Current Consumption and Future Income Growth: Synthetic Panel Evidence

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Abstract

Using group means computed from twenty years of high quality survey data, I show a strong and robust relation between households' consumption growth and subsequent realizations of their income growth, including realizations as distant as six years later. The relation appears in multiple types of variation in income growth: variation across cohort-education groups, variation over the life cycle, and even some variation over the business cycle. The results may be evidence of forward-looking households altering their current consumption in response to information they receive about their future income; other interpretations are explored as well.

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1 Introduction

To what extent do households make their consumption-savings decisions in a forward-looking manner? While this question is of fundamental importance to many aspects of economics, a wide range of viewpoints prevail. The massive empirical literature studying consumer behavior with Euler equations has produced mixed results (see Martin Browning and Annamaria Lusardi (1996) for a survey), with a rough consensus emerging that consumption growth responds to some types of predictable variation in income, in violation of the orthogonality tests characteristic of basic life-cycle/permanent-income (LC/PIH) models. Indeed, it has been shown that a number of empirical facts do not accord well with the implications of basic forward-looking models. But despite these misgivings, other evidence has been gathered indicating that the forward-looking model may have more than a grain of truth to it. For example, evidence dating back to Milton Friedman (1957) indicates that consumption responds more strongly to permanent income innovations than to transitory ones.[1]

Further potential support for the forward-looking model is provided by a number of papers by John Y. Campbell and others, which document a relation in macroeconomic data between consumption, usually scaled by income, and income changes a quarter later.[2] More recently, Lettau and Ludvigson (2001, 2002a) have shown that a consumption measure scaled by a combination of assets and income (which they call *cay*) is related to investment returns from a quarter to several years later. Such regressions of income or asset returns on prior scaled consumption variables may be evidence that households receive information about their future income or investment opportunities

[1] More recent evidence includes Christina H. Paxson (1992).

[2] See John Y. Campbell (1987); Campbell and Angus Deaton (1989); Campbell and N. Gregory Mankiw (1989); C.L.F. Attfield, David Demery and Nigel W. Duck (1990); and John H. Cochrane (1994). Antecedent or concurrent work along the same lines occured in Thomas J. Sargent (1978); Marjorie Flavin (1981); and Lars P. Hansen, William Roberds, and Sargent (1991).

and alter their consumption in response, as the forward-looking model predicts they should. Under this interpretation, these regressions essentially tell the econometrician what households' know about their future income or asset returns, which is nice since households' information about these variables, especially their own future income, is generally vastly superior to what an econometrician can discern from observeables other than consumption. So, compared to other strategies where the econometrician characterizes the household income process and tests whether consumption behaves as it should, these regressions bring more information to bear in characterizing households' forward-looking nature. Any characterization of the household income process by the econometrician will always be limited by the his or her potentially much smaller information set, and in fact the econometrician's characterizations must coincide with households' perceptions of the income process for these tests to be valid (see Hansen et al., 1991). Similarly, Euler equation orthogonality tests, while robust to households' potentially superior information, do not exploit it as consumption forecasting regressions do, as the universe of testing variables will always be limited by the information set of the econometrician.

While this macroeconomic evidence for forward-looking behavior is intriguing and potentially very valuable, corroborating evidence from micro data would take it to a new level of credibility. This is because in the macro data, plausible non-forward-looking interpretations are readily available; as Deaton (1992) points out:

> In the aggregate economy, it is easy to think of other mechanisms - simple Keynesian feedback mechanisms being the obvious example - that generate correlation between saving and future income change, for example if positive consumption shocks are propagated into income increases in subsequent periods. (Angus Deaton, 1992b, p. 133.)

The microeconomic data employed in this paper permit exploration of these competing explanations, as well as providing more types of usable variation than the macro data. While prior microeconomic studies of the relation between current consumption and future income have produced no convincing evidence for such a relation,[3] the work here employs a long, high quality synthetic panel to arrive at a different result. In addition, I employ an econometric specification that I believe to be superior to what has been used in prior empirical work, which generally uses consumption scaled by other variables as a predictor. It always hard to know whether the predictive power uncovered in these specifications really stems from consumption, rather than the variables used to scale consumption; see the recent exchange between Lettau and Ludvigson (2002b) and Brennan and Xia (2002). The specification I employ here does not suffer from these problems of interpretation; in addition, it allows easier decompositions of the predictive power of consumption by time horizon.

Although the main contribution of this paper is empirical, I begin in section 2 in the usual way, with a theory section designed to aid interpretation of the empirical results, through the lense of a forward-looking model of consumer behavior. Section 3 discusses the twenty years of micro data used in the paper (from the Consumer Expenditure Surveys (CEX) and Current Population Surveys (CPS)), and computation of the synthetic panel - 28 time series of group means of income and consumption, with households grouped according to the educational attainment and birth cohort of their male heads. Section 4 shows the main empirical result: a statistically significant relation between growth rates of group means of income (computed from the CPS) and growth rates of group means of consumption (computed from the CEX) from one to five years earlier. Section 5 undertakes an extensive robustness analysis, breaking down the relation between consumption and future income by different types of variation and different types of households; the main results are found to be remarkably robust. Sec-

[3] See Deaton (1992a), Christopher D. Carroll (1994), Deaton (1997), and Rob Alessie and Lusardi (1997).

tion 6 discusses explanations of the results other than the forward-looking explanation; section 7 concludes.

2 Theory

The baseline empirical specification in this paper is a synthetic panel estimate of:

$$\Delta y^i_{t+1} = \beta_0 \Delta c^i_{t+1} + \beta_1 \Delta c^i_t + \quad \ldots \quad + \beta_q \Delta c^i_{t+1-q} + e^i_{t+1}, \tag{1}$$

where Δy^i_t denotes time t income growth for group i, estimated from CPS sample means, and where Δc^i_t denotes time t consumption growth for group i, estimated from CEX sample means. We provide a derivation of this equation in the context of the certainty equivalent LC/PIH, and briefly discuss how interpretations change when we relax some of the LC/PIH assumptions.

2.1 Hueristic Derivation

Taking the simplest possible case, consider an infinitely-lived household h whose information about its income derives entirely from past realizations of the income process - i.e. the household information set about its income is univariate. The growth rate of household income Δy^h_{t+1}[4] is assumed covariance stationary; no other assumptions are required to write Δy^h_{t+1} in its Wold moving average representation:

$$\begin{aligned} \Delta y^h_{t+1} &= \kappa^h_{t+1} + \rho^h_0 \varepsilon_{t+1} + \rho^h_1 \varepsilon_t + \rho^h_2 \varepsilon_{t-1} + \ldots \\ &= \kappa^h_{t+1} + \rho^h \left(\mathrm{L}\right) \varepsilon_{t+1}. \end{aligned} \tag{2}$$

[4] Appendix B directs us to include dividend and interest income in this measure.

The ε_{t+1-k} are realizations of an independent and identically distributed random variable representing innovations to the household's information about Δy^h_{t+1}; $\rho^h(\mathrm{L})$ is a polynomial in the lag operator (assumed of order q); κ^h_{t+1} is the linearly deterministic component of the income process.

Household h's consumption growth Δc^h_{t+1} follows a version of the standard LC/PIH: Δc^h_{t+1} is unpredictable and equals the time $t+1$ innovation to the present discounted value of h's current and expected future income growth. Taking a constant interest rate r, and letting $\lambda = \frac{1}{1+r}$, consumption growth is then:

$$\begin{aligned}\Delta c^h_{t+1} &= \sum_{j=1}^{\infty} \lambda^{j-1}\left(E_{t+1} - E_t\right)\Delta y^h_{t+j} \\ &= \left(\rho^h_0 + \rho^h_1\lambda + \rho^h_2\lambda^2 + \ldots\right)\varepsilon_{t+1} \\ &= \rho^h(\lambda)\,\varepsilon_{t+1}, \qquad (3)\end{aligned}$$

where E_t is an expectation taken with respect to the time t information set of the household. Appendix A works through one possible derivation such a LC/PIH consumption function, clarifying its implicit assumptions. Since $\varepsilon_{t+1} = \frac{1}{\rho^h(\lambda)}\Delta c^h_{t+1}$, the consumption growth rates can be used to substitute the innovations out of (2):

$$\begin{aligned}\Delta y^h_{t+1} &= \rho^h_0\varepsilon_{t+1} + \rho^h_1\varepsilon_t + \ldots + \kappa^h_{t+1} \\ &= \frac{\rho^h_0}{\rho^h(\lambda)}\Delta c^h_{t+1} + \frac{\rho^h_1}{\rho^h(\lambda)}\Delta c^h_t + \ldots + \kappa^h_{t+1} \\ &= \frac{\rho^h(\mathrm{L})}{\rho^h(\lambda)}\Delta c^h_{t+1} + \kappa^h_{t+1}.\end{aligned}$$

This is equation (1) at the household level rather than the group level, although in (1) we have truncated the potentially infinite number of lags of consumption growth at k lags. The model tells us to interpret $\beta(\mathrm{L}) = \frac{\rho^h(\mathrm{L})}{\rho^h(\lambda)}$; so the βs are the Wold moving average coefficients governing the household income process, normalized so their discounted sum is unity - i.e. $\sum_{k=0}^{q} \lambda^k \beta_k = \beta(\lambda) = 1$. A statistically significant β_k translates to a statistically significant ρ_k^h, implying that some information is revealed to households about their income growth k periods in advance of its arrival.

2.2 Superior Household Information

The restrictive assumption in the previous subsection on the information set of the household is both unrealistic and unnecessary to derive (1), as Hansen, Roberds and Sargent (HRS, 1991) show. They consider an information set for household h that consists of n linearly independent,[5] covariance-stationary variables, including Δy_{t+1}^h; n may be arbitrarily large, so the information set of the household may be arbitrarily larger than the information set of the econometrician. The vector process can be written in a Wold moving average representation, with one row characterizing income growth again as in (2), but with ε representing an n-dimensional column vector of (white noise) innovations to the information set of the household,[6] and $\rho^h(\mathrm{L})$ representing an n-dimensional row vector of polynomials of order q in the lag operator. Given the LC-PIH consumption function, we again have: $\Delta c_{t+1}^h = \rho^h(\lambda)\, \varepsilon_{t+1}$.[7]

Appendix B shows the HRS derivation of (1) in this multi-dimensional setting; in addition to showing the general derivation, it works through an example for a specific

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[5] This "assumption" of n linearly independent variables in the household information set, to quote a previous referee who objected, is without loss of generality.

[6] Without loss of generality, we assume the variance-covariance matrix of ε is the identity matrix I_n.

[7] This consumption function assumes that households observe different types of shocks separately. While this assumption produces the cleanest derivation of (1), other models may be considered as well in interpreting the paper's empirical results. As an example, take the case where $n = 2$, with one shock being household-specific, and the other economy-wide or specific to the household's entire education-cohort group. The household observes only an average of these two shocks, however; it cannot disentangle one from the other. So the household may receive a shock indicating that its income will increase over the next few years, not knowing whether the shock will hit the economy or its cohort-education group as a whole, or just the household itself. Combined with the aggregation scheme employed in this paper, such a model may make the paper's empirical results more palatable to some economists; see the next footnote. For analysis of a model of this kind, see also Jorn-Steffen Pischke (1992).

time series process where $n = 2$. In the derivations, we see that consumption growth reveals to the econometrician a linear combination of the n elements of ε_{t+1}, which can be substituted out of the reinterpeted (2); the remaining $n-1$ elements of household information end up in the error term of the regression, and are necessarily orthogonal to consumption growth. The linear combination of ε_{t+1} revealed to us by consumption growth is $\frac{\rho^h(\lambda)}{|\rho^h(\lambda)|}\varepsilon_{t+1}$, where $|\rho^h(\lambda)| = \sqrt{\rho^h(\lambda)\,\rho^h(\lambda)'}$. $\frac{\rho^h(\lambda)}{|\rho^h(\lambda)|}\varepsilon_{t+1}$ weights more heavily those elements of ε_{t+1} with larger discounted sums of polynomial coefficients; as posited by Friedman (1957), consumption reflects more strongly those innovations that have a more persistent effect on the income process. The implication that $\beta(\lambda) = 1$ continues to hold in the multivariate setting - this is the HRS test of present value budget balance.

2.3 Aggregation

Aggregation of this model is easy. Let ε_{t+1} represent the vector of innovations to a new information set equal to the union of the information sets of all households in the economy. Then we can write equation (2) for an individual household using the expanded ε_{t+1} and simply setting to zero those rows of $\rho^h(\mathrm{L})$ corresponding to elements of ε_{t+1} not in the individual household's information set. Averaging into groups, the main results of sections 2.1-2.2 carry over with $\rho^h(\mathrm{L})$ replaced by $\overline{\rho^i}(\mathrm{L})$, the average moving average polynomials for households in group i. This produces equation (1) at the group level, with $\beta(\mathrm{L}) = \frac{\overline{\rho^i}(\mathrm{L})}{\overline{\rho^i}(\lambda)}$. More on aggregation can be found in my dissertation, Nalewaik (2003).[8]

[8] Again, this model where households observe different types of shocks separately produces the cleanest aggregation, but other models of household information may be more reasonable. Continuing with the example from the previous footnote, a household observes a shock indicating its income will increase over the next few years, but does not know whether the shock will hit the economy as a whole or just itself; in any event, it increases its consumption in response. It may know that most of the shocks it receives are idiosyncratic (so the variance of the idiosyncratic component of the shocks it observes is much larger than the variance of the aggregate component), in which case the household will place little stock in this shock as a predictor for the economy as a whole, and will have little to say about the future state of the economy if asked. Its *individual* consumption decisions are uninformative about

2.4 Extensions of the LC/PIH

Much empirical evidence rejects the strictest version of the LC/PIH where consumption growth is completely unpredictable, and there are sound theoretical reasons to expect some predictability, including precautionary savings motives, liquidity constraints, and non-separabilities between consumption and other determinants of utility such as leisure and demographics variables. This is one rationale for including control variables in (1): appropriately chosen controls may increase the ratio of news to predictable variation in consumption growth, bringing the data more in line with the LC/PIH theory in sections 2.1-2.3. In particular, some empirical specifications below employ controls to remove from the data its mean cross-sectional and life-cycle variation, likely the types of variation most predictable to households. However the appropriateness of these predictability assumptions is not always clear cut, and will be discussed more later.

Whatever control variables the econometrician includes in the regression, consumption growth is unlikely to conform exactly to the predictions of the LC/PIH. Liquidity constraints, precautionary savings motive, and complementarity between consumption and leisure may skew the βs away from their LC/PIH interpretation as scaled moving average coefficients; in my dissertation, Nalewaik (2003), I show that these factors will dampen the response of consumption growth to variation in expected future income growth, so consumption responses will be more muted than the one-for-one relation predicted by the LC/PIH. At the macro level, decreasing returns to capital may also

the aggregate economy as well, their movements being dominated by idiosyncratic variation. However when a shock really does hit the entire economy or group, all households in that group will be racheting up their consumption simultaneously, with each one thinking the shock is specific to itself. As econometricians, when we average household consumption into groups, this is exactly the type of variation we will isolate, as we will average away much of the idiosyncratic variation in consumption, isolating and cumulating the small pieces of information about aggregate and group-level income in individual households' consumption decisions. The aggregation is key to interpreting the paper's empirical results in this story: with its increased signal-to-noise ratio, the semi-aggregated consumption growth may be a useful predictor of the state of the business cycle several years in the future, or the fate of demographic groups, even if no individual household has much of a clue about these things.

dampen the response of consumption to expected future income; elastic labor supply and saving for retirement could dampen consumption's response to both current and expected future income. Interestingly, this dampening of consumption responses will tend to *increase* the size of the βs in (1), as small consumption changes signal larger, more than proportionate changes in current or expected future income.[9]

Since some of these extensions to the LC/PIH surely play an important role in consumer behavior, the LC/PIH implication of $\beta(\lambda) = 1$ probably should not be taken too seriously; the extensions to the theory broadly predict $\beta(\lambda) > 1$. In addition, the interpretation of the β_k as scaled moving average coefficients will remain a matter of judgement. We could make powerful statements if such an interpretation held exactly: for example a result of $(\beta_k)^2 > (\beta_j)^2$ says households learn more about their income growth k periods ahead of its arrival than j periods ahead. While such statements should be taken with a grain of salt, my personal view is that the intuition from forward-looking models distilled into the LC-PIH, and its accompanying interpretation of the βs, remains a very useful place to start in thinking about regression results from (1).

3 Data and Econometrics

The Annual Demographic Files from the CPS provide the paper's primary source of data on household income from 1980-1999; the CEX Interview Surveys provide data on household consumption over the same time period. Both sets of surveys are short rotating panels, with CPS sample sizes (50,000-60,000 households) roughly an order of magni-

[9] Other modifications to the LC/PIH will have different effects. Campbell and Mankiw (1989) consider models with "rule-of-thumb" consumers, who set $\Delta c^h_{t+1} = \Delta y^h_{t+1}$ each period. For these consumers, estimates of (1) would yield $\beta_0 = 1$, with all other $\beta_k = 0$. If some fraction of consumers behaved as "rule-of-thumb" consumers and the rest behaved as LC/PIH consumers, our estimated βs would be a weighted average of the moving average coefficients of the LC/PIH consumers, and the "rule-of-thumb" βs ($\beta_0 = 1$ and $\beta_k = 0$, $k \neq 0$). In other words, we should observe a spike at β_0.

tude larger than CEX sample sizes. Household income includes earned (labor) income,[10] transfer income, and asset income,[11] and subtracts an estimate of taxes paid computed using the National Bureau of Economic Research (NBER)'s TAXSIM program. The CEX is the most comprehensive source of micro data available on expenditures of US households, reporting several hundred expenditure categories; the consumption measure used here is non-durable goods and services and excludes durables, medical care, education, and housing.[12] The CEX data on food consumed at home was corrected for discontinuities introduced by changes in survey design in 1982 and 1987. Both income and consumption were deflated by the annual personal consumption expenditures (PCE) deflator from the National Income and Product Accounts (NIPA). For further details on the raw consumption and income data used in the paper, see the data appendix available from the author.

The sample of households studied here, households with a male head aged 23 to 59, includes about half of all households in the survey data.[13] The CEX and CPS samples in each year are partitioned by the characteristics of their male household heads: four categories for their educational attainment (high school drop-outs, high school graduates with no other schooling, high school graduates with additional schooling less than a 4-year college degree, and 4-year college graduates), crossed with seven 5-year birth cohorts, ranging from the 1931-1935 birth cohort (i.e. male heads born in those years)

[10]Some top-coding adjustments are made to the earned income variables following Lawrence Katz and Kevin M. Murphy (1992).

[11]Empirical results that excluded asset income from the household income measure were virtually identical to the results reported in this paper.

[12]This consumption measure matches that of Orazio P. Attanasio and Steven J. Davis (1996), whose programs I used to create it. I use non-durables consumption to avoid additional dynamics that may be introduced into the basic LC/PIH by durability, and because durable goods expeditures are partially savings, not the pure consumption that is the topic of the theory.

[13]The CEX sample also excludes rural households and households classified as incomplete income reporters; these are fairly standard sample selection restrictions - see Attanasio and Davis (1996).

to the 1961-1965 birth cohort.[14] The synthetic panel on consumption and income is the set of means of log consumption and log income taken over the sample of households in each group in each year. For each group there is a time series of up to 20 annual cell means, but due to the sample selection restrictions on age the panel is unbalanced; we have 524 cell means in total for the 28 groups.

Stacking together the 28 time series, our baseline specification is a synthetic panel estimate of (1). Unfortunately, random differences from sample to sample introduce sampling errors into the panel - i.e. errors due to the measured sample means being different from their corresponding population means from year to year. The variance of the sampling error for each synthetic panel cell mean, on either income or consumption, is inversely proportional to the number of households used to compute it (its cell count for short); table 1 reports summary statistics on these 524 cell counts. They vary widely from observation to observation, leading heteroskedasticity to be a source of concern. As a remedy, the paper's least squares estimates of panel equations such as (1) weight by the average cell count of the cells used to produce the explanatory variables, effectively downweighting the thinner synthetic panel observations more contaminated with sampling error. Note that the sampling errors in Δy_t^i will be independent of the sampling errors in Δc_t^i, as the CPS and CEX are independent random samples; then the sampling errors in Δc_t^i should bias the βs in (1) generally towards zero, making it more difficult to identify a relation between consumption and income growth.

Table 2 reports summary statistics for the panel. Autocorrelations are computed using weighted least squares, controlling for a full set of fixed effects and education-specific quartic polynomials in the age of the male household heads.[15] The controls

[14]Nine 5-year birth cohorts met the sample selection restrictions on age, but our specification also requires computation of several lags of growth rates, which caused the two cohorts with the shortest time series (the 1926-1930 cohort and the 1966-1970 cohort) to drop from the sample.

[15]A five year birth cohort is assigned the age of its middle-aged members.

purge the data of most of its variation over the life cycle and its mean cross-sectional variation, leaving mainly the time series variation in the panel. While we do see a large negative first order autocorrelation for consumption growth, this is the expected outcome of substantial sampling variability; otherwise there is little autocorrelation in either variable's time series variation. To compute the standard errors here and throughout the paper, I use an asymptotic variance-covariance matrix (described in Appendix C) that is robust to heteroskedasticity, contemporaneous cross correlation, and seventh order autocorrelation.

Before proceeding to the main result, we should note that the model in section 2.1-2.3 is particularly amenable to estimation on panel data. By construction, the errors are orthogonal to the regressors; see Appendix B. Cohort effects biasing the βs is a non-issue, since these effects (cohort averages of κ_{t+1}^{h}) are linearly deterministic and hence orthogonal to the innovations captured by consumption growth. Furthermore, consumption growth is white noise, so no complications arise regarding estimation of distributed lags on short panels (see Ariel Pakes and Zvi Griliches (1984)). The only real complication arises in the case where the βs are heterogeneous across cohorts; for the panel estimates to consistently estimate the mean βs across (appropriately weighted) cohorts, the heterogeneity in the βs must be independent of consumption growth (again see Pakes and Griliches (1984)). However the results in section 5.4 will indicate little heterogeneity in the βs: the relation between consumption and future income appears fairly uniformly distributed across households of different ages and education levels.

4 The Basic Result

Panel A in table 3 shows weighted least squares estimates of (1) with various cutoffs q, with no additional control variables beyond a constant. We see a statistically significant relation between consumption growth and income growth as far as five years into the future, with the size of the regression coefficients peaking at the two to five year horizon. The results at longer horizons depend very little on whether or not we include contemporaneous consumption growth and the first lag, as the last line of the main panel shows. If consumers behave as in the LC/PIH, table 3 indicates that households receive more information about their income growth five years before it arrives than at the date of its actual arrival.

For comparison, panel B in table 3 shows univariate regressions, regressing income on each lag of consumption growth separately. These regressions hold the sample fixed for comparability, each utilizing only the 268 observations for which we can compute the sixth lag of consumption growth.[16] The R^2 here may seem small, but it should be kept in mind that sampling variability in income and consumption growth is reducing R^2; its maximum attainable value is considerably less than unity.

For an additional comparison, table 4 reverses the roles of Δc_t and Δy_t in equation (1). While I give these results no structural interpretation, I simply note that these regressions are similar to what has been done in the Euler equation literature. While we find a statistically significant relation between Δc_t and Δy_{t-1}, a relation similar to what has shown up as a violation of the orthogonality conditions in many Euler equation estimates, we also find very little evidence of a relation between consumption growth and further lags of income growth. The coefficients here are sometimes larger than the coefficients found in table 3, but this is to be expected: the sampling error variance of the explanatory variables is about ten times smaller here than in table 3, due to the much larger CPS sample sizes. Comparing t-statistics is probably more informative, as may be a comparison (as we change q) of patterns in R^2 between the two tables. The incremental additional explanatory power of the lags of consumption growth for income

[16] One thing to notice here is that restricting the sample to these 268 observations reduces the contemponeous correlation between consumption growth and income growth, reflecting a weakening over time of the degree to which consumption tracks income contemporaneously (the restricted sub-sample starts in 1986-7, as opposed to 1980-1 in the full sample).

is remarkable given the total lack of incremental additional explanatory power of the lags of income growth for consumption.

The bottom line from tables 3 and 4 is that consumption growth predicts income growth far into the future, consistent with households actively changing consumption in response to forecasts of their income growth several years ahead, forecasts that turn out to be accurate. And the reverse is not true: consumption seems to fully incorporate the information in realizations of income growth after one year. While the LC/PIH predicts that consumption should incorporate all available information about income growth *immediately*, if we allow a one year lag the theory does not perform so badly.

5 Robustness Analysis

5.1 Types of Variation: Cross Sectional, Life-Cycle, and Time-Series

What types of variation drive the results in table 3? Consider first the variation in mean growth rates across our 28 cohort-education groups. If we orthogonalize Δy and contemporaneous and lagged Δc with respect to a set of year effects (removing mean business cycle effects from the data) and then take group means, the group means of the sum of Δc_{t-4} to Δc_{t-7} (the longer lags of consumption growth) explain about 55 percent of the variation in group means of Δy_t, while group means of the sum of Δc_t to Δc_{t-3} (the shorter lags) explain only 49 percent. In a simple cross-sectional regression of the 28 group means of Δy on both sets of group means of Δc, only the average of the fourth to seventh lags is significant. Such evidence suggests that the relation between consumption and future income derives at least in part from cross sectional variation in mean growth rates, arising from such sources as the continuing expansion of income inequality between more and less educated earners in this sample period.

Next consider variation over the life cycle. The highly influential work of Carroll and Lawrence H. Summers (1991) uses CEX data to show what is essentially a contemporaneous "one-for-one" relationship between income and consumption, as they put it. The data used here tells a different story, primarily because it employs multiple repeated cross sections to track fixed cohorts over time, unlike Carroll and Summers who confound cohort and age effects in their life-cycle profiles by using a single cross section of data to produce each plot.[17] Figure 1 shows, for each of our four education categories, predicted values from a synthetic panel regression of CEX consumption and CPS income on a fifth-order polynomial in the age of the male household head, controlling for a full set of cohort effects. For every education category, the peak in the age-consumption profile clearly precedes the peak in the age-income profile, indicating that the relation in table 3 may stem in part from life-cycle variation.[18]

We next use control variables to purge our income and consumption data of its mean cross sectional variation and its variation over the life cycle. While the strictest version of the LC/PIH in sections 2.1-2.3 provides no justification for control variables, there are at least three good reasons to include them. First, they help provide a general decomposition of the results in table 3 by different types of variation. Second, given the persistent rise in the returns to education over our sample period, some readers may question the stationarity of some components of the Δy (even in growth rates). Such concerns argue for the inclusion of group fixed effects in (1), as these controls will remove

[17]Part of the variation in Carroll and Summers' plots stems from age effects, but part of it stems from cohort effects as well, since the groups they differentiate by 5-year age bands are also differentiated by 5-year cohorts. Being time invariant, cohort effects in income will translate one-for-one into cohort effects in consumption even in models where households are completely forward-looking; contemporaneous "tracking" of consumption by income is no evidence against forward-looking models when it appears in variation driven by cohort effects.

[18]Various other papers use synthetic panel data to plot income and consumption over the life cycle, including Attanasio and Weber (1995), Attanasio and Browning (1995), and Banks, Blundell, and Tanner (1998). Pierre-Olivier Gourinchas and Jonathan A. Parker (2002) use techniques similar to those employed here and find similar results, showing plots where consumption clearly leads income over the life-cycle for various cohort-occupation and cohort-education groups.

from the regression much of this potentially non-stationary across-group variation. And third, as discussed in section 2.4, controls may purge consumption growth of much of its predictable variation, leaving variation in consumption growth that is mostly news, as the LC/PIH posits. However the appropriateness of purging the regression of a particular type of variation will depend on assumptions about its predictability, which in turn may depend on assumptions about the information set of households. Consider again the differences in mean consumption growth across cohort-education groups. Under one set of assumptions, these differences represent differences in the average values of innovations to households' information about their income growth over the sample period: since mean Δc for households headed by college graduates exceeded mean Δc for households headed by high-school graduates, the college graduates on average received better news about their current and expected future income in the 1980's and 1990's. The fact that the wage gap between college and high school graduates grew more or less continually over this time period does not mean that households knew this would occur ex-ante; for example it may be that only midway through the 1980's did households conclude that this gap would likely continue growing throughout the decade and into the next. Under this interpretation, group means are simply another source of variation to exploit in estimating (1), and there is no need to control for group fixed effects. However under other sets of assumptions, across group differences in mean consumption growth are driven by predictable variation rather than news, so any correlation with group means of income growth would not be the result of forward-looking behavior on the part of households. Inclusion of fixed effects in (1) would then be appropriate.

To compute estimates of (1) purging the data of its mean cross sectional variation, I simply included a set of group fixed effects. To purge the data of its variation over the life cycle, I tried various sets of controls, including many measures of family size and composition (numbers of children of different ages, numbers of elderly, whether a wife was present, etc.), and various polynomials in the age of the male household head. However once I included quartic polynomials in the age of the male household head interacted with education fixed effects, all the other demographics controls had virtually no effect on the explanatory power of consumption growth or the coefficients in (1); for this reason I report results that include only these education-specific age polynomials as controls for variation over the life cycle. Estimates of (1) that include these controls are reported in the second specification of table 5. This table reports the regression βs, as well as the discounted sum of the regression coefficients $\beta(\lambda) = \sum_{k=0}^{q} \lambda^k \beta_k$, where $\lambda = \frac{1}{1+r}$ and r is the interest rate set to 0.025; the HRS test of present value budget balance predicts that this quantity equal one. Table 5 also reports implied r, the estimated value of r that sets $\beta(\lambda) = 1$,[19] and $R^2_{\Delta c}$, the regression R^2 after orthogonalizing the data with respect to the control variables.

Remarkably, the primary effect of including in (1) the fixed effects and age polynomials is to increase the size of the βs; just as remarkably, the controls do very little to change the relative magnitudes of the coefficients, as the peak in the βs remains at the two to five year horizon. The discounted sum of the regression coefficients $\sum_{k=0}^{q} \lambda^k \beta_k$ increases by about 25-30 percent compared to the first specification with no controls. While $R^2_{\Delta C}$ drops substantially and standard errors increase, the βs are plainly statistically significant. Given the nature of the controls, the variation that is left in the data is largely time series variation; the results indicate that consumption growth predicts some time series variation in income growth years in advance.[20] For some graphical evidence, see Nalewaik (2003), who plots the aggregate business cycle variation in the data and deviations of groups' business cycle experiences from the aggregate.

[19] The standard error of this quantity is computed using the delta method and numerical derivatives.

[20] I reiterate that this does not *necessarily* imply that, on average, individual households are able to forecast the state of the business cycle several years into the future. See footnotes 7 and 8.

5.2 Aggregate vs. Non-Aggregate Variation

The next two estimates in table 5 address concerns that a single aggregate effect may be influential, by including as controls a set of year fixed effects (the fourth estimate includes the age polynomials and cohort effects as well). The year effects have little impact on $R^2_{\Delta C}$, and the majority of the coefficients remain statistically significant.[21] The HRS test $\beta(\lambda) = 1$ fails on the low side in these specifications, but it should be kept in mind that sampling errors are biasing these βs towards zero, more in these specifications than in others, as the control variables remove from consumption growth much of its true variation and little or none of its noise from sampling errors.

Interestingly, the year effects increase the βs on the longer lags of consumption growth at the expense of the βs on contemporaneous consumption growth and the shorter lags. The βs now die out at the seven year horizon, as the relation between consumption growth and income growth six years ahead is now relatively large and statistically reliable. The fourth estimate in table 5 indicates that a typical group's consumption growth contains information about how its business cycle experience will differ from the aggregate business cycle, at horizons four, five and six years in the future.

5.3 Consumption as a Proxy for Income

The final two specifications of table 5 include seven lags of CPS income growth as control variables. Prior work on current consumption and future income has often worked with variables like savings or consumption-income ratios, essentially scaling the explanatory variable consumption by income; some have argued that the empirical results in those papers are driven by variation in the scaling variable rather than variation in consumption as the basic forward-looking theory predicts. While such criticisms are a non-issue

[21] Additional analysis confirmed that one influential year does not drive the results; dropping any individual year (any of 1987-1999) does not appreciably impact the βs.

for an econometric specification such as (1) where consumption is left to its own devices to explain future income, concerns may remain that consumption is simply proxying for income in (1). The final estimates in table 5 address these concerns, and given the large *increases* in βs and $R^2_{\Delta C}$ when the lags of income growth are included in the regression, the argument that consumption is simply proxying for income has little to no credibility. The argument loses even more credibility when one realizes that the largest source of measurement error in these data are sampling errors, and that the variance of the sampling errors in consumption growth is about an order of magnitude larger than the variance of the sampling errors in income growth. The facts from this table are clear: lags of consumption growth have substantial additional explanatory power for income growth above and beyond lags of income growth.

5.4 Heterogeneity by Age and Education

Table 6 explores heterogeneity in the βs by age, reporting six sets of regression coefficients from three specifications of (1). Two sets of consumption growth terms are included in each specification: one interacted with dummies for whether the cohort was younger than a specified age cutoff (at the time of the consumption growth), and another interacted with dummies for whether the cohort was older. The age cutoffs reported are 33, 38 and 43; the first and fourth set of reported estimates in table 6 consider an age cutoff of 33, for example. Controls are quartic age polynomials and birth cohort fixed effects interacted with education fixed effects.

The results in table 6 show some relatively large βs for the age 23-33 group. However the standard errors are large, and examination of other age cutoffs indicates that the drop in $\sum_{k=0}^{q} \lambda^k \beta_k$ occurs quite suddenly as the cutoff increases from 34 to 35. There is some evidence of an increase in $\sum_{k=0}^{q} \lambda^k \beta_k$ for older cohorts as the age cutoff increases, but the increase is neither large nor statistically significant. Overall the case for heterogeneity in the βs over the life cycle is not strong.

Table 7 reports regression estimates for each of the four educational classifications of the male household head; estimation for each classification is done separately employing cohort specific intercepts and a quartic polynomial in age as controls. The poor results for high-school drop-outs stand out most in this table, but the lack of a statistically significant relation may be due to relatively small sample sizes and hence relatively large measurement error in consumption growth for this group (see table 1). The βs for college graduates appear to be more concentrated at longer lags than the βs for other groups, but again the evidence for heterogeneity is not so strong. Overall, the explanatory power of consumption growth for future income growth is fairly uniformly distributed across the groups in our synthetic panel, further evidence of the robustness of the paper's main results.

6 Non-Forward Looking Explanations

6.1 Aggregate Feedback

Table 5 shows that the relation between consumption and future income extends beyond the aggregate business cycle to relative variation, illustrating that the Keynesian feedback effects discussed by Deaton cannot be the whole story behind the empirical results. For such feedback effects to explain the relation in group-specific relative variation, the groups would need to function as at least somewhat autarkic economies, a condition which is clearly not met for cohort-education groups in an integrated modern economy. More generally, the results in table 5 cast doubt on all stories that work primarily through aggregate feedback or aggregate effects, such as correlation of consumption growth with aggregate variables that forecast output growth, including interest rates and stockmarket returns.[22]

6.2 "Gotta Pay the Bills"

One interesting explanation for the empirical results, quite different from the models discussed in sections 2.1-2.4, posits that non-forward-looking consumption changes (caused by random taste shocks, for example) force households to increase their income later to meet the budget constraint; for short, call this the "gotta pay the bills" story. The most obvious means by which households increase their income is by working longer hours, so if "gotta pay the bills" largely explains the empirical results, we may expect the relation between consumption and future income to stem largely from the work hours component of income, and not much from the wage component. To examine this issue, table 8 shows results from estimating several of the same regressions as in table 5, substituting the real after-tax wage of the male household head[23] for total household income.

The coefficients in table 8 are somewhat more more erratic than those in table 5, but broadly speaking the results are similar. For time series fluctuations, the $R^2_{\Delta c}$ indicate that lags of consumption growth pick up at least as much variation in wage growth as in income growth. For the specifications with year effects, the strong relation at longer lags clearly remains, and in fact statistically significant coefficients do not die out even at the seventh lag.[24] Consumption growth contains information about how groups' male wages will differ from aggregate male wages over the business cycle, at horizons from

[22] Given the highly skewed distribution of asset holdings across cohort-eduction groups, we cannot rule out the possibility that such stories may explain some of the across-group relation between consumption and future income. However arguing against the importance of these stories is the available evidence indicating that stock market returns and interest rates do not predict output growth more than about a year in advance, see Eugene F. Fama (1990) and Nai-Fu Chen (1991).

[23] Computed as the annual labor income of the male head divided by his annual work hours, from March CPS data. Tax rates are computed from NBER's TAXSIM program.

[24] Additional lags of consumption growth were not added to the regression because of concerns about dropping more years from the sample.

four to seven years in the future. For more on the relation between consumption and future wage growth, as well as on the relation between wives' leisure and future wage growth, see my dissertation, Nalewaik (2003).

Table 8 indicates that the simplest version of "gotta pay the bills" can at best explain only part of the results in tables 3 and 5. Further, most economists believe that much of the variation used to estimate (1) in those tables, including the aggregate business cycle variation and variation in the returns to education, are caused by shifts in labor demand rather than shifts in labor supply, as quantities and prices covary positively. However other arguments could be made in favor of "gotta pay the bills": hours may be mismeasured, and earners may be able to increase their earnings without increasing work hours, for example by taking more difficult jobs, increasing work effort, and undertaking on-the-job training, all of which would translate into measured wages rather than work hours. It would be interesting to see if corroborating evidence could be marshalled to examine the validity of these more sophisticated "gotta pay the bills" stories. They certainly could be part of the story; it should be noted that the competing explanations of the results are not mutually exclusive. However I believe the evidence favors forward-looking behavior as the greater part of the explanation for this paper's results.

7 Conclusion

It is probably safe to say that very few economists would have predicted the main empirical results observed in this paper; that being the case, the evidence here should provide substantial stimulus to the debate about the extent to which households conform to basic forward-looking models. More importantly, the results open up potentially promising new avenues for future research; for example income could be broken down into its various components - taxes, transfers, the work hours and wages of the male and female household heads. Table 8 started this work, and Nalewaik (2003) goes further down such a path.

More generally, the results in this paper argue for moving beyond traditional Euler equation specifications to examine other implications of basic forward-looking models, such as the implication that consumption should reflect household information about future income. While specifications designed to examine such implications generally employ more assumptions than Euler equation estimates, namely assumptions about the structure of the budget constraint, the additional uncertainty induced by these assumptions can be combat at least in part by a vigorous robustness analysis, including examination of different control variables and types of variation in income growth. Since the specification studied here was specifically designed to exploit households' superior information about their own future income, information that is left out of studies based on Euler equation orthogonality tests, we should at least consider the possibility that the added value of this additional information may swamp the added cost of incorporating some additional auxiliary assumptions into our econometric estimates. The intriguing empirical results in this paper certainly argue that this is the case.

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Appendix A: A Derivation of the Consumption Function

Household h's liquid asset holdings follow: $A_{t+1}^h = (1+r)\left(A_t^h + X_t^h - C_t^h\right)$, where C_t^h the household's level of consumption at time t, A_t^h is asset holdings, r is the (assumed constant) interest rate, and X_t^h is the level of time t exogeneous "labor" income. The present value version of the budget constraint is:

$$\text{(A1)} \qquad A_t^h + \sum_{j=0}^{\infty} \frac{X_{t+j}^h}{(1+r)^j} = W_t^h = \sum_{j=0}^{\infty} \frac{C_{t+j}^h}{(1+r)^j},$$

where we've defined wealth W_t^h in the standard way. Employing log-linearizations, the expected value of this budget constraint (with respect to the information set of the household) can be converted into a decomposition of consumption growth.

Consider first the log-linearization of $W_t^h = \sum_{j=0}^{\infty} \frac{C_{t+j}^h}{(1+r)^j}$. Divide each side by C_t^h and take logs, letting lower case variables denote variables for which logs have been taken:

$$\begin{aligned} c_t^h - w_t^h &= -\ln\left(1 + \frac{1}{(1+r)}\frac{C_{t+1}^h}{C_t^h} + \frac{1}{(1+r)^2}\frac{C_{t+2}^h}{C_t^h} + \ldots\right) \\ &= -\ln\left(1 + \frac{1}{(1+r)}\exp\left(\Delta c_{t+1}^h\right) + \frac{1}{(1+r)^2}\exp\left(\sum_{k=1}^{2}\Delta c_{t+k}^h\right) + \ldots\right) \end{aligned}$$

Take a Taylor series expansion of the expression on the right with respect to the consumption growth rates, around the points of zero growth. This yields:

$$\begin{aligned} \ln\left(1 + \sum_{j=1}^{\infty}\frac{1}{(1+r)^j}\exp\left(\sum_{k=1}^{j}\Delta c_{t+k}^h\right)\right) &\approx \ln\left(\frac{1+r}{r}\right) \\ &\quad + \left(\frac{r}{1+r}\right)\sum_{j=1}^{\infty}\frac{1}{(1+r)^j}\sum_{k=1}^{j}\Delta c_{t+k}^h \\ &= \ln\left(\frac{1+r}{r}\right) + \sum_{j=1}^{\infty}\frac{1}{(1+r)^j}\Delta c_{t+j}^h, \end{aligned}$$

which can be substituted into the previous equation to arrive at:

$$c_t^h \approx w_t^h - \sum_{j=1}^{\infty} \frac{1}{(1+r)^j} \Delta c_{t+j}^h - \left(\frac{1+r}{r}\right). \tag{A2}$$

Next consider the log-linearization of $W_t^h = A_t^h + \sum_{j=0}^{\infty} \frac{X_{t+j}^h}{(1+r)^j}$. In this expression for wealth, labor income is expressed as a discounted sum of future dividends, although it could also have been expressed more compactly as the cum-dividend price of human capital: $X_t^h + \sum_{j=1}^{\infty} \frac{1}{(1+r)^j} X_{t+j}^h = X_t^h + \frac{1}{1+r} H_{t+1}^h = H_t^h$. Asset income is expressed as such a cum-dividend price in the our current expression for wealth; consider breaking it up into a stream of future income flows from liquid assets - i.e. dividends. One way to do this is to write: $A_t^h = D_t^h + \frac{1}{1+r} A_{t+1}^h = D_t^h + \sum_{j=1}^{\infty} \frac{1}{(1+r)^j} D_{t+j}^h$, where the dividend at each time period is $(1 - \frac{1}{1+r}) A_t^h$. Campbell and Mankiw (1989) suggest that the level of liquid assets can be broken up in such a way, and suggest pooling together the income flows from human capital and liquid assets. Write the log of the left hand side of (A1) as:

$$\begin{aligned} w_t^h &= \ln\left(X_t^h + D_t^h + \sum_{j=1}^{\infty} \frac{1}{(1+r)^j} \left(X_{t+j}^h + D_{t+j}^h\right)\right) \\ &= \ln\left(\sum_{j=0}^{\infty} \frac{1}{(1+r)^j} Y_{t+j}^h\right), \end{aligned}$$

where Y_t^h is total "dividend payments" from human capital and non-human capital. Following the same steps as the previous log-linearization yields:

$$w_t^h \approx y_t^h + \sum_{j=1}^{\infty} \frac{1}{(1+r)^j} \Delta y_{t+j}^h + \ln\left(\frac{1+r}{r}\right). \tag{A3}$$

Next take the time t conditional expectation of (A2); this equation and its lead are:

$$c_{t+1}^h \approx E_{t+1}w_{t+1}^h - \sum_{j=1}^{\infty} \frac{1}{(1+r)^j} E_{t+1}\Delta c_{t+1+j}^h - \ln\left(\frac{1+r}{r}\right)$$

$$\text{(A4)} \qquad c_t^h \approx E_t w_t^h - \sum_{j=1}^{\infty} \frac{1}{(1+r)^j} E_t \Delta c_{t+j}^h - \ln\left(\frac{1+r}{r}\right).$$

We'd like to write the expression for c_{t+1}^h as a function of w_t^h. We can do this using the approximate law of motion for wealth derived in Campbell and Mankiw (1989) and Campbell (1993): $w_{t+1}^h = r + k + \left(\frac{1}{\lambda}\right)\left(w_t^h\right) + \left(1 - \frac{1}{\lambda}\right)\left(c_t^h\right)$, where $\lambda = 1 - \overline{C/W}$ is one minus the mean consumption-wealth ratio.[25] Notice that if we take the unconditional mean of the right hand side of (A1), we get $\frac{1}{1+r} = \lambda$. So these are interchangeable; the paper largely employs the λ notation. Use this law of motion to substitute out w_{t+1}^h from the first equation of (A4), then multiply the second equation of (A4) by $\frac{1}{\lambda}$ and add $c_t^h - \frac{c_t^h}{\lambda}$ to both sides. These manipulations yield the two equation system:

$$c_{t+1}^h = \left(\frac{1}{\lambda}\right) E_{t+1}\left(w_t^h\right) + \left(1 - \frac{1}{\lambda}\right)\left(c_t^h\right) - \sum_{j=1}^{\infty} \lambda^j E_{t+1}\left(\Delta c_{t+j+1}^h\right) + \ln(1-\lambda) + r + k$$

$$c_t^h = \left(\frac{1}{\lambda}\right) E_t\left(w_t^h\right) + \left(1 - \frac{1}{\lambda}\right)\left(c_t^h\right) - \left(\frac{1}{\lambda}\right)\sum_{j=1}^{\infty} \lambda^j E_t\left(\Delta c_{t+j}^h\right) + \left(\frac{1}{\lambda}\right)\ln(1-\lambda).$$

Subtracting the first equation from the second, and rearranging using $r + \ln(\lambda) \approx 0$, we have:

$$\Delta c_{t+1}^h \approx E_t \Delta c_{t+1}^h - \sum_{j=1}^{\infty} \lambda^j \left(E_{t+1} - E_t\right) \Delta c_{t+j+1}^h + \left(\frac{1}{\lambda}\right)\left(E_{t+1} - E_t\right) w_t^h.$$

Finally, use (A3) to substitute income growth terms for the innovation in w_t^h. This yields

[25] The constant $k = \ln(\lambda) - \left(1 - \frac{1}{\lambda}\right)\ln(1-\lambda)$.

our decomposition of consumption growth:

$$\begin{aligned} \Delta c_{t+1}^h &= E_t \Delta c_{t+1}^h - \sum_{j=1}^{\infty} \lambda^j \left(E_{t+1} - E_t\right) \Delta c_{t+j+1}^h \\ &\quad + \sum_{j=1}^{\infty} \lambda^{j-1} \left(E_{t+1} - E_t\right) \Delta y_{t+j}^h + \nu_{t+1}^{h,BC}. \end{aligned} \tag{A5}$$

The last term here, $\nu_{t+1}^{h,BC}$, is a summary statistic representing the approximation errors or remainders from taking the first order approximations (A2) and (A3).

If consumption growth is unpredictable, so that conditional expectations of consumption growth are constant, (A5) essentially reduces to (3).[26] To make this unpredictability assumption more concrete, consider a utility function for household h that takes the following standard form:

$$U_t^h = E_t \sum_{j=0}^{\infty} \left(\beta^h\right)^j N_{t+j}^h \frac{\left(C_{t+j}^h\right)^{1-\gamma^h}}{1-\gamma^h},$$

where the N_{t+j}^h are taste shifters that impact the household's utility from consumption, such as household size and possibly leisure. For illustrative purposes, assume that consumption and the taste shifters are jointly log-normal,[27] so we can write (see Hansen and Kenneth J. Singleton (1982)):

$$E_t\left(\Delta c_{t+j}^h\right) = \frac{r-\delta^h}{\gamma^h} + \frac{E_t\left(\Delta n_{t+j}^h\right)}{\gamma^h} + \frac{1}{2\gamma^h} \operatorname{var}_t\left(-\gamma^h \Delta c_{t+j}^h + \Delta n_{t+j}^h\right), \tag{A6}$$

where $-\delta^h = \ln(\beta^h)$. Then a constant conditional expectation of consumption growth amounts to assuming constant conditional expectations for the taste shifters and a con-

[26] Higher order moments of consumption growth and other variables entering the budget constraint (in $\nu_{t+1}^{h,BC}$) must be constant as well for (A5) to reduce to (3).

[27] If the normality condition is not met we can still write a first order approximation to the nonlinear Euler equation similar to (A6), with the conditional variance term replaced by a composite approximation error including all higher order moments.

stant conditional variance for the marginal utility of consumption.

Appendix B: The HRS Derivation of Equation (1), and a Two Dimensional Example

HRS start by constructing the matrix Q, whose first row is $\frac{\rho^h(\lambda)}{|\rho^h(\lambda)|}$, where $|\rho^h(\lambda)| = \sqrt{\rho^h(\lambda)\,\rho^h(\lambda)'}$, and whose $n-1$ other rows are orthonormal vectors orthogonal to $\rho^h(\lambda)$. Then $\rho^h(\lambda)\,Q'$ is a row vector of zeros, except for its first element which is $|\rho^h(\lambda)|$. Define $\varepsilon^+_{t+1} \equiv Q\varepsilon_{t+1}$, and break up ε^+_{t+1} into its first element, $\varepsilon^+_{1,t+1}$, and its following $n-1$ elements, $\varepsilon^+_{2,t+1}$, so $Q\varepsilon_{t+1} = [\varepsilon^+_{1,t+1} \quad \varepsilon^+_{2,t+1}]$. Then since $Q'Q = I_n$ write:

$$\begin{aligned}\Delta c^h_{t+1} &= \rho^h(\lambda)\,\varepsilon_{t+1} \\ &= \rho^h(\lambda)\,Q'Q\varepsilon_{t+1} \\ &= |\rho^h(\lambda)|\varepsilon^+_{1,t+1}.\end{aligned} \tag{B1}$$

$\varepsilon^+_{1,t+1}$ is the one dimension of the consumer's information set revealed to the econometrician by consumption growth; as noted in the text it is a linear combination of elements of ε_{t+1}.

Define $\rho^{h,+}(\mathrm{L}) \equiv \rho^h(\mathrm{L})\,Q'$, and again break up $\rho^{h,+}(\mathrm{L})$ into its first element, $\rho^{h,+}_1(\mathrm{L})$, and the following $n-1$ elements, $\rho^{h,+}_2(\mathrm{L})$, so $\rho^h(\mathrm{L})\,Q' = [\rho^{h,+}_1(\mathrm{L}) \quad \rho^{h,+}_2(\mathrm{L})]$. Then:

$$\begin{aligned}\Delta y^h_{t+1} &= \kappa^h_{t+1} + \rho^h(\mathrm{L})\,\varepsilon_{t+1} \\ &= \kappa^h_{t+1} + \rho^h(\mathrm{L})\,Q'Q\varepsilon_{t+1} \\ &= \kappa^h_{t+1} + \rho^{h,+}_1(\mathrm{L})\,\varepsilon^+_{1,t+1} + \rho^{h,+}_2(\mathrm{L})\,\varepsilon^+_{2,t+1}.\end{aligned} \tag{B2}$$

The polynomial coefficients $\rho^{h,+}_1(\mathrm{L}) = \frac{\rho^h(\lambda)}{|\rho^h(\lambda)|}\rho^h(\mathrm{L})'$ are the moving average coefficients corresponding to $\varepsilon^+_{1,t+1}$.

We can use the expression for consumption growth (B1) to substitute $\varepsilon^+_{1,t+1}$ out of

(B2), yielding:

$$\begin{aligned}\Delta y_{t+1}^{h} &= \frac{\rho_{1}^{h,+}(\mathrm{L})}{|\rho^{h}(\lambda)|}\Delta c_{t+1}^{h} + \kappa_{t+1}^{h} + \rho_{2}^{h,+}(\mathrm{L})\,\varepsilon_{2,t+1}^{+} \\ &= \beta_0 \Delta c_{t+1}^{h} + \beta_1 \Delta c_{t}^{h} + \quad \dots \quad + \beta_q \Delta c_{t+1-q}^{h} + e_{t+1}^{h},\end{aligned}$$

where in the second line we have rewritten the regression coefficients in the notation of equation (1), where $\beta(\mathrm{L}) = \frac{\rho_1^{h,+}(\mathrm{L})}{|\rho^h(\lambda)|} = \frac{\rho^h(\lambda)}{|\rho^h(\lambda)|^2}\rho^h(\mathrm{L})'$. The $\beta(\mathrm{L})$ in (1) are the normalized moving average coefficients corresponding to $\varepsilon_{1,t+1}^{+}$. The other $n-1$ dimensions of household information about income growth end up in the error term: $e_{t+1}^{h} = \kappa_{t+1}^{h} + \rho_{2}^{h,+}(\mathrm{L})\,\varepsilon_{2,t+1}^{+}$.

To clarify this general HRS derivation, we'll work through an example where $n=2$. Assume the income process of the household takes the following form:

$$\begin{aligned}\Delta y_{t+1} &= \varepsilon_{1,t+1} + \phi\varepsilon_{1,t} + \varepsilon_{2,t+1} \\ &= \begin{bmatrix} 1+\phi\mathrm{L} & 1 \end{bmatrix}\begin{bmatrix} \varepsilon_{1,t+1} \\ \varepsilon_{2,t+1} \end{bmatrix},\end{aligned}$$

where we've dropped the h superscripts and ignore the linearly deterministic component of income growth. The innovations are uncorrelated and each has a variance of unity, so $\operatorname{var}\Delta y_{t+1} = 2+\phi^2$. The econometrician would forecast Δy_{t+1} with $R_{MAX}^2 = \frac{\phi^2}{2+\phi^2}$ if the two shocks were separately observeable; this is the maximum possible R^2 attainable in forecasting Δy_{t+1}. Hamilton (1994, Ch. 4) derives the univariate representation of this income process: $\Delta y_{t+1} = \varepsilon_{t+1} + \theta\varepsilon_t$. Not suprisingly, $|\theta| < |\phi|$, and the precision with which the econometrician forecasts Δy_{t+1} deteriorates when only the composite univariate shock process is observed.

For consumption growth, the benchmark model predicts: $\Delta c_{t+1} = (1+\phi\lambda)\,\varepsilon_{1,t+1} +$

$\varepsilon_{2,t+1}$, and it can be verified that a valid Q matrix is:

$$Q = \begin{bmatrix} \frac{1+\phi\lambda}{\sqrt{(1+\phi\lambda)^2+1}} & \frac{1}{\sqrt{(1+\phi\lambda)^2+1}} \\ \frac{-1}{\sqrt{(1+\phi\lambda)^2+1}} & \frac{1+\phi\lambda}{\sqrt{(1+\phi\lambda)^2+1}} \end{bmatrix}.$$

Decomposing the income process as in (B1):

$$\begin{aligned} \Delta y_{t+1} &= \begin{bmatrix} 1+\phi \mathrm{L} & 1 \end{bmatrix} Q'Q \begin{bmatrix} \varepsilon_{1,t+1} \\ \varepsilon_{2,t+1} \end{bmatrix} \\ &= \frac{(1+\phi\lambda)(1+\phi \mathrm{L})+1}{(1+\phi\lambda)^2+1} \left[(1+\phi\lambda)\,\varepsilon_{1,t+1}+\varepsilon_{2,t+1}\right] \\ &\quad + \frac{-(1+\phi \mathrm{L})+(1+\phi\lambda)}{(1+\phi\lambda)^2+1} \left[-\varepsilon_{1,t+1}+(1+\phi\lambda)\,\varepsilon_{2,t+1}\right]. \end{aligned}$$

Use Δc_{t+1} to substitute $(1+\phi\lambda)\,\varepsilon_{1,t+1}+\varepsilon_{2,t+1}$ out of this equation; after some rearrangements and simplifications, we have:

$$\begin{aligned} \Delta y_{t+1} &= \frac{(2+\phi\lambda)}{(1+\phi\lambda)^2+1}\Delta c_{t+1} + \frac{\phi\,(1+\phi\lambda)}{(1+\phi\lambda)^2+1}\Delta c_t \\ &\quad + \frac{\phi^2\lambda^2}{(1+\phi\lambda)^2+1}\left(1-\frac{1}{\lambda}\mathrm{L}\right)\left[\varepsilon_{1,t+1}+\varepsilon_{2,t+1}\right], \end{aligned}$$

where it can be verified that $\beta(\lambda)=1$. The fraction of variance of Δy_{t+1} captured by consumption growth lagged one period, Δc_t, can be written as $R^2_{\Delta c_t} = \left(\frac{(1+\phi\lambda)^2}{(1+\phi\lambda)^2+1}\right)\frac{\phi^2}{2+\phi^2}$, and is strictly less than R^2_{MAX}.[28] This is sensible: Δc_t is a weighted average of two shocks, one white noise, and the part of Δc_t reflecting this shock will contribute nothing towards predicting Δy_{t+1}. The residual from a regression of Δy_{t+1} on $(\Delta c_{t+1}, \Delta c_t)$ is itself partially predictable. Write this residual, $\rho_2^+(\mathrm{L})\,\varepsilon^+_{2,t+1}$, in its invertible representation

[28] For $\phi > 0$, Δc_t has more explanatory power for Δy_{t+1} than does the history of the univariate representation of Δy_{t+1}. For $\phi < 0$, the history of the univariate reprentation of Δy_{t+1} has more explanatory power than Δc_t.

(see Hamilton, 1994, Ch. 3):

$$\rho_2^+ (\mathrm{L})\, \varepsilon_{2,t+1}^+ = \frac{\phi^2 \lambda^2}{(1+\phi\lambda)^2 + 1} \left(\frac{1}{\lambda}\right) (1 - \lambda \mathrm{L})\, \varepsilon_{t+1},$$

where we now let ε_{t+1} denote $\varepsilon_{1,t+1} + \varepsilon_{2,t+1}$. One thing to notice is that the regressors $(\Delta c_{t+1}, \Delta c_t)$ draw out of the income process all of its persistence, leaving behind only transitory variation in levels. In the more general n-dimensional case, the variation left behind in $\rho_2^+ (\mathrm{L})\, \varepsilon_{2,t+1}^+$ will exhibit less persistence than the variation in the income process as a whole; empirical results bear out this implication.

Appendix C: Standard Errors for the Weighted Least Squares Estimator

Let $N\overline{T} = \sum_{j=1}^{N} T_j$ denote the total sample size where j indexes synthetic persons and T_j denotes the number of annual observations for synthetic individual j; let $\mathbf{X}$ denote the $N\overline{T} \times K$ matrix of regressors; let $\boldsymbol{\Omega}$ represent the $N\overline{T} \times N\overline{T}$ variance-covariance matrix of regression residuals; finally let $\mathbf{W}$ denote the $N\overline{T} \times N\overline{T}$ diagonal matrix with the vector of weights on the diagonal.[29] Then, following standard practice, the variance-covariance matrix of the OLS parameter estimates is computed as:

$$(\mathbf{X'WX})^{-\mathbf{1}}\mathbf{X'W\Omega WX}(\mathbf{X'WX})^{-\mathbf{1}}.$$

$\mathbf{X'W\Omega WX}$ is the sum of two additive components. The first component (which we shall call $\mathbf{X'W\Omega_0 WX}$) is robust to both arbitrary heteroskedasticity and cross correla-

[29]The weights in this paper are the square root of the average of the synthetic cohort cell counts of the cells used to produce the explanatory consumption variables - i.e. in regression specification (1) if $w_{i,t+1}$ is the weight on the ith synthetic person at time $t+1$ and $f_{i,t+1}$ is the number of households in the sample at time $t+1$ who meet the qualifications to belong to the ith synthetic cohort, we have $w_{i,t+1} = \sqrt{\frac{\sum_{k=0}^{q+1} f_{i,t+1-k}}{q+2}}$.

tion. The matrix can be represented as:

$$\mathbf{X'W\Omega_0WX} = \sum_{i=1}^{N}\sum_{j=1}^{N}\sum_{t=1}^{T_{ij}}(x'_{i,t}w_{i,t}u_{i,t}u_{j,t}w_{j,t}x_{j,t} + x'_{j,t}w_{j,t}u_{j,t}u_{i,t}w_{i,t}x_{i,t}),$$

where T_{ij} is the number of periods where there is an observation for both i and j, $w_{i,t}$ is the weight for the tth observation on the ith synthetic person, and $x_{i,t}$ corresponds to the appropriate row vector of $\mathbf{X}$. Rearranging summations yields the convenient expression for computing this matrix used in this paper:

$$\begin{aligned}\mathbf{X'W\Omega_0WX} &= \sum_{t=1}^{T}\sum_{i=1}^{N_t}\sum_{j=1}^{N_t}(x'_{i,t}w_{i,t}u_{i,t}u_{j,t}w_{j,t}x_{j,t} + x'_{j,t}w_{j,t}u_{j,t}u_{i,t}w_{i,t}x_{i,t}) \\ &= \sum_{t=1}^{T}\mathbf{X'_tW_t\Omega_{0,t}W_tX_t}.\end{aligned}$$

Here N_t denotes the number of cross sectional observations in year t, and $\mathbf{X_t}$ denotes the N_t rows of $\mathbf{X}$ that correspond to the year t cross sectional observations. Similarly, $\mathbf{\Omega_{0,t}}$ denotes the matrix $\mathbf{u_tu'_t}$, the outer product of the vector of time t regression residuals, and $\mathbf{W_t}$ denotes the diagonal weighting matrix for time t observations. The last expression makes clear that, after sorting the data by year, the cross-correlation corrected variance-covariance matrix of residuals will be block diagonal (ignoring any autocorrelation for the moment), with each each block corresponding to a year. This variance-covariance matrix has the same form as those used in clustered samples to correct for arbitrary within-cluster correlations (see Deaton (1997), p.76), the only difference being that each year plays the role of a cluster.

A second component of the estimated matrix $\mathbf{X'W\Omega WX}$ corrects for autocorrelation as suggested by Whitney K. Newey and Kenneth D. West (1987):

$$\mathbf{X'W\Omega_k WX} = \sum_{k=1}^{k'} \left(\frac{k'+1-k}{k'+1} \right) \sum_{j=1}^{N} \sum_{t=1+k}^{T_j} \left(\begin{array}{c} x'_{j,t} w_{j,t} u_{j,t} u_{j,t-k} w_{j,t-k} x_{j,t-k} \\ +x'_{j,t-k} w_{j,t-k} u_{j,t-k} u_{j,t} w_{j,t} x_{j,t} \end{array} \right).$$

In this paper k' is set to seven, so the matrix corrects for seventh order autocorrelation. The full $\mathbf{X'W\Omega WX}$ is then computed as:

$$\mathbf{X'W\Omega WX} = \mathbf{X'W\Omega_0 WX} + \mathbf{X'W\Omega_k WX}.$$

Table 1: Cell Count Summary Statistics
Number of Households per Cell

Variable	Data Source	Min	Means by Education				Max
			< 12	12	$13-15$	> 16	
Income	CPS	289	638	1401	995	1183	2120
Consumption	CEX	26	56	121	106	130	269

Notes to Table 1: Summary statistics on the number of households in each of the 524 group-year cells (i.e each of the 524 synthetic panel observations). Each CEX household is assigned to a unique year to avoid double counting, although its monthly consumption data may span two years.

Table 2: Summary Statistics

Variable	Data Source	Standard Deviation	Autocorrelations 1	2	3	4	5	6	7
Δy	CPS	**0.035**	**-0.11**	**-0.02**	**-0.05**	**-0.09**	**-0.14**	**-0.21**	**-0.19**
			(0.09)	(0.07)	(0.08)	(0.06)	(0.08)	(0.08)	(0.08)
Δc	CEX	**0.054**	**-0.34**	**-0.11**	**-0.05**	**0.06**	**-0.03**	**-0.09**	**0.09**
			(0.04)	(0.06)	(0.05)	(0.05)	(0.05)	(0.06)	(0.08)

Notes to Table 2: Standard deviations are computed weighting each observation by the average cell counts of the two observations used to compute each growth rate. Autocorrelations are computed by weighted least squares, where the weights are the average cell counts of the explanatory variables. Asymptotic standard errors are in parentheses; details of their computation are in Appendix A. Control variables are quartic age polynomials and birth cohort fixed effects, both interacted with education fixed effects.

Table 3:

Panel A: Estimates of $\Delta y_t = \beta_0 \Delta c_t + \beta_1 \Delta c_{t-1} + \quad \ldots \quad + \beta_q \Delta c_{t-q} + e_t$

q	β_0	β_1	β_2	β_3	β_4	β_5	β_6	R^2	obs
0	**0.17**							0.07	
	(0.04)								484
1	**0.16**	**0.12**						0.07	
	(0.04)	(0.03)							444
2	**0.13**	**0.12**	**0.16**					0.11	
	(0.04)	(0.03)	(0.03)						408
3	**0.13**	**0.14**	**0.18**	**0.12**				0.15	
	(0.04)	(0.03)	(0.04)	(0.03)					372
4	**0.10**	**0.13**	**0.19**	**0.14**	**0.09**			0.16	
	(0.04)	(0.03)	(0.04)	(0.03)	(0.03)				336
5	**0.06**	**0.09**	**0.18**	**0.16**	**0.13**	**0.12**		0.18	
	(0.04)	(0.04)	(0.04)	(0.03)	(0.05)	(0.04)			300
6	**0.08**	**0.07**	**0.16**	**0.15**	**0.16**	**0.14**	**0.04**	0.17	
	(0.05)	(0.04)	(0.04)	(0.03)	(0.05)	(0.04)	(0.05)		268
6			**0.14**	**0.16**	**0.18**	**0.16**	**0.06**	0.16	
			(0.04)	(0.03)	(0.05)	(0.04)	(0.05)		268

Panel B: Univariate Estimates of $\Delta y_t = \beta_k \Delta c_{t-k} + e_t$

	β_0	β_1	β_2	β_3	β_4	β_5	β_6
β	**0.09**	**0.05**	**0.13**	**0.10**	**0.12**	**0.13**	**0.06**
	(0.04)	(0.03)	(0.04)	(0.04)	(0.06)	(0.04)	(0.04)
R^2	**0.02**	**0.00**	**0.04**	**0.02**	**0.03**	**0.03**	**0.01**

Table 4:

Panel A: Estimates of $\Delta c_t = \beta_0 \Delta y_t + \beta_1 \Delta y_{t-1} + \quad \ldots \quad + \beta_q \Delta y_{t-q} + e_t$

q	β_0	β_1	β_2	β_3	β_4	β_5	β_6	β_7	R^2	obs
0	**0.40**								0.07	
	(0.09)									484
1	**0.26**	**0.35**							0.10	
	(0.07)	(0.06)								444
2	**0.23**	**0.36**	**0.02**						0.09	
	(0.07)	(0.08)	(0.07)							408
3	**0.24**	**0.35**	**0.01**	**0.01**					0.08	
	(0.07)	(0.09)	(0.09)	(0.07)						372
4	**0.20**	**0.31**	**0.03**	**0.01**	**0.11**				0.07	
	(0.08)	(0.10)	(0.09)	(0.09)	(0.10)					336
5	**0.18**	**0.28**	**0.02**	**-0.03**	**0.10**	**0.07**			0.06	
	(0.08)	(0.11)	(0.09)	(0.10)	(0.11)	(0.11)				300
6	**0.21**	**0.28**	**0.05**	**-0.06**	**0.01**	**-0.06**	**0.22**		0.07	
	(0.09)	(0.11)	(0.09)	(0.10)	(0.15)	(0.11)	(0.10)			268
7	**0.20**	**0.26**	**0.09**	**-0.08**	**0.03**	**-0.07**	**0.22**	**0.02**	0.07	
	(0.11)	(0.12)	(0.09)	(0.10)	(0.17)	(0.15)	(0.13)	(0.17)		240

Panel B: Univariate Estimates of $\Delta c_t = \beta_k \Delta y_{t-k} + e_t$

	β_0	β_1	β_2	β_3	β_4	β_5	β_6	β_7
β	**0.20**	**0.24**	**0.13**	**-0.02**	**0.09**	**-0.02**	**0.20**	**0.01**
	(0.12)	(0.12)	(0.10)	(0.08)	(0.13)	(0.14)	(0.12)	(0.16)
R^2	**0.02**	**0.02**	**0.01**	**0.00**	**0.00**	**0.00**	**0.01**	**0.00**

Notes to Tables 3 and 4: Annual synthetic panel data grouped by 5-year birth cohort and a 4-way educational classification, 1980-1999; 36 synthetic individuals, 524 observations before differencing and lagging. The Δy_{t-k} terms are income growth computed from the CPS; the Δc_{t-k} terms are consumption growth computed from the CEX. The regressions are weighted by the average cell counts of the explanatory variables. Asymptotic standard errors are in parentheses; details of their computation are in Appendix A.

Table 5: Estimates of $\Delta y_t = \beta_0 \Delta c_t + \beta_1 \Delta c_{t-1} + \quad \dots \quad + \beta_q \Delta c_{t-q} + \textbf{controls} + e_t$

Controls for:	β_0	β_1	β_2	β_3	β_4	β_5	β_6	β_7	$\sum_{k=0}^{q} \lambda^k \beta_k$	Implied r	$R^2_{\Delta c}$
	0.08	**0.07**	**0.16**	**0.15**	**0.16**	**0.14**	**0.04**		**0.75**	**-0.07**	0.17
	(0.05)	(0.04)	(0.04)	(0.03)	(0.05)	(0.04)	(0.05)		(0.05)	(0.02)	
Age, Cohorts	**0.09**	**0.12**	**0.22**	**0.21**	**0.22**	**0.18**	**0.08**		**1.05**	**0.04**	0.07
	(0.06)	(0.06)	(0.05)	(0.06)	(0.06)	(0.06)	(0.06)		(0.25)	(0.08)	
Years	**0.02**	**0.02**	**0.09**	**0.09**	**0.15**	**0.20**	**0.15**	**0.03**	**0.67**	**-0.07**	0.18
	(0.05)	(0.04)	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.07)	(0.02)	
Age, Cohorts, Years	**-0.00**	**0.01**	**0.11**	**0.12**	**0.20**	**0.25**	**0.16**	**0.02**	**0.79**	**-0.03**	0.07
	(0.06)	(0.06)	(0.05)	(0.02)	(0.06)	(0.04)	(0.03)	(0.05)	(0.18)	(0.05)	
Δy^{CPS}_{t-k}	**0.11**	**0.14**	**0.23**	**0.26**	**0.31**	**0.31**	**0.23**	**0.05**	**1.50**	**0.16**	0.29
	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)	(0.05)	(0.05)	(0.04)	(0.15)	(0.04)	
Δy^{CPS}_{t-k}, Age, Cohorts	**0.09**	**0.15**	**0.28**	**0.34**	**0.42**	**0.43**	**0.30**	**0.08**	**1.91**	**0.24**	0.20
	(0.04)	(0.05)	(0.04)	(0.05)	(0.05)	(0.07)	(0.06)	(0.05)	(0.17)	(0.04)	

Notes to Tables 5: Annual synthetic panel data grouped by 5-year birth cohort and a 4-way educational classification, 1980-1999; 36 synthetic individuals, 524 observations before differencing and lagging. The dependent variable Δy_t is income growth computed from the CPS. The explanatory variables Δc_{t-k} are consumption growth computed from the CEX. The controls for age are quartic age polynomials interacted with education fixed effects. The controls for cohorts are a set of 5-year birth cohort fixed effects interacted with education fixed effects. The controls for years are a set of year fixed effects. The controls Δy_{t-k}^{CPS} are q lags of income growth computed from the CPS.

The regressions are weighted by the average cell counts of the explanatory consumption growth variables. Asymptotic standard errors are in parentheses; details of their computation are in Appendix A.

In computing the discounted sum of the regression coefficients $\sum_{k=0}^{q} \lambda^k \beta_k$, $\lambda = \frac{1}{1+r}$ is set to $\frac{1}{1.025}$. The implied r is the value of r for which the discounted sum of the regression coefficients sums to one. $R^2_{\Delta c}$ is fraction of variance the dependent variable explained by consumption growth, after orthogonalizing the data with respect to the control variables.

Table 6:

Estimates of $\Delta y_t = \beta_0 \Delta c_t + \beta_1 \Delta c_{t-1} + \quad \ldots \quad + \beta_q \Delta c_{t-q} +$ **controls** $+ e_t$,

with Age Heterogeneity

Cutoff	β_0	β_1	β_2	β_3	β_4	β_5	β_6	$\sum_k \lambda^k \beta_k$
Age $\leq$ 33	**0.48**	**0.29**	**0.37**	**0.33**	**0.28**	**0.18**	**0.11**	**1.93**
	(0.18)	(0.16)	(0.12)	(0.09)	(0.13)	(0.09)	(0.08)	(0.64)
Age $\leq$ 38	**0.22**	**0.08**	**0.19**	**0.13**	**0.10**	**0.11**	**0.09**	**0.88**
	(0.09)	(0.06)	(0.08)	(0.07)	(0.05)	(0.07)	(0.06)	(0.29)
Age $\leq$ 43	**0.14**	**0.17**	**0.25**	**0.22**	**0.15**	**0.13**	**0.07**	**1.05**
	(0.08)	(0.06)	(0.07)	(0.06)	(0.07)	(0.06)	(0.06)	(0.22)
Age $>$ 33	**0.07**	**0.11**	**0.20**	**0.20**	**0.24**	**0.21**	**0.07**	**1.01**
	(0.06)	(0.06)	(0.06)	(0.06)	(0.08)	(0.07)	(0.07)	(0.27)
Age $>$ 38	**0.03**	**0.09**	**0.20**	**0.24**	**0.31**	**0.25**	**0.05**	**1.09**
	(0.06)	(0.07)	(0.06)	(0.05)	(0.09)	(0.06)	(0.08)	(0.24)
Age $>$ 43	**0.05**	**0.05**	**0.22**	**0.19**	**0.41**	**0.37**	**0.13**	**1.30**
	(0.09)	(0.09)	(0.08)	(0.10)	(0.09)	(0.08)	(0.10)	(0.43)

Table 7:

Estimates of $\Delta y_t = \beta_0 \Delta c_t + \beta_1 \Delta c_{t-1} + \quad \ldots \quad + \beta_q \Delta c_{t-q} +$ **controls** $+ e_t$,

with Education Heterogeneity

Yrs of School	β_0	β_1	β_2	β_3	β_4	β_5	β_6	$\sum_k \lambda^k \beta_k$
Less than 12	**0.09**	**0.09**	**0.14**	**0.08**	**-0.11**	**0.08**	**-0.02**	**0.33**
	(0.09)	(0.08)	(0.09)	(0.13)	(0.17)	(0.12)	(0.13)	(0.55)
12	**0.04**	**0.08**	**0.33**	**0.25**	**0.23**	**0.14**	**0.12**	**1.10**
	(0.11)	(0.12)	(0.10)	(0.09)	(0.10)	(0.09)	(0.08)	(0.36)
13-15	**0.18**	**0.18**	**0.19**	**0.21**	**0.29**	**0.18**	**0.11**	**1.25**
	(0.08)	(0.11)	(0.07)	(0.06)	(0.11)	(0.08)	(0.07)	(0.28)
16 or More	**0.03**	**0.02**	**0.09**	**0.20**	**0.36**	**0.28**	**0.06**	**0.94**
	(0.12)	(0.11)	(0.09)	(0.10)	(0.10)	(0.06)	(0.10)	(0.37)

Notes to Tables 6 and 7: Annual synthetic panel data grouped by 5-year birth cohort and a 4-way educational classification, 1980-1999; 36 synthetic individuals, 524 observations before differencing and lagging. The Δy_t terms are income growth computed from the CPS; the explanatory variables Δc_{t-k} are consumption growth computed from the CEX. In computing the sum of the regression coefficients, $\lambda = \frac{1}{1+r}$ is set to $\frac{1}{1.025}$. Observations are weighted by the average cell counts of the explanatory consumption growth variables. Asymptotic standard errors are in parentheses; details of their computation are in Appendix A.

Table 6 reports six sets of regression coefficients from three regression specifications with varying age cutoff values. A five year birth cohort is assigned the age of its middle-aged members, and for a given age cutoff (either 33, 38, or 43), two sets of consumption growth terms are included in the regression: one interacted with dummies for whether the cohort was younger than the cutoff at the time of the consumption growth, and another interacted with dummies for whether the cohort was older. Controls are quartic age polynomials and birth cohort fixed effects interacted with education fixed effects.

In table 7, the estimation is done separately for each education group, with a quartic age polynomial and birth cohort fixed effects.

Table 8: **Estimates of** $\Delta w_t = \beta_0 \Delta c_t + \beta_1 \Delta c_{t-1} + \quad \ldots \quad + \beta_q \Delta c_{t-q} + \textbf{controls} + e_t$

Controls for:	β_0	β_1	β_2	β_3	β_4	β_5	β_6	β_7	$R^2_{\Delta c}$
	-0.01	**0.10**	**0.14**	**0.15**	**0.14**	**0.05**	**-0.00**		0.14
	(0.04)	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)	(0.06)		
Age, Cohorts	**0.07**	**0.22**	**0.27**	**0.26**	**0.22**	**0.08**	**0.03**		0.13
	(0.05)	(0.05)	(0.07)	(0.07)	(0.05)	(0.06)	(0.05)		
Years	**-0.00**	**0.06**	**0.03**	**0.00**	**0.08**	**0.08**	**0.14**	**0.07**	0.15
	(0.03)	(0.03)	(0.03)	(0.04)	(0.03)	(0.03)	(0.04)	(0.03)	
Age, Cohorts, Years	**0.00**	**0.08**	**0.07**	**0.05**	**0.14**	**0.13**	**0.17**	**0.07**	0.07
	(0.04)	(0.03)	(0.03)	(0.03)	(0.05)	(0.05)	(0.06)	(0.03)	

Notes to Table 8: Annual synthetic panel data grouped by 5-year birth cohort and a 4-way educational classification, 1980-1999; 36 synthetic individuals, 524 observations before differencing and lagging. The dependent variable Δw_t is the wage growth of male household heads, computed from the CPS. The explanatory variables Δc_{t-k} are consumption growth computed from the CEX. The controls for age are quartic age polynomials interacted with education fixed effects. The controls for cohorts are a set of 5-year birth cohort fixed effects interacted with education fixed effects. The controls for years are a set of year fixed effects.

The regressions are weighted by the average cell counts of the explanatory consumption growth variables. Asymptotic standard errors are in parentheses; details of their computation are in Appendix A.

In computing the discounted sum of the regression coefficients $\sum_{k=0}^{q} \lambda^k \beta_k$, $\lambda = \frac{1}{1+r}$ is set to $\frac{1}{1.025}$. The implied r is the value of r for which the discounted sum of the regression coefficients sums to one. $R^2_{\Delta c}$ is fraction of variance the dependent variable explained by consumption growth, after orthogonalizing the data with respect to the control variables.

Figure 1: Life Cycle Log Income (solid) and Log Consumption (dashed) Profiles, by Education of Male Household Head