Technical Appendix of

"Consumption over the Life Cycle:

Facts from Consumer Expenditure Survey Data"

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September 14, 2004

Abstract

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1. Introduction

This technical appendix offers detailed information about the data, variable definitions, estimation, results, and robustness analysis that could not be included in the main part of the paper due to space limitations.

The appendix is organized as follows. Section 2 provides further details on the CEX data and the definition of the variables. Section 3 presents details on the specification and estimation of the statistical model. Section 4 comments on the results and section 5 on the bootstrap. Section 6 explains different alternatives to control for family size. Section 7 explores the importance of labor supply as a mechanism explaining the hump in consumption, and section 8 concludes with some results on the importance of housing.

2. The CEX Data

We take our consumption data from the Consumer Expenditure Survey (CEX), as provided by the Bureau of Labor Statistics. Our sample years consist of 1980-1981 and 1984-2001, with a total of 80 longitudinal surveys. Our sample is only limited by data availability. Prior to 1980, the CEX was conducted about every 10 years and not on a regular basis. Data for years after 2001 are still not fully available. We excluded the years 1982 and 1983 because of methodological differences in the survey. See Attanasio (1998) for details.

As mentioned in the main text, the CEX is a rotating panel. Each household is interviewed every three months over five calendar quarters and every quarter 20 percent of the sample is replaced by new households. In the initial interview information on demographic characteristics and on the inventory of major durable goods of the consumer unit is collected. Further consumption expenditure information is gathered in the second through the fifth interview. We take each household as one observation and use the demographic information of the reference person to define cohort membership, independent of this person's gender.

The CEX definition of a household is a consumer unit that consists of any of the following: (1) all members of a particular household who are related by blood, marriage, adoption, or other legal arrangements; (2) a person living alone or sharing a household with others or living as a roomer in a private home or lodging house or in permanent living quarters in a hotel or motel, but who is financially independent; or (3) two or more persons living together who use their incomes to make joint expenditure decisions. Financial independence is determined by the three major expense categories: housing, food, and other living expenses. To be considered financially independent, at least two of the three major expenditure categories have to be provided entirely or in part by the respondent.

The CEX defines the reference person of the consumer unit as the first member mentioned by the respondent when asked to "Start with the name of the person or one of the persons who owns or rents the home". It is with respect to this person that the relationship of the other consumer unit members is determined.

We select only those households with both positive income and consumption expenditure. As most of the literature we do not attempt to control for topcoding of consumption observations. The very high topcoding limits (or their nonexistence for food consumption and other items) in the CEX and the very low survey response rates of the wealthiest households in the U.S. imply that only a extremely small fraction of our sample is right-censored. As a consequence, it is unlikely that the lack of proper topcoding treatment affects the results in a significant manner.

We compute "total expenditures" using the variable with the same name in the detailed expenditure files. We divide consumption in these files into three different groups. The data on "expenditures on nondurables" include food, alcohol beverages, tobacco, utilities, personal care, household operations, public transportation, gas and motor oil, entertainment and miscellaneous expenditures. The variable "expenditures on durables" sums expenditures on owned dwelling, rented dwelling, house equipment, vehicles, books and electronic equipment. We define as ambiguous expenditures apparel, out-of-pocket health and education expenditures (unless we analyze "total expenditures" which includes all expenditures in the CEX). We account for changes in the consumption classification methodology over the sample years in the CEX, in order to assure consistency of our consumption measures.

Finally, each expenditure category is deflated using its own specific, not seasonally adjusted, Consumer Price Index (CPI) component for urban consumers. The dollar figures are adjusted to 1982-84 dollars using the "current methods" version of the CPI. This version rebuilds past CPI's with the present methodology to produce a price deflator series that is consistent over time.

An alternative to the pseudopanel approach is to rely exclusively on the cross-sectional nature of the CEX survey and pool all observations. This alternative is closely related to a pseudopanel constructed with CEX-provided weights, except that in a balanced pseudopanel we disregard observations from those cohorts that are not covered in the data during the entire sample period (i.e. those that are too young in 1980 to be already in the CEX) and from those cohorts that were already of advanced age at the beginning of the sample period and thus have small cohort sizes because of mortality. Since both types of households are relatively rare, their quantitative impact is small, and it is not clear to us that the information they provide compensates for the problems associated with their inclusion. Also the size of a pseudopanel (800 observations) is much smaller than the size of the pooled data (over 435.000 observations) which makes the pseudopanel easier to handle.. Nevertheless, for completeness we studied the effects of using pooled data. The results were basically equivalent to the use of the pseudopanel.

3. Specification and Estimation of Life Cycle Profiles

As described in the main text, in order to control for cohort, time and age effects, we choose a seminonparametric model, in particular a specification known as Partially Linear Model. Now we first explain why we choose this specification. Second, we justify our regression error. Third, we explain how the Speckman estimator works. Finally, we show how our results differ from those obtained with an application of age dummies.

3.1. Our Specification Choice

Nonparametric econometrics attempts to estimate regression curves by imposing only a minimum set of conditions on the data. It searches for versatile methods to discover relations between variables without forcing the data into an overly rigid structure of a fixed parametrization. Since the objective of this paper is to document empirical life cycle profiles of consumption expenditures that can be used to evaluate theoretical models, nonparametric methods seem the natural choice to us.

The unconstrained optimal choice then would be to estimate a fully nonparametric model of the form

$$C_{it} = M\left(cohort_i, \gamma_t, age_{it}, \varepsilon_{it}\right) \tag{1}$$

Estimating the function M with CEX data is hopeless, however. The flexibility and weak assumptions of nonparametric methods come at a cost: their lack of efficiency. Conditional on the model being correctly specified, nonparametric regressions need many more observations than parametric methods to achieve the same precision of the estimates.[1] This lack of efficiency is especially important in multidimensional settings since nonparametric methods suffer from a severe "curse of dimensionality".

[1] Of course the nonparametric regression is much more robust to misspecification than any parametric alternative, which is the basic advantage that makes us use it.

In the last view years, however, the joint development of new estimators and the arrival of powerful computational techniques have made it possible to apply flexible but efficient models (see for example, Horowitz, 1998) to empirical questions. A key insight of the new theoretical literature has been the finding that one can obtain most of the robustness advantages of nonparametric methods using semiparametric (also sometimes called seminonparametric) procedures which keep some parametric structure but allow for full nonparametrics along the dimensions of interest in a particular application. Possibly the most popular of these methods is the Partially Linear Model that we use (see Härdle *et al.*, 2001). This model keeps the traditional linear structure on the variables the researcher believes are of less importance a priori, but allows a nonparametric form for those variables that the researcher postulates as crucial for the analysis.

The division of the variables in our application is intuitive. The observation that the U.S. has been a relatively stable economy from 1980 to 2001 with moderate and fairly smooth income growth suggests that cohort and quarter effects are unlikely to be large. As a consequence, we approximate their effect through linear dummies. On the other hand, consumption variation along the age dimension is the main focus of our paper; thus we model it nonparametrically. Our estimates confirm this division since the effects of time and cohort dummies are fairly small, while there is substantial variation of consumption along the age dimension of households.

As we explained above our procedure pre-imposes as little structure on the data as possible while achieving very satisfactory outcomes in terms of efficiency, as indicated by the small bootstrap standard errors that we documented in the paper.

3.2. Origin of the Regression Error

Our specification implicitly assumes the following origin of the regression error. For ease of exposition we abstract from cohort, time and family size changes here (but obviously not in our empirical work). We postulate that the relation between consumption and age at the household level is given by

$$U_{it}C_{it} = \mathcal{G}\left(age_{it}\right) \tag{2}$$

where C_{it} is measured consumption expenditures of household i at time t, age_{it} the age of the household, the function $\mathcal{G}$ is an unknown mapping, and U_{it} a classical (i.e. log-normally and i.i.d. distributed), multiplicative error. This specification is exactly the same as the one employed by Gourinchas and Parker (2002), with the exception that we allow the effect of age to enter through a general function $\mathcal{G}$, while their equation (12) implies a function of age parametrized by the statistical model. Since they estimate the equation using age dummies (see our discussion about age dummies below) and their specification is similar to ours, it is not surprising that they find qualitatively similar results. Also, as Gourinchas and Parker point out, it is possible to interpret U_{it} as capturing measurement error as well as individual heterogeneity, with nothing substantive depending on this interpretation.

After taking logs on both sides of (2) we obtain

$$\log U_{it} + \log C_{it} = \log \mathcal{G}\left(age_{it}\right). \tag{3}$$

Since measurement error is classical, we can write $\log U_{it} = -\varepsilon_{it}$ where ε_{it} is normally distributed, and thus

$$\log C_{it} = \log \mathcal{G}\left(age_{it}\right) + \varepsilon_{it}. \tag{4}$$

Note that, since the nonparametric regressor does not impose any particular structure for $\mathcal{G}$, we can always redefine $m\left(age_{it}\right) = \log \mathcal{G}\left(age_{it}\right)$ to obtain the equation

$$\log C_{it} = m\left(age_{it}\right) + \varepsilon_{it}. \tag{5}$$

For building the pseudo-panel used in the paper we take the average of (5) over all N households of same age:

$$\frac{1}{N}\sum_{i}^{N} \log C_{it} = \frac{1}{N}\sum_{i}^{N} m\left(age_{it}\right) + \frac{1}{N}\sum_{i}^{N} \varepsilon_{it},$$

or

$$\frac{1}{N}\sum_{i}^{N} \log C_{it} = m\left(age_{it}\right) + \frac{1}{N}\sum_{i}^{N} \varepsilon_{it},$$

since by construction all households have the same age. Denoting cohort averages by a star, we arrive at

$$\left(\log C_{it}\right)^{*} = m\left(age_{it}\right) + \varepsilon_{it}^{*}, \tag{6}$$

which is the basic specification we run on our data.

Attanasio and Weber (1995) offer an extensive discussion for why using the mean of the logs is preferable to using the log of the mean. They show that the second alternative suffers from an aggregation bias while the first does not.

Repeating the same steps as before with time and cohort dummies, and using consumption adjusted by household size using an equivalence scale, our estimated partially linear model is:

$$\left(\log \overline{C}_{it}\right)^{*} = \pi_{i} cohort_{i} + \pi_{t}\gamma_{t} + m\left(age_{it}\right) + \varepsilon_{it}^{*} \tag{7}$$

where $cohort_i$ is a dummy for cohort i (we do not include a dummy for the youngest cohort) and γ_t a dummy for quarter t. This specification is also convenient because it provides a more natural interpretation of the cohort and time effects as percentage deviations from age-averages.

3.3. How to Estimate the Partially Linear Model

Now we explain how the Speckman estimator works. We borrow the following description from Speckman (1988), where many more details are provided.

Suppose we want to estimate the partially linear model:

$$c_{it} = \beta^{T} X + m\left(age_{it}\right) + \varepsilon_{it} \tag{8}$$

where, to ease notation, we have stacked all the dummies in the matrix X.

Speckman proposes the following estimator that has gained widespread popularity:

1. Estimate first:

   $$c_{it} = m_{1}\left(age_{it}\right) + \varepsilon_{it} \tag{9}$$

   where $\widehat{m}_{1}\left(\cdot\right)$ is computed using Nadaraya-Watson estimator of the form

   $$\widehat{m}_{1}\left(age\right) = \frac{\sum_{i=1}^{n}\sum_{t=1}^{T} K_{h}\left(age - age_{it}\right) * c_{it}}{\sum_{i=1}^{n}\sum_{t=1}^{T} K_{h}\left(age - age_{it}\right)} \tag{10}$$

   where $K_{h}\left(u\right) = \frac{0.75}{h}\left(1 - \left(\frac{u}{h}\right)^{2}\right) I\left(\left|\frac{u}{h}\right| \leq 1\right)$ is an Epanechnikov kernel and h is the bandwidth parameter. Härdle (1990) discusses in detail the advantages of an Epanechnikov kernel for applications like ours. Beyond Härdle's arguments, the approximate lack of bias of this kernel in small samples will prove useful when applying bootstrap methods below. For our benchmark estimates cross validation methods suggest we choose a bandwidth parameter of $h = 5$ years. We performed an extensive sensitivity analysis with respect to this parameter without finding important quantitative changes in our results.

2. Define the smoother matrix $\mathcal{S}$ as $\widehat{c}_{it} = \mathcal{S}y = m_{1}\left(age_{it}\right)$. Note that since the kernel is a local average, we only need to back up the weights in that average to find the matrix

$\mathcal{S}$. This matrix transforms the vector of observations y into fitted values $\widehat{y}$.

3. Create the partial residual vectors by defining $\widetilde{c} = (I - \mathcal{S})\, c$ and $\widetilde{X} = (I - \mathcal{S})\, X$.

4. Estimate the parameter β as:

$$\widehat{\beta} = \left(\widetilde{X}^T \widetilde{X}\right)^{-1} \widetilde{X}^T \widetilde{c} \tag{11}$$

5. Finally, estimate the function $\widehat{m}\,(age_{it})$ by kernel smoothing using as dependent variable $\widetilde{y} - \widetilde{X}\widehat{\beta}$.

Speckman (1988) discusses the motivation for the estimator, its asymptotic properties, and why the method may be superior to the alternatives in the literature.

Here is important to remember that, following Deaton (1997), we assume that time effects are orthogonal to a time trend and that their sum is normalized to zero. Thus there are no dummies for the first two quarters. These effects are recovered using the orthogonalization and normalization conditions.

Two sources of errors in variables may affect our results. First, because of sampling variance, the observed consumption means may differ from the cohort means. Since this error only affects the left-hand side variable (it is plausible that the average age is measured with high accuracy; in all cells, age samples averages are very close to the age interval midpoints), it only increases the variance of the residuals, provided that the error has a zero mean. Second, consumption data may suffer from large measurement errors. If these errors are linear and have zero cohort mean, the pseudopanel helps us because aggregation over the cohort sample average them out.

3.4. Comparison with Age Dummies

Our previous arguments in section 3.1. in favor of our seminonparametric approach of course does not answer what, *in practice*, are the differences of our approach, compared to an estimation using age dummies? One additional advantage of the flexibility of our seminonparametric specification is that it allows us to analyze this question almost immediately. Going back to our specification

$$c_{it} = \pi_i cohort_i + \pi_t \gamma_t + m\,(age_{it}) + \varepsilon_{it} \tag{12}$$

we observe that age enters the regression through the function $m\,(\cdot)$.

How is the function $m(\cdot)$ estimated? Abstracting from the parametric component the nonparametric regression is, loosely speaking, a local average along the age dimension. We use information from the data around a point, in a data window with a given bandwidth. As a benchmark we take a window of 10 years, five prior to the observation of interest, and five after, as suggested by several standard optimal bandwidth choice criteria (see again Härdle, 1990). However, repeating our exercise with a bandwidth window of one year is formally equivalent to using age dummies, since only information for one age is used.

We carried out this exercise in figures A1a, A1b and A1c, with one panel for total consumption expenditures, one for nondurable consumption expenditure and one for expenditures on durables. Each panel contains two lines, one for the 10 years window (the smooth blue line, our benchmark) and one line for age dummies (the red line with wiggles). We observe that the general shape of the estimated life cycle profiles is identical with both techniques, but that the use of age dummies leads to more age variation year by year. This variation is due to the use of only very local information, rather than smoothing over ages within the 10 year window.

Even though the basic results for the size and shape of the life cycle consumption profiles do not vary too drastically across techniques we want to put forward three advantages for using our procedure:

1. The results from using age dummies, with its local variations, are difficult to use as empirical benchmark for quantitative economic models. It is for this reason that frequently papers employing age dummies display the results after smoothing the results from the dummy estimation. But if the final goal is to obtain a smoothed profile it is more efficient to estimate a Partially Linear Model to generate a smooth profile directly, rather than to estimate a linear model using age dummies, and then to smooth the output (see Härdle *et al.*, 2001).

2. If the model with age dummy structure is misspecified, the linear regression may deliver poor estimates. For example, Heckman and Vytlacil (2001) discover a related problem in a study of the role of cognitive ability for explaining changes in returns to schooling.

3. Since the use of age dummies is nested in a partially linear model, we can use standard optimal bandwidth tests to check for the best choice of smoothness. These tests strongly suggest longer bandwidths (approximately the one used as our benchmark), pointing to a potential misspecification problem with the use of age dummies.

To summarize: employing our specification and using age dummies delivers qualitatively similar results, but there are good reasons to believe that the results from our specification are more robust to misspecification and more useful for economists wanting to empirically evaluate theoretical models.

3.5. Controlling for Family Size: Household Equivalence Scales

Note that the chosen scale in the main text of the paper is very close to the equivalence scale of the HHS, the estimates of Johnson and Garner (1995) and to the constant-elasticity equivalence scales used by Atkinson *et al.* (1995), Buhmann *et al.* (1988) and Johnson and Smeeding (1998), among others.

To evaluate our choice it is important to remember that our measures of nondurable consumption do not include expenditures on either health or education, two major causes of increases in expenditures for households with children.

It is also important to argue why the use of household equivalence scales may be superior to other alternatives like including additional demographic regressors in an Euler equation for consumption.

First, a regression specification that includes a large number of demographic variables to capture shocks to marginal utility of consumption may result in overparametrization and loss of efficiency in estimation. The resulting reduction in the precision of the parameter estimates may explain why some papers in the literature, such as Attanasio and Weber (1995) cannot reject the null hypothesis of correct model specification. Second, demographic variables may proxy for liquidity constraints. Forming a household with an additional earner may relax borrowing constraints; in the absence of other regressors controlling for these constraints demographic variables may pick up these effects which makes the parameter estimates hard to interpret. Third, if liquidity constraints are really present, the estimation of a log-linearized Euler equation is misspecified (see Attanasio and Low, 2000, Carroll, 2001, and Ludvigson and Paxson, 2001, for a discussion of this problem). Fourth, since labor income is hump-shaped over the life cycle, households with limited access to intertemporal trade and endogenous fertility choices will choose both a hump in consumption expenditure and family size, even though one does not cause the other. If the consumption Euler equation regression is not estimated simultaneously with an optimality condition for fertility, the consumption regression may spuriously pick up the hump in consumption through the parameter estimates for the demographic variables.

All four reasons share a common theme: the problem of lack of identification. It is difficult to separate, just from observing consumption expenditures, which percentage of its change is induced by a change in age and which by a change in family size. In contrast, the use of household equivalence scales exploits substantial additional information. Researchers that estimate these scales use expenditure pattern for individual consumption items. This is informative since observing a household with a newborn child and increased purchases of diapers, one may reasonably attribute this change in expenditures to changes in family size. On the other hand, if we observe the same household buying an expensive gold watch, one may plausibly attribute this expenditure to higher adult-equivalent consumption. It is highly inefficient not to exploit this additional information contained in itemized consumption data and rather use a regression approach with (at least) the four problems discussed above. It therefore seems preferable to use results of the household equivalence scale literature that has extensively studied how to identify the effects of changes in family size using weaker assumptions than those required by the Euler equation regressions.

4. Results

As we mention in the main text, the finding of a hump on durables expenditures is consistent with related evidence in the literature suggesting that households cannot perfectly smooth their consumption of services from durables. Alessie *et al.* (1997), Attanasio *et al.* (2000), and Eberly (1994) provide evidence of credit constraints for car purchases, Barrow and McGranahan (2000) document a spike in purchases of durables by low income households at the time Earned Income Credit checks are received and Browning and Crossley (1999) present evidence that expenditures on small consumer durables are cut back during unemployments spells. Finally Fisher and Johnson (2002) compute imputed services from a subset of durables using CEX data (and additional assumptions) and document a hump for these services, suggesting a lack of consumption smoothing over the life cycle.

Figures A2a, A2b and A2c report the profiles of total consumption, nondurables, and durables expenditures separately for each education group controlling for cohort and time effects. Figures A3a, A3b and A3c does the same in adult equivalent terms. We refer to the text of the main paper for the discussion of the figures.

5. Using the Bootstrap to Evaluate Sampling Uncertainty

Horowitz (2001) provides a theoretical explanation for the need of undersmoothing. This undersmoothing is achieved with a choice of a new smoothing parameter $h' = e \cdot h$, where

$e < 1$ such that $nh'^{r+1} \to 0$ as $n \to \infty$ (here $r \geq 2$ is an even integer). As shown in Hall (1992), using the Edgeworth expansion of a properly defined pivotal statistics, the bootstrap estimator of the confidence interval will be accurate up to $O\left((nh')^{-1}\right)$. This asymptotic result does not provide clear advice for the appropriate choice of e in small samples. We tried several values of e without obtaining large differences in the results.

Figures A4 and A5 report the results of the bootstrap for adult-equivalent expenditures on nondurables and durables controlling for cohort and quarter effects. As in the results reported in the main text, our life cycle consumption profiles are precisely estimated. Similar figures (not included in this appendix) are obtained for specifications without cohort and quarterly effects, with either only quarter or cohort effects, defining durables and nondurables in different ways, including and excluding housing, correcting for family size in different ways, and with and without using the CEX weights. We conclude that sampling uncertainty is unlikely to change our main findings.

We also implemented an strategy that resampled from the pseudopanel (with and without block sampling and with and without subsampling). The results were again nearly identical.

6. Different Alternatives to Control for Family Size

There are at least four alternatives to equivalence scales to control for household size and composition. First, one can divide the original sample into groups corresponding to different household sizes. With the resulting separate samples of households with size 1, size 2 and so on we can repeat our estimation for each of these groups. This procedure may be interpreted as a bivariate kernel on age and family size where the smoothing parameter for family size dimension is less than one. We do not use this approach as our benchmark because of the endogeneity of household size. Individuals living alone at age 25 constitute a very different subsample of the population than individuals living alone at age 45 since the first group includes both individuals that will still live alone in 20 years and those who will form households with more than one member during the next 20 years. Despite these caveats we carried out the exercise as sensitivity analysis. For nearly all household sizes we observed humps in life cycle consumption expenditures of similar size and location as in our benchmark estimates.

A second alternative to correct for family size is to use a flexible specification of preferences that allows to control for demographic factors through the use of additional regressors. We have discussed this correction in the main part of the paper.

A third approach is to use dummies, f_{it}, for different household sizes in our partial linear model in the form:

$$c_{it} = \pi_i cohort_i + \pi_t \gamma_t + \pi_{it} f_{it} + m\left(age_{it}\right) + \varepsilon_{it} \tag{13}$$

This use of dummies to correct for household size is the approach Gourinchas and Parker (2002) employ.[2] Their results for nondurables suggest that this alternative approach yields results that are qualitatively similar to the ones presented in this paper.

Finally, an innovative alternative to controlling for household size is to estimate profiles for *individuals* directly. Deaton and Paxson (2000) report individual life cycle *saving* profiles for Taiwan. We do not follow this strategy because an analysis of profiles for individuals requires an explicit model of resource allocation within the household, and there does not seem to be widespread agreement about a "standard" model for this. The problem is especially severe for consumer durables: what is the portion of services from a TV, car or refrigerator owned by a household that each individual consumes? We do not attempt to provide an answer to these difficult questions in this paper.[3]

7. Labor Supply and Consumption

As first pointed out by Heckman (1974), nonseparabilities between consumption and leisure are another possible explanation for the existence and size of the hump in lifetime consumption. If the age-wage profile is hump-shaped and consumption and leisure are substitutes, then theory predicts consumption to track the life-cycle hump in wages.

A careful empirical analysis of this channel requires a whole paper on its own. However, we have performed some results that may provide a first suggestive step towards a complete analysis. We computed labor supply profiles over the life cycle using CEX data, proceeding in a very similar fashion as with consumption. First we built a pseudopanel, and then estimated a partially linear model, controlling for cohort and time effects. In carrying out this exercise we face the same issue of changes in demographics, as we did in our study of consumption life cycle profiles. Since the size of households change over time, the total number of hours available for market work and home production of the household varies as well.

[2] Instead of a kernel estimator they use a set of age dummies in (13) to capture age effects (also, they deal with the multicollinearity problem by employing unemployment rates instead of time dummies to capture time effects). As we have argued, using dummies is equivalent to a kernel estimator with a small smoothing parameter.

[3] On a technical level, implementing this strategy with U.S. data does require the integration of the member files with the family files from the CEX, not a trivial task. Future research on this issue seems particularly important.

As a benchmark we divided total hours worked by a household by the number of adult members to arrive at hours worked per adult.[4] In the absence of direct data on home production, for which economies of scale are potentially important (it takes roughly the same amount of time to cook for one person as to cook for two), the simple adjustment by the number of adults seems most justified.

The life cycle profile per adult labor supply is plotted in figure A6, together with total consumption expenditures, adjusted by the equivalence scale. Judged from this picture changes in labor supply do not seem to stand a chance to explain a significant part of the hump in consumption. Hours rise very slightly to about the age of 30 (as more people enter into the labor force after completing their education), but decline steadily afterwards, as women leave the labor force to raise children and, later, as some adults retire.

We repeated our exercise of computing life cycle labor supply profiles separately for different education groups. We found little change and variation in the results, which are plotted in figure A7. Given the evidence on differences in income and consumption profiles mentioned above, this finding further weakens the case for the importance of nonseparabilities.

The "best case scenario" for nonseparabilities as an explanation of the consumption hump is to make labor supply hump-shaped over the life cycle by considering total hours worked by a household, unadjusted by its size. We plot this profile, together with adult equivalent consumption expenditures, in figure A8. To enhance readability, we have normalized both profiles to one at age 22. We observe that labor supply and expenditures rise simultaneously until age 32. After that, hours worked are roughly flat until 45, and then begin to decline. Consumption rises from age 22 to 52, roughly at the same rate as hours, during the first 10 years, but continues to increase well after hours flatten out.

Beyond the issue of the timing of the hump, to determine whether quantitatively labor supply variations can explain a sizeable part of the remaining hump one has to take a stand on the elasticity of substitution between labor and consumption. The empirical evidence is quite mixed. For example, Attanasio and Weber (1993), Blundell *et al.* (1994) and Attanasio and Browning (1995) find significant complementarities between consumption and male labor supply, whereas Browning *et al.* (1985) and Meghir and Weber (1996) find that consumption is additively separable from male labor supply. The evidence for female labor supply is more mixed still, with some papers (Attanasio and Weber, 1995, and Attanasio and Browning,

[4] This measure of labor supply is most informative if household preferences are defined over per-person consumption services and per person labor supply directly. But even if preferences are defined over consumption, per-person leisure and services from home production, if the latter two goods are perfect substitutes, then it is per capita endowment of hours minus per capita labor supply what enters the utility function.

1995) even finding substitutability. Using the upper bounds on elasticities of substitution between consumption and leisure reported in the review of the micro evidence by Browning *et al.* (1999), the increase in hours may account for at most 10 to 15 percent of the hump. In addition the timing of the hump remains unexplained.

8. Assessing the Importance of Housing

A large fraction of expenditures on consumer durables stems from housing. Since out-of pocket expenses of owning a home are potentially significant in the first years of ownership and then decline, while consumption services from the home are roughly constant, the link between expenditure on owned dwellings and its services, the ultimate object of interest, may be particularly weak.[5] In this section we therefore want to, at least partially, assess whether our results for consumer durables are primarily driven by its biggest component.

Figure A9a plots the estimation results for adult equivalent expenditure on durables, *excluding* housing and figure A9b plots the same for expenditures on housing. Both figures display a clear hump over the life cycle, suggesting that our previous results were not driven by the aggregation of expenditures on durables. It is worth noting that expenditures on housing increase more steeply over the first ten years of adult life than expenditures on other durables, so that the peak of the hump occurs earlier (mid 30's vs. 50) and is more sizeable (45 percent vs. 37 percent).

Housing is also the only component of durables for which the CEX contains useful information about its services, since the survey collects information about the monthly rental value of the owned residence, as estimated by the household head.[6] Figure A10 plots the estimated unadjusted life cycle profile, and figure A11 does the same for the data deflated by our equivalence scales. The first figure shows that, when controlling for quarter and cohort effects, the peak of (market valued) housing services does not occur until the mid fifties, then decreases slightly, only to mildly increase towards the end of the life cycle. Figure A10 also is one of the few instances in this paper where cohort effects play a significant role for the results, with later cohorts living in more expensive homes. The pattern in figure A10 is roughly consistent with a hypothetical model in which households face financial constraints

[5] Our definition of housing expenditures includes expenditures on owned dwellings and rented dwellings used for residential purposes by the household. Expenditures on owned dwellings include mortgage interest, property taxes, repairs, maintenance and insurance. Expenditures on rented dwellings correspond to rent payments by the household.

[6] Households are asked: "If someone were to rent your home today, how much do you think it would rent for monthly, unfurnished and without utilities?". Note that this question was not asked in 1980 and 1981.

that prevent them from obtaining their desired home at the beginning of the life cycle. As they age, these households move into better and better homes, until they reach their target house, which is kept until the end of their life cycle, to assure a smooth flow of housing services.

Figure A11, which adjusts for household size, shows a similar picture, except for the end of the life cycle. The late increase in the household-size-adjusted rental value of the home is due to the reduction in household size (usually one spouse dies) which are not associated with changes in residence. This empirical finding is suggestive of models with (financial or psychological) adjustment costs or models in which durables provide important collateral services (for instance, to hedge against catastrophic health expenditures), in which households at the end of the life cycle own more valuable houses than otherwise optimal. Note that the same findings emerge if we use the new variable of housing services defined by Fisher and Johnson (2002), where they generate a series for the rental value of each households' dwelling, equal to the paid rent, equal to the imputed rent, or equal to the sum of both.

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Figure A1a: Total Expenditure, Adult Equivalent

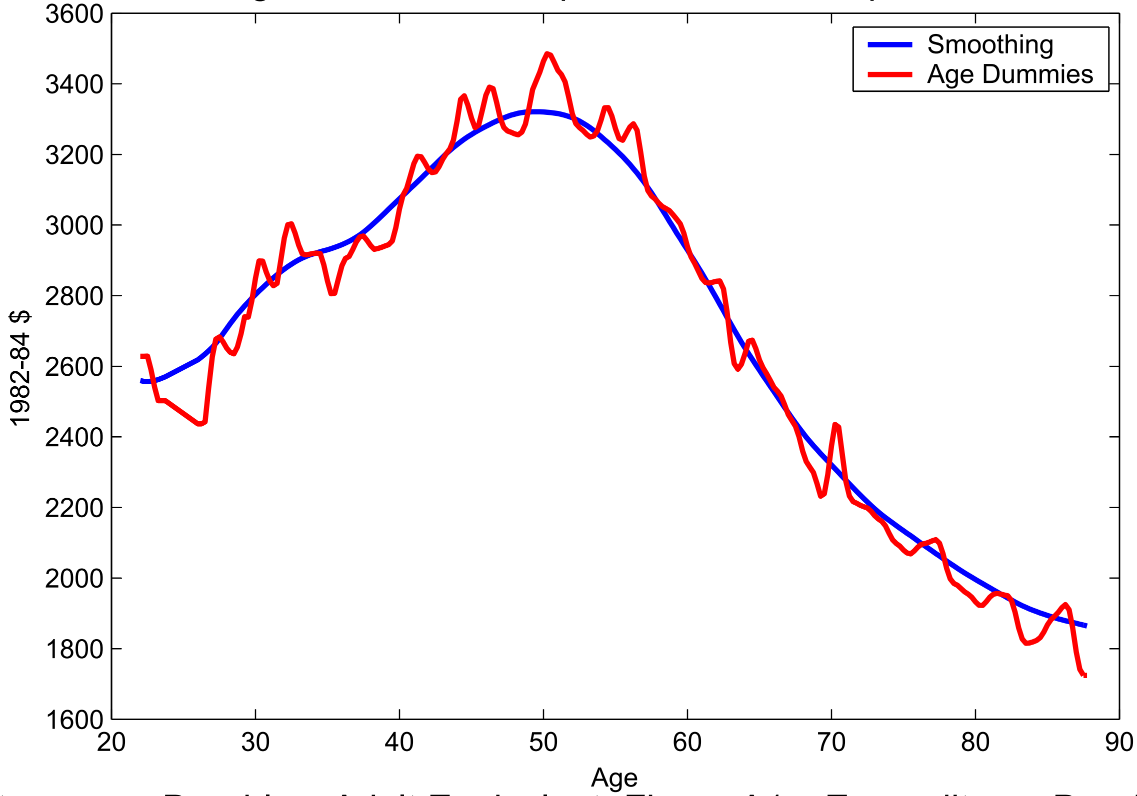


Figure A1b: Expenditures non Durables, Adult Equivalent

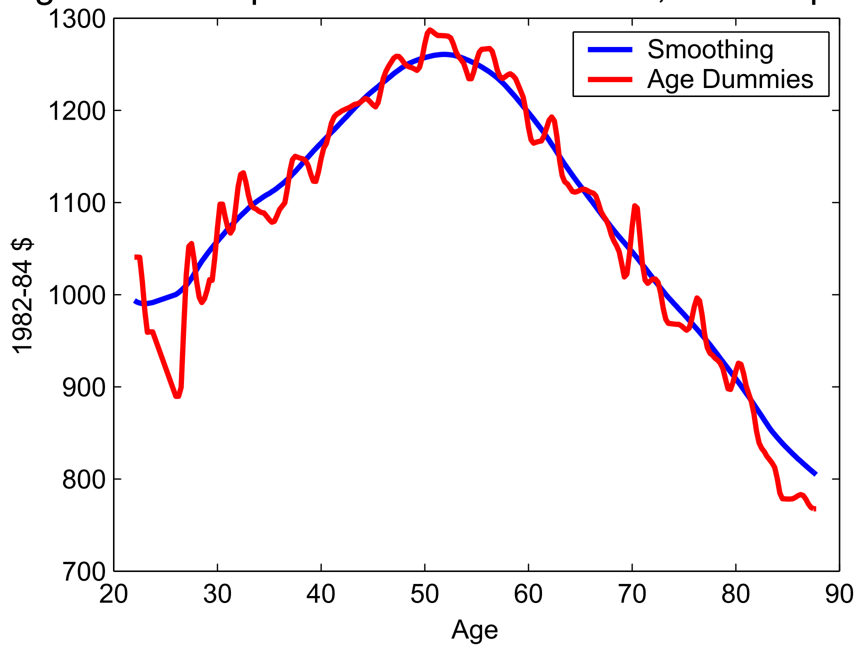


Figure A1c: Expenditures Durables, Adult Equivalent

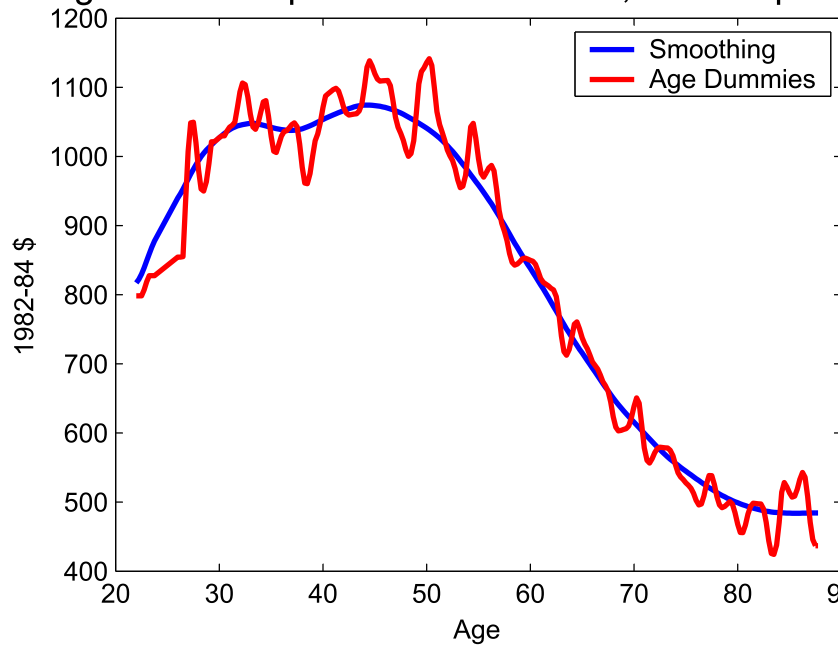


Figure A2a: Total Expenditure

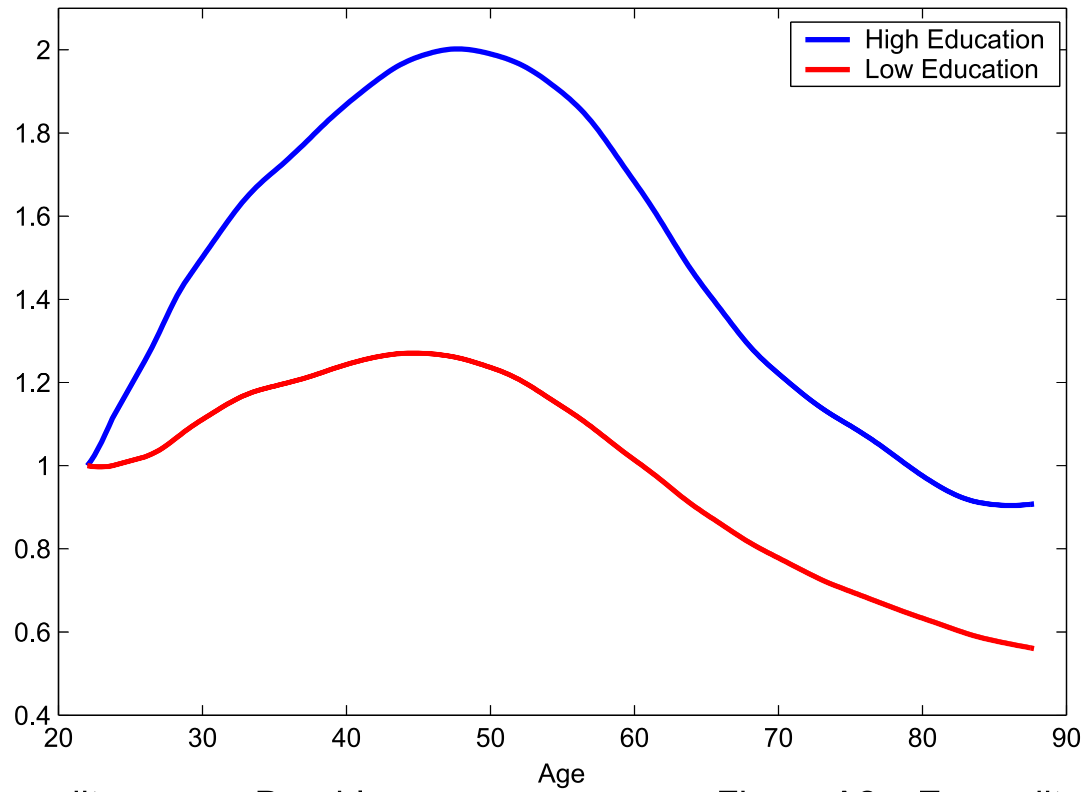


Figure A2b: Expenditures non Durables

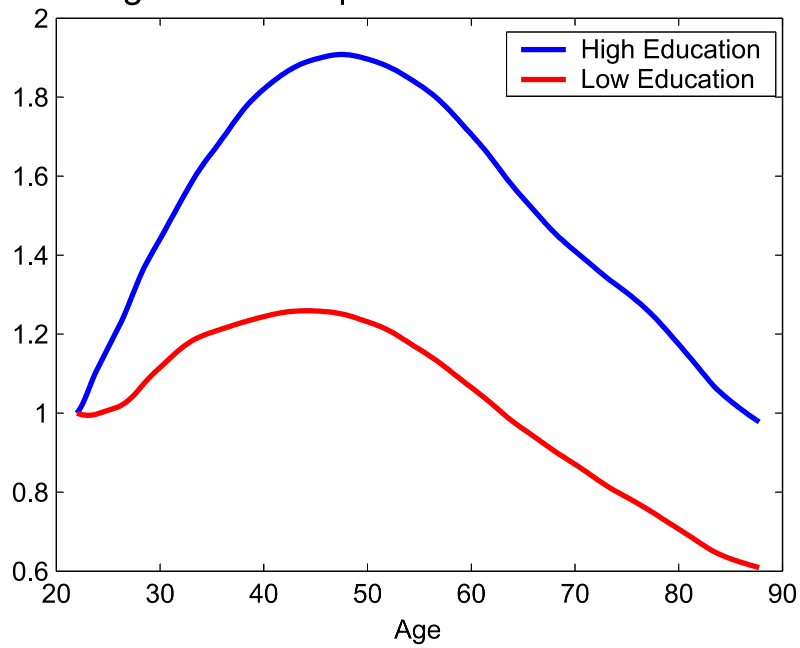


Figure A2c: Expenditures Durables

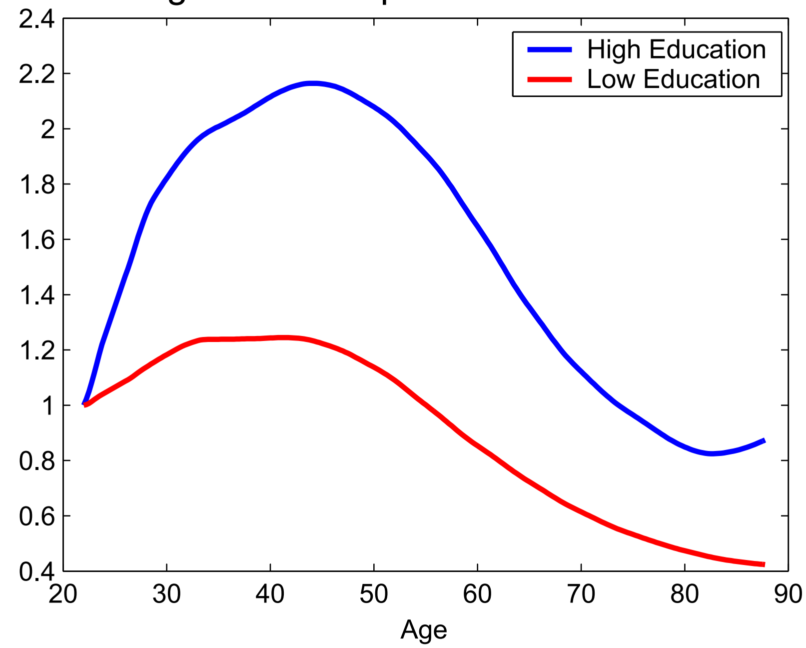


Figure A3a: Total Expenditure, Adult Equivalent

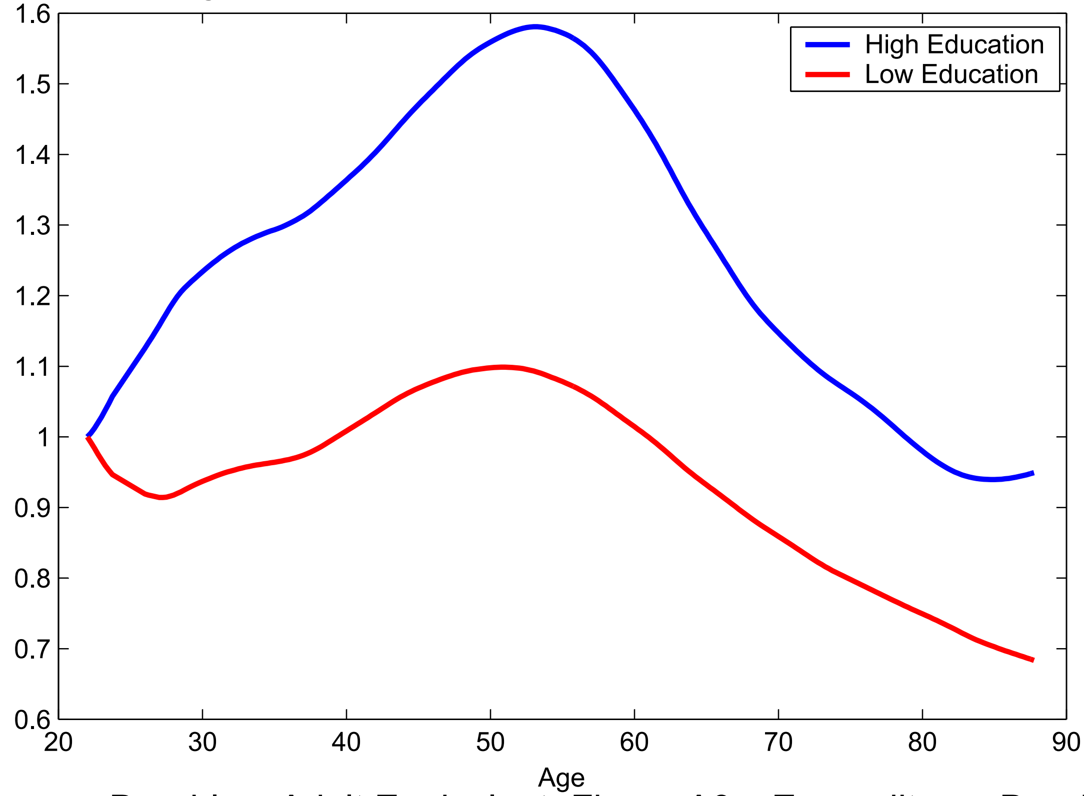


Figure A3b: Expenditures non Durables, Adult Equivalent

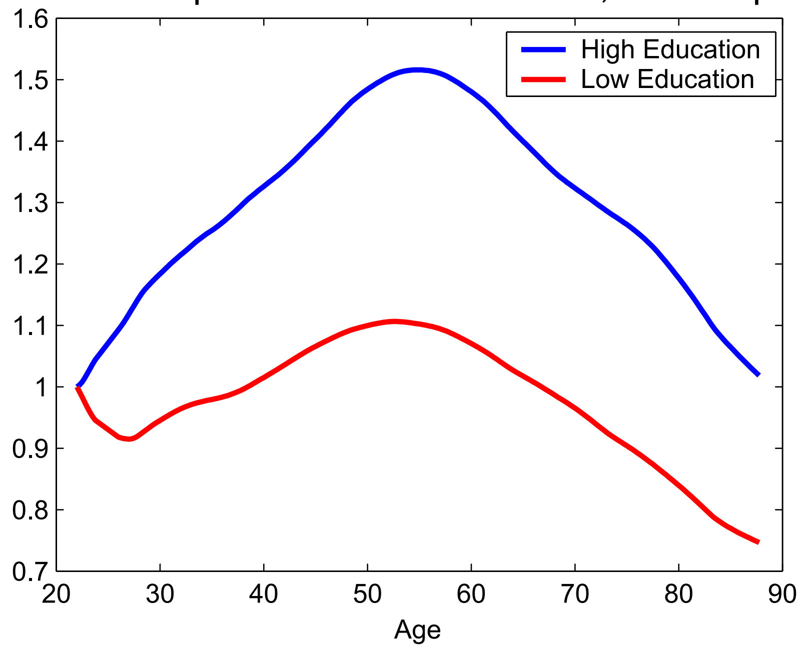


Figure A3c: Expenditures Durables, Adult Equivalent

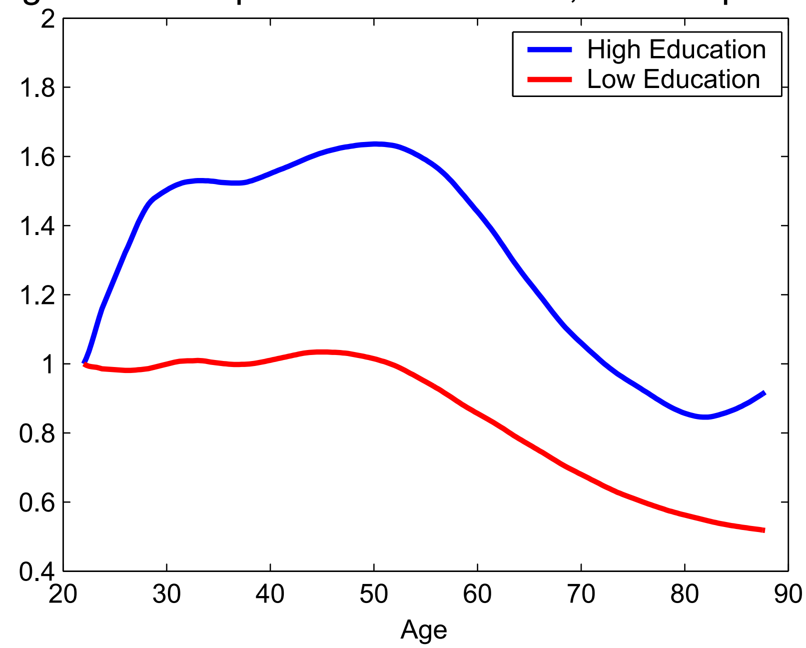


Figure A4a: 95% confidence interval

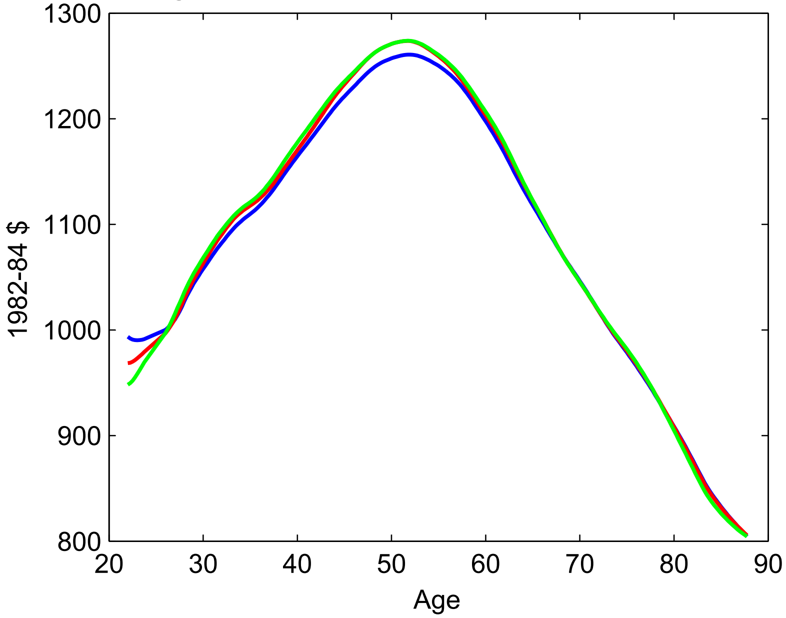


Figure A4b: Widest confidence interval

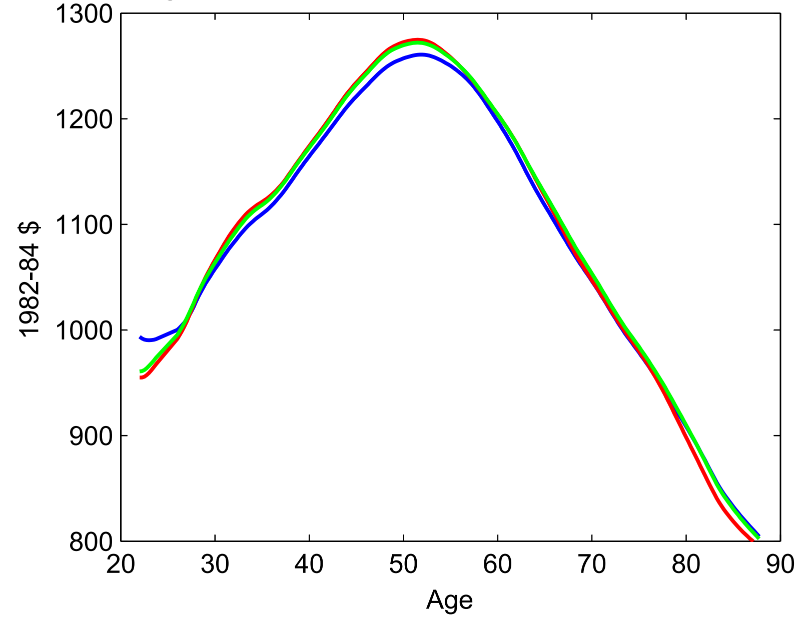


Figure A4c: 95% confidence band

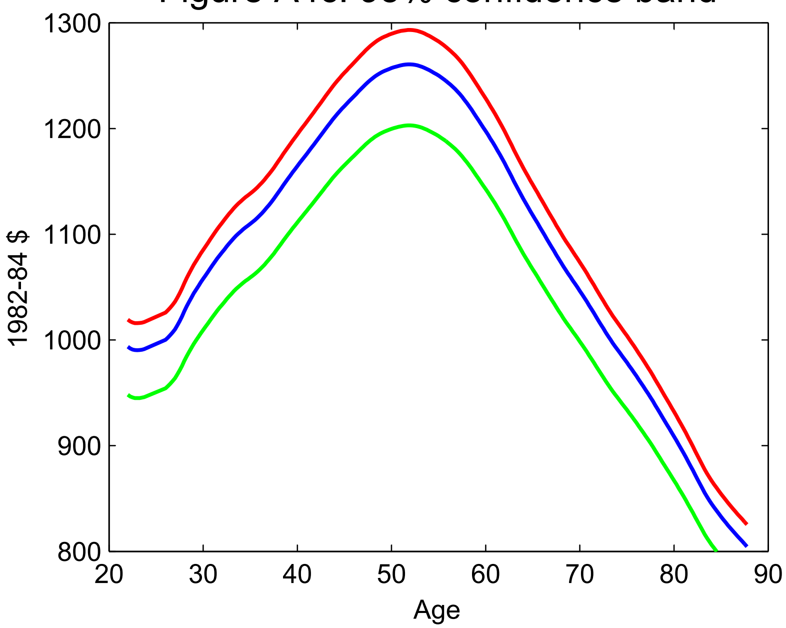
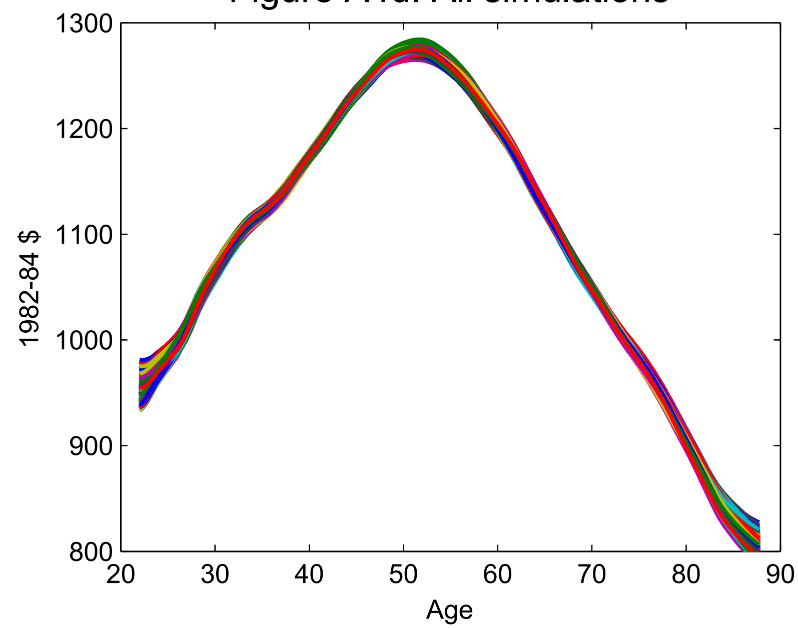


Figure A4d: All simulations



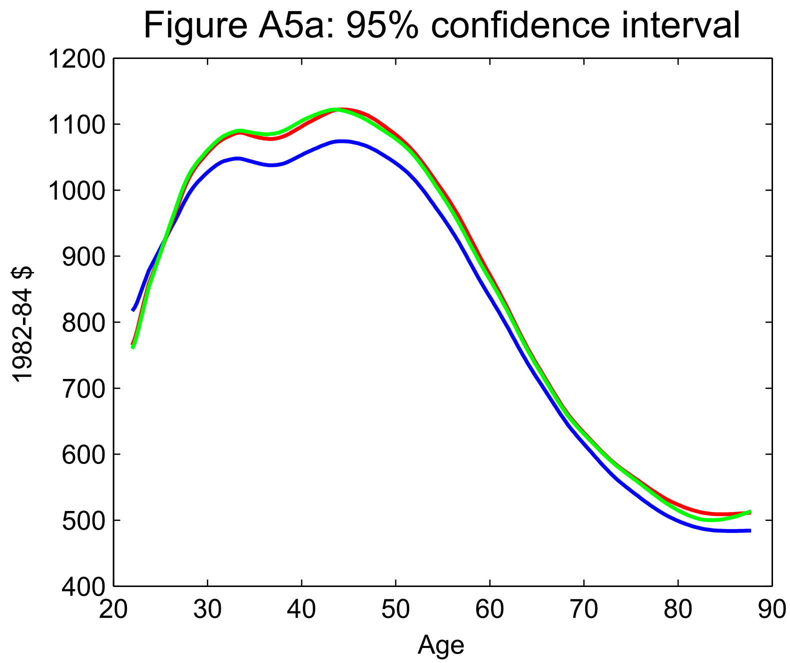


Figure A5a: 95% confidence interval
1982-84 $
Age

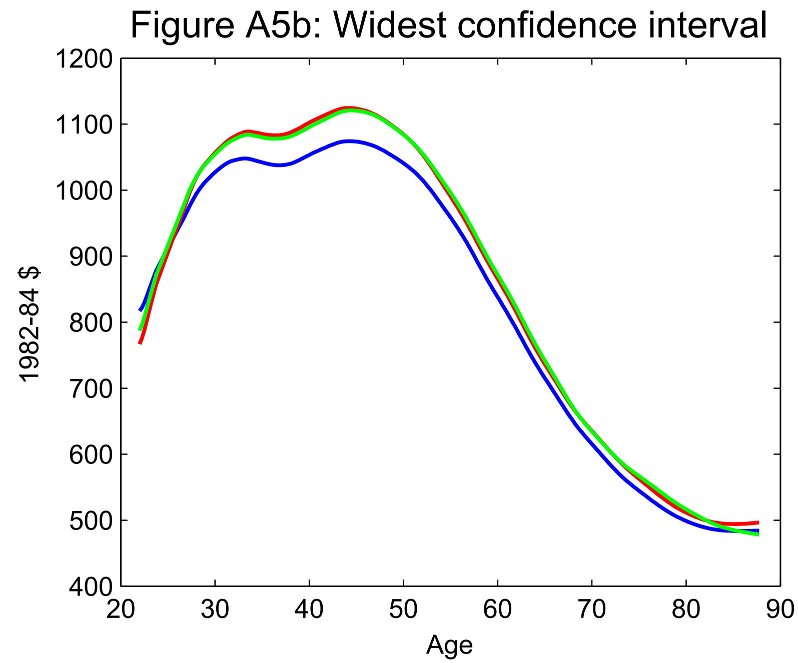


Figure A5b: Widest confidence interval
1982-84 $
Age

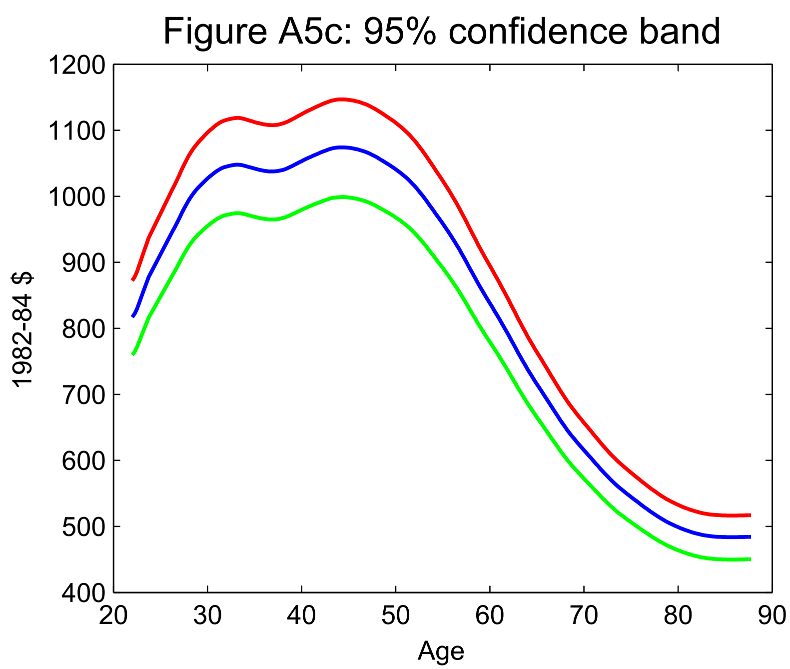


Figure A5c: 95% confidence band
1982-84 $
Age

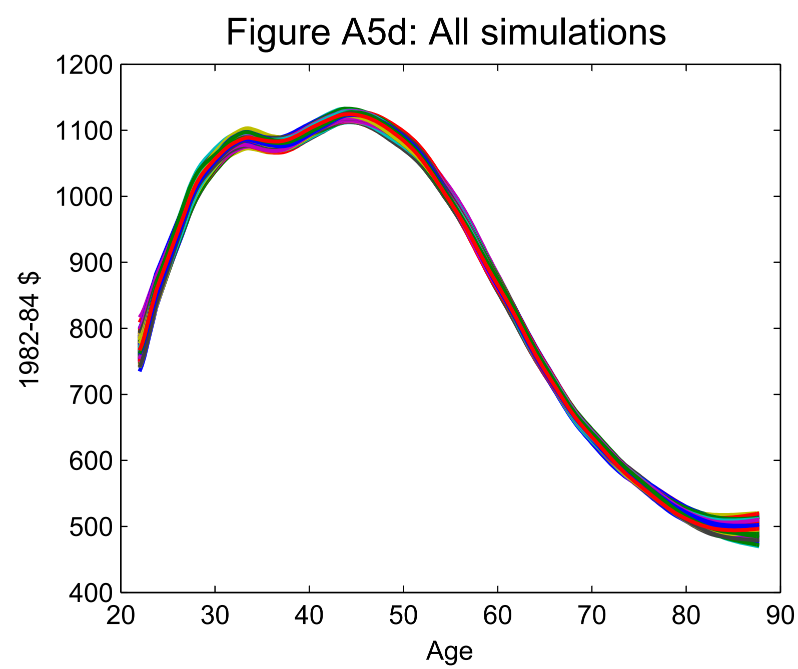


Figure A5d: All simulations
1982-84 $
Age

Figure A6: Expenditure versus Labor Supply per Adult

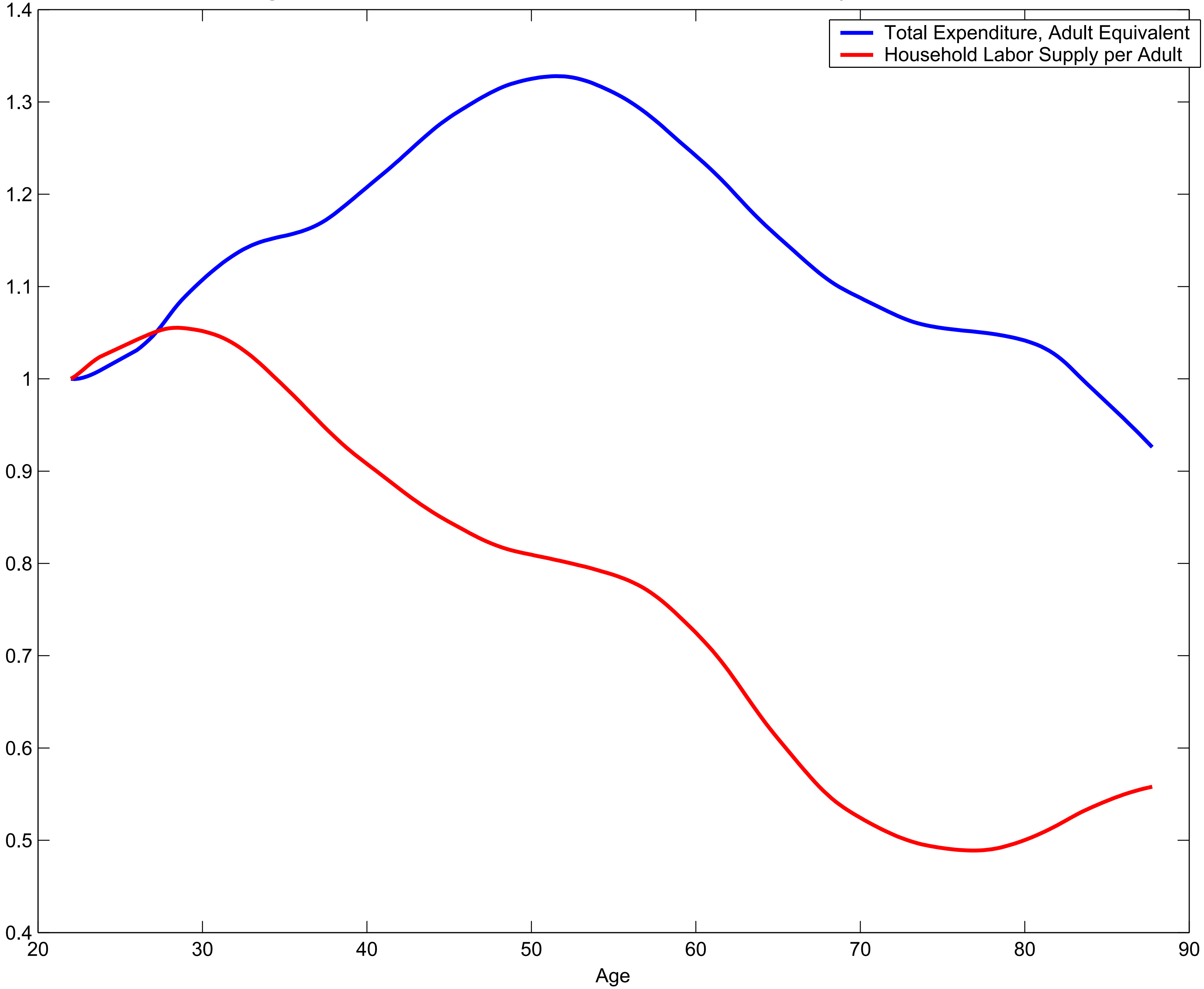


Figure A7a:
Expenditure versus Labor Supply, High Education

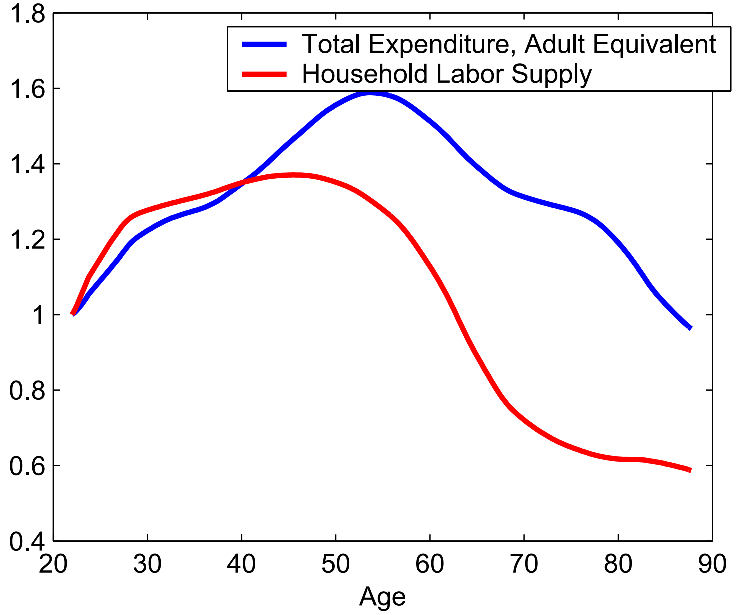


Figure A7b:
Expenditure versus Labor Supply per Adult, High Education

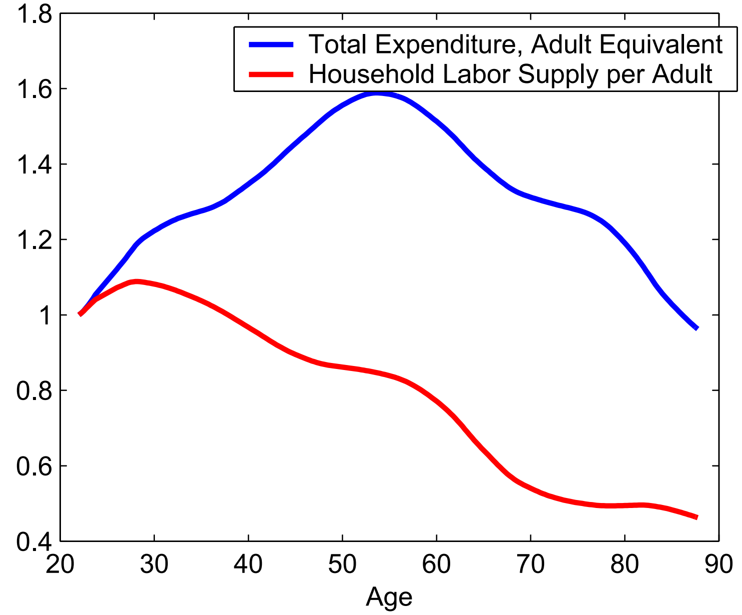


Figure A7c:
Expenditure versus Labor Supply, Low Education

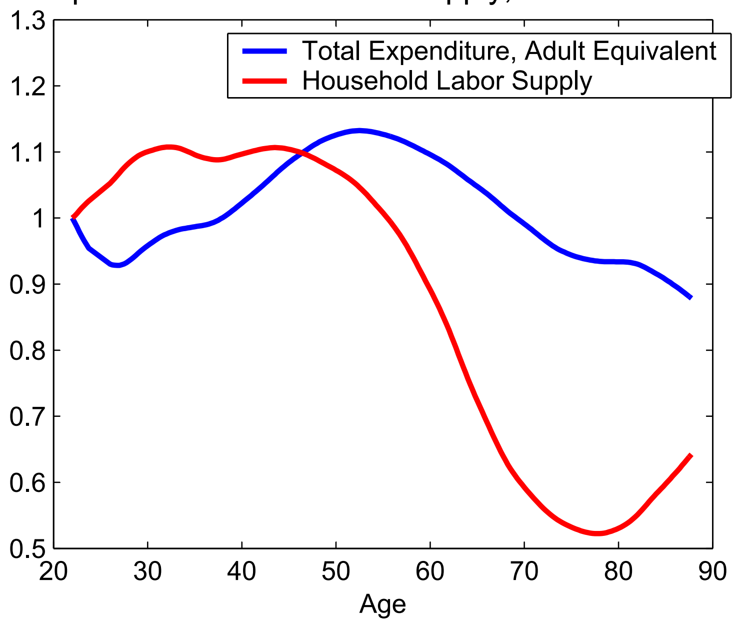
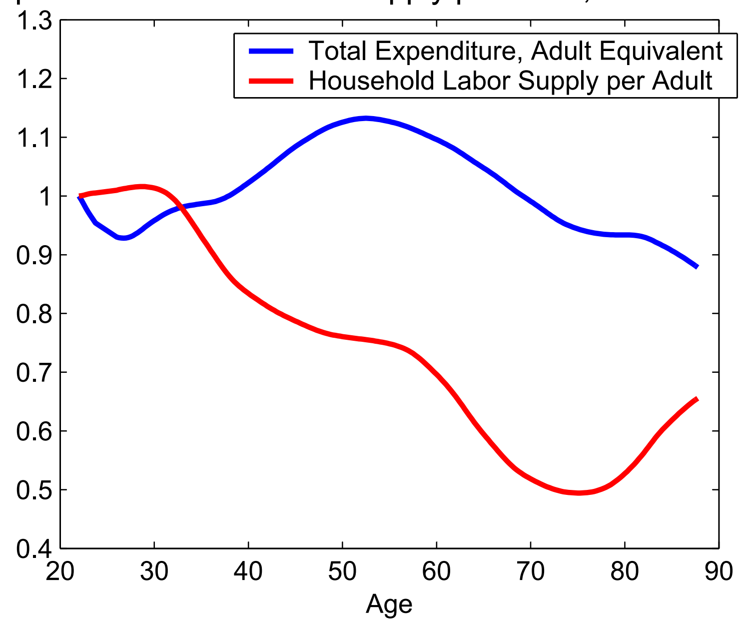


Figure A7d:
Expenditure versus Labor Supply per Adult, Low Education



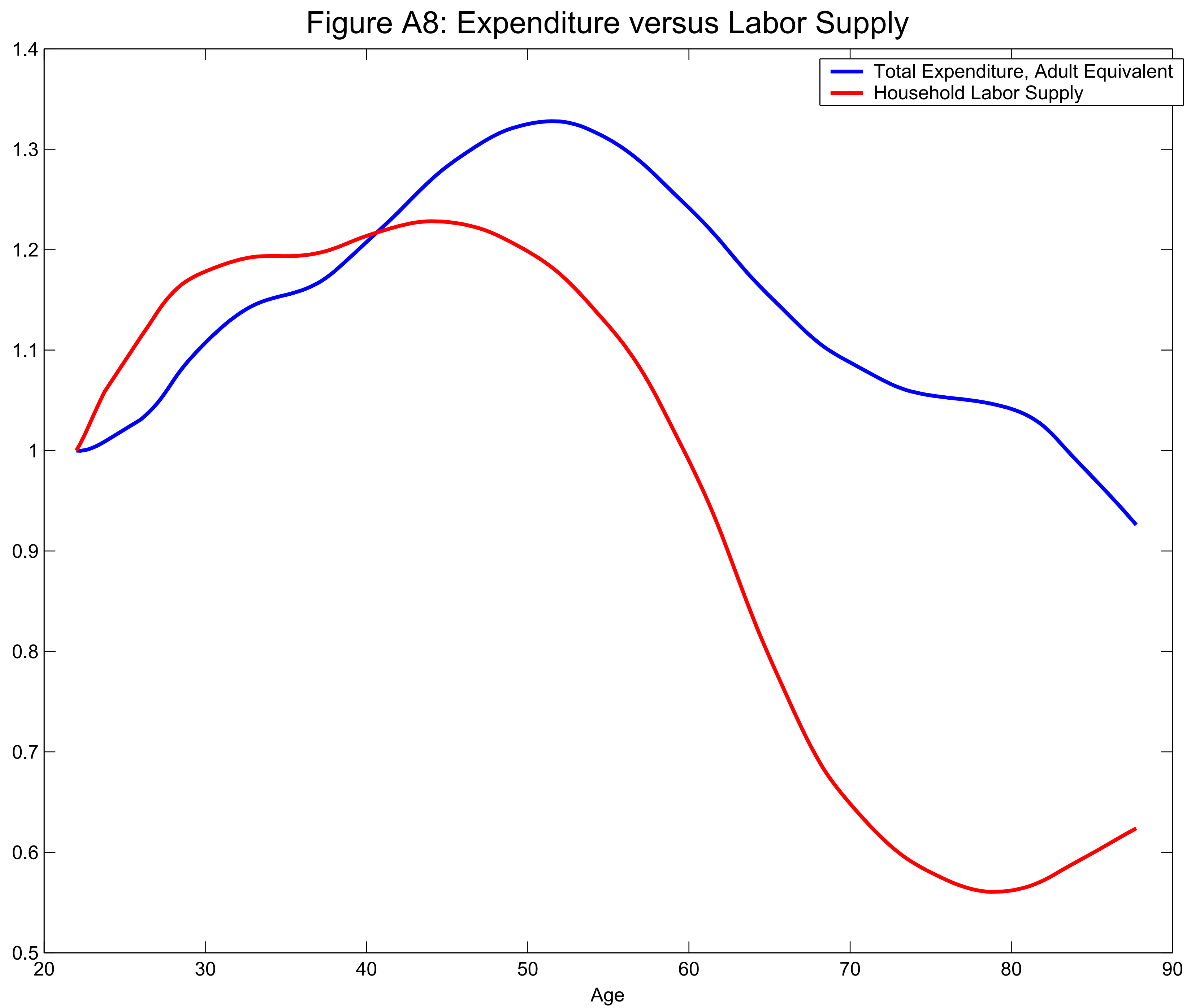


Figure A8: Expenditure versus Labor Supply
Total Expenditure, Adult Equivalent
Household Labor Supply
1.4
1.3
1.2
1.1
1
0.9
0.8
0.7
0.6
0.5
20
30
40
50
60
70
80
90
Age

Figure A9a: Expenditures Durables Non Housing, Adult Equi.

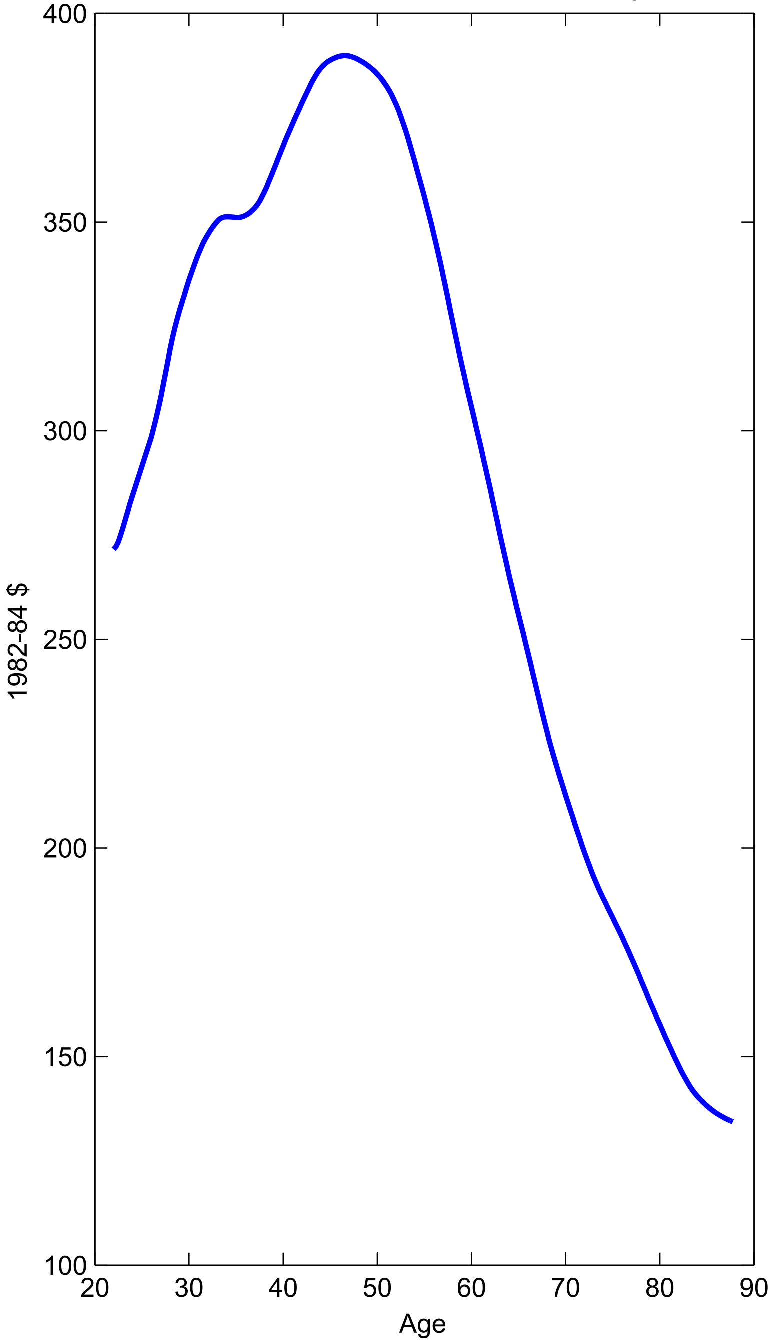


Figure A9b: Expenditures Durables Housing, Adult Equi.

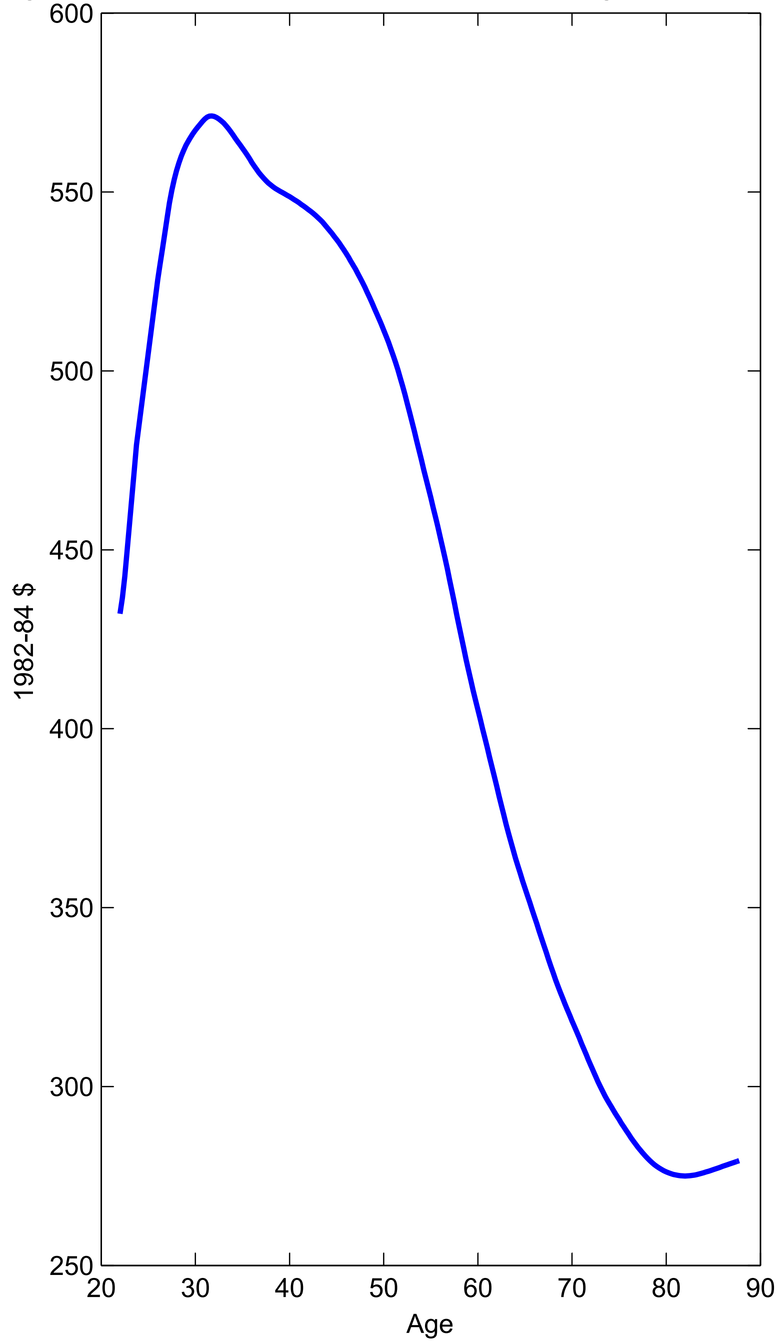
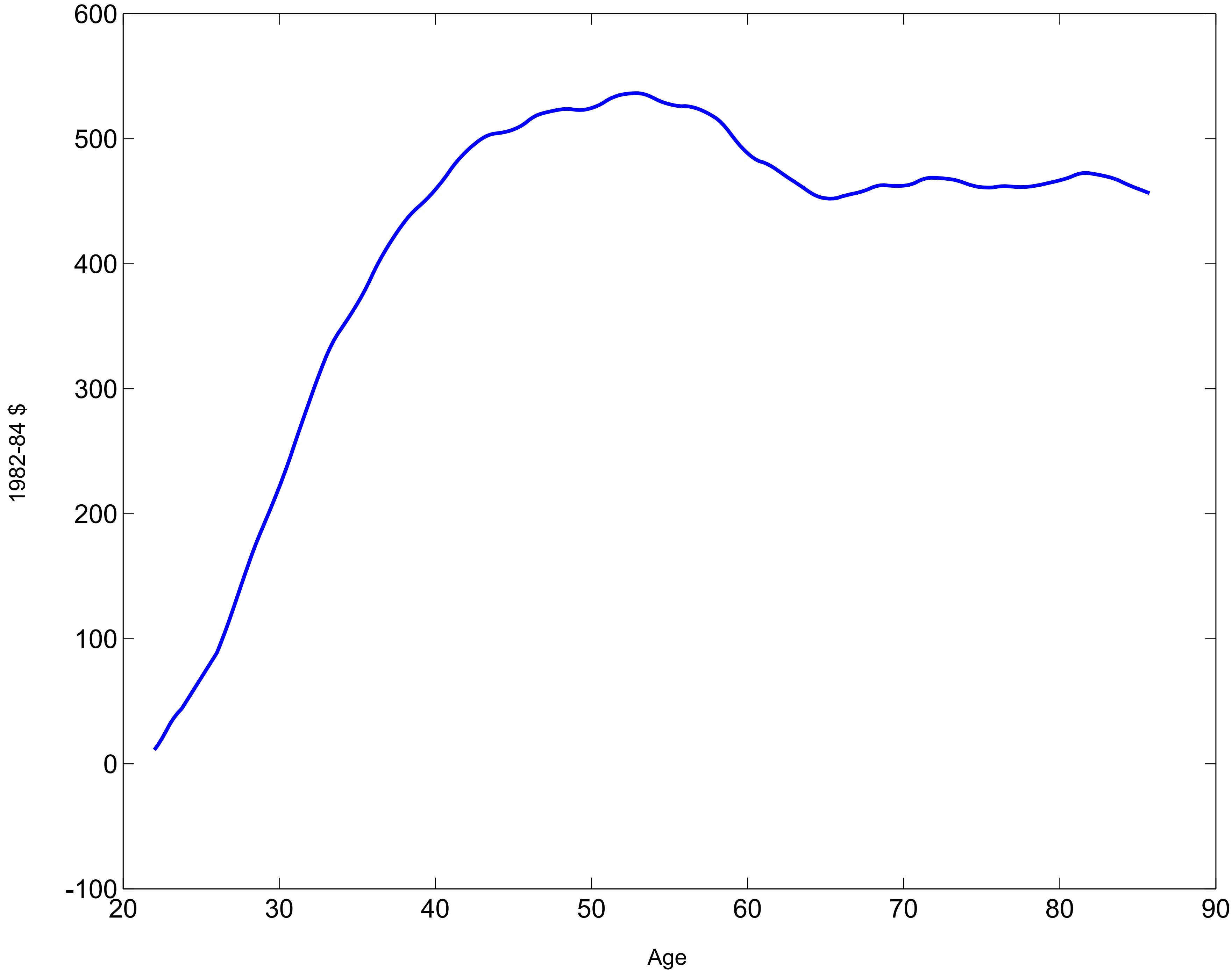


Figure A10: Equivalent Rental Value



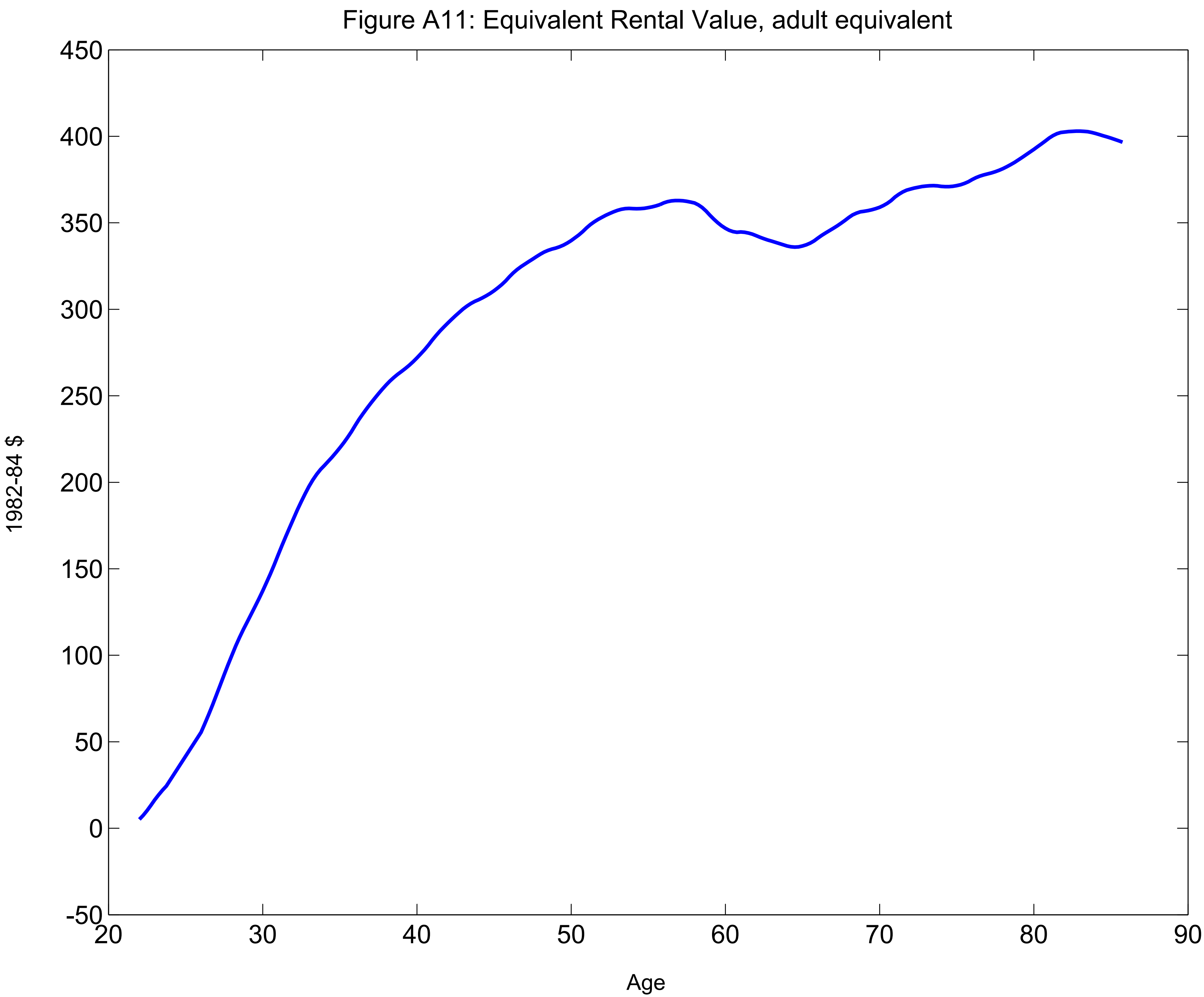


Figure A11: Equivalent Rental Value, adult equivalent
1982-84 $
450
400
350
300
250
200
150
100
50
0
-50
20
30
40
50
60
70
80
90
Age