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Medical Consumption over the Life Cycle:
Facts from a U.S. Medical Expenditure Panel Survey

by

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Medical Consumption over the Life-Cycle:

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Abstract

We investigate the association between age and medical spending in the U.S. using data from the Medical Expenditure Panel Survey (MEPS). We estimate a partial linear seminonparametric model and construct "pure" life-cycle profiles of health spending simultaneously controlling for time effects (i.e. institutional changes and business cycles effects) and cohort effects (i.e. generation specific conditions). We find that time and cohort effects introduce a significant estimation bias into predictions of health expenditures per age group, especially for individuals older than 60 years. The estimation biases introduced by cohort effects increase monotonically with age while time effects are non-monotone. Overall, cohort effect biases dominate time effect biases in magnitude for high age groups.

JEL: I10, I11, C14, C23, D12, D91, J10

Keywords: life-cycle profiles, time and cohort effects, partial linear seminonparametric models, pseudo panels, medical expenditure panel survey (MEPS)

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1 Introduction

U.S. households spend a significant share of their income on health care. Total aggreg- ate spending on health care in the U.S. amounted to about 17 percent of GDP in 2010 and is expected to increase to 20 percent of GDP by 2020. Upward trends in health expenditures have been widely observed across all OECD countries over the last few decades. Population aging as well as the introduction of new technology intensive treat- ment techniques have been identified as some of the main contributing factors to this increase.

The natural process of health depreciation implies that the use of health services varies significantly by age. These age effects are not easily identified as there are many other factors that drive health spending, and many of them correlate with age in a non-causal way. Constructing life-cycle profiles of medical consumption that can isolate the pure age effect is therefore a crucial step towards our understanding of how ageing shapes the demand for health and the utilization of health care. This will inform projections about future increases in health expenditures and will help with building efficient health insurance systems.

Health status is highly correlated with age and health expenditures due to the biological aging process. However, our ability to estimate the "true" effect of age on medical consumption is limited by data constraints. Previous studies use cross-country data or household survey data to estimate health expenditures by age group (e.g. Fisher(1980), Waldo, Sonnefeld, McKusick and Amett (1989), Cutler and Meara (1998), Cutler and Meara (2001), Meara, White and Cutler (2004), and Hartman, Catlin, Lassman, Cylus and Heffler (2008)). Some of these studies find, surprisingly, that the age structure is insignificant in explaining health care expenditures (e.g. Gerdtham and Jönsson (2000)) and that aging could even contribute to a decrease in spending on health care as the cost of death is lower for very high age groups (e.g. Zweifel, Felder and Meier (1999) and Zweifel, Felder and Werblow (2004)). On the other hand, more recent studies find that aging does play an important role in explaining the rise of health care spending (e.g. Sheiner (2009) and Baltagi and Moscone (2010)).[1]

Constructing life-cycle patterns of medical expenditures from cross-sectional or panel data is a complex task because factors other than age do influence an individual's health state and, by extension, her demand for health care services. First, generation specific characteristics or early-life living conditions could influence health status in later years. Generations born during periods of war or generations that reach their productive peak

[1](Zweifel, Breyer and Kifmann, 2009, p. 471) presents a comparison of the competing theories of the effect of ageing on health care expenditures.

during war periods will exhibit a different pattern of health care spending at any given age than generations that were spared from such misfortunes. We refer to this as *cohort effect.* Cohort effects can be thought of as “historical time” effects or “initial conditions” effects as they tend to be triggered by events that potentially happened at birth or even earlier. If, in a sample, a certain age group is primarily represented by a war cohort and the sample lacks observations for individuals of the same age group that were born at a different time (as it is the case in cross sections or in short panels), then a cohort effect may falsely be attributed to an age effect and a bias is created.

Second, changes in macroeconomic conditions can significantly affect a person’s health (e.g. Ruhm (2005)) and by extension spending on health care over time. These *time effects* are caused by more contemporary events like changes in aggregate trends including economic growth, business cycle fluctuations, demographic shifts, inflation, etc. When using household data to estimate “pure” age driven health expenditure profiles, we need to control for these *cohort* and *time effects*.

To the best of our knowledge, there is no study that identifies the pure age effect on health expenditures over the life-cycle while controlling simultaneously for the time and cohort effects. In addition, there is no study that estimates the size of time and cohort effects or the bias generated by these effects. The goal of this paper therefore is to (i) separate the pure age effect from time and cohort effects; (ii) construct life-cycle profiles of health expenditures that contain only age effects; and (iii) evaluate the quantitative importance of the time and cohort effects.

In order to control for cohort and time effects simultaneously we use a seminon-parametric partial linear econometric model based on Speckman (1988). We then apply this method to U.S. data from the Medical Expenditure Panel Survey (MEPS) from $1996-2007$ and construct pure age driven health expenditure profiles. Our results are summarized as follows.

First, health expenditures, on average, follow a distinct upward trend over the life- cycle with exponential increases at very high ages. Individuals in their twenties spend about $\$2,000$ per year on average on health care. Older individuals in their fifties spend around $\$3,000$ per year on average.[2] Once individuals are in their sixties, their health expenditures start to increase very rapidly. The highest expenditures are incurred by old individuals at the end of their life at an average of around $\$10,000$ per year. *Second*, time and cohort effects are large and significant. More specifically, the bias (due to time and cohort effects) in health expenditure estimates is less than $\$1,000$ for individuals younger than 50, but starts to increase exponentially for older individuals. At higher ages

[2] All dollar values are denominated in 2005 dollars.

the bias amounts to $\$2,000$ and $\$4,000$ at the age of 70 and 85, respectively. Life-cycle profiles of total health expenditure based on simple cross section averaging per age group therefore overpredict the effects of age on health expenditures, especially for individuals older than 60. *Third,* the bias is mostly caused by cohort effects rather than time effects. *Fourth,* biases generated by the cohort effect are positive and increase monotonically with age; whereas biases introduced by time effects are non-monotone. *Finally*, the pattern of cohort effects is consistent across gender and education levels, while the patterns of time effects vary.

Literature. Our paper is related to the literature studying the life-cycle theory of consumption (e.g. Carroll and Summers (1991), Deaton (1992), Kotlikoff (2001), Gourinchas and Parker (2002), Fernandez-Villaverde and Krueger (2007)). Note that previous studies leave out medical consumption when constructing these life-cycle profiles of non-medical consumption. Our work also contributes to the health economics literature on health capital (Grossman (1972a) and Grossman (1972)). Grossman argues that since health capital depreciates at age-dependent rates, individuals consume more health care services at higher ages to maintain or improve their health capital. There is an empirical literature based on the Grossman model with emphasis on testing the consumption and investment motives of health capital (see Grossman (2000) for a review). Deaton and Paxson (1998) and Kippersluis, Ourti, O'Donnell and van Doorslaer (2009) detect decreasing patterns of health status over the life-cycle in the U.S. and Europe. The decreasing health status measures hint at accelerating depreciation rates of health capital over the life-cycle as do the upward trends in the health expenditure profiles. However, due to data constraints these previous studies do not estimate age-profiles of health expenditure. Finally, "pure" health expenditure profiles provide an important benchmark for assessing the quantitative properties of macroeconomic models with endogenous health capital (e.g. Suen (2006), Jung and Tran (2008), Forseca, Michaud, Galama and Kapteyn (2009), Feng (2009), Jung and Tran (2009), Halliday, He and Zhang (2010), and De Nardi, French and Jones (2010)).

The paper is structured as follows. Section 2 introduces the estimation procedures. Section 3 briefly describes the data and stylized facts. Section 4 reports our results. We conclude in section 5. All tables and figures are presented in the appendix.

2 Estimation methods

In this section we discuss the econometric methods that we use to control for cohort and time effects when constructing life-cycle profiles of medical health expenditures.

2.1 Linear models

We first consider a linear regression model with dummy variables for age, year, and birth cohort which can be written as

$$y_{it} = \beta_0 + \sum_{j=j_0}^{J} \alpha_j D_{age_{jit}} + \sum_{t=t_0}^{T} \tau_t D_{year_{it}} + \sum_{c=c_0}^{C} \gamma_c D_{cohort_{cit}} + \varepsilon_{it}, \qquad (1)$$

where y_{it} is the dependent variable (e.g. health expenditures) for $i = 1, ..., N$ where N is the number of individuals in the sample; $j = j_0, ..., J$ is an indicator for an individual's age; $t = t_0, ..., T$ is an indicator for calendar year in which the observation was collected; $c = c_0, ..., C$ is an indicator for calendar year in which the individual was born; β_0 is a constant; $D_{age_{jit}}$ is a dummy variable equal to unity whenever individual i turns age j at time t; $D_{year_{it}}$ is a dummy variable equal to unity whenever the observation year is equal to t and zero otherwise; and $D_{cohort_{cit}}$ is a dummy variable equal to unity whenever individual i in year t is from a cohort born in year c. Errors ε_{it} are assumed to be iid.

The slope coefficient α_j measures the pure age effect on health expenditures that we need for constructing the health expenditure age profile. However, with this estimation model we face an identification issue due to the linear dependence of age, cohort, and calendar time. If we know two out of the three variables, we can always infer the third. Consequently, we cannot simply run an OLS regression of health expenditures on dummy variables of age, cohort, and time as this would result in multicollinearity problems.

As an alternative, some previous studies (e.g. Fjeldvig (2009)) resort to simply controlling for two out of the three effects and use a model with age and time effects only. Basically, this method assumes that the cohort effect is small and can therefore be ignored. Employing this estimation method also introduces difficulties, since the dependent variable (e.g. health expenditures) has many zero entries which requires selection models. Moreover, this method requires long balanced panel data that are rarely available. Therefore, some researchers further simplify their linear estimation models and concentrate on cross sections, ignoring year and cohort effects altogether. This approach simply averages the dependent variable over all age groups. In order to resolve these identification issues, we propose a partial linear model based on Speckman (1988).[3]

[3] Deaton (1997), Härdle, Liang and Gao (2001), and Fernandez-Villaverde and Krueger (2007) are other studies that employ this modeling idea.

2.2 Partial linear seminonparametric models

Intuitively, the identification strategy of this method rests on a non-linearity restriction which breaks the perfect linear dependence of the three sets of dummy variables (i.e. age, time, and cohort dummies). That is, the age effect is assumed to be non-linear, described by function $m\,(age_{ct})$, while the time and cohort effects are still linear. The partial linear seminonparametric model can be written as follows:

$$y_{ct} = \beta_0 + m(age_{ct}) + \sum_{t=t_0}^{T} \tau_t D_{year_t} + \sum_{c=c_0}^{C} \gamma_c D_{cohort_{ct}} + \varepsilon_{ct}, \tag{2}$$

where m is a non-linear transformation of the cohort age in time t denoted as age_{ct}, and y_{ct} is the log transformation of the average of the dependent variable across cohorts. We suppress the log notation in order to not clutter the notation.[4] Fernandez-Villaverde and Krueger (2007) suggest to use the Nadaraya-Watson estimator of the form

$$\hat{m}\,(age) = \frac{\sum_{c=1}^{N} \sum_{t=t_0}^{T} K_h\,(age - age_{ct}) \times y_{ct}}{\sum_{c=1}^{N} \sum_{t=t_0}^{T} K_h\,(age - age_{ct})}, \tag{3}$$

where

$$K_h\,(u) = \frac{0.75}{h}\left(1 - \left(\frac{u}{h}\right)^2\right) \times I\left(\left|\frac{u}{h}\right| \leq 1\right) \tag{4}$$

is an Epanechnikov kernel and h is the bandwidth parameter. Note that the Nadaraya-Watson estimator using a kernel with bandwidth $h = 1$ is identical to simply calculating averages of y per age group, whereas a bandwidth parameter $h > 1$ calculates local averages and smoothes the age profile of y. Note that the Kernel smoother should only be applied to the interval variable age and not to the ordinal variables year or cohort.

In order to simplify the notation, we rewrite expression (2) in matrix notation and summarize the dummy variables in matrix $X_{C\times T,1+C+T-2}$. We also add a column of ones for the constant. The estimation equation can then be written as

$$y_c = \beta^T X + m\,(age) + \varepsilon.$$

The estimation procedure has six steps:

Step 1 : Estimate

$$y_c = m\,(age) + \varepsilon,$$

[4] Taking logs after averaging introduces an aggregation bias according to Attanasio and Weber (1993)

that could be prevented by taking logs before averaging. However, since many individuals do not spend anything on health in any given year, we cannot make the log transformation before the aggregation, unless we are willing to replace the zero entries with arbitrary small positive numbers.

using the Nadaraya-Watson estimator as described above.

Step 2 : Build a smoothing matrix S that satisfies

$$\hat{y}_c = S \times y = m\,(age_{ct})\,.$$

Step 3: Transform the system and create partial residual vectors using the smoothing matrix S which results in

$$\tilde{y}_c = (I - S)\,y \text{ and } \tilde{X} - (I - S)X.$$

Step 4: Estimate parameter β from $\tilde{y}_c = \beta\tilde{X} \;+\varepsilon$ as

$$\hat{\beta} = \;\; \tilde{X}^T\tilde{X} \;\; ^{-1}\,\tilde{X}^T\tilde{y}_c.$$

Step 5: Use expression $y_c - X\hat{\beta}$ as dependent variable in the kernel smoothing function and estimate $\hat{m}\,(age_{ct})$.

Step 6 : Transform the predicted (and smoothed values) of y_c back into levels using the exponential function.

These predictions, denoted $\hat{y}_c$, are now cleared of cohort and time effects and represent the pure age effects of health expenditure. For more details see Speckman (1988).

3 Data, summary statistics and stylized facts

3.1 Data

We use U.S. data from the Medical Expenditure Panel Survey (MEPS) for our empirical investigation. MEPS is a longitudinal survey that pays particular attention to medical expenditures and financing. MEPS is an overlapping rotating panel where an individual is surveyed five times over a two year horizon. Each year contains approximately $20,000$ individuals between the age of 20 and 87. The pooled data over all 12 waves contains $240,329$ individuals. For our estimation we exclude all individuals who do not report health expenditures and concentrate on the 20 to 87 year olds. Individuals who either passed away or were institutionalized in the second year of the survey, but who still report health expenditures in that second year, are kept in the panel. We are then left with $209,932$ person-year observations. We focus on a data sample from from the years 1996 to 2007.

MEPS data is particularly useful to analyze health expenditures as it contains many variables that allow us to decompose health expenditures into various spending categories. In addition, MEPS does not suffer from an out-of-pocket spending bias like data from the Health and Retirement Survey (HRS) as pointed out in Hurd and Rohwedder (2009). However, Selden and Sing (2008) find problems with under reporting of health care spending and selective attrition bias as is common in many household surveys. We use the consumer price index for all urban consumers (CPI) to deflate income and health expenditure measures in order to maintain comparability across spending categories. We denominate all dollar values in 2005 dollars.[5]

3.2 Summary statistics

We present summary statistics of the pooled data in Table 1. Our sample consists of individuals born between 1921 and 1976, they are between 20 and 86 years old (including the 20 and 86 year olds), and we observe them for at most two years between 1996 to 2007. The majority is female (53.7 percent). A total of 63 percent are either married or live with a partner. The average annual wage income is \$24,633 and the average total household income is \$30,508. The average years of education are 12.5 years. The sample contains 0.5 percent students.

Total health expenditure is the sum of spending on doctor/office visits, outpatient/hospital visits, inpatient hospital stays, emergency room visits, home health care, prescriptions, and others (e.g. dental and vision). Note that insurance premium payments are not included in total health expenditures. Total average annual health care expenditures per person are \$3,611. Health expenditures are broken down into office visits with doc- tors (\$777 annual average per person), outpatient care (\$355), inpatient care (\$1,194), emergency room care (\$110), expenditures incurred in one's home (\$143), prescriptions (\$745), and other health expenditures (\$287).

The fraction of individuals without health insurance is 16.5 percent. Of the insured population, 16.5 percent have only public insurance whereas 67 percent have private insurance as well.[6] Total health care expenditures, as defined above, are financed with out-of-pocket funds (\$649 annual average per person), Medicare (\$848), Medicaid (\$394), private insurance (\$1,367), veteran's benefits (\$94), CHAMPUS payments (\$3), Tricare (\$22), federal insurance (\$15), state insurance (\$27), worker's compensation (\$62), and other sources (\$36).

Various proxy measures of health capital have been used in empirical studies. The MEPS data provides one such measure, the Short-Form 12 Version 2 ($SF-12v2$) health index. The $SF-12v2$ includes twelve health measures about physical and mental health.

[5] See the following website for more information about the consumer price indices used: http://data.bls.gov/cgi-bin/surveymost?cu

[6] Some of the individuals with private insurance also have public insurance.

We report two versions of this index, one for physical health (*Health index physical components*) and one for mental health (*Health index mental components*). Both measures use the same variables to construct the index but the physical health index puts more weight on variables measuring physical health components and the mental health index puts more weight on variables measuring mental health components (compare Ware, Kosinski and Keller (1996) for further details about this health index). In addition, we use self reported health status measures (1. excellent, 2. very good, 3. good, 4. fair, and 5. poor health) and construct a "healthy" index. An individual is considered to be healthy if the health status measure is either excellent, very good, or good and unhealthy otherwise. This classification is standard in the literature. Our sample consists of 85.4 percent healthy individuals.

3.3 Stylized facts

Health status. The physical component of the SF-12v2 index, as well as the "healthy" index described above, show comparable trends over the life-cycle (compare panel 1 and 2 of figure 1). Young individuals hold relatively high levels of health capital. Thereafter the average health status decreases as an individual ages. The mental health component of the SF-12v2 follows a different trend and exhibits a slight "M" shape. Young individuals (around age 20) and very old individuals (around age 75 and higher) report the lowest mental health status. Interestingly, individuals in the age range between 40 and 55 have lower mental health status than younger cohorts in their thirties and older cohorts in their sixties. This could be a reflection of that cohort's strong exposure to career pressures while fulfilling the role of double caretakers (i.e. caring for the very young and the very old generations).

Health expenditures. We next present results from a simple cross sectional ana- lysis where we simply average health expenditures per age group. Note that these profiles do not control for the cohort and time effects and are therefore biased. Panel 3 in figure 1 presents the average and the median total health expenditure by age group. We ob- serve a pronounced increase of health expenditures as individuals get older. On average, individuals in their twenties spend about $1,500 per year on health care whereas older individuals in their fifties spend about $4,000 per year. Once individuals are older than fifty, their health expenditures start to increase significantly. The highest expenditures are incurred by old individuals at the end of their life and amount to approximately $12,000 on average per year.

We find that mean health expenditures are consistently higher than median health expenditures and the gap between mean and median health expenditures widens as individuals age. This indicates that averages are likely to be distorted by "outliers" with very high health expenditures (e.g. out of 209, 932 individual observations, there are 13 individuals with annual health expenditures exceeding \$500, 000, 996 individuals spend more than \$100, 000, and 3, 772 individuals spend more than \$50, 000).

Comparing the results from the health expenditure profiles (panel 3 and 4) with the health status profiles (panel 1 and 2), we find that the two profiles are inversely related over the life-cycle. Exponentially depreciating health capital levels (i.e. a combination of natural age depreciation rates and health shocks) are some of the main causes behind the upward trend in medical consumption over the life-cycle.[7]

Health expenditure inequality. In order to get a sense for the distribution of health expenditures we report the Gini coefficient of health expenditure per age group in panel 4 of figure 1. The Gini coefficient of health expenditures is very high at around 0.8 when individuals are younger than 40 and then sharply drops as individuals get older. Higher Gini coefficients at younger ages indicate that health expenditures among the young are much more concentrated than health expenditures of the old. This is probably driven by relatively rare, but catastrophic health events amongst the young. Lower Gini coefficients at older ages imply that the higher incidence of health problems at higher ages "equalizes" health spending across individuals. Moreover, it may suggest that the availability of public health insurance programs plays a role in reducing uneven access to health care services and therefore evens out health expenditure differences across different income groups as well.

When comparing health expenditures as fraction of household income, we also observe an increase over age. At the end of their life individuals spend on average 100 percent of their income on health care. Due to large public programs like Medicare and Medicaid the insurance coverage rate of the elderly is close to 100 percent. As a consequence the share of health expenditures as fraction of income is contained at less than 15 percent. For the very old this ratio drops as insurance covers an even a larger percentage. The latter is likely due to individuals meeting Medicaid eligibility thresholds after they run down their assets.

3.4 Pseudo panel

MEPS is a rotating panel data so one individual is only followed over two consecutive years. This feature allows more flexibility in collecting more data while maintaining sample size. However, we can not use the original MEPS data in estimating our partial

[7] Similar cross-sectional results for health expenditures by gender, insurance status, and income groups are available upon request from the authors.

linear seminonparametric model as this requires longer panel data to effectively control for time effects. To get around this issue we construct a pseudo panel data set. [8]

Since the surveys are repeated with new individuals joining every year, we can easily construct a pseudo panel that follows a cohort from 1996 to 2007. In order to construct a balanced pseudo panel we define 12 five-year cohorts, starting cohort one with birth years from 1920 to 1924, cohort two covers birth years from 1925 to 1929, etc. Finally cohort 12 covers the birth years from 1975 to 1979. As cohorts age, we assign the age of the oldest member of the cohort as cohort age, so that all members who are, say, between 75 and 81 years in 2000 are identified to belong to cohort 2, with birth years between 1925 − 1929 and uniform cohort age of 81.

We calculate the cohort average y_c of the dependent variable y across all members of this cohort in year 2000. The pseudo panel therefore consists of 144 observations. Table 6 presents the absolute observation frequencies for each cohort in each year. Table 2 presents summary statistics for the pseudo panel, averaged over all 12 waves (from 1996 to 2007) and over all 12 cohorts.

Our interpretation of an observation in the pseudo panel is that of a representative household with multiple members that spend y_c per head on their health. Some of the advantages of the pseudo panel are that it reduces the attrition problem of a standard panel survey, it averages out expectations errors, it eliminates the need to control for individual effects as we average across individuals of a given birth cohort, and it eliminates the problem of health expenditure entries equal to zero when log-transforming the data. Figure 2 summarizes the pseudo panel health expenditures along the age, time, and cohort dimension. More specifically, we report averages of health expenditures per head over time in panel 1, average health expenditures per cohort in panel 2, average health expenditures per age and cohort in panel 3, and average health expenditures per age in panel 4. The graph in panel 4 is the smoothed cross section of health expenditures from the earlier section, panel 3 in Figure 1.

4 Results

We next use the partial linear model in expression (2) to control for the time and cohort effects. Note that our Pseudo panel has 144 observations, $N = 144$, $j_0 = 20$ and $J = 85$, $t_0 = 1996$ and $T = 2007$, and $c_0 = 1915$ and $C = 1984$. Our results are summarized in figures 3 to 7. We first present the pure age effects on the life-cycle profiles of health expenditures. We then analyze the quantitative importance of time and cohort effects.

[8] See Fernandez-Villaverde and Krueger (2007) for a similar approach.

[9]

Age effect

Life-cycle profiles. In Figure 3, panel 1, we report estimated age profiles of health expenditures, cleared of time and cohort effects. Average health expenditures follow a distinct pattern and monotonically increase over the life-cycle. As predicted in previous studies, individuals spend relatively low levels of their income on medical services when young and spend larger amounts on health care when old. More specifically, individuals in their twenties, on average, spend about $1, 000 per year on health care whereas older individuals in their fifties spend around $2, 000 per year. Once individuals are older than fifty, their health expenditures start to increase very rapidly. The highest expenditures are incurred by old individuals at the end of their life and average around $7, 000 per year.[10]

Robustness. In order to check the robustness of our predictions we use a bootstrap procedure and construct 95 percent confidence bands around the point estimates for health expenditures without time and cohort effects. We create bootstrap samples of size $n = 144$ by drawing from the pseudo-panel with replacement and applying our estimation/projection procedure. We then create 500 predictions over the entire age range and plot the 2.5^{th} percentile and the 97.5^{th} percentile. Figure 3, panel 1 presents the predictions of the health expenditure profile without time and cohort effects including confidence bounds. The confidence bounds track the point estimates closely. In addition, panel 2 compares the health expenditure profile cleared of time and cohort effects to the cross section profile which still includes prediction biases caused by the time and cohort effects. Predictions that are cleared of time and cohort effects are significantly lower than simple cross sections for older cohorts (> 60).

4.1 Time and cohort effects

The size of time and cohort effects. The big difference between the simple cross section profiles and profiles based on the partial linear model hint at the quantitative

[9] We do not control for ageing nor time-to-death effects in the current analysis. In our model, the effect of age is a composite of the effect of calendar age and time-to-death which has been found to be a main explanatory component for health expenditures according to Zweifel, Felder and Meier (1999) and Zweifel, Felder and Werblow (2004).

[10] There is a potential issue that retransformation will fail to provide consistent inferences about parameters when zero health expenditures are observed with sufficient frequency (e.g. see Mullahy (1998) for a formal discussion). However, since we use a pseudo panel rather than a real panel we eliminate the problem of frequent zero health expenditure entries.

importance of additional factors (i.e. additional to age and inflation in the medical sector) that push up health expenditures as individuals age. As discussed in the previous section, these factors are summarized as cohort and time effects. *Cohort effects* reflect initial condition effects or effects triggered by events before the data collection date, i.e. events in very early stages of individuals' lives. *Time effects* include effects triggered by events during the data collection process. Cohort effects control for aging and since aging contributes to increases in health expenditures, the inclusion of cohort effects will lead to overstating the importance of age itself as an explanatory factor for health spending. On the other hand, time effects control for events contributing to increases in health expenditures during the collection period of the data from 1996 to 2007 and could include business cycle effects other than inflation (which we control for separately by indexing our data to year 2005), effects triggered by changes in government policies, changes in preferences, sectorial changes in the economy like economic growth, and many more.

To analyze the potential bias introduced by time and cohort effects, we plot the estimated age profile from the partial linear model and the estimates from simple cross sectional averaging in panel 2 of Figure 3. Age profiles that are cleared of time and cohort effects predict lower average health expenditures for each age group than the simple cross section estimates. The gap between these two curves is the size of the estimation bias caused by the time and cohort effects. We find that the bias is large, statistically significant, and increasing over age. More specifically, the bias in health expenditure estimates is less than $1, 000 for individuals younger than 60 but starts to increase exponentially for older individuals. At higher ages, the bias amounts to about $2, 000 and $3, 000 at the age of 70 and 85, respectively. We conclude that life-cycle profiles of health expenditures based on simple cross sectional averaging overpredict the effects of age on health expenditures, especially for individuals older than 60.

This finding is consistent with Zweifel, Felder and Meier (1999) and Zweifel, Felder and Werblow (2004) who, after controlling for time-to-death, also find that projections based on current status quo measures overpredict the effect of aging on health expenditures.

Decomposing time and cohort effects. We next analyze the implications of the time and cohort effects for health expenditures separately. To isolate their quantitative importance, we consider three alternative models: Model 1 not controlling for time and cohort effects (i.e. the simple cross section model from before); Model 2 controlling for time effects but ignoring cohort effects; and Model 3 controlling for cohort effects but ignoring time effects. We can write the three models as follows:

$$\text{Cross section - Model 1} \quad : \quad y_{ct}^{1} = \beta_0 + m\,(age_{ct}) + \varepsilon_{ct}^{1},$$

$$\text{Model 2} \quad : \quad y_{ct}^{2} = \beta_0 + m(age_{ct}) + \sum_{t=1996}^{2007} \tau_t D_{year_{it}} + \varepsilon_{ct}^{2}, \text{ and}$$

$$\text{Model 3} \quad : \quad y_{ct}^{3} = \beta_0 + m(age_{ct}) + \sum_{c=1915}^{1984} \gamma_c D_{cohort_{ct}} + \varepsilon_{ct}^{3}.$$

We then quantify the size of time and cohort effects by comparing predicted health expenditures per age group generated by the Benchmark Model described in expression (2) to predicted values generated by models 1, 2, and 3, respectively. The differences in the predicted averages of health expenditures per age group allow us to isolate cohort and time effects. More specifically, we first check differences in the predicted values of the Benchmark Model and Model 1 and call it the time and cohort effects bias, $\Delta_{time+cohort} = (\hat{y}_c - \hat{y}_c^1)$. Next, we measure the size of the cohort bias by comparing predictions of the benchmark model in expression (2) and Model 2, $\Delta_{cohort} = (\hat{y}_c - \hat{y}_c^2)$. Finally, we estimate the bias introduced by the time effect by calculating the difference between the predictions of the benchmark model and Model 3, $\Delta_{time} = (\hat{y}_c - \hat{y}_c^2)$.

Figure 4, panel 1, presents the health expenditure age-profile estimates of the benchmark model, Model 1 and Model 3. The age profile that still includes both the time and cohort effects (i.e. the cross section average) is denoted "Age+cohort+time" (Model 1). The health profile purged of the cohort effect (but including the time effects) is marked as "Age + time" (Model 3). The life-cycle profiles of health expenditure by age after removing time and cohort effects is marked as "Age only" profile (i.e. the red line marked with the letter x). We find that the health expenditure profile, purged of both effects, results in the lowest predictions for average health expenditure over age.

To get a clearer picture about the bias introduced by the cohort effect (Δ_{cohort}) and the bias introduced by the time effect (Δ_{time}), we plot the average biases over age as defined above separately in panel 2 of Figure 4. We find that cohort biases are on average far larger in magnitude per age group than their time bias counterparts. This has partly to do with the fact that discounting health expenditures with the consumer price index has already removed some of the time effects triggered by inflation.

All biases are relatively small for individuals younger than 50. Thereafter, the biases become larger. The bias due to cohort effects increases exponentially at higher ages, whereas the bias due to time effects slightly decreases. Overall, the cohort effects dominate time effects in size. More interestingly, biases generated by the cohort effect are positive and monotone increasing over age, whereas biases introduced by time effects are non-monotone, smaller, and become even negative at higher ages.

The monotone increasing trend of the cohort effect bias indicates that initial conditions such as early education and childhood nutrition etc. account for a very important part of life-cycle medical expenditures, especially at the end of the life-cycle. On the other hand, the hump shape of the time effects bias is indicative of the complex interaction between time and age effects. The effects of changing aggregate factors on medical expenditures are non-homogeneous across all ages.

It is interesting to note that for the practitioner who does not want to estimate the complete partial linear semiparametric model, it is best to use Model 3 as a good approximation. This model only carries a small time effects bias as some of the time effects can be controlled for by adjusting the expenditure data for inflation.

Out-of-pocket vs. total health expenditures. Total health expenditures may be more relevant for policy makers in terms of balancing public insurance programs. However, out-of-pocket health expenditures are more relevant for individuals' decision making. In addition, they more directly represent the burden on households as the financing side is factored in more explicitly. As reported in Figure 2, there are big gaps between total health expenditures and out-of-pocket health expenditures.

We next apply our estimation procedure to out-of-pocket health expenditures and report the results in 2005 dollars in Figures 5, 6 and 7. Comparing figures 5 and 4 we find similar biases although smaller in magnitude. Out-of-pocket health expenditures follow an upward trend over the life-cycle with exponential increases after age 70. Individuals in their twenties on average spend less than $300 per year out-of-pocket on health care. Individuals in their fifties spend around $600 per year on average. Older individuals in their sixties spend around a $1,000 out-of-pocket per year. Once individuals reach their seventies, their health expenditures start to increase very rapidly. The highest expenditures are incurred by old individuals at the end of their life at an average of around $1,600 per year out-of-pocket.

4.2 Other factors

We next examine how age, time and cohort effects vary across gender and educational levels. We concentrate on out-of-pocket health expenditures.[11]

Gender. We divide our sample into males and females and then implement the estimation procedure from the previous section. We report the results for health ex-

[11] The patterns for total health expenditure are very similar and the results are available upon request from the authors.

penditures in 2005 dollars in Figures 6. The patterns of cohort and time effects biases change significantly across gender. For males, the time effects bias is positive and dominates the cohort effects bias until age 55. Thereafter the pattern reverses and positive cohort effects dominate. In addition, the bias due to time effects becomes negative after age 70. For females the time effects bias is negative and becomes positive only after age 55.

Educational levels. Education is considered one of the important determinants of health expenditures. To understand how education would influence health expenditures over the life cycle we construct two separate age profiles of health expenditures for low and high skills. We use a very simple measure of skill. An individual who has more than 12 years of education is considered high skilled. The estimation procedure for the health expenditure profile is otherwise identical to the one described in the previous section. We find similar upward patterns of health expenditures across educational levels (compare figure 7). We do not find a large difference in the biases between the low skilled and high skilled groups. One could easily extend our methodology to construct age profiles of health expenditures according to other demographic factors like race or immigrant status etc.

5 Conclusion and discussion

In this paper we use a seminonparametric partial linear model to isolate the pure age effect on medical consumption controlling for cohort and time effects. Our results imply that the age effect (a proxy for the natural depreciation rate of health) is an important source of the observed upward trend in medical service consumption over the life-cycle. Moreover, we find that the time and cohort effect biases are significant and large. Health expenditure profiles based on simple cross section averages of inflation adjusted health expenditure per age group overpredict the effects of age on health expenditures. In addition, we assess the quantitative importance of the estimation bias of health expenditures caused by time and cohort effects. We find that the cohort effects bias dominates the time effects bias in size and that the respective biases of time and cohort effects follow distinct but differing trends over age.

Our findings raise some interesting theoretical and empirical questions for health economists and macroeconomists. First, the shape of the life-cycle profile for medical consumption is different than the shape of the life-cycle profile for non-medical consumption established in previous studies (e.g. see Gourinchas and Parker (2002) and Fernandez-Villaverde and Krueger (2007)). The age effect causes health to depreciate faster at higher ages and triggers increases in health expenditures. Our results indicate that individuals are not able to smooth their medical consumption over age. This raises the question about how individuals should re-allocate resources using savings or various insurance options in order to smooth their non-medical consumption, while financing increasing levels of medical spending over the life-cycle. The former has been analyzed extensively in macroeconomics whereas the latter has been analyzed in health economics and insurance economics.

Medical consumption accounts for a substantial part of consumption (more than 16 percent of GDP in the U.S. in 2009), however, the work horse models of consumption and savings in the macroeconomic literature focus only on explaining the hump-shape of non-medical consumption over the life-cycle (e.g. see Fernandez-Villaverde and Krueger (2007)). This raises the theoretical question about whether a macroeconomic model is able to reconcile these two distinct consumption profiles. In other words, a macroe- conomic model with micro-foundations of health capital and demand for health care demand is needed. Dynamic life-cycle heterogeneous agents models that include the ideas of the Grossman human capital model would be natural candidates to address these questions. Unbiased estimates of the age profile of health expenditures will un- doubtedly have an effect on the results from these macro models. Future research will show how important these effects will be.

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6 Appendix

Variable	Mean	(Std. Dev.)	Min.	Max.	N
Birth year	1953.867	(14.527)	1921	1976	209932
Year	2001.665	(3.375)	1996	2007	209932
Age	47.798	(14.795)	20	86	209932
Female	0.537	(0.499)	0	1	209932
Married/Partnered	0.63	(0.483)	0	1	209932
Black	0.081	(0.273)	0	1	209932
Wage income (in $1,000)	24.633	(29.039)	0	632.951	209932
Total income (in $1,000)	30.508	(30.106)	0	658.615	209932
Years of education	12.508	(3.155)	1	17	206428
Student	0.005	(0.072)	0	1	209932
Healthy	0.854	(0.353)	0	1	208143
Uninsured	0.165	(0.371)	0	1	209932
Public health insurance	0.165	(0.371)	0	1	209932
Private health insurance	0.67	(0.47)	0	1	209932
Total health expenditures (in $1,000)	3.611	(10.076)	0	504.921	209932
Health expenditues: Home	0.143	(2.082)	0	315.076	209932
Health expenditues: Other	0.287	(0.861)	0	59.047	209932
Health expenditues: Prescriptions	0.745	(1.912)	0	212.604	209932
Health expenditues: Inpatient	1.194	(7.511)	0	500.963	209932
Health expenditues: Emergency room	0.11	(0.658)	0	56.694	209932
Healthexpenditues: Outpatient/hospital	0.355	(2.031)	0	225.282	209932
Health expenditues: Doctor/office	0.777	(2.641)	0	335.86	209932
Source: Out-of-pocket	0.649	(1.491)	0	109.051	209932
Source: Medicare	0.848	(5.283)	0	402.716	209932
Source: Medicaid	0.394	(3.332)	0	406.057	209932
Source: Private insurance	1.367	(6.016)	0	490.521	209932
Source: Veteran’s benefits	0.094	(1.929)	0	501.258	209932
Source: CHAMPUS	0.003	(0.19)	0	53.558	209932
Source: Tricare	0.022	(0.583)	0	100.781	209932
Source: Federal insurance	0.015	(0.437)	0	109.706	209932
Source: State insurance	0.027	(0.705)	0	118.904	209932
Source: Worker’s compensation	0.062	(1.053)	0	117.834	209932
Source: Other	0.036	(0.836)	0	187.041	209932
Health index physical components	48.52	(11.059)	4.560	76.13	129888
Health index mental components	50.401	(10.029)	-0.54	77.370	129946
Healthy	0.854	(0.353)	0	1	208143

Table 1: Summary statistics of the pooled data: MEPS 1996 - 2007

Variable	Mean	(Std. Dev.)	Min.	Max.	N
Mean(Cohort age)	53	(17.664)	20	86	144
Mean(Female)	0.526	(0.033)	0.474	0.666	144
Mean(Married/Partnered)	0.604	(0.127)	0.076	0.75	144
Mean(Black)	0.053	(0.055)	0	0.139	144
Mean(Wage income (in $1,000))	24.171	(12.452)	2.592	38.133	144
Mean(Total income (in $1,000))	32.421	(7.473)	11.206	42.511	144
Mean(Years of education)	12.905	(0.589)	11.634	13.64	144
Mean(Student)	0.014	(0.066)	0	0.525	144
Mean(Healthy)	0.866	(0.068)	0.735	0.974	144
Mean(Uninsured)	0.112	(0.075)	0	0.275	144
Mean(Public health insurance)	0.167	(0.144)	0.052	0.53	144
Mean(Private health insurance)	0.722	(0.092)	0.47	0.85	144
Mean(Total health expenditures (in $1,000))	4.225	(2.524)	1.023	9.967	144
Mean(Health expenditues: Home)	0.166	(0.226)	0	1.137	144
Mean(Health expenditues: Other)	0.344	(0.113)	0.094	0.579	144
Mean(Health expenditues: Prescriptions)	0.844	(0.588)	0.094	2.425	144
Mean(Health expenditues: Inpatient)	1.451	(1.073)	0.27	4.350	144
Mean(Health expenditues: Emergency room)	0.113	(0.042)	0.055	0.245	144
Mean(Health expenditues: Outpatient/hospital)	0.411	(0.211)	0.051	1.083	144
Mean(Health expenditues: Doctor/office)	0.897	(0.472)	0.224	2.039	144
Mean(Source: Out-of-pocket)	0.777	(0.409)	0.206	1.817	144
Mean(Source: Medicare)	1.275	(1.882)	0	6.667	144
Mean(Source: Medicaid)	0.29	(0.122)	0.094	0.833	144
Mean(Source: Private insurance)	1.512	(0.777)	0.392	4.345	144
Mean(Source: Veteran's benefits)	0.116	(0.125)	0	0.556	144
Mean(Source: CHAMPUS)	0.004	(0.014)	0	0.108	144
Mean(Source: Tricare)	0.027	(0.041)	0	0.211	144
Mean(Source: Federal insurance)	0.017	(0.023)	0	0.143	144
Mean(Source: State insurance)	0.028	(0.031)	0	0.167	144
Mean(Source: Worker's compensation)	0.054	(0.039)	0	0.174	144
Mean(Source: Other)	0.033	(0.021)	0.004	0.122	144
Mean(Health index physical components)	48.108	(4.869)	36.523	54.684	96
Mean(Health index mental components)	51.066	(0.807)	49.455	52.805	96
Mean(Healthy)	0.866	(0.068)	0.735	0.974	144

Table 2: Summary statistics of the pseudo panel data: MEPS 1996 - 2007

						Year						
Cohort	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007
1	670	997	626	593	602	801	844	621	566	550	917	761
2	714	1,023	712	767	739	928	1,011	888	871	778	763	627
3	801	1,199	771	787	814	1,025	1,134	981	963	870	894	772
4	872	1,297	904	911	879	1,220	1,384	1,113	1,046	1,068	1,099	965
5	1,124	1,668	1,119	1,158	1,164	1,526	1,681	1,364	1,338	1,310	1,356	1,231
6	1,422	2,130	1,515	1,534	1,499	2,012	2,283	1,840	1,842	1,815	1,820	1,625
7	1,570	2,321	1,563	1,684	1,722	2,257	2,467	2,038	2,075	2,089	2,108	1,926
8	1,755	2,600	1,790	1,849	1,796	2,471	2,857	2,397	2,369	2,261	2,335	2,110
9	1,753	2,534	1,695	1,911	1,956	2,465	2,806	2,398	2,370	2,350	2,334	2,073
10	1,529	2,261	1,594	1,658	1,648	2,262	2,695	2,317	2,306	2,230	2,207	2,014
11	1,446	2,194	1,486	1,547	1,600	2,141	2,551	2,275	2,311	2,267	2,203	1,972
12	270	402	308	326	299	411	500	467	446	413	423	374
Sum	13,926	20,626	14,083	14,725	14,718	19,519	22,213	18,699	18,503	18,001	18,459	16,450

Table 3: Frequencies per cohort and year: MEPS 1996 - 2007

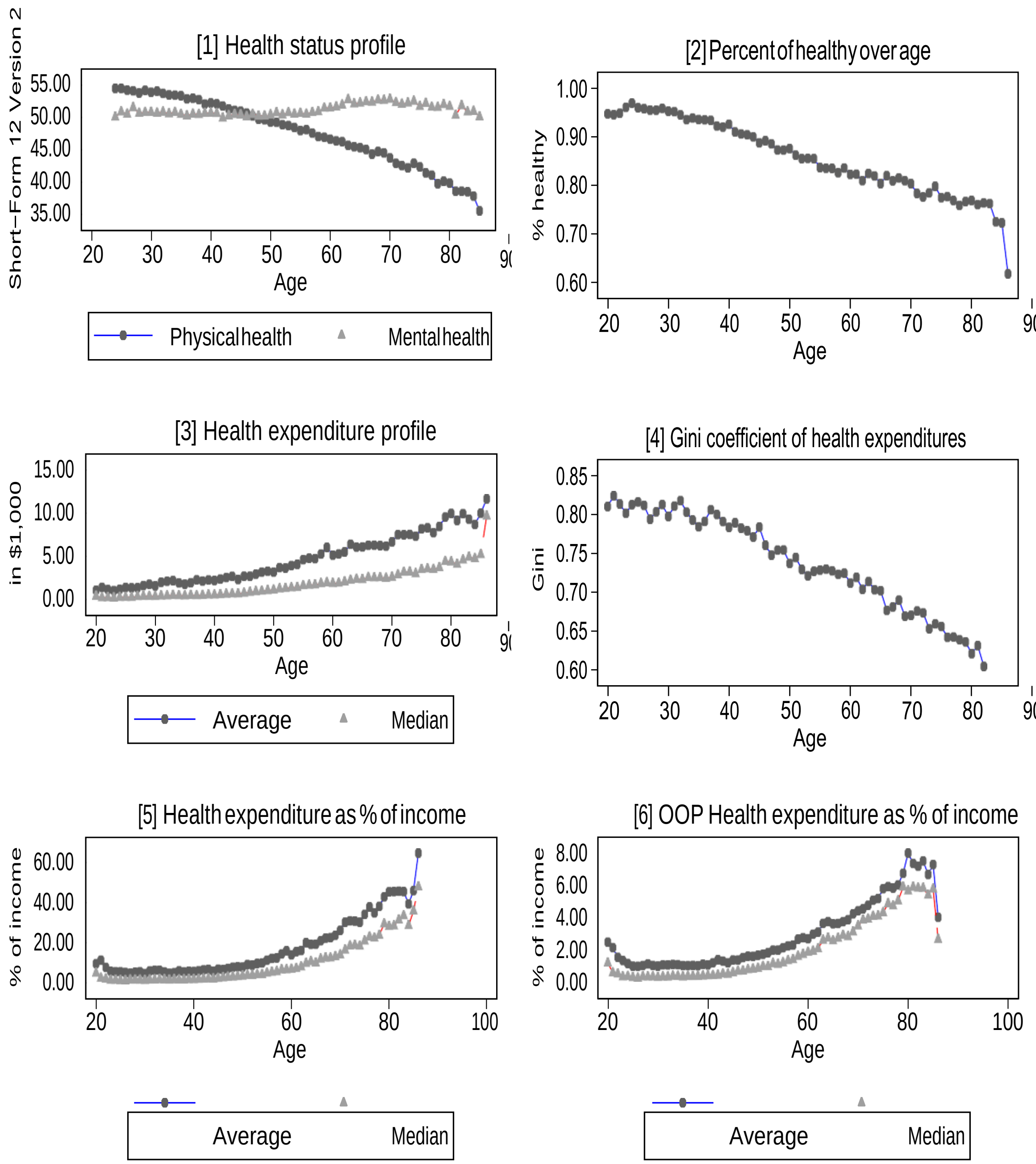

Figure 1: Stylized facts from cross section summary data. Source: MEPS 1996-2007

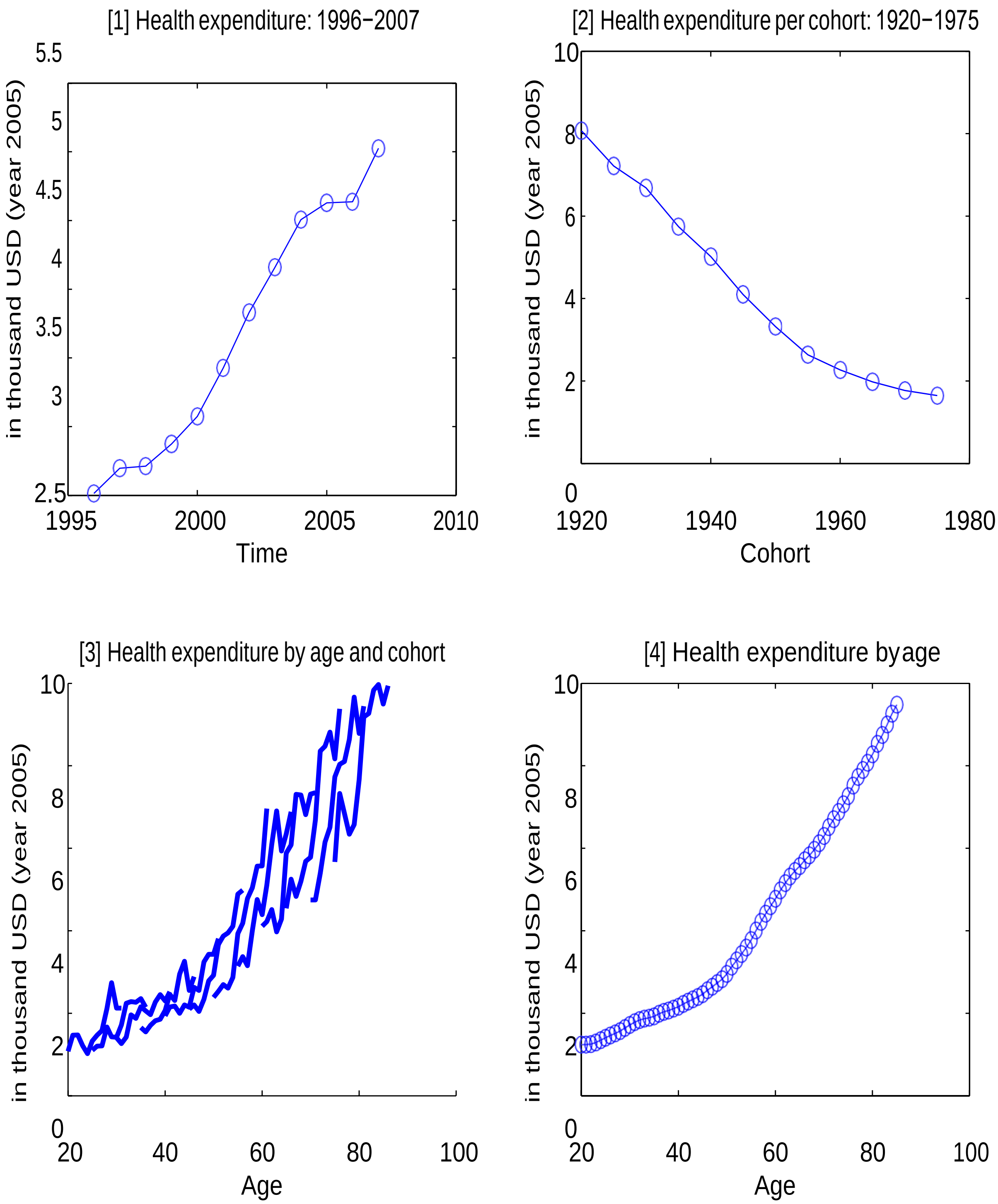

Figure 2: Cross section of health expenditure using a constructed pseudo panel. Source: MEPS 1996-2007

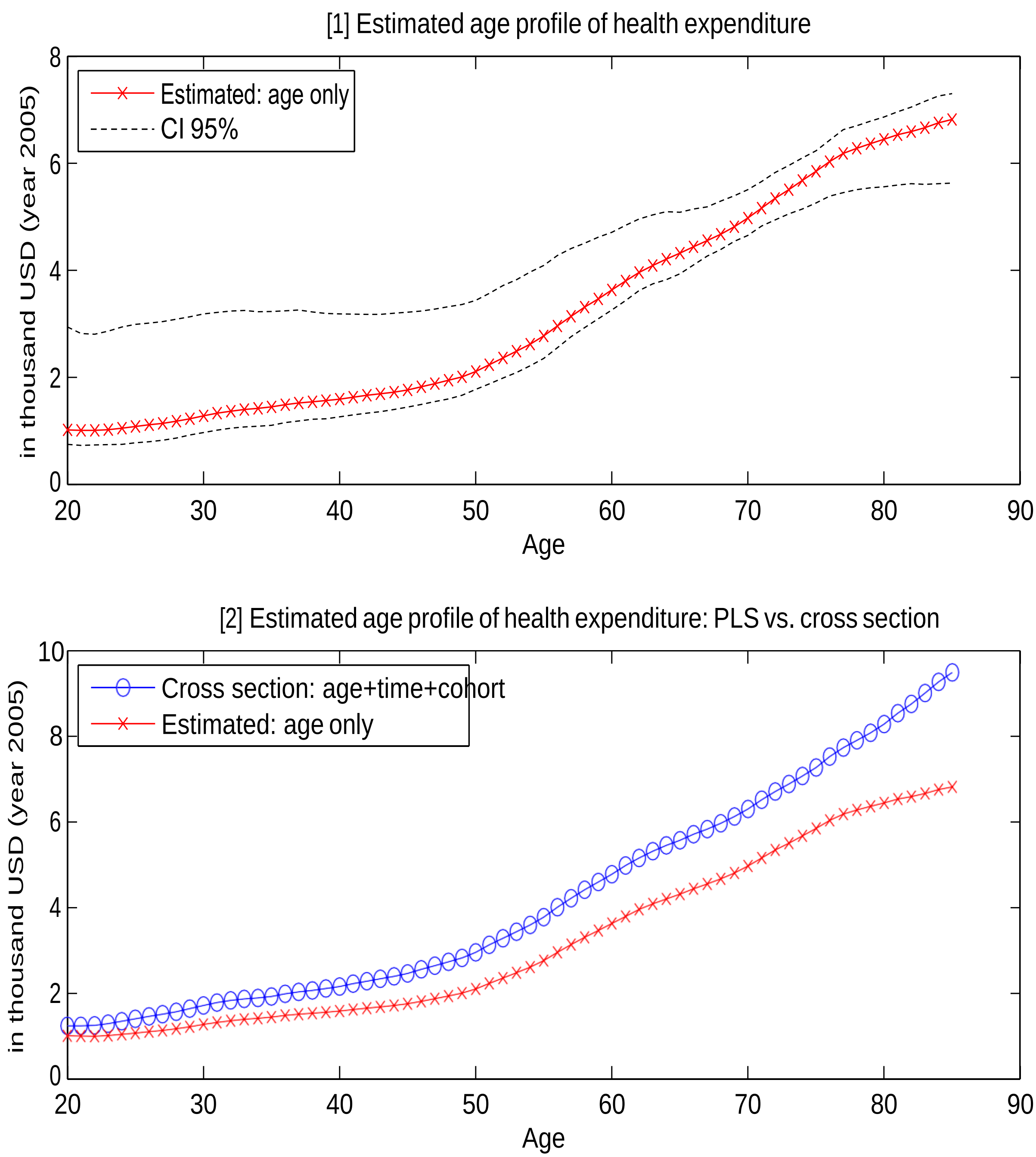

Figure 3: Health expenditure profiles controlling for time and cohort effects, including bootstrapped confidence intervals. Source: MEPS 1996-2007

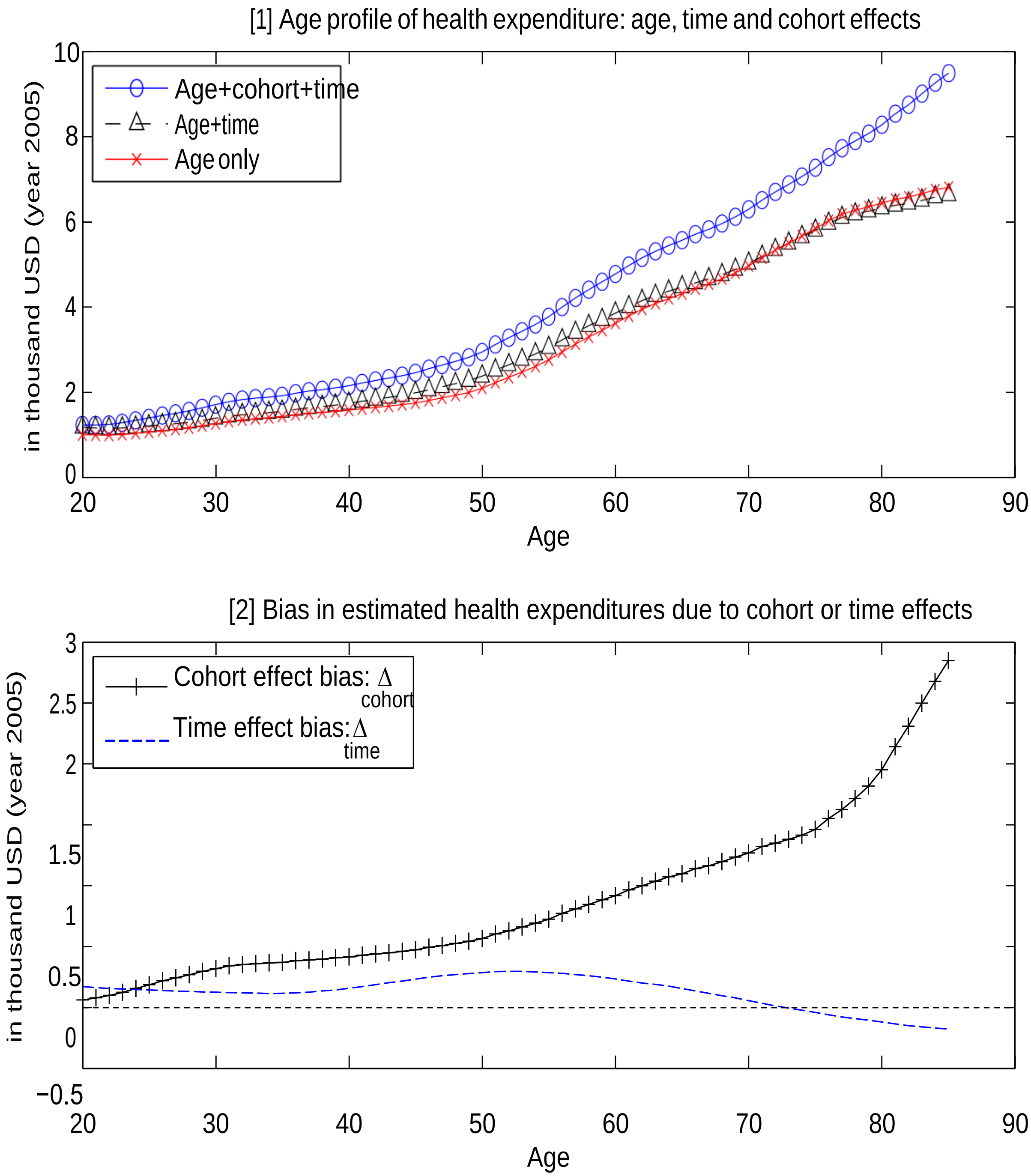

Figure 4: Health expenditure profiles controlling for time and cohort effects. Source: MEPS 1996-2007

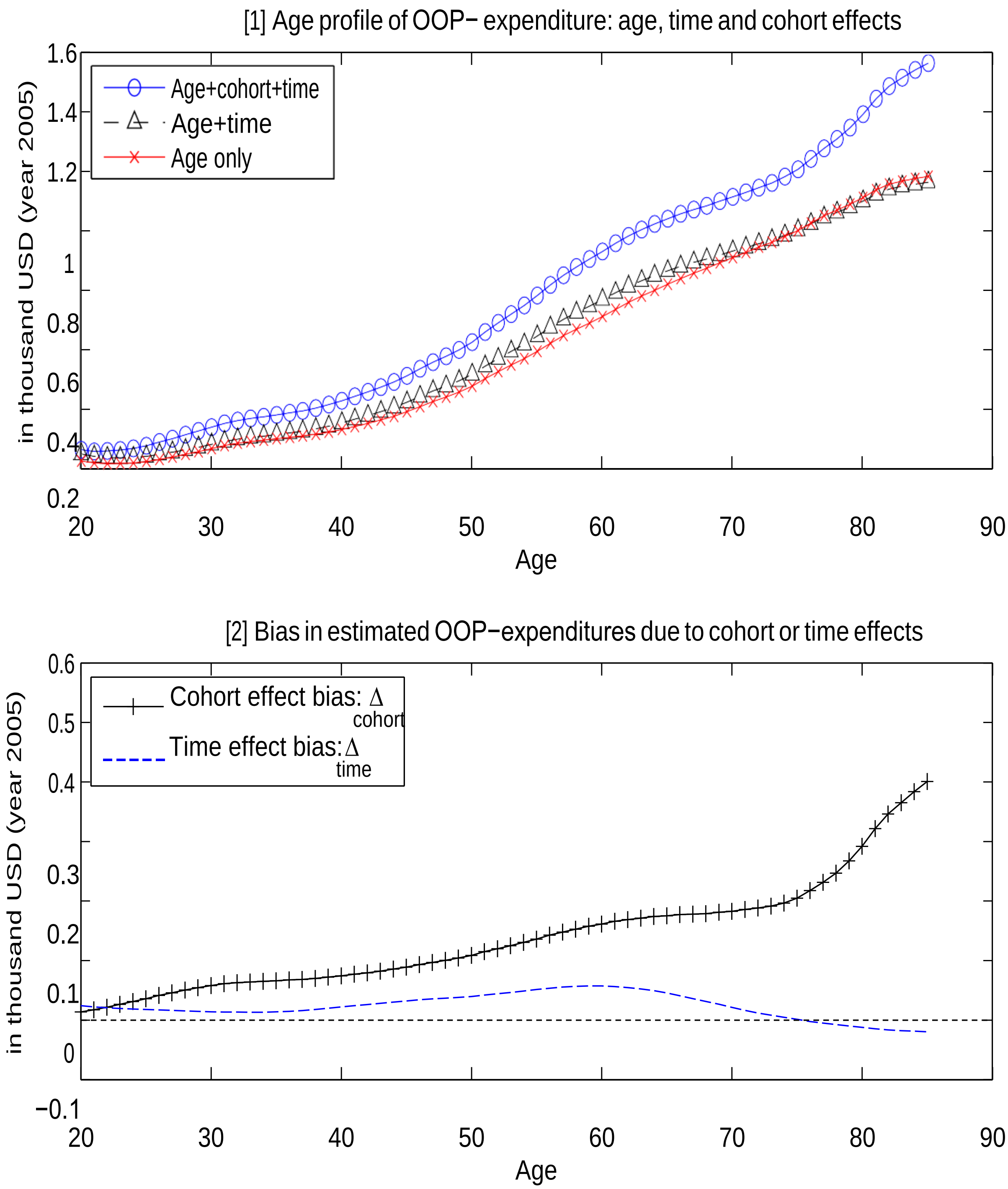

Figure 5: Out-of-pocket health expenditure profiles controlling for time and cohort effects. Source: MEPS 1996-2007

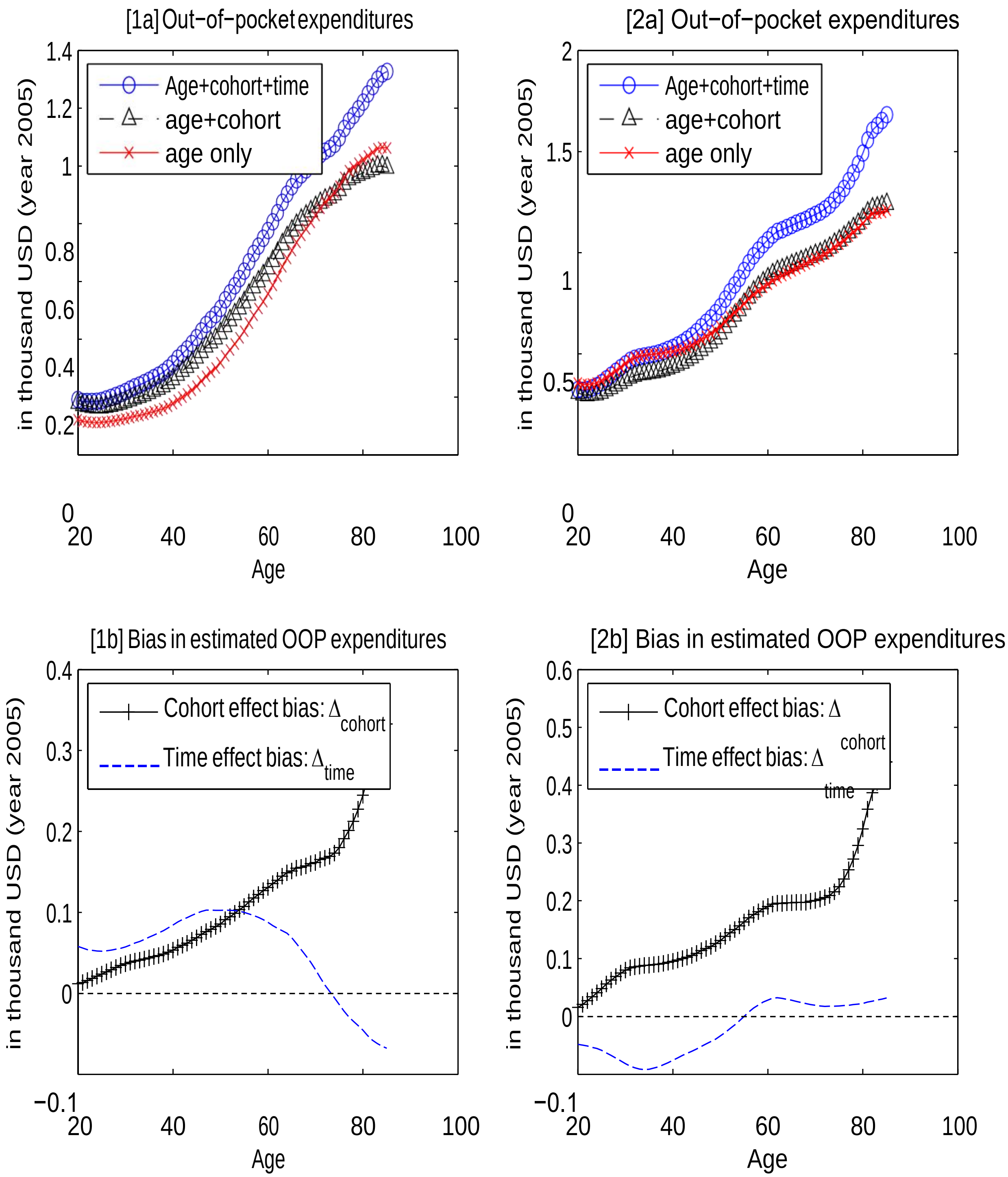

Figure 6: Out-of-pocket health expenditure profiles controlling for time and cohort effects by gender. Males are presented in panels [1a] and [1b]. Females are presented in panels [2a] and [2b]. Source: MEPS 1996-2007

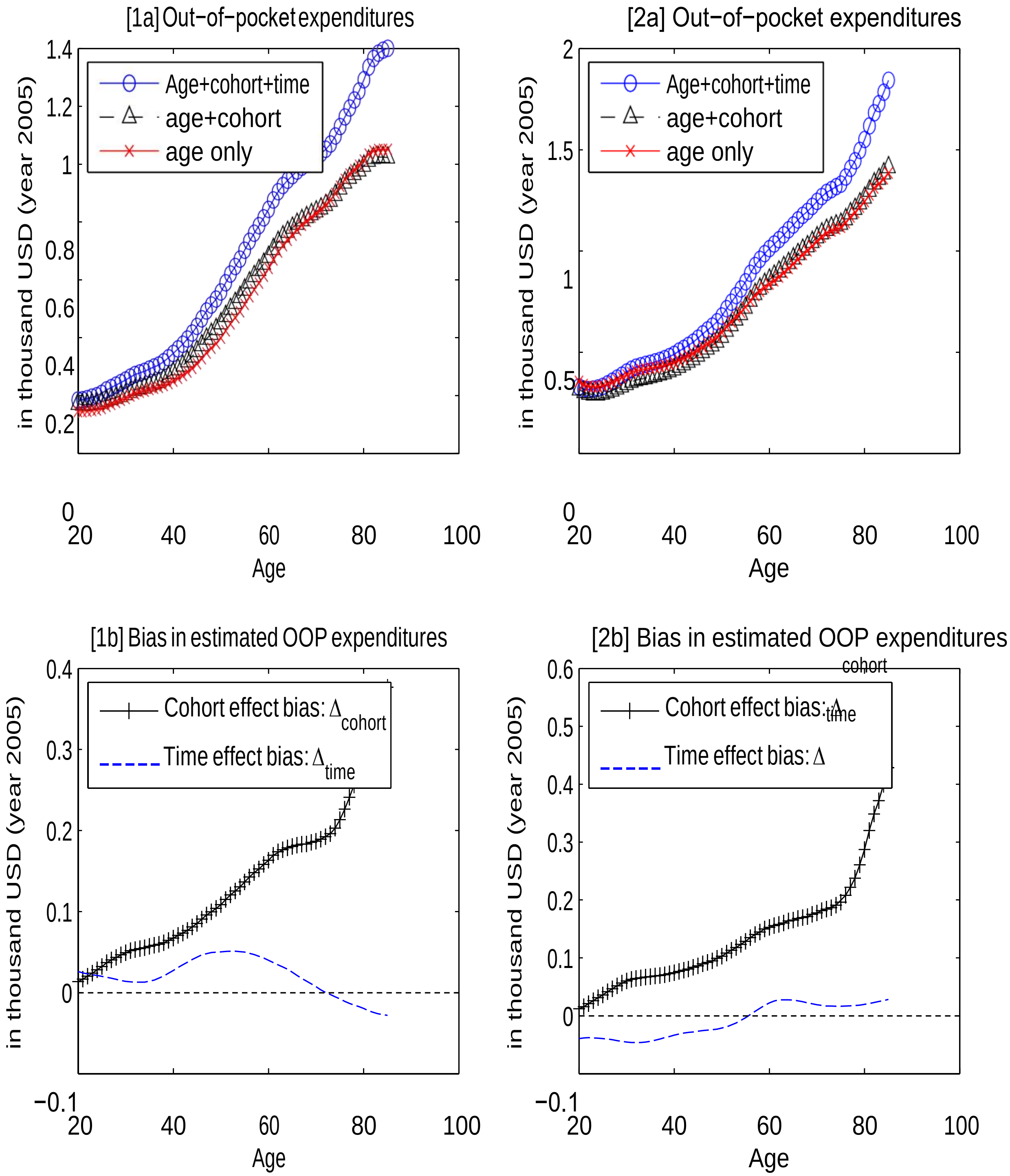

Figure 7: Out-of-pocket health expenditure profiles controlling for time and cohort effects by skill level. Low skilled individuals (years of education <= 12) are presented in panels [1a] and [1b]. High skilled individiuals (years of education > 12) are presented in panesl [2a] and [2b]. Source: MEPS 1996-2007