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Abstract

We document systematic and significant time variation in US lifecycle non-durable consumption profiles. Consumption profiles have consistently become flatter: differences in consumption across generations have decreased. Pooling data across different periods to identify lifecycle profiles masks relevant time variations and may artificially generate hump-shaped consumption age profiles. The main driver behind lifecycle consumption variations are lifecycle income changes, which display similar flattening. Employing a lifecycle model we show changes in income are sufficient to match the movements in consumption. The contributions of credit, housing and interest rates changes are quantitatively small.

Key Words: Age Profile of Consumption, Age Profile of Income, Consumption Heterogeneity, Time Variation, Pooling

JEL Classification Codes: E21, J11

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1 Introduction

The lifecycle profile of consumption, defined as the curve that depicts the level of consumption across ages, has been studied in the seminal paper of Deaton and Paxson (1994) and more recently by Fernandez-Villaverde and Krueger (2007) and Aguiar and Hurst (2013). The consensus view is that consumption expenditures are hump-shaped and peak around the age of 55 and fall at the later part of the lifecycle.

While analysing lifecycle consumption patterns, a commonly made implicit assumption is that across time (waves) households of the same age behave in an identical fashion and face identical age specific structural economic conditions . Data is thus pooled across time in order to identify the lifecycle profile of consumption. This approach may be misleading. Given changes in macroeconomic and microeconomic conditions, in the technological environment and mode of production, in demographic structures and in the evolution of asset prices and income, the consumption decisions of 35 years old households in 1999 and in 2015 are bound to be different. Hence, we relax this assumption and investigate whether lifecycle consumption profiles are time varying.

We study consumption expenditures using a longitudinal panel of US households for the period 1998-2014 that allows us to determine the age effects after controlling for household characteristics and fixed effects. First by pooling all the data and ignoring age-time variation we confirm non-durable consumption expenditures display lifecycle properties and are hump-shaped in line with the literature (e.g. Deaton and Paxson (1994) and Aguiar and Hurst (2013)). We then allow for age and time interactions and document that there are systematic and significant time variations in lifecycle consumption expenditures of households in the US in the sample period we study (1998-2014). We show that differences between consumption expenditures across age groups have declined and lifecycle consumption profiles became flatter over time. Our findings also suggest that in the aftermath of the Global Financial Crisis lifecycle consumption profiles became downward sloping in age groups. These results are robust with respect to longer longitudinal data covering the period 1980-2014, altering the size of age groups (necessary to identify age effects when time and age fixed effects are included), education levels, inclusion of household level economic controls (income and housing wealth), exclusion of households who do not own a house, and different ways of adjusting for family size. Thus, we find that pooling data across different periods to identify consumption profiles masks significant and economically relevant time variation and may artificially generate the well known hump-shaped lifecycle consumption profiles.

Aguiar and Hurst (2013), using pooled data from the Consumer Expenditures Survey (CEX) for the period of 1980-2003, study the lifecycle consumption of different expenditure categories and find that work-related consumption expenditures, such as clothing, transportation and food away from home decline as households get older, driving the hump-shaped nature of consumption profiles. We observe a flattening of lifecycle consumption profiles in almost all sub-categories in our sample, including work-related categories, such as transportation and food-away, suggesting our conclusions extend to consumption sub-categories.

The key intuition motivating our analysis is that, when studying lifecycle consumption, agents of the same age at different points in time should not be treated as homogeneous and, as a consequence, should not be pooled together. That is subtly distinct from taking into account cohort effects only. In fact, our results are robust to the inclusion of the households' birth year as an additional control, confirming constant cohort effects are not driving our results. We document that with the systematic flattening of lifecycle consumption profiles the difference of consumption across cohorts decreases through time. The appropriate interpretation therefore is not that we identify constant cohort effects but rather that the relative consumption levels across cohorts are time varying.

What might be behind this time variation in the consumption profiles we uncover? Fernandez-Villaverde and Krueger (2011) and Berger, Guerrieri, Lorenzoni, and Vavra (2018) stress the importance of housing in shaping consumption in the lifecycle and indeed since the early 2000's there are clear dynamic co-movements between US aggregate consumption expenditures and

Case-Shiller National Home Price Index. By interacting age-specific effects with subjective house values we attempted to investigate whether housing wealth may be driving variation in lifecycle consumption and find it not to be the case. Although changes in subjective housing wealth affect consumption, particularly for older households, controlling for it does not alter the flattening we observe.

Ever since the work of Keynes (1936), Modigliani and Brumberg (1954) and Friedman (1957) it has been well established that consumption is a function of permanent income and therefore changes in income are the natural potential drivers of lifecycle consumption variations. After controlling the age-specific component that depends on the lifecycle income, we find that consumption profiles are no longer flattening. Higher income in the lifecycle has become strongly associated with higher consumption levels. To confirm the relevance of time variation in income profiles as the driver of our results, we extract the age-specific profiles of income following the same procedure as the one applied to consumption. We find very similar patterns of time variation in income to the one we observe for consumption: income lifecycle profiles have also become systematically flatter. These results do not imply that 35 year old households today are relatively better off than 35 year old households in the 1990s, rather, the results indicate that at each fixed point in time throughout the period we study, the intergenerational consumption and income differences have decreased in both income and consumption.

Finally, we provide a theoretical justification to our empirical findings. By employing a lifecycle model with consumption, housing and liquid assets choices, and feeding the estimated changes in the age profile of income, we find that variations in lifecycle income are sufficient to generate the observed changes in consumption profiles, confirming our suggestive evidence that income is driving the systematic changes in the age profiles of consumption. We find that incorporating higher volume of credit and house price changes do not significantly affect consumption profiles. However, only after incorporating the changes in credit markets and the dynamics of house prices observed from 1998 onwards the match between the theoretical lifecycle patterns of asset holdings (housing and non-housing wealth) and the one observed in the data improves.

The remainder of the paper is organised as follows. Data, the econometric methodology and results are presented in Section 2. In Section 2.2 we present our benchmark Time-varying Lifecycle results, and Section 2.3 investigates whether subjective house valuation and income are behind the variation in lifecycle consumption profiles we observe. The theoretical model is discussed in Section 3. Finally, Section 4 concludes.

2 Empirical Evidence

We study consumption expenditure using a longitudinal panel of US households that allows us to determine the age effects after controlling for household characteristics, fixed effects, income and perceived housing wealth. We then consider whether age effects depend on housing wealth and income. We start by presenting the data, then discuss the methodology and main empirical results.

2.1 Data

Data are from the nationally representative longitudinal US household survey, the Panel Study for Income Dynamics (PSID).[1] The survey was conducted annually from 1968 to 1997[2] and biannually thereafter. It contains detailed information on household employment, income, consumption, assets and various household characteristics such as health status and social behaviour of around 5000 households (about 18,000 individuals) and their descendants with

[1]An alternative data set is the CEX. In general, this is considered the gold standard of consumption data in the US. The PSID is selected over the CEX because of its longitudinal structure. This allows us to control for unobserved household effects which is not possible in the CEX. Also, we capitalise on the expanded consumption questions introduced in the PSID in 1999. With this, the consumption in the PSID covers 70% of the consumption measured in the CEX (cite).

[2]Each wave of the survey asks households about the previous year's expenditures. We follow convention by labelling each wave, t as time period $t-1$. This means that information gathered in the 2003 wave will be labelled in the data set as 2002.

the addition of new households to maintain a nationally representative sample.[3]

Non-durable consumption expenditures, $C_{i,t}$, is defined as the sum of imputed rent, house insurance, utilities, non-durable vehicle costs, childcare, education costs, health insurance, non-durable transport costs such as parking, cabs and public transport, medical expenses, food at home, food away from home and the cash value of food stamps.[4]

The benchmark sample, using data from 1998 up until 2014, capitalises on the expanded non-durable consumption questions introduced in 1999 (data labelled 1998). This additional information, listed above, is used to construct a full measure of non-durable consumption. We have 42,720 observations. The average length of household participation in the survey in this data set is 6.722 waves, with a maximum of 9 waves (40.45 percent) and a minimum of one wave (3.3 percent). About 66.28% of households in the sample are homeowners. For robustness we repeat our analysis over a longer time period 1980 to 2014 based on imputed data as in Attanasio and Pistaferri (2014). We also report robustness analysis based on different methods of deflating the consumption data as in Aguiar and Hurst (2013) and how best to adjust for household size and composition. (see Section 2.2.1)

In some specifications we include a measure of total family income. The PSID includes a number of measures of income and earnings. We define total family money income $Y_{i,t}$ as the sum of taxable family income, family transfers and social security benefits. Taxable family money income is the sum of the head's asset income (dividends, interest, rental income and asset income from farm business), the spouse's asset income, and head and spouse labour income. Family transfer income consists of transfer income for family members other than husband and wife and aid to dependent children. All income measures are deflated and scaled following the

[3] For a full explanation of sample selection see A.

[4] As is standard in the literature, these expenditures act as a proxy for consumption. In fact, it underestimates the true amount by not accounting for consumption of leisure, home production and durable goods but assumes separable utility between these groups. Estimating the age profile over different categories; total consumption expenditures, non-durables and durables all yield the hump shape over the lifecycle. (Fernandez-Villaverde and Krueger (2007)). The issue of defining durables and non-durable goods. Mankiw (1982) points out that durables and non-durables differ only in their rate of depreciation and that some non-durables, for example, clothing, are partly durable. So if the weight of durability relates to the type of consumption then the mix matters. Also, simply removing perceived durables is not sufficient to exclude durability altogether.

same procedure adopted for consumption. (See the B for details.)

Figure 1 displays unconditional (log) non-durable consumption expenditures and income for all households and for homeowners sorted by all ages pooled over the sample period 1998-2014 similar to the ones presented in Aguiar and Hurst (2013). We observe a clear hump-shaped profile in both consumption expenditures and income peaking roughly around the age of 55. Given our interest in the effect of housing wealth in influencing lifecycle patterns we also plot the income and consumption profile for homeowners. While homeowners do have a higher income than the overall population and their consumption expenditures are uniformly higher, consumption expenditures display similar statistical properties over the lifecycle as the overall population sample.

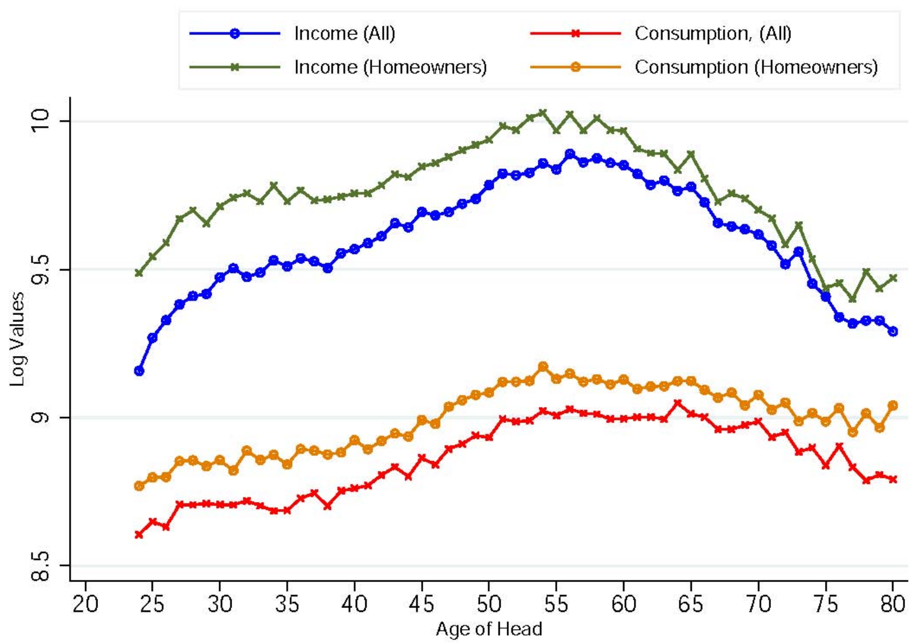


Figure 1: Unconditional Consumption Expenditures and Income by Age

Finally, in some specifications we include a measure of subjective housing wealth. Our preferred subjective home value proxy is based on the responses of homeowners to a question in the PSID survey and reported in housing, mortgage distress and wealth data. Specifically homeowners are asked:

'A20. Could you tell me what the present value of (your/their) (apartment/mobile home/house) is (including the value of the lot if (you/they) own the lot)–I mean about how much would it bring if (you/they) sold it today?'

The question offers an insight into subjective expectations of households about their perceived wealth over a 50 year time period. Household responses to this question define our subjective variable $H_{i,t}$=Subjective Current Home Value. The average values of $H_{i,t}$ in our sample are strongly correlated (0.96) with the Case-Shiller House Price Index (see the Appendix for detail).

2.2 Lifecycle Consumption Profiles

Our empirical model leverages the panel dimension of the dataset postulating that the log of non-durable consumption expenditure $c_{i,t}$ for household $i = 1, ..., N$ at time $t = 1998, ..., 2014$ depends on a households fixed effect α_i, on a set of time-varying household characteristics[5] $Z_{i,t}$, time fixed effects, $D^{Time}_{i,t}$, capturing time trends or the business cycle effects for all ages, and finally, on age effects described by a group of dummies denoted $Age_{i,g,t}$, to capture lifecycle patterns. Additional controls for cohorts (birth year of the household head) do not alter our results and thus in the benchmark we select a more parsimonious specification without year of birth effects. Formally, the benchmark fixed effects specification is

$$
\begin{aligned}
c_{i,t} &= \alpha_i + \beta_{g,t} Age_{i,g,t} + \delta_t D^{Time}_{i,t} + \psi_Z Z_{i,t} + \epsilon_{i,t} \qquad (1)\\
Age_{i,g,t} &= \begin{cases} D^{Age}_{i,g} & \text{Case 1 - \textit{Pooled Lifecycle}} \\ D^{Age}_{i,g} \times D^{Time}_{i,t} & \text{Case 2 - \textit{Time-varying Lifecycle}} \end{cases}
\end{aligned}
$$

We consider two configurations for the age dependent control. In the first, denoted *Pooled Lifecycle*, and in line with the literature (e.g. Aguiar and Hurst (2013)), we assume lifecycle

[5]These include dummy variables for the level education of the head of the household (grade school only (EDD1), high school education (EDD2), incomplete university education (EDD3), and a university degree or higher (EDD4)), dummy variables for the number of children (#Children) and adults (#Adults) in the household, race, life-limiting disability (Disability), employment status (ES), marital status (Marital Status), state of residence (State) and home ownership (Nohome)

effects do not change over time, setting $Age_{i,g,t} = Age_{i,g} = D_{i,g}^{Age}$, where $D_{i,g}^{Age}$ is a dummy variable that takes the value one if the age of the head of household i is within the age group g and zero otherwise. We initially select 4 age groups $g = 1, \dots, 4 \quad (24-35, 36-50, 51-65, 65+)$ to ensure each age group is well populated but also consider 5 year age groups, with $g = 1, \dots, 10 \quad (24-30, ..65-70, 71+)$ for robustness. $\beta_{g,t} = \beta_g$ in this case captures the log difference in mean consumption of the youngest age group (reference group) to the other age groups across the lifecycle for the entire sample period.

In the second, denoted *Time-varying Lifecycle*, we account for time variation in lifecycle consumption expenditures by setting $Age_{i,g,t} = D_{i,g}^{Age} \times D_{i,t}^{Time}$. In this specification we allow the consumption allocations not explained by household characteristics and business cycles effects of a 30 year old to potentially change with time. $\beta_{g,t}$ in this case captures the log difference in mean consumption of the youngest age group (reference group) to the other age groups across the lifecycle for each wave/year in our sample.[6]

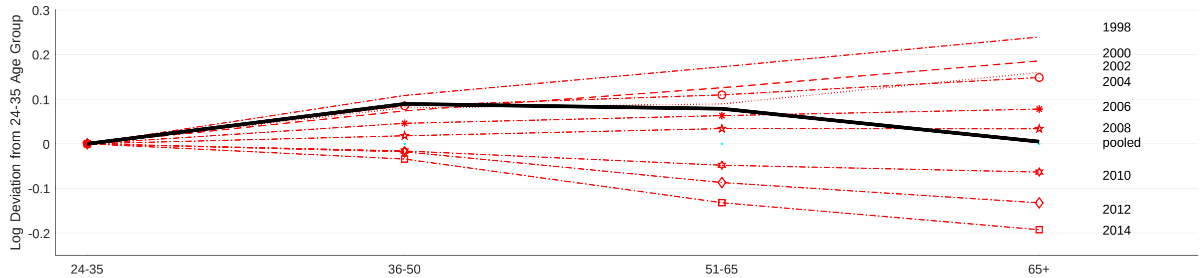
In Figure 2 we display the lifecycle coefficients ($\beta_{g,t}$'s) for both specifications for the age effect variable.[7] The upper panel shows estimates for broadly defined (15 years) and lower panel for narrowly (5 years) defined age groups. The thick dark line shows β_g's from the regression that pools the information across the entire sample to measure age effects. The results are well known and depict a hump-shaped pattern of consumption in the lifecycle. The dashed lines display the lifecycle coefficients ($\beta_{g,t}$) for each year $(1998, \dots, 2014)$ separately.[8] We observe a systematic time variation in lifecycle consumption patterns. At the beginning of the sample (1998 - 2000) consumption is increasing in age groups. With time the lifecycle profile pivots down and towards the end of the sample period (2014) consumption is decreasing in age groups. Our estimates show that the established hump-shaped lifecycle consumption profile is a result

[6]Note that by adding $Age_{i,g,t} = D_{i,g}^{Age} \times D_{i,t}^{Time}$ without also adding a control on $D_{i,g}^{Age}$ separately, we simply sum two components in computing the lifecycle consumption: the average age effects and the time-varying component, and obtain a full representation of age specific effects on consumption.

[7]Table A.6 in the Appendix shows estimation results (suppressing state dummies) for i. the Pooled Lifecycle model, ii. the Time-varying Lifecycle model (Benchmark) *iii*. Time-varying Lifecycle model with economic controls including total family income and subjective house value as additional controls.

[8]Although qualitatively comparable, β_g's for the pooled age effects regression (thick dark line) are not a direct function of the $\beta_{g,t}$'s estimated for each year/wave (dashed lines).

of pooled data and masks significant time variations.



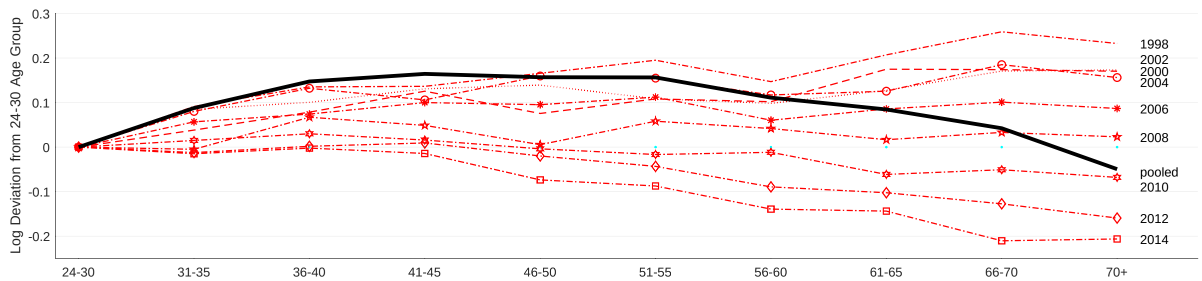


Figure 2: Lifecycle Consumption Patterns

Note: Each dashed line depicts $\beta_{g,t}$ for each year of the wave of the survey, $(1998, \ldots, 2014)$, depicting the estimated lifecycle pattern of consumption for each year. The dark line depicts the age effects β_g when $Age_{i,g,t}$ pools information for the entire sample. The top graph considers 4 age groups, while the bottom graph show the results for 10 age groups.

In Figure 3 we show the age effect coefficients and their 90% confidence interval organised in the form of a time series (in the top panel). As such, we plot $\beta_{g,t}$ by age group over all time periods, comparing the within age group changes across time. To assess the significance of these changes, we test the hypothesis that the coefficients for each age group do not change over time, formally $H : \beta_{g=s,t=1998} = \beta_{g=s,t=1998+x}$, which is an implicit assumption of the pooled approach. This null hypothesis is rejected in almost all cases (results are displayed in Table 1). We thus observe that age group coefficients, showing the relative difference w.r.t. the young age group (24-35) for each year, are economically and statistically different from each other. In Figure 3 (bottom panel) we present age group coefficients grouped by time. Set out this way, these represent a sequence of lifecycle consumption profiles. This further illustrates the decrease in slope of lifecycle consumption profiles, with older age groups observing larger variations than the young and middle aged households. Finally, we compare the information criteria of the two cases for $Age_{i,g,t}$, *Pooled Lifecycle* versus *Time-varying Lifecycle*. Because the latter nests the former model, we can use the information criteria as a likelihood ratio test with a penalty for complexity. Two popular information criteria, AIC and BIC, favour time variation in age effects. We also apply this test to the more granular age group specification and find strong evidence that allowing age effects to vary with time fits that data better than pooling age effects over time (see Table A.6 in the Appendix for details).

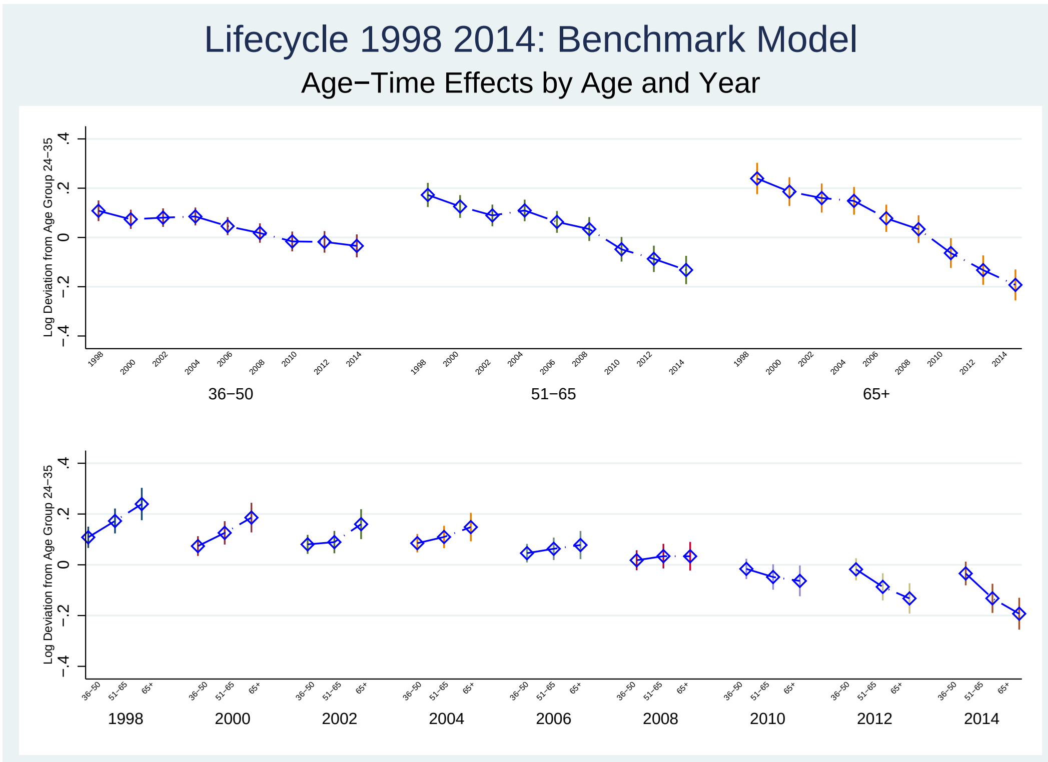


Figure 3: Age group coefficients ($\beta_{g,t}$) plotted by age group (Top) and by year (Bottom).

	Year			
Age Group	2002	2006	2010	2014
35 - 50	0.2298	0.0185	0.0000	0.0000
51 - 65	0.0003	0.0000	0.0000	0.0000
> 65	0.0037	0.0000	0.0000	0.0000

Table 1: $\beta_{g,t}$ - Time Variation Statistical Test

Note: We test the hypothesis that the coefficients for each age group do not change over time. Results are shown for the base year, 1998 against 2002, 2006, 2010 and 2014, $\beta_{g=s,t=1998} = \beta_{g=s,t=1998+x}$.

Finally, we complement our lifecycle estimates for each wave by taking into account the consumption behaviour of the reference (youngest age) group (24-35), which may be changing over time. In order to evaluate this potential business cycle effects on the evolution of the lifecycle of the reference group we re-estimate the model where the reference group now is 24-35 age group in 1998 (thus we drop time dummies to avoid perfect collinearity). Figure 4 records the coefficient estimates for the young age group w.r.t. the 1998 reference year.[9] Consumption expenditures of the young age group have in general drifted up from 1998 till 2014 (with a large fall and subsequent recovery due to the most recent crisis). The evidence presented in Figure 4 together with Figure 3 suggests that lifecycle consumption expenditure evolution has at least two dimensions. One is related to the shifts in the consumption behaviour of the young age group with respect to the business cycle; the other relates to the systematic shifts in the consumption behaviour of older age groups with respect to the young.

We conclude that the hump-shaped lifecycle patterns as reported by Deaton and Paxson (1994) and Aguiar and Hurst (2013) may be a product of pooling that considers lifecycle profiles as being time invariant. We show lifecycle consumption profiles have systematically shifted over the years and thus pooling the data across all households in sample masks changes in the lifecycle behaviour of age groups over time.

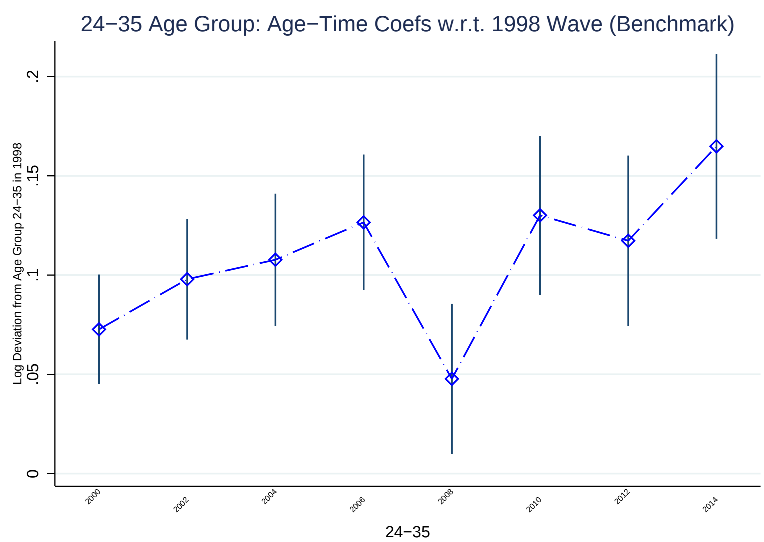


Figure 4: Consumption Drifts in Age Group 24-35

[9]This exercise is equivalent to reporting the time dummies δ_t's in Equation 1.

2.2.1 Robustness

In this section, we verify the robustness of our results.

Fixed Effects versus OLS: Our benchmark model takes advantage of the panel dimension of the PSID and estimates lifecycle consumption controlling for household fixed effects (α_i). An alternative approach (see for instance Aguiar and Hurst (2013)) is to estimate the model by OLS when using cross-sectional data such as the CEX. In this case, there is no way of controlling for household unobserved heterogeneity and thus the covariance between age (Age_{it}) and α_i may introduce biases in the lifecycle profiles (β_g's) estimated. Both the Case 1 - *Pooled Lifecycle* and the Case 2 - *Time-varying Lifecycle*, can be estimated by OLS. We re-estimate both cases this way and compare the results using information criteria as a likelihood ratio test with a penalty for complexity.

Model	df	AIC	BIC
Pooled Lifecycle - OLS	91	63229.33	64015.38
Pooled Lifecycle - FE	87	26137.63	26889.12
Time-varying Lifecycle - OLS	115	63237.01	64230.37
Time-varying Lifecycle - FE	111	25903.35	26862.16

Table 2: Information Criteria - OLS versus Fixed Effect

For both the *Pooled* and *Time-varying* models, the information criteria strongly favour the fixed effects (FE) approach (See Table 2). Indeed, inspecting the values of the estimated β_g's over the lifecycle from the FE and OLS estimations reveals significant differences (reported in the Appendix, Figures A.5 and A.6). The *pooled* OLS lifecycle profiles are increasing and no longer displayed the humped-shaped profile commonly known and the *timevarying* estimates no longer display a clear systematic variation as obtained in the benchmark model.

Potential differences between estimation of lifecycle consumption by FE and OLS is addressed by Aguiar and Hurst (2013) using food data in the PSID.[10] They find little difference between the two approaches and conclude unobserved household effects may be safely excluded

[10] A fuller measure of consumption was not introduced in the PSID until 1999.

when estimating lifecycle consumption profiles. We re-estimate the model by OLS and FE, replacing our measure of non-durable consumption with food, also from the PSID, and confirm their results. However, our non-durable consumption includes a broader range of spending categories (not available before 1999) for which household unobserved heterogeneity appears to be more relevant. Our results indicate that for non-durable consumption, not controlling for fixed effects masks important household heterogeneity. This suggests that the assumption that OLS and FE are equivalent cannot necessarily be extended to non-food consumption.

Panel versus Cross-sectional Estimation: Our model makes use of the panel dimension of the data to control for household fixed effects and average (across the sample period) effects of the time varying household characteristics (Z_{it}). An alternative is to estimate the model $c_i = \delta + \beta_g Age_{ig} + \psi_z Z_i + v_i$ for each wave, obtaining a set of β_g's for each wave (t) independently. This model no longer controls for household fixed effects but does allow ψ_z to vary across time (see Equation 1). By information criteria the preferred approach for estimation is still fixed effects estimation of Equation 1. Results are shown in Appendix B.6.

Long Sample: We estimate the Equation (1) over a longer sample using an imputed non-durable consumption variable, 1980 - 2014.[11] Whilst the imputation process introduces uncertainty, the results show that the flattening of lifecycle consumption profiles has been occurring since 1980 (see Figure 5).[12]

5 Year Age Groups: We re-estimate the benchmark model with 10 age groups, $g = 1, \ldots, 10$ $(24-30, ..65-70, 71+))$. The systematic changes in consumption lifecycle patterns remain the same, thus averaging the behaviour of households across larger age groups does not alter the main conclusions derived from our empirical evidence. Results are displayed in Figure A.7 in the Appendix.

Controlling for Average Income and Subjective House Values: We estimate the model

[11] The imputation method follows Blundell, Pistaferri, and Preston (2008), see the Appendix for details.

[12] As a further check we estimate the model over food data from 1980 - 2014; data on food have been recorded in almost every wave of the PSID since 1968. Time variation in lifecycle profiles are also present. Results from the estimation with consumption of food are available from the authors upon request.

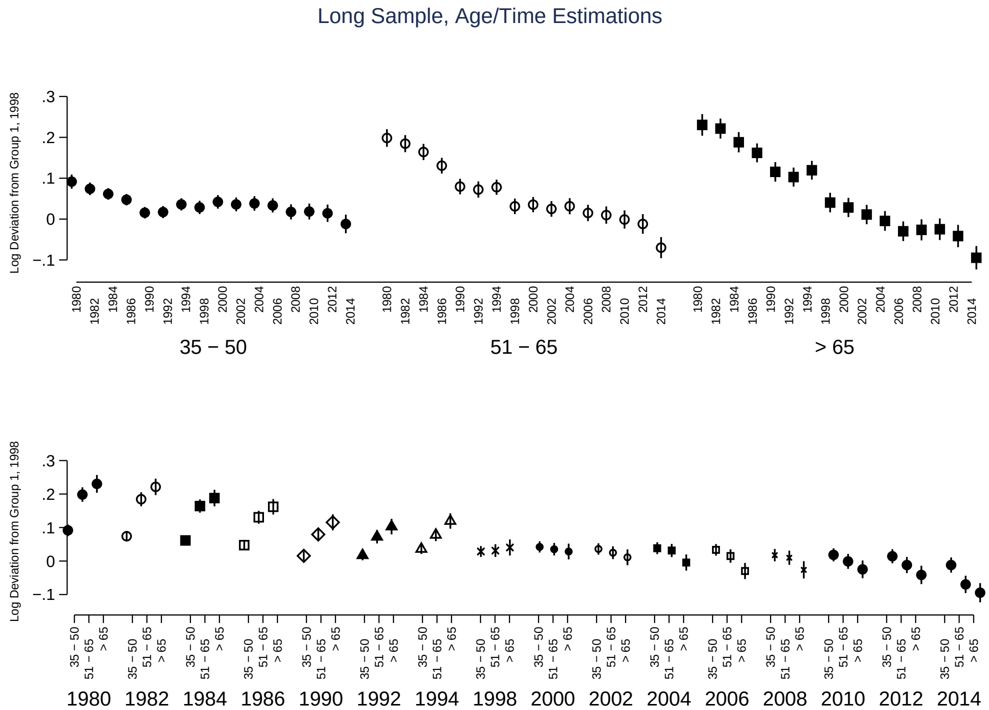


Figure 5: Age group coefficients: Results from Long Data Set. **Top** Coefficients by age group. **Bottom** Lifecycle plots by year.

controlling for household's income ($y_{i,t}$) and household's subject value of housing $H_{i,t}$ (Economic Controls). The modified econometric model is

$$c_{i,t} = \alpha_i + \beta_{gt} Age_{i,gt} + \gamma_y y_{i,t} + \gamma_H H_{i,t} + \delta_t D_{i,t}^{Time} + \psi_Z Z_{i,t} + \epsilon_{i,t} \tag{2}$$

Figure 6 display the results. The time variation in lifecycle consumption patterns is unchanged. We also re-estimate the model using only homeowners. Results remain qualitatively similar.

Cohort Effects: We hypothesise that the age related consumption profile of a 40 year old in 1998 is not the same as a 40 year old in 2008. This may be interpreted as recognising that some features of lifetime consumption are specific to the year of birth, requiring the inclusion of controls for cohort effects in the empirical model. Because we are estimating age effects we have the well known problem that $cohort + age = year$, and thus age and cohort effects become business cycle effects. Deaton and Paxson (1994) devised a method to accommodate all three controls and we use this to test the goodness of fit of our benchmark model, both the pooled

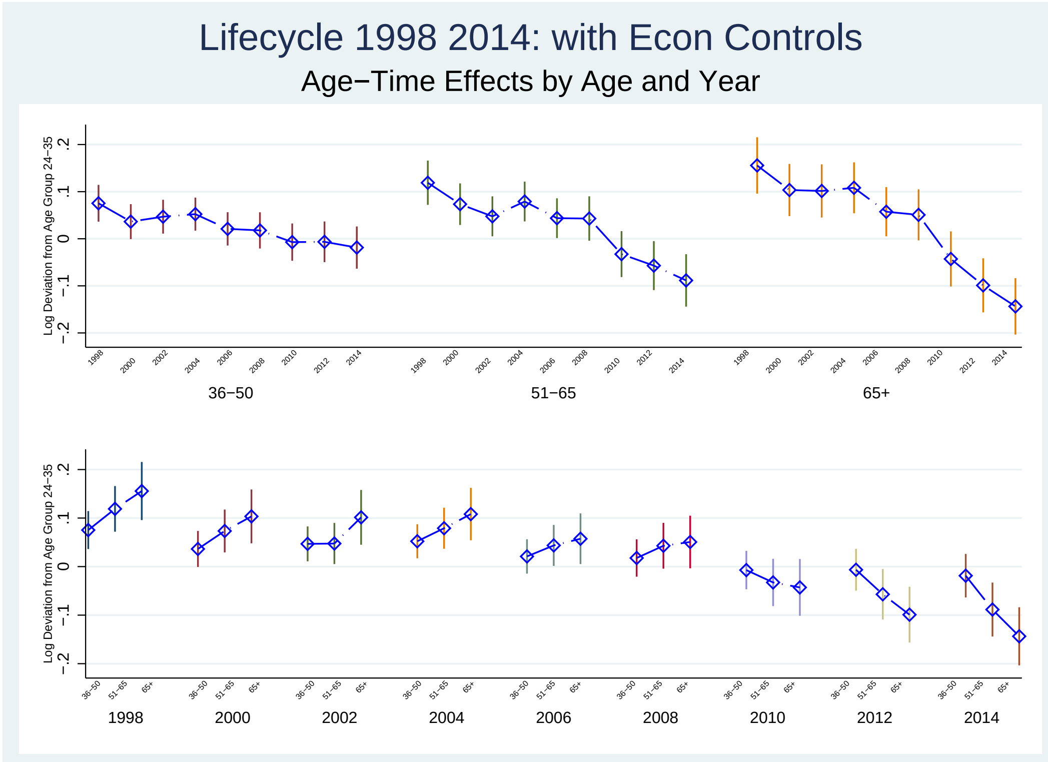


Figure 6: Age group coefficients: Model with additional economic controls: **Top** Coefficients by age group. **Bottom** Lifecycle plots by year.

and time varying, with the each different combinations of controls (see the Appendix B.3 for details).

We find that for both the *Time-varying* and *Pooled* models, having time controls and our Age_{igt} dummies provide a better fit, according to information criteria, than additionally including cohort dummies. In fact, in our specification tests, estimated constant cohort effects are found to be not significant. As the model already controls for household time varying controls and unobserved household average effects, and that the Age_{igt} dummies nest the constant cohort effects, we find that the characteristics that are specific to the year of birth are not a relevant driver of consumption. Standard cohort dummies will only pick up the average effects of the year of birth over an entire lifecycle whereas the β_{gt} coefficients estimate the consumption of a cohort in each point in time; our framework allows the cohort effects to change over the lifecycle. Hence, our methodology uncovers time-variation in relative consumption levels across cohorts and not constant cohort effects.

Consumption Sub-categories: By studying the pooled Consumer Expenditures Survey (CEX) data for the period of 1980-2003, Aguiar and Hurst (2013) show that the lifecycle consumption behaviour for different subcategories are quite distinct. Their findings suggest that possible work-related consumption expenditures, such as clothing, transportation and food away, decline more significantly as households get older. We re-estimate our benchmark model for 9 consumption subcategories in the PSID data (Figure A.9 in the Appendix displays the resulting age-time coefficient estimates). We observe a flattening of lifecycle consumption profiles in almost all sub-categories in our sample, including for the work-related categories, such as transportation and food-away. Thus, our conclusions extend to consumption sub-categories.

Education: The composition of education levels within the population has been changing in the past decades and therefore the time variation we observe could be related to composition effects. To test for this possibility we estimate the lifecycle model for sub-samples of households with different levels of education (i. the grade school only (9.8% of the sample), ii. with high school education (26.9%), iii. some incomplete university education (27.1%) and iv. a university degree or higher (36.1%)). We find that lifecycle time variation occurs irrespective of the education levels. However the observed flattening of lifecycle consumption behaviour is most pronounced by those who have at least high school education. (See Figure A.10 in the Appendix.)

Scaling: We verify the robustness to different ways to adjust for family size, and to deflate consumption expenditures in line with St Aubyn (2018). In the benchmark model we include dummies for number of adults and children but also scaled consumption to reflect family size following Blundell, Browning, and Meghir (1994). We estimate the model without scaling, including dummies only, and with scaling but excluding dummies, the main qualitative results are robust to these changes. We test the robustness to different methods of deflation and find that our results are not driven by our choice of using expenditure category specific price indexes. (for details see Appendix B.1).

Family Composition: Although results are robust to different scaling methodologies, changes in family composition may be endogenous, potentially introducing selection bias. We re-estimate our model including only stable households (the ones where the head or the spouse did not change). Results once again are qualitatively unaffected. (See Figure A.11)

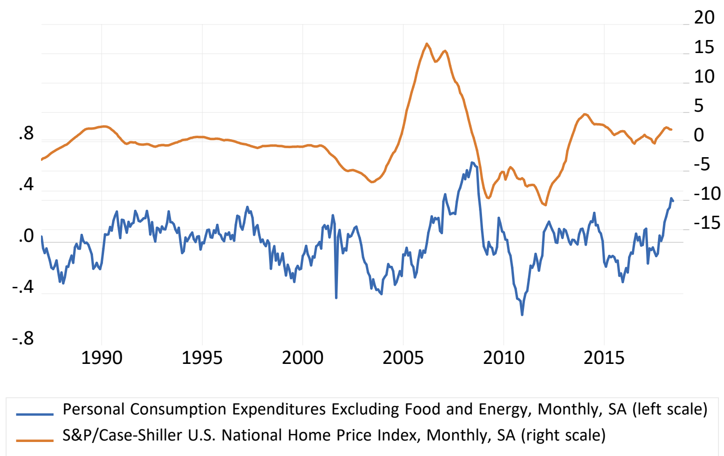
2.3 Lifecycle Consumption: The Role of the Income and Housing

We document systematic and significant time variation in the profiles of lifecycle consumption expenditures in the US. Lifecycle consumption profiles have consistently become flatter through time. What may be behind this time variation in the consumption profiles we uncover?

Fernandez-Villaverde and Krueger (2011) stress the importance of housing investment in shaping consumption in the lifecycle and indeed for most households investment in a house (typically purchased via mortgage credit) to live-in constitutes the largest asset investment in their lifetime. Moreover, during the first part of our sample, borrowing constraints have relaxed and house prices increased substantially (see Favilukis, Ludvigson, and Nieuwerburgh (2017), Kaplan, Mitman, and Violante (2017) and Cox and Ludvigson (2018)). We plot in Figure 7 business cycle components of US aggregate consumption expenditures and Case-Shiller National Home Price Index together. Causal observation suggests that as of early 2000's there are clear dynamic co-movements between these two variables with episodes before and after the Great Recession particularly marked.[13] Thus, our first variable of interest is the time variation in housing wealth. Although many contributions have looked at the effects of housing wealth in consumption, most have focused on the marginal propensity to consume due to changes in housing wealth (e.g. Carroll, Otsuka, and Slacalek (2011), Aladangady (2017), Berger, Guerrieri, Lorenzoni, and Vavra (2018)). In contrast, our interest is in the role of housing in the lifecycle variations of consumption expenditures across generations.

There is an extensive literature that analyses how consumption responds to income changes. Keynes (1936) was the first to stress that consumption is primarily a function of income, and Modigliani and Brumberg (1954) and Friedman (1957) life-cycle and permanent income

[13] The simple dynamic correlation between 12 month lagged Case-Shiller index and consumption expenditures is in the order of 55%.



Source: FRED

Figure 7: Business Cycle Components of Consumption and Case-Shiller House Price Index

models posit that people use savings to smooth consumption across the lifecycle responding to income fluctuations only when they are unanticipated. As discussed by Jappelli and Pistaferri (2010) identifying which income fluctuations are anticipated may not be easy and there are well-known departures to the these canonical theoretical models (i.e. the inclusion of binding liquidity constraints, durable of goods, nonseparabilities between consumption, leisure and housing) that may result in consumption responding to anticipated changes. Although we have introduced a control of current income into our benchmark model, showing the results are unaffected, unanticipated and in some cases anticipated variations in lifecycle income may affect consumption profiles. Therefore, our second object of interest is the lifecycle variations of income across generations.

In order to extract the role of variations in income and housing wealth across the lifecycle on consumption profiles we allow the age-time specific components in consumption expenditures not related to household characteristics to vary depending on our variable(s) of interest, namely, household's total family income and subjective housing value. We thus add to our benchmark specification interaction dummies $Age_{i,g,t}X_{i,t}$, that incorporate a variable $X_{i,t} \in \{Y_{i,t}, H_{i,t}\}$ next to our age-time dummies.

Formally, the econometric model (denoted the *Interaction model*) is

$$c_{i,t} = \alpha_i + \theta_{g,t} Age_{i,g,t} + \theta_{g,X,t} Age_{i,g,t} X_{i,t} + \delta_t D_{i,t}^{Time} + \psi_1 Z_{i,t} + \epsilon_{i,t} \tag{3}$$

To assess the relevance of each of the variable of interest in driving the time variation we can decompose the age-time effects as follows

$$\beta_{g,t} = \theta_{g,t} + \theta_{g,X,t}. \tag{4}$$

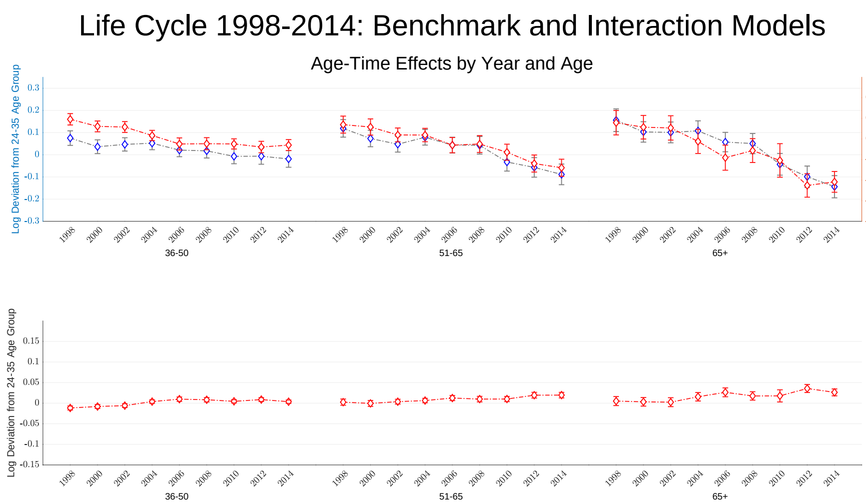
As such, age-time dummies ($\theta_{g,t}$) aim to capture age specific variation in consumption expenditures that cannot be explained by age specific time-variation in our variable of interest (total family income or subjective house value) while $\theta_{g,X,t}$ reflect the contributions of income or housing on the lifecycle consumption profiles.

We report the results in Figures 8 (a) for subjective housing value and 8 (b) for total family income.[14] The top panels depict the age-time coefficient estimates for the benchmark model and the *Interaction model* by age group, over all time periods. The bottom panels plot the three-way estimates, $\theta_{g,X,t}$, depicting the relevance of housing and income in shaping lifecycle consumption patterns.[15]

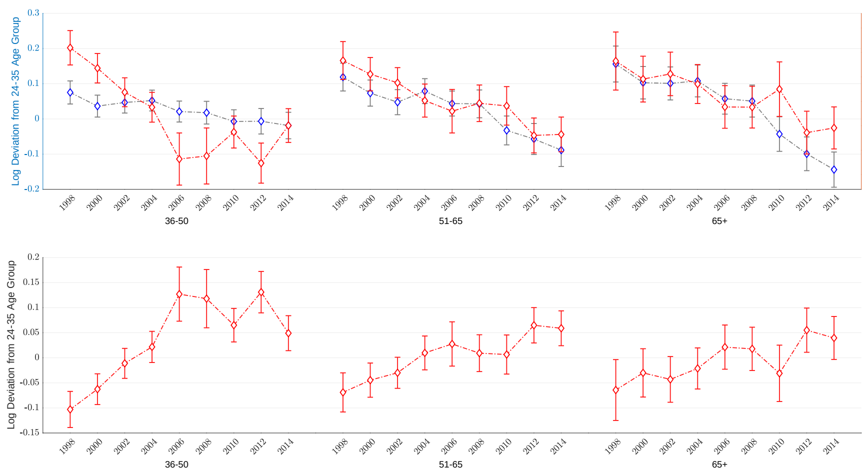
First, the role of housing in shaping the lifecycle profile of consumption seems minimal. From the top panel, we still observe the same time-varying lifecycle behaviour of each age group when we control for age-time specific house valuation; $\beta_{g,1998} - \beta_{g,2014}$ and $\theta_{g,1998} - \theta_{g,2014}$ are nearly the same and thus variations in house wealth are not behind the flattening of consumption profiles. The bottom panel shows that $\theta_{g,H,t}$ are generally small, particular for the first 2 age

[14] In the Appendix (Table A.7) we provide a full description of the estimation results for benchmark and interaction models. i. Time-varying Lifecycle model (Benchmark) ii. Three-way interaction model with Subjective House Value (Interaction SHV model), iii. Three-way interaction model with Total Family Income and finally (Interaction: TFI model) iv. Three-way interaction model with Subjective House Value and Total Family Income jointly (Joint SHV and TFI model). We report coefficient estimates for age-time dummies as well as estimates for all other controls together with AIC and BIC information criteria.

[15] In both cases the top panels have two y axis to help make visual comparisons between the age time coefficients from the benchmark and the Interaction model. We keep the bottom panels with the same y axis to aid in the comparison of the role of housing and income in influencing lifecycle consumption.



(a) Interaction Model - Subjective House Value



(b) Interaction Model - Total Family Income

Figure 8: Age group coefficients: Benchmark Model (Equation 2) and Interaction Model (Equation 3). **Top** Panel (a) and (b): $\beta_{g,t}$ from Equation 2 (blue) and $\theta_{g,t}$ from Equation 3 (red); **Bottom** Panel (a) and (b): $\theta_{g,X,t}$, Equation 3

groups. Therefore, high subjective house values seems to sustain consumption particularly for the older households and after the first half of 2000's. Housing wealth seems to be wealth only towards the end of lifecycle and after the 2008 correction (see Buiter (2010)).

In contrast, lifecycle variations in income are more relevant in shaping the changes we observe in consumption profiles. First, from the top panel, in the benchmark model $\beta_{g,1998} - \beta_{g,2014}$ increases with age, while after controlling for income $\theta_{g,1998} - \theta_{g,2014}$ is fairly constant with age. Thus, after extracting the age-specific component that depend on income, lifecycle consumption are no longer flattening (the only time variation left is a level effect, diametrically opposed to the increasing positive effect of income in driving the age-profile of consumption). Second, $\theta_{g,H,t}$ increases, indicating that higher income in the lifecycle has become strongly associated with higher consumption levels.

In order to further investigate whether time variation in lifecycle consumption are closely linked to time variation in lifecycle income, we re-estimate the benchmark model for total family income instead of consumption, extracting the age-specific path of income for each year ($\beta^{Y}_{g,t}$). Formally, we estimate

$$Y_{i,t} = \alpha + \beta^{Y}_{g,t}(D^{Age}_{i,g} \times D^{Time}_{i,t}) + \delta_t D^{Time}_{i,t} + \psi_Z Z_{i,t} + \epsilon_{i,t}. \tag{5}$$

Results are displayed in Figure 9. Indeed we observe a very similar pattern of time variation in income than the one we observe for consumption. After controlling for observable household characteristics, the age-profile of income has also flattened, with the difference in income across ages decreasing to the point that in 2014 younger households had a higher age-specific total family income than their older counterparts. We perform the same estimation using labour income instead of total family income and find that a similar pattern emerges (results are shown in the Appendix). Note that these results do not imply 35 year old households today are relatively better off than 35 year old households in the 1990s, rather, the results indicate that at each fixed point in time throughout the sample, the differences across generations have decreased in both income and consumption.

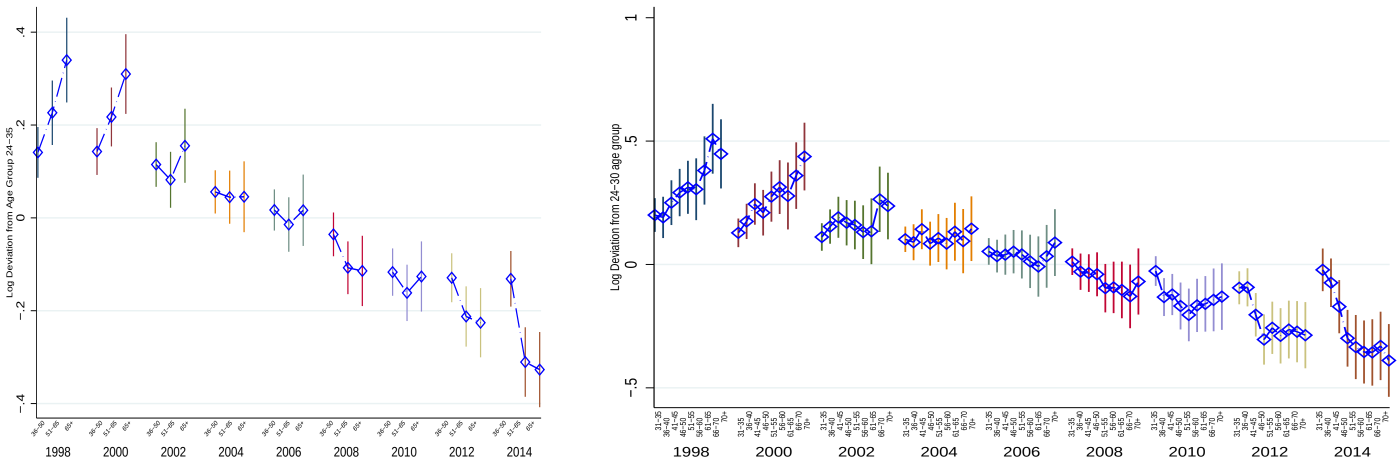


Figure 9: Age group coefficients ($\beta^{Y}_{g,t}$) plotted by age group by year. **Left** - 4 age groups, **Right** - 10 age groups.

We conclude that accounting for time variation in lifecycle total family income explains most of the time variations in lifecycle consumption. Allowing for time variation in subjective house values has statistically significant but small impact on lifecycle patterns in consumption. We also note that consumption responses with respect to variations in subjective house values are stronger among older households and particularly after the Global Financial Crisis.

3 Lifecycle Model

We now present a theoretical model to gain understanding of the roles housing wealth, credit and income fluctuations may play in driving lifecycle consumption and asset choices. We develop a dynamic, incomplete markets model of household lifecycle consumption similar to the one in Berger, Guerrieri, Lorenzoni, and Vavra (2018). Time is discrete, we set one period of the model to correspond to one year. Population is constant, households enter the economy, work for J_w years, retire and live for another J_r years. A household thus lives for $J = J_w + J_r$ years. Working households face uninsurable idiosyncratic income risk and invest in two assets: a risk-free asset paying a constant interest rate r, and housing. We denote the holdings of each asset by household i at time t as, respectively, $a_{i,t}$ and $h_{i,t}$.

Households born at time t maximize the expected lifecycle utility given by

$$E\left[\sum_{j=1}^{J}\beta U(c_{i,t+j},s_{i,t+j})+\beta^{J+1}\mathbb{B}(B_{i,t+J+1})\right]$$

where $c_{i,t+j}$ is non-durable consumption, $s_{i,t+j}$ housing services and $B_{i,t+J+1}=a_{i,t}(1+r)+(1-\delta)P_{i,t+J+1}h_{i,t+J}$ are bequests.

Households are allowed to go short the risk-free asset but must abide by a borrowing constraint. We assume a fraction θ of the current value of owned houses and a fraction ϕ of current income (y_{it}) can be pledge as collateral. Thus, household's asset position must satisfy the borrowing constraint

$$a_{i,t}\geqslant-(\theta P_{i,t}h_{i,t}+\phi y_{it})$$

Working household's income is given by $y_{it}=exp(\nu(age_{i,t})+z_{i,t})$, where $\nu(age_{i,t})$ is a known age-dependent term and $z_{i,t}$ is a transitory shock that follows an AR1 process. Retirement income is fixed and is assumed to be a function of the income in the last working-age period.

Houses are traded at prices $P_{i,t}$.[16] We assume house prices follow a geometric random walk with a drift $P_{i,t}=x_tP_{i,t-1}$, where $ln(x_t)\sim N(\mu_P,\sigma_P)$. μ_P thus denotes the trend growth rate of house prices. Households who trade houses must pay an transaction cost $\Xi P_t h_{i,t}$. Owned houses yield a per-period service equals to $\omega h_{i,t}$, $\omega>1$, and carry a maintenance cost of $\delta P_{i,t}h_{i,t}$ that fully offsets physical depreciation. Households that decide not to own a house can rent it paying a rental cost of ϕP_t for each unit of housing (the price-rent ratio is constant). Rented houses yield a per-period service equal to $h_{i,t}$, thus owned houses deliver higher services.

At any time t, the household state is fully described by the vector $\mathbf{x}\equiv(a,h,z,P,age)$ given by the liquid asset, housing, income shock, house prices and age. Households face four possible

[16] Although we include the subscript i since in our model households may experience different realisations of house price, these are the prices for the existing house of household i and the newly transacted house and in that sense reflect an aggregate shock from the perspective of the household as in Berger, Guerrieri, Lorenzoni, and Vavra (2018).

scenarios: (i) household becomes a renter (R), selecting current housing from the set $\mathfrak{H}^R$ and have no house holdings to carry for the next period; (ii) households that own a house may decide to refinance (F), increasing their borrowing and keeping house holdings $h_{i,t}$ constant, paying a refinancing cost of $\Xi_{Rf} P_{i,t} h_{i,t}$; (iii) household maintains house holdings constant and pays amortization or reduces borrowing (N); and (iv) household is (becomes) an owner and alters housing stock at time t (T), selecting housing from the set $\mathfrak{H}$.

Therefore, the value of expected utility of the household is

$$V(\mathbf{x}) = max\{V^R, V^F, V^N, V^T\},$$

where, the value function for each scenario is given by

Renting	Trading Houses
$V^R(\mathbf{x}){=}\max_{c,a',h'} u(c,s){+}\mathbb{E}_t[\beta(V(\mathbf{x}')\|z,P]$	$V^T(\mathbf{x}){=}\max_{c,a',h'} u(c,s){+}\mathbb{E}_t[\beta V(\mathbf{x}')\|z,P]$
s.t. $c{+}a'{+}\phi Ph'{\leqslant}y{+}a(1{+}r){+}(1{-}\Xi{-}\delta)Ph$	s.t. $c{+}a'{+}Ph'{\leqslant}y{+}a(1{+}r){+}(1{-}\Xi{-}\delta)Ph$
$a'{\geqslant}\phi y$, $s{=}h'$, $\mathbf{x'}{=}(a',0,z',P',age{+}1)$	$a'{\geqslant}(\theta Ph{+}\phi y)$, $s{=}\omega h'$, $\mathbf{x'}{=}(a',h',z',P',age{+}1)$
$h'{\in}\mathfrak{H}^R$	$h'{\in}\mathfrak{H}$
Refinancing	**No Housing Adjustment**
$V^F(\mathbf{x}){=}\max_{c,a'} u(c,s){+}\mathbb{E}_t[\beta(V(\mathbf{x}')\|z,P]$	$V^N(\mathbf{x}){=}\max_{c,a'} u(c,s){+}\mathbb{E}_t[\beta(V(\mathbf{x}')\|z,P]$
s.t. $c{+}a'{+}{\leqslant}y{+}a(1{+}r){+}({-}\delta{-}\Xi_{Rf})Ph$	s.t. $c{+}a'{+}{\leqslant}y{+}a(1{+}r){+}({-}\delta)Ph$
$a'{\geqslant}(\theta Ph{+}\phi y)$, $s{=}\omega h$, $\mathbf{x'}{=}(a',h,z',P',age{+}1)$	$s{=}\omega h$, $\mathbf{x'}{=}(a',h,z',P',age{+}1)$
	$a'{>}$[amort a if $a{<}0$, $0{=}$ if $a{>}0$]

Parameterizations

We assume the per period utility and bequest functions are given by

$$u(c,s) = \frac{1}{1-\sigma}(c^{(1-\alpha)}s^{\alpha})^{(1-\sigma)}, \quad \mathbb{B}(B) = \frac{\psi}{1-\sigma}(B-\bar{B})^{(1-\sigma)}.$$

Households enter the economy with 25 year of age, work for 35 years (J_w), retire and live an additional 20 years (J_r). We set the coefficient of relative risk aversion σ to 2 and the interest rate to 2.4%.

As in Berger, Guerrieri, Lorenzoni, and Vavra (2018), we calibrate the house price process by setting $\mu_P = 0.012$ and $\sigma_P = 0.046$ to match the annual standard deviation and real growth rate of aggregate house prices in FHFA data from 1990 until 2019. We choose a depreciation rate of housing $\delta = 2.2$ to match the depreciation rate in BEA data from 1960 to 2014. The collateral constraints parameter θ determines the minimum mortgage down payment, and we choose a value of 0.8 in our baseline calibration. The ratio of non-collateral debt and income in Survey of Consumer Finance (SCF) in 1998 is around 25% we thus set $\phi = 0.25$. We set Ξ=0.05. This transaction cost is equal to the value of housing adjustment costs calibrated in Díaz and Luengo-Prado (2010).

The working age income process has a age-dependent and a transitory component. Following Floden and Lind (2001), the temporary component z follows an AR1 process with autocorrelation $\rho_z = 0.91$ and standard deviation $\sigma_z = 0.21$ to match PSID earnings statistics (after removing age-dependent components). We calibrate the model using the age dependent component of income estimated for 1998, denoted $\nu(age_{98})$ and depicted in Figure 9. Finally, households receive a social security payment of forty percent of their labour income prior to retirement.

Rented and owned housing are selected within the sets $\mathfrak{H}^R = [0, HRmax]$ and $\mathfrak{H} = [Hmin, Hmax]$, respectively, where $HRmax < Hmax$. Thus, owned houses cannot be too small and rented houses are in general smaller than owned houses. $Hmax$ is set such that households are not constrained in choosing big houses.

Parameters, $HRmax$, $Hmin$, and α, which controls the share of housing in the utility, β, the discount factor, ψ and $\bar{B}$, which control the bequests, ω, which controls the added utility of house ownership, and ϕ, which controls the rental price, are calibrated to match the ratio of the average earnings of owners to renters of 2.1 (1998 SCF) and the lifecycle profiles of housing wealth, non-housing wealth and homeownership in the 1998 SCF data, following a similar procedure as in Berger, Guerrieri, Lorenzoni, and Vavra (2018). We compute average housing wealth and average liquid wealth net of debt for households in nine age groups (25-29, 30-34,…, 60-64, 65 and over). Housing wealth comprises primary residence and other residential and nonresidential real state. Liquid wealth net of debt is the sum of cash, money market, checking, savings and call accounts and holdings of mutual funds, stocks and bonds net of credit cards and mortgages (we only have one asset in the model).[17] For retired households (above the age of 60 years) we also include retirement accounts. In the model, payments from retirement accounts take the form of a lump sum transfer at retirement and a pension annuity, which within our calibration procedure are set, respectively, as fractions ϑ_0 and ϑ_{pa} of the labour income prior to retirement.

Finally, a household enters the economy at 25 years of age with an amount of housing, liquid assets and income such that we match the distribution of age 20-30 year old households in the 1998 SCF. Based on our calibration procedure, α, β, ψ, $\bar{B}$, ω, ϕ, ϑ_0, ϑ_{pa}, $Hmin$ and $HRmax$ are:

α	β	ψ	$\bar{B}$	ω	ϕ	ϑ_0	ϑ_{pa}	$Hmin$	$HRmax$
0.165	0.9375	2	1.4	1.18	0.05	1.2	0.35	0.1	0.75

Table 3: Parameter Values

As in Berger, Guerrieri, Lorenzoni, and Vavra (2018), the model does a good job in matching the SCF asset holdings data.[18] The lifecycle profiles of housing wealth, non-housing wealth and homeownership in the data and model are show in Figure 10.

Time Variation in Lifecycle Consumption Profiles

Our empirical results suggest the key driver of the flattening of lifecycle consumption profiles

[17] To normalise data and model we divide both measures of wealth by average income of working age households.

[18] In order to solve the model we select a grid of 50 points for assets and housing. To incorporate trend in house prices we solve the model such that household select housing wealth $P_{i,t}h_{i,t}$, discounting the continuation value in the Bellman equation by the expected trend in house prices (see Berger, Guerrieri, Lorenzoni, and Vavra (2018) for detail). Invariant lifecycle measures are calculated after we simulated lifecycle decisions for 10000 households.

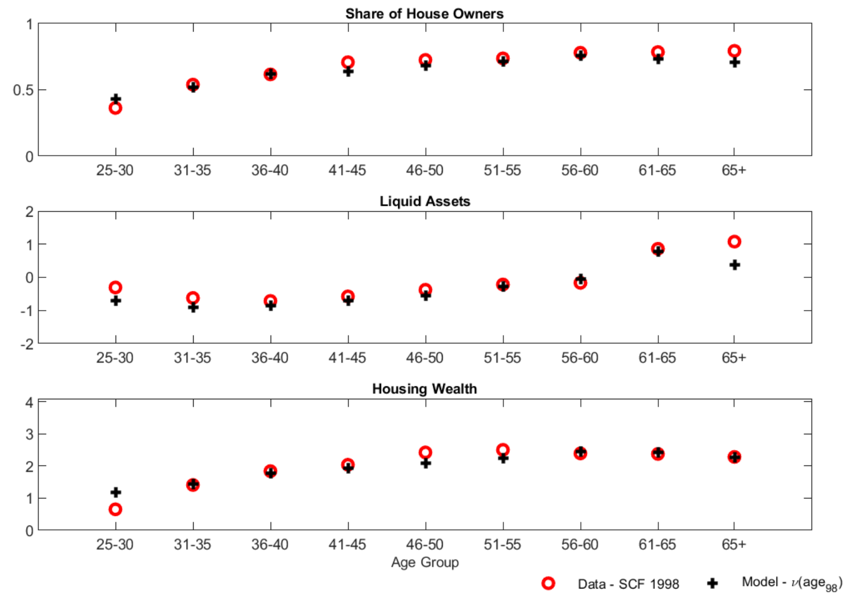


Figure 10: Calibration: Lifecycle profiles of homeownership, non-housing wealth and housing wealth. Model versus SCF 1998 Data

is the change in the lifecycle income profiles. Our benchmark model incorporates the age dependent component of income estimated for 1998, denoted $\nu(age_{98})$. As our empirical results show the age dependent component of income has been consistently changing from 1998 to 2014, with the difference of total income across age groups decreasing as time passes. We obtain from our estimation two additional age-dependent component curves, one for 2006, $\nu(age_{06})$, and one for 2014, $\nu(age_{14})$ and re-simulate the model using different age dependent income profiles.

First, although not part of our calibration, the model does a good job in matching the age profile of consumption observed in 1998. Second, by only changing the age component of income $\nu(age)$ we can assess the role of changing income profiles on lifecycle consumption in our model economy. Results are displayed in Figure 11. In all cases we depict the invariant lifecycle profiles for which the age income profiles differ but average income remains constant. The theoretical results confirm the empirical evidence that changes in income profiles are crucial to explain the decrease in the difference of consumption across households of different ages observed in the data. The model is able to match the estimated flattening in consumption profiles reasonably well.

Next we focus on the role of interest rates, credit and housing market dynamics on consump-

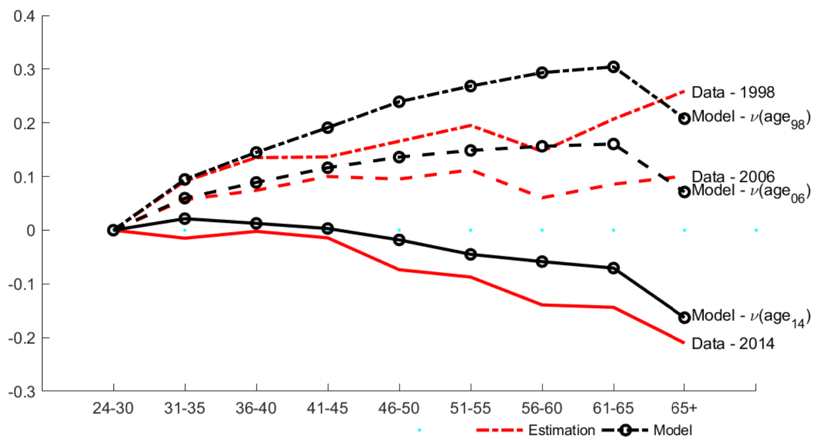


Figure 11: Consumption Life Cycle Profiles: Model with different income profiles versus Estimation

Note: For each model simulation we use either the income profiles $\nu(age_{98})$ - Calibration, $\nu(age_{06})$ or $\nu(age_{14})$ obtained from the estimation (5) - (lines with circles). Data comes from the benchmark estimation of age profiles of consumption ($\beta_{g,t}$).

tion profiles. From 1998 till 2006 debt to income has increased by 40% (Using data from SCF 1998 and 2007). As we mentioned above, several contributions highlight the importance of relaxed credit constraints during this period. House prices (FHFA data) from 1990 until 2006 increase on average 2.3% as opposed the 1.2%, our calibrated figure, which relies on data until 2019. Finally, several contributions highlight that in the last decades the equilibrium real rate of interest has consistently fallen (see for instance Aksoy, Basso, Smith, and Grasl (2019) and Del Negro, Giannone, Giannoni, and Tambalotti (2019)). To account for these changes in economic conditions from 1998 till 2006 as potential drivers for the movements in consumption profiles we (i) increase the trend in house prices to $\mu_P = 0.023$, (ii) relax credit constraints (a 10% increase in θ - using the SCF of 1998 and 2007, leverage ratios of new house buyers increase by 10% from 1998 till 2007) and (iii) decrease interest rates by 100 basis points. Results are shown in Figure 12. Relaxed credit constraints and lower interest rates imply households borrow more and bring consumption forward, flattening lifecycle profiles. Higher trends in house prices imply home owners become richer during the lifecycle and consumption profiles become steeper. Overall, consumption profiles are not as significantly affected by the level of interest rates, credit and housing market changes as they do when the age component of income changes.

Time Variation in Assets Holdings and Housing Values

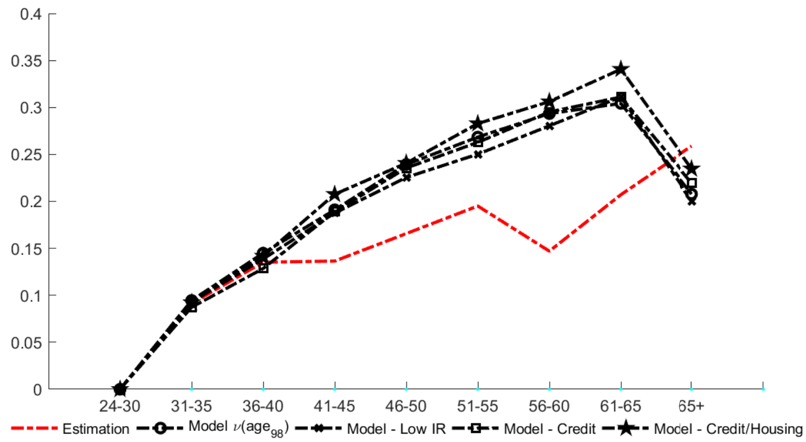


Figure 12: Consumption Life Cycle Profiles: Impact of Credit and House Prices

Note: Model $\nu(age_{98})$ - Benchmark, Model - Credit, incorporates relaxation in credit constraints in the Benchmark Calibration, Model - Credit/Housing, incorporates both the relaxation in credit constraints and the increase in the trend in house prices and Model - Low IR, lowers interest rates in the Benchmark Calibration. Estimation (dash line) comes from the benchmark model of lifecycle consumption for 1998 ($\beta_{g,1998}$)

Although the change in the income profiles are sufficient to produce the changes in consumption profiles, we cannot generate the asset accumulation changes observed during the same period. Nonetheless, combining both the changes in income profile and incorporating the changes in the trend in house prices and the relaxation of credit constraints improves the match between data and model both in the changes in consumption profiles and the changes in asset holdings before the Great Recession. In Figure 13 we plot the lifecycle profiles of housing wealth, non-housing wealth and homeownership in the 2007 SCF data and compare them with our model incorporating income changes only and income and house prices/credit changes.

In the aftermath of the Great Recession, credit constraints tightened and house prices fell substantially, recovering after 2010. In fact, the average growth rate of house prices from 2007 to 2019 (FHFA data) is close to 0%. To account for these changes in economic conditions since 2007 as potential drivers for the movements in asset holdings we decrease the trend in house prices to $\mu_P = 0$, and tightens credit constraints ($\theta = 0.5$ and $\phi = 0.15$) and compare the figures from the simulated model with the SCF 2013 data (see Figure 14). Once again, including only income changes imply simulated asset profiles do not match the data. Incorporating changes in credit and house market conditions help the model in matching asset holdings, although we find the age profile of liquid assets under the new income profile portray a much stronger desire

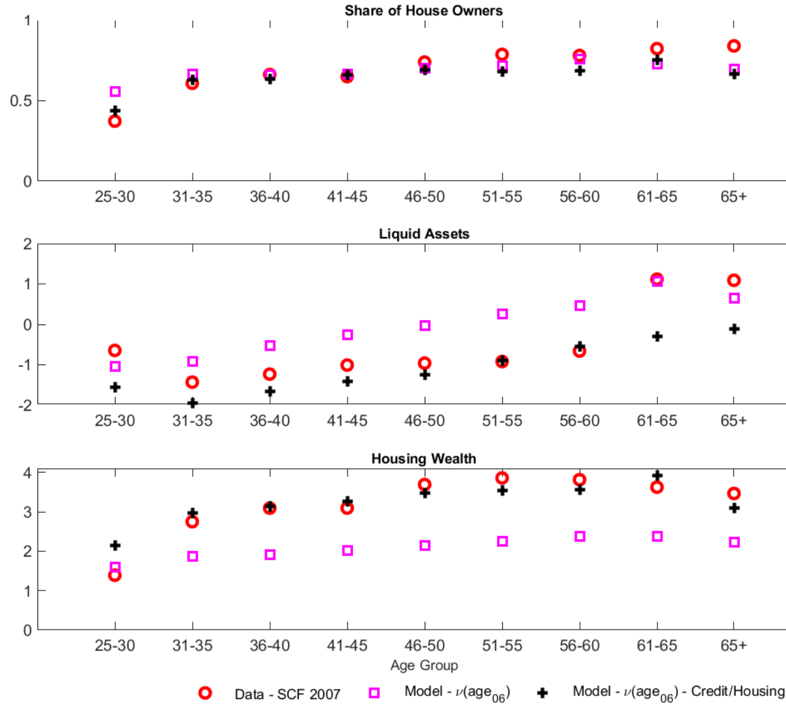


Figure 13: Asset Life Cycle Profiles: The Role of Changes in Income Profiles and Credit/House Prices During the Boom. Data: Survey of Consumer Finance - 2007)

Note: Model $\nu(age_{06})$, incorporates the change in income profile only (pink squares) - Model $\nu(age_{06})$ - Credit/Housing, incorporates change in income profile, the relaxation in credit constraints and the increase in the trend in house prices (dark plus sign).

to save during the lifecycle as income is no longer expected to increase with age. In all cases we depict the invariant lifecycle profiles from the theoretical model. As such, as we compare different simulations all the adjustment/transition process has already occurred. Stock variables such as housing wealth and liquid assets may vary slowly in the data and thus the changes in income profiles we contemplate might take time to affect them. That could be a reason why the model is able to match consumption profiles more closely than the asset lifecycle profiles.

4 Conclusions

We empirically show that hump-shaped lifecycle profiles of US consumption expenditures are an artefact of pooling data across years from an entire sample. When we account for age time interactions not only the hump-shaped profile disappears but we also document clear time varying trends in lifecycle consumption patterns that are robust to a battery of changes in

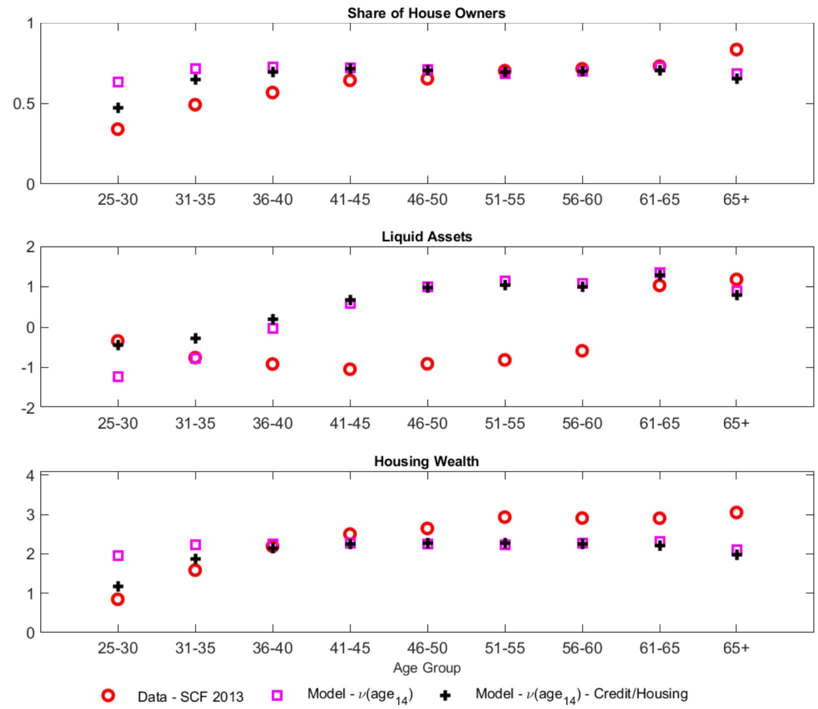


Figure 14: Asset Life Cycle Profiles: The Role of Changes in Income Profiles and Credit/House Prices During the Recession. Data: Survey of Consumer Finance - 2013)

Note: Model $\nu(age_{14})$, incorporates the change in income profile only (pink squares) - Model $\nu(age_{14})$ - Credit/Housing, incorporates change in income profile, the tightening in credit constraints and the decrease in the trend in house prices (dark plus sign).

data, in specification and the introduction of additional controls on household characteristics and economic variables. While analysing the potential drivers of this time variation we find that variation in subjective house wealth in the lifecycle do not seem to affect consumption profiles. In contrast, lifecycle income profiles have shown the same time variation and may be behind the systematic variation in consumption we uncover. A lifecycle model of consumption, housing and liquid asset choice shows that indeed changes in lifecycle income profiles are able to generate the observed change in lifecycle consumption patterns. Changes in credit availability and house price dynamics have a much less pronounced effect on consumption in the lifecycle. Nonetheless, in order to also match asset and housing choice, one need to incorporate both changes in income and in housing and credit dynamics. Overall, our results do not imply 35 year old households today are relatively better off than 35 year old households in the 1990s, rather, the results indicate that at each fixed point in time throughout the last decades, the differences across generations have decreased in both income and consumption.

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A Appendix-Data

i. We begin with household heads of the entire Survey, that is 1968 - 2014; there are 270,578 observations. The initial motivation for the PSID was the study of low income households. This original survey is identified as the Survey for Economic Opportunity (SEO). The Survey Research Centre (SRC) later introduced a sample drawn from all income groups and representative of the population. This is the known as the SRC survey and a sample initially of 2,930 households made up this group. In 1990 a new cohort was added to the sample to correctly represent the level of Mexican, Cuban, and Puerto Rican immigrants in the population.

Households with income less that zero (64) are dropped. All the variables in the sub sample are truncated at the top and bottom. We convert variables on the truncation boundary to missing. Also heads younger than 25 and older than 80 are dropped. Obvious outliers for food at home, food away from home, food stamps, rent, and from the imputed variable are dropped. The final sub-sample comprises 102,644 observations. There are 11,534 households. The average time in the sample is 8.3 years with a minimum of one and a maximum of 29 years.

ii. Because a proportion of households are not homeowners many observations of *house* are zero. This can mean the house is worth zero, or that the household does not own a home. We also have data on the value of mortgage principal remaining, $M_{it} = M^1_{i,t} + M^2_{i,t}$, where $M^1_{i,t}$ is the first mortgage and $M^2_{i,t}$ is a second, on the same property. Again, the response of zero has more than one meaning; (1) home owners have paid off their mortgage, or (2) have never had one or (3) are not home owners. To distinguish between these groups we define the indicator function $\mathbf{1}(..) = 1$ if the condition in the brackets is true, $\mathbf{1}(..) = 0$ otherwise.

We define dummies for no house and no mortgage: $IH_{it} = \mathbf{1}(H_{it} = 0)$ and $IM_{it} = \mathbf{1}(M_{it} = 0)$. We then estimate equations of the form

$$C_{it} = \gamma_i + \gamma_1 \ln(H_{it} + 1) + \gamma_2 \ln(M_{it} + 1) + \gamma_3 IH_{it} + \gamma_4 IM_{it} + ...$$

so for those with no housing wealth it is $\ln(1) = 0$ and we do not lose any observations. Predicted log consumption for a home-owner with a mortgage is

$$\gamma_i + \gamma_1 \ln(H_{it} + 1) + \gamma_2 \ln(M_{it} + 1)$$

home owner without a mortgage

$$\gamma_i + \gamma_1 \ln(H_{it} + 1) + \gamma_4 IM_{it}$$

renter

$$\gamma_i + \gamma_3 IH_{it} + \gamma_4 IM_{it}.$$

We could also interact the dummies with other variables, e.g.

$$C_{it} = \gamma_i + \gamma_1 \ln(H_{it} + 1) + \gamma_2 \ln(M_{it} + 1) + \gamma_3 IH_{it} + \gamma_4 IM_{it} + \beta_1 y_{it} + \beta_2 y_{it} IH_{it}.....$$

iii. We consider two measures of housing wealth. Our preferred subjective home value proxy is based on the responses of homeowners to a question in the PSID survey and reported in housing, mortgage distress and wealth data. Ever since the PSID began home-owners are asked what value they attach to their home. Specifically homeowners are asked:

> 'A20. Could you tell me what the present value of (your/their) (apartment/mobile home/house) is (including the value of the lot if (you/they) own the lot)–I mean about how much would it bring if (you/they) sold it today?'

The question offers an insight into subjective expectations of households about their perceived wealth over a 50 year time period. Household responses to this question define our subjective variable $H_{i,t}$=Subjective Current Home Value. How well do household's subjective home values match prices in the market? In Figure A.1 we compare average values in our sample to the Case-Shiller House Price Index.[19] The two series have a correlation coefficient in the order of 0.96. The relationship holds across house values by income groups; house values in the 10th, 25th, 75th and 95th percentiles have a similar correlation value to the overall value.

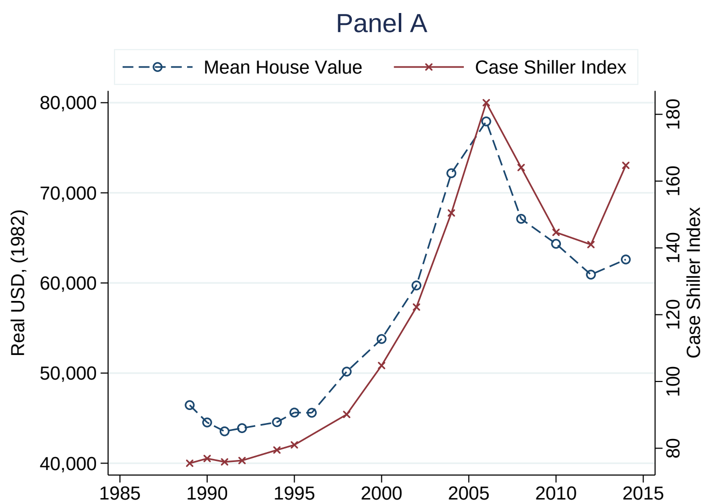


Figure A.1: **S**ubjective House Value and Case Shiller Index

The second proxy is the Subjective Net Home Equity ($HE_{i,t}$) defined as the difference between the subjective house value $H_{i,t}$ and the outstanding mortgage debt ($MD_{i,t}$). $HE_{i,t}$ can take negative values.[20] The relevant questions are:

[19]This is compiled from repeat sales values of houses in the US across nine census divisions.

[20]From 1993 this is extended to include additional mortgages on the same home. Around 200 households have these second mortgages in any year. Because the proportion is small (about 10%) we do not include additional (third, forth etc) mortgages in this data set. Until 1993 mortgage costs were an annual amount. Since then, monthly, and we adjust accordingly to calculate an annual mortgage cost. This question is not included years 1972- 1974, 1981, 1978 - 1988 and 1997. Households with no mortgage, or which have paid off their mortgage, have a value zero. Together with home insurance and property tax, mortgage costs are an alternative way of thinking about the costs and benefits of home ownership. Using Mortgage costs rather than imputed rent in expenditures addresses non linear distortions across the income distribution, implicit in the imputed rent calculation. For example, a wealthy household which has inherited property, may pay no mortgage but imputation assigns a cost based on the value of the property. US mortgage rates are determined by the 'back end ratio' and 'front end ratio'. The ratios are decreasing in income and increasing in house purchase value. If house value and income are not perfectly correlated, interest rates won't be either. Wealthy households may have proportionately lower mortgage payments; because their debt to income ratios are lower and so they face

‘A23. Do you have a mortgage or loan on this property?’ ‘A24. About how much is the remaining principal on this loan?’ ‘A25. How much are your monthly loan payments?’

Figure A.2 displays share of homeowners with positive and negative subjective home equity from mid-80’s. While most homeowners anticipate a positive home equity throughout the sample period, the share of homeowners reporting a negative equity reached to almost %7 in 2010 and their share drops thereafter. We include both positive and negative home equity in our estimations.

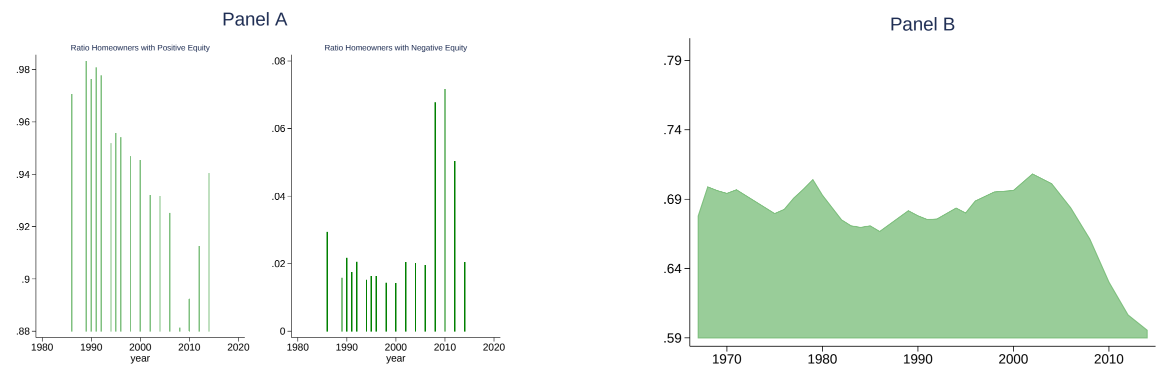


Figure A.2: Panel A: Sample percentage of Home Owners with Positive and Negative Home Equity, by Year. Panel B: Percentage of Home-Owners, by Year.

As subjective Net Home Equity can take positive $HMEQP_{it}$, negative values $HMEQN_{it}$ or zero $HMEQZ_{it}$ values. To retain negative values in the log transformation, we define

$$\begin{aligned} HMEQP_{it} &= \mathbf{1}(HMEQ_{it} > 0) \times HMEQ_{it}, \\ HMEQZ_{it} &= \mathbf{1}(HMEQ_{it} = 0), \\ HMEQN_{it} &= -\mathbf{1}(HMEQ_{it} < 0) \times HMEQ_{it}. \end{aligned}$$

We now present some summary statistics.

Appendix A.1 Unconditional Lifecycle Consumption by Year

We plot the mean consumption by age, by year, $\bar{c}_{age} = \frac{1}{N_{age}} \sum_{age=20}^{80} c_{it}$. There are no controls for household size, composition or any other household level effects. Results are shown in Figure A.3. The typical hump shape over the lifecycle is evident in each of the years.

lower interest rates. A correlation between low income and other debts will add to this distortion, meaning, if low income households have proportionately higher debt than high income households, they may face a higher rate on their mortgage. If this is the case it would be expected that the standard deviation for mortgage costs would be lower than imputed rent (which is a linear function of house value) and we see this after 2000. Imputed rent is a different idea. It is not the costs faced by households at different income levels. Imputed rent is often the variable used when computing consumption. This data set allows use of both mortgage costs/actual rent for renters *and* imputed rent.

	1980 - 1989	1990 - 1999	2000 - 2014
Age of Head	44.60	45.55	46.13
max	80.00	80.00	80.00
min	24.00	24.00	24.00
No. Children	0.88	0.84	0.75
max	7.00	7.00	11.00
min	0.00	0.00	0.00
Married	1.69	1.76	1.77
max	5.00	5.00	5.00
min	1.00	1.00	1.00
Non Home Owner	0.32	0.31	0.34
Grades 0-11 Completed	0.19	0.13	0.10
High School or Equivalent	0.31	0.31	0.27
College Drop Out	0.22	0.24	0.27
BA Degree of Higher	0.28	0.32	0.36
Observations	13369	19855	38438

Table A.1: Household Characteristics

Appendix A.2 Imputation

We again use the PSID, but now include data from 1980 - 1998. The expanded consumption questions were introduced in the 1999 wave. Before this the PSID consistently collected information on a few consumption items: food, home rent and utility payments. For the 1980 - 2015 analysis, we construct an imputed measure of non-durable consumption expenditures following Attanasio and Pistaferri (2014). The imputation approach is based on predicting non-food consumption using an approximate demand system that relates consistently available consumption data (food) to non-durable expenditures.[21] A final adjustment is to drop all odd years to match the biennial structure of the survey after 1998. The final sample consists of 71,662 observations with an average household participation length of 5 waves (or 10 years as we retain biennial waves), a maximum of 17 (16.68 percent), and a minimum of 1 period (2.58 percent). In the long sample homeowners make up about 67.18% of the households.

To estimate imputed non-durable consumption in the pre 1999 data we estimate a log/levels equation by OLS. Specifically, to estimate imputed non-durable consumption in the pre 1998 data we estimate a log/levels equation by OLS in the short sample.

$$\mathbf{nf}_{it} = \mathbf{Z}'_{it}\beta_k + g(f_{it};\theta) + \mathbf{P}'_t\gamma$$

Where

- $nf_{i,t} = \ln(\sum_k C_{it,k})$ is total non-durable, non-food expenditures, with $C_{it,k}$ the expenditure on non-food category k by household i in time t.

[21] Any prediction using this proxy for non-durable consumption expenditures makes assumptions about the stability of relationships between household characteristics and expenditures that we unfortunately cannot test. To limit uncertainty, we choose 1980 as our earliest data point.

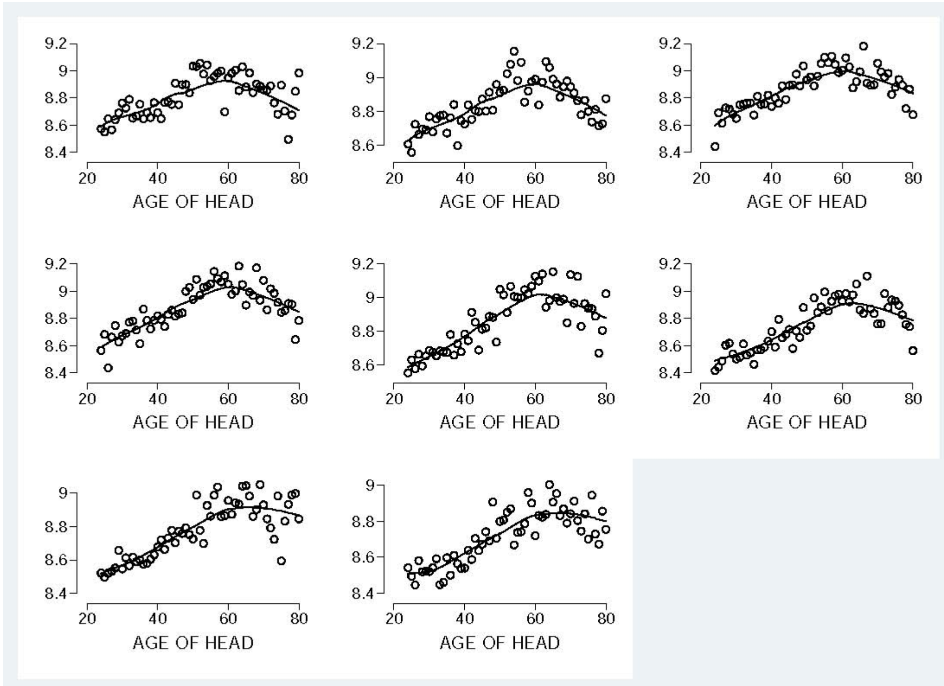


Figure A.3: The panel show mean consumption plotted by age for each year. There are no controls on the data here.

- $\mathbf{Z_{it}}$ is a vector of socio-economic variables in the food demand equation.
- g is a polynomial function for f, the total of food at home, away, and the monetary value of food stamps received. These data are available for all waves except 1981 and 1982.
- $\mathbf{P}$ is a vector of annual price indexes; for overall CPI, food at home and food away from home and rent.

Imputed log total non-durable consumption for 1980 - 2014, $\hat{\mathbf{c}}_{\mathbf{i,t}}$ is then

$$\hat{\mathbf{c}}_{\mathbf{it}} = \log[\mathbf{food}_c + exp(\mathbf{Z}'\hat{\beta} + g(f_{it}; \hat{\theta}_c) + \mathbf{P}'\hat{\gamma})]$$

B Appendix - Specification Issues

Appendix B.1 Scaling of the Data

We investigate how best to adjust for household size and composition. Our findings lead us to control for the number of adults and number of children with dummies and also to use OECD equivalence scales ((Blundell, Browning, and Meghir, 1994)). We show our results are robust to using only dummies to correct for family size as in Aguiar and Hurst (2013).

As is well documented, family composition influences consumption. Failing to control for family composition distorts the intertemporal pattern of consumption and over states the relationship between consumption and income ((Blundell, Browning, and Meghir, 1994)). Scaling for family composition explains over half of the hump shape seen in the data over the lifecycle ((Fernandez-Villaverde and Krueger, 2007)). There are different ways of implementing these controls. One method is to scale consumption using one of the available equivalence scales. The scales attach different weights to adults and children and, in some cases, account for economies of scale also; two adults do necessarily require twice the amount of everything. Each scale has benefits and costs (Fernandez-Villaverde and Krueger (2007))[22]. Another approach is to include dummies for numbers of children and adults, or more elaborate versions of this. (Aguiar and Hurst, 2013) have eleven dummies specifying age groups and gender of children.

One point to note is that although it is clear that controlling for composition is important in measuring the age profile of consumption, it does not account for the fact that household composition is endogenous. For example, the arrival of children is not usually a complete surprise, nor is their departure. This information is known somewhat in advance and so probably influences spending and savings decisions before the econometric control appears.

In the absence of an agreed approach, we compare results from estimating Equation 1 with consumption adjusted for household composition in three different ways, set out below. There are six cases to consider. Three for the Pooled Lifecycle model and three for the Time-varying Lifecycle model. We take the information criteria as a measure of best fit.

1. 20 Dummies are included in the model to allow for the number of children and adults, but the consumption variable itself is not treated in any way. Attanasio et al (1995) and Aguiar and Hurst (2013) also allow for age and gender of children.

2. OECD equivalence scales.
   These are many equivalence scales to choose from but OECD scales are used in similar work. To apply this, $C_{i,t}$ is divided by the scale value, $scale_{i,t} = 1 + 0.7(n_{i,t} - 1) + 0.5k_{i,t}$, where n is the number of adults and k the number of children. We estimate equations with log values so
   $$c^{sc}_{i,t} = ndc_{i,t} - ln(scale_{i,t})$$
   where $c^{sc}_{i,t}$ = log scaled non-durable consumption$_{i,t}$ and $ndc_{i,t}$ is log non-durable.

[22] See http://www.oecd.org/eco/growth/OECD-Note-EquivalenceScales.pdf or (Attanasio, Banks, Meghir, and Weber, 1999).

3. Consumption is adjusted by OECD scale and a full set of dummies are also included. The motivation for this configuration is that after the log transformation, $c^{sc}_{i,t}$ is not equivalent to its levels counterpart $C^{sc} = \frac{C_{i,t}}{Scale_{i,t}}$ and so further controls are needed to capture household composition effects.

	1	2	3
Pooled Lifecycle, equation 1, case 1			
AIC	26203.9	28990.9	25962.6
BIC	27007.8	29665.1	26766.5
df_m	92	77	92
Time Varying Lifecycle, equation 1, case 2			
AIC	26165.2	28990.3	25929.6
BIC	27591.5	30286.9	27355.9
df_m	164	149	164

Table A.2: Comparison of Different Adjustments of Consumption for Household Composition. 1) Dummies, 2) OECD Scales, 3) Both, Short Data Set

Adjusting consumption by OECD scales *and* including separate dummies for numbers of children and adults in the household, (3) above, provides the best fit. Note that this is in spite of the cost of the introduction of 15 additional parameters. The OECD scaling applies a fixed adjustment to each household but this obviously does not completely describe how household composition changes affect consumption. The dummies are more flexible. We note that the model does not account for differences in returns to scale for different expenditure categories as in (Aguiar and Hurst, 2013) or the endogeneity of family composition.

We can test whether the scaling is correct. Define scale as $S_{i,t} = \sum w_i N_i$, some weight w applied to household size and composition. Then the equation has the form $\ln ndc_{i,t} - ln(scale)_{i,t} = \sum \alpha_i N_i$. Or $\ln ndc_{i,t} = \gamma ln(\sum w_i N_i)_{i,t} + \sum \alpha_i N_i$. The hypothesis that $\gamma = 1$ is not rejected so imposing the scaling on the dependent variable is acceptable. This equation brings out the different way that the number in each category influences log consumption; linearly through the dummies and logarithmically through the scaling. Plotting the coefficient values by year, Figure A.4 makes it easy to see the effects of the different scaling approaches on the lifecycle consumption estimations. The less restricted approach, 2, captures household specific household composition effects left behind by the more restrictive OECD scaling treatment. (See St Aubyn (2018) for details.)

Appendix B.2 Deflating the Data

We compare two methods for deflating the consumption data. The first uses expenditure category specific price indices in order to account for relative price variations and is applied in the short data set. The second more commonly used method utilises the simple CPI across all expenditure categories. We use CPI to deflate the long data set that is imputed. This is because we do not impute category by category, but by the aggregated non-durable consumption variable. For the short data set, we show that results are robust to either deflation method.

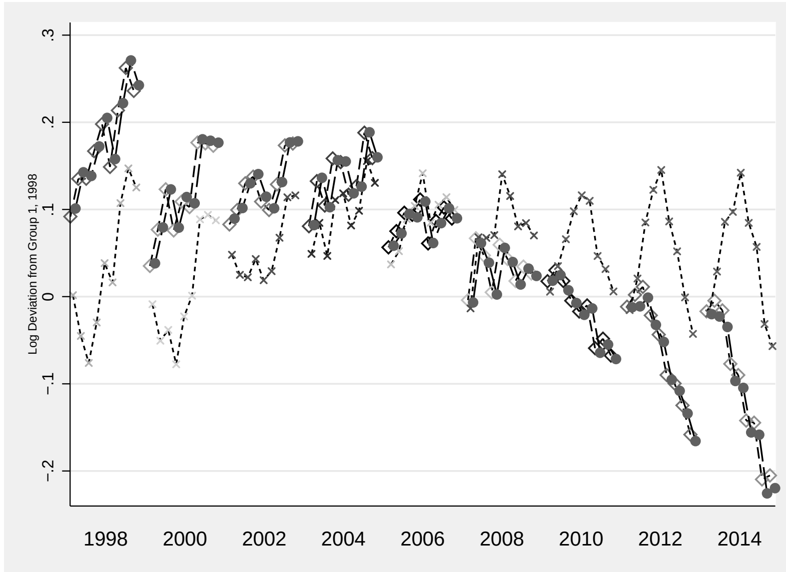


Figure A.4: Cross sectional lifecycle plots: scaled versus non scaled plots. Diamond, dashed line, includes equivalence scales *and* controls for number of adults and children. X's, dot plot, equivalence scales but no controls for number of adults and children, O's long dash, no scaling but controls for number of adults and children.

In general, consumption data are deflated for lifecycle analysis by a measure such as overall CPI, or a weighted average of price indices. But some work Aguiar and Hurst (2013) deflates by price indexes specific to spending category. We check the impact of deflation approach by these two methods on lifecycle consumption and find it has only a small affect on the outcome (See St Aubyn (2018) for details.)

Appendix B.3 Cohort Effects

When measuring the age profile of consumption, controls should be included for cohort effects and business cycle effects. The first recognises that some features of lifetime consumption influences are specific to year of birth. The second, picks up shocks that affect the whole population but in a particular time period.

The difficulty here is that $cohort + age = year$. Deaton and Paxson (1994) devised a method to make the columns of the time dummies sum to zero, thus making them orthogonal to the year effects, t. This is a popular approach and is adopted in much of the literature. [23] We define the orthogonalised dummies, $d{*}_t$ in the model instead of the standard time dummies D_t. Jappelli and Pistaferri (2017) state age, cohort and time effects cannot all be identified without "imposing non testable assumptions". [24]

[23] To do this, two columns of the time dummies are dropped (coefficients for the first two years can be recovered) and a set of treated time dummies for $t = 3, .., 8$, is defined, dropping the *year* superscript for simplicity, $d_t^* = D_t + (1-t)D_2 + (t-2)D_1$. D_t are the usual dummies for time that equal 1 when the year is t and 0 otherwise.

[24] Note that this control only captures the additive effect of macroeconomic shocks of time (Jappelli and Pistaferri (2017)), not those where time effects are not additively separable from age. The assumption then is

	All_Controls	Cohort	Time
AIC	26007.0	26455.6	25982.6
BIC	27398.6	27786.8	26777.8
df_m	160	153	91

t statistics in parentheses

Table A.3: Pooled Lifecycle Model: Comparison of Information Criteria for Different Controls

Even when controls for all three effects, cohort, age and time, can be identified, they only control for additive effects. There will be a difference across ages that vary with time. For example, the age coefficients, β_a, will be stripped of average cohort and average time effects for all ages. This assumes, for example, that a macroeconomic shock affects all ages in the same way. There will also be household specific effects (e.g. a household with high debt may have a different response to a rise in interest rate than a household with high savings).

We are interested in estimating the lifecycle profile of consumption (Equation 1), for the Pooled Lifecycle model, the Time-varying Lifecycle model. Given the discussion around the time, cohort and age effects, we experiment with estimations using different combinations of these controls. To establish the best specification, the information criteria are compared.

The modified model for this exercise is

$$c_{i,t} = \alpha_i + \beta_{g,t} Age_{i,g,t} + \gamma_c Cohort_{i,t} + \delta_t d^*_{i,t} + \psi_Z Z_{i,t} + \epsilon_{i,t} \tag{A.1}$$

$$Age_{i,g,t} = \begin{cases} D^{Age}_{i,g} & \text{Case 1 - } \textit{Pooled Lifecycle} \\ D^{Age}_{i,g} \times D^{Time}_{i,t} & \text{Case 2 - } \textit{Time-varying Lifecycle} \end{cases}$$

Where $Cohort_{i,t}$ is a set of cohort dummies, one for each year of birth, with the last one (youngest person) dropped. d^*_t are the orthogonalised time dummies, one for each year from period 3 - 9.

Results are reported in Table A.3 for the Pooled Lifecycle, and Table A.4 for the Time-varying Lifecycle. Including time dummies *and* cohort dummies is labelled *All Controls*, including only cohort dummies, *Cohort*, and including only time dummies, *Time*. Note that age is controlled for in both models by Age_{ig} and Age_{igt}.

Both the Pooled and Time-varying Lifecycle estimations favour including time dummies and excluding cohort dummies. Also, the coefficients for cohort, γ_c are not significant. We thus drop cohort dummies from the model and retain pure time dummies, D_{it} and age dummies, Age_{it}, for the Pooled Lifecycle model, age time dummies, β_{gt}, for the Time-varying Lifecycle model.

In summary, we ask an age-time question; is the spending allocation of a 30 year old in 1980 the same as a 30 year old in 1990? This is the same question as asking if the spending

that time effects are the same for all ages. There are other solutions in the literature. For example McKenzie (2006) suggests a second differencing approach. In this paper, we will begin with cohort, age and follow Deaton and Paxson (1994) with orthogonalised time.

	All_Controls	Cohort	Time
AIC	25962.4	25993.2	25942.1
BIC	27976.4	27946.7	27359.7
df_m	232	225	163

t statistics in parentheses

Table A.4: Time-varying Lifecycle Model: Comparison of Information Criteria for Different Controls,

of someone born in 1950 is the same as someone born in 1960 when they are 30, ie in 1980 and 1990. However, posing it as an age-time question, rather than a cohort - time question, seems more productive for several reasons. First, it is more parsimonious. Given the life span, there are a fixed number of ages whereas the number of cohorts keeps increasing. Second, there is quite a lot of economic theory about the lifecycle, but relatively little about cohort effects. Third, the lifecycle story can be interpreted more directly. From the mid 1990's there are relative changes in consumption allocations between the age groups. We could not observe this from the cohort perspective.

Appendix B.4 Household Time-varying Controls

We also consider the contribution of the household characteristics included in Z. The initial choice follows other work in lifecycle consumption, variables which are known to affect consumption are included, see Section 2.2. All the are significant except education, which is dropped due to multicollinearity. Education dummies denote maximum education level achieved. There are four of these, the highest is a college degree or higher. The sample has ages 24 to 80. Education level will only change after the age of 24 either in non standard cases of adult education or, in the sub set of graduates. Otherwise, after the age 24, there will be no change. Estimation is by fixed effects. There is not sufficient time variance in the data to estimate the impact of education level. We thus drop education from the model.

In the final specification we control for time but not cohort, and because of this, can include standard time dummies, d_t, not the orthogonalised version. From the vector Z, education is dropped. We use data that are scaled by the OECD equivalence scale and also include dummies for number of children and number of adults.

Appendix B.5 Reference Group

In Equations 1 - 2 we want to identify age effects in time. We have g age groups, 1,...,G and t time periods, 1,..., T.

$Age_{i,g,t}$, is abbreviated as $A_g T_t$ in this Section for ease of notation.

$\beta_{g,t}$ can be interpreted as the log difference in average consumption for each age-time pair, from the reference group. However, there are different ways to parameterise the age/time and time effects and this may affect this interpretation. Because the parameters of interest have two dimensions, age and time, for the reference group we can drop the first age group in the first time period or we can drop the first age group for all time periods. We want to be able to interpret the β_{gt} coefficients with reference to their own age group and also in a specific time period, i.e. across time in groups (time series) and as lifecycles for different years (cross-sections). We estimate both specifications described above and compare the results;

Case A

Leave out age group 1, for all t, include age group 2 - G for all time periods; $A_2T_1 - A_GT_T$. Include T-1 time dummies, dropping $t = 1$. There are $NT - 1$ parameters.

Case B

Leave out age group 1 in time period 1 only, A_1T_1 and leave out all time dummies. Again we have $NT - 1$ parameters. Both cases are estimated. Comparing the results we find the following:

In Case A, the coefficients of the $T - 1$ time dummies δ_t^A, are identical to the coefficients $\beta_{1,t}^B$ on the $A_1T_2 - A_1T_T$ dummies in model B (where time dummies are excluded). That is

$$\delta_{t+1}^A = \beta_{1,t+1}^B \tag{A.2}$$

The coefficient of A_2T_1, $\beta_{2,1}^A$ in A is identical to the coefficients on $A_2T_1, \beta_{2,1}^B$ in B.

The coefficient of A_2T_{t+1} in model B is equal to the coefficient of A_2T_{t+1} in model A *plus* the coefficient $\beta_{1,t+1}^B$, which by (A.2) is identical to the time dummy in the corresponding period in model A

$$\beta_{1,t+1+i}^B = \beta_{1,t+1+i}^A + \delta_{t+1+i}^A$$

where $i = (0, 1, ..., T - 1)$

In both cases, the base case is $\beta_{1,1}$ and this acts to scale all the other coefficients.

In Case A, the age time coefficients are

$$\beta_{g,t}^A = \beta_{g,t} - \underbrace{\beta_{1,t}^B}_{=\delta_t^A} - \beta_{1,1}^B \tag{A.3}$$

for $g = 2, ..., G$ and $t = 2, ..., T$

The δ_t coefficients capture average time effects from the perspective of the omitted age group. Although the time effects affect all age groups together, they nonetheless are a configuration of year effects and the consumption of the omitted age group; the two cannot be disentangled. In our example age group 1 is omitted. If a different age group was left out, the value of the δ_t's would be different.

In Case B

$$\beta_{g,t}^B = \beta_{g,t} - \beta_{1,1}^B \tag{A.4}$$

for $g = 1, ..., G$ and $t = 2, ..., T$

In Case B, the age time coefficient includes the value of δ_t; the average time effect plus the omitted age group's consumption.

In summary, from Equations (A.3) and (A.4)

$$\beta^A_{g,t} = \beta^B_{g,t} - \delta^A_t$$

for $g = 2, ..., G$ and $t = 2, ..., T$

$$\beta^B_{1,t} = \delta^A_t$$

for $g = 1, ..., G$ and $t = 2, ..., T$

$$\beta^A_{2,1} = \beta^B_{2,1}$$

Being clear about the effects of different parameterisations is important for interpretation of the age-time coefficients. In Cases A and B, the base group is always the first age group in the first time period. This is a constant, subtracted from each age-time coefficient from group 2 - G. The group one coefficients, for the remaining time periods (t+1) - T are a configuration of average time effects and the consumption level of the youngest age group, δ_t. In Case A, these δ_t's are subtracted from the corresponding age - time coefficients, Equation (A.4) which can then be interpreted as a cross-sectional lifecycle from the perspective of the youngest age group in each of the time periods. Alternatively, organised by age group over time, the coefficients can be interpreted as a time series of consumption by age group from the perspective of the first time period for that age group. If this were not the case then drawing conclusions about the evolution of the β_{gt}'s would be less clear. Thus Case A is selected, noting that although we cannot separate time effects entirely, we can at least narrow it down to the an age group specific response. For further details on the data and specification issues see St Aubyn (2018).

Appendix B.6 Different Approaches to Estimating Consumption over the Lifecycle

Consumption over the lifecycle can be estimated in different ways. What effect do different approaches have on the results? As an additional robustness check, and because the estimation method is important to our results, we consider the effect of alternative specifications.

Three models and estimation approaches are considered here. We estimate Equation 1. Because the data are in panels, we can compare estimation results from 1) pooling all the ages over all time periods (Pooled Lifecycle model), and 2) interacting age and time (Time-varying Lifecycle model). We can separate this approach in another way, 3) estimating the age effects by year as a cross-section (Repeated Cross-sectional model). Pooled Lifecycle models and Cross-sectional models are commonly used in the literature. Both Pooled Lifecycle and Time-varying Lifecycle models can be estimated by OLS or by fixed effects that differ in their treatment of unobserved household effects. We can therefore differentiate the impact of controlling for unobserved household effects, which are likely to be correlated with age by inspecting the fixed effects versus OLS estimates.

B.6.1 Pooled Lifecycle Model: OLS versus Fixed Effects

OLS Estimation

This is a standard approach in estimating consumption over the lifecycle. The households in each age group in every time period are pooled and the average effect estimated by β_g.

Estimating by OLS means there are no controls for unobserved household level effects, α_i so the residuals take the form $v_{it} = \alpha_i + \epsilon_{it}$. It is likely that they will be correlated with age; $cov(Age_{ig}, \alpha_i) \neq 0$. This means the estimators will likely be biased. If the covariance of Z_{it} with Age_{ig} is not zero this will also effect the value of the β_g's.

Fixed Effects Estimation

Now unobserved household effects can be controlled for. The approach means that the α_i's are subtracted out of the data. This removes any bias in the nine β_g's that resulted from $cov(Age_{ig}, \alpha_i)$. The remaining impact of this estimation approach is a scaling effect on all the variables that change over time. The fixed effects procedure is to subtract the mean effect over all time periods from each observation, $x_{it}^{FE} = x_{it} - \frac{1}{T}\sum_{t=1}^{T} x_{it}$.

The effect of the bias of unobserved household effects is striking, Figure A.5. When household effects are not controlled for, consumption slopes upwards over the life cycle. This changes to a downward slope in the fixed effects specification.

As a further robustness check, both estimation approaches are carried out over log of food consumption. In this instant, there is not much difference between FE and OLS, implying the bias from household effects is smaller for food than for overall non-durable consumption. This makes sense, everyone has to eat, whereas the other spending categories can be much more discretionary and household heterogeneity has more impact. Aguiar and Hurst (2013) provide evidence that uninsurable income risk is overstated by aggregate non-durable consumption. Disaggregation by spending categories reveals individual heterogeneity and substitution effects arising from retirement and explains part of the hump-shaped profile over the lifecycle. Estimation is by OLS over data from the CEX. Aguiar and Hurst (2013) also estimate lifecycle effects over food consumption in the PSID by OLS and FE as a robustness check for unobserved household effects.[25] It finds similar results as we do; there is not much difference between the two approaches when the dependent variable is food consumption. Our extension of this to non-durable consumption in the PSID, suggests that this assumption cannot necessarily be extended to non-food consumption. This makes the (Aguiar and Hurst, 2013) conclusions potentially sensitive to the absence of controls for household effects.

B.6.2 Time-varying Lifecycle: OLS versus Fixed Effects

We are estimating Equation 1, the Time-varying Lifecycle model. Each estimate is the difference with reference to the youngest age group in the first period.

1. By OLS, where we do not control for unobserved household effects.

[25] A full measure of consumption was not available at this time in the PSID, before 1999, it only asked questions about food consumption.

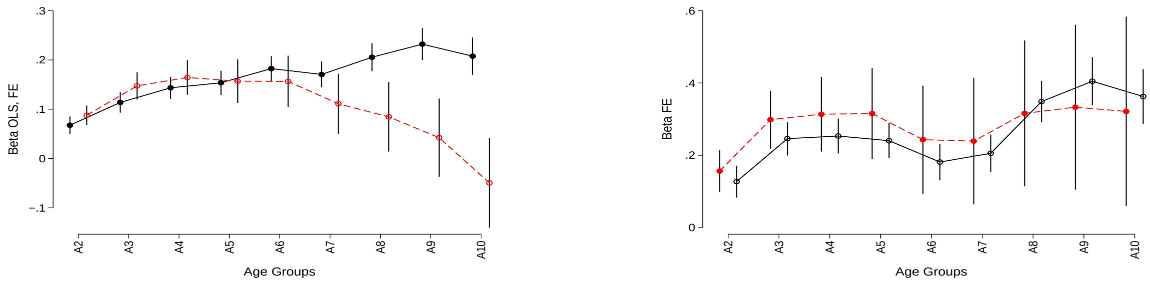


Figure A.5: Estimates of age effects for non-durable consumption (left) and food (right). Age groups are pooled over all time periods, 1998 - 2014. Fixed effects (dashed line) and OLS (solid line).

2. By fixed effects, where we do and $v_{it} = \epsilon_{it} + \alpha_i$

From the pooled estimation we know that fixed effects estimates are different to those from OLS estimation. However, when we disaggregate by time, there are systematic cross year differences within the fixed effects estimations that are not obvious in the OLS specification, Figure A.6. The fixed effects pattern pivots over the years from an upward slope to a downward one.

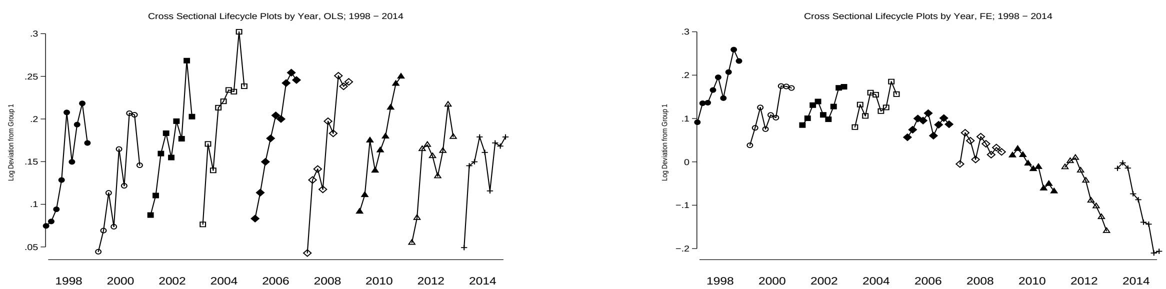


Figure A.6: β_{gt}^{OLS} (left panel) and coefficients β_{gt}^{FE} (right panel)

B.6.3 Repeated Cross-sections

We estimate Equation 1, by OLS over repeated cross-sections, i.e. T sets of estimates, one for each time period. Each estimation yields $G - 1$ coefficients, $\beta_g t$.

There are three sorts of bias that can arise in estimates of β_{gt} from this approach. The vector of controls in Z_{it} varies in each time period, so rather than estimating their effect as an average over all time periods it is an average for one time period. The covariance $cov(Age_{igt}, Z_{it})$ may or may not equal zero and this may vary in each period and thus in each set of estimation results. Second, we cannot control for unobserved household effects α_i and these are very likely to be correlated with age in each year. The above introduce bias in β_{gt}. Third, we cannot control for average time effects in this approach. If correlated with the Age_{igt}, this will also bias the estimators β_{gt}.

The plots of the estimated coefficients are not reported here but show that although there is variation from year to year, the overall shape of the lifecycle plot is sloping upwards with age.

This is consistent with the estimation of Pooled Lifecycle model estimated with OLS above. The difference between these two approaches is the covariance of the unobserved household effects, ϵ and controls, Z_{it} with Age_{igt}. Information criteria are reported in Table A.5.

B.6.4 Comparison by Information Criteria

Various models estimated here are sometimes nested versions of each other and sometimes not. One way of comparing all of them, regardless of the structure and relationship, is by information criteria.

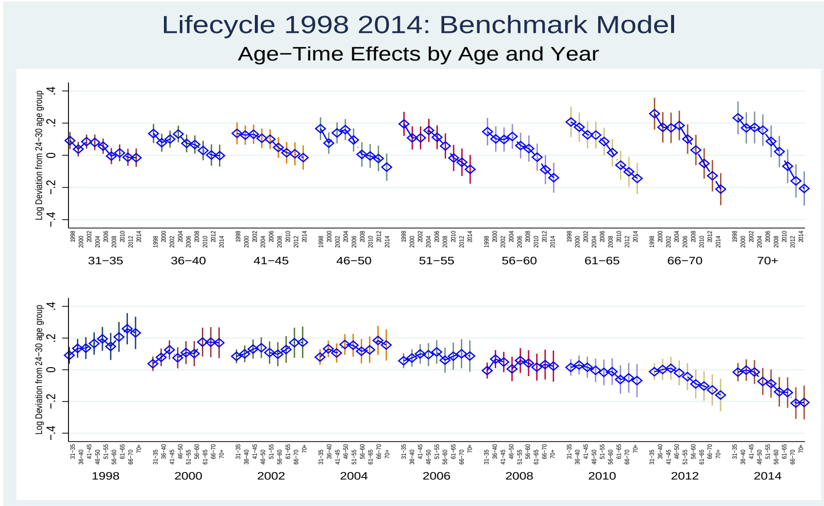
For the repeated cross-sections estimation the AIC and BIC are summed for each time period. The sum of the individual information criteria is an appropriate comparison to the AIC and BIC of the benchmark model estimated by the fixed effects specification. Table A.5 displays our results.

Model	obs	LL Null	LL Mod	df	AIC	BIC
Equation 1: FE, Time-varying,	41,685	-15601.62	-12777.64	165	25885.29	27310.54
Equation 1: OLS, Time-varying	41,685	-41888.93	-31448.08	169	63234.17	64693.97
Equation 1: FE, Pooled	41,685	-15601.62	-13108.35	85	26386.7	27120.92
Equation 1: OLS, Pooled	41,685	-41888.93	-31750.17	89	63678.34	64447.11
Equation 1: Repeated Cross-sections						
Year						
1998	4156	-3613.81	-2710.25	84	5588.5	6120.413
2000	4395	-3908.11	-2887.67	84	5943.349	6479.959
2002	4557	-4238.76	-3033.18	84	6234.364	6774.016
2004	4605	-4489.16	-3159.45	85	6488.902	7035.868
2006	4706	-5000.71	-3710.55	86	7593.093	8148.36
2008	4832	-5140.64	-3933.82	86	8039.631	8597.171
2010	4838	-4971.75	-3734.82	86	7641.633	8199.279
2012	4833	-5167.16	-3932.54	84	8033.086	8577.676
2014	4763	-4925.37	-3687.68	83	7541.352	8078.249
Total					63103.91	68010.99

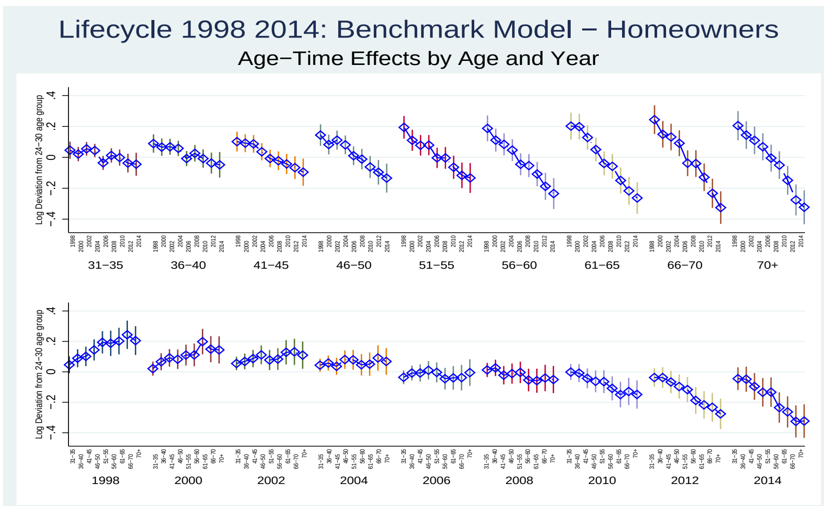
Table A.5: Information criteria for the different approaches for estimating the lifecycle consumption profile.

C Additional Robustness Results

We run several specifications for robustness. Figures not presented in the main text are presented here. First we report the estimates of the benchmark model with 10 age groups and the results of the estimation of the benchmark model using a sample of homeowners.



(a) Full Sample



(b) Homeowners

Figure A.7: Age group coefficients: Model with 10 age groups: **Top** Coefficients by age group. **Bottom** Lifecycle plots by year.

We re-estimated the model with the long sample and 10 age groups. Results of are shown in Figure A.8.

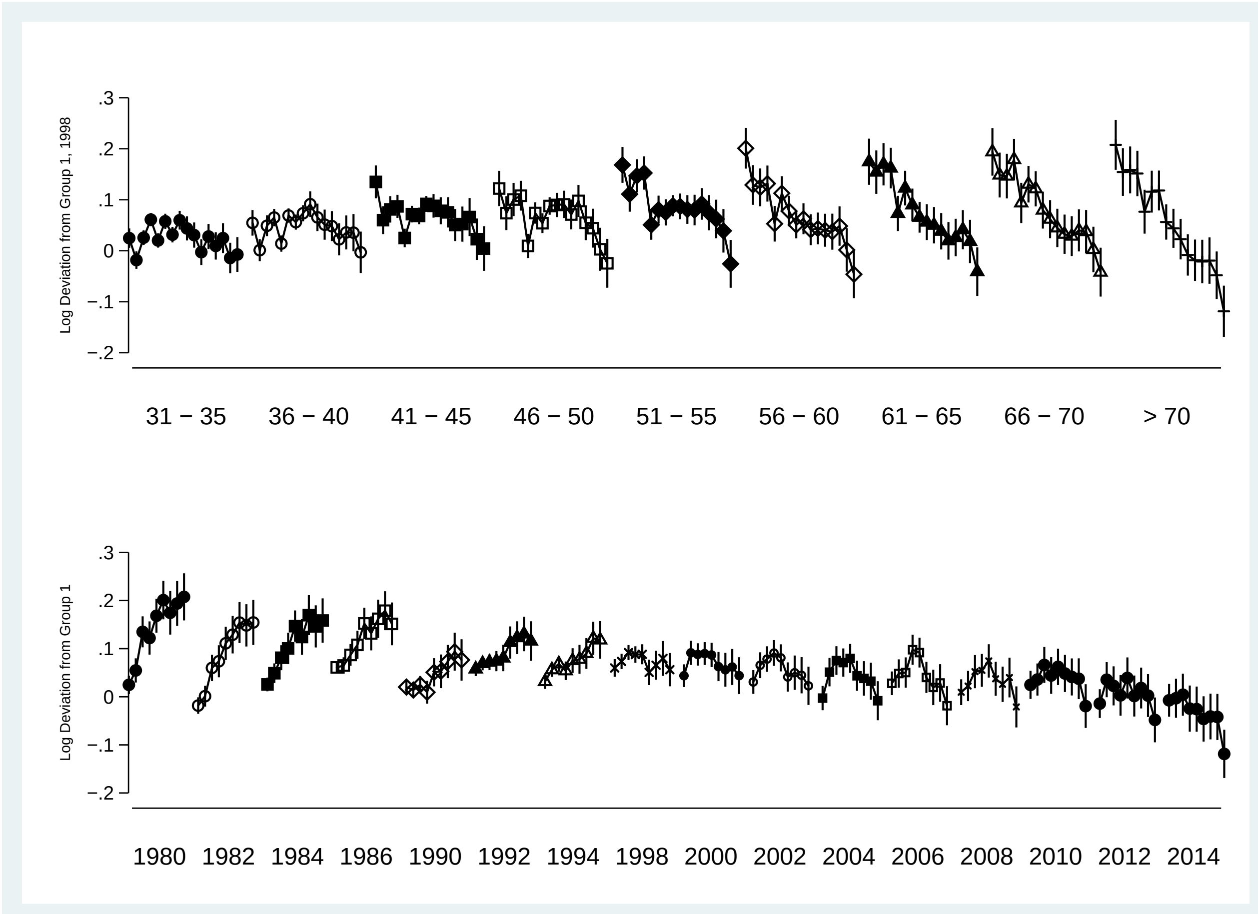


Figure A.8: Results from Long Data Set with age groups refined to smaller, 5 year, groups. **Top** Time series by age group. **Bottom** Cross sectional lifecycle plots by year.

We also estimate the model for consumption subcategories. Results are shown in Figure A.9

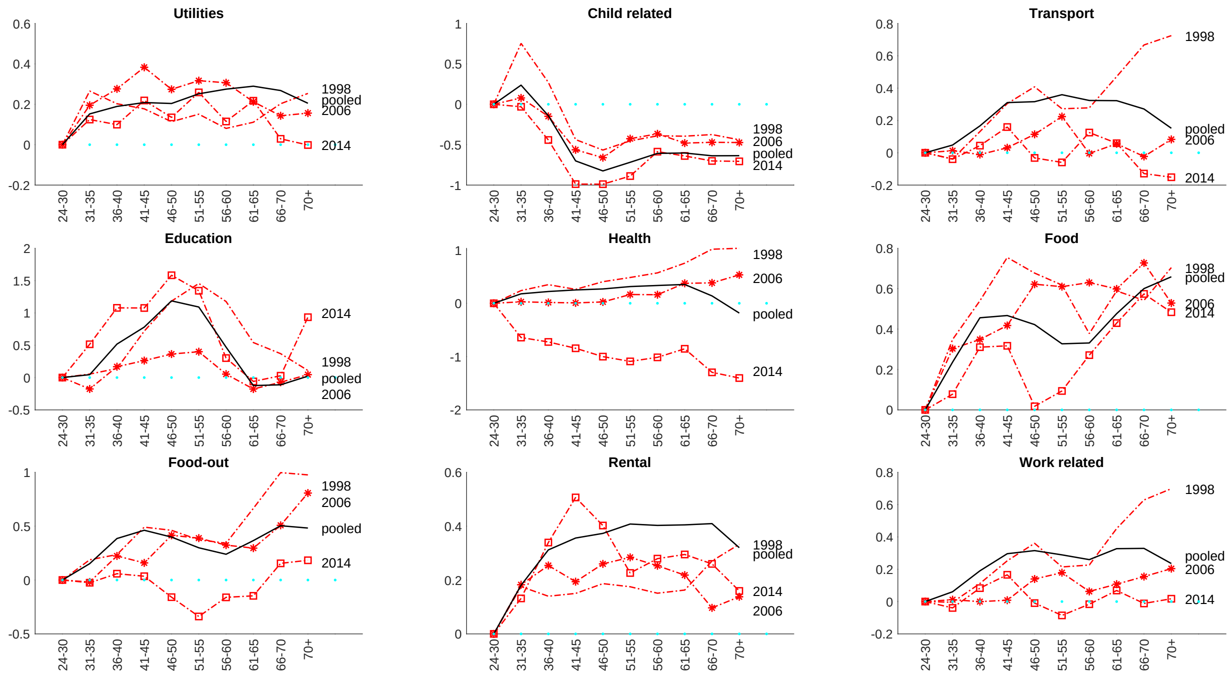


Figure A.9: Sub-categories age group coefficients: Each dashed line depicts $\beta_{g,t}$ for a selected year of the wave of the survey, $(1998, 2006$ and $2014)$, depicting the estimated lifecycle pattern of consumption for each year. The dark line depicts the age effects β_g when age effects pools information for the entire sample. The graph considers 10 age groups.

We also estimate the model for different education groups. Results are shown in Figure A.10

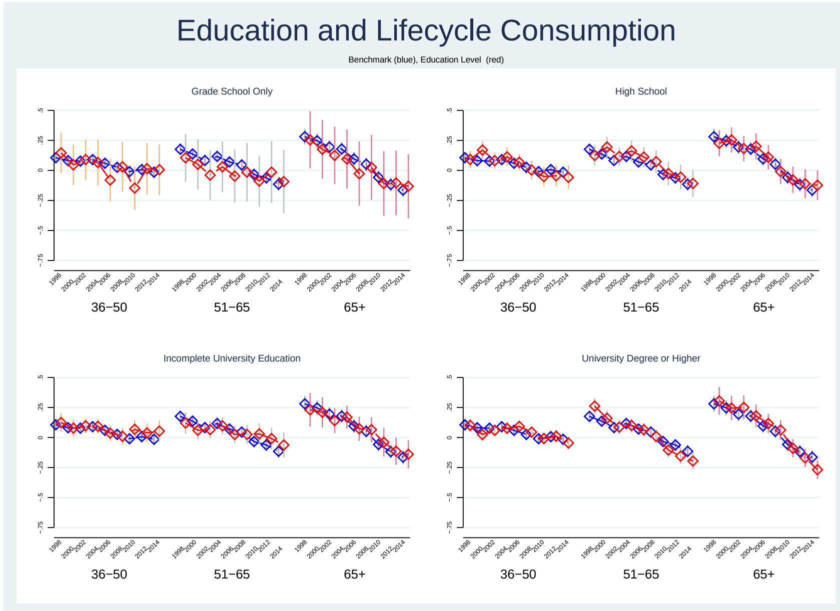


Figure A.10: Age Group Estimates for Groups with Different Education Levels (red) versus the Benchmark (blue)

Finally, we estimate the model including only stable households (the ones for which the head or the spouse do not change). Results are shown in Figure A.11

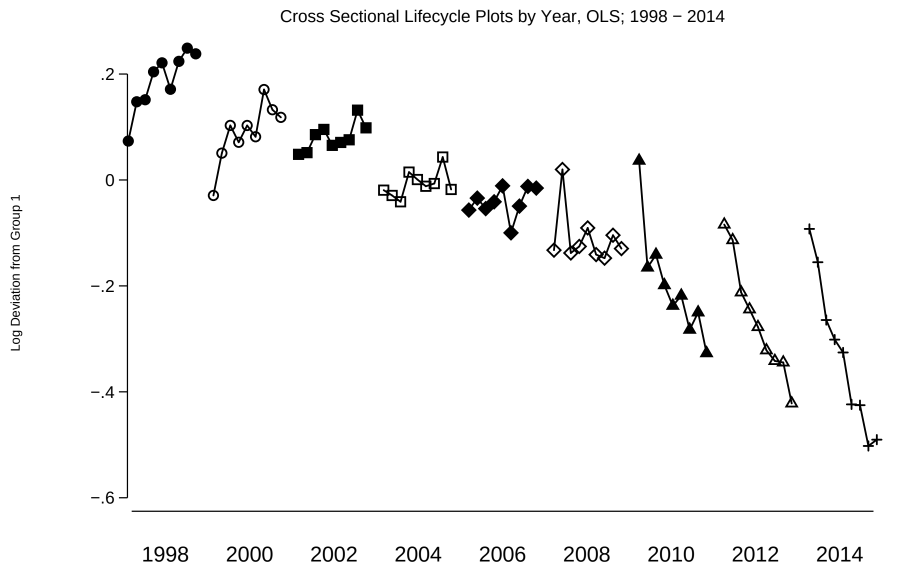


Figure A.11: Age Group Estimates including only Stable Households

D Additional Results - Interaction Models

We report the results of the interaction model when both house value and income are included.

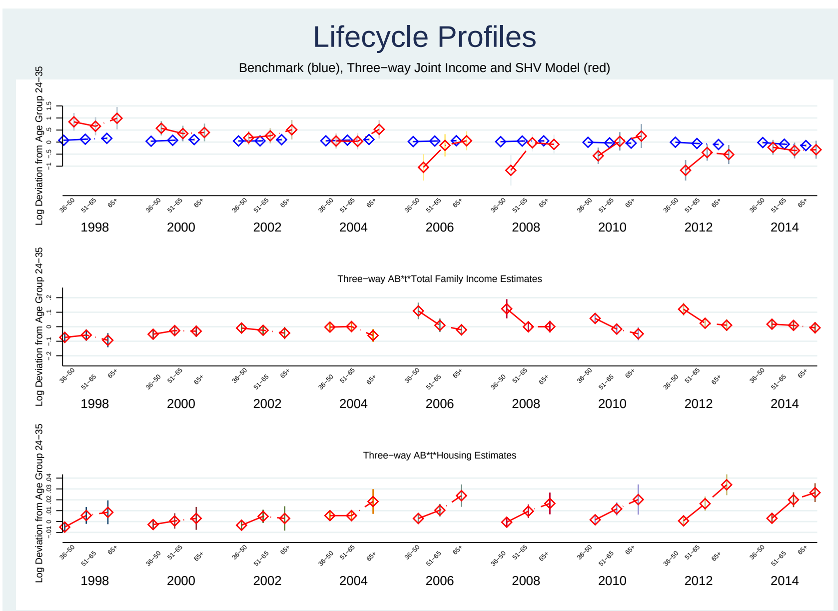


Figure A.12: Age group coefficients: Benchmark Model (Equation 2) and Joint Income and Housing Interaction Model (Equation 3), Whole Sample. Top Panel: $\beta_{g,t}$ from Equation 2 (blue) and Equation 3 (red); Middle Panel: $\theta_{g,Y,t}$ Bottom Panel: $\theta_{g,H,t}$

E Additional Results - Income Lifecycle Variation

We report the results of the income estimation using labour income instead of total family income.

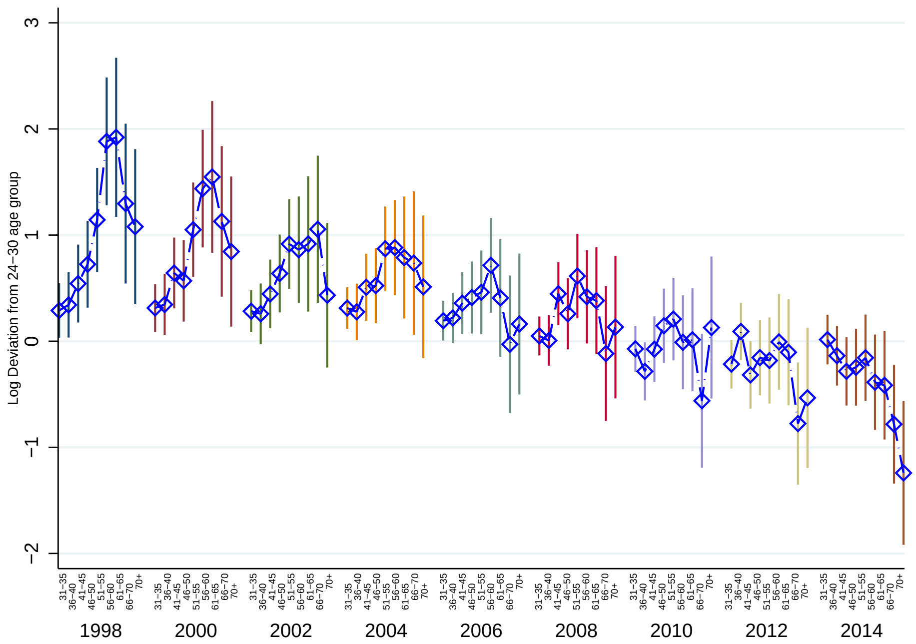


Figure A.13: Age group coefficients ($\beta^{Y}_{g,t}$) plotted by age group by year - Labour Income

F Full Estimation Results: Age-Time Effects with 4 Age Groups

Table A.6 show the full results of the estimation of the benchmark model Case 1 - *Pooled Lifecycle* and Case 2 - *Time-varying Lifecycle* with and without economic controls. Table A.7 show the full results of the estimation of the benchmark model Case 2 - *Time-varying Lifecycle* and the *Interaction Models*.

Table A.6: Benchmark Estimations: Nondurable Consumption Expenditures

	(1) Pooled		(2) Benchmark: Time-Varying Lifecycle		(3) Benchmark: Time-varying Lifecycle with TFI and SHV	
A2	0.09***	(0.00)				
A3	0.08***	(0.00)				
A4	0.00	(0.85)				
t2000	0.05***	(0.00)	0.07***	(0.00)	0.06**	(0.00)
t2002	0.07***	(0.00)	0.10***	(0.00)	0.07***	(0.00)
t2004	0.08***	(0.00)	0.11***	(0.00)	0.05*	(0.02)
t2006	0.07***	(0.00)	0.13***	(0.00)	0.05*	(0.02)
t2008	-0.04**	(0.00)	0.05	(0.06)	-0.03	(0.22)
t2010	-0.00	(0.80)	0.13***	(0.00)	0.05	(0.05)
t2012	-0.04**	(0.00)	0.12***	(0.00)	0.03	(0.32)
t2014	-0.03	(0.07)	0.16***	(0.00)	0.06	(0.06)
# Adults=2	-0.14***	(0.00)	-0.15***	(0.00)	-0.04*	(0.04)
# Adults=3	-0.27***	(0.00)	-0.28***	(0.00)	-0.10***	(0.00)
# Adults=4	-0.39***	(0.00)	-0.41***	(0.00)	-0.15***	(0.00)
# Adults=5	-0.52***	(0.00)	-0.54***	(0.00)	-0.26***	(0.00)
# Adults=6	-0.53***	(0.00)	-0.54***	(0.00)	-0.23	(0.05)
# Adults=7	-0.76***	(0.00)	-0.77***	(0.00)	-0.32**	(0.01)
# Adults=8	0.58***	(0.00)	0.60***	(0.00)	0.78***	(0.00)
# Child=1	-0.15***	(0.00)	-0.16***	(0.00)	-0.08***	(0.00)
# Child=2	-0.31***	(0.00)	-0.33***	(0.00)	-0.20***	(0.00)
# Child=3	-0.46***	(0.00)	-0.49***	(0.00)	-0.31***	(0.00)
# Child=4	-0.60***	(0.00)	-0.63***	(0.00)	-0.41***	(0.00)
# Child=5	-0.69***	(0.00)	-0.72***	(0.00)	-0.46***	(0.00)
# Child=6	-0.68***	(0.00)	-0.71***	(0.00)	-0.42***	(0.00)
# Child=7	-0.58***	(0.00)	-0.63***	(0.00)	-0.31*	(0.02)
# Child=8	-0.59***	(0.00)	-0.63***	(0.00)	-0.31***	(0.00)
# Child=9	-0.80***	(0.00)	-0.84***	(0.00)	-0.55**	(0.00)
# Child=10	-1.80***	(0.00)	-1.84***	(0.00)	-0.79***	(0.00)
# Child=11	-0.82***	(0.00)	-0.93***	(0.00)	-0.57***	(0.00)
White	-0.05	(0.21)	-0.05	(0.21)	-0.06	(0.13)
Black	0.21	(0.23)	0.20	(0.25)	0.20	(0.25)
State2	0.39***	(0.00)	0.38***	(0.00)	0.31***	(0.00)
State3	0.20	(0.06)	0.20	(0.06)	0.20	(0.06)
State 4	0.57***	(0.00)	0.56***	(0.00)	0.48***	(0.00)
State 5	0.44***	(0.00)	0.44***	(0.00)	0.37***	(0.00)
State 6	0.35**	(0.01)	0.32*	(0.02)	0.29*	(0.02)
State 7	0.38***	(0.00)	0.37**	(0.00)	0.31**	(0.01)
State 8	0.36**	(0.00)	0.35**	(0.00)	0.29**	(0.01)
State 9	0.24**	(0.00)	0.23**	(0.00)	0.23**	(0.01)
State10	0.33***	(0.00)	0.32***	(0.00)	0.29**	(0.00)
State11	0.24	(0.09)	0.24	(0.10)	0.25	(0.07)
State12	0.31**	(0.00)	0.29**	(0.01)	0.26*	(0.01)
State13	0.06	(0.55)	0.04	(0.66)	-0.00	(0.96)
State14	0.13	(0.20)	0.13	(0.20)	0.14	(0.18)
State15	0.24*	(0.04)	0.23*	(0.05)	0.27*	(0.01)
State16	0.03	(0.76)	0.02	(0.87)	0.00	(0.97)
State17	-0.11	(0.44)	-0.12	(0.41)	-0.11	(0.48)
State18	0.45*	(0.02)	0.43*	(0.02)	0.31	(0.08)
State19	0.42***	(0.00)	0.41***	(0.00)	0.32**	(0.00)
State20	0.35**	(0.00)	0.35**	(0.00)	0.32**	(0.01)
State21	0.26**	(0.01)	0.25**	(0.01)	0.22*	(0.02)
State22	0.44***	(0.00)	0.43***	(0.00)	0.36***	(0.00)
State23	0.32*	(0.01)	0.31*	(0.01)	0.28*	(0.04)
State24	0.23*	(0.02)	0.22*	(0.03)	0.22*	(0.01)
State25	0.27*	(0.05)	0.28*	(0.04)	0.23	(0.09)
State26	0.15	(0.14)	0.15	(0.15)	0.09	(0.39)
State27	0.45***	(0.00)	0.44***	(0.00)	0.38***	(0.00)
State28	0.47**	(0.01)	0.47**	(0.01)	0.33	(0.07)
State29	0.36***	(0.00)	0.35***	(0.00)	0.28**	(0.01)
State30	0.41***	(0.00)	0.39***	(0.00)	0.31**	(0.00)
State31	0.34***	(0.00)	0.33***	(0.00)	0.32***	(0.00)
State32	0.24**	(0.00)	0.23**	(0.01)	0.23**	(0.01)
State33	0.59**	(0.01)	0.59*	(0.01)	0.58**	(0.00)
State34	0.26*	(0.02)	0.25*	(0.02)	0.23*	(0.04)
State35	0.14	(0.32)	0.13	(0.36)	0.06	(0.68)
State36	0.32**	(0.01)	0.31**	(0.01)	0.25*	(0.02)
State37	0.34***	(0.00)	0.34***	(0.00)	0.29**	(0.00)
State38	0.44	(0.08)	0.44	(0.09)	0.43	(0.08)
State39	0.31***	(0.00)	0.30***	(0.00)	0.27**	(0.00)
State40	0.23	(0.09)	0.20	(0.13)	0.22	(0.07)
State41	0.31***	(0.00)	0.30***	(0.00)	0.22*	(0.01)
State42	0.37***	(0.00)	0.36***	(0.00)	0.33***	(0.00)
State43	0.38**	(0.00)	0.38**	(0.00)	0.31**	(0.01)
State44	0.08	(0.66)	0.06	(0.75)	-0.02	(0.89)
State45	0.35***	(0.00)	0.34***	(0.00)	0.27**	(0.00)
State46	0.36**	(0.00)	0.35**	(0.00)	0.34**	(0.00)
State47	0.49**	(0.00)	0.49**	(0.00)	0.41**	(0.01)
State48	0.28**	(0.00)	0.26**	(0.01)	0.19	(0.06)
State49	0.35**	(0.01)	0.34**	(0.01)	0.23	(0.09)
State50	0.44**	(0.00)	0.42**	(0.00)	0.34*	(0.01)
State51	0.80***	(0.00)	0.80***	(0.00)	0.72***	(0.00)
ES2	-0.14***	(0.00)	-0.14***	(0.00)	-0.11***	(0.00)
ES3	-0.12***	(0.00)	-0.09***	(0.00)	-0.06***	(0.00)
ES4	-0.15***	(0.00)	-0.14***	(0.00)	-0.11**	(0.01)
ES5	0.06	(0.14)	0.07	(0.10)	0.12**	(0.00)
ES6	-0.11	(0.37)	-0.10	(0.41)	-0.15	(0.25)
Nohome	-0.21***	(0.00)	-0.20***	(0.00)	2.09***	(0.00)
SelfEmp	0.01	(0.54)	0.00	(0.77)	0.00	(0.87)
Disability	-0.02	(0.06)	-0.02	(0.08)	-0.01	(0.43)
Marital_Status	-0.01	(0.32)	-0.01	(0.10)	-0.01	(0.45)
A2t1998			0.11***	(0.00)	0.08***	(0.00)

A2t2000		0.07^{***}	(0.00)	0.04	(0.09)
A2t2002		0.08^{***}	(0.00)	0.05^{*}	(0.02)
A2t2004		0.09^{***}	(0.00)	0.05^{**}	(0.01)
A2t2006		0.05^{*}	(0.03)	0.02	(0.30)
A2t2008		0.02	(0.43)	0.02	(0.42)
A2t2010		-0.02	(0.48)	-0.01	(0.75)
A2t2012		-0.02	(0.47)	-0.01	(0.79)
A2t2014		-0.03	(0.20)	-0.02	(0.47)
A3t1998		0.17^{***}	(0.00)	0.12^{***}	(0.00)
A3t2000		0.13^{***}	(0.00)	0.07^{**}	(0.00)
A3t2002		0.09^{***}	(0.00)	0.05	(0.05)
A3t2004		0.11^{***}	(0.00)	0.08^{**}	(0.00)
A3t2006		0.06^{*}	(0.01)	0.04	(0.07)
A3t2008		0.03	(0.22)	0.04	(0.11)
A3t2010		-0.05	(0.09)	-0.03	(0.24)
A3t2012		-0.09^{**}	(0.00)	-0.06	(0.06)
A3t2014		-0.13^{***}	(0.00)	-0.09^{**}	(0.01)
A4t1998		0.24^{***}	(0.00)	0.16^{***}	(0.00)
A4t2000		0.19^{***}	(0.00)	0.10^{**}	(0.00)
A4t2002		0.16^{***}	(0.00)	0.10^{**}	(0.00)
A4t2004		0.15^{***}	(0.00)	0.11^{***}	(0.00)
A4t2006		0.08^{*}	(0.01)	0.06	(0.05)
A4t2008		0.03	(0.29)	0.05	(0.10)
A4t2010		-0.06	(0.07)	-0.04	(0.20)
A4t2012		-0.13^{***}	(0.00)	-0.10^{**}	(0.00)
A4t2014		-0.19^{***}	(0.00)	-0.14^{***}	(0.00)
Income				0.11^{***}	(0.00)
SHV				0.21^{***}	(0.00)
Observations	41685	41685		41135	
Adjusted R^2	0.116	0.122		0.183	
AIC	26137.63	25903.35		21446.74	
BIC	26889.12	26862.16		22421.32	

p-values in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.7: Nondurable Consumption Expenditures

	(1)		(2)		(3)		(4)	
	Benchmark		Interaction: SHV		Interaction: TFI		Interaction: Joint SHV and TFI	
A2t1998	0.08***	(0.00)	0.18***	(0.00)	0.24	(0.25)	0.01	(0.97)
A2t2000	0.04	(0.09)	0.10**	(0.00)	-0.16	(0.35)	-0.33	(0.06)
A2t2002	0.05*	(0.02)	0.07*	(0.04)	-0.63***	(0.00)	-0.74***	(0.00)
A2t2004	0.05**	(0.01)	-0.02	(0.66)	-0.93***	(0.00)	-0.91***	(0.00)
A2t2006	0.02	(0.30)	-0.11**	(0.01)	-1.94***	(0.00)	-1.94***	(0.00)
A2t2008	0.02	(0.42)	-0.11**	(0.01)	-1.87***	(0.00)	-2.04***	(0.00)
A2t2010	-0.01	(0.75)	-0.11**	(0.00)	-1.33***	(0.00)	-1.38***	(0.00)
A2t2012	-0.01	(0.79)	-0.14***	(0.00)	-1.92***	(0.00)	-1.98***	(0.00)
A2t2014	-0.02	(0.47)	-0.12***	(0.00)	-1.08***	(0.00)	-0.99***	(0.00)
A3t1998	0.12***	(0.00)	0.12*	(0.04)	-0.09	(0.68)	-0.28	(0.22)
A3t2000	0.07**	(0.00)	0.08	(0.12)	-0.37	(0.06)	-0.54**	(0.00)
A3t2002	0.05	(0.05)	0.01	(0.91)	-0.54**	(0.00)	-0.71***	(0.00)
A3t2004	0.08**	(0.00)	-0.03	(0.47)	-0.90***	(0.00)	-0.99***	(0.00)
A3t2006	0.04	(0.07)	-0.15**	(0.00)	-1.12***	(0.00)	-1.20***	(0.00)
A3t2008	0.04	(0.11)	-0.12*	(0.03)	-0.95***	(0.00)	-1.05***	(0.00)
A3t2010	-0.03	(0.24)	-0.20***	(0.00)	-1.00***	(0.00)	-1.06***	(0.00)
A3t2012	-0.06	(0.06)	-0.32***	(0.00)	-1.59***	(0.00)	-1.55***	(0.00)
A3t2014	-0.09**	(0.01)	-0.38***	(0.00)	-1.57***	(0.00)	-1.44***	(0.00)
A4t1998	0.16***	(0.00)	0.15	(0.08)	-0.12	(0.75)	-0.06	(0.84)
A4t2000	0.10**	(0.00)	0.08	(0.29)	-0.49	(0.09)	-0.59**	(0.00)
A4t2002	0.10**	(0.00)	0.07	(0.38)	-0.38	(0.16)	-0.56*	(0.02)
A4t2004	0.11***	(0.00)	-0.07	(0.37)	-0.59*	(0.01)	-0.57*	(0.01)
A4t2006	0.06	(0.05)	-0.26**	(0.00)	-1.06***	(0.00)	-1.00***	(0.00)
A4t2008	0.05	(0.10)	-0.19*	(0.02)	-1.07***	(0.00)	-1.16***	(0.00)
A4t2010	-0.04	(0.20)	-0.29*	(0.01)	-0.69	(0.05)	-0.79*	(0.02)
A4t2012	-0.10**	(0.00)	-0.54***	(0.00)	-1.59***	(0.00)	-1.62***	(0.00)
A4t2014	-0.14***	(0.00)	-0.52***	(0.00)	-1.49***	(0.00)	-1.42***	(0.00)
t2000	0.06**	(0.00)	0.08***	(0.00)	0.07***	(0.00)	0.07***	(0.00)
t2002	0.07***	(0.00)	0.11***	(0.00)	0.09***	(0.00)	0.10***	(0.00)
t2004	0.05*	(0.02)	0.12***	(0.00)	0.10***	(0.00)	0.11***	(0.00)
t2006	0.05*	(0.02)	0.15***	(0.00)	0.11***	(0.00)	0.13***	(0.00)
t2008	-0.03	(0.22)	0.07**	(0.01)	0.03	(0.18)	0.05*	(0.04)
t2010	0.05	(0.05)	0.15***	(0.00)	0.12***	(0.00)	0.14***	(0.00)
t2012	0.03	(0.32)	0.15***	(0.00)	0.10***	(0.00)	0.13***	(0.00)
t2014	0.06	(0.06)	0.20***	(0.00)	0.15***	(0.00)	0.18***	(0.00)
# Adults=2	-0.04*	(0.04)	-0.13***	(0.00)	-0.13***	(0.00)	-0.12***	(0.00)
# Adults=3	-0.10***	(0.00)	-0.27***	(0.00)	-0.25***	(0.00)	-0.24***	(0.00)
# Adults=4	-0.15***	(0.00)	-0.38***	(0.00)	-0.36***	(0.00)	-0.34***	(0.00)
# Adults=5	-0.26***	(0.00)	-0.52***	(0.00)	-0.48***	(0.00)	-0.47***	(0.00)
# Adults=6	-0.23	(0.05)	-0.50***	(0.00)	-0.50***	(0.00)	-0.46***	(0.00)
# Adults=7	-0.32**	(0.01)	-0.67***	(0.00)	-0.68***	(0.00)	-0.62***	(0.00)
# Adults=8	0.78***	(0.00)	0.41***	(0.00)	0.69***	(0.00)	0.45***	(0.00)
#Child=1	-0.08***	(0.00)	-0.15***	(0.00)	-0.14***	(0.00)	-0.13***	(0.00)
#Child=2	-0.20***	(0.00)	-0.32***	(0.00)	-0.31***	(0.00)	-0.30***	(0.00)
#Child=3	-0.31***	(0.00)	-0.48***	(0.00)	-0.46***	(0.00)	-0.45***	(0.00)
#Child=4	-0.41***	(0.00)	-0.62***	(0.00)	-0.59***	(0.00)	-0.58***	(0.00)
#Child=5	-0.46***	(0.00)	-0.70***	(0.00)	-0.67***	(0.00)	-0.65***	(0.00)
#Child=6	-0.42***	(0.00)	-0.70***	(0.00)	-0.62***	(0.00)	-0.60***	(0.00)
#Child=7	-0.31*	(0.02)	-0.65***	(0.00)	-0.54***	(0.00)	-0.54***	(0.00)
#Child=8	-0.31***	(0.00)	-0.60***	(0.00)	-0.50***	(0.00)	-0.49***	(0.00)
#Child=9	-0.55**	(0.00)	-0.82***	(0.00)	-0.67**	(0.00)	-0.66**	(0.00)
#Child=10	-0.79***	(0.00)	-1.76***	(0.00)	-1.62***	(0.00)	-1.58***	(0.00)
#Child=11	-0.57***	(0.00)	-0.97***	(0.00)	-0.92***	(0.00)	-0.93***	(0.00)
White	-0.06	(0.13)	-0.03	(0.39)	-0.05	(0.22)	-0.03	(0.37)
Black	0.20	(0.25)	0.23	(0.18)	0.19	(0.26)	0.22	(0.20)
State2	0.31***	(0.00)	0.37***	(0.00)	0.37***	(0.00)	0.36***	(0.00)
State3	0.20	(0.06)	0.18	(0.08)	0.20*	(0.05)	0.19	(0.06)
State4	0.48***	(0.00)	0.54***	(0.00)	0.54***	(0.00)	0.53***	(0.00)
State5	0.37***	(0.00)	0.43***	(0.00)	0.41***	(0.00)	0.41***	(0.00)
State6	0.29*	(0.02)	0.36**	(0.01)	0.33**	(0.01)	0.36**	(0.01)
State7	0.31**	(0.01)	0.37***	(0.00)	0.37***	(0.00)	0.37***	(0.00)
State8	0.29**	(0.01)	0.33**	(0.00)	0.33**	(0.00)	0.31**	(0.01)
State9	0.23**	(0.01)	0.23**	(0.00)	0.23**	(0.01)	0.22**	(0.01)
State10	0.29**	(0.00)	0.32***	(0.00)	0.30***	(0.00)	0.30***	(0.00)
State11	0.25	(0.07)	0.20	(0.16)	0.23	(0.12)	0.21	(0.16)
State12	0.26*	(0.01)	0.29**	(0.00)	0.31**	(0.00)	0.31**	(0.00)
State13	-0.00	(0.96)	0.04	(0.67)	0.04	(0.68)	0.03	(0.78)
State14	0.14	(0.18)	0.13	(0.17)	0.12	(0.22)	0.12	(0.22)
State15	0.27*	(0.01)	0.24*	(0.03)	0.22	(0.06)	0.22	(0.05)
State16	0.00	(0.97)	-0.01	(0.95)	-0.02	(0.89)	-0.04	(0.76)
State17	-0.11	(0.48)	-0.11	(0.44)	-0.12	(0.39)	-0.12	(0.40)
State18	0.31	(0.08)	0.40*	(0.04)	0.41*	(0.03)	0.38	(0.05)
State19	0.32**	(0.00)	0.40***	(0.00)	0.37***	(0.00)	0.37***	(0.00)
State20	0.32**	(0.01)	0.36**	(0.00)	0.37**	(0.00)	0.38***	(0.00)
State21	0.22*	(0.02)	0.23*	(0.01)	0.25**	(0.01)	0.23*	(0.02)
State22	0.36***	(0.00)	0.41***	(0.00)	0.41***	(0.00)	0.39***	(0.00)
State23	0.28*	(0.04)	0.32*	(0.01)	0.33*	(0.01)	0.34*	(0.01)
State24	0.22*	(0.01)	0.22*	(0.03)	0.23*	(0.01)	0.23*	(0.01)
State25	0.23	(0.09)	0.32*	(0.03)	0.28*	(0.03)	0.30*	(0.04)
State26	0.09	(0.39)	0.15	(0.13)	0.16	(0.11)	0.16	(0.11)
State27	0.38***	(0.00)	0.43***	(0.00)	0.42***	(0.00)	0.42***	(0.00)
State28	0.33	(0.07)	0.45**	(0.01)	0.44*	(0.02)	0.43*	(0.02)
State29	0.28**	(0.01)	0.36***	(0.00)	0.34***	(0.00)	0.35***	(0.00)
State30	0.31**	(0.00)	0.36**	(0.00)	0.34**	(0.00)	0.32**	(0.00)
State31	0.32***	(0.00)	0.34***	(0.00)	0.33***	(0.00)	0.33***	(0.00)
State32	0.23**	(0.01)	0.24**	(0.00)	0.21*	(0.01)	0.22*	(0.01)
State33	0.58**	(0.00)	0.54*	(0.01)	0.58*	(0.02)	0.53*	(0.02)
State34	0.23*	(0.04)	0.24*	(0.02)	0.25*	(0.02)	0.25*	(0.02)
State35	0.06	(0.68)	0.10	(0.44)	0.13	(0.31)	0.11	(0.38)
State36	0.25*	(0.02)	0.29*	(0.01)	0.30**	(0.01)	0.29**	(0.01)
State37	0.29**	(0.00)	0.32***	(0.00)	0.33***	(0.00)	0.32***	(0.00)

State38	0.43	(0.08)	0.40	(0.13)	0.49	(0.08)	0.46	(0.09)
State39	0.27^{**}	(0.00)	0.29^{***}	(0.00)	0.27^{**}	(0.00)	0.27^{**}	(0.00)
State40	0.22	(0.07)	0.22	(0.10)	0.20	(0.14)	0.21	(0.12)
State41	0.22^{*}	(0.01)	0.29^{**}	(0.00)	0.26^{**}	(0.00)	0.25^{**}	(0.00)
State42	0.33^{***}	(0.00)	0.37^{***}	(0.00)	0.34^{***}	(0.00)	0.34^{***}	(0.00)
State43	0.31^{**}	(0.01)	0.34^{**}	(0.00)	0.34^{**}	(0.00)	0.31^{**}	(0.01)
State44	-0.02	(0.89)	0.06	(0.75)	0.02	(0.92)	0.04	(0.84)
State45	0.27^{**}	(0.00)	0.35^{***}	(0.00)	0.34^{***}	(0.00)	0.35^{***}	(0.00)
State46	0.34^{**}	(0.00)	0.34^{**}	(0.00)	0.35^{**}	(0.00)	0.34^{**}	(0.00)
State47	0.41^{**}	(0.01)	0.41^{**}	(0.00)	0.55^{***}	(0.00)	0.46^{***}	(0.00)
State48	0.19	(0.06)	0.24^{*}	(0.01)	0.23^{*}	(0.02)	0.20^{*}	(0.03)
State49	0.23	(0.09)	0.31^{*}	(0.02)	0.32^{*}	(0.01)	0.29^{*}	(0.02)
State50	0.34^{*}	(0.01)	0.43^{**}	(0.00)	0.40^{**}	(0.01)	0.42^{**}	(0.00)
State51	0.72^{***}	(0.00)	0.78^{***}	(0.00)	0.78^{***}	(0.00)	0.76^{***}	(0.00)
ES2	-0.11^{***}	(0.00)	-0.14^{***}	(0.00)	-0.12^{***}	(0.00)	-0.13^{***}	(0.00)
ES3	-0.06^{***}	(0.00)	-0.09^{***}	(0.00)	-0.06^{***}	(0.00)	-0.06^{***}	(0.00)
ES4	-0.11^{**}	(0.01)	-0.13^{***}	(0.00)	-0.12^{***}	(0.00)	-0.12^{**}	(0.00)
ES5	0.12^{**}	(0.00)	0.06	(0.12)	0.07	(0.07)	0.07	(0.09)
ES6	-0.15	(0.25)	-0.12	(0.35)	-0.13	(0.28)	-0.15	(0.23)
Nohome	2.09^{***}	(0.00)	-0.08^{***}	(0.00)	-0.19^{***}	(0.00)	-0.09^{***}	(0.00)
SelfEmp	0.00	(0.87)	0.01	(0.50)	0.00	(0.82)	0.01	(0.60)
Disability	-0.01	(0.43)	-0.02	(0.13)	-0.01	(0.51)	-0.01	(0.55)
Marital_Status	-0.01	(0.45)	-0.01	(0.21)	-0.01	(0.17)	-0.01	(0.26)
Income	0.11^{***}	(0.00)						
SHV	0.21^{***}	(0.00)						
SHVxA2t1998			-0.01	(0.09)			-0.00	(0.65)
SHVxA2t2000			-0.00	(0.80)			0.00	(0.66)
SHVxA2t2002			0.00	(0.29)			0.00	(0.40)
SHVxA2t2004			0.01^{***}	(0.00)			0.01^{***}	(0.00)
SHVxA2t2006			0.02^{***}	(0.00)			0.01^{**}	(0.01)
SHVxA2t2008			0.02^{***}	(0.00)			0.00	(0.23)
SHVxA2t2010			0.01^{***}	(0.00)			0.01	(0.08)
SHVxA2t2012			0.02^{***}	(0.00)			0.00	(0.21)
SHVxA2t2014			0.01^{***}	(0.00)			0.01	(0.05)
SHVxA3t1998			0.01^{*}	(0.03)			0.01^{*}	(0.02)
SHVxA3t2000			0.01	(0.06)			0.01	(0.12)
SHVxA3t2002			0.01^{**}	(0.00)			0.01^{**}	(0.01)
SHVxA3t2004			0.02^{***}	(0.00)			0.02^{***}	(0.00)
SHVxA3t2006			0.03^{***}	(0.00)			0.02^{***}	(0.00)
SHVxA3t2008			0.02^{***}	(0.00)			0.02^{***}	(0.00)
SHVxA3t2010			0.02^{***}	(0.00)			0.02^{***}	(0.00)
SHVxA3t2012			0.03^{***}	(0.00)			0.02^{***}	(0.00)
SHVxA3t2014			0.03^{***}	(0.00)			0.03^{***}	(0.00)
SHVxA4t1998			0.01	(0.09)			0.01	(0.09)
SHVxA4t2000			0.01	(0.07)			0.01	(0.17)
SHVxA4t2002			0.01	(0.10)			0.01	(0.24)
SHVxA4t2004			0.03^{***}	(0.00)			0.03^{***}	(0.00)
SHVxA4t2006			0.04^{***}	(0.00)			0.03^{***}	(0.00)
SHVxA4t2008			0.03^{***}	(0.00)			0.02^{***}	(0.00)
SHVxA4t2010			0.03^{**}	(0.01)			0.03^{**}	(0.01)
SHVxA4t2012			0.05^{***}	(0.00)			0.04^{***}	(0.00)
SHVxA4t2014			0.04^{***}	(0.00)			0.03^{***}	(0.00)
IncomexA2t1998					-0.01	(0.57)	0.01	(0.50)
IncomexA2t2000					0.03	(0.13)	0.04^{*}	(0.01)
IncomexA2t2002					0.07^{***}	(0.00)	0.08^{***}	(0.00)
IncomexA2t2004					0.11^{***}	(0.00)	0.10^{***}	(0.00)
IncomexA2t2006					0.21^{***}	(0.00)	0.20^{***}	(0.00)
IncomexA2t2008					0.20^{***}	(0.00)	0.21^{***}	(0.00)
IncomexA2t2010					0.14^{***}	(0.00)	0.14^{***}	(0.00)
IncomexA2t2012					0.20^{***}	(0.00)	0.20^{***}	(0.00)
IncomexA2t2014					0.11^{***}	(0.00)	0.09^{***}	(0.00)
IncomexA3t1998					0.03	(0.21)	0.04	(0.08)
IncomexA3t2000					0.05^{**}	(0.01)	0.06^{***}	(0.00)
IncomexA3t2002					0.07^{***}	(0.00)	0.08^{***}	(0.00)
IncomexA3t2004					0.11^{***}	(0.00)	0.10^{***}	(0.00)
IncomexA3t2006					0.12^{***}	(0.00)	0.11^{***}	(0.00)
IncomexA3t2008					0.10^{***}	(0.00)	0.10^{***}	(0.00)
IncomexA3t2010					0.10^{***}	(0.00)	0.09^{***}	(0.00)
IncomexA3t2012					0.16^{***}	(0.00)	0.13^{***}	(0.00)
IncomexA3t2014					0.15^{***}	(0.00)	0.11^{***}	(0.00)
IncomexA4t1998					0.03	(0.38)	0.02	(0.56)
IncomexA4t2000					0.07^{*}	(0.02)	0.07^{***}	(0.00)
IncomexA4t2002					0.06^{*}	(0.04)	0.07^{*}	(0.01)
IncomexA4t2004					0.08^{**}	(0.00)	0.05	(0.06)
IncomexA4t2006					0.12^{***}	(0.00)	0.08^{***}	(0.00)
IncomexA4t2008					0.12^{***}	(0.00)	0.10^{***}	(0.00)
IncomexA4t2010					0.07	(0.06)	0.05	(0.08)
IncomexA4t2012					0.15^{***}	(0.00)	0.12^{***}	(0.00)
IncomexA4t2014					0.14^{***}	(0.00)	0.10^{***}	(0.00)
Observations	41135		41237		41574		41135	
Adjusted R^2	0.183		0.130		0.149		0.152	
AIC	21446.74		24588.24		24063.57		23030.98	
BIC	22421.32		25778.77		25255.23		24454.04	

p-values in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$