Epidemiological Expectations and Consumption Dynamics

Christopher D. Carroll* and Martin Sommer†

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Abstract

In this paper, we propose an alternative theory of consumption that is consistent with excess sensitivity and smoothness of aggregate consumption. At the same time, consumption of individual households follows a random walk as in Dynan (2000). The model is based on the assumption that consumers' expectations are not completely up-to-date at every instant of time. Our formalization follows the recent literature on modeling inflation expectations (Roberts (1998), Mankiw and Reis (2003)). We show that the degree of serial correlation in aggregate consumption growth is an approximate measure of the fraction of the population that does not update its macroeconomic expectations in any given period. Our point estimates indicate a highly statistically significant serial correlation coefficient in the range of 0.7 to 0.8 in quarterly aggregate U.S. data. This would imply that approximately 25% of households are up-to-date in their information set in any given quarter.

Keywords: consumption, excess sensitivity, epidemiological expectations, habit formation, consumer sentiment

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*Department of Economics, Johns Hopkins University, Baltimore, MD 21218. E-mail: CCarroll@jhu.edu.

†International Monetary Fund, 700 19th Street N.W., Washington DC 20431. E-mail: MSommer@imf.org.

1 Introduction

It has long been known that the dynamic behavior of aggregate consumption does not match the predictions of classic versions of the permanent income hypothesis very well. A large literature in the 1980s tested Hall's (1978) proposition that consumption should follow a random walk, but found instead that many lagged variables had statistically robust and economically important ability to predict future consumption growth.

This literature was effectively distilled by Campbell and Mankiw (1989) with a model that proposed that lagged variables help predict current consumption growth because about half of all aggregate income goes to 'rule-of-thumb' consumers who set spending equal to income in every period. Campbell and Mankiw showed that the consumption-predicting variables had no statistically significant ability to predict consumption beyond the information they contained about future income growth.

But subsequent research (Acemoglu and Scott (1994), Carroll, Fuhrer, and Wilcox (1994), Bram and Ludvigson (1998)) found at least one category of variable (consumer sentiment) whose predictive power for consumption could not be explained in the Campbell-Mankiw framework. And recent efforts to match aggregate consumption dynamics to the predictions of optimizing models (e.g. by Rotemberg and Woodford (1997)) have found that the reaction of consumption to monetary policy and other shocks is sluggish in ways that are not well captured simply by the addition of rule-of-thumb consumers. Finally, examination of microeconomic data on household saving and consumption behavior provides no support for the proposition that a large fraction of households set consumption equal to income even on a yearly basis, much less every quarter (for more on the microeconomic consumption/income divergence, see Carroll (1997)).

In response to these and other problems, several authors have recently proposed models in which habits exert an important influence over high-frequency consumption dynamics. (Habits provide an alternative explanation for the consumption-predicting power of lagged information, because in habit-formation models consumption adjusts gradually rather than instantly to shocks.) Both Fuhrer (2000) and Sommer (2001) have estimated empirical models that nest the Campbell-Mankiw model in a framework that allows (but does not impose) habits, and both authors found highly statistically significant evidence for habits, and only marginally significant evidence of 'rule-of-thumb' consumers.

While habit-formation models have considerable empirical and intuitive appeal, unfortunately they are not very tractable; the addition of a habit stock as a second state variable considerably complicates the mathematical consumption problem, which may explain why such models have not yet been used much for general purpose macro modeling. Furthermore, evidence for habit formation in micro data is at best equivocal: Dynan (2000) and Meghir and Weber (1996) found no evidence of habit-formation effects using data from the Consumer Expenditure Survey, while Carrascoy, Labeagazand and Lopez-Salido (2002) found evidence of habits in a Spanish expenditure survey which has the advantage of providing more observations per household than the U.S. survey.

In this paper, we propose an alternative theory that is consistent with the same facts about the dynamics of aggregate consumption as the habit formation theory, but is both easier to work with and consistent with the lack of evidence for habits in the micro data. The idea is to relax the assumption that all consumers' expectations are completely up-to-date at every instant of time. The model we use is based on a simple framework that several papers have now used for modeling inflation expectations (Roberts (1998), Mankiw and Reis (2003, 2001), Carroll (2003, 2001)). Carroll (2001) provides microfoundations for the model by showing that it can be interpreted as a particularly simple case of a standard model of disease from epidemiology, where the source of the 'infection' is press reports on the state of the economy and the model essentially tracks the spread of the information through the population in the same way that epidemiological models track the spread of disease.[1]

We show that when the epidemiological model is applied in the consumption context, it implies that the degree of serial correlation in consumption growth is an approximate measure of the fraction of the population that does not update its macroeconomic expectations in any given period. When we estimate the model using quarterly data, our point estimates indicate a highly statistically significant serial correlation coefficient in the range of 0.7 to 0.8 - a very long way from the random walk model's prediction of zero. Indeed, these estimates of the serial correlation coefficient may seem implausibly large, since previous researchers have generally found serial correlation in the raw data in the range

[1] A related but distinct approach has recently been explored by Gabaix and Laibson (2001), who present a model in which there are costs of recalculating the optimal level of consumption. Their model, like ours, implies only occasional adjustment rather than continuous adjustment, and as a result the two models appear to have similar qualitative predictions.

of 0.3 (Deaton (1992)). We obtain our higher estimates primarily because we control for measurement error in the consumption data (which the Bureau of Economic Analysis, the producer of the data, believes is very substantial; BEA (1990)).

Surprisingly, our model is also consistent with Dynan's (2000) finding that there is little or no serial correlation in consumption growth at the household level. It turns out that the serial correlation of aggregate consumption growth in our model is entirely a consequence of aggregation; consumption innovations follow a random walk for any individual household.

Finally, when we estimate a version of the model that allows for the possible presence of Campbell-Mankiw style 'rule-of-thumb' consumers, the fraction of income that is estimated to accrue to such consumers is at most about 0.25 (as compares with the original Campbell-Mankiw estimate of 0.5), and is only marginally statistically significant. Such coefficients are well within the range of values that would be predicted by standard 'buffer-stock' models of consumption, and therefore need not be interpreted as reflecting the presence of many true rule-of-thumb consumers who set consumption equal to income in every period. This suggests that much of the predictability in consumption growth captured by the coefficient on predictable income growth in the Campbell-Mankiw model reflects the serial correlation in true consumption growth rather than rule-of-thumb behavior.

We have not yet considered whether the model we propose is consistent with the (many) other puzzles that researchers have recently attempted to explain with habits.[2] Since the specification of our model for the process of consumption growth is indistinguishable from the process implied by the Muellbauer (1988) and Constantinides (1990) model of habits, we suspect that it will be generically possible to reinterpret many existing results in the literature as supporting this model, but such an exploration remains an interesting project for future work. In this paper we concentrate on presenting the model and showing that it is consistent with the evidence on consumption dynamics that rejects the standard model.

2 Theory

To provide a basis for comparison with our epidemiological model, this section begins by presenting sketches of the standard theoretical frameworks that have been used to analyze aggregate consumption dynamics in the recent literature. It then lays out a detailed derivation of the empirical implications of the epidemiological model, and finally discusses the complications arising from measurement and time aggregation issues that must be addressed in estimation.

2.1 The Existing Theoretical Landscape

2.1.1 The Random Walk Model

Consider a consumer solving a standard consumption problem

$$\max E_t \left[\sum_{s=t}^{\infty} \beta^{t-s} u(\tilde{c}_s) \right] \tag{1}$$

[2] For a brief overview of the range of puzzles for which habits have been proposed as a solution, see the introduction to Carroll, Overland, and Weil (2000).

subject to the constraint

$$m_{t+1} = R[m_t + y_t - c_t]$$

where m_t is the consumer's beginning-of-period 'market' wealth, y_t is current labor income, R is the constant gross interest factor and $\beta = 1/(1+\delta)$ is the time preference factor where δ is the time preference rate. Suppose the consumer has quadratic utility $u(c) = -(\rho/2)(c - c^*)^2$ where c^* is the 'bliss point' level of consumption and assume that $\beta = 1/R$. Hall (1978) showed that under these circumstances the level of consumption follows a random walk, as can be derived from the first order condition:

$$\begin{aligned} u'(c_t) &= R\beta E_t[u'(\tilde{c}_{t+1})] \qquad (2) \\ -\rho c_t &= E_t[-\rho \tilde{c}_{t+1}] \\ E_t[\tilde{c}_{t+1}] &= c_t \\ c_{t+1} &= c_t + \epsilon_{t+1} \\ \Delta c_{t+1} &= \epsilon_{t+1} \qquad (3) \end{aligned}$$

where ϵ_{t+1} is an expectational error uncorrelated with any variable whose value was known at time t or earlier.

If we define human wealth h_t as the present discounted value of future labor income,

$$h_t = E_t\left[\sum_{s=0}^{\infty} R^{-s} y_{t+s}\right],$$

then the consumer's total wealth is the sum of market wealth and human wealth,

$$w_t = m_t + h_t$$

and the intertemporal budget constraint can be combined with the random walk proposition (27) to show that this consumer will set consumption equal to permanent income, defined as

$$p_t = (r/R)w_t.$$

Since consumption must be equal to this quantity, we know that the process for permanent income must be a random walk with the same innovation as in consumption:

$$\Delta p_{t+1} = \epsilon_{t+1}. \tag{4}$$

Subsequent work by Hall (1988) and others showed that the perfect foresight version of the model under CRRA utility $u(c) = c^{1-\rho}/(1-\rho)$ implies a similar equation in log changes rather than in levels, with an additional term related to the predicted level of the real interest rate,

$$\Delta \log c_{t+1} = \rho^{-1}(E_t[\tilde{r}_{t+1}] - \delta) + \epsilon_{t+1},$$

but empirical tests found a variety of lagged variables (stock market returns, consumer sentiment, interest rate changes, the unemployment rate) had predictive power for consumption growth, rejecting the model's proposition that ϵ_{t+1} should be an expectational variable uncorrelated with information available at earlier periods.

2.1.2 The Buffer-Stock Model

Beginning with Zeldes (1989), a substantial literature has argued that a great deal of microeconomic evidence is much more consistent with a version of the dynamic optimization problem that treats uncertainty seriously rather than either assuming uncertainty does not affect behavior (the certainty equivalence model) or does not exist (the perfect foresight model). Carroll (1992, 1997) also suggests that a particular version of this framework in which impatient consumers engage in 'buffer-stock' saving may help to explain the dynamics of aggregate consumption. Ludvigson and Michaelides (2000), however, show that a model in which all consumers engage in buffer-stock saving of the kind proposed in Carroll (1992) can explain at most about half of the excess smoothness of aggregate consumption.

2.1.3 The Campbell-Mankiw Model

Campbell and Mankiw (1989, 1991) argued that all of the available macroeconomic evidence (at the time of their writing) was consistent with a simple model in which a fraction λ of income flows to consumers who set spending equal to income in each quarter, while the remainder of income goes to consumers whose behavior is well captured by the traditional rational expectations PIH model. Their case for this model rested upon their estimation of an empirical specification derived from this hybrid model. They showed that if their model were true, then in a regression of the form

$$\log C_{t+1} = \alpha_0 + \alpha_1 E_{t-1}[\Delta \log Y_{t+1}] + \zeta_{t+1} \tag{5}$$

the estimate of the coefficient α_1 would reveal the fraction λ of income going to rule-of-thumb consumers, so long as expectations of income growth were formed using a valid set of instruments dated in period $t-1$ or earlier.

They showed that estimates of (29) using US and international data typically yielded coefficient estimates around $\lambda = 0.5$, and furthermore (from overidentification tests) that the lagged consumption-predicting instruments from the 1980s literature had no statistically significant predictive power for consumption growth that was independent of their ability to predict income growth.

2.1.4 The Perfect Foresight Model with Habits

Starting with Muellbauer (1988), a substantial literature has examined the dynamics of consumption when consumption habits matter for utility. There are two common specifications of the precise way in which habits influence utility. The first, used by Fuhrer (2000) following Carroll, Overland, and Weil (2000) and Abel (1990), assumes that the utility function takes the form

$$u(c, h) = v(c/h^{\gamma})$$

The parameter γ indexes the importance of habits: If $\gamma = 0$ the model collapses to the standard problem in which consumers care only about the level of consumption and not about its growth, while if $\gamma = 1$ consumers care only about the growth rate of consumption and not at all about its level. Dynamics of the habit stock are governed by a partial adjustment process of the form

$$h_t = h_{t-1} + \chi(c_{t-1} - h_{t-1}).$$

Fuhrer (2000) estimated a version of this model in which the 'outer' utility function was CRRA, $v(\bullet) = \bullet^{1-\rho}/(1-\rho)$. He found an estimate of χ that was very close to one (implying that this period's habits equal last period's consumption) and obtained estimates of γ in the vicinity of $\gamma = 0.8$.

The other common specification in this literature assumes that utility depends on the level of current consumption and the stock of habits via a function of the form

$$u(c, h) = v(c - \gamma h),$$

and simply imposes $h_t = c_{t-1}$.

When the outer utility function is of the CRRA form the implied process for consumption growth in the perfect foresight version of this model is

$$\Delta \log c_{t+1} = \mu + \gamma \Delta \log c_{t+1} + \epsilon_{t+1}. \tag{6}$$

Sommer (2001) estimates a model of the form of (30) on US data and obtains highly statistically significant estimates of the habits parameter in the range of 0.7 to 0.8. We follow the methods of his paper fairly closely, and will discuss them further below.

2.2 The Epidemiological Expectations Model

Suppose that consumers do not update their views about permanent income every period. If the period is considered to be sufficiently short (a month, say), and if there is any cost at all to making a new estimate of the entire future path of income that takes into consideration the latest macro statistics on productivity, unemployment, and so on, it seems entirely plausible that it would not be worthwhile for the average consumer to make a new forecast every period. We will assume instead that consumers update their information probabilistically: With probability λ any given consumer will gather the information required to make a new assessment of his permanent income. We further assume that during the interval between forecasts, consumers continue to spend at the level that they have last calculated as their permanent income. That is, if we designate as c_t^r the 'rational' (that is, full-information) level of consumption that would be chosen by this consumer if he updated in period t, then he continues to consume

$$\begin{aligned} c_{t+1} &= c_t^r \\ c_{t+2} &= c_t^r \\ \vdots \quad & \quad \vdots \end{aligned}$$

until he happens to update again. Since the rational forecast of his optimal change in consumption was zero in the full information case, these future levels of consumption are rational with respect to the information the consumer had in hand the last time his information was updated.

Now consider a consumer who happens to update in periods t and $t+n$ (but not between). For such a consumer, the change in consumption between t and $t+n$ will still be a white noise variable with respect to information available at time t; to see this, recall that the definition of permanent income is the level of spending that leaves total wealth (human and nonhuman) unchanged. The evolution of total wealth for the non-updating consumer will be

$$
\begin{aligned}
w_{t+1}^r &= w_t \\
w_{t+2}^r &= w_{t+1}^r + R\epsilon_{t+1} \\
&= w_t + R\epsilon_{t+1} \\
w_{t+3}^r &= w_t + R^2\epsilon_{t+1} + R\epsilon_{t+2} \\
\vdots \quad & \quad \vdots \\
w_{t+n}^r &= w_t + \sum_{s=1}^{n-1} R^s \epsilon_{t+n-s}
\end{aligned}
$$

so the change in consumption for a consumer who updates after n periods is simply

$$c_{t+n} - c_t = c_{t+1}^r - c_t^r = (r/R)\left[\sum_{s=1}^{n-1} R^s \epsilon_{t+n-s}\right],$$

and since the term in brackets is a weighted sum of white noise variables it is itself a white noise variable.

Now consider an economy populated by a set of measure one of such consumers distributed along the interval $[0, 1]$. Indexing consumers by subscript i, define aggregate values of all variables as the integral over all individuals in the economy, and designate aggregate values by the upper case. Thus,

$$C_t = \int_0^1 c_{i,t} \; di$$

and so on, where the assumption of an aggregate population mass of one implies that the capital letters designate both aggregate and mean per-capita levels.

The level of consumption per capita that would prevail if all consumers were rational is

$$C_t^r = (r/R)W_t^r,$$

where W_t^r is the level of total (human and market) wealth that consumers would perceive if all consumers were to update their estimates of $w_{i,t}$ to $w_{i,t}^r$ at time t.

Now assume that a set of randomly-chosen individuals constituting fraction λ of the population updates their expectations in period t; designating this set Λ, the average level of rational-consumption-per-capita for the updaters must be equal to the average level of rational-consumption-per-capita for the population as a whole, so the total consumption of the updaters in period t will be given by

$$\int_{\Lambda} c_{i,t}^r di = \lambda C_t^r,$$

because by assumption these consumers are chosen randomly.

Now consider the remaining population mass $(1 - \lambda)$. Among these consumers, a fraction λ will have updated in the previous period, when they will have set their consumption level to C_{t-1}^r. These consumers will by assumption continue consuming the same amount per capita until they update again. The total population mass in period t of those who did not update in period t but did update in $t - 1$ is $(1 - \lambda)\lambda$, so *in toto* these consumers will be contributing an amount $(1 - \lambda)\lambda C_{t-1}^r$ to period-t consumption. Recursive application of the same logic leads to the conclusion that the level of aggregate consumption in period t can be expressed as

$$C_t = \lambda C_t^r + \lambda(1 - \lambda)C_{t-1}^r + \lambda(1 - \lambda)^2 C_{t-2}^r + \dots$$

Now rewrite this as

$$
\begin{aligned}
C_t &= \lambda \left[C_t^r + (1-\lambda)C_{t-1}^r + (1-\lambda)^2 C_{t-2}^r + \ldots\right] \\
C_{t+1} &= \lambda \left[C_{t+1}^r + (1-\lambda)C_t^r + (1-\lambda)^2 C_{t-1}^r + \ldots\right] \\
C_{t+1} &= \lambda \left[C_{t+1}^r\right] + (1-\lambda)\lambda \left(C_t^r + (1-\lambda)C_{t-1}^r + \ldots\right) \\
C_{t+1} &= \lambda \left[C_{t+1}^r\right] + (1-\lambda)C_t \qquad (7) \\
\Delta C_{t+1} &= \lambda \Delta C_{t+1}^r + (1-\lambda)\Delta C_t. \qquad (8)
\end{aligned}
$$

Now consider the ΔC_{t+1}^r term. It might seem that theory implies this term should be a white noise error, since we showed above that the rational level of consumption follows a random walk. This is almost right, but not quite. To see why, write

$$
\begin{aligned}
C_{t+1}^r &= (r/R)[M_{t+1} + H_{t+1}] \\
C_t^r &= (r/R)[M_t + H_t] \\
C_{t+1}^r - C_t^r &= (r/R)[M_{t+1} - M_t + H_{t+1} - H_t] \\
C_{t+1}^r - C_t^r &= (r/R)[R(Y_t + M_t - C_t) - M_t + H_{t+1} - H_t]. \qquad (9)
\end{aligned}
$$

What theory tells us is that *if aggregate consumption were chosen fully rationally in period* t then this expression would be white noise; that is, we know that

$$(r/R)[R(Y_t + M_t - C_t^r) - M_t + H_{t+1} - H_t] = \eta_{t+1}$$

for some white noise η_{t+1}. The only difference between this expression and the

RHS of (33) is the r superscript on the C_t. Thus, substituting, we get

$$\begin{aligned}
C_{t+1}^r - C_t^r &= (r/R)[R\left(Y_t + M_t - (C_t + C_t^r - C_t^r)\right) - M_t + H_{t+1} - H_t] \\
C_{t+1}^r - C_t^r &= (r/R)[R(Y_t + M_t - C_t^r) - M_t + H_{t+1} - H_t] + (r/R)(C_t^r - C_t) \\
&= \eta_{t+1} + (r/R)(C_t^r - C_t).
\end{aligned}$$

So equation (9) can be rewritten as

$$\Delta C_{t+1} = (1-\lambda)\Delta C_t + (r/R)(C_t^r - C_t) + \eta_{t+1} \tag{10}$$

where η_{t+1} is a white noise variable.

However, (8) implies

$$\begin{aligned}
C_t &= \lambda C_t^r + (1-\lambda)C_{t-1} \\
C_t^r &= \frac{C_t - (1-\lambda)C_{t-1}}{\lambda} \\
C_t^r - C_t &= \frac{C_t - (1-\lambda)C_{t-1}}{\lambda} - C_t \\
&= \frac{(1-\lambda)C_t - (1-\lambda)C_{t-1}}{\lambda} \\
&= \left(\frac{1-\lambda}{\lambda}\right)\Delta C_t
\end{aligned}$$

which can be substituted into (10) to yield

$$\begin{aligned}
\Delta C_{t+1} &= (1-\lambda)\Delta C_t + (r/R)\left(\frac{1-\lambda}{\lambda}\right)\Delta C_t + \eta_{t+1} \\
&= \left[1 - \lambda + \left(\frac{r}{R}\right)\left(\frac{1-\lambda}{\lambda}\right)\right]\Delta C_t + \eta_{t+1}. \qquad (11)
\end{aligned}$$

Thus, the model suggests estimating an equation of the form

$$\Delta C_{t+1} = \mu + \alpha \log C_{t+1} + e_{t+1} \tag{12}$$

and the α coefficient should in principle be a direct measure of the fraction of the population who do not update their expectations in a typical period. The estimate of α will imply an estimate of λ via the quadratic equation,

$$\alpha = \left[1 - \lambda + \left(\frac{r}{R}\right)\left(\frac{1-\lambda}{\lambda}\right)\right] \tag{13}$$

$$\lambda = \left(\frac{1}{2}\right)\left[1 - (r/R) - \alpha + \sqrt{4(r/R) + (r/R + \alpha - 1)^2}\right] \tag{14}$$

where we pick the positive root to guarantee that the estimate of λ is positive for $0 \leq \alpha \leq 1$.

Note that the form of (12) is virtually identical to that of (6); however, rather than revealing the magnitude of the habits parameter in utility, in the epidemiological model the serial correlation coefficient yields an estimate of the proportion of consumption performed by consumers who do not update their expectations in every period.

3 Complications

If the model as developed so far were an exact description of the typical household's consumption problem, and if the National Income and Product Accounts had a perfect measure of consumption corresponding to the theoretical construct, we could estimate the model's key parameter λ by a direct AR(1) regression for NIPA consumption growth, per equation (12). It has long been known that such regressions do produce a highly statistically significant coefficient (e.g. Deaton (1992) reports an estimate of about 0.3), which would imply a modest but statistically significant portion of the population consists of households who do not update their expectations every quarter.

However, since Working (1960) it has been known that if a variable follows a random walk at some frequency, but is measured at a lower freqency, then the growth rates of the measured data will exhibit serial correlation caused by the time aggregation of the higher-frequency random walk. As discussed below, in the particular case of monthly consumption decisions measured quarterly, the implied serial correlation coefficient is about 0.2, not far from the 0.3 Deaton reported for US data. This problem has been acknowledged and accounted for in the consumption literature since the early 1980s, and many researchers have concluded that the modest serial correlation in measured consumption spending actually bolsters the case that true consumption follows a random walk, but at a frequency higher than quarterly.

However, there is another set of problems that have been largely neglected by the literature but that are conceptually as important as time aggregation: Problems of measurement. And measurement problems should create a bias in precisely the opposite direction from that created by time aggregation. Suppose, for example, that actual consumption growth were equal to the 'true' measure of consumption growth plus a white noise measurement error (more realistic specifications of the measurement error process will be considered below). Then the classic errors-in-variables econometric logic implies that the coefficient on lagged consumption growth will be biased downward by an amount related to the relative magnitude of measurement errors versus true consumption shocks. The raw coefficient from a regression of the form of (12) would therefore *under-*

estimate the degree of serial correlation in 'true' consumption growth.

The remainder of this section discusses the measurement error and time aggregation problems in the detail necessary to motivate our estimation strategies to get around these problems.

3.1 Measurement Error

The consumption literature has traditionally proxied for the theoretical object in consumption models by using the sum of spending on nondurables and services. Quarterly measures of services spending, however, are very problematic for the purposes of such analysis. One of the largest component of services spending is imputed rent on housing, which corresponds to the flow of virtual income that owner-occupied homes are assumed to provide to their owners. In principle, this object depends on the market value of the homes in question, so construction of the data requires data on home prices. However, the only regular source of such data is the Annual Housing Survey. The Bureau of Economic Analysis (BEA), producer of the US NIPA data, therefore constructs quarterly measures of growth in services spending by interpolating between annual house price surveys. Such a procedure is perfectly reasonable given the limited data at the disposal of the government statisticians, but obviously creates severe problems for any analysis that purports to be of the quarterly dynamics of 'true' consumption growth. There are similarly grave conceptual problems with a variety of other components of services consumption, and in our judgment the best solution is simply to exclude spending on services from the analysis altogether (though for comparability to the existing literature will later report results for nondurables and services consumption).

However, even nondurables spending has serious measurement problems. The estimate of aggregate nondurables spending is constructed mainly using data obtained from a rotating overlapping panel of retail sales outlets. This is not a universal sample, and the BEA is quite forthright about the existence of substantial measurement error in these data (see the BEA's manual of data construction methods, BEA (1990), and the discussion in Wilcox (1992)). Sommer (2001) contains a thorough analysis of the likely nature and time series characteristics of the measurement error produced by the various problems discussed in BEA (1990) and Wilcox (1992). In the end, Sommer concludes that most of the measurement error is likely to take a simple form that is additive in logs; that is, if the true level of consumption spending in period t is $\bar{C}_t$, then the measured value of consumption will be

$$\log C_t = \log \bar{C}_t + \zeta_t.$$

A further problem is that not all real-world nondurables consumption expenditures fit neatly into the conceptual framework of the pure consumption-smoothing model. The cleanest example is shocks to spending that are caused by natural disasters. These can be quite substantial at a quarterly frequency, as is well known to professional forecasters and staff at the Federal Reserve in charge of tracking spending on an ongoing basis [examples: Hurricane Andrew, Sept 11]. The effects of such shocks are usually confined to a few days or weeks, and therefore are generally contained entirely within a particular quarter. As a result, defining $\hat{C}$ as the level of consumption that would have taken place in the absence of the shock, it seems appropriate to think of these shocks affecting the level of true consumption (that is, consumption abstracting from the measurement error ζ_t) in a form like

$$\log \bar{C}_t = \log \hat{C}_t + \omega_t.$$

One can think of the problem caused by transitory disaster-related spikes as being a different form of measurement error, because what is being measured is not the object postulated by theory (which abstracts from these kinds of events). In practice, ω_t and ζ_t are essentially indistinguishable anyway, so henceforth we will combine these two shocks into a variable of the form $\mu_t = \zeta_t + \omega_t$ and will suppose that measured log consumption is equal to the 'true' consumption that corresponds to our model plus a white noise error,

$$\log C_t = \hat{C}_t + \mu_t. \tag{15}$$

Now suppose that 'true' consumption follows a random walk,

$$\Delta \log \hat{C}_{t+1} = \eta_{t+1}$$

where η_{t+1} is a white-noise expectational error, and consider the implications of (15) for the growth rate of measured consumption in sucessive periods:

$$\begin{aligned}
\Delta \log C_{t+1} &= \log \hat{C}_{t+1} + \mu_{t+1} - (\log \hat{C}_t + \mu_t) \\
&= \eta_{t+1} + \mu_{t+1} - \mu_t \\
\Delta \log C_t &= \eta_t + \mu_t - \mu_{t-1}. \qquad (16)
\end{aligned}$$

Note the presence of μ_t on the RHS of $\Delta \log C_{t+1}$ with a positive sign, and on the RHS of $\Delta \log C_t$ with a negative sign. This implies that a regression of this quarter's consumption growth on last quarter's consumption growth will obtain a negative coefficient even if true consumption growth at the quarterly frequency follows a random walk. This is a worse problem than even the usual errors-in-variables problem - here the error is not white noise, but actually negatively correlated with the dependent variable. These considerations suggest that if measurement error is at all substantial, it should lead to a very strong downward bias in the serial correlation coefficient for measured consumption compared to the serial correlation coefficient for true consumption.

The traditional solution to measurement error problems is to instrument for the erroneously-measured variable with an instrument that is correlated with the true value and uncorrelated with the measurement error. There are plenty of macroeconomic variables that are strongly correlated with contemporaneous consumption growth but plausibly uncorrelated with measurement errors caused by sampling problems in the retail sales survey or disasters. Consumer sentiment, recent changes in unemployment rates, and interest rate spreads are only a few examples. In the end, we will indeed pursue an IV strategy, but one that will be somewhat modified by the additional problem (discussed momentarily) of time aggregation.

If the true time-series structure of measurement error is known (as we are assuming here), there is also a more sophisticated approach to controlling for measurement error, which is to estimate a structural model that includes a term corresponding to the measurement error component, under the assumption that we know the analytical structure of consumption dynamics from the model. Such a model can be estimated by maximum likelihood, and an advantage of this technique is that it returns an estimate of the variance of the measurement error. This will be our second estimation method.

3.2 Time Aggregation

If we directly pursued either of these strategies for dealing with consumption measurement error, our estimates would still be subject to the time aggregation bias mentioned above. Our estimation method must therefore address both time aggregation and measurement problems to produce a credible estimate of the critical serial correlation parameter.

Our analysis begins by examining the pure time aggregation problem (neglecting measurement error and assuming the true variable follows a random walk at at a monthly frequency but is measured quarterly) in order to develop notation and provide a baseline. We need a notation capable of distinguishing consumption measured at a quarterly frequency from measurements at a monthly frequency. Our approach is to use a q subscript when examining quarterly data and an m for monthly data. We normalize q and m around some particular quarter for which

$$\bullet_q = \bullet_m + \bullet_{m+1} + \bullet_{m+2}$$

for any variable $\bullet$, implying that

$$\bullet_{q+n} = \bullet_{m+3n} + \bullet_{m+3n+1} + \bullet_{m+3n+2}$$

for any n. We also need to define the first difference operators at both a monthly and a quarterly frequency. Thus, define

$$\begin{aligned}
\Delta_M \bullet_m &= \bullet_m - \bullet_{m-1} \\
\Delta_Q \bullet_q &= \bullet_q - \bullet_{q-1} \\
&= \quad \bullet_m + \bullet_{m+1} + \bullet_{m+2} \\
&\quad - \bullet_{m-3} + \bullet_{m-2} + \bullet_{m-1} \,.
\end{aligned}$$

Suppose monthly consumption C_m^r follows a random walk,

$$C_{m+1}^r = C_m^r + \epsilon_m^r$$

so that total consumption for the next three months starting in month m is

$$\begin{aligned}
C_q^r &= C_m^r + C_{m+1}^r + C_{m+2}^r \\
&= C_m^r + C_m^r + \epsilon_{m+1}^r + C_m^r + \epsilon_{m+1}^r + \epsilon_{m+2}^r \\
&= 3C_m^r + 2\epsilon_{m+1}^r + \epsilon_{m+2}^r \\
C_{q+1}^r &= C_{m+3}^r + C_{m+4}^r + C_{m+5}^r \\
&= 3C_{m+3}^r + 2\epsilon_{m+4}^r + \epsilon_{m+5}^r \\
&= 3(C_m^r + \epsilon_{m+1}^r + \epsilon_{m+2}^r + \epsilon_{m+3}^r) + 2\epsilon_{m+4}^r + \epsilon_{m+5}^r \\
C_{q+1}^r - C_q^r &= 3(\epsilon_{m+1}^r + \epsilon_{m+2}^r + \epsilon_{m+3}^r) + 2\epsilon_{m+4}^r + \epsilon_{m+5}^r - 2\epsilon_{m+1}^r - \epsilon_{m+2}^r \\
C_{q+1}^r - C_q^r &= \epsilon_{m+1}^r + 2\epsilon_{m+2}^r + 3\epsilon_{m+3}^r + 2\epsilon_{m+4}^r + \epsilon_{m+5}^r \\
C_{q+2}^r - C_{q+1}^r &= \epsilon_{m+4}^r + 2\epsilon_{m+5}^r + 3\epsilon_{m+6}^r + 2\epsilon_{m+7}^r + \epsilon_{m+8}^r
\end{aligned}$$

Now note that, because the consumption innovations are white noise by definition,

$$
\begin{aligned}
\mathrm{var}(C^r_{q+1} - C^r_q) &= \mathrm{var}(\epsilon^r_{m+1} + 2\epsilon^r_{m+2} + 3\epsilon^r_{m+3} + 2\epsilon^r_{m+4} + \epsilon^r_{m+5}) \\
&= \sigma^2_\epsilon + 4\sigma^2_\epsilon + 9\sigma^2_\epsilon + 4\sigma^2_\epsilon + \sigma^2_\epsilon \\
&= 19\sigma^2_\epsilon \\
\mathrm{cov}(\Delta C^r_{q+2}, \Delta C^r_{q+1}) &= \mathrm{cov}(2\epsilon^r_{m+4} + \epsilon^r_{m+5}, \epsilon^r_{m+4} + 2\epsilon^r_{m+5}) \\
&= 2\sigma^2_\epsilon + 2\sigma^2_\epsilon = 4\sigma^2_\epsilon
\end{aligned}
$$

Now consider performing the regression

$$
\Delta C^r_{q+1} = \mu + \gamma \Delta C^r_q + \zeta_{q+1}.
$$

Standard regression theory tells us that

$$
\begin{aligned}
\gamma &= \left(\frac{\mathrm{cov}(\Delta C^r_{q+2}, \Delta C^r_{q+1})}{\mathrm{var}(\Delta C^r_{q+1})} \right) \\
&= \left(\frac{4\sigma^2_\epsilon}{19\sigma^2_\epsilon} \right) \\
&\approx 0.2105
\end{aligned}
$$

even though for the underlying series from which the quarterly data are constructed, increments are white noise.

Now consider what happens for a variable that contains an intrinsic serial correlation component of the form derived above for our model, e.g. suppose the true monthly model of consumption is

$$
\Delta C_{m+1} = \alpha_M \Delta C_m + \eta_{m+1} \tag{17}
$$

where η_{t+1} is a white noise variable.

It is useful to begin by noting that

$$C_m = C_{m-3} + \Delta_M C_{m-2} + \Delta_M C_{m-1} + \Delta_M C_m$$

so that

$$\begin{aligned} C_m - C_{m-3} &= C_{m-3} + \Delta_M C_{m-2} + \Delta_M C_{m-1} + \Delta C_m - C_{m-3} \\ &= \Delta_M C_{m-2} + \Delta_M C_{m-1} + \Delta C_m \end{aligned}$$

This implies that

$$\begin{aligned} \Delta_Q C_q &= \Delta_M C_{m-2} + 2\Delta_M C_{m-1} + 3\Delta_M C_m \quad + 2\Delta_M C_{m+1} + \Delta_M C_{m+2} \\ \Delta_Q C_{q+1} &= \Delta_M C_{m+1} + 2\Delta_M C_{m+2} + 3\Delta_M C_{m+3} + 2\Delta_M C_{m+4} + \Delta_M C_{m+5} \end{aligned}$$

But

$$\begin{aligned} \Delta_M C_{m+3} &= \alpha_M \Delta_M C_{m+2} + \eta_{m+3} \\ &= \alpha_M(\alpha_M \Delta_M C_{m+1} + \eta_{m+2}) + \eta_{m+3} \\ &= \alpha_M(\alpha_M(\alpha_M \Delta_M C_m + \eta_{m+1}) + \eta_{m+2}) + \eta_{m+3} \\ &= \alpha_M^3 \Delta_M C_m + \alpha_M^2 \eta_{m+1} + \alpha_M \eta_{m+2} + \eta_{m+3} \end{aligned}$$

implying that

$$
\begin{aligned}
\Delta_Q C_{q+1} \quad = \quad & \alpha_M^3 \Delta_Q C_q + \\
& \alpha_M^2 \eta_{m-1} + \alpha_M \eta_m + \eta_{m+1} + \\
& 2(\alpha_M^2 \eta_m + \alpha_M \eta_{m+1} + \eta_{m+2}) + \\
& 3(\alpha_M^2 \eta_{m+1} + \alpha_M \eta_{m+2} + \eta_{m+3}) + \\
& 2(\alpha_M^2 \eta_{m+2} + \alpha_M \eta_{m+3} + \eta_{m+4}) + \\
& \alpha_M^2 \eta_{m+3} + \alpha_M \eta_{m+4} + \eta_{m+5} \\
= \quad & \alpha_M^3 \Delta_Q C_q + \alpha_M^2 \eta_{m-1} + (\alpha_M + 2\alpha_M^2)\eta_m + (1 + 2\alpha_M + 3\alpha_M^2)\eta_{m+1} \\
& +(2 + 3\alpha_M + 2\alpha_M^2)\eta_{m+2} + (3 + 2\alpha_M + \alpha_M^2)\eta_{m+3} + (2 + \alpha_M)\eta_{m+4} + \eta_{m+5}.
\end{aligned}
$$

This equation means that quarterly consumption growth follows an MA(2) process; to wit, if we define

$$\nu_q = (3 + 2\alpha_M + \alpha_M^2)\eta_m + (2 + \alpha_M)\eta_{m+1} + \eta_{m+2}$$

then the MA(2) process can be written

$$\Delta_Q C_q \quad = \quad \alpha_M^3 \Delta_Q C_{q-1} + \nu_q + \theta_1 \nu_{q-1} + \theta_2 \nu_{q-2} \qquad (18)$$

where the coefficients θ_1 and θ_2 are analytical functions (albeit complicated ones) of the underlying parameters of the model (see the appendix for the formulas). Note that the ν variables are various different aggregations of the expectational errors in the underlying monthly consumption process; since the ν's are the sum of expectational errors, they are by definition uncorrelated with any information that was possessed before the earliest of the shocks was realized.

In practice, we show in the appendix that the coefficient θ_2 is of trivial magnitude, so that current consumption growth should be quantitatively uncorrelated with any information known in period $q-2$, as in the normal time aggregation problem.

If time aggregation were our only problem, we could in principle estimate the parameters of our model using a nonlinear estimation strategy (such as maximum likelihood) that constrained the parameters on the lagged ν terms to be what the time aggregation theory requires them to be. Of course, if the consumption data were subject to measurement error this method would still produce biased estimates for the reasons discussed above. However, in the nonlinear estimation strategy it is relatively straightforward to also allow for an MA(1) measurement error in consumption in addition to the intrinsic time series dynamics that come from time aggregation. Such an estimation, allowing for both time aggregation and measurement error effects, will constitute one of our methods for estimating the model's key parameter α_Q. Our main estimation strategy, however, will be based on instrumental variables techniques, to which we now turn.

4 Empirical Results

4.1 Two Stage Least Squares Estimates

Consider a regression using quarterly data (where quarters are now indexed by t, dropping our earlier notation) of the form

$$\Delta \log C_t = \mu + \gamma \Delta \log C_{t-1} + e_t. \tag{19}$$

The analysis above indicated that either measurement error in C or time aggregation problems will imply that OLS estimates of γ will be biased. However, statistical theory tells us that γ can be estimated consistently if we can find instruments for $\Delta_Q \log C_{t-1}$ that are uncorrelated both with measurement error and with the period-$t-1$ and $t-2$ information. In principle, any information known in period $t-3$ or before that is correlated with period-$t-1$ consumption growth (but uncorrelated with period-$t-1$ measurement error) should do.

We use a fairly traditional set of variables that have been found to be robustly correlated with consumption growth in the literature: the University of Michigan's measure of unemployment expectations, recent changes in T-bill rates, recent changes in unemployment rates, and recent changes in the S&P 500. Of these measures, it is very hard to see why changes in the T-bill rate or lagged unemployment expectations should be correlated with measurement errors in or natural-disaster shocks to consumption. As a stretch, one could conceivably spin a story in which stock prices might react to (mismeasured) reports about retail sales, which would then provide a reason why stock price changes would not be a valid instrument. We therefore report results for a restricted set of instruments that exclude stock prices, as well as the full set of instruments. Results in all cases are similar.

We estimate the model over two sample periods: 1962q1-2001q4 and 1978q1-2001q4, using, first, data on per capita real personal consumption expenditures on nondurables and services (following the literature), and, alternatively, using data on nondurables only (which we regard as more appropriate). The starting date of the longer sample is determined by the fact that the unemployment expectations variable, which is a powerful instrument for consumption growth, is available since 1961. The start of second sample is chosen at 1978 for two reasons. First, the methodology of constructing consumption data changed in 1977 (see Wilcox (1992) for details). Second, sentiment index data began to be measured consistently at the monthly frequency in 1978. Either or both of these changes could have resulted in a break in the reduced-form relationship between consumption and sentiment. Finally, we estimate for two separate periods in order to get a sense of the time stability of the estimated consumption correlation.

Table 1 presents the results when our measure of consumption is nondurables and services. The top panel reports the results of a raw OLS regression of nondurables and services consumption growth on a lag of itself; the coefficient is around 0.4 for both samples, with standard errors that imply that the coefficient is highly statistically different from the zero that would be predicted by the random walk theory if consumption decisions were made quarterly. Interestingly, it is also statistically much larger than the 0.21 that is implied by the random walk theory that allows for time aggregation of monthly decisions into quarterly data.

The next two rows present the results of estimating the 2SLS model when lagged consumption growth is instrumented using further lags of consumption growth. While the estimated coefficient on lagged consumption growth increases, as would be expected if the instrumenting procedure helped to correct biases due to measurment error, recall that lagged consumption growth is not really valid as an instrument in this context because of the presumed serial correlation of the measurement error itself. Thus it is not surprising that the overidentification test presented in the final column of the table rejects this specification of the model.

The middle panel of the table presents results when we use our restricted set of instruments, which should produce consistent estimates of the serial correlation parameter and therefore allows us to use equation (13) to back out an estimate of the fraction of consumers who update their estimates of their permanent income in the typical quarter. The estimates range from about 0.15 to about 0.20 for both sample periods. Results in the bottom panel, using the full set of instruments, are very similar. In no case does the overidentification test provide evidence against the model. While it is true that overidentification tests of this kind generically have low power, the fact that the OID tests strongly rejected the model with lagged consumption growth as the only instrument means that this is not a context in which these tests are powerless.

Table 2 presents results using only spending on nondurable goods; we view these results as our central case. The OLS estimate of the serial correlation of consumption growth, at about 0.27, is no longer very far from the figure that would be implied by the pure time aggregation story, which reinforces our suspicion that the services spending data may be problematic. The overidentification test again rejects the use of lagged consumption as an instrument.

Our baseline estimates of λ are contained in the bottom two panels of this table. Across all the samples and instrument sets the estimates range from a bit below 0.15 to just under 0.35. These estimates are therefore quite close to the estimate of 0.27 that Carroll (2003) obtained for the fraction of consumers who update their inflation expectations every quarter.

The next two Tables 3 and 4 present results when the model is estimated using annual data. Although estimation with annual data is somewhat unconventional, there are several reasons it may be valuable in this context. First, the problems with services consumption data are considerably less compelling at an annual frequency than at a quarterly frequency, so it becomes at least arguably appropriate to use the conventional measure of nondurables and services consumption in this context. Second, even for nondurable goods the problems of measurement error even for nondurables are much less severe at an annual frequency than at a quarterly frequency; over the course of an entire year, we would expect most of the measurement error to wash out. To the extent that measurement error problems were responsible for biasing downard the coefficient on lagged consumption growth, we should expect this bias to be less and therefore we should expect the 2SLS and OLS estimates to be closer in the annual data.

Finally, using annual data allows a test of an attractive property of the theoretical model proposed above is geometric scaling: since a year is composed of four quarters, the model implies that if one obtains an estimate α_Q using quarterly data, then the estimate obtained using annual data should be α_Q^4.

The results generally fulfill all of these expectations.

Note first that the implication that the OLS and 2SLS estimates should be closer than in the quarterly data is well supported. For nondurables and services, for example, the gap is only about 0.25, as opposed to a gap of almost 0.5 in the quarterly data. The convergence is even more substantial for other measures.

The geometric scaling implication is also reasonably well supported: Estimates of the quarterly value of λ from the annual data are in the range of 0.25 to 0.30 for nondurables and services and just a bit higher for nondurables alone, easily overlapping with the intervals containing the quarterly estimates.

4.2 Maximum Likelihood Estimation

When estimating the epidemiological model using 2SLS, it is necessary to find instruments that are correlated with true consumption growth but uncorrelated with measurement error in the reported consumption data. To estimate the model using maximum likelihood, no variable other than consumption growth is needed to proceed. However, it is necessary to specify the exact process for measured consumption growth and for measurement error.

Our formulation simply combines the derived dynamics of the time-aggregated data from Section 3.2 and the assumed dynamics for measurement error described in Section 3.1:[3]

$$\begin{aligned}\Delta \log C_t &= \Delta \log \hat{C}_t + u_t - u_{t-1} \\ \Delta \log \hat{C}_t &= \alpha \Delta \log \hat{C}_{t-1} + v_t + f_1(\alpha) v_{t-1} + f_2(\alpha) v_{t-2}. \qquad (20)\end{aligned}$$

As we showed in the section on the effects of time aggregation, the coefficients of the process for the innovation depend on λ, the parameter that determines how often consumers update their expectations. However, the equation can be simplified without much loss of consistency: Appendix I shows that a fairly precise characterization of $f_1(\alpha)$ and $f_1(\alpha)$ for a broad range of possible realizations of α is $f_1(\alpha) \approx 0.40$ and $f_1(\alpha) \approx 0$.

We therefore estimate a baseline model in the form:

$$\Delta \log C_t = \Delta \log \hat{C}_t + u_t - u_{t-1} \qquad (21)$$

$$\Delta \log \hat{C}_t = \alpha \Delta \log \hat{C}_{t-1} + v_t + 0.40 v_{t-1}. \qquad (22)$$

Equation (21) can be substituted into equation (20) to obtain:

$$\Delta \log C_t = \alpha \Delta \log C_{t-1} + u_t + v_t - (\alpha + 1) u_{t-1} + 0.40 v_{t-1} + \alpha u_{t-2} \qquad (23)$$

$$\Delta \log C_t = \alpha \Delta \log C_{t-1} + \xi_t + \theta_1 \xi_{t-1} + \theta_2 \xi_{t-2} \qquad (24)$$

Therefore, once we allow for measurement error and time aggregation, consumption growth should follow an ARMA(1,2) process. Note that the epidemiological model and the particular assumption about the process for measurement

[3] Sommer (2001) experimented with an MA(1) specification of the measurement error. His estimation results of habit formation model that similarly as the epidemiological model general AR(1) process in aggregate consumption growth are comparable to those reported in this paper.

error impose an overidentifying restriction on the coefficients θ_1 and θ_2 (we provide details in Appendix II). We will test this restriction below.

We estimate equation (23) using the Kalman filter in both unrestricted and restricted versions. The estimation results are summarized in Table 5. Fortunately, the MLE estimator produces estimates of λ that are comparable to those obtained using 2SLS. The unrestricted estimate is 0.32 for nondurables and services, and 0.41 for nondurables.

One interesting feature of the results is that the estimated signal to noise ratio in consumption growth rates is around 1:1, which is roughly consistent with the gap between OLS and 2SLS estimates reported earlier. The restricted and unrestricted MLE estimates of λ are very similar. The overidentification test does not reject the restriction of model (23) on the values of α, θ_1 and θ_1 at the 10 percent level. The value of likelihood ratio statistic for nondurables and services is 0.17 and for nondurables 0.65, compared to a 10 percent critical value for the test of 2.71. Results from the sample 1978:1-2001:4 are similar.

In sum, the conclusions reached using nonlinear estimation of the pure time series process of consumption are similar to those obtained using the very different instrumental variables technique; this suggests that our findings do not reflect any particular peculiarity of our estimation method, instruments, or time period, but rather a general feature of the underlying consumption data.

4.3 The Campbell-Mankiw Model

The above estimates suggest a very high degree of serial correlation in consumption growth. However, this finding is not necessarily a rejection of the Campbell-Mankiw model; indeed, none of the results presented so far could rule out the possibility that the reason predictable lagged consumption growth is correlated with current consumption growth is that lagged consumption growth is a good predictor of current income growth. The only way to sort out the two possibilities is to estimate a model that nests the two possibilities and see if the empirical evidence is capable of distinguishing them. Thus, our next step is to estimate an equation of the form

$$\Delta \log C_{t+1} = \alpha_0 + \alpha_1 \Delta \log C_t + \alpha_2 E_{t-1}[\Delta \log Y_{t+1}] + \epsilon_{t+1}.$$

Results are presented in Tables 6 and 7. In comparison with results from the baseline model without the Campbell-Mankiw term, the standard errors on the serial correlation coefficient are somewhat larger, suggesting that there is indeed a significant amount of correlation between lagged consumption growth and current income growth. However, considerably more damage is done to the Campbell-Mankiw model: the estimated proportion of rule-of-thumb consumers averages only about 10 percent, and is never statistically significantly different from zero at conventional significance levels. The fact that the coefficient is almost always estimated to be positive does hint that at least some aggregate income goes to some consumers who bear some resemblance to the Campbell-Mankiw rule-of-thumb consumers. And there is plenty of microeconomic evidence that the MPC out of transitory income is much higher than predicted in the standard PIH model. So a hybrid model that allows for both excess serial correlation in consumption growth and some excess sensitivity to current income growth seems attractive. Still, these empirical results tell us that if we were forced to choose only one of these two deviations from the standard PIH framework, the one the data seem to want is the one that allows for serial correlation in 'true' consumption growth.

5 Conclusions

In this paper, we propose an alternative theory that is consistent with the same facts about the dynamics of aggregate consumption as the habit formation theory, but is both easier to work with and consistent with the lack of evidence for habits in the micro data. We show that when the epidemiological model is applied in the consumption context, it implies that the degree of serial correlation in consumption growth is an approximate measure of the fraction of the population that does not update its macroeconomic expectations in any given period. When we estimate the model using quarterly data, our point estimates indicate a highly statistically significant serial correlation coefficient in the range of 0.7 to 0.8. We have not yet considered whether the model we propose is consistent with the (many) other puzzles that researchers have recently attempted to explain with habits. Since the specification of our model for the process of consumption growth is indistinguishable from the process implied by the Muellbauer (1988) and Constantinides (1990) model of habits, we suspect that it will be generically possible to reinterpret many existing results in the literature as supporting this model, but such an exploration remains an interesting project for future work.

Appendix I: Time aggregation in the epidemiological and habit formation models

Quarterly aggregate consumption growth evolves according to:

$$
\begin{aligned}
\Delta C_T &= \alpha^3 \Delta C_{T-1} + \varepsilon_t + (2+\alpha)\varepsilon_{t-1} + [(1+\alpha)^2 + 2]\varepsilon_{t-2} + [2 + \alpha(3+2\alpha)]\varepsilon_{t-3} \\
&\quad + [1 + \alpha(2+3\alpha)]\varepsilon_{t-4} + \alpha(1+2\alpha)\varepsilon_{t-5} + \alpha^2 \varepsilon_{t-6} \\
\Delta C_T &= \alpha^3 \Delta C_{T-1} + \nu_T + \theta_1 \nu_{T-1} + \theta_2 \nu_{T-2}
\end{aligned}
$$

We would like to derive expressions for θ_1 and θ_2 in terms of the coefficient α. This is done by matching variance and the first two autocovariances of the innovations (the higher-order autocovariances are zero).

$$
\begin{aligned}
(1+\theta_1^2+\theta_2^2)\sigma_v^2 &= \{1 + (\alpha+2)^2 + \left[(1+\alpha)^2+2\right]^2 + [\alpha(3+2\alpha)+2]^2 + \\
&\quad [\alpha(2+3\alpha)+1]^2 + [\alpha(1+2\alpha)]^2 + \alpha^4\}\sigma_\varepsilon^2 \\
\theta_1(1+\theta_2)\sigma_v^2 &= \{[\alpha(3+2\alpha)+2] + [\alpha(2+3\alpha)+1][\alpha+2] + \\
&\quad \alpha(1+2\alpha)[\alpha(2+\alpha)+3] + \alpha^2[\alpha(3+2\alpha)+2]\}\sigma_\varepsilon^2 \\
\theta_2 \sigma_v^2 &= \alpha^2 \sigma_\varepsilon^2
\end{aligned}
$$

It is useful to express the first two autocorrelations of the quarterly innovation ν_T as a function of α :

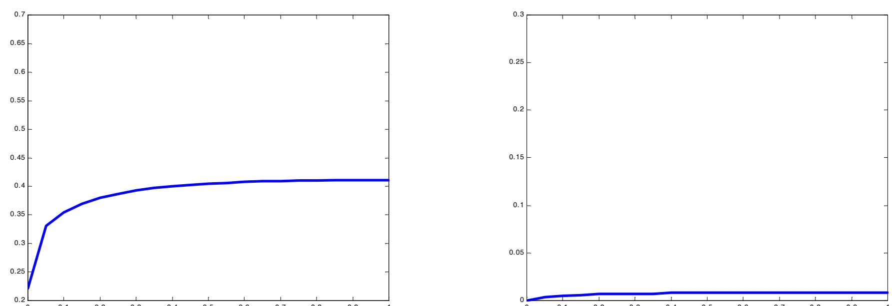
$$
corr(\nu_T, \nu_{T-1}) = \frac{\theta_1(1+\theta_2)}{(1+\theta_1^2+\theta_2^2)} = \frac{4+\alpha(11+\alpha(20+\alpha(11+4\alpha)))}{19+\alpha(32+\alpha(39+\alpha(32+19\alpha)))} \quad (25)
$$

$$
corr(\nu_T, \nu_{T-2}) = \frac{\theta_2}{(1+\theta_1^2+\theta_2^2)} = \frac{\alpha^2}{19+\alpha(32+\alpha(39+\alpha(32+19\alpha)))} \quad (26)
$$

These two equations determine θ_1 and θ_2 as a function of α. Under the PIH ($\alpha = 0$), the first order autocorrelation is 4/19=0.21, while the second autocorrelation is 0. With epidemiological expectation ($\alpha > 0$), both autocorrelations are an increasing function of α for $\alpha \in (0, 1)$. We solve equations (25) and (26) numerically. Figure 1 captures the relationship between θ_1, θ_2 and α graphically. For a wide range of $\alpha > 0$, θ_1 is very close to 0.4 and θ_2 is practically zero.

Figure 1

Moving-average coefficients θ_1, θ_2 as a function of α



Appendix II: Details on the MLE estimation

In this appendix, we derive the restriction of model (21) and (22) on estimates of equation (23) and the expression for a signal-to-noise ratio. The restricted and unrestricted forms of the estimated model are:

$$\Delta \ln C_t = \alpha \Delta \ln C_t^* + u_t + v_t - (\alpha + 1)u_{t-1} + 0.40 v_{t-1} + \alpha u_{t-2} \quad (27)$$

$$\Delta \ln C_t = \alpha \Delta \ln C_t^* + \xi_t + \theta_1 \xi_{t-1} + \theta_2 \xi_{t-2} \quad (28)$$

By matching the variance and the first two autocovariances of the errors processes in these two equations, we arrive at:

$$\begin{aligned}(1+\theta_1^2+\theta_2^2)\sigma_\xi^2 &= 2(1+\alpha+\alpha^2)\sigma_u^2+(1+0.4^2)\sigma_v^2\\ \theta_1(1+\theta_2)\sigma_\xi^2 &= -(\alpha+1)^2\sigma_u^2+0.4\sigma_v^2\\ \theta_2\sigma_\xi^2 &= \alpha\sigma_u^2\end{aligned}$$

We impose the overidentifying restriction as a contraint on the value of coefficient θ_2 given the values of α and θ_1. The relevant formula is:

$$\theta_2=\frac{\alpha[1+\theta_1^2+\theta_2^2-4(1+0.4^2)\theta_1(1+\theta_2)]}{1+\alpha+\alpha^2+4(1+0.4^2)(1+\alpha)^2},$$

or in closed form:

$$\theta_2=\frac{1}{50\alpha}[166\alpha^2+166+282\alpha+116\alpha\theta_1-2\sqrt{\begin{array}{c}6889\alpha^4+33034\alpha^2+23406\alpha^3+9628\alpha^3\theta_1\\+6889+23406\alpha+9628\alpha\theta_1+19256\alpha^2\theta_1+2739\alpha^2\theta_1^2\end{array}}.$$

The signal-to-noise ratio is defined here as $\frac{(1+0.4^2)\sigma_v^2}{2\sigma_u^2}$ and can be expressed from the moment conditions as:

$$\frac{1+0.4^2}{2}*\frac{2(1+\alpha+\alpha^2)+\frac{(\alpha+1)^2(1+\theta_1^2+\theta_2^2)}{\theta_1(1+\theta_2)}}{\frac{0.4(1+\theta_1^2+\theta_2^2)}{\theta_1(1+\theta_2)}-(1+0.4^2)}.$$

In the unrestricted case, the signal-to-noise ratio is overidentified: it can be computed based on 3 different combinations of moments. We report the signal-to-noise ratio based on the variance and the first autocovariance. In the restricted case, the signal-to-noise ratio is exactly identified.

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Table 1

2SLS estimates: nondurables and services consumption per capita (quarterly data)

$$\Delta \ln C_t = \alpha \Delta \ln C_{t-1} + \eta_t = (1 - \lambda + \frac{r}{R}\frac{1-\lambda}{\lambda}) \Delta \ln C_{t-1} + \eta_t$$

	1962:1-2001:4			1978:1-2001:4		
	α	*Implied* λ	**p-val.**	α	*Implied* λ	**p-val.**
OLS						
	0.417** (0.062)	**0.590**** [0.491, 0.690]	**N.A.**	0.369** (0.095)	0.637** [0.484, 0.790]	**N.A.**
Instruments: MIU, U						
T-2, T-3	**0.918**** (0.118)	**0.142**** [0.056, 0.300]	**0.558**	**0.929**** (0.149)	**0.135**** [0.044, 0.336]	**0.511**
T-3, T-4	**0.870**** (0.124)	**0.177**** [0.066, 0.352]	**0.073**	**0.874**** (0.148)	**0.174**** [0.054, 0.385]	**0.617**
Instruments: MIU, U, TB, SP500						
T-2, T-3	**0.848**** (0.122)	**0.194**** [0.074, 0.370]	**0.619**	**0.817**** (0.170)	**0.219**** [0.060, 0.474]	**0.784**
T-3, T-4	**0.884**** (0.121)	**0.166**** [0.063, 0.335]	**0.309**	**0.890**** (0.162)	**0.162**** [0.047, 0.392]	**0.934**

Notes: $\alpha = (1 - \lambda + \frac{r}{R}\frac{1-\lambda}{\lambda})$ and $\lambda = \frac{1}{2}[1 - \frac{r}{R} - \alpha + \sqrt{4\frac{r}{R} + (\frac{r}{R} + \alpha - 1)^2}]$. $\frac{r}{R}$ is calibrated at 0.01. Instruments: MIU - the University of Michigan index of unemployment expectations, U - seasonally adjusted civilian unemployment rate, TB - change in the three-month T-bill rate, SP500 - annual return of S&P 500. P-val. is the probability value of tests of overidentifying restrictions. Coefficient α has an asymptotically normal distribution, standard errors are reported in parentheses. The distribution of coefficient λ was simulated, the 90% confidence interval is reported in brackets. Two stars denote significance at the 1% level, a single star denotes significance at the 5% level. Tests for α's: $H_0 = 0$, $H_1 <> 0$. Tests for λ's: $H_0 = 1$, $H_1 < 1$.

Table 2

2SLS estimates: nondurables consumption per capita (quarterly data)

$$\Delta \ln C_t = \alpha \Delta \ln C_{t-1} + \eta_t = (1 - \lambda + \frac{r}{R}\frac{1-\lambda}{\lambda})\Delta \ln C_{t-1} + \eta_t$$

	1962:1-2001:4			1978:1-2001:4		
	α	**Implied** λ	**p-val.**	α	**Implied** λ	**p-val.**
OLS						
	0.265** (0.071)	**0.739**** [0.623, 0.854]	**N.A.**	**0.219**** (0.129)	**0.784*** [0.575, 0.993]	**N.A.**
Instruments: MIU, U						
T-2, T-3	**0.870**** (0.177)	**0.177**** [0.046, 0.434]	**0.866**	**0.800**** (0.175)	**0.233**** [0.062, 0.498]	**0.519**
T-3, T-4	**0.883**** (0.208)	**0.167**** [0.037, 0.470]	**0.497**	**0.742**** (0.206)	**0.284**** [0.064, 0.603]	**0.523**
Instruments: MIU, U, TB, SP500						
T-2, T-3	**0.685**** (0.166)	**0.335**** [0.116, 0.595]	**0.302**	**0.835**** (0.152)	**0.204**** [0.063, 0.428]	**0.840**
T-3, T-4	**0.882**** (0.167)	**0.168**** [0.047, 0.407]	**0.814**	**0.738**** (0.158)	**0.287**** [0.095, 0.531]	**0.895**

Notes: See Table 12.

Table 3

2SLS estimates: nondurables and services consumption per capita (annual data)

$$\Delta \ln C_t = \alpha^A \Delta \ln C_{t-1} + \eta_t = (1 - \lambda + \frac{r}{R}\frac{1-\lambda}{\lambda})^4 \Delta \ln C_{t-1} + \eta_t$$

	1962 - 2001			1978 - 2001		
	α^A	**Implied quarterly $\boldsymbol{\lambda}$**	**p-val.**	α^A	**Implied quarterly $\boldsymbol{\lambda}$**	**p-val.**
OLS						
	0.408** (0.120)	**0.296**** $[0.234, 0.367]$	N.A.	**0.513**** (0.098)	**0.265**** $[0.225, 0.309]$	N.A.
Instruments: MIU, U						
T-2, T-3	**0.523**** (0.188)	**0.262**** $[0.192, 0.350]$	**0.147**	**0.526**** (0.120)	**0.262**** $[0.214, 0.315]$	**0.119**
T-3, T-4	**0.636**** (0.209)	**0.236**** $[0.175, 0.315]$	**0.666**	**0.411*** (0.172)	**0.295**** $[0.211, 0.398]$	**0.135**
Instrument Set: MIU, U, TB, SP500						
T-2, T-3	**0.509**** (0.175)	**0.266**** $[0.198, 0.349]$	**0.284**	**0.628**** (0.158)	**0.238**** $[0.189, 0.297]$	**0.150**
T-3, T-4	**0.530*** (0.197)	**0.261**** $[0.188, 0.351]$	**0.359**	**0.485**** (0.134)	**0.272**** $[0.216, 0.339]$	**0.158**

Notes: $\lambda = \frac{1}{2}[1 - \frac{r}{R} - (\alpha^A)^{\frac{1}{4}} + \sqrt{4\frac{r}{R} + (\frac{r}{R} + (\alpha^A)^{\frac{1}{4}} - 1)^2}]$. $\frac{r}{R}$ is calibrated at 0.04. For the description of instruments, see Table 1. The distribution of λ was approximated in two stages. In the first stage, the distribution of annual α^A was mapped to the distribution of quarterly $(\alpha^A)^{\frac{1}{4}}$ using the Delta method.

In the second stage, the distribution of quarterly λ was simulated given the approximate normal distribution of $(\alpha^A)^{\frac{1}{4}}$.

Table 4

2SLS estimates: nondurables consumption per capita (annual data)

$$\Delta \ln C_t = \alpha^A \Delta \ln C_{t-1} + \eta_t = (1 - \lambda + \frac{r}{R}\frac{1-\lambda}{\lambda})^4 \Delta \ln C_{t-1} + \eta_t$$

	1962 - 2001			1978 - 2001		
	α^A	**Implied quarterly $\boldsymbol{\lambda}$**	**p-val.**	α^A	**Implied quarterly $\boldsymbol{\lambda}$**	**p-val.**
OLS						
	0.217 (0.113)	**0.382**** [0.276, 0.503]	**N.A.**	**0.441**** (0.113)	**0.285**** [0.231, 0.346]	**N.A.**
Instruments: MIU, U						
T-2, T-3	**0.131** (0.211)	**0.448**** [0.180, 0.807]	**0.408**	**0.335*** (0.161)	**0.323**** [0.225, 0.440]	**0.283**
T-3, T-4	**0.606** (0.448)	**0.243**** [0.126, 0.437]	**0.979**	**0.515** (0.298)	**0.264**** [0.160, 0.412]	**0.151**
Instruments: MIU, U, TB, SP500						
T-2, T-3	**0.235** (0.186)	**0.372**** [0.219, 0.562]	**0.462**	**0.560*** (0.205)	**0.253**** [0.183, 0.342]	**0.100**
T-3, T-4	**0.266** (0.258)	**0.355**** [0.178, 0.596]	**0.682**	**0.339*** (0.156)	**0.322**** [0.227, 0.434]	**0.083**

Notes: See Tables 12 and 14.

Table 5

MLE estimation (quarterly data)

Unrestricted model:

$$\Delta \ln C_t = \alpha \Delta \ln C_{t-1} + \xi_t + \theta_1 \xi_{t-1} + \theta_2 \xi_{t-2}$$

Restricted model:

$$\begin{aligned}
\Delta \ln C_t &= \Delta \ln C_t^* + u_t - u_{t-1} \\
\Delta \ln C_t^* &= \alpha \Delta \ln C_{t-1}^* + v_t + 0.4 v_{t-1} \\
\Delta \ln C_t &= \alpha \Delta \ln C_{t-1} + u_t + v_t - (\alpha + 1) u_{t-1} + 0.40 v_{t-1} + \alpha u_{t-2}
\end{aligned}$$

	α	**Implied** λ	θ_1	θ_2	**SNR**	**LogLik**
Nondurables and services						
Unrestricted	$\mathbf{0.703}^{**}$	$\mathbf{0.319}^{**}$	$\mathbf{-0.457}^{**}$	**0.106**	**0.711**	**1671.53**
	(0.087)	$[0.194, 0.452]$	(0.089)	(0.085)		
Restricted	$\mathbf{0.677}^{**}$	$\mathbf{0.342}^{**}$	$\mathbf{-0.442}^{**}$	**0.139**	**0.686**	**1671.45**
	(0.062)	$[0.250, 0.438]$	(0.085)	(−−)		
Nondurables						
Unrestricted	$\mathbf{0.601}^{**}$	$\mathbf{0.413}^{**}$	$\mathbf{-0.406}^{**}$	**0.047**	**0.799**	**1513.87**
	(0.123)	$[0.229, 0.608]$	(0.124)	(0.083)		
Restricted	$\mathbf{0.524}^{**}$	$\mathbf{0.487}^{**}$	$\mathbf{-0.349}^{**}$	**0.107**	**0.799**	**1513.55**
	(0.090)	$[0.346, 0.630]$	(0.112)	(−−)		

Notes: Sample 1962:1-2001:4. SNR denotes the signal-to-noise ratio, which is defined as $\frac{(1+0.4^2)\sigma_v^2}{2\sigma_u^2}$.

Table 6

Sensitivity of consumption to predicted income: nondurables and services consumption per capita (quarterly data)

$$\Delta \ln C_t = \alpha \Delta \ln C_{t-1} + \gamma \Delta \ln Y_t + \eta_t = (1 - \lambda + \frac{r}{R}\frac{1-\lambda}{\lambda}) \Delta \ln C_{t-1} + \gamma \Delta \ln Y_t + \eta_t$$

1962:1-2001:4

	$\boldsymbol{\alpha}$	**Implied** $\boldsymbol{\lambda}$	γ	**p-val.**
Instruments: MIU, U, TB, SP500				
T-2, T-3	**0.760*** (0.354)	**0.268*** [0.026, 0.825]	**0.072** (0.277)	**0.417**
T-3, T-4	**0.562**** (0.211)	**0.451**** [0.147, 0.788]	**0.269** (0.149)	**0.334**

1978:1-2001:4

	$\boldsymbol{\alpha}$	**Implied** $\boldsymbol{\lambda}$	γ	**p-val.**
Instruments: MIU, U, TB, SP500				
T-2, T-3	**0.709*** (0.338)	**0.314*** [0.032, 0.849]	**0.085** (0.219)	**0.646**
T-3, T-4	**0.826**** (0.293)	**0.212**** [0.029, 0.661]	**0.063** (0.195)	**0.874**

Notes: 2SLS estimates.

Table 7

Sensitivity of consumption to predicted income: nondurables per capita (quarterly data)

$$\Delta \ln C_t = \alpha \Delta \ln C_{t-1} + \gamma \Delta \ln Y_t + \eta_t = (1 - \lambda + \frac{r}{R}\frac{1-\lambda}{\lambda})\Delta \ln C_{t-1} + \gamma \Delta \ln Y_t + \eta_t$$

1962:1-2001:4

	α	**Implied** λ	γ	**p-val.**
Instruments: MIU, U, TB, SP500				
T-2, T-3	**0.409** (0.254)	**0.598** [0.208, 1.009]	**0.328** (0.234)	**0.170**
T-3, T-4	**0.587*** (0.295)	**0.427*** [0.066, 0.899]	**0.281** (0.281)	**0.739**

1978:1-2001:4

	$\boldsymbol{\alpha}$	**Implied** $\boldsymbol{\lambda}$	γ	**p-val.**
Instruments: MIU, U, TB, SP500				
T-2, T-3	**0.708**** (0.187)	**0.314**** [0.087, 0.606]	**0.139** (0.157)	**0.731**
T-3, T-4	**0.753**** (0.195)	**0.274**** [0.066, 0.575]	**−0.018** (0.198)	**0.831**

Notes: 2SLS estimates.