidity constrained. Interactions of liquidity constraints and precautionary savings motives with the incomplete information assumption are considered in Deaton (1991). In numerical simulations Deaton finds a regression coefficient of consumption growth on lagged income growth of 0.42 and a smoothness ratio just below one. His results are for logs of the variables and are therefore not directly comparable to mine. Nevertheless, it seems that incomplete information may be the major factor driving these results.

Since the specifications in this paper are very restrictive, future research should incoporate incomplete information into more sophisticated models. Finite lifetimes and superior information of consumers about income changes are possible candidates that may play an important role in bringing the results presented here better in line with the data.

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Manuscript received August, 1991; final revision received October, 1994.

APPENDIX A

DERIVATION OF CONDITIONS FOR EXCESS SMOOTHNESS

Let $\beta \equiv 1/(1+r)$ so that excess smoothness in the aggregate is given by $\sigma_{\Delta c}^2 < \phi^2(\beta)\sigma_\varepsilon^2$ or

$$\Psi \equiv \frac{\sigma_{\Delta c}^2}{\phi^2(\beta)\sigma_\varepsilon^2} < 1. \tag{A1}$$

Consider the no information case. Using (27) in the text the spectral density of aggregate consumption changes is

$$h_{\Delta c}(\omega) = \frac{A^2(\beta)}{2\pi} \frac{|\phi(e^{-i\omega})|^2}{|A(e^{-i\omega})|^2} \sigma_\varepsilon^2. \tag{A2}$$

The variance of consumption changes can be found by integrating (A2):

$$\sigma_{\Delta c}^2 = \int_{-\pi}^{\pi} h_{\Delta c}(\omega)\, d\omega = \int_{-\pi}^{\pi} \frac{A^2(\beta)}{2\pi} \frac{|\phi(e^{-i\omega})|^2}{|A(e^{-i\omega})|^2} \sigma_\varepsilon^2\, d\omega \tag{A3}$$

so that the quantity Ψ is given by

$$\begin{aligned} \Psi &= \frac{1}{2\pi} \frac{A^2(\beta)}{\phi^2(\beta)} \int_{-\pi}^{\pi} \frac{|\phi(e^{-i\omega})|^2}{|A(e^{-i\omega})|^2} d\omega \\ &= \frac{1}{2\pi} \frac{A^2(\beta)}{\phi^2(\beta)} \frac{\sigma_\eta^2}{\sigma_\varepsilon^2} \int_{-\pi}^{\pi} \frac{h_\phi(\omega)}{h_A(\omega)} d\omega \\ &= \frac{1}{2\pi} \frac{A^2(\beta)}{\phi^2(\beta)} \frac{\sigma_\eta^2}{\sigma_\varepsilon^2} \frac{\sigma_{\Delta y}^2}{\sigma_{\Delta yi}^2} \int_{-\pi}^{\pi} \frac{f_\phi(\omega)}{f_A(\omega)} d\omega \end{aligned} \tag{A4}$$

where $f_x(\omega) = h_x(\omega)/\sigma_x^2$ is the normalized spectral density of process x. Taking limits as the interest rate approaches zero gives the following expression which appears as (28) in the text:

$$\lim_{r\to 0} \Psi = \frac{1}{2\pi} \frac{f_A(0)}{f_\phi(0)} \int_{-\pi}^{\pi} \frac{f_\phi(\omega)}{f_A(\omega)} d\omega. \tag{A5}$$

Now turn to the lagged information model. From (31)

$$\frac{\sigma_{\Delta c}^2}{\sigma_\varepsilon^2} = [\phi(\beta)\omega + \theta(\beta)(1-\omega)]^2 + (1+r)^2[\phi(\beta) - \theta(\beta)]^2(1-\omega)^2. \tag{A6}$$

Using condition (A1) and letting interest rates get small we obtain

$$\lim_{r\to 0} \Psi < 1 \quad \Rightarrow \quad [\phi(1)\omega + \theta(1)(1-\omega)]^2 + [\phi(1) - \theta(1)]^2(1-\omega)^2 < \phi^2(1). \tag{A7}$$

Define $K(\omega) \equiv [\phi(1) - \theta(1)]\omega + \theta(1)$ which will be positive given $\phi(1) > \theta(1) > 0$. The latter inequality holds if $\theta(z)$ is invertible. Notice that (A7) can be rewritten as

$$K^2(\omega) + [\phi(1) - K(\omega)]^2 < \phi^2(1). \tag{A8}$$

Thus we have to show that (A8) is satisfied. Use $\phi(1) > \theta(1)$, multiply both sides by $1-\omega$ and rearrange to get

$$K(\omega) = [\phi(1) - \theta(1)]\omega + \theta(1) < \phi(1). \tag{A9}$$

Recall that $K(\omega)$ is positive, multiply both sides of (A9) by twice $K(\omega)$ and add $\phi(1)^2$ to complete the square. Rearranging yields (A8) which completes the proof.

Empirical Formulation. In the empirical model in Section 5 both the aggregate and the individual income component are described by an MA(2). Then $A(L) = 1 + a_1 L + a_2 L^2$. The roots of this polynomial are defined by $\mu^2 + a_1\mu + a_2 = 0$. Writing consumption changes in its series representation,

$$\Delta c_t = \frac{A\left(\frac{1}{1+r}\right)}{\mu_1 - \mu_2} \sum_{i=0}^{\infty} (\mu_1^{i+1} - \mu_2^{i+1})(\varepsilon_{t-i} + \phi_1 \varepsilon_{t-1-i} + \phi_2 \varepsilon_{t-2-i}). \tag{A10}$$

This can be used to derive the regression coefficient of consumption changes on lagged income changes:

$$\text{(A11)}\qquad \hat{\beta}=\frac{A\left(\frac{1}{1+r}\right)}{(\mu_1-\mu_2)\left(1+\phi_1^2+\phi_1^2\right)}\Big\{(\mu_1-\mu_2+\mu_1^3-\mu_2^3)(\phi_1+\phi_1\phi_2)+(\mu_1^2-\mu_2^2)\left(1+\phi_1^2+\phi_2^2\right)+(\mu_1^4-\mu_2^4)\phi_2\Big\}.$$

The variance of consumption changes can either be found by solving (A3) for the relevant processes or by solving the Yule-Walker equations corresponding to the ARMA(2, 2) given by (A10). I have done the latter numerically.

APPENDIX B

SAMPLE SELECTION AND VARIABLE DEFINITIONS

Construction of the SIPP Sample. The 1984 Survey of Income and Program Participation was conducted in nine interview waves. The sample consisted of four rotation groups. The households in the first rotation group were interviewed in October, 1983. The ninth interview for the first rotation group was in June, 1986. Similarly, rotation group two was interviewed nine times from November, 1983 to July, 1986. Rotation groups three and four were only interviewed eight times so that their first interviews were in November and December, 1983, and their last interviews were in April and May, 1986. In each interview, questions were asked about income for each of the previous four months. For example, the October, 1983 interview for rotation group one collected information on each month from June to September, 1983 (see U.S. Bureau of the Census (1991) for details).

Monthly income data for all rotation groups are available from September, 1983 to March, 1986. For the quarterly estimates, I constructed ten observations for the calendar quarters starting with October, 1983 (for the last quarter of 1983) up to March, 1986 (for the first quarter of 1986). Because the quarterly data refer to calendar time, the three income records for a particular quarter and rotation group may come from one or two different interviews.

I started by matching household heads from the eight or nine interview waves. This resulted in 12,874 matches. I then restrict the matched sample as described in the text by selecting continuous heads for the period of analysis, that did not change marital status or their level of schooling in any month. Family income is constructed by subtracting property income (*F*-PROP*) from total family income (*F* TOTINC*). Income is deflated by the monthly CPI for urban consumers (base 1982–84). Finally, I corrected reported age of the head so that age increments by one every four quarters. The sample only includes heads that were older than 16 years and younger than 70 years throughout the sample. Only families with complete records on income are included in the final sample which has 8,174 observations.

The same observations were utilized for the estimation of the structural models at the monthly frequency but the data were arranged in a different manner. Only waves 1 to 8 were used. For the estimates based on one month differences the data were stacked in the following way. Let y_{ijt} denote income for household i $(i=1,\dots,N)$ in the tth month $(t=1,\dots,4)$ of interview j $(j=1,\dots,8)$. Let $x_{ijt}=y_{ijt}-y_{ijt-1}$. Form the following matrix:

$$X=\begin{bmatrix} x_{121} & x_{122} & \cdots & x_{134} \\ x_{132} & \cdots & \cdots & x_{144} \\ \cdots & \cdots & \cdots & \cdots \\ x_{172} & \cdots & \cdots & x_{184} \\ x_{221} & \cdots & \cdots & x_{234} \\ \cdots & \cdots & \cdots & \cdots \\ x_{N72} & \cdots & \cdots & x_{N84} \end{bmatrix}$$

where X is of dimension $6 \cdot N \times 8 = 49{,}044 \times 8$. This means that six income records from each household are pooled. Each row in this matrix contains eight income changes. Notice that the first four columns of X and the second four columns are not independent. For example, x_{134} is the

(1,8)th element as well as the (2,4)th element of this matrix. All elements in columns five to eight will be independent.

Separate variances for each interview month ($t = 1, \ldots, 4$) are estimated as the main diagonal of the matrix $(6N)^{-1}X'_{\ldots,5\ldots8}X_{\ldots,5\ldots8}$ where the subscript notation refers to columns five to eight of the data matrix. Similarly, four separate first autocovariances are estimated as the main diagonal of the matrix $(6N)^{-1}X'_{\ldots,4\ldots7}X_{\ldots,5\ldots8}$; second autocovariances from $(6N)^{-1}X'_{\ldots,3\ldots6}X_{\ldots,5\ldots8}$; third autocovariances from $(6N)^{-1}X'_{\ldots,2\ldots5}X_{\ldots,5\ldots8}$; fourth autocovariances from $(6N)^{-1}X'_{\ldots,1\ldots4}X_{\ldots,5\ldots8}$. Autocovariances at higher lags are not utilized.

For the estimates based on four month differences the data had to be pooled in a slightly different fashion because now seven autocovariances are needed. Let $z_{ijt} = y_{ijt} - y_{ij-1t}$ be the fourth difference of the data. The matrix of the pooled data has the form

$$Z = \begin{bmatrix} z_{121} & z_{122} & \cdots & z_{144} \\ \cdots & \cdots & \cdots & \cdots \\ z_{161} & \ddots & \cdots & z_{184} \\ \cdots & \cdots & \cdots & \cdots \\ z_{N61} & \cdots & \cdots & z_{N84} \end{bmatrix}$$

so that Z is a matrix of dimension $5 \cdot N \times 12 = 40{,}870 \times 12$. Variances are estimated as the main diagonal of the matrix $(5N)^{-1}Z'_{\ldots,9\ldots12}Z_{\ldots,9\ldots12}$; first autocovariances from $(5N)^{-1}Z'_{\ldots,8\ldots11}Z_{\ldots,9\ldots12}$, and so forth up to the seventh autocovariance which is estimated from $(5N)^{-1}Z'_{\ldots,2\ldots5}Z_{\ldots,9\ldots12}$.

Notice that part of the data is not used due to the requirement that the panel be balanced so that an equal number of observations is used in calculating each of the moments. Corresponding fourth moments to the estimated sample moments were also obtained. For the bootstrap estimation of standard errors household records were drawn with replacement from the set of 8,174 households before the data were pooled.

Construction of the Aggregate Series. I created the consumption and income series from the National Income and Product Accounts largely following Blinder and Deaton (1985). The labor income series consists of labor and transfer income (the Citibase Series $GW + GPOL + GPT$) less social insurance contributions ($GPSIN$). To subtract the portion of taxes on labor income I created the ratio of wages, salaries and other labor income to income including interest, dividends, and rents. Personal tax payments ($GPTX$) were multiplied by this ratio and the result subtracted from income. Proprietors' income ($GPROP$) was multiplied by the same ratio before adding it to the income series. Unlike Blinder and Deaton I did not add nontax payments to state and local governments to income and consumption because Citibase only reports this series starting from 1958. Income was adjusted in the second quarter of 1975 by subtracting the tax rebate and social security bonus. The amount of this adjustment is taken from Blinder (1981, Table 2).

The real consumption series is constructed by adding the constant dollar expenditures on nondurables and services and subtracting expenditures on clothing and shoes because these have rather durable characteristics ($GCN82 + GCS82 - GCNC82$). The consumption deflator obtained by dividing the nominal consumption series by the real series is used to deflate income. Both income and consumption are first divided by the total population ($GPOP$) and then multiplied by the average number of household members. No quarterly series of average household size is available for the sample period. I used the figures pertaining to March from the Current Population Reports, Series P-20, No. 467 for the first quarter and interpolated the remaining quarters linearly. Since average household size is only changing very slowly, this approximation should be rather good.

Finally, to make the scale of the consumption series comparable to the income series it is multiplied by the ratio of total expenditures ($GC82$) to expenditures on nondurables and services. Quarterly NIPA series are reported at annual rates. I divided all series by four to obtain quarterly amounts.

APPENDIX C

CALCULATIONS OF UTILITY LOSS

In this Appendix I discuss how to calculate the utility loss the household suffers by ignoring aggregate information in consumption decisions. The basic setup is taken from the Appendix in

Cochrane (1989, pp. 334–335). The second part gives the matrix representations ot the full information model and the no information model used in the utility calculations.

Utility for the quadratic model can be written as

$$\text{(C1)} \qquad U(X_t) = E_t \sum_{j=0}^{\infty} \beta^j X'_{t+j} R X_{t+j}$$

where $\beta = 1/(1+r)$ and X_t represents the state vector of the system which evolves according to

$$\text{(C2)} \qquad \begin{aligned} X_t &= A X_{t-1} + \Gamma \xi_t, \\ E_t(\xi_{t+1}) &= 0, \\ E_t(\xi_t \xi_t') &= \Sigma. \end{aligned}$$

Equation (C1) can be rewritten as

$$\text{(C3)} \qquad U(X_t) = X_t' P X_t + \frac{1+r}{r} \operatorname{trace}(P \Gamma \Sigma \Gamma')$$

where

$$\text{(C4)} \qquad P = R + \beta A' P A.$$

P will be a symmetric matrix; therefore (C4) cannot be solved directly for P. Cochrane shows, however, that

$$\text{(C5)} \qquad M \operatorname{vec}(P) = (I - \beta M(A' \otimes A')N)^{-1} M \operatorname{vec}(R)$$

where M is a transformation matrix that deletes the redundant rows of a stacked symmetric matrix and N does the opposite operation, i.e.

$$\begin{aligned} \operatorname{vech}(P) &= M \operatorname{vec}(P), \\ N \operatorname{vech}(P) &= \operatorname{vec}(P). \end{aligned}$$

Cochrane uses (C3) and (C5) to solve analytically for $U(X_t)$. Instead, once the model is expressed in the form (C1) and (C2), these equations can easily be used to calculate utility numerically. Due to the complexity of the models I took this latter route. Since the quantity of interest is the difference between lifetime utility for two alternative models it is rather small compared to total utility. Computational inaccuracies can therefore play a large role in these numerical calculations. The results should therefore be taken as indicative of magnitudes rather than as precise amounts.

The full information model. Instead of comparing the no information model to Goodfriend's model with lagged information I chose to use a model with full contemporaneous information on aggregate variables as the benchmark. This model will yield higher utility than Goodfriend's. The utility comparisons I present will therefore be upper bounds for the choice relevant to the consumer.

Since all the variables refer to a single household and the distinction between aggregate and individual variables is not important here I suppress i subscripts for notational convenience. Income in the full information model is given by the first line in (37) in the text.

$$\text{(C6)} \qquad \Delta y_t = \left(1 + \phi_1 L + \phi_2 L^2\right) \varepsilon_t + \left(1 - \alpha_1 L - \alpha_2 L^2\right) u_t.$$

Optimal consumption is given by

$$\text{(C7)} \qquad \begin{aligned} c_t &= \frac{r}{1+r}\left[W_t + \sum_{i=0}^{\infty} \frac{E_t y_{t+i}}{(1+r)^i}\right] \\ &= \frac{r}{1+r} W_t + y_t + \left[\frac{\phi_1}{1+r} + \frac{\phi_2}{(1+r)^2}\right]\varepsilon_t + \frac{\phi_2}{1+r}\varepsilon_{t-1} \\ &\quad - \left[\frac{\alpha_1}{1+r} + \frac{\alpha_2}{(1+r)^2}\right] u_t - \frac{\alpha_2}{1+r} u_{t-1} \end{aligned}$$

where W_t is nonhuman assets. This variable follows

$$\text{(C8)}\qquad \begin{aligned} W_t &= (1+r)[W_{t-1}+y_t-c_t] \\ &= W_{t-1} - \left[\phi_1 + \frac{\phi_2}{1+r}\right]\varepsilon_{t-1} - \phi_2\varepsilon_{t-2} + \left[\alpha_1 + \frac{\alpha_2}{1+r}\right]u_{t-1} + \alpha_2 u_{t-2}. \end{aligned}$$

Define the state vector as

$$\text{(C9)}\qquad X_t = [1 \quad W_t \quad y_t \quad \varepsilon_t \quad \varepsilon_{t-1} \quad u_t \quad u_{t-1}]'.$$

Using (C7) and (C9) we can write

$$\text{(C10)}\quad \begin{aligned} c_t - \bar{c} &= \left[-\bar{c} \quad \frac{r}{1+r} \quad 1 \quad \frac{\phi_1}{1+r} + \frac{\phi_2}{(1+r)^2} \quad \frac{\phi_2}{1+r} \quad -\left[\frac{\alpha_1}{1+r} + \frac{\alpha_2}{(1+r)^2}\right] \quad -\frac{\alpha_2}{1+r}\right] X_t \\ &\equiv F'X_t. \end{aligned}$$

Then R in (C1) is given by

$$\text{(C11)}\qquad R = -\tfrac{1}{2}FF'.$$

The transition equation for the system in (C2) becomes

$$\text{(C12)}\qquad \begin{bmatrix} 1 \\ W_t \\ y_t \\ \varepsilon_t \\ \varepsilon_{t-1} \\ u_t \\ u_{t-1} \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & -\left(\phi_1 + \dfrac{\phi_2}{1+r}\right) & -\phi_2 & \alpha_1 + \dfrac{\alpha_2}{1+r} & \alpha_2 \\ 0 & 0 & 1 & \phi_1 & \phi_2 & -\alpha_1 & -\alpha_2 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} 1 \\ W_{t-1} \\ y_{t-1} \\ \varepsilon_{t-1} \\ \varepsilon_{t-2} \\ u_{t-1} \\ u_{t-2} \end{bmatrix} + \begin{bmatrix} 0 & 0 \\ 0 & 0 \\ 1 & 1 \\ 1 & 0 \\ 0 & 0 \\ 0 & 1 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} \varepsilon_t \\ u_t \end{bmatrix},$$

$$\Sigma = \begin{bmatrix} \sigma_\varepsilon^2 & 0 \\ 0 & \sigma_u^2 \end{bmatrix}.$$

The no information model. The income process to the household in the no information model looks like

$$\text{(C13)}\qquad \Delta y_{it} = \left(1 - \theta_1 L - \theta_2 L^2\right)\eta_t.$$

Consumption is given by

$$\text{(C14)}\qquad c_t = \frac{r}{1+r}W_t + y_t - \left[\frac{\theta_1}{1+r} + \frac{\theta_2}{(1+r)^2}\right]\eta_t - \frac{\theta_2}{1+r}\eta_{t-1}$$

and assets follow

$$\text{(C15)}\qquad W_t = W_{t-1} + \left[\theta_1 + \frac{\theta_2}{1+r}\right]\eta_{t-1} + \theta_2\eta_{t-2}.$$

Define the state vector as

(C16) $$X_t = [1 \quad W_t \quad y_t \quad \eta_t \quad \eta_{t-1}]'.$$

Using (C14) and (C16)

(C17) $$c_t - \bar{c} = \left[-\bar{c} \quad \frac{r}{1+r} \quad 1 \quad -\left[\frac{\theta_1}{1+r} + \frac{\theta_2}{(1+r)^2}\right] \quad -\frac{\theta_2}{1+r} \right] X_t \equiv F'X_t.$$

The transition equation becomes

(C18) $$\begin{bmatrix} 1 \\ W_t \\ y_t \\ \eta_t \\ \eta_{t-1} \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & \theta_1 + \dfrac{\theta_2}{1+r} & \theta_2 \\ 0 & 0 & 1 & -\theta_1 & -\theta_2 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} 1 \\ W_{t-1} \\ y_{t-1} \\ \eta_{t-1} \\ \eta_{t-2} \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ 1 \\ 1 \\ 0 \end{bmatrix} \eta_t.$$

Once both models have been solved for the level of utility attained the utility difference is converted to quarterly rates by multiplying by $r/(1+r)$. To convert the utility loss to dollar terms divide the utility loss by the expected value of marginal instantaneous utility

(C19) $$\$ \text{ loss/quarter} = \frac{r}{1+r}\frac{\Delta U}{Eu'(c_t)} = \frac{r}{1+r}\frac{\Delta U}{(\bar{c}-\bar{y})} = \frac{r}{1+r}\frac{\gamma \Delta U}{\bar{y}}$$

where γ is the coefficient of relative risk aversion. The calculations in the paper are for a coefficient of relative risk aversion of two and a mean income level of \$6,929.

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