Essays on Macroeconomics

by

Ali Güneş

Submitted in Partial Fulfillment

of the

Requirements for the Degree

Doctor of Philosophy

Supervised by

Professor Yongsung Chang

Department of Economics
Arts, Sciences and Engineering
School of Arts and Sciences

University of Rochester
Rochester, New York

2013

Biographical Sketch

Ali Güneş was born in Tarsus, Turkey on February 10, 1984. He attended Bogazici University from 2002 to 2007, and graduated with a Bachelor of Arts degree in Economics. He received a graduate fellowship and tuition scholarship for Ph.D. studies from 2007 to 2012 at the University of Rochester. He took qualifying exams in Macroeconomics and International Economics and pursued his research in Macroeconomics under the supervision of Professor Yongsung Chang. He received a Master of Arts degree from the University of Rochester in 2010.

Acknowledgments

I am indebted to Yongsung Chang for his invaluable guidance and support. I would also like to thank Omer Acikgoz, Mark Aguiar, Kartik Athreya, Mark Bils, Gregorio Caetano, Juan Carlos Hatchondo, Andreas Hornstein, Baris Kaymak, Marianna Kudlyak, Ryan Michaels, Ronni Pavan, and Kemal Yildiz for their useful comments and discussions along with other participants at the University of Rochester, the Federal Reserve Bank of Richmond, and Midwest Macroeconomics Meetings, Nashville. Part of this research was conducted while I was visiting the Federal Reserve Bank of Richmond, and I am grateful for the bank's financial support and hospitality. I benefited also from my friends. In particular, I am grateful to Azer Abizade, Hong Kee Bahng, Eray Cumbul, Tuo Deng, Battal Dogan, Mehmet Fatih Ekinci, Salim Furth, Jongsuk Han, Cheuk Yin Ho, Syed Muhammad Hussain, Yusuke Jinnai, Mike Kuklik, Lin Liu, Patrick Macnamara, Jiyoon Oh, Joon Song, Karol Szwagrzak, and Temel Taskin. Finally, special thanks go to my mother for her delicious cooking, my father for his continuous praying, and my siblings for their permanent support.

Abstract

This dissertation considers two different issues in macroeconomics. The first chapter reconciles the savings rate profile with the earnings profile by education. The second chapter tries to uncover the health production function.

In the first chapter, I reconcile the savings rate profile with the earnings profile by education. The permanent income hypothesis suggests that an individual with a steeper income profile should save a lower fraction of his income. However, life-cycle profiles of the savings rate in U.S. data are at odds with this prediction. College graduates, who on average experience a much steeper income profile than non-college graduates, exhibit a higher savings rate profile. To reconcile this, I incorporate imperfect information about deterministic (ability, skill) and stochastic (shock) components of earnings profiles into a life-cycle model of consumption with heterogeneous agents and incomplete markets. I find that the imperfect information model is able to achieve a higher savings rate profile for college graduates. Higher skill heterogeneity for college graduates, which calls for a precautionary savings motive under imperfect information, accounts for this at the early ages. As labor market outcomes are realized, this uncertainty is gradually resolved. However, agents with low ability, who fail to accumulate assets in the early period, are unable to dissave in the later period. This accounts for the higher savings rate

for college graduates at the later ages. I also quantitatively assess an alternative hypothesis, different time preference rates, for the savings rate gap by education. I conclude that accounting for the savings rate profile that we see in the data requires an unrealistically large gap between the time preference rates of the two groups.

In the second chapter, I try to uncover the health production function. Just like any production or consumption activity, the production of health involves both time and goods. For example, a typical household in the U.S. spends $3,000 on health each year and 20 minutes per day on exercise activity. However, most existing studies that incorporate health accumulation into life-cycle models focus on the expenditure as the only input for health production. Based on detailed data from the Medical Expenditure Panel Survey (MEPS) and the American Time Use Survey (ATUS), I construct the life-cycle profiles of health status, health expenditure, and time allocated to exercise. I find that there are important and interesting differences in the profile of inputs and output of health: (i) more educated individuals are persistently healthier, (ii) health expenditures across education groups are similar, and (iii) more educated individuals allocate persistently more time to exercise. These profiles imply that the educational gaps in time allocated to exercise might contribute to the educational gaps in health capital. To quantitatively assess this, I compute a life-cycle model with an augmented health production function. I find that the higher relative efficiency of exercise to expenditure for more educated individuals might account for inputs and output of health at the early ages. However, it does not have much effect at the later ages, since the aging effect trivializes the education effect in the health production technology.

Contributors and Funding Sources

This work was supervised by a dissertation committee consisting of Professors Yongsung Chang (advisor) and Ryan Michaels of the Department of Economics and Professor Minjae Song of the Simon Graduate School of Business. All work for the dissertation was completed independently by the student. Graduate study was supported by a Graduate Fellowship from the University of Rochester and a Dissertation Internship from the Federal Reserve Bank of Richmond.

Table of Contents

List of Tables

List of Figures

1 Why Do College Graduates Save More? Imperfect Information about Ability

1.1 Introduction

The permanent income hypothesis suggests that an individual with a steeper income profile should save a lower fraction of his income. However, life-cycle profiles of the savings rate in U.S. data are at odds with this prediction. College graduates, who on average experience a much steeper income profile than non-college graduates, exhibit a higher savings rate profile. To reconcile this, I incorporate imperfect information about earnings profiles into a life-cycle model of consumption with heterogeneous agents and incomplete markets.

Based on various measures of savings from the Panel Study of Income Dynamics (PSID), the Survey of Consumer Finances (SCF), and the Consumer Expenditure Survey (CEX), I establish the fact that college graduates have a higher savings rate than non-college graduates over the life-cycle. The fact that more

educated individuals tend to save more is also well known from the previous studies.[1] However, these studies do not offer any coherent explanation for the higher savings rate profile for the better educated that we observe in the data.

Life-cycle income profile is decomposed into deterministic (ability, skill) and stochastic (shock) components. Under imperfect information framework, individuals observe their labor income at a given point in time but they don't observe its components separately. They have prior beliefs on the components of their earnings profile, which are updated in a Bayesian learning method. The resolution of uncertainty gradually occurs as labor market outcomes are realized. Individual consumption decisions depend on the priors of each component. For instance, individuals who experience permanent increase in their earnings assign the probability to the case that the increase in their labor income is a temporary one. Instead of consuming more in response to this increase, they accumulate more assets due to the consumption smoothing motive. College graduates, despite their steeper labor income profile on average, face a larger heterogeneity in their skill components. The pronounced higher skill heterogeneity for college graduates, which calls for a precautionary savings motive under imperfect information, paves the way for flipping the savings rate gaps both at the early stage and at the later stage of the life-cycle.

[1] In analyzing the decline in the personal savings rate in the U.S. in the 1980s, Attanasio (1998) uses the CEX and finds that the savings rate is considerably higher for better educated individuals. Juster et al. (2005) use the PSID to distinguish active and passive savings during the 1980s-1990s and show that college graduates save more than less educated individuals. Finally, Dynan et al. (2004) compute the savings rate via a regression of the savings rate on education using the CEX, SCF and PSID from the 1980s. In their regressions, they control for various instruments such as labor earnings of the head and wife. They find that more educated individuals save more.

Higher skill heterogeneity generates more precautionary savings for college graduates. This driving force itself is able to obtain higher savings rate for college graduates at the early stage of the life-cycle. This uncertainty is resolved over time as labor market outcomes are realized. However, the imperfect information model is still able to obtain higher savings rate for college graduates at the later stage of the life-cycle. This stems from the fact that low ability agents, who expect higher earnings under imperfect information in the early period, fail to accumulate the assets that they would otherwise. In the later period, these agents learn that they in fact have low ability in regard to their earnings. However, they are unable to dissave at the later stage, since they do not have much wealth. This explains why college graduates save more even at the end of the work period.

I also quantitatively assess an alternative hypothesis, different time preference rates, for the savings rate gap between education groups. I do computational analyses with time preference heterogeneity under the perfect information case. The underlying assumption with this hypothesis is that the schooling decision critically depends on patience. So college graduates and non-college graduates might be different in their timing of consumption. Based on the computational analyses, I show that accounting for the savings rate profile that we see in the data requires an unrealistically large gap between the time preference rates of the two groups. Also, I show that a moderate heterogeneity in time preference rates, which can explain the savings rate gap at the early ages, fails to explain the savings rate gap at the later ages.[2] The failure of the perfect information case with time preference heterogeneity to explain the savings rate gap at the later

[2]Dynan et al. (2004) also find little support for theories to explain the positive correlation between the marginal propensity to save and lifetime income by relying solely on time preference rates.

stage of the life-cycle results from the fact that, among college graduates, agents with low ability, who also have a low time preference rate, accumulate so many assets in the early period that they dissave too much at the end of the work period.

Labor income risk plays a central role in the savings decision of individuals. For a life-cycle model with perfect information to explain the savings rate gap profile by education, one possibility would be that college graduates have substantially higher uncertainty in their labor income shock process. However, my empirical analysis shows that there is no such variation in shock process across education groups.[3] The observed heterogeneity in shock process does not have much explanatory power for savings rate profiles by education.

There are various reasons why it is important to understand the different savings behavior across education groups. First, it opens a door for optimal capital taxation across demographic groups, since the tax incidence depends on how strong the savings motive is. Second, and more directly, it provides an opportunity to design an optimal mix of college subsidy and taxation. The multi-dimensional effect of reform proposals can be analyzed more coherently if they are taken into account in the same framework. Finally, clarifying why college graduates save more helps us to better understand the wealth inequality in the data as the upper tail of the wealth distribution is highly concentrated with college graduates.[4]

Imperfect information has recently been incorporated into macro-labor mod-

[3]Guvenen (2009), with a different specification than the one in this paper, also shows that the estimated persistence and variances of income shocks are similar across education groups.

[4]See the Appendix for the distribution of college graduates in the U.S. wealth quantiles.

els to explore explanations for different stylized facts. In a study with a life-cycle model of consumption choice, Guvenen (2007) explains the increasing consumption inequality over the life-cycle. Venkateswaran (2011) uses an imperfect information setup in a search model to explore the effect of imperfect information on the cyclicality of recruitment activity. Sanders (2011) studies an occupational choice model and uses a similar framework to explain worker mobility across different task ratios. In this paper, I investigate a different question, one that seems puzzling from the standard view of the permanent income hypothesis. I try to reconcile the savings rate profile with the earnings profile by education.

The study in this paper is based on ex-ante heterogeneity in labor income profiles. In the empirical analysis, I show that college graduates, who have steeper earnings profiles, also have greater heterogeneity in their skill components. Becker (1975) sets the theoretical basis by emphasizing the heterogeneity in human capital investments across equally able individuals. Mincer (1974) and Card (1994) find empirical evidence for the higher rates of earnings growth for more educated individuals. Previous studies support income profile heterogeneity (Lillard and Weiss (1979), Baker (1997), Haider (2001)). In a paper with structural estimates of a dynamic model of schooling, work, and occupational choice decisions, Keane and Wolpin (1997) draw our attention to the skill components of the labor income profile by finding that ex-ante heterogeneity accounts for 90% of the variance in lifetime utility. Guvenen (2007) shows that a basic version of the heterogeneous income profile model is able to match the increase in consumption inequality over the life-cycle whereas the baseline of a restricted (no growth heterogeneity) income profile model is not. Guvenen and Smith (2012) use the joint dynamics of con-

sumption and income using panel data to conduct a formal structural estimation and they find that differences in income growth rates are large.

The paper proceeds as follows. Section 1.2 shows the empirical analysis using the data and the methods for labor income profiles estimation and savings rate computation. Section 1.3 presents the imperfect information model. Section 1.4 shows the computation results of the model. Section 1.5 considers an alternative hypothesis, time preference heterogeneity, for savings rate profiles. Section 1.6 concludes.

1.2 Empirical Analysis

This section shows the data analysis for (i) the estimation of the parameters of the labor income profiles and (ii) the computation of the savings rate. For the former, I use the 1968-93 waves of the Panel Study of Income Dynamics (PSID). For the latter with various definitions of the savings rate, I use various data sources: the 1984-89 waves of the PSID, the 1983-89 panel of the Survey of Consumer Finance (SCF), and the 1980-93 waves of the cross-sectional Consumer Expenditure Survey (CEX).

1.2.1 Earnings Profile

I estimate the parameters of the heterogeneous income profiles for college and non-college graduates. First, I present the relevant data. Second, I show the

statistical method used in the estimation process. Then, I show the estimation results and the implications.

PSID Data: The PSID is a U.S. panel data set that provides the longest earnings history for each household. Labor earnings are drawn from data on the male heads of the family over the 1968-93 period. An individual is included in the sample if he (i) is between 25 and 64 years old, (ii) has at least 9 years of education, (iii) has between 520 and 5200 annual hours of work, (iv) earns an hourly wage between \$2 and \$400 in 1993 dollars, (v) is interviewed for at least three years, and (vi) is the same head at the time of these interviews. I consider the individuals with 16 years of education or more as college graduates and with 15 years of education or less as non-college graduates. There are around 16,000 individual-year observations for the former and around 48,000 individual-year observations for the latter.

Statistical Model: I assume that log labor earning profiles are quadratic in working experience (Mincer (1974)). This specification makes the interpretation of the coefficients more straightforward, since the individual fixed effect is assumed to be quadratic in experience as well. In addition, this assumption is fairly empirically innocuous in the sense that higher order polynomials in experience do not improve the fit much (Heckman et al. (2003)). I run the regressions separately for college and non-college individuals. For notational simplicity, I suppress the education subscripts. The log labor earnings of an individual i at year t, $y_{i,t}$, is specified as follows.

$$y_{i,t} = \overbrace{(\overline{\gamma}_{0,t} + \gamma_{0,i}) + (\overline{\gamma}_{1,t} + \gamma_{1,i})x_{i,t} + (\overline{\gamma}_{2,t} + \gamma_{2,i})x_{i,t}^2}^{\textbf{deterministic}} + \overbrace{z_{i,t} + \epsilon_{i,t}}^{\textbf{stochastic}} \tag{1.1}$$

where $x_{i,t}$ is the potential experience calculated as $(age_{i,t} - max(schooling_{i,t}, 12) - 6)$. $\overline{\gamma}_{0,t}, \overline{\gamma}_{1,t}, \overline{\gamma}_{2,t}$ are means of skill levels and allowed to be time varying. The time-dependent life-cycle components capture the skill-biased technological change that has been occuring for the last three decades; this change is well established in the previous studies. $\gamma_{0,i}, \gamma_{1,i}, \gamma_{2,i}$ are individual fixed effects in intercept, linear, and quadratic components of the skill. These skill components are distributed across individuals with means of zero, variances of $\sigma^2_{\gamma_0}$, $\sigma^2_{\gamma_1}$, and $\sigma^2_{\gamma_2}$, and covariances of $\sigma_{\gamma_0\gamma_1}$, $\sigma_{\gamma_0\gamma_2}$, and $\sigma_{\gamma_1\gamma_2}$.

The shock components are modeled as an AR(1) process

$$z_{i,t} = \rho z_{i,t-1} + \eta_{i,t} \tag{1.2}$$

plus a purely transitory shock. The innovations $\eta_{i,t}$ and $\epsilon_{i,t}$ are assumed to be independent of each other, over time, and the skill components, with zero mean, and variances of σ^2_η and σ^2_ϵ.

After obtaining the residuals from a regression of log labor income on the quadratic polynomial in experience, I apply the minimum distance estimation method (Chamberlain (1984)) to get the second-order moments of the income residuals. The estimation method is based on minimizing the distance between the elements of the empirical covariance matrix of income residuals and its counterpart implied by the specification. The source of identification is the variance-covariance matrix of the residuals. I use the autocovariances up to the 25th order, where the aim is to use as much available information as possible. The variances and covariances of the residuals for an individual with an experience of x at any year of observation can be obtained as follows:

$$
\begin{aligned}
var(y_{i,t} - \overline{y}_t) &= \sigma^2_{\gamma_0} + \sigma^2_{\gamma_1} x^2 + \sigma^2_{\gamma_2} x^4 + 2[\sigma_{\gamma_0\gamma_1} x + \sigma_{\gamma_0\gamma_2} x^2 + \sigma_{\gamma_1\gamma_2} x^3] + \\
&\quad \sigma^2_\eta \sum_{j=0}^{x-1} \rho^{2j} + \sigma^2_\epsilon
\end{aligned}
$$

$$
\begin{aligned}
cov(y_{i,t+n} - \overline{y}_{t+n}, y_{i,t} - \overline{y}_t) &= \sigma^2_{\gamma_0} + \sigma^2_{\gamma_1} x(x+n) + \sigma^2_{\gamma_2} x^2 (x+n)^2 + \\
&\quad \sigma_{\gamma_0\gamma_1}(2x+n) + \sigma_{\gamma_0\gamma_2}(x^2 + (x+n)^2) + \\
&\quad \sigma_{\gamma_1\gamma_2}(x(x+n)^2 + x^2(x+n)) + \rho^n \sigma^2_\eta \sum_{j=0}^{x-1} \rho^{2j}
\end{aligned}
$$

Through these formulas, I obtain the direct averages of innovation variances, σ^2_η and σ^2_ϵ. An alternative would be to allow heteroskedasticity in them, obtain time-variant estimates, and use the averages of the estimates. However, the latter process would entail grouping the residuals according to time as well, which would lead to very few observations in each moment equation. On the other hand, applying the former process brings about more observations for each equation that is used to estimate the second-order moments. More specifically, I solve

$$
\min_c \left[\sum_i (d_i - m(c)) \right]' W \left[\sum_i (d_i - m(c)) \right]
$$

where W is the weighting matrix, d is the vector of elements of the variance-covariance matrix of income residuals, and m is the corresponding model variance-covariances depending on the parameters c to be determined. I do the estimation in two stages depending on the weighting matrix used. In the first stage, I use

the identity matrix as the weighting matrix. In the second stage, after obtaining the first stage estimates $\hat{c}$, I use $W = L^{-1}$ as the weighting matrix, where $L = var(d_i - m(\hat{c}))$ is the covariance matrix weighted by the number of observations that contribute to each moment. After obtaining the second stage estimates $\widetilde{c}$, I obtain $var(\widetilde{c}) = (G'WG)^{-1}(G'WLWG)(G'WG)^{-1}$, where $G = \partial(d_i - m(c))/\partial_c$ is the Jacobian of the vector of moments and L is again obtained with the second stage estimates $\widetilde{c}$.

Empirical Findings: An OLS regression of log labor income on the quadratic polynomial in potential experience gives the time variant estimates of $\overline{\gamma}_{0,t}, \overline{\gamma}_{1,t}$, and $\overline{\gamma}_{2,t}$. The time averages of these estimates[5] are used as the average levels for the skill components, $\overline{\gamma}_0, \overline{\gamma}_1$, and $\overline{\gamma}_2$. Table 1 presents the education dependent means of skill components.

At the beginning of the life-cycle, labor income growth for college and non-college graduates turns out to be 6% and 4%, respectively. Note that there are lessening effects depending on the level of experience due to the quadratic component. However, they are small relative to the linear component, especially at low levels of experience. On average, college graduates have steeper labor income profiles than non-college graduates.

Table 2 presents the estimates of the variances and covariances of skill components. The variance of the intercept component in skill, $\sigma^2_{\gamma_0}$, for college graduates is around 1.5 times as high as the one for non-college graduates. More important,

[5]See the Appendix for the implications with the obtained time-dependent estimates.

the dispersion of the linear component in skill, $\sigma^2_{\gamma_1}$, for college graduates is 2.5 times as high as the one for non-college graduates. Also, the dispersion of the quadratic component in skill, $\sigma^2_{\gamma_2}$, for college graduates is more than 3 times as high as the one for non-college individuals.

However, the shock process does not vary much across education groups. Table 3 shows the estimates of the shock process by education. The persistence parameter of the AR(1) process, ρ, turns out to be 0.835 for college individuals and 0.844 for non-college individuals. The variance of persistent innovation, σ^2_η, turns out to be a little higher for college individuals, whereas the variance of the purely transitory component, σ^2_ϵ, becomes a little higher for non-college individuals. Overall, the estimation results of the shock components are not likely to generate different savings motives across education groups.

Figure 1 plots the log labor income profiles for different skill groups within each education group. Panel A plots the profiles for college graduates with an average level of skills (solid line) and with one standard deviation in the linear skill component (dashed lines). Panel A also plots the profiles for non-college individuals with an average level of skills (dash-dot line) and with one standard deviation in the linear skill component (point lines). Panel B plots the same profiles but with one standard deviation in the quadratic skill component. These figures show that the skill components overlap across education groups and skill heterogeneity is much higher for college graduates. Notice that the effect of the quadratic component on income inequality grows more rapidly as the cohort gets older but it remains secondary to the effect of the linear component, especially at

the beginning of the life-cycle.

Table 4 decomposes the total log earnings inequality into its skill and shock components. This decomposition shows that the increase in income inequality over the life-cycle is mainly driven by skill heterogeneity for both education groups. The increase in income inequality is much higher for college graduates. Higher skill heterogeneity leads to this. The share of the skill components in total income inequality increases from 33% to 66% for college graduates. The corresponding shares for non-college graduates are 32% and 53%.

I further decompose the skill heterogeneity into its intercept, linear, and quadratic components. Table 5 shows the decomposition. Among the skill components, the effect of the intercept component goes down over the life-cycle. The quadratic component plays a non-trivial role toward the end of the working period but its effect is small at the early stage of the life-cycle. However, the linear component plays a substantial role in earnings heterogeneity both at the early and at the later stages of the life-cycle.

1.2.2 Savings Rate Profile

This section shows samples in detail from various surveys for savings rate computations. Using the various definitions of saving from the PSID, the SCF, and the CEX data, I robustify the fact that college graduates save a higher share of their income than non-college individuals. Education and age of the households are determined according to the head. For the sample, I include male heads only for

comparability with the data used in the estimation. I also include female heads for the robustness check (not reported) and obtain similar savings rate profiles. The sample selection process is similar to the one described in the estimation analysis.

PSID Data: I use the first two waves, 1984 and 1989, of the wealth data from households with the same characteristics that are used in the estimation. Savings rate is computed as the change in real net worth between 1984 and 1989 divided by five times the average of total real household after-tax income in 1983, 1984, 1985, 1986, 1987, and 1988. Since this variable spans several years, it is likely to be a less noisy measure of average saving than a one-year measure. Net worth is calculated as the sum of the net value of the main house, vehicles, farm and business, other real estate, checking and savings accounts, stocks, and other assets. I classify ages according to 1984. For instance, a 59-year-old individual means that he is 64 years old in 1989 and retired. Households that save or borrow more than their after-tax income, which correspond to 5% of the data, are considered outliers and are dropped from the sample. My sample includes 568 and 1,487 individuals for college and non-college individuals, respectively.

SCF Data: The SCF is a triennial interview survey of U.S. families that contains high quality information about assets and liabilities as well as total income before taxes for the calendar year preceding the survey. For savings rate calculations, I use the 1983-89 SCF panel, which contains 1,479 households that were surveyed in 1983 and then again in 1989. The age groups are classified according to 1983. Hence, I classify the last age group as those ages 45 to 58. Households that save or borrow more than their after-tax income are considered outliers and are dropped

from the sample. The outliers correspond to around 10% of the data. My sample includes 1,836 observations, which implies 612 households since each household's data are repeated three times with different random draws of imputed variables.

The savings rate variable is defined as the change in real net worth between 1983 and 1989 divided by six times the average of total real household income in 1982 and 1988. Similar to the definition in the PSID, this variable is a less noisy measure of average savings than a one-year measure. Net worth is calculated as the value of financial assets (transaction accounts, certificates of deposit, savings bonds, bonds, stocks, investment funds, retirement accounts, cash value of life insurance and other managed assets), primary residence, other real estate, vehicles, business equities, and other nonfinancial assets *minus* credit card debt, real estate debt, vehicle debt, business loans, home loans, and other consumer loans.

CEX Data: Harris-Sabelhaus extracts of the CEX, available from the NBER, are used for computations of the savings rate. The processed data collapse the hundreds of spending, income, and wealth categories into a consistent set of categories across all years, so the data are useful for analyzing the average individual savings rates using all available years. About 5,000 households have been interviewed in each quarter since 1980 in the CEX survey. Each household remains in the survey for four quarters and then is rotated out and replaced with a new household. It has detailed expenditure data which makes it possible to construct different definitions of consumption and therefore of saving. The harmonized data are available up to 2002. Available surveys from 1980 to 1993 are used in order to have a fair comparison with the data used in the estimation analysis of the

labor income profiles. I also look at whole surveys from 1980-2002 and the results (not reported) show that savings rate patterns are similar across education and age groups. A household head is included only if he is interviewed for a full year and is a complete income reporter. Furthermore, households that save or borrow more than their after-tax income are considered outliers and are dropped from the sample. The outliers correspond to around 5% of the sample for each case. I am left with around 16,000 households.

Four different measures of the savings rate are defined in the CEX data. The first one, CEX(1), defines the savings rate as the change in net worth divided by after-tax income. Net worth includes both housing and non-housing assets and liabilities.[6] The other three measures define the savings rate as the difference between consumption and after-tax income divided by after-tax income. These three measures are different in the sense that they use different definitions of consumption. The first of these, CEX(2), uses consumption as total household expenditures. The second one, CEX(3), equals total household expenditures *plus* rental equivalence for homeowners *minus* expenditures on new and used vehicles, mortgage payments, expense of handling life insurance, and expenditures on furniture and other durable household goods. This definition considers expenditures for houses and vehicles as part of saving. I further subtract expenditures on health and education from CEX(3) in order to obtain the last measure of the savings rate, CEX(4). CEX(4) considers health and education as investments in human capital.

[6]Non-housing assets and liabilities include change in checking accounts, saving accounts, stocks, bonds, own firm and businesses, private pension and other retirement contributions, vehicle loans, installment credit, and amount owed to the consumer unit.

Savings Rate Gap by Education: The average savings rate by age and education for each sample is presented in Table 6. Using different definitions of the savings rate and various data sources, we can observe from the results that college graduates save more than non-college graduates for all age groups considered during the work period.

In the early stage of the life-cycle, the 25-34 age cohort, college graduates save more than non-college graduates by two to eight percentage points. In the later stage of the life-cycle, the 55-64 age cohort, the former group still saves a higher fraction of their income than the latter group by two to nine percentage points. Between these two age groups, during middle age, a higher savings rate for college graduates prevails.

1.3 Model

This section outlines the life-cycle model of consumption with heterogeneous agents, incomplete markets, and imperfect information, where the information problem is about an individual's earnings profile.

1.3.1 Imperfect Information Model

Demographics: The economy is populated by overlapping generations of individuals of age $j = 1, 2, ..., j_R, ..., J$, where j_R is the mandatory retirement age

and J is the maximum life span.[7] Each period a continuum of individuals are born with population growth rate n. Each individual i is born with a completed level of education denoted by ed. Each education group consists of individuals with various skill levels denoted by sk. Each individual has one unit of time as an endowment in each period. The conditional probability of surviving from age $j-1$ to j is ψ_j. The time-invariant distribution of generation j can be obtained by $\mu_j = \frac{\psi_j}{1+n}\mu_{j-1}$. The capital market is incomplete: the individual is allowed to borrow assets up to $\underline{a}$.

Preferences: Individuals do not derive utility from leisure and therefore supply their labor endowment inelastically throughout the working period. All individuals have identical preferences on consumption good, c.

$$u(c) = \frac{c^{1-\sigma}}{1-\sigma} \tag{1.3}$$

where σ is the coefficient of relative risk aversion. Each newborn individual's aim is to maximize the present discounted value of his expected lifetime utility.

$$E\left[\sum_{j=1}^{J} \beta^j u(c_{i,j})\right] \tag{1.4}$$

where β is the subjective discount factor.

Labor Endowments: Individuals' log labor endowment profiles, $\{y_{i,j,ed,sk}\}_{j=1}^{j_R-1}$, are heterogeneous in terms of deterministic (ability, skill, ex-ante) and stochastic (shock, ex-post) components.

$$y_{i,j,ed,sk} = \overline{\gamma}_{0,ed} + \gamma_{1,ed,sk} j + \overline{\gamma}_{2,ed} j^2 + z_{i,j} + \epsilon_{i,j} \tag{1.5}$$

[7] For notational simplicity, I suppress the individual time t subscripts. I use them only if necessary.

$$z_{i,j} = \rho z_{i,j-1} + \eta_{i,j} \tag{1.6}$$

where $\overline{\gamma}_{0,ed}$ and $\overline{\gamma}_{2,ed}$ are education-specific means of the intercept and quadratic skill components. They are allowed to be education variant, but within each education group, skill heterogeneity is not allowed in them. Skill heterogeneity is allowed to exist in the linear component with $\gamma_{1,ed,sk} \sim N(\overline{\gamma}_{1,ed}, \sigma^2_{\gamma_{1,ed}})$.

The stochastic component of income is modeled as a persistent AR(1) process with persistence parameter ρ plus a purely transitory shock. The persistent innovation $\eta_{i,j}$ and transitory innovation $\epsilon_{i,j}$ are assumed to be independent of each other, over time, and the skill component, with zero mean, and variances of σ^2_η and σ^2_ϵ.

Bayesian Updating: Workers observe their labor income each period but not the components separately. They start with prior beliefs on each component. After each income realization, they update their priors, obtain their posteriors, and construct their next period prior beliefs. Their updating process is implemented in a Bayesian learning fashion. I use the state-space representations of the Kalman filter for the Bayesian learning equations as follows. For notational simplicity, I suppress the education and skill subscripts from the relevant vectors. Let $H_j = [j; 1]$, $V_{i,j} = [0; \eta_{i,j}]$ and

$$F = \begin{bmatrix} 1 & 0 \\ 0 & \rho \end{bmatrix} \quad S_{i,j} = \begin{bmatrix} \gamma_{1,ed,sk} \\ z_{i,j} \end{bmatrix} \quad P = \begin{bmatrix} \sigma^2_{\gamma_{1,ed}} & 0 \\ 0 & \sigma^2_z \end{bmatrix}$$

The income process can be represented as $y_{i,j} = H_j S_{i,j} + \epsilon_{i,j}$. Let Q and R be variances of $V_{i,j}$ and $\epsilon_{i,j}$. Let $S^e_{i,j}$ denote prior means and P_j denote prior variances

as follows:

$$S^e_{i,j} = \begin{bmatrix} \gamma^e_{1,ed,sk,i,j} \\ z^e_{i,j} \end{bmatrix} \qquad P_j = \begin{bmatrix} \sigma^2_{\gamma_{1,ed},j} & 0 \\ 0 & \sigma^2_{z,j} \end{bmatrix}$$

Evolutions of prior means and prior variances can be represented as follows:

$$S^e_{i,j+1} = F\left[S^e_{i,j} + G_j(y_{i,j} - H_j S^e_{i,j})\right] \tag{1.7}$$

$$P_{j+1} = F\left[P_j - G_j H'_j P_j\right] F' + Q \tag{1.8}$$

where $G_j = P_j H_j [H'_j P_j H_j + R]^{-1}$ is the Kalman gain. Note that P_j evolves in a deterministic manner and independent of individual realizations of labor income. Finally, expected earning has a normal distribution conditional on agents' beliefs

$$y^e_{i,j+1} | S^e_{i,j+1} \sim N(H'_{j+1} S^e_{i,j+1}, H'_{j+1} P_{j+1} H_{j+1} + R) \tag{1.9}$$

Firm Production: There is a representative firm that operates with a constant returns to scale production technology.

$$Y = F(K, N) = AK^{\alpha} N^{1-\alpha} \tag{1.10}$$

where α is capital share, A denotes the level of technology, N is the aggregate labor efficiency, and K is the aggregate capital, which depreciates each period at rate δ.

Government Services: There is a social security tax τ imposed on labor income to fully fund the pay-as-you-go social security system. Retired agents of education

ed and skill sk obtain retirement benefit $b_{ed,sk}$. The retirement benefit is a constant proportion of the agent's lifetime earnings from labor income, which is given as:

$$b_{ed,sk} = \frac{\kappa}{j_R - 1} \sum_{j=1}^{j_R - 1} \overline{y}_{j,ed,sk} \tag{1.11}$$

where κ is the pension replacement ratio and $\overline{y}_{j,ed,sk}$ is the average earning at age j, education ed, and skill level sk. The government also collects all the assets of deceased agents and distributes them to each surviving individual in all generations as an equal amount of accidental transfer tr.

1.3.2 Recursive Formulation

This section describes the individual's problem in a dynamic programming fashion. A working individual from generation j, with education level ed, and skill level sk has state variables $\{a_j, y_{j,ed,sk}, S_j^e\}$, where a_j is the asset holdings carried into the period, $y_{j,ed,sk}$ is the observed log labor income, and S_j^e denotes priors on unobserved components of income, $\gamma_{1,ed,sk,j}^e$ and z_j^e. Then, the worker's recursive problem for $j \leq j_R - 1$ is as follows:

$$V_j(a_j, y_{j,ed,sk}, S_j^e) = \max_{a_j} u(c_j) + \beta\psi_{j+1} E[V_{j+1}(a_{j+1}, y_{j+1,ed,sk}, S_{j+1}^e) | y_{j,ed,sk}, S_j^e]$$

subject to

$$a_{j+1} + c_j = a_j(1 + r) + (1 - \tau)exp(y_{j,ed,sk})w + tr$$

$$a_{j+1} \geq \underline{a}$$

and Bayesian updating equations (7)-(9). Expectation is taken with respect to a conditional distribution of $y_{j+1,ed,sk}$. During the retirement period, there are no

labor earnings and hence no information problem. A retired individual's state variables at a point in time diminish to only a_j. The retiree's recursive problem for $j \geq j_R$ is as follows:

$$V_j(a_j) = \max_{a_j} u(c_j) + \beta\psi_{j+1}V_{j+1}(a_{j+1})$$

subject to

$$a_{j+1} + c_j = a_j(1+r) + b_{ed,sk} + tr$$

$$a_{j+1} \geq \underline{a}$$

1.3.3 Equilibrium

Let $x \equiv \{a, y, S^e, j, ed, sk\}$ be the individual state vector with asset $a > \underline{a}$, observed labor income $y \in [\underline{y}, \overline{y}]$, priors on components of labor income S^e, age $j = 1, 2, ..., J$, education level $ed \in [\underline{ed}, \overline{ed}]$, and skill level $sk \in [\underline{sk}, \overline{sk}]$. Given the survival probabilities $\{\psi_j\}_{j=1}^J$ and labor income probabilities $\pi(y'|y)$, a *stationary recursive competitive equilibrium* is a set of: (i) value functions V(x), (ii) decision rules $\{c(x), a(x)\}$, (iii) prices $\{r, w\}$, (iv) aggregates $\{N, K\}$, (v) fiscal variables $\{\tau, tr, b_{ed,sk}\}$, and (vi) time-invariant distributions $\mu(x)$ such that:

1. Given the prices and fiscal variables, the individual's decision rules optimally solve the value functions.

2. The input markets are competitive: $r = F_K(K, N) - \delta$ and $w = F_N(K, N)$.

3. Markets clear:

$$K = \sum_X a\mu(x)$$

$$N = \sum_{X|j<j_R} exp(y_{j,ed,sk})\mu(x)$$

$$F(K,N) = \sum_{X} c(x)\mu(x) + (\delta + n)K$$

4. Distributions are consistent with individual behavior:

$$\mu(x') = \sum_{X} \mathbf{1}_{a'=a(x)} \mathbf{1}_{S'^e=S^e(x)} \Pi(y'|y, S^e, j)\mu(x)$$

5. Social security benefits equal taxes:

$$\tau w N = \sum_{X|j\geq j_R} b_{ed,sk}\mu(x)$$

6. The accidental transfer satisfies:

$$tr = \sum_{X} (1-\psi_j) a \mu(x)$$

Since this economy does not feature aggregate shocks, preferences are of the CRRA class, the prior means never exceed the bounds of the components of labor income due to the Bayesian updating, there exists a unique stationary equilibrium, and any initial distribution eventually converges to the unique invariant μ (Huggett (1993)).

1.4 Results

In this section, I present the performance of the imperfect information model. First, I show the parameterization strategy. Second, I show the computation results. Third, I re-do the computational analysis for the cases in which there is no information problem and compare the results.

1.4.1 Parameterization

Education-specific skill level parameters are obtained from estimation results. Table 7 shows the parameters of the labor income profiles by education that are used in the computation of the model.

I keep the shock component parameters the same across education groups, since the data analysis shows that estimates are almost similar. Also, I focus on the pure effect of the educational gap in skill heterogeneity on the savings rate gap. As explained so far, heterogeneity is allowed in the linear component of skill. Therefore, parameterization for labor income profiles does not consider the heterogeneity in the intercept and quadratic components of skill. Covariances are taken to be zero between the skill components. Given all these, I shrink the linear skill heterogeneity for each education group.

Other parameters of the imperfect information model are summarized in Table 8. The model period is set to one year. The individuals are assumed to be born at the real age of 25 (corresponds to j=1) with an exogenously given level of education: the college share of the population is picked to be 30%, as observed in the data. All individuals are assumed to be employed until the mandatory retirement age at $j_R = 41$ (real age of 65). The maximum life span is chosen as J=56, which corresponds to the real age of 80.

Conditional survival probabilities $\{\psi_j\}_{j=1}^{J}$ are taken from the U.S. Life Tables 2005. The population rate $n = 0.3\%$ is pinned down by the retirees/workers population ratio, which is 20% in the data. The capital market is incomplete

and individuals are not allowed to borrow, $\underline{a} = 0$. The coefficient of relative risk aversion is set to $\sigma = 2$, which is commonly used in the macro literature and implies an intertemporal elasticity of substitution in consumption of 0.5. The subjective discount factor $\beta = 0.998$ is calibrated to match the capital/output ratio of 3. The firm's technology level $A = 0.8422$ is pinned down to normalize the unit efficiency wage to one. The depreciation rate of capital $\delta = 0.0637$ is picked to match the investment/output ratio of 20%. The capital share in the production function $\alpha = 0.36$ is picked to be standard. The social security tax rate turns out to be 10% to clear the pay-as-you-go social security system. The accidental transfer $tr = 0.07$ clears the accidental transfer market. Retirement benefits are education and skill dependent. There are 7 skill cohorts within each education group. These are within -3 to 3 standard deviations of the average linear skill. The retirement benefits are: $b_{col} = [0.22, 0.30, 0.43, 0.65, 1.02, 1.69, 2.90]$ and $b_{ncol} = [0.22, 0.26, 0.32, 0.39, 0.49, 0.62, 0.79]$.

1.4.2 Model Performance

At Table 9, I summarize the average savings rate by education group over the life-cycle from the data and the model.

The imperfect information model is able to obtain a higher savings rate for college graduates by 2 percentage points at the early stage of the life-cycle. This is within the range of savings rate gaps observed in the data. During middle age, the imperfect information model performs well. It is able to obtain the educational savings rate gap that we see in the data. At the last stage of the work period, college graduates still save more than non-college graduates by 2 percentage points,

which we observe in the data.

Figure 2 plots the evolution of the prior variance of the linear component in skill. For both education groups, the resolution of uncertainty is gradual. For instance, 50% of the initial uncertainty is resolved at age 35 for college graduates; 95% of the initial uncertainty is resolved at age 55 for the same education group.

Figure 3 plots the real profiles of average earnings for each education group with their 95% confidence intervals of prior beliefs in skill. Belief profiles are constructed according to the prior variance at the age of 25, 45, and 60. We observe that uncertainty is gradually resolved and the prior intervals shrink over the life-cycle.

To better understand the performance of the imperfect information model, I re-do the computation analysis under different cases. First, I consider the perfect information case in which the earnings profiles are exactly the same but this time agents have full information about the components of the earnings profiles. Second, I consider the deterministic income case in which the deterministic component of the earnings profiles are the same but this time there are no shock components. Table 10 compares the results of these two cases.

Under the perfect information case, college graduates save less than non-college graduates by 1.1 percentage points at the early stage of the life-cycle. Also, during middle age, the perfect information case is far from explaining the savings rate gap by education. Furthermore, perfect information fails to generate a higher

savings rate for college graduates at the end of the work period. In the age cohort of 55-64, college graduates save a lower share of their income than non-college graduates by 1.5 percentage points.

Under the deterministic income case, where there is no uncertainty at all, college graduates initially save less than non-college graduates by 2.3 percentage points. Again, during middle age, the deterministic income case is far from explaining the savings rate gap patterns that we observe in the data. Finally, at the later stage of the life-cycle, college graduates still save less than non-college graduates by 0.8 percentage point.

Now, I explain in detail why the imperfect information case matches the savings rate profiles that we observe in the data, while the perfect information case fails. To analyze this, I compare the perfect information case with the imperfect information model by looking at the skill decomposition of the educational savings rate gap in Figure 4 for the early ages and in Figure 5 for the later ages.

In Figure 4, I plot the results for the early stage of the life-cycle, the 25-34 age cohort. Due to the higher skill heterogeneity, the imperfect information model is able to generate more precautionary savings motives for college graduates with high skills. At the low skill levels, individuals expect higher earnings in the future. Hence, the imperfect information model generates less of a savings rate gap between education groups at the low skill levels. On average, the perfect information case generates a -1.1-percentage-point savings rate gap between education groups, while the imperfect information model achieves a 2.0-percentage-point

savings rate gap. This establishes the fact that the imperfect information model is able to achieve the savings rate gap that we see in the data at the early ages.

In Figure 5, I plot the results for the later stage of the life-cycle, the 55-64 age cohort. At the high skill levels, the imperfect information model and the perfect information model generate similar savings rate gaps between education groups. This happens because almost all of the uncertainty is resolved and the two models' performance converges from the view of high skilled agents. The distinction between these two models comes from the low skill groups. The perfect information case generates a much lower savings rate for college graduates. This is because the earnings of low skill agents peak at the early age. They save a higher fraction of their income under perfect information to smooth their consumption. However, this is not the case for the imperfect information model. Under the imperfect information model, low ability agents, who expect higher earnings in the future, do not accumulate assets at the early ages. Even after these agents learn that they are, in fact, low ability, they are unable to dissave since they do not have much wealth. On average, college graduates save more than non-college graduates by 2.1 percentage points under the imperfect information model, whereas the perfect information case generates a -1.5-percentage-point educational savings rate gap, in conflict with the data. This establishes that the imperfect information model is able to generate a savings rate gap even at the end of work periods.

1.5 An Alternative Hypothesis: Time Preference Heterogeneity

In this section, I quantitatively assess an alternative hypothesis, different time preference rates between education groups. I let education groups have different discount factors under the perfect information case. The underlying story behind this hypothesis is as follows. With greater investment in education and other forms of human capital, college graduates might be considered farsighted group. Being farsighted, they might choose more rapid growth in their consumption profiles over the life-cycle. This would make them inclined to save more during the work periods. Under the perfect information model, I allow college graduates to have a higher discount factor than non-college graduates and try to see how much time preference heterogeneity we need to explain the savings rate profiles that we observe in the data. I summarize the results of this computational analysis in Figure 6.

Figure 6 plots the savings rate gap obtained under the perfect information model over the discount factor gap by education groups for both early ages (solid line with triangles) and later ages (dotted line with circles). At ages 25-34, the perfect information model requires a 1-percentage-point difference in the discount factor to obtain 2-percentage-point savings rate gap. With 2-percentage-point difference in the discount factor, the perfect information model is able to obtain around a 5-percentage-point higher savings rate for college graduates. In this respect, a reasonable heterogeneity in time preference rates between the two education groups is able to obtain the savings rate gap at the early ages under

the perfect information model. However, the perfect information model with time preference heterogeneity fails to explain the savings rate gap at the later ages. For the time preference rate heterogeneity hypothesis to achieve a *just positive* savings rate gap between college graduates and non-college graduates, we need more than a 3-percentage-point difference in the discount factor between education groups.

Even though this much heterogeneity is not able to explain the savings rate gap at the later ages, this much of a gap in the discount factor is unrealistically large and more than the estimates found in previous studies.[8] For the perfect information model to obtain a 2-percentage-point higher savings rate for college graduates at the later ages, we need much more than a 4-percentage-point difference in discount factors between education groups. These analyses establish that the time preference heterogeneity hypothesis fails to explain the savings rate profiles we observe in the data.

For further explanation to why this is the case, I will consider and compare the results of a 1-percentage-difference in the discount factor under the perfect information case with the results of the same discount factor under imperfect information model. Table 11 summarizes the savings rate profiles for these two cases.

Note that these two cases obtain the same savings rate gap at the early ages. However, at the later ages, the imperfect information model performs much better. While the imperfect information model with identical time preference rates

[8]Cagetti (2003), in an analysis of wealth accumulation over the life-cycle, estimates that college graduates have a higher discount factor by 1.3 percentage points. Gourinchas and Parker (2002), in a life-cycle analysis of consumption, estimate that college graduates have in fact a lower discount factor by 2 percentage points.

across education groups is able to achieve a 2-percentage-point savings rate gap, the perfect information model with a 1-percentage-point gap in the discount factor, β, obtains a -0.9-percentage-point savings rate gap.

The failure of the time preference heterogeneity hypothesis to explain the savings rate profile is examined further in Figure 7 and Figure 8, where I plot the educational savings rate gap over the skill groups as I did before. I include the performance of the perfect information case with time preference heterogeneity.

Figure 7 shows that while both cases obtain a 2-percentage-point savings rate gap between education groups, the underlying dynamics are different. The difference in the time preference rate leads the savings rate gap profile to shift up over the skill cohorts, whereas the imperfect information model flattens the profile. These differences in dynamics lead to the predominance of the imperfect information model at the later ages. Figure 8 plots the savings rate gap over the skill groups for the 55-64 age cohort.

Figure 8 shows that time preference heterogeneity is unable to change the failure of the perfect information model to explain the savings rate profile by education groups. It obtains a similar profile over the skill groups since it is still the perfect information model and low ability agents are able to dissave because of the assets they accumulated before. However, under the imperfect information case, as explained before, low ability agents, who expect higher earnings in the future, fail to accumulate assets at the early ages and hence are unable to dissave at the later ages. This establishes the fact that the imperfect information model

alone is able to achieve the savings rate profile by education at both ends of the work period while the different time preference rate hypothesis fails to explain the savings rate profile by education at the later ages.

1.6 Conclusion

The fact that college graduates, who on average have steeper earnings profiles, exhibit a higher savings profile over the life-cycle is puzzling from the aspect of the permanent income hypothesis in a life-cycle model with perfect information. However, a life-cycle model with imperfect information, where the information problem is about the earnings profile, is capable of reconciling the odd evidence we see in the data. Higher skill heterogeneity for college graduates, which calls for a precautionary savings motive under imperfect information, is able to generate a higher savings rate profile for college graduates over the life-cycle. At the early ages, the higher skill uncertainty itself is able to obtain a savings rate gap by education. As labor market outcomes are realized, this uncertainty is gradually resolved. However, within the dynamics of the imperfect information model, low ability agents are unable to dissave at the later ages. This is due to the fact that they expect higher earnings in the future under the imperfect information model. This generates higher savings rate for college graduates at the later ages. To summarize, the imperfect information model is able to generate the savings rate gap profile that we see in the data. The imperfect information model provides us with an environment to explain the positive correlation between permanent income and the savings rate.

I quantitatively test the alternative hypothesis that college graduates are more

patient than non-college graduates. The computation analysis shows that while a reasonable gap in time preference rates between the two groups is able to obtain a higher savings rate for college graduates at the early ages, it fails to obtain a higher savings rate at the later ages. The different time preference rate hypothesis fails to reconcile the savings rate profile with the earnings profile by education. For future work, it would be interesting to endogenize labor supply choice under the imperfect information model and explore the working hours profile by education groups. It would be interesting to separate precautionary savings and precautionary hours under such an imperfect information framework.

2 Uncovering the Health Production Function Using Life-Cycle Profiles

2.1 Introduction

It is well-known that exercise can reduce morbidity from many diseases (U.S. Department of Health and Human Services 2002). Millions of Americans suffer from chronic diseases that can be prevented through regular exercise.[1] This situation has substantial economic consequences for the U.S.[2] Despite its high economic value, exercise as a health investment has been one of the understudied factors in the macro-health literature.

[1]The National Health Interview Survey 2002 reports that 12.6 million people suffer from coronary heart disease, 1.1 million people suffer from heart attack, 50 million adults (27% of adults) are obese, 107,000 people are newly diagnosed with colon cancer each year, 17 million people have diabetes (about 90% of which is type 2, which is associated with obesity from inactivity), and 300,000 suffer from hip fractures.

[2]According to the National Institutes of Health 2000, the estimated total cost of major chronic diseases is: $183 billion for heart attack, $117 billion for obesity and overweight, $157 billion for cancer, $100 billion for diabetes, and $65 billion for arthritis.

Just like any production or consumption activity, the production of health involves both time and goods. For example, a typical household in the U.S. spends around $3,000 on health each year and around 20 minutes per day on exercise activity. However, most existing studies that incorporate health accumulation into life-cycle models focus on the expenditure as the only input for health production. To explore the effects of exercise on health, I try to uncover the health production function using life-cycle profiles of inputs and output of health.

Uncovering the exact nature of the health production technology is important for evaluating health policies, often designed to alleviate the financial stress of households and government agencies. Most health insurance plans have deductible and copayment provisions (Gruber (2002), (2005)). Out-of-pocket expenditure makes up a considerable share of total health expenditure. Medicare does not cover prescription drugs. Depending on the substitutability between the health expenditure and exercise, changes in government health insurance programs might lead to reallocation of inputs in an agent's health investment.

Based on detailed data from the Medical Expenditure Panel Survey (MEPS) and the American Time Use Survey (ATUS), I construct the life-cycle profiles of health status, health expenditure, and time allocated to exercise. I find that there are important and interesting differences in these profiles: (i) more educated individuals are persistently healthier, (ii) health expenditures across education groups are similar, and (iii) more educated individuals allocate persistently more time to exercise. These facts imply that the educational gaps in exercise contribute to the educational gaps in health capital. To quantitatively assess this contribution, I

calibrate a life-cycle model with an augmented health production function. Computation results suggest that more educated individuals have a higher relative efficiency of exercise to expenditure. However, this accounts for educational differentials only at the early ages. As agents get older, the aging effect trivializes the education effect in the health production function.

The fact that a more educated individual is a more efficient producer of health has been mentioned in previous studies (Grossman (1975), (2000), (2008), Fuchs (1982), Kenkel (1991)). While the strong positive correlation between education and health capital might stem from the causality from health to education at the early stages of life or a third variable such as differences in the rate of time preference, this paper depends on the causality from education to health. Grossman (1975) combines these three alternative, but not mutually exclusive, explanations and finds that there is still a pure positive causality from education to health.[3] This efficiency can take two forms: (i) productive efficiency, which implies that a more educated individual obtains higher output from a given amount of inputs and (ii) allocative efficiency, which pertains to the situation in which education increases the information about the true effects of inputs on health. Kenkel (1991) analyzes the latter and shows that more educated individuals are more likely to choose healthy life-styles: they are less likely to smoke, less likely to heavily consume alcohol, and more likely to participate in vigorous activity. Cutler and Lleras-Muney (2006) consider various mechanisms for the relationship between education and health. They argue that obvious economic explanations such as occupation and income can explain only a part of the education effect. They sug-

[3]In fact, in his estimation, the effect of schooling on health turns out to be 3%, compared to a 5.5% percent effect of schooling on the wage rate.

gest that higher levels of education lead to different thinking and decision-making patterns.

In his seminal paper, Grossman (1972) sets up the theoretical foundations of demand for health inputs. An individual's health is considered as a stock that depreciates at an age-dependent rate. It can be improved by investment, which can take place in a variety of ways, e.g., consumption of medical services, nutrition, and occupational choice (Cropper (1977)). Palumbo (1999) takes medical expenses as uncertain and explains the slow dissaving of the elderly. In a general eqilibrium overlapping generations model, Attanasio et al. (2008) explore Medicare financing where health expenditure is taken as an exogenous process. Jeske and Kitao (2009) endogenize health insurance decision but treat health expenditure as an exogenous shock. De Nardi et al. (2010) explore the roles of risky medical consumption in the savings of single retired agents. Halliday et al. (2009) endogenize the medical expenditure and investigate the underlying reasons that lead to increased medical consumption over the life-cycle. Ozkan (2011) separates curative and preventive medical expenditures to explore the hump-shaped age profile of medical expenditures of the poor relative to the rich. However, none of these papers consider exercise as an input into health investment. Khwaja (2007) analyzes the effects of Medicare on individual health incentives and finds small levels of moral hazard in exercise among the elderly due to Medicare. He models exercise only at the extensive margin because of the data limitations of the Health and Retirement Survey. He does not exploit the intensive margin, which is associated more with the substitutability between inputs of health investment. Podor and Halliday (2011) explore the effect of health status on the allocation of time.

They find a positive effect of health on market production and a larger effect on non-market production. In this paper, I explore the contribution of exercise to health differentials.

The importance of time allocated to physical activity has been emphasized in different frameworks. Russell et al. (2007) study time spent on a variety of health-related activities and report that exercise makes up the vast majority of total time spent on health. Saffer et al. (2011) find, in their estimation, that the racial-ethnic-gender differentials in non-work physical activity contribute to the health gradients. Mullahy and Robert (2008) explore the effect of time constraints on physical activity and find that educational attainment is positively related to time allocated to exercise on weekends/holidays, but not on weekdays, which implies that the higher opportunity cost of time may be most acutely felt during weekdays. Wolin et al. (2008) suggest that low levels of discretionary time may serve as a barrier to physical activity among socio-demographically diverse populations.

At retirement, the opportunity cost of spending time on exercise declines, since individuals no longer forgo wages to engage in it. This generates a discontinuity in time allocated to exercise. Such discontinuities can be found in previous studies that analyze exercise over the business cycle. Colman and Dave (2011) find that recreational exercise tends to increase as employment decreases. Aguiar et al. (2011) look at the time allocation during recessions and show that individuals allocate 5% of forgone market hours to their time investment in their own health care. For the same reason, Ruhm (2000) documents that recessions are good for

individuals' health.

The rest of the paper is organized as follows. Section 2.2 shows the empirical analysis. Section 2.3 presents an intuitive static framework and sets up the full dynamic model. The parameterization strategy is shown in Section 2.4. Section 2.5 shows the model's performance. Section 2.6 concludes.

2.2 Empirical Analysis

This section describes the data used to construct the life-cycle profiles of inputs and output of health. For health capital and health expenditure, the Medical Expenditure Panel Survey (MEPS) is used. For time allocated to exercise, the American Time Use Survey (ATUS) is used. In what follows, I describe each sample in detail.

2.2.1 Health Profiles

To construct the life-cycle profiles of health capital and health expenditure, I use the 1996-2009 waves of the Household Component (HC) of the Medical Expenditure Panel Survey (MEPS). The MEPS-HC is a nationally representative survey of the U.S. civilian noninstitutionalized population and collects detailed data on health status, health expenditure, demographics, health insurance coverage, income, and employment at both the individual and the household levels. I categorize the individuals as either employed or retired. An employed individual

is included in the sample if he (i) is not self-employed, (ii) is actively working (not absent, not unemployed), (iii) is between 25 to 64 years old, (iv) has at least 12 years of completed education, (v) has weekly work hours between 4 and 84, and (vi) earns an hourly wage between \$2 and \$200 in 2010 prices. A retired individual is included in the sample if he (i) is not disabled, (ii) is between 65 to 80 years old, (iii) has at least 12 years of completed schooling, (iv) has reported zero wage income, and (v) has reported zero weekly work hours. I further decompose each group into college graduates (16 years of schooling or more) and high-school graduates (15 years of schooling or less). I am left with around 34,000 employed college graduates, 70,000 employed high-school graduates, 3,400 retired college graduates, and 8,500 retired high-school graduates.

For health capital, I use the self-reported health status (1. excellent, 2. very good, 3. good, 4. fair, and 5. poor health). This measure of health capital is a categorical variable and depends on an individual's subjective evaluation of the state of his own health. Following Grossman (1975), I rescale this variable by regressing the work-loss days on a set of dummy variables representing each health status category. Specifically, the production function of healthy time is given by $h = 365 - WLD = 365 - BH^{-C}$, where h is healthy days in a given year, WLD is work-loss days, B and C are positive constants, and H is health capital. Solving this for H will result in $H = B^{1/C} WLD^{-1/C}$. To express the stock of health in an index number form with $H_1 = 1$, write $H_2/H_1 = (WLD_1/WLD_2)^{1/C}$, etc.

Using the first wave of the MEPS-HC data, I obtain $WLD_1/WLD_2 = 0.87$, $WLD_1/WLD_3 = 0.51$, $WLD_1/WLD_4 = 0.31$, $WLD_1/WLD_5 = 0.19$. C is as-

sumed to be equal to one as in Grossman (1975). Hence, the rescaled health status turns out to be $H_1 = 1$, $H_2 = 0.87$, $H_3 = 0.51$, $H_4 = 0.31$, $H_5 = 0.19$. In addition, I construct a standard classification of the healthy ratio. As prevalent in the literature, an individual is considered to be healthy if the health status measure is excellent, very good, or good and unhealthy otherwise.

Figure 10 shows the life-cycle profiles of healthy ratios and the rescaled health index for each education group. Both variables show that the more educated are persistently healthier than the less educated over the life-cycle. The averages are presented in Table 14. Considering the rescaled health index, college graduate workers' health status is 0.82 on average, whereas it is 0.76 for high-school graduate workers. Corresponding levels for retired individuals are 0.71 and 0.65, respectively. The standard healthy index shows qualitatively the same patterns in terms of the health status gap between education groups. Of the workers, 96% of college graduates are considered healthy, whereas 93% of high-school graduates are considered healthy. The corresponding healthy proportions for retired agents are 86% and 81%, respectively. Table 14 also provides the average health levels for men and women. A persistent health status gap across education groups can be observed within each gender cohort as well.

For the health expenditure variable,[4] I use the total health expenditure, which is the sum of spending on office visits (26%), inpatient stays (26%), prescriptions (20%), outpatient care (12%), dental (9%), emergency room visits (3%), others

[4]Simple averaging for each age group might overpredict the age effect on health expenditure. However, Jung and Tran (2010) separate the pure age effect from cohort and time effects and find no difference in biases across education groups.

(e.g., vision and home health care)(4%). Total health care expenditures are financed by out-of-pocket funds (20%), private insurance (56%), Medicare (15%), Medicaid (2%), and others (e.g., veteran's benefits, tricare and worker's compensation) (7%). While private insurance dominates other sources of financing for total health expenditures for employed agents at 69%, Medicare is the dominant source for retirees' expenditures at 55%. Note that out-of-pocket payments are similar: 21% for employed and 18% for retired. Table 15 provides the expenditures as well as percentages for each type and each source of health expenditure for the total sample, for employed agents, and for retired agents.

Figure 11 shows the life-cycle profiles of health expenditure for each education group. College graduates spend slightly more on health care at the beginning of the life-cycle. From middle age on, they spend as much as high-school graduates do. Among retired agents, the health expenditure gap between education groups fluctuates. Therefore, we do not observe persistent differentials in health expenditure across education groups. This leads to a search for better explanatory power for the persistent gap in health levels by education over the life-cycle. Table 14 provides health expenditures by education, employment, and gender. College graduate workers on average spend $2,800, whereas high-school graduate workers spend $2,580. The corresponding expenditures for retired agents are $8,330 and $8,000, respectively for each education group. Educational gaps in health expenditure turn out to be fairly narrow provided that there is a persistent health status gap across education groups over the life-cycle.

2.2.2 Exercise Profiles

To construct the life-cycle profiles of time allocated to exercise, I use the 2003-2011 waves of the American Time Use Survey (ATUS). The ATUS is the first federally administered survey on time use in the United States. The survey measures how people divide their time among life's activities. Individuals are randomly selected from a subset of the existing sample of the Current Population Survey. I use the *Participation in Sports, Exercise, and Recreation (1301–)* category to obtain the average time spent engaging in exercise. In order to combine multiple years of ATUS data from the single-year data files, I use the variable *tu06fwgt* to weight the 2003 to 2005 data and the variable *tufinlwgt* to weight 2006 and later data. I categorize the individuals either as employed or as retired. An employed individual is included in the sample if he (i) is not self-employed, (ii) is actively working (not absent, not unemployed), (iii) is between 25 to 64 years old, (iv) has at least 12 years of completed education, (v) has weekly work hours between 4 and 84, and (vi) earns an hourly wage between \$2 and \$200 in 2010 prices. A retired individual is included in the sample if he (i) is not disabled, (ii) is between 65 to 80 years old, (iii) has at least 12 years of completed schooling, (iv) has no wage income, and (v) has reported zero weekly work hour so. I further categorize each group into college graduates (16 years of schooling or more) and high-school graduates (15 years of completed schooling or less). This sample selection gives me around 21,000 employed college graduates, 28,000 employed high-school graduates, 3,000 retired college graduates, and 8,700 retired high-school graduates.

Figure 12 plots the life-cycle profiles of time spent on exercise for each education cohort. We observe that college graduates allocate time to exercise per-

sistently more than high-school graduates. Table 16 shows the averages. College graduate workers engage in exercise 18.5 minutes per day, whereas high-school graduate workers spend 12.8 minutes per day in exercise. College graduate retirees exercise 22.8 minutes per day and high-school graduate retirees exercise 14.6 minutes.

Figure 13 separates the extensive and intensive margins. Participation ratios for college graduate workers and high-school graduate workers are 23% and 13%, respectively. For retired, the corresponding ratios are 28% and 17%. Conditional on participation, average minutes spent in exercise per day by college graduate workers and high-school graduate workers are 80.8 minutes and 99.7 minutes. Conditional on participation, average minutes spent in exercise per day by college graduate retired and high-school graduate retired are 80.5 minutes and 84.3 minutes. While the more educated participate in exercise more than the less educated, conditional on participation the former spends less time than the latter.

I further decompose the groups into men and women, since they go through different biological processes. Within each cohort, men outspend women in exercise time. However, the trend is similar even within each gender. Whether male or female, the more educated participate in exercise more than the less educated, and conditional on participation, the former spends less time than the latter. Overall, it turns out that the more educated spend more time in exercise on average than the less educated. Table 16 provides more summary statistics for the total sample across education groups and for men and women separately.

2.3 Model

This section outlines the life-cycle model with an augmented health production function. I start by building an intuitive static framework to show that the educational differentials in exercise at both the intensive and the extensive margins can be rationalized by heterogeneity in the relative efficiency of exercise to expenditure. Then, I show the general equilibrium overlapping generations model.

2.3.1 An Intuitive Static Case

Consider a worker who derives utility from non-medical good c and health status h. He is endowed with one unit of time to allocate either to work n or to exercise e. He earns wage w per unit of time spent at work. He is exogenously given health insurance: he allocates copayment share q of his earnings to his medical expenditure m. His medical consumption and time spent on exercise jointly determine his health capital with the production function $h = f(m) + \gamma g(e)$, where f and g are increasing and concave functions in their arguments and γ is the relative efficiency of exercise to expenditure. His one-period problem is to maximize $(c + h)$ subject to his budget constraint $(c + qm = wn)$, his time constraint $(n + e = 1)$, and the health production function. Rewriting his problem:

$$\max_{m,e} [w(1 - e) - qm + f(m) + \gamma g(e)]$$

Conditional on participating in exercise, first-order conditions will be

$$q = \frac{df(m)}{dm}$$

$$w = \gamma \frac{dg(e)}{de}$$

Now consider two individuals from different education groups who are otherwise the same with $w_2 > w_1$. First-order conditions indicate $m_2 = m_1$ and $e_2 < e_1$, and hence $h_2 < h_1$. The more educated worker, whose opportunity cost of time is higher, spends less time on exercise and has a lower health status. Now, in addition assume $\gamma_2 > \gamma_1$ and consider $\frac{w_2}{w_1} = \frac{\gamma_2}{\gamma_1}$. The second optimality condition gives $e_2 = e_1$ and hence $h_2 > h_1$. One can show that there exists $\{\gamma_1, \gamma_2\}$ with $\frac{w_2}{w_1} > \frac{\gamma_2}{\gamma_1} > 1$ such that in optimization $e_2 < e_1$ and $h_2 > h_1$. The presumption that the better educated individual has higher productive efficiency in health production might give results more consistent with the data, from which we observe that conditional on participation, better educated individuals spend less time on exercise but obtain more health capital.

Now consider an individual's decision to participate in exercise. The worker with wage w will spend positive time on exercise if $\gamma g(\widetilde{e}) - w\widetilde{e} \geq 0$, where $\widetilde{e}$ denotes the optimal choice given $\{\gamma, w\}$. Let the better educated worker be $w_2 \in [\underline{w}_2, \overline{w}_2]$ and the less educated worker be $w_1 \in [\underline{w}_1, \overline{w}_1]$. Let w_s^* be the cut-off wage at which the individual of education level s is indifferent between being inactive or active. Under the condition that the median wage for the better educated individual is no less than the median wage for the less educated, which is a realistic assumption, for the better educated to participate more in exercise, $w_2^* > w_1^*$ should hold. If the productivity of exercise on health is invariant across education groups, then

$$0 = \gamma g(\widetilde{e}_2) - w_2^* \widetilde{e}_2 < \gamma g(\widetilde{e}_2) - w_1^* \widetilde{e}_2 \leq \gamma g(\widetilde{e}_1) - w_1^* \widetilde{e}_1$$

which is a contradiction, since the cut-off constraint is not satisfied for the less educated group. Once again, if we have $\gamma_2 > \gamma_1$, the cut-off rules are likely to be satisfied for both education groups and the more educated individual participates more in exercise. Note that the higher productive efficiency for the more educated individual contributes to the higher participation in exercise and, conditional on participation, less time spent on exercise, which is consistent with what we observe in the data.

2.3.2 Dynamic Framework

This section develops the general equilibrium overlapping generations model where agents face uncertainty in their survival and labor productivity. Health affects utility only, i.e., the consumption motive, in the model. The completed level of education and health insurance are exogenously provided to the agents. Choices of consumption, labor supply, and the input mix of health investment are endogenously determined in each period.

Demographics: The economy is populated by overlapping generations of individuals of age $j = 1, 2, ..., j_R, ..., J$, where j_R is the mandatory retirement age and J is the maximum life span. Each period, a continuum of agents are born with population growth rate *pop*. Each agent is born with a completed level of education s. The conditional probability of surviving from age $j-1$ to j is ψ_j. The time-invariant distribution of generation j can be obtained by $\mu_j = \frac{\psi_j}{1+pop}\mu_{j-1}$. The capital market is incomplete: the individual is allowed to borrow assets up to $\underline{a}$.

Preferences: The individual's preference is over non-medical consumption c, leisure l, and health capital h. The period utility function is specified as

$$u(c,l,h) = \left(\frac{c^{1-\sigma_c}}{1-\sigma_c} + \phi_{s,j} \frac{l^{1-\sigma_l}}{1-\sigma_l} \right) h^{\theta} \tag{2.1}$$

where σ_c is the coefficient of relative risk aversion in non-medical consumption, σ_l implies the Frisch elasticity, $\phi_{s,j}$ is the education- and age-dependent utility obtained from leisure, and θ determines the impact of health on utility. Note that individuals obtain utility from health itself. This is consistent with Grossman's (1972) notion of a consumption motive of health care. Each newborn agent's problem is to maximize the present discounted value of his expected life time utility

$$E\left[\sum_{j=1}^{J} \beta^j u(c_j, l_j, h_j) \right] \tag{2.2}$$

where β is the subjective discount factor.

Labor Productivity: The agent's log labor efficiency profile $\{y_{s,j}\}_{j=1}^{j_R-1}$ consists of ex-ante and ex-post components.

$$y_{s,j} = g_{0,s} + g_{1,s} j + g_{2,s} j^2 + z \tag{2.3}$$

$$z' = \rho_z z + \epsilon \tag{2.4}$$

where $g_{0,s}, g_{1,s}, g_{2,s}$ are education-dependent ex-ante components. z is the ex-post component modeled as an AR(1) process, with $\epsilon \sim N(0, \sigma_\epsilon^2)$ being the innovation

to the labor productivity and ρ_z being the degree of persistence of the innovation.

Time Allocation: Each agent has one unit of time as an endowment in each period. A typical worker allocates his endowment to paid work n, leisure activity l, and exercise e. Hence, the time constraint for the worker is given as:

$$1 = n + l + e \tag{2.5}$$

A typical retired agent's time constraint is $1 = l + e$.

Firm Production: There is a representative firm that operates with a constant returns to scale production technology:

$$Y = F(K, N) = AK^{\alpha}N^{1-\alpha} \tag{2.6}$$

where A denotes the level of production technology, N is the aggregate labor efficiency, and K is the aggregate capital, which depreciates each period at rate δ_k.

Health Accumulation: Gross health investment $f(m, e)$ depends on medical expenditure m and exercise e. I assume a flexible CES specification for the gross health production function.

$$f(m, e) = \overline{\gamma}(m^{\rho} + \gamma_{j,s,r}e^{\rho})^{\eta/\rho} \tag{2.7}$$

where $\overline{\gamma}$ denotes the overall technology of health production and $\gamma_{j,s,r}$ determines the relative efficiency of exercise to expenditure, which depends on age, education, and retirement. The health capital accumulation follows

$$h' = (1 - \delta_j)h + f(m, e) \tag{2.8}$$

where δ_j is the age-dependent depreciation rate of health capital.

Health System: There is a private competitive firm that periodically collects a premium p_w from each worker and pays the $(1-q_w)$ share of the worker's health expenditure; hence, q_w is the copayment that each worker pays upon usage of health care. Given the coinsurance share, the private health insurance firm chooses the amount of premium that needs to be collected to satisfy the zero profit condition $(1-q_w)M_w = p_w L$, where M_w is the total health expenditure of all workers and L is the total labor force.

At retirement, each agent starts using the Medicare health system. The system entails a beneficiary premium p_r to be collected each period and a copayment ratio q_r. In addition, in order to fully finance the Medicare system, there is a federal tax τ_{fed} imposed on workers' labor earnings. Note that part of the federal tax can be considered a Medicare tax. Medicare is self-financing, so that the government has to solve for a federal tax that satisfies $(1-q_r)M_r = p_r U + \tau_{fed} wN$, where M_r is the total medical expenditure of retired agents and U is the population share of retirees.

Government Services: There is a Social Security tax τ_{ss} imposed on labor income to fully fund the pay-as-you-go Social Security system. Retired agents of education s obtain retirement benefit b_s, which is a constant proportion of the agent's lifetime earnings from labor income:

$$b_s = \frac{\kappa}{j_R - 1} \sum_{j=1}^{j_R-1} \overline{y}_{s,j} \tag{2.9}$$

where κ is the pension replacement ratio and $\overline{y}_{s,j}$ is the average earning of age j and education type s. The government also collects all the assets of deceased agents and distributes them to each surviving individual of all generations as an equal amount of accidental transfer, tr.

2.3.3 An Agent's Recursive Problem

The individual worker's problem is given recursively as follows:

$$V_{j,s}(a,z,h) = \max_{n,a',m,e} u(c,l,h) + \beta\psi_{j+1}E_{z'}\left[V_{j+1,s}(a',z',h')|z\right]$$

subject to

$$c + p_w + q_w m + a' = (1+r)a + (1-\tau_{ss}-\tau_{fed})wnexp(y_{s,j}) + tr$$

$$h' = (1-\delta_j)h + \gamma(m^\rho + \gamma_{j,s,r}e^\rho)^{\eta/\rho}$$

$$y_{s,j} = g_{0,s} + g_{1,s}j + g_{2,s}j^2 + z$$

$$z' = \rho_z z + \epsilon$$

$$1 = n + l + e$$

$$a' \geq \underline{a}$$

The corresponding problem for the retired agent is:

$$V_{j,s}(a,h) = \max_{a',m,e} u(c,l,h) + \beta\psi_{j+1}V_{j+1,s}(a',h')$$

subject to

$$c + p_r + q_r m + a' = (1 + r)a + b_s + tr$$

$$h' = (1 - \delta_j)h + \overline{\gamma}(m^\rho + \gamma_{j,s,r} e^\rho)^{\eta/\rho}$$

$$1 = l + e$$

$$a' \geq \underline{a}$$

2.3.4 Equilibrium

Let $x \equiv \{a, z, h, j, s\}$ be the individual state vector with asset $a \geq \underline{a}$, labor productivity $z \in [\underline{z}, \overline{z}]$, health capital $h \in [\underline{h}, \overline{h}]$, age $j = 1, 2, ..., J$, and education level $s \in [\underline{s}, \overline{s}]$. Given the survival probabilities $\{\psi_j\}_{j=1}^J$ and labor productivity shock process $\pi(z'|z)$, a *stationary recursive competitive equilibrium* is a set of: (i) value functions V(x), (ii) decision rules $\{c(x), a(x), n(x), m(x), e(x)\}$, (iii) prices $\{w, r\}$, (iv) aggregates $\{K, N\}$, (v) health insurance system $\{p_w, p_r, q_w, q_r\}$, (vi) fiscal variables $\{\tau_{ss}, \tau_{fed}, b_s, tr\}$, and (vii) time-invariant distributions $\mu(x)$ such that:

1. Given the prices, health system variables, and fiscal variables, agents' decision rules optimally solve the value functions.

2. The input markets are competitive:

   - $w = AF_N(K, N)$
   - $r + \delta_k = AF_K(K, N)$

3. Capital, labor, and good markets clear:

- $K = \sum_X a(x)\mu(x)$
- $N = \sum_{X|j<j_R} n(x)we^{y_{s,j}}\mu(x)$
- $\sum_X c(x)\mu(x) + \sum_X m(x)\mu(x) + (\delta_k + pop)K = AF(K, N)$

4. The private health insurance system is self-financing:

   - $p_w \sum_{X|j<j_R} \mu(x) = (1 - q_w) \sum_{X|j<j_R} m(x)\mu(x)$

5. The Medicare is self-financing:

   - $p_r \sum_{X|j\geq j_R} \mu(x) = (1 - q_r) \sum_{X|j\geq j_R} m(x)\mu(x) + \tau_{fed}wN$

6. The Social Security system is self-financing:

   - $\tau_{ss}wN = \sum_{X|j\geq j_R} b_s\mu(x)$

7. The accidental transfer satisfies:

   - $tr = \sum_X (1 - \psi_j)a(x)\mu(x)$

8. Distributions are consistent with agents' behavior:

   - $\mu(x') = \sum_X \mathbf{1}_{a'=a(x)}\mathbf{1}_{h'=h(x)}\pi(z'|z)\mu(x)$

2.4 Parameterization

This section describes the parameterization strategy used in the computation of the model. The calibration process turns out to be successful in obtaining salient features of the data. Table 17 summarizes the model parameters.

Demographics: The model period is set to one year. The agents are assumed to be born at the real age of 25 with an exogenously given level of education: 30% of the newborns are college graduates. All agents are assumed to be employed until the mandatory retirement age, which occurs at $j_R = 41$ (real age of 65). The maximum life span is set at $J = 56$, which corresponds to the real age of 80. Conditional survival probabilities $\{\psi_j\}_{j=1}^{J}$ are taken from the U.S. Life Tables 2005. The population rate $pop = 0.3\%$ is pinned down by the retirees/workers population ratio which is 20% in the data. The capital market is incomplete and agents are not allowed to borrow, i.e., $\underline{a} = 0$.

Preferences: The subjective discount factor, $\beta = 0.988$, is calibrated to match the capital/output ratio of 3. The coefficient of relative risk aversion in non-medical consumption is set to $\sigma_c = 2$, which is commonly used in the macro literature. The utility parameter of leisure is specified as $\phi_{s,j} = (1 + \mathbf{1}_{hs}\phi_s - \mathbf{1}_{col}\phi_s)(\phi_0 + \phi_1 j + \phi_2 j^2)$. These parameters are pinned down by the working hour profiles by education over the life-cycle. The results turn out to be $\phi_0 = 0.22$, $\phi_1 = -0.006$, $\phi_2 = 0.00006$, and $\phi_s = 0.3$. The leisure parameter, $\sigma_l = 4.44$, is determined such that the Frisch elasticity of the average worker's labor supply turns out to be 0.4 as in the ranges of estimates obtained in the literature. The utility effect of the health status, $\theta = -0.02$, is pinned down by the average health status of the workers, which is 0.78 in the data.

Labor Productivity: The skill components of the log labor productivity $\{g_0, g_1, g_2\}$ are jointly pinned down by the average wage of the workers at the beginning age of 25, 55, and 64. This gives $\{1.9, 0.033, -0.0006\}$ for high-school graduates and

$\{2.2, 0.05, -0.0009\}$ for college graduates. Shock components are taken to be the same for both education groups. The persistence parameter of the innovation to labor productivity, $\rho_z = 0.9$, and the standard deviation of the innovation, $\sigma_\epsilon = 0.17$, are picked so that I obtain wage dispersion profiles over the life-cycle for both education cohorts as close as possible.

Firm Production: Capital share, $\alpha = 0.36$, is standard in the literature. The depreciation rate of capital, $\delta_k = 0.0637$, is pinned down by the investment/output ratio of 20% as in the data. The technology level, $A = 0.8422$, is picked to normalize the unit efficiency wage to 1.

Health Investment: For illustration purposes, I pick $\rho = 0.8$, which implies that the elasticity of substitution between expenditure and exercise is 5. The focus here is to see how great the effect of exercise on health can be with a high degree of substitutability between the inputs of health. In addition, $\eta = 1$ is assumed for the sake of simplicity.

The overall technology parameter for health production, $\overline{\gamma} = 0.35$, is calibrated to obtain the average level of medical expenditure of all agents, which is $\$3,240$ in the data. The relative efficiency of exercise to expenditure is specified as $(1+\mathbf{1}_{col}\gamma_s-\mathbf{1}_{hs}\gamma_s)(\gamma_0+\gamma_1 j+\mathbf{1}_{ret}\gamma_r)$. The parameters of relative efficiency of exercise, $\{\gamma_0, \gamma_1, \gamma_s, \gamma_r\}$, can be calibrated to match the exercise profiles by education over the life-cycle. The ones used in the computation are $\gamma_0 = 20$, $\gamma_1 = -0.09$, $\gamma_s = 0.25$, and $\gamma_r = -14$.

The depreciation rate of health capital is assumed to be age and retirement dependent: $\delta_j = d_0 + d_1 j + d_2 j^2 + \mathbf{1}_{ret} d_r$. These parameters $\{d_0, d_1, d_2, d_r\} = \{0.1, 0.002, 0.00015, 0.05\}$ can be pinned down by the profiles of health capital over the life-cycle. In the model's computation, d_0 and d_r are very sensitive to health-related utility and exercise parameters. Hence, these values are used for illustration purposes.

Health Insurance: The copayment ratio, $q_w = 0.2$, is picked due to the fact that out-of-pocket health expenditure contributes to one fifth of workers' total health expenditure. The health insurance premium, paid by each worker each period, $p_w = \$2,700$ is obtained to guarantee the zero-profit condition for the insurance firm.

The copayment share of health expenditure, $q_r = 0.2$, that retirees have to pay is picked to represent the total out-of-pocket shares of old-age medical expenditure. Each period, $p_r = \$1,500$ is collected from each retired agent as a premium for the use of the Medicare system. The rest of the total Medicare cost is financed by a federal tax on labor income, which turns out to be $\tau_{fed} = 8\%$. This is associated with the fact that almost half of the Medicare system is financed by federal government outlays, which are mainly obtained from the taxation on labor income.

Government Services: The pension replacement ratio, $\kappa = 0.40$, is widely used in the literature. The government provides retirees with retirement benefits $b_{hs} = \$15,000, b_{col} = \$25,000$, which are the κ share of average earnings of high-school workers and college graduate workers. $\tau_{ss} = 10\%$ clears the pay-as-you-go

Social Security system. Finally, an equal amount of $tr = \$2,100$ is transferred to each agent as an accidental bequest.

2.5 Results

This section shows the performance of the benchmark model. To have a fair evaluation, I recompute the model with the same parameters but with no educational difference in the relative efficiency of exercise to expenditure ($\gamma_s = 0$) and compare it with the benchmark model.

Figure 14 plots the life-cycle profiles of time allocated to exercise for both cases. Panel A shows the profiles for the benchmark model where college graduates have a higher relative efficiency of exercise to expenditure. On average, college graduates allocate more time to exercise than high-school graduates. During the working period, the education groups allocate more time to exercise almost persistently. During the retirement period, college graduates still spend more time on exercise than high-school graduates. Panel B plots the profiles obtained from the model with the same relative efficiency of exercise across education groups. In this case, college graduates allocate persistently less time to exercise over the life-cycle, which contradicts what we observe in the data. The higher opportunity cost of time for college graduates leads to a different input allocation in health investment. Taking into account the performance of the model with the same efficiency of exercise, the higher relative efficiency of exercise to expenditure for college graduates plays an important role in explaining the life-cycle profiles of exercise by education that we observe in the data.

Figure 15 plots the life-cycle profiles of health expenditure for each education group. The higher relative efficiency of exercise for college graduates plays a substantial role in explaining the health expenditure profiles at the early ages. The benchmark model generates similar health expenditure across education groups on average at the early ages, which is what we observe in the data. In contrast, the model with the same efficiency of exercise generates persistently much higher health expenditure for college graduates at the early ages. In this respect, the benchmark model performs much better in explaining the health expenditure profiles at the early ages. However, both cases result in a similar educational gap in health expenditure at the later ages: college graduates persistently spend more on health care than high-school graduates. In this respect, the benchmark model fails to account for the similar health expenditure profiles across education groups at the later ages. This happens because the aging effect on the efficiency of exercise trivializes the education effect in the health production technology at the later ages.

Figure 16 plots the profiles of health status by education. College graduates, who have a higher consumption motive of health, possess more health capital than high-school graduates. Educational differentials in the relative efficiency of exercise contribute to the educational gaps in health capital at the early ages. Even with the similar health expenditure across education groups, college graduates possess more health capital at the early ages. However, at the later ages, both cases result in a similar educational gap in health status profiles: college graduates are persistently healthier. At the later ages, the higher relative efficiency

of exercise for college graduates does not have much effect on health status. As mentioned before, the education effect on the efficiency of exercise becomes more obsolete as the agents get older.

2.6 Conclusion

Most of the existing studies that incorporate health accumulation into life-cycle models focus on expenditure as the only input for health investment. I augment the health production function by incorporating the time allocated to exercise. I find that, at the early ages, the model is compatible with the features of the data that have been at odds with the standard life-cycle models: (i) college graduates are persistently healthier, (ii) health expenditures are similar across education groups, and (iii) college graduates allocate persistently more time to exercise. The key to obtaining these profiles is that college graduates have higher relative efficiency of exercise to expenditure in the health production function. The underlying story with this driving force might be the fact that college graduates have more information on the true effects of health inputs. However, as agents get older, the aging effect on exercise trivializes the education effect in the health production function. Hence, there is still room for improvement in the model to account for educational differentials at the later ages.

Uncovering the health production function is important for evaluating health policies. The financial consequences of health reforms depend on how individuals allocate their time to health-related behaviors. Educational differentials in the time allocated to exercise contribute to the educational differentials in health sta-

tus. Depending on the substitutability between health inputs, government policies might lead to the reallocation of health investment choices. For future work, it would be interesting to analyze various health reforms in a realistically calibrated life-cycle model with an augmented health production function.

Bibliography

[1] **Aguiar, M., E. Hurst, and L. Karabarbounis (2011)**: "Time Use During Recessions," NBER Working Paper No. 17259.

[2] **Attanasio, P. O. (1998)**: "Cohort Analysis of Saving Behavior by U.S. Households," Journal of Human Resources, 33, 575-609.

[3] **Attanasio, O., S. Kitao, and G. L. Violante (2008)**: "Financing Medicare: A General Equilibrium Analysis," Working Paper.

[4] **Baker, M. (1997)**: "Growth Heterogeneity and the Covariance Structure of Life-Cycle Earnings," Journal of Labor Economics, 15, 338-375.

[5] **Becker, G. (1975)**: "Human Capital," Chicago: University of Chicago Press, 1975.

[6] **Card, D. (1994)**: "Intertemporal Labor Supply: An Assessment," In Advances in Econometrics: The Sixth World Congress, vol. 2, edited by Christopher A. Sims, 49-78. New York: Cambridge University Press, 1994.

[7] **Cagetti, M. (2003)**: "Wealth Accumulation over the Life Cycle and Precautionary Savings," Journal of Business and Economic Statistics, 0, 1-15.

[8] **Chamberlain, G. (1984)**: "Panel data," Handbook of Econometrics, in: Z. Griliches and M. D. Intriligator (ed.), Handbook of Econometrics, 1-2, 1247-1318.

[9] **Colman, G. J., and D. M. Dave (2011)**: "Exercise, Physical Activity, and Exertion over the Business Cycle," NBER Working Paper No. 17406.

[10] **Cropper, M. L. (1977)**: "Health, Investment in Health, and Occupational Choice," Journal of Political Economy, 85-6, 1273-1294.

[11] **Cutler, D. M., and A. Lleras-Muney (2006)**: "Education and Health: Evaluating Theories and Evidence," NBER Working Paper No. 12352.

[12] **De Nardi M., E. French, and J. B. Jones (2010)**: "Why Do the Elderly Save? The Role of Medical Expenses," Journal of Political Economy, 118-1, 39-75.

[13] **Dynan, K. E., J. Skinner, and S. P. Zeldes (2004)**: "Do the Rich Save More?," Journal of Political Economy, 112, 397-444.

[14] **Fuchs, V. (1982)**: "Time Preference and Health: An Exploratory Study," Economic Aspects of Health, Second NBER Conference on Health in Stanford, 93-119.

[15] **Gourinchas, P. O., and J.A. Parker (2002)**: "Consumption over the Life Cycle," Econometrica, 70, 47-89.

[16] **Grossman, M. (1972)**: "On the Concept of Health Capital and the Demand for Health," Journal of Political Economy, 80-2, 223-255.

[17] **Grossman, M. (1975)**: "The Correlation Between Health and Schooling," Household Production and Consumption, N. Terleckyj (Ed.), 147-211.

[18] **Grossman, M. (2000)**: "The Human Capital Model," Handbook of Health Economics, Volume 1A, edited by Anthony J. Culyer and Joseph P. Newhouse. Amsterdam: North-Holland, Elsevier Science, 347-408.

[19] **Grossman, M. (2008)**: "The Relationship Between Health and Schooling," Eastern Economic Journal, 34, 281-292.

[20] **Gruber, J. (2002)**: "Taxes and Health Insurance," NBER Book Series Tax Policy and the Economy, 16, 37-66.

[21] **Gruber, J. (2005)**: "Tax Policy for Health Insurance," NBER Book Series Tax Policy and the Economy, 19, 39-64.

[22] **Guvenen, F. (2007)**: "Learning Your Earning: Are Income Shocks Really Very Persistent?," American Economic Review, 97, 687-712.

[23] **Guvenen, F. (2009)**: "An Empirical Investigation of Labor Income Processes," Review of Economic Dynamics, 12, 58-79.

[24] **Guvenen, F. and A. Smith (2012)**: "Inferring Labor Income Risk From Economic Choices: An Indirect Inference Approach," Working Paper.

[25] **Haider, J. S. (2001)**: "Earnings Instability and Earnings Inequality of Males in the United States: 1967-1991," Journal of Labor Economics, 19, 799-836.

[26] **Halliday, T., H. He, and H. Zhang (2009)**: "Health Investment Over the Life-Cycle," IZA Discussion Paper No. 4482.

[27] **Heckman, J. J., L. J. Lochner, and P. E. Todd (2003)**: "Fifty Years of Mincer Earnings Regressions," NBER Working Papers 9732, National Bureau of Economic Research, Inc.

[28] **Huggett, M. (1993)**: "The Risk-Free Rate in Heterogeneous-Agent Incomplete-Insurance Economies," Journal of Economic Dynamics and Control 17, 953-969.

[29] **Jeske, K., and S. Kitao (2009)**: "U.S. Tax Policy and Health Insurance Demand: Can a Regressive Policy Improve Welfare?," Journal of Monetary Economics, 56, 210-221.

[30] **Jung, J., and C. Tran (2010)**: "Medical Consumption over the Life Cycle: Facts from a U.S. Medical Expenditure Panel Survey," Towson University Working Paper No. 2010-09.

[31] **Juster, F. T., J. P. Lupton, J. P. Smith, and F. Stafford (2005)**: "The Decline in Household Saving and The Wealth Effect," The Review of Economics and Statistics, 87, 20-27.

[32] **Keane, M., and K. Wolpin (1997)**: "The Career Decisions of Young Men," Journal of Political Economy, 105, 473-522.

[33] **Kenkel, D. S. (1991)**: "Health Behavior, Health Knowledge, and Schooling," Journal of Political Economy, 99-2, 287-305.

[34] **Khwaja, A. W. (2007)**: "A Life Cycle Analysis of the Effects of Medicare on Individual Health Incentives and Health Outcomes," Duke University Working Paper.

[35] **Lillard, L.A., and Y. Weiss (1979)**: "Components of Variation in Panel Earnings Data: American Scientists, 1960-1970," Econometrica, 47, 437-454.

[36] **Mincer, J. (1974)**: "Schooling, Experience, and Earnings," New York: Columbia University Press.

[37] **Mullahy, J., and S. A. Robert (2008)**: "No Time to Lose? Time Constraints and Physical Activity," NBER Working Paper No. 14513.

[38] **Ozkan, S. (2011)**: "Income Inequality and Health Care Expenditures over the Life Cycle," Federal Reserve Board.

[39] **Palumbo, M. G. (1999)**: "Uncertain Medical Expenses and Precautionary Saving Near the End of the Life Cycle," Review of Economic Studies, 66-2, 395-421.

[40] **Podor, M. and T. J. Halliday (2011)**: "Health Status and the Allocation of Time," Working Paper, University of Hawai.

[41] **Ruhm, C. J. (2000)**: "Are Recessions Good for Your Health?," Quarterly Journal of Economics, 115-2, 617-650.

[42] **Russell, L. B., Y. Ibuka, and K. G. Abraham (2007)**: "Health-Related Activities in the American Time Use Survey," Medical Care, 45-7, 680-685.

[43] **Saffer, H., D. M. Dave, and M. Grossman (2011)**: "Racial, Ethnic, and Gender Differences in Physical Activity," NBER Working Paper No. 17413.

[44] **Sanders, K. (2011)** "Skill Uncertainty, Skill Accumulation, and Occupational Choice," Mimeo, University of Wisconsin, Madison.

[45] **U.S. Department of Health and Human Services (2002)**: "Physical Activity Fundamental to Preventing Disease," Office of the Assistant Secretary for Planning and Evaluation.

[46] **Venkateswaran, V. (2011)**: "Heterogeneous Information and Labor Market Fluctuations," Mimeo, UCLA.

[47] **Wolin, K. Y., G. G. Bennett, L. H. McNeill, G. Sorensen, and K. M. Emmons (2008)**: "Low Discretionary Time as a Barrier to Physical Activity and Intervention Uptake," American Journal of Health Behavior, 32-6, 563-569.

A Appendix

A.1 Characteristics of Wealth Distribution and College Share

In this section, I show the characteristics of wealth distribution and the shares of college graduates in wealth quantiles. *All* households are from any education level and any age, whereas *Primary* households consist of individuals 25-64 years of age with a completed education level of 9 years or more.

Table 12 shows that there is a high concentration of college graduates in the upper tail of the wealth distribution. The wealth-richest top 1 percent families have 25.88 percent of the wealth in the U.S. Of this group, 61.11 percent have a college degree. Given that the overall college graduate share is 21.13 percent, this implies a high concentration of college graduates in the wealth-richest group in the U.S. For households in the 95-99 quantile, which possess 24.24 percent of the wealth, the college graduate share is 50.93 percent. As we move to the lower tail of the wealth distribution, the college share diminishes. For the primary households,

the college share in the wealth distribution is similar. For the wealth-poorest quantile, the college share is only 12.50 percent for the primary households.

A.2 Skill-Biased Technological Change

In order to see the implications of the skill-biased technological change that occurred during the 1980s, using the estimates of the common components, I compute the ratio between the present discounted value of life-cycle earnings for college workers and the counterpart for non-college workers (worker-earnings-ratio (WER)) as given by

$$WER_t = \frac{\sum_{x=0}^{40} \frac{1}{(1+r)^x} Y_{t,x}^{col}}{\sum_{x=0}^{40} \frac{1}{(1+r)^x} Y_{t,x}^{ncol}}$$

where $Y_{t,x}^{ed} = exp\left(\overline{\gamma}_{0,t}^{ed} + \overline{\gamma}_{1,t}^{ed} x + \overline{\gamma}_{2,t}^{ed} x^2\right)$ for ed being either college or non-college graduate and for $t = 1968, 1969, ..., 1993$. I use the annual interest rate as 4% in this calculation. Figure 9 shows that the skill-biased technological change is an increasing ratio from 1980 onward. The WER ratio increases from 1.4 in 1980 to almost 1.8 in 1993.

Table 1: Means of Skill Components

Parameter	Description	College	Non-college
$\overline{\gamma}_0$	intercept	10.17***	9.91***
		(0.11)	(0.08)
$\overline{\gamma}_1$	linear	0.061***	0.040***
		(0.013)	(0.007)
$\overline{\gamma}_2$	quadratic	-0.00116***	-0.00076***
		(0.00036)	(0.00016)

p-values: ***<0.01, **<0.05, *<0.10

Table 2: Variances of Skill Components

Parameter	Description	College	Non-college
$\sigma^2_{\gamma_0}$	variance of intercept	0.246**	0.157***
		(0.122)	(0.036)
$\sigma^2_{\gamma_1}$	variance of linear	0.0025**	0.0010**
		(0.0011)	(0.0004)
$\sigma^2_{\gamma_2}$	variance of quadratic	0.0000013***	0.0000004***
		(0.0000005)	(0.0000001)
$\sigma_{\gamma_0\gamma_1}$	intercept-linear covariance	-0.0182	-0.0072**
		(0.0143)	(0.0029)
$\sigma_{\gamma_0\gamma_2}$	intercept-quadratic covariance	0.00039	0.00011*
		(0.00042)	(0.00006)
$\sigma_{\gamma_1\gamma_2}$	linear-quadratic covariance	-0.000054**	-0.000018**
		(0.000026)	(0.000008)

p-values: ***<0.01, **<0.05, *<0.10

Table 3: Shock Process

Parameter	Description	College	Non-college
ρ	persistence of AR(1)	0.835***	0.844***
		(0.152)	(0.049)
σ_η^2	variance of persistent	0.052	0.044***
		(0.034)	(0.014)
σ_ϵ^2	variance of transitory	0.067**	0.075
		(0.032)	(0.055)

p-values: ***<0.01, **<0.05, *<0.10

Table 4: Decomposition of Earnings Heterogeneity

Group	Age	Total	Skill	Shock
College	34	.350	.115 (33%)	.235
	44	.413	.174 (42%)	.238
	54	.482	.243 (50%)	.238
	64	.693	.454 (66%)	.238
Non-college	34	.327	.103 (32%)	.224
	44	.361	.133 (37%)	.228
	54	.403	.175 (43%)	.228
	64	.481	.253 (53%)	.228

Table 5: Decomposition of Skill Heterogeneity

Group	Age	Total	Intercept	Linear	Quadratic	Covariances
College	34	.115	.246	.25	.013	-.394
	44	.174	.246	1.00	.208	-1.280
	54	.243	.246	2.25	1.053	-3.306
	64	.454	.246	4.00	3.328	-7.120
Non-college	34	.103	.157	.10	.004	-.158
	44	.133	.157	.40	.064	-.488
	54	.175	.157	.90	.324	-1.206
	64	.253	.157	1.60	1.024	-2.528

Table 6: Savings Rate Profile in the Data

Data	Age	College	Non-college	Gap
SCF	25-34	11.2	9.4	**1.8**
	35-44	18.5	7.6	**10.9**
	45-58	13.7	11.5	**2.2**
CEX(1)	25-34	3.9	2.1	**1.8**
	35-44	6.1	2.9	**3.2**
	45-54	6.6	4.4	**2.2**
	55-64	10.5	5.8	**4.7**
PSID	25-34	15.2	7.3	**7.9**
	35-44	15.0	7.3	**7.7**
	45-59	19.0	9.9	**9.1**
CEX(2)	25-34	13.6	6.8	**6.8**
	35-44	14.9	10.6	**4.3**
	45-54	17.1	13.7	**3.4**
	55-64	20.3	14.9	**5.4**
CEX(3)	25-34	24.8	19.4	**5.4**
	35-44	26.3	23.3	**3.0**
	45-54	29.5	26.5	**3.0**
	55-64	31.2	25.2	**6.0**
CEX(4)	25-34	29.2	23.8	**5.4**
	35-44	31.2	27.7	**3.5**
	45-54	35.6	31.1	**4.5**
	55-64	36.0	30.3	**5.7**

Table 7: Parameters of the Earnings Profile

	Parameter	**Description**	**College**	**Non-college**
Skill	$\overline{\gamma}_0$	intercept	10.2	9.9
	$\overline{\gamma}_1$	linear	0.06	0.04
	$\overline{\gamma}_2$	quadratic	-0.0012	-0.0008
	$\sigma^2_{\gamma_1}$	variance of linear	0.0004	0.0001
Shock	ρ	persistence	0.85	0.85
	σ^2_η	variance of persistent	0.05	0.05
	σ^2_ϵ	variance of transitory	0.07	0.07

Table 8: Other Parameters of the Model

Parameter	**Description**	**Value**	**Source-Target**
J	max life span	56	age 80
j_R	retirement age	41	age 65
σ	risk aversion	2	standard
β	discount factor	0.998	K/Y = 3
α	capital share	0.36	standard
δ	depreciation rate	0.06	I/Y = 0.2
A	firm technology	0.84	norm. wage = 1
τ_{ss}	soc. security tax	0.10	clears soc. sec.
tr	acc. bequest transfer	0.07	clears acc. beq.

Table 9: Savings Rate Profile: Model vs Data

	Age	College	Non-college	Gap
SCF	25-34	11.2	9.4	**1.8**
	35-44	18.5	7.6	**10.9**
	45-58	13.7	11.5	**2.2**
CEX	25-34	3.9	2.1	**1.8**
	35-44	6.1	2.9	**3.2**
	45-54	6.6	4.4	**2.2**
	55-64	10.5	5.8	**4.7**
MODEL	25-34	7.4	5.4	**2.0**
	35-44	15.5	9.9	**5.6**
	45-54	17.7	12.3	**5.4**
	55-64	11.7	9.6	**2.1**

Table 10: Savings Rate Profile: Perfect Information vs Deterministic Income

	Age	College	Non-college	Gap
Perfect Information	25-34	8.5	9.6	**-1.1**
	35-44	12.7	12.4	**0.3**
	45-54	15.0	13.7	**1.3**
	55-64	4.9	6.4	**-1.5**
Deterministic Income	25-34	10.2	12.5	**-2.3**
	35-44	19.9	21.1	**-1.2**
	45-54	23.4	22.2	**1.2**
	55-64	12.3	13.1	**-0.8**

Table 11: Savings Rate Profile: Imperfect Information vs Time Preference

Model	Age	College	Non-college	Gap
II with same β	25-34	7.4	5.4	**2.0**
	35-44	15.5	9.9	**5.6**
	45-54	17.7	12.3	**5.4**
	55-64	11.7	9.6	**2.1**
PI with $\Delta\beta = 0.01$	25-34	10.4	8.3	**2.1**
	35-44	15.1	10.4	**4.7**
	45-54	17.0	12.4	**4.6**
	55-64	5.4	6.3	**-0.9**

Table 12: College Distribution in Wealth Quantiles

		0-20	20-40	40-60	60-80	80-95	95-99	99-100	Total
All	Share of wealth	-.94	1.22	4.91	13.86	30.82	24.24	25.88	100
	Share of college	10.71	12.52	18.73	23.77	35.81	50.93	61.11	21.13
Primary	Share of wealth	-.91	1.48	5.59	14.48	31.38	23.83	24.15	100
	Share of college	12.50	14.79	21.14	25.58	39.77	54.10	63.04	23.56

Table 13: Summary Statistics for the PSID 1968-1993

Year	Observation	Age	Income	Wage	Education	College %
1968	1,114	39.24	38,099	16.50	13.03	21.99
1969	1,155	39.65	39,723	17.24	13.04	21.90
1970	1,386	39.65	39,537	17.37	13.02	22.22
1971	1,479	39.61	38,867	17.60	13.03	22.52
1972	1,559	39.51	39,028	17.96	13.10	23.22
1973	1,690	39.00	40,367	18.25	13.15	24.26
1974	1,834	38.49	40,701	18.27	13.21	24.81
1975	1,975	38.13	38,181	17.56	13.27	25.52
1976	2,047	37.81	36,555	17.10	13.35	26.18
1977	2,166	37.64	38,092	17.55	13.36	26.18
1978	2,298	37.48	38,405	17.58	13.35	25.89
1979	2,440	37.22	38,822	17.89	13.35	25.29
1980	2,570	37.12	37,270	17.22	13.36	24.98
1981	2,674	36.99	35,321	16.62	13.38	25.13
1982	2,779	36.98	34,245	16.15	13.41	25.12
1983	2,788	37.09	34,902	16.56	13.50	26.47
1984	2,874	37.20	35,369	16.62	13.51	26.65
1985	2,978	37,24	36,924	17.03	13.52	26.76
1986	3,061	37.26	36,949	17.11	13.51	26.26
1987	3,129	37.55	37,089	17.06	13.52	26.27
1988	3,216	37.65	37,453	16.93	13.50	26.15
1989	3,292	37.91	37,708	17.08	13.51	25.97
1990	3,338	38.22	37,566	16.81	13.54	26.39
1991	3,731	38.57	36,880	16.54	13.44	24.66
1992	3,620	39.35	36,768	16.79	13.45	24.89
1993	3,280	40.12	39,629	18.25	13.50	25.55

Table 14: Summary Statistics for the MEPS 1996-2009

Employed		**College**			**High-School**	
	All	Men	Women	All	Men	Women
Health Exp	2838	2214	3431	2581	2100	3066
Health Status	0.82	0.83	0.81	0.76	0.77	0.75
Healthy Ratio	0.96	0.96	0.96	0.93	0.93	0.92
Age	41.0	41.4	40.6	42.0	41.0	42.5
Hourly wage	28.3	30.9	25.7	17.7	19.8	15.6
Weekly hour	41.7	44.0	39.5	40.1	42.9	37.3
White	0.83	0.84	0.82	0.81	0.83	0.79
Black	0.08	0.07	0.10	0.14	0.13	0.16
Married	0.66	0.69	0.62	0.62	0.64	0.59
Single	0.22	0.22	0.23	0.19	0.21	0.16
Observations	33815	16186	17629	69732	33451	36281
Retired		**College**			**High-School**	
	All	Men	Women	All	Men	Women
Health Exp	8330	8767	7574	8004	8199	7819
Health Status	0.71	0.70	0.72	0.65	0.64	0.67
Healthy Ratio	0.86	0.85	0.87	0.81	0.80	0.82
Age	72.0	72.0	72.0	72.4	72.3	72.5
White	0.89	0.90	0.88	0.90	0.91	0.89
Black	0.05	0.04	0.07	0.07	0.06	0.08
Married	0.71	0.82	0.52	0.62	0.76	0.49
Single	0.06	0.04	0.09	0.03	0.03	0.03
Observations	3369	2090	1279	8496	4101	4395

Table 15: Types and Sources of Health Expenditure

Type		**Expenditures**			**Percentages**	
	All	Employed	Retired	All	Employed	Retired
Total	3239	2675	8099	100	100	100
Office based	852	733	1873	26	27	23
Inpatient	827	611	2690	26	23	33
Prescription	648	523	1724	20	20	21
Outpatient	386	335	830	12	13	10
Dental	301	289	407	9	11	5
Emergency	104	102	128	3	4	2
Other	121	83	447	4	3	6
Source		**Expenditures**			**Percentages**	
	All	Employed	Retired	All	Employed	Retired
Total	3239	2675	8099	100	100	100
Out of Pocket	652	560	1454	20	21	18
Private	1816	1851	1516	56	69	19
Medicare	483	22	4455	15	1	55
Medicaid	59	55	95	2	2	1
Other	228	187	580	7	7	7
Observations	115412	103547	11865	115412	103547	11865

Table 16: Summary Statistics for the ATUS 2003-2011

Employed		**College**			**High-School**	
	All	Men	Women	All	Men	Women
Exercise, average	18.5	22.1	14.8	12.8	16.4	8.7
Exercise, extensive	0.23	0.25	0.21	0.13	0.13	0.12
Exercise, intensive	80.8	89.4	70.2	99.7	122.8	71.9
Age	41.9	42.4	41.4	43.1	42.2	44.1
Hourly wage	29.8	32.4	27.0	18.7	20.6	16.5
Weekly hour	43.6	46.2	40.8	41.4	44.3	38.3
White	0.83	0.84	0.82	0.83	0.84	0.81
Black	0.08	0.07	0.10	0.13	0.11	0.15
Married	0.67	0.71	0.63	0.62	0.64	0.60
Single	0.21	0.20	0.22	0.19	0.21	0.16
Observations	20778	10075	10703	28416	13288	15128
Retired		**College**			**High-School**	
	All	Men	Women	All	Men	Women
Exercise, average	22.8	28.6	16.6	14.6	22.1	10.2
Exercise, extensive	0.28	0.31	0.26	0.17	0.20	0.16
Exercise, intensive	80.5	93.2	64.3	84.3	108.3	66.0
Age	73.4	73.5	73.3	73.8	73.3	74.1
White	0.90	0.91	0.88	0.90	0.89	0.91
Black	0.07	0.06	0.09	0.08	0.09	0.07
Married	0.67	0.79	0.53	0.59	0.72	0.50
Single	0.05	0.04	0.07	0.03	0.04	0.03
Observations	3025	1385	1640	8726	2830	5896

Table 17: Parameters of the Benchmark Model

Parameter	Description	Value	Source-Target
	Demographics		
J	maximum life span	56	age 80
j_R	mandatory retirement age	41	age 65
	Preferences		
β	discount factor	0.988	K/Y = 3
σ_c	risk av. in consumption	2	standard
σ_l	utility parameter of leisure	4.44	frisch elasticity = 0.4
θ	utility parameter of health	-0.2	$h_{25,64} = 0.78$
$\phi_{s,j}$	utility from leisure	see text	labor supply profiles
	Firm Production		
α	capital share	0.36	standard
A	firm technology	0.84	wage = 1
δ_k	depr. rate of capital	0.06	I/Y = 0.20
	Health Investment		
ρ	exp.-exer. substitution	0.8	illustration
η	returns to scale in health	1	illustration
$\overline{\gamma}$	health technology	0.35	$m_{25,80} = \$3{,}240$
γ_0	efficiency of exercise	20	$e_{25,64} = 15$ mins
γ_1	age effect	-0.09	$e_{25,44}/e_{45,64} = 1.2$
γ_s	education effect	0.25	$e_{col}/e_{hs} = 1.5$
γ_r	retirement effect	-14	$e_{64}/e_{65} = 0.5$
d_0	depreciation rate	0.1	illustration
d_1	age effect	0.002	$h_{25,34}/h_{35,44} = 1.05$
d_2	age effect	0.00015	$h_{25,34}/h_{45,64} = 1.08$
d_r	retirement effect	0.05	illustration
	Health Insurance		
q_w	worker-copayment	0.2	data
q_r	retired-copayment	0.2	data
p_r	retired-premium	\$1,500	data
p_w	worker-premium	\$2,700	clears priv. ins.
	Government Services		
τ_{fed}	fed tax	0.08	clears Medicare
τ_{ss}	Soc. Sec. tax	0.10	clears Soc. Sec.
tr	acc. beq. transfer	\$2,100	clears acc. beq.

Figure 1: Earnings Profile Heterogeneity Implied by Estimates

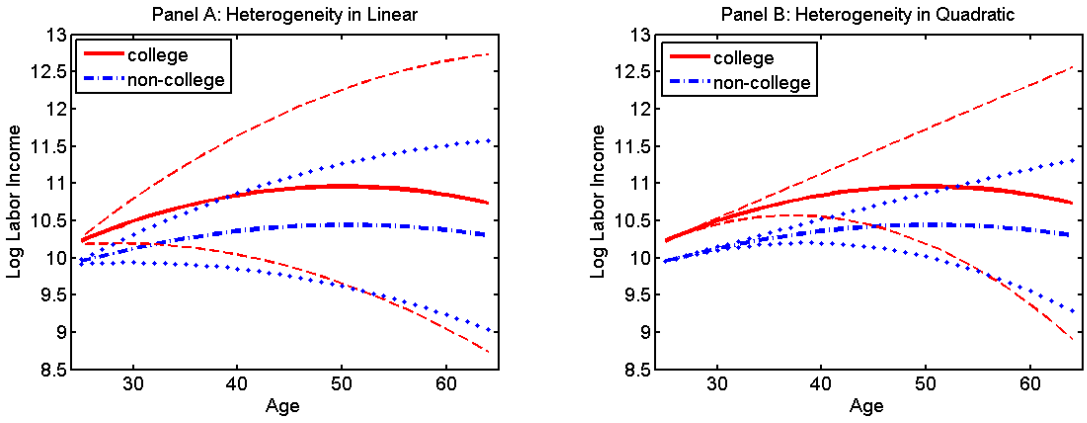

Figure 2: Evolution of Prior Variance

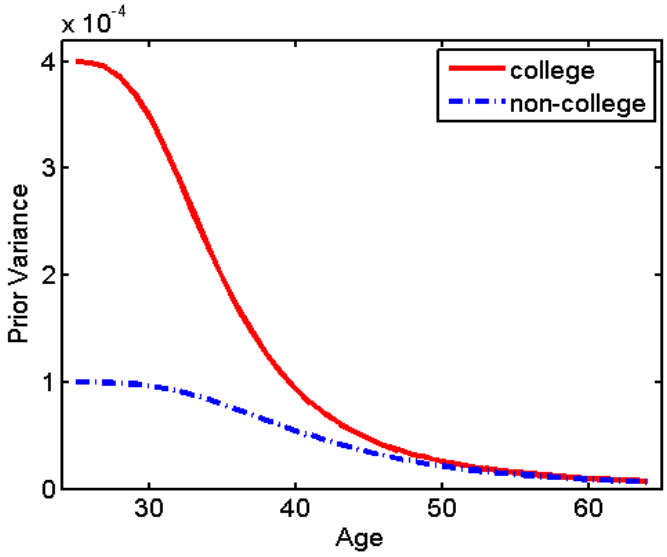

Figure 3: Expected Earnings Profile

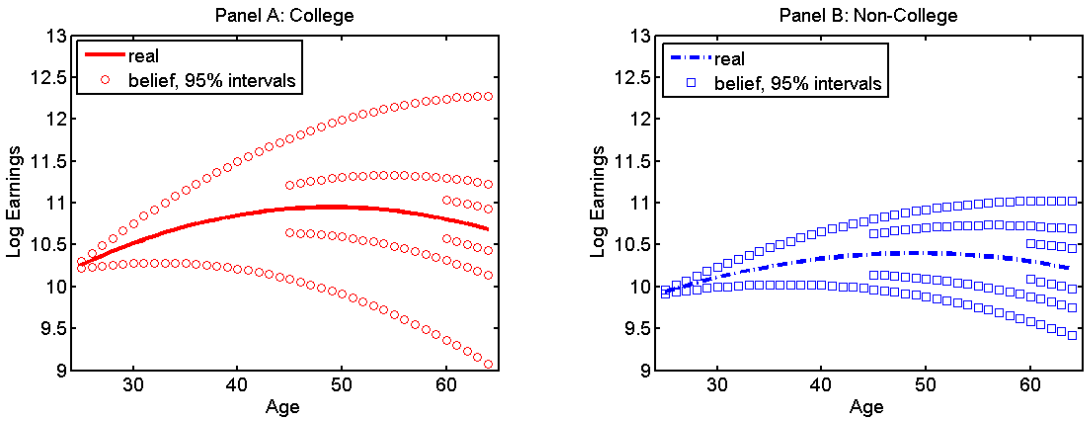

Figure 4: Savings Rate Gap at Age 25-34

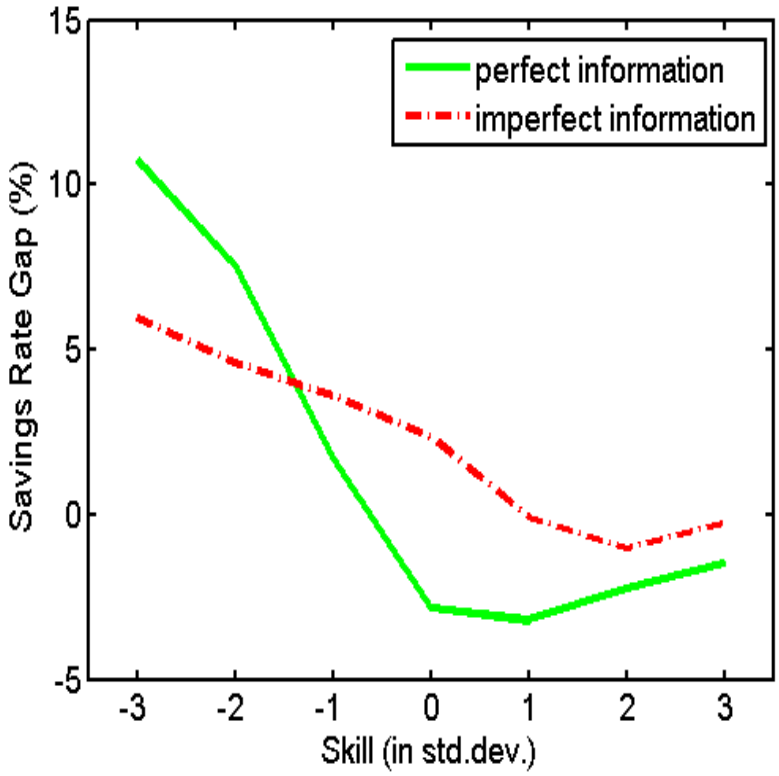

Figure 5: Savings Rate Gap at Age 55-64

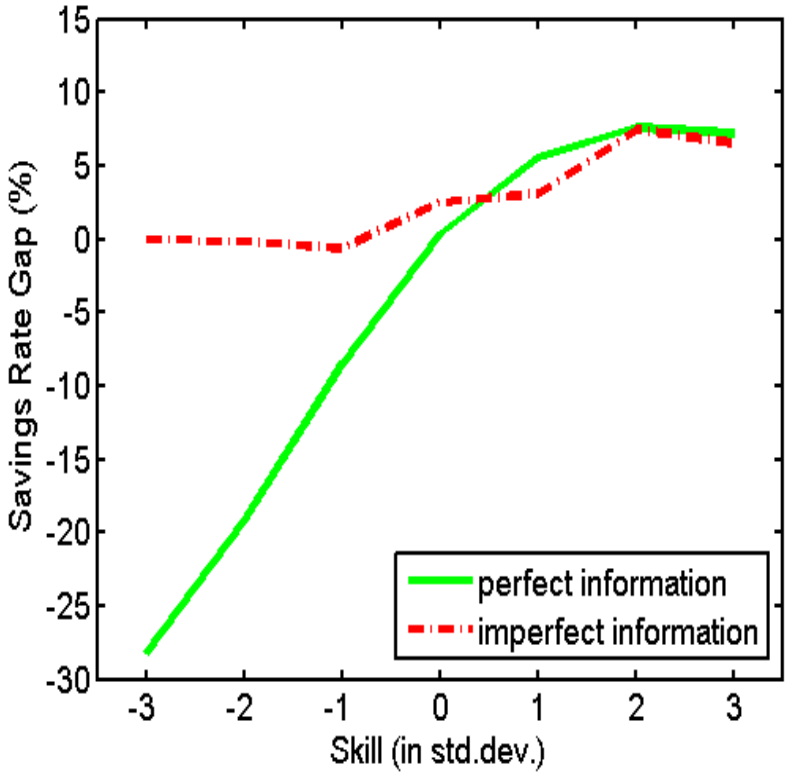

Figure 6: Time Preference Heterogeneity

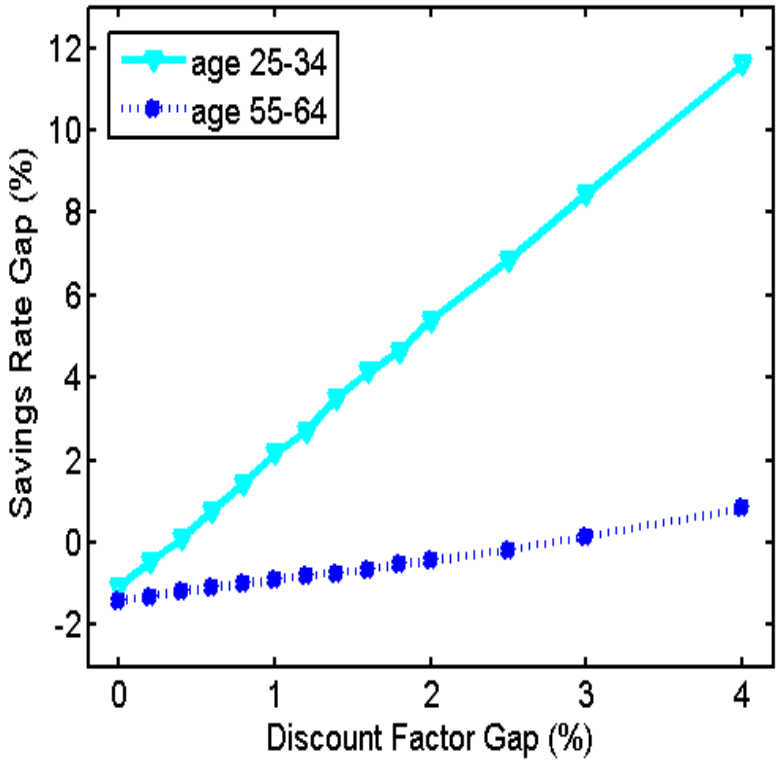

Figure 7: Savings Rate Gap at Age 25-34 with Time Preference

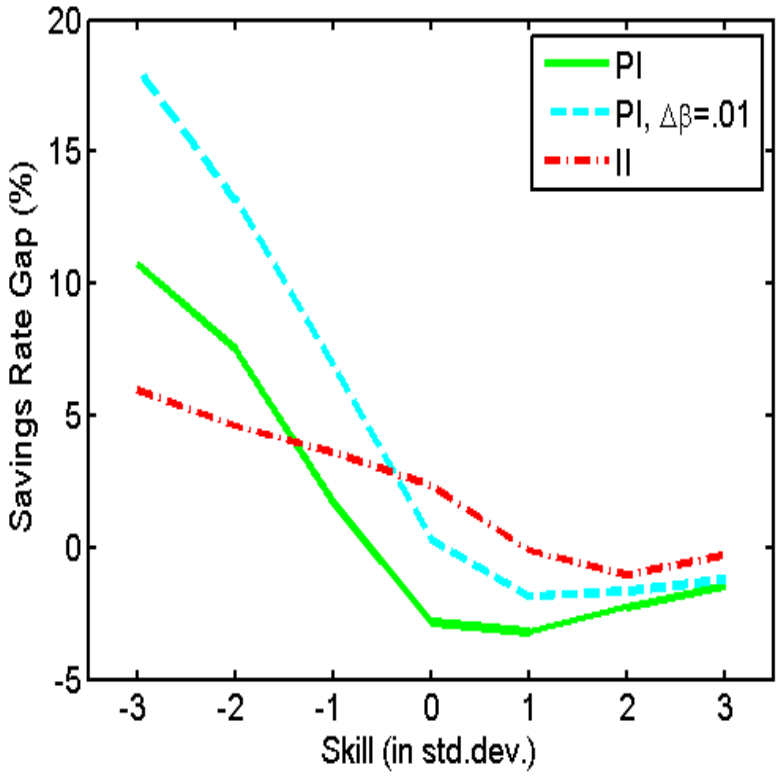

Figure 8: Savings Rate Gap at Age 55-64 with Time Preference

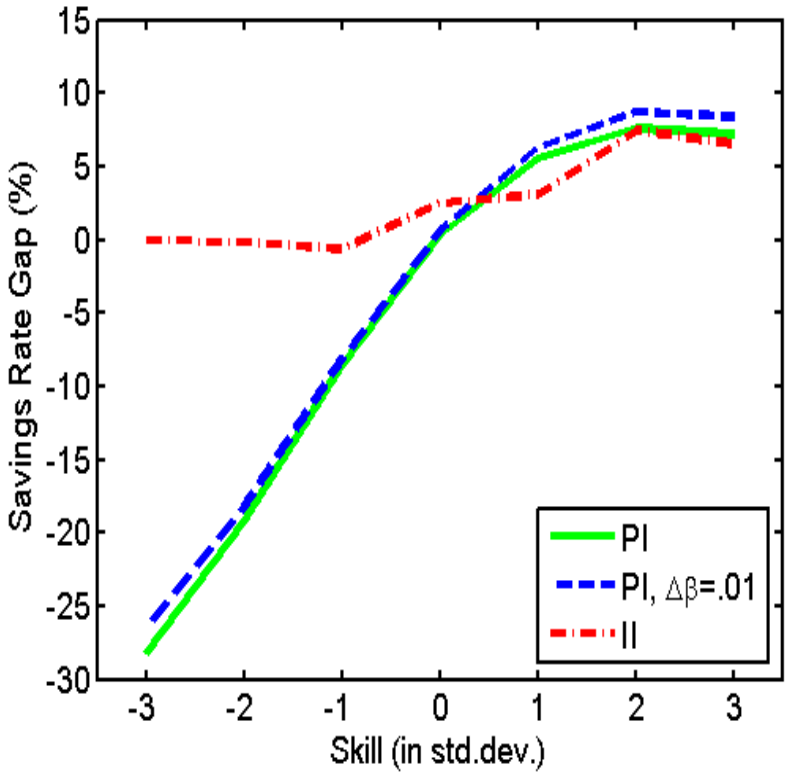

Figure 9: Worker Earnings Ratio

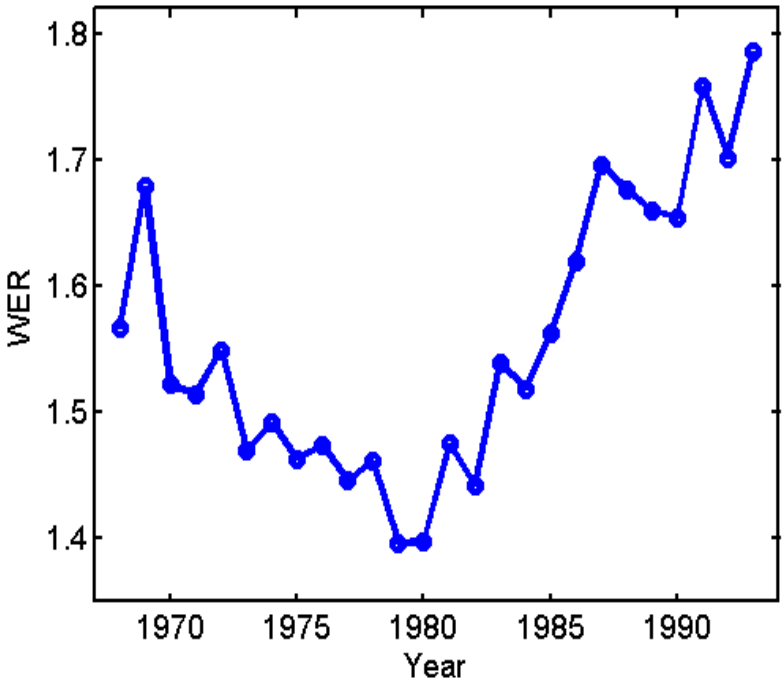

Figure 10: Healthy Ratio and Health Index in the Data

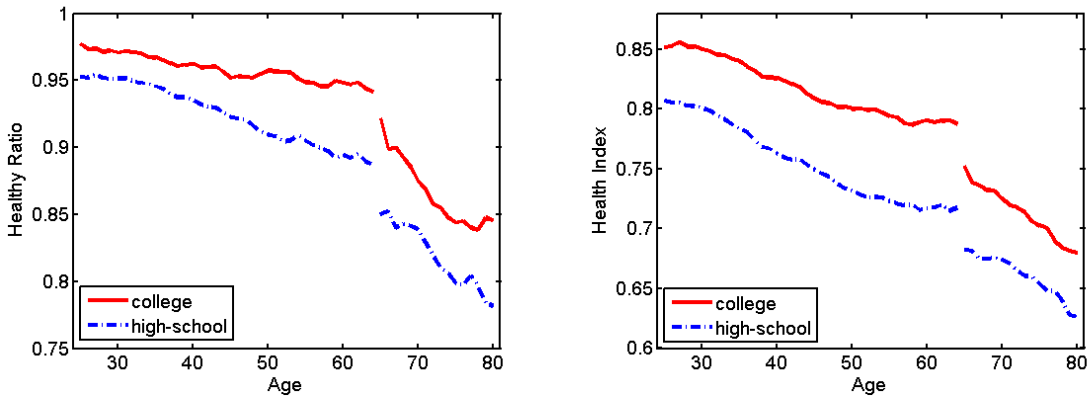

Figure 11: Health Expenditure in the Data

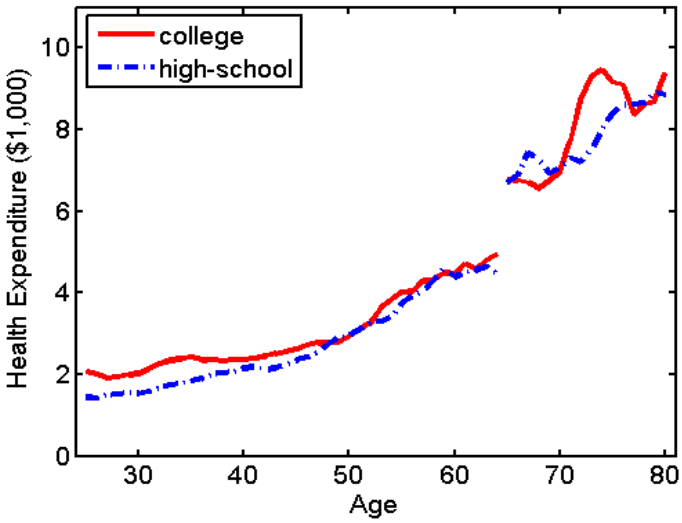

Figure 12: Time Allocated to Exercise in the Data

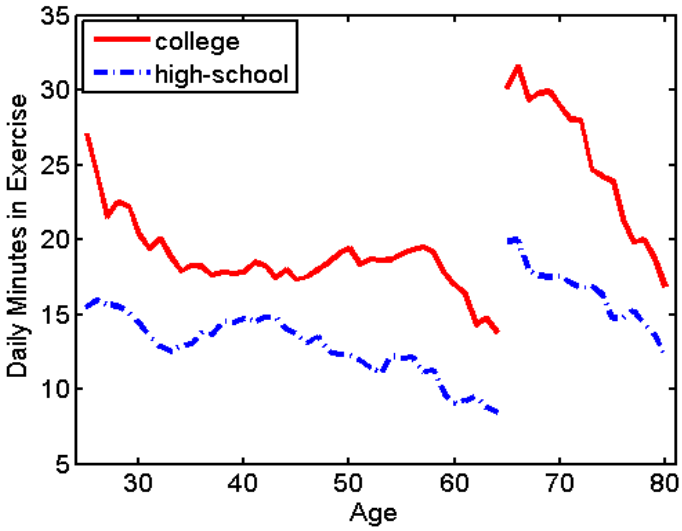

Figure 13: Extensive-Intensive Margins in Exercise in the Data

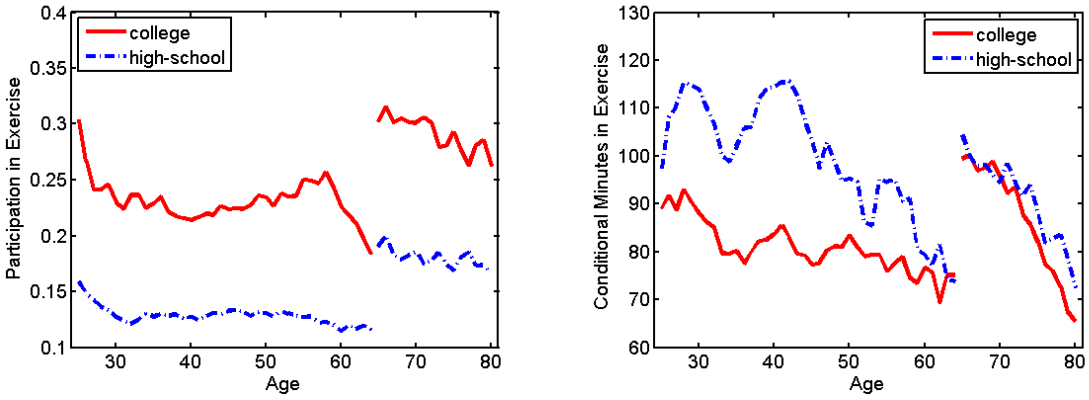

Figure 14: Time Allocated to Exercise in the Model

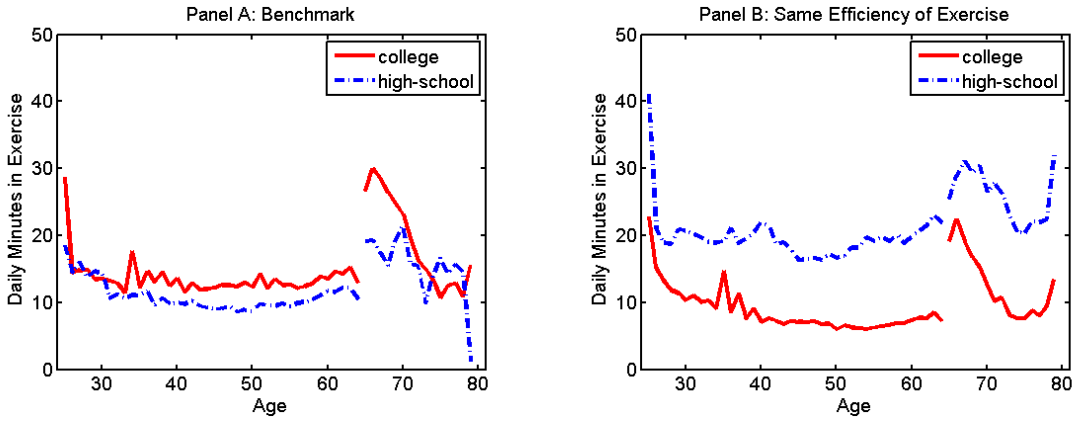

Figure 15: Health Expenditure in the Model

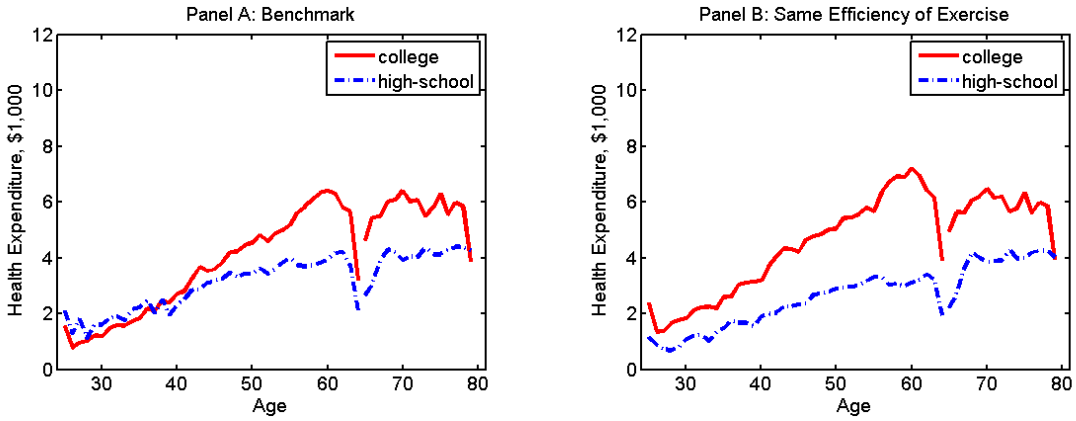

Figure 16: Health Status in the Model