The Dynamics of Educational Choices in the United States[†]

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Abstract

In this paper we develop and estimate a structural dynamic programming model following the seminal work by Keane and Wolpin (1997). We expand the model and introduce two types of schooling: Basic schooling and General schooling. These two types of schooling require different investment in human capital and have direct effect on the type of occupation that an individual can choose. Individuals can, in addition to being in school, be engaged in work activity. We also extend the model to include 16 different occupation-industry employment combinations. We use data from the National Longitudinal Survey, 1979. The results shed new light on the decision process individuals go through, especially at the early stages of their life cycle. The results indicate that it is extremely important to allow individual to be engaged in work activity while at school, as there have severe budget constraints that would not allow them to attend school otherwise. Also, the choice of education has huge and meaningful effects on the occupational choices in general, and their career paths in particular.

1 Introduction

What is the process by which individuals choose their career path and their investment in human capital? While it has always been recognized that these choices are dynamic by nature, obtaining estimates for a particular model was not feasible, mainly due to computing limitations. Recently dynamic models have been developed that made it possible to more thoroughly investigate issues related the decision process of individuals.

In a very influential paper, Keane and Wolpin (1997) (hereafter KW) investigated the career choices of young men, using a dynamic programming model and data from the 1979 National Longitudinal Survey of Youth (NLSY). In this paper they model the schooling and occupational choices of young men in the early part of their career, namely age 16 to 27. Our starting point in this paper is the model developed by KW. However, we expand the model in several important dimensions, which allows us to investigate more realistic situations. As in KW, the model is based on basic investment in human capital theory. Investment in one's human capital is the basis for occupational choice made later in life, and hence serves as the basis for our ability to understand and interpret observed schooling, occupational, and industrial choices.

As is typical in structural modeling, the estimation imposes the restrictions implied by the theory. In doing so, we make it possible to investigate the relevance of the theoretical restrictions. In particular it allows us to examine the fitness of the model's predictions against observed data. We find that the life-cycle human capital investment model does a remarkable job in fitting observed data on school attendance (by two types), work, occupational choices, industrial allocation of individuals, and wages in the NLSY data. The out-of-sample performance makes it quite clear that the model is very suitable for analyzing alternative policy measures as is done below.

The structural approach adopted here allows one to directly interpret the parameters' estimates. While these estimates are of interest in their own right, they also allow us to conduct careful examinations of the relative importance of various factors in one's career path. Specifically, we demonstrate the quantitative importance of school attainment and occupation-industry specific accumulation of skills. Moreover, we quantify a number of effects on decisions that stem from altering some of the parameters of the underlying environment. We consider: (a) changes in the monetary incentives for attending college and/or other educational attainments; (b) the impact of government intervention on the career path of individuals and occupational choices; (c) the impact of government intervention on acquisition of education later in life; and (d) examination of welfare implications and

distributional consequences of lifetime wealth and utility.

Recall that the general theory of human capital accumulation was developed primarily to interpret life cycle earnings profiles. From the very beginning, the theory concentrated mostly on explaining human capital investments in the form of schooling (e.g. Mincer 1958, Becker 1964, and Ben-Porath 1967). Consequently, the earlier empirical work concentrated exclusively on estimating the rates of return to schooling. The main problem with this literature is that, essentially, school attainment has been assumed to be exogenous, and not as it should be treated, namely a choice variable. Furthermore, there was almost no consideration of the effect of (unmeasured) ability on investment in human capital.

It has long been demonstrated in the literature that individuals are not similar on observe characteristics, let alone unobserved ones. Hence, their calculation on the individuals' rates of returns are likely to be different as well. As has been demonstrated by Willis and Rosen (1979) and Keane and Wolpin (1997), self-selection, based on their individual, observed and unobserved, characteristics plays a major role in the decision making process, one must incorporate these into the estimation as we do here.

It has also been documented in the literature the importance of on-the-job training in enhancing one's human capital. In that respect, we usually examine accumulation of job market experience, in general, and tenure within a firm in particular. While we abstract here from mobility decisions, and hence tenure on the job, we do treat experience as an additional endogenous variable, which stems from the decision making by the individuals regarding labor supply. Just like in the schooling decision, differences in endowments or other unobserved characteristics are likely to affect the choices made by different individuals. Hence, these considerations will also affect the interpretation of any cross-sectional relationship between earnings and work experience. We adopt here the general idea set forth by KW, but extend the model to allow for more realistic choices faced by the individuals.

Recent literature, specifically in KW, has demonstrated the vital need for controlling for unobserved heterogeneity, particularly that type of multidimensional heterogeneity which has varying skills across different occupations and industries. One line of research has taken a hedonic approach, where specific kinds of skills can be extracted from observed outcomes of workers, and each type of skill is priced differently in the market place (See e.g. Tinbergen 1951, Welch 1969, and Rosen 1974). An alternative approach is that adopted by KW, Heckman and Sedlacek (1985), and Willis (1986), where each individual's skill bundle maps into "task" units for which there is a market-determined price. We adopt here, as in KW the latter approach, and allow the tasks to be occupation-industry specific. Workers self-select themselves into occupations based on the occupation-specific skills they

possess (i.e., their occupation specific endowments) and the rental price of these skills. It is worth noting that, just as in the case of schooling and experience, one cannot compare earnings of observationally equivalent individuals across different occupations, because of the self-selection mechanism that drives the observed occupational choices.

This paper extends on the earlier work by KW. As in KW we consider self-selection in several dimensions, namely schooling, work, and occupational choices. However, we also allow the choices not to be mutually exclusive, in that one can work while at school, or can choose to work only part-time even after he/she finished his/her schooling. In addition we allow for two different types of schooling, which we term general and basic schooling.

An integral component for modeling schooling decisions is individuals' perception of the future returns to education relative to the alternative. However, there are at least two significant obstacles for empiricists when incorporating a satisfactory forecasting behavior in this context. First, the presence of unobservable heterogeneity which influences both outcomes and expectations. Second, even controlling for heterogeneity, future conditional wage distributions are unknown. To deal with the first problem we control, as explained above, for the individuals' multidimensional heterogeneity of skills. In order to get at the expectation of individuals about future outcomes, we allow the coefficients of the model to change over time, especially in a response to macro level changes in the factors affecting wages across occupations and industries. In a unique study carried out along these lines, Buchinsky and Leslie (2010) found that uncertainty about future outcomes play a major role, especially on schooling decisions. Also, recent literature provides considerable reasons to question the validity of the rational expectations assumption in this context. In a sequence of papers, Manski (1989, 1993a, 1993b) and Dominitz and Manski (1997) focus their attention on individual's perceptions of the rewards from education and rationalize the process by which people form expectations and make their decisions. The current study draws on the ideas expounded in these papers. This extends on the model of KW in which the conditional distribution of wages were assumed to be stationary.

A particularly important issue in the literature on human capital is the direct and indirect cost of education.[1] The structural nature of our model is well suited to studying this issue, so we also provide an analysis of the impact of tuition costs. In addition, we investigate the effects of liquidity constraints on individuals' educational choices by varying the initial level of wealth in the period immediately following high school graduation.

The remainder of the paper is organized as follows. In Section 2 we present our dynamic behavioral model and its unique features relative to the earlier literature. Section 3 describes

[1] See, for example, Flyer and Rosen (1997), Fuller, Manski and Wise (1982) and Kane (1995).

the NLSY data, based on which the model is estimated. It also provides details about the particular patterns observed in the data. Section 4 provides the results of the estimated model, and discusses their implications. In Section 5 will provide a set of policy experiments that are designed to answer specific questions and discuss the implications of alternative policy instruments. A summary and some concluding remarks are offered in Section 6. An appendix details the estimation method employed and provides some general descriptions of all the approximation methods employed for computing the value functions at each calendar time.

2 The Model

The model is a dynamic programming (DP) model in which individuals make investment decisions in human capital and choices of their occupations over time. An individual maximizes the discounted present value of the utility given by

$$\sum_{t=t_0}^{T} \delta^{t-t_0} E\left[U\left(c_{it}, l_{it}, s_{Git}, s_{Bit}\right) | z_{it}\right],$$

subject to the following constraints:

$$\begin{aligned}
s_{Git} &\leq \overline{S}_G, \\
s_{Bit} &\leq \overline{S}_B, \\
l_{it} &= 5,824 - hp_{it} - hw_{it} - tc^I_{t11} d_{1it} - tc^I_{t21} d_{2it}, \\
B_{it} &= R_t[B_{it-1} + A_{it} + \sum_{j=1}^{5}\sum_{m=1}^{4} d^O_{jit} d^I_{mit} R_{jm}\left(z_{it}, t\right) - c_{it} - \left(tc^D_{t1} + tc^I_{t12}\right) d_{1it} \\
&\quad - \left(tc^D_{t2} + tc^I_{t22}\right) d_{2it}], \\
B_{ii} &\geq \underline{B},
\end{aligned}$$

where z_{it} denotes the state vector to be defined below. The quantity $U\left(c_{it}, l_{it}, s_{Git}, s_{Bit}\right)$ denotes the single-period utility, which is a function of a single consumption good, denoted c_{it}, leisure, denoted l_{it}, and the level of completed education. We allow education to be of two possible types, namely *general education*, denoted s_{Git}, and *basic education*, denoted s_{Bit}.

The quantities hp_{it} and hw_{it} denote the time invested in home production and at work (if the individual chooses to work). We assume here that there is an upper bound on the

amount of attainable general and basic education, denoted $\overline{S}_G$ and $\overline{S}_B$, respectively. To simplify the presentation below, we define two dummy variables corresponding to the two possible types of education an individual can obtain.

The quantities tc_{t1}^D and tc_{t12}^I represent the monetary costs associated with general education, while tc_{t2}^D and tc_{t22}^I represent the monetary costs associated with basic education, as is explained below. Hence, the "budget" on the total amount of possible leisure time is given by the number of available hours (i.e., $5,824$) minus all time spent on other tasks.

The quantity $R_{jm}(z_{it}, t)$ represents the reward associated with employment at occupation j and industry m. Also R_t is the gross interest rate on the net wealth, that is, B_{it}, carried over to the next period, while A_{it} is non-earned income. Note that we assume that there is a constraint on borrowing, in that B_{it} cannot go below a certain minimum level of $\underline{B}$.

The single-period utility is given by

$$\begin{aligned} U(c_{it}, l_{it}, s_{Git}, s_{Bit}) &= \frac{c_{it}^{1-\alpha_c}}{1-\alpha_c} + \frac{l_{it}^{1-\alpha_l}}{1-\alpha_l} + \gamma_{11}^e d_{1it} \exp(\gamma_{12} s_{Git}) + \gamma_{21}^e d_{2it} \exp(\gamma_{22} s_{Bit}) \\ &\quad + \mathbf{1}(s_{Git} > 0)\left(a_e^G s_{Git} - b_e^G s_{Git}^2\right)(1 - \exp(-\rho_{cG} c_{it}))(1 - \exp(-\rho_{lG} l_{it})) \\ &\quad + \mathbf{1}(s_{Bit} > 0)\left(a_e^B s_{Bit} - b_e^B s_{Bit}^2\right)(1 - \exp(-\rho_{cB} c_{it}))(1 - \exp(-\rho_{lB} l_{it})), \end{aligned} \tag{1}$$

where the first two terms represent the direct utility from the single-good consumption and leisure, respectively. The third and forth terms are included to allow for the individual to have direct utility (or disutility, depending on the coefficients γ_{11}, γ_{12}, γ_{21}, and γ_{22}) from acquiring education, that is, when one of the dummy variables, d_{1it} or d_{2it}, takes the value one. These dummy variables are choice variables as is explained in detail below.

The last two terms are included to allow for an effect of education on the quality of consumption and leisure. Specifically, the level of utility from education depends on the level of consumption and leisure, that is, the higher the level of education the greater the utility that one obtains from a given level of consumption and leisure. We hypothesize that, for example, the general education $a_e^G > 0$, $b_e^G > 0$, $\rho_{cG} > 0$, and $\rho_{lG} > 0$. That is, the utility of consumption rises with the level of education at a decreasing rate, because of one's ability to consume more quality goods, such as cultural amenities, etc. Nevertheless, the increase of the utility as a function of education is bounded, as implied by the terms $(1 - \exp(-\rho_{cG} c_{it}))$ and $(1 - \exp(-\rho_{lG} l_{it}))$. That is, above a certain level of education the ability to extract more utility from the same level of consumption declines. The same principal applies for basic education, only that we permit the parameters to differ from those for the general education.

2.1 The Choices

There are a number of choices that individuals make in each and every period. First, an individual chooses whether or not to attend school. Second, an individual chooses whether or not to work and in which specific occupation.

Schooling choices:

In each period an individual chooses whether or not to attend school. The individual is faced with two schooling choices. One choice is a four-year college, while the other is a two-year college or any other basic type school. We refer to the first educational alternative as the *general education*, and similarly, we refer to the second educational alternative as the *basic education*. We assume that the first choice provide a more valuable education, in that the quality of the first alternative is higher than that of the second alternative. However, this hypothesis is testable. In the estimation we do not restrict the parameters to be such that this hypothesis will be satisfied, but rather test it. We define two dummy variables to denote the particular educational choice. Let

$$d_{1it} = \begin{cases} 1 & \text{if the individual } i \text{ chooses general education in period } t, \\ 0 & \text{otherwise,} \end{cases}$$

and similarly, let

$$d_{2it} = \begin{cases} 1 & \text{if the individual } i \text{ chooses basic education in period } t, \\ 0 & \text{otherwise.} \end{cases}$$

Occupational choices:

It has been documented in the literature that there are considerable number of individuals who choose to work while at school. After specifying the educational choices faced by an individual we further extend the model to allow each individual to be engaged in (at least some) work while at school.

In case an individuals chooses to work, he/she chooses among five alternative occupations, given by:

1. *Technical*: Including technical, professional, kindred workers, sales workers, and all service workers (except for workers in private households) ;

2. *Managerial*: Including managerial and administrators including farm managers;

3. *Laborers*: Including all operatives workers, laborers (including farm laborers, forestry, and fishing), clerical and unskilled workers; and

4. *Expert workers*: Including precision production, craft, and repair occupations.

There are also four possible industries in which an individual can work. These are given by:

1. *Production*: Including agriculture, mining, construction, manufacturing, transportation, communication, or public utility;

3. *Trade*: Including both wholesale and retail;

3. *Services*: Including finance, insurance, real estate, repair services, personal services, entertainment, and recreation services; and

4. *Professional*: Including professional and related services and public administration.

However, unlike the occupational choice, industry is not chosen by the individual, but rather depends, in a distributional sense, on the occupational choice and the state vector z_{it}. An individual can find himself/herself in one of the four alternative industries.

We define two sets of dummy variables for the occupational and industrial allocations, respectively. For the occupations we have for each individual in each time period:

$$d_{jit}^{O} = \begin{cases} 1 & \text{if the } j\text{th occupation is chosen,} \\ 0 & \text{otherwise,} \end{cases}$$

for $j = 1, ..., 5$.

Similarly for the industrial allocation we have

$$d_{mit}^{I} = \begin{cases} 1 & \text{if located in the } m\text{th industry,} \\ 0 & \text{otherwise,} \end{cases}$$

for $m = 1, ..., 4$.

As indicated above, the main difference between d_{jit}^{O} and d_{mit}^{I} is that the former is chosen and the latter is realized after the occupation has been chosen. Specifically, conditional on the occupational choice, we assume the following multinomial distribution for the industry in which the individual will be located:

$$\begin{aligned} \varphi_{mj}(z_{it}, d_{jit}^{O}) &= \Pr\left(d_{lit}^{I} = 1 | d_{jit}^{O}, z_{it}\right) \\ &= \Phi\left(x'_{mjit}\eta_{mj} + \sum_{m=1}^{4} \tau_m d_{mit-1}^{I} + \tau_p d_{3it}^{p}\right), \end{aligned} \tag{2}$$

where d_{3it}^{p} denotes whether or not the individual works in a part-time job (see the exact definition below). Note that in this specification the probability of being in a certain industry

is a function of past assignments, i.e., d^I_{mit-1}, which allows us to capture the time dependence inherent in the data. The variables in x_{mit} affecting the industrial assignment include the experience accumulated in the relevant occupation-industry composition, the level of education of the individual, and the overall situation in the economy, as represented by the macro indicators described below, that is

$$x_{mjit} = \left(s_{Git}d_{1it} + s_{Bit}d_{2it}, x^O_{jit}, x^I_{mit}, MC'_{it}\right)',$$

where x^O_{jit} and x^I_{mit} denote the experience accumulated in occupation j and industry m ($j = 1, ..., 5;\ m = 1, ...4$), $s_{Git}d_{1it} + s_{Bit}d_{2it}$ gives the acquired level of education, which either general or basic education, depending whether $d_{1it} = 1$, or $d_{2it} = 1$, and MC_{it} is a vector of macro variables as explained in detail below.

Note that in order to estimate these probabilities we need not solve the DP model. These probabilities can be estimated for all industries $m = 1, ...4$, from the sub-sample of individuals who choose occupations $j = 1, ..., 5$. In principle (subject to the availability of data) we can let the coefficients vary over time, but this will create a problem of forecasting into the future for the purpose of computing the value function at each period.

Note that one can actually allow the industry to be chosen as well, but it would add considerable complication into the model, in that four more choices would be available. Instead, the current assumption allows the individual to simply integrate over the conditional distribution of the industrial allocations, conditional on his/her occupational choice.

2.2 Part- Versus Full-time Activity

As indicated above we allow an individual to work while at school. Specifically, we assume that an individual can work part-time if he/she chooses general schooling, while if the individual can work part-time or full-time if he/she chooses basic schooling.

Moreover, there is considerable evidence that there are many individuals who do not work full-time even when do not attend school. To incorporate this feature we allow an individual to choose between a full-time job, a part-time job, or completely be engaged in home production. Therefore, we define the following dummy variables for each individual i in each time period t:

$$d^h_{3it} = \begin{cases} 1 & \text{if full-time in home production,} \\ 0 & \text{otherwise.} \end{cases} \tag{3}$$

Similarly, we define the full-time and part-time choices

$$d_{3it}^{f} = \begin{cases} 1 & \text{if a full-time job is chosen} \\ 0 & \text{otherwise,} \end{cases} \tag{4}$$

and

$$d_{3it}^{p} = \begin{cases} 1 & \text{if a part-time job is chosen} \\ 0 & \text{otherwise,} \end{cases} \tag{5}$$

Note that, by definition, we have that

$$d_{3it}^{h} + d_{3it}^{f} + d_{3it}^{p} = 1,$$

regardless of what the other activity (school or work) that the individual is engaged in.

Even if an individual has a full-time job he/she has to take care of some tasks at home. Nevertheless, the amount of time invested in home production varies with the choice, that is, a person who works in a full-time job is likely to invest less in home production than a person who is engaged in only part-time job, or does not work at all. To capture these potential differential effects across the three employment choices we specify the following equations for the number of hours one is engaged in home production:

$$hp_{it} = hp_{it}^{h} d_{3it}^{h} + hp_{it}^{f} d_{3it}^{f} + hp_{it}^{p} d_{3it}^{p},$$

where d_{3it}^{h}, d_{3it}^{f}, and d_{3it}^{p} are defined in (3), (4), and (5), while for the time spent in home production, in hours per year, we have:

$$\begin{aligned} hp_{it}^{h} &= \exp\left\{\alpha_i^{h} + x_{hit}'\beta_{hh} + \varepsilon_{hit}\right\}, \\ hp_{it}^{f} &= \exp\left\{\alpha_i^{f} + x_{hit}'\beta_{hf} + \varepsilon_{hit}\right\}, \quad \text{and} \\ hp_{it}^{p} &= \exp\left\{\alpha_i^{p} + x_{hit}'\beta_{hp} + \varepsilon_{hit}\right\}, \end{aligned} \tag{6}$$

which contains variables of family characteristics, job market experience of the individual, education, etc. Note that in this specification it is assumed that the error ε_{hit} is common to all choices, that is, the idiosyncractic shock that affects the number of hours worked at home is independent of the specific employment choice.

We also define the number of hours of work per year on the job. If a person works in a full-time job then he/she spends 2,000 hours per year working (40 hour per week $\times$ 50 weeks). If a person works in a part-time job, then he/she works 1,000 hours per year.

2.3 The Cost of Education

We now define the costs associated with the alternative choices of education.

General schooling:

Here we have

$$C_1(z_{it}, t) = tc_{t1}^D I(s_{Git} \geq 12) + tc_{t1}^I I(s_{Git} \geq 12) + \varepsilon_{1it}, \tag{7}$$

where α_{1i} denotes the endowment of the person at the beginning of the sample period, tc_{t1}^D denotes the direct costs associated with attending a school (i.e., tuition, registration fees, books, etc.), while tc_{t1}^I denotes the indirect costs associated with school attendance. More specifically,

$$tc_{t1}^I = tc_{t11}^I + tc_{t12}^I, \tag{8}$$

where tc_{t11}^I denotes the costs associated with the fact the an individual might be out of school for a while and hence might have to incur the cost of "forgetting how to study". The costs tc_{t12}^I denotes the costs that are associated with having to go to school and are related to the family and background variables.

Specifically we have

$$tc_{t11}^I = \alpha_{1i} + \sum_{m=1}^{M-1} \lambda_m^G I\left(s_{Git}^O = m\right) + \lambda_M^G I\left(s_{Git}^O \geq M\right),$$

where s_{Git}^O denotes the number of years the individual was out of school at the beginning of period t.

For the other indirect costs we have

$$tc_{t12}^I = x_{cit}' \phi_{t1}^G, \tag{9}$$

where x_{cit} is a vector of variables containing family characteristics, similar to the ones included in x_{hit} defined in (6).

Basic schooling:

Here we have

$$C_2(z_{it}, t) = tc_{t2}^D I(s_{Bit} \geq 12) + tc_{t2}^I I(s_{Bit} \geq 12) + \varepsilon_{2it}, \tag{10}$$

where α_{2i} denotes the endowment of the person at the beginning of the sample period. Similar to the choice of general schooling, we let tc_{t1}^D denote the direct costs associated with attending a school. We also let tc_{t2}^I denote the indirect costs associated with basic school attendance. As for the general school choice we break down the indirect costs into two components:

$$tc_{t2}^I = tc_{t21}^I + tc_{t22}^I. \tag{11}$$

The cost tc_{t21}^I denotes the costs associated with the fact the an individual might be out of school for a while and hence might have to incur the cost of "forgetting how to study", and is given by

$$tc_{t21}^I = \alpha_{2i} + \sum_{m=1}^{M-1} \lambda_m^B I\left(s_{Bit}^O = m\right) + \lambda_M^B I\left(s_{Bit}^O \geq M\right),$$

where s_{Git}^O denotes the number of years the individual was out of school at the beginning of period t. As for the general education, the costs tc_{t22}^I denotes the costs that are associated with having to go to school and are related to the family and background variables, that is,

$$tc_{22}^I = x_{cit}' \phi_{t2}^B, \tag{12}$$

where x_{cit} is the same as defined above for general schooling.

We define two different types of education for several reasons. In reality these types of choices, although more refined, are quite common. Second, people with different educational attainment do choose different career paths, likely because there are people who are good at doing some tasks, but not good at others. Consequently, the return to their investment would be maximized by self-selecting themselves into the right occupation. Here we want to examine this aspect and capture the (potential) differential effects of educational attainments across alternative occupations and industries.

To do that we separate the two types of educations and measure the individual's respective achievement in each of these types. We assume that if a person has up to high school education then his/her education is basic education, and denote it by s_{Bit}. However, if an individual continues with acquiring general schooling, then we consider his schooling, including that obtained at the elementary and high school level, to be general schooling and denote it by s_{Git}. A third possible case is that the individual decides to switch from one type of education to another, in which case the last level of obtained education is the one that determines which of the two types of education the individual has. Note that, by definition, we have that either $s_{Git} = 0$, or $s_{Bit} = 0$.

2.4 The Occupations-Industry Reward Functions

It is important to emphasize here that the individual knows exactly what is the outcome of the industrial allocation right after he/she makes his/her occupational choice.

In general there are 20 different possible occupation-industry combinations. However, some are not feasible in reality. Below we specify a generic reward function for an occupation-industry combination. Specifically, the reward function is simply the wage in the particular occupation-industry combination, given by

$$\begin{aligned} R_{jm}(z_{it},t) &= d_{3it}^{f} w_{jm}^{f}(z_{it},t) + d_{3it}^{p} w_{jm}^{p}(z_{it},t) \\ &= r_{jm}^{*}(t) e_{jm}(z_{it},t), \end{aligned} \tag{13}$$

where $w_{jm}^{f}(z_{it},t)$ and $w_{jm}^{p}(z_{it},t)$ represent the wage associated with full- and part-time jobs, respectively, where

$$\begin{aligned} w_{jm}^{f}(z_{it},t) &= r_{jm}^{f*}(t) e_{jm}(z_{it},t), \\ w_{jm}^{p}(z_{it},t) &= r_{jm}^{p*}(t) e_{jm}(z_{it},t), \end{aligned}$$

and $r_{jm}^{f*}(t)$ and $r_{jm}^{p*}(t)$ represent the unit of skill prices in occupation j and industry m for full- and part-time workers, respectively. The quantity $e_{jm}(z_{it},t)$ represents the total number of productive units that the individual has. This number, as well as the unit price, can, and likely does, change over time as a result of macro economic shock, change in technology, etc. in the economy as a whole. In general we have

$$e_{jm}(z_{it},t) = \exp\left\{\alpha_{ijm} + x_{jmit}^{*\prime}\beta_{jm}^{*}(t) + \varepsilon_{jmit}\right\}, \tag{14}$$

where ε_{jmit} represents idiosyncratic skill technology shock (or any other shock) to the individual agent.

Below we discuss in detail the specific structure of the regressor vector x_{jmit}^{*} and the evolution of $\beta_{jm}^{*}(t)$, $r_{jm}^{f*}(t)$, and $r_{jm}^{p*}(t)$ over time. However, to do that it is convenient to first introduce additional notations and some definitions of new variables.

As explained above we allow individuals to have differential returns on their human capital. These returns are allowed to vary across the different occupation-industry combinations, as well as across the alternative types of educations, namely general and basic education.

We also distinguish between the different types of human capital that are accumulated

on the job. Obviously, experience that is accumulated in a given occupation, and/or an industry, adds to the general human capital of the individual, but it cannot be fully transferred across different occupations and industries. Hence, the rewards for a given composition of experiences will differ across all occupation-industry combinations. To take into account these possible differential effects we also keep track of all the experiences acquired at each of the feasible occupation-industry combinations. We denote an experience accumulated at a given occupation by x_j^O (for $j = 1, ..., 5$) and an experience accumulated at a given industry by x_m^I (for $m = 1, ..., 4$).

Before we specify the content of $x^*_{jmit}$from (14) we first rewrite $R_{jm}(z_{it}, t)$ from (13) as follows

$$\begin{aligned} R_{jm}(z_{it}, t) &= r^{f*}_{jm}(t) \exp\left\{\alpha^{OI}_{ijm} + x^{*\prime}_{jmit}\beta^*_{jm}(t) + \varepsilon_{jmit}\right\} d^f_{3it} \\ &\quad + r^{p*}_{jm}(t) \exp\left\{\alpha^{OI}_{ijm} + x^{*\prime}_{jmit}\beta^*_{jm}(t) + \varepsilon_{jmit}\right\} d^p_{3it} \\ &= \exp\left\{\alpha^{OI}_{ijm} + r^f_{jm}(t) + x^{*\prime}_{jmit}\beta^*_{jm}(t) + \varepsilon_{jmit}\right\} d^f_{3it} \\ &\quad + \exp\left\{\alpha^{OI}_{ijm} + r^p_{jm}(t) + x^{*\prime}_{jmit}\beta^*_{jm}(t) + \varepsilon_{jmit}\right\} d^p_{3it} \\ &= \exp\left\{\alpha^O_{ij}\alpha^I_{im} + x'_{jmit}\beta^f_{jm}(t) + \varepsilon_{jmit}\right\} d^f_{3it} \\ &\quad + \exp\left\{\alpha^O_{ij}\alpha^I_{im} + x'_{jmit}\beta^p_{jm}(t) + \varepsilon_{jmit}\right\} d^p_{3it}, \end{aligned} \tag{15}$$

where

$$\begin{aligned} r^v_{jm}(t) &= \log r^{v*}_{jm}(t), \\ x'_{jmit} &= \left(1, x^{*\prime}_{jmit}\right), \quad \text{and} \\ \beta^v_{jm}(t)' &= \left(r^v_{jm}(t), \beta^*_{jm}(t)'\right), \quad \text{for } v = f, p. \end{aligned}$$

Note that in the last equality of (15) we explicitly add an assumption that $\alpha^{OI}_{ijm} = \alpha^O_{ij}\alpha^I_{im}$, that is, the fixed effect across a given occupation-industry combination is simply the product of an occupation specific effect and an industry specific effect. Also, there might be a difference between the unit price of skill for part- and full-time worker, that is, $r^f_{jm}(t)$ need not be equal to $r^p_{jm}(t)$. In fact, empirical studies indicate that $r^f_{jm}(t) > r^p_{jm}(t)$. Finally, the vector x^*_{jmit} is given by

$$x^{*\prime}_{jmit} = \left(s_{Git}d_{1it} + s_{Bit}d_{2it}, s^2_{Git}d_{1it} + s^2_{Bit}d_{2it}, x^O_{jit}, \left(x^O_{jit}\right)^2, x^I_{mit}, \left(x^I_{mit}\right)^2\right).$$

Distributional assumptions:

Given the specification above one needs to make some simplifying assumptions about the distribution of the vector of errors given, from (6), (7), (10) and (15), by

$$\varepsilon_{it} = \left(\varepsilon_{1it}, \varepsilon_{2it}, \varepsilon_{3it}, \varepsilon_{11it}, ..., \varepsilon_{14it}, \varepsilon_{51it}, ..., \varepsilon_{54it}\right)', \tag{16}$$

which is a vector with 23 entries. Practically, one cannot hope to estimate the dynamic model without further simplification of the error structure.

We assume that for each occupation-industry combination we have

$$\varepsilon_{jmit} = \varepsilon^O_{jit} + \tau_m \varepsilon^I_{mit}, \tag{17}$$

for $j = 1, ..., 5$ and $m = 1, ..., 4$.

Hence ε_{it} from (16) is reduced to

$$\varepsilon_{it} = \left(\varepsilon_{1it}, \varepsilon_{2it}, \varepsilon_{3it}, \varepsilon^O_{1it}, ..., \varepsilon^O_{5it}, \varepsilon^I_{1it}, ..., \varepsilon^I_{4it}\right)',$$

a vector with only 12 entries. We further assume that ε_{it} follows a multivariate normal distribution with

$$\text{Cov}\left(\varepsilon_{it}, \varepsilon_{it-1}\right) = \Sigma_{\varepsilon 1},$$

that is, we assume that

$$\begin{aligned} \varepsilon_{it}|\varepsilon_{it-1} &\sim N\left(\mu_t, \Sigma_t\right), \quad \text{and} \\ \varepsilon_{it} &\sim N\left(0, \Sigma_\varepsilon\right), \end{aligned}$$

where

$$\begin{aligned} \mu_t &= \Sigma'_{\varepsilon 1}\varepsilon_{it-1}, \quad \text{and} \\ \Sigma_t &= \Sigma_\varepsilon - \Sigma'_{\varepsilon 1}\Sigma^{-1}_\varepsilon \Sigma_{\varepsilon 1}. \end{aligned}$$

The state vector:

The state vector is quite large and it is therefore necessary that we extensively use

approximation methods when evaluating the value function at different points of the state space.

The state vector z_{it} consists of the following variables: (i) education level by education type; (ii) experience levels in each occupation and industry; (iii) savings; (iv) a set of dummy variables indicating the occupation of the individual at time $t-1$; and (v) a set of errors from each of the wage equations and educational choice (10 in total).

2.5 The Law of Motion for the Model's Parameters

In this section we described the law of motion for the model's parameters, which change over time. We first denote the vectors containing all the parameters that are related to the reward function specified in (7), (10), and (15) by $\theta(t)$. This vector includes only the parameters in the reward and cost functions, but does not include the more primitive parameters of the model, that is, the parameters that are associated with the utility function, etc.

Naturally, there is no reason to believe that the parameter vector $\theta(t)$ will remain constant over time. In fact, all of the research in the past few decades regarding the changing wage structure in the United States indicates that the underlying parameters of the conditional wage distributions have dramatically changed. In the statistical model assumed below we do not directly take into account the general equilibrium effects that stem from large changes in the choices of the population as a whole. However, to the extent that the world behaves in a stationary way, the statistical model described below captures this aspect.

We assume that $\theta(t)$ follows a simple augmented vector auto-regression (VAR) model given by

$$\theta(t) = \gamma_\theta + \Gamma_\theta \theta(t-1) + \Delta_\theta MC(t) + \nu_t, \tag{18}$$

where $MC(t)$ is a vector of exogenously given macro variables that affect $\theta(t)$ over time.

Note that the parameter vector $\theta(t)$ is part of the model written above, so we can estimate it given the data we use from the NLSY. In contrast, while the macro variables are endogenously determined in the economy as a whole, they are exogenous to the decision making by the individual agents temporally maximizing their utility functions. Therefore, we specify the following VAR model for the macro vector $MC(t)$:

$$MC(t) = c_m + C_m MC(t-1) + \xi_t. \tag{19}$$

Note that the model in (19) needs to be estimated only once and the estimated parame-

ters, say $\widehat{c}_m$ and $\widehat{C}_m$, are taken as given for the DP model specified above.

3 The Data

The data for this study are taken from the 1979 youth cohort of the National Longitudinal Surveys of Labor Market Experience (better known as the NLSY). The NLSY consists of 12,686 individuals, split evenly between men and women, who were between the age of 14 and 21 in January 1, 1979. The sample consists of a core random sample and an oversample of blacks, Hispanics, poor whites, and the military. The first interviews were conducted in 1979 and have been conducted annually until 1994. Since 1994 the interviews were conducted only in 1996, 1998, and 2000. The analysis here is based on all men and women from the core sample for whom we have at least five consecutive observations in the first ten years of the sample. For the estimation we use only the years 1979 through 1994, while the rest of the years, namely 1996, 1998, and 2000, we use for validation purposes. The sample consists of over 4,000 individuals depending on the sample period (see Table 1).

The NLSY collects schooling and employment data retrospectively back to the preceding interview date. The survey also includes information on schooling including information about the highest grade attended and the highest grade completed at each interview. It also provides the monthly attendance in each calendar month (beginning in 1980), the date of termination of each schooling episode, and the dates at which the individuals obtained their degrees (or diplomas).

The employment data include the beginning and ending dates (to the exact calendar week) of all job episodes, all gaps in employment within the same job, usual hours worked on each job, the usual rate of pay on each job, three-digit occupation, and three-digit industry for each job.

Following KW, the discrete decision period is assumed to be a school year, that is, the period that starts on October 1 and ends on the following September 30. Note that while this period corresponds approximately to a school year, this timing is not of any significance with respect to the timing of employment and occupational choice decisions.

Essentially the data we used provides weekly observations, so that individuals may actually be in several alternatives in any given year. We use here some clear rules regarding the actual annual activity for each person. Of course, any such rule is somewhat arbitrary, but, nevertheless, needed, in order to convert the data into annual observations. Unlike in KW some of the choices need not be mutually exclusive alternatives. For example, an individual may hold a full-time job while attending a basic school. Below we provide details about all

the possible choices.

3.1 Definition of Choices and Wages

Schooling:

To simplify the determination of school attendance, we look at an individual's activity each month of every calendar year. An individual is considered to have attended school during the year if he/she attended school in at least half of the points during the calendar year, and the he/she reported to have completed an additional grade level by October 1 of the next calendar year. We further classify whether the individual attended a general school or basic school, according to the information on the highest degree ever received.[2] Also, as noted above in Section 2.2, an individual who chooses general schooling can, but need not, choose to work at a part-time job, while an individual who chooses basic schooling can, but need not, work at a part- or full-time job.

Working:

The work assignment used data on work status in all weeks between October 1 and June 30. Note that we do not take into account the summer quarter, since we do not to count summer jobs of those individuals that are in school. An individual is considered to have worked during the year if he/she was employed in at least two-thirds of the weeks for an average of at least 15 hours per week. If the work status is missing for less than two-thirds of the weeks, then the work criterion assigned for those weeks is the same as the one based on the weeks for which the information is available. If more than two-third of the weeks have missing information the observation is truncated at that point of time.

[2] As is well-known in the literature that uses the NLSY, there is a relatively large number of observations with longitudinally inconsistent data on enrollment and highest grade completed. However, with careful examination of the records, we were able to resolve most of the inconsistencies and construct accurate history of school attendance and grade completion. To do that we use other information provided in the NLSY, that is, the monthly attendance calendar, survey date attendance, highest grade attended, highest grade completed, dates of departure from school leaving, dates of diplomas received, and the highest grade completed as of May 1 of the relevant calendar year. Attention was given to those who obtained a general equivalency diploma (GED), but have not completed regular high school. For each such observation the level of education assigned is the actual number of years of completed education rather than twelve years of education. As indicated in KW, this treatment is consistent with recent work by Cameron and Heckman (1993). Determining school attendance was a bit more problematic and required us to use a somewhat more complicated rule because some of the attendance data was also missing. When we could not determine whether or not the individual attended school, we determined school attendance by whether or not a grade was completed. If this variable was also missing, then we truncated at that period.

Occupation:

A working individual is assigned to one of the four occupations: (1) technical; (2) managerial; (3) laborers; and (4) expert workers.[3] The exact one-digit occupation assigned to an individual is the one in which the individual worked for most the weeks during the year. (based on the same nine months used to determine work status). Note that we employ here a more disaggregated classification than the one employed KW (who use only blue- and white-collar occupations). As in KW, we assume here that the disaggregated occupations within each category utilize the same type of skill units, so that the wage differences within the aggregated occupations reflect differences in units of homogeneous skills.

Industry:

A working individual is also assigned to one of the four industries: (1) production; (2) trade; (3) services; and (4) professional.[4] The exact one-digit industry assigned to an individual is the one in which the individual worked for most the weeks during the year. (based on the same nine months used to determine work status). We assume here that the number of units of skills an individual has is a function of his/her occupation, and the industry in which the individual works. Although, as modelled above, the exact industry is not chosen, but is assigned stochastically to each individual, the returns on units of skills accumulated in each industry are allowed to differ across industries. Within each occupation-industry occupation we assume that variation among individuals is due to differences in the number of homogeneous units of skills.

Real wages: Occupation-industry specific real wages are obtained by multiplying the average real weekly wage for the weeks worked in the specific occupation-industry (assigned as above) times 50 weeks. However, we compute different average wages for those who worked at full-time jobs and for those who worked at a part-time job. All wages are deflated by the gross national product deflator and are expressed in 1987 dollars.

Home:

Recall that above we allow individuals to be engaged in part-time work, so that the rest of their available time they spend at home. Accordingly, we classify an individual to be full-time at home if during the year in question the individual was neither enrolled in school nor worked, according to the definitions above.

[3] The exact classification into the various occupations is given above in Section 2.1.

[4] As for the occupation classification, the exact classification into the various industries is given above in Section 2.1.

3.2 Descriptive Statistics and Observed Patterns

This section is intended to present the basic patterns observed in the data and motivate the particular structure of the modeling strategy adopted here.

In Table 1 we present available data by year and age. By construction the distribution of ages in 1979, the first sample year, is between 16 and 22. We do not use the individuals who were younger than 16 in the first year, but do include them when they turn 16. As a result, in 1981 we have a set of individuals who are 16 to 24. By 1993, the end of the sample period, this set of individuals is between the ages of 28 and 36. Using this methodology, the number of observations in the first few years is actually increasing, and declines thereafter, largely due to attrition. Overall, the number of individual-year observations we use is 64,534.

Table 2 presents the distribution of individuals across the various possible activities by age. A graphic illustration of Table 2 is provided in Figure 1. At younger ages the individuals spend most of their time at school. Nevertheless, a significant number of individuals do engage in some work activity while at school. For example over 24% of the individuals who are 18 years old do work while at school. This fraction declines over time, as the individuals complete their studies, or when decide to quit school and concentrate on working only. But, even at the relatively older age of 30 years, a significant fraction, of about 5% is still engaged in schooling, while working. Table 2 clearly demonstrates that schooling and work decisions are not mutually exclusive as is typically assumed in the literature. This is in our model we allow for individuals to be engaged in work while at school.

Who are the individuals that choose to work while at school? We address this question in Table 3, which presents the distribution of individuals in *general* and *basic* education categories. In Figures 2a–2c we provide graphical presentations of the fractions of individuals in the two education categories from the population as a whole (Figure 2a), from those attending school (Figure 2b), and for those with at least 12 years of education (Figure 2c). Until an individual goes to college, either a two-year college or a four-year college, his education is counted as basic. If the individual does not continue with the accumulation of post-secondary education or if he chooses to go to a two-year college his education is considered to be basic. If the individual goes to a four-year college and complete his education it is then considered to be general. The education of an individual that transfers from a two-year college to a four-year college is also counted as general. These definitions of basic and general education explain the specific patterns observed in Table 3 and Figures 2a–2c.

Note from Figures 2b and 2c that there is a substantial number of individuals who attend some kind of school which is not a four-year college. As noted above, the fraction of individuals acquiring basic education, who are older than 18 years, is about 24%, while

the fraction of individuals going to two-year colleges is over 30%. Not surprisingly, school attendance in general declines significantly as individuals age. Nevertheless, a significant fraction acquire basic, and only basic, education. A large fraction of these individuals do so while working either in a part-time job or a full-time job.

The evidence provided in Table 3 and Figures 2a–2c further highlight the need for one to allow individuals to choose a working option while at school. This is especially important, since most of the individuals who continue acquiring only basic education will not be able to do so without working, at least at part-time jobs. These individuals are severely affected by liquidity constraints, not being able to borrow against their future human capital.

In Table 4 we present the transition probabilities between the various alternative activities considered in this paper. Panel A of the table provides the transition probabilities for the age group of 16-25 years old, while those for the 26-35 age group are provided in Panel B of the table.

Note that all activities have strong state dependence, in that the probability that one will continue in an activity at time t in which he was engaged in at period $t-1$ is quite large for all activities. Nevertheless there are also significant transitions between the various activities as well. In particular, individuals that are at school at time $t-1$ are very likely to be engaged in some working, while continuing school, at time t. Also, individuals that are working while at school frequently transition to the school only activity.

To examine this issue further, we present in Figure 3 the fraction of individuals in the basic and general education categories by their enrollment status, i.e., part-time versus full-time students. Restricting attention to individuals who are older than 18 years we see that there is a large fraction of individuals who acquire both basic and general schooling on a part-time basis. Most of the individuals who acquire general schooling do so full-time, but that fraction declines over time. In contrast the fraction of individuals who acquire general schooling on a part-time basis increases over time. In their late 20s, about 30% of the individuals do so only on a part-time basis. Most of these individuals are also engaged in full- and part-time work.

From the individuals who acquire basic education, the fraction of those who are doing so on a part-time basis is almost the same, in most years, as the fraction of those doing so full-time.

The mirror image of the patterns of school attendance is seen in Figure 4 where we present the fraction of individuals working part- and full-time. As the figure clearly shows, at younger ages a relatively large fraction of the individuals in our sample work part-time. But that fraction declines over time. Nevertheless, even by age 35 over 12% of the individuals

in the sample only work part-time. In complete contrast, the fraction of individuals who work full-time rises significantly until age 22, where most of them complete their college education.

How do individual who end up having basic education compare with those who obtain general education? To see this we plot in Figure 5 the average hourly wages for the two groups. As can be clearly seen, investment in human capital seems to pay off. While the individuals who have basic education earn more than their general education counterparts early on, as soon as the latter complete their college education their hourly wage exceeds that of those who have only basic education. Moreover, there a steeper increase in the hourly wage for those who have general education. By age 30 the hourly wage for those who have general schooling is over 25% larger than those who only have basic schooling.

We now turn to the examination of the distribution of individuals with the two types of schooling across industries and occupations. In Table 5 we present the distribution of individuals by type of schooling across the four industries defined here. A graphical presentation is also provided in Figures 6a–6c, where we show the distribution across industries for the entire population (Figure 6a), for those with general schooling (Figure 6b), and for those with basic schooling (Figure 6c). The pattern of changes in the distribution across the various industries is remarkably different for the two educational groups. For both groups the fraction in *production* industry increases dramatically over the sample period. But for those with basic schooling the fraction to begin with is quite high (25%) relative to that those with general education (less than 15%). By the end of the sample period, over 55% of the individuals with basic education end up in the production industry, while less than 45% of their general education counterpart ending in that industry. Those with general schooling are a lot more likely to be working in the *professional* industry. The distribution for the other two industries is quite similar.

In Table 6 we report the joint distribution of occupation and industry by age group. In Panel A we present the younger group, age 16-25, while the 26-35 group is presented in Panel B of the table. As one might expect, there is larger fraction of the older individuals in the *technical* and *managerial* occupations and in the professional industry. More of the younger group are in the *laborer* occupation category, especially working in the production industry. Overall a larger fraction of the older workers is in the occupation-industry combinations requiring more highly skilled worker. As has been demonstrated before, the more highly skilled workers are largely those who obtained general, rather than basic, education.

In Figures 7a–7c we present the fraction of individuals across the various occupations (Figure 7a) broken down by the type of education. In Figure 7b we present the individuals

with general education, while Figure 7c provide the distribution for individuals with basic education. As can be seen from Figure 7a the fraction of individuals working as laborers declines significantly as people age, but there is a more dramatic drop for those with general education (Figure 7b) of more than 20 percentage points than for those with basic education (Figure 7c) for whom the drop is about 12 percentage points. Furthermore, individuals with general education are a lot more likely to be in the technical occupations and are more likely to switch to the managerial occupations than their basic education counterparts. These figures clearly demonstrate that there is a clear difference between general and basic education, as the more highly educated individuals find themselves in better occupations with higher wages.

In Tables 7 and 8 we present the transition between occupation and industry, respectively. In both tables we provide the transition probabilities for the young (16-25) and older (26-35) age groups. Table 7 shows that generally the older group, as we may expect, has more stability in their occupational choices. Also, individuals generally move up to higher paying occupation, starting at the low end occupations, such as laborers, and then moving to expert and managerial position over time. Nevertheless, a significant number of individuals do stay in their occupation over time.

The same general picture is transparent for industrial mobility, as is demonstrated in Table 8. In general, production workers who consist in large part of individuals with basic education transit, if they transit, to the trade and services industries. Individuals in the professional industries tend to stay in this industries even at relatively young ages. Over 80% of the individuals who are 16-25 stay in the professional industries conditional on being there at the preceding period. This number climbs to almost 86% for the individuals in the 26-35 age group.

4 Results

The estimation is carried out using simulated maximum likelihood (SML). Given the relatively large number of state variable and choices, one needs to combine the estimation with some advanced approximation methods. We use the general techniques of approximation by Chebychev's orthogonal polynomial. A more detailed description of the method and the justification for some choices we had to be made is provided in a web appendix.

4.1 Parameter Estimates

The results for the point estimate are summarized in Table 9 through Table 14.[5] In Table 9 we provide estimates for the industrial transition probabilities described above in (2). These parameters are estimated outside the model and not as part of the SML procedure described above. Note that because the experience across all occupations and industries are linearly dependent we omit the experience in Industry 4 (professional) from the estimation. The results show that experience acquired in an industry induces individuals to stay in that industry, since, as it is shown below, the return to experience acquired at any given industry is not fully compensated for when switching to a different industry. Moreover, individuals in all occupations have a higher likelihood of being in the professional industry (Industry 4), largely because wages in this industry are larger than those in any other industry.

Note that there is very large degree of state dependence. That is, individuals tend to stay at time t in the industry in which they were at time $t-1$, as is demonstrated by the large coefficient estimate on the industry dummy variables. Also, individuals in part-time jobs have higher tendency to remain at time t in the industry they were at time $t-1$. This is because the individuals in part-time jobs are also engaged in some type of human capital accumulation, either of basic education or general education, and will change industry when they acquire more permanent jobs.

In Table 10 we present the results for the parameters that correspond to the utility function defined in (1). The estimates for α_c and α_l, .560 and .767, respectively, corresponding to the utility from consumption and leisure, indicate that the elasticity of substitution of consumption is 1.8, while that of leisure is 1.3, which is consistent with estimates found in the consumption literature. Interestingly, the estimates indicate that individuals obtain higher utility from simply having better education and more so for the general education. The positive, and highly significant, estimate for γ_{11} indicates that individuals get more utility from having general education. Moreover, the estimate for the slope parameter γ_{12} of .122 indicates an increasing utility as the function of the level of education. The point estimate for the constant for basic education is negative, but it is not statistically, or economically, significant, so that the effect of increasing level of basic education, namely γ_{22}, while is positive and significant, is completely muted.

In Table 11 we present parameter estimates which correspond to the wage functions. As before, for identification purposes we omit from all equations the experience in the

[5] The standard errors have been computed using numerical derivatives, which are known to be sensitive and, at least sometime, inaccurate. Standard errors using the bootstrap method are currently in computation and will be provide in future versions of the paper.

professional industry. As we can see the return to experience in any occupation is most highly rewarded in that occupation. For Technical occupation the return for an additional year of experience is 5.6%, in *managerial* it is 5.5%, in *laborer* it is the highest, at 7.4%, while in the *expert* occupation it is 6.8%. These returns are much larger compared to experience obtained in other occupations. Moreover the return to experience accumulated in a particular industry is rather negligible, except maybe for the return in the production industry when being in the expert occupation. The returns to education do vary across the two types of education. Interestingly, the return to general education in the technical and managerial occupation exceeds that of the return to basic education in these two occupation. However, in the other two occupations the return to basic education is higher than that for general education. Overall, the returns to education are higher in the occupations that require more comprehensive training, namely the technical and managerial occupations, than in the laborer and expert occupation.

It is worth noting that the estimated returns control for selection of individuals into a particular education type and occupation. If an individual were to be randomly assigned to one of the educational categories, the return to education in these occupations would not be as nearly that high.

In Table 12 we present the results for the cost of schooling. Interestingly, the cost of an additional year of post-secondary schooling in both the general and basic categories is about the same. However, the total cost of a college degree in a four-year college is twice as high because more years are needed in order to obtain what seems to be a more valuable degree. The cost of additional year of schooling in graduate school, $\$2,700$ in 1987 dollars, exceeds that of an additional year of undergraduate degree.

Note also that we estimate the additional time required for obtaining an additional year of schooling if an individual were to rejoin school after first quitting it. We estimate that this would cost 400 more hours if a person pursues general schooling, and 351 more hours if a person pursues basic schooling. This is very large relative to the number of hours we assume are needed for schooling at the post-secondary level, which we set at 750 hours per year.

In Table 13 we present the estimate which corresponds to the stochastic terms, more specifically the estimate of the standard error for the stochastic terms in the four occupations four industries and the two schooling alternatives. Recall from (17) that the error structure in each occupation-industry combination is given by $\varepsilon_{jmit} = \varepsilon^{O}_{jit} + \tau_m \varepsilon^{I}_{mit}$. We estimate for all industries (estimates are omitted) that τ_m, $m = 1, ...4$, are all equal to 1, so that the error in each occupation-industry combination is merely the sum of the errors, namely

$\varepsilon_{jmit} = \varepsilon^O_{jit} + \varepsilon^I_{mit}$. From the results in Table 13 we see that the estimated standard errors for the errors that are due to the occupation are much smaller than those which correspond to the industries. While the estimate for the formers vary between .20 and .23, those that are associated with the industries are estimated to be at least twice as large varying between .52 and .80.

Note also that the standard error associated with general schooling is larger than that associate with basic schooling. In both cases the estimated standard errors are quite large relative to the estimated mean cost of schooling in the two types of schooling venues which is around \$2,700 (see Table 12).

The estimate for τ^G_{PT} and τ^B_{PT} of .55 and .56, respectively indicate that the standard error associated with the cost of schooling when one attends school only on a part-time basis, are about half those that are associated with the full-time schooling activity.

Finally, we report in Table 14 the estimated correlation between the various error components in the model. Note that except for very few cases, all the correlations are estimated to be essentially zeros. Even those that are not zeros are quite small in magnitude. The only correlation coefficient that seems to be of meaningful magnitude is $\rho_{GB} = .1186$, the correlation between the errors in the two schooling cost equations.

4.2 Goodness of Fit

We assess the goodness of fit of the model by presenting a number of figures representing the most important aspects of the data that we want to match. In some cases we do a very good job, while in others further improvement is required. It is worth while noting that we do not use any time dummy variables nor do we use any other type of dummy variable to improve fitness of the model. The estimation is carried out using variables that are defined by the model.

In Figure 8a we present the fraction of individuals in school, while in Figures 8b–8c we present the fraction of individuals in school by type of school, namely general schooling (Figure 8b) and basic schooling (Figure 8c). As can be seen in all three figure we match schooling attendance quite well, with relatively small deviations. In particular we match the shape of schooling attendance, as a function of age, for the general schooling, which has a hump shape.

In Figures 9a–9b we provide the fraction of individuals who attend school on a part-time basis (Figure 9a) and a full-time basis (Figure 9b). While we do a very good job fitting the pattern in the data of full-time attendance we do not do a particularly good job in fitting

the part-time school attendance pattern in the data. Nevertheless, the pattern predicted by the model for part-time attendance has a very similar shape to that observed in the actual data.

The main reason why we do not do such a good job in predicted part-time school attendance is because we systematically underestimate the wages in all occupation. This can be clearly seen from Figure 10 which depicts the average hourly wage across all occupation-industry combinations, for those who decide to work. Since we are underpredicting the hourly wages the cost of attending school because of foregone wages declines. Consequently, more individuals decide to acquire basic schooling instead of working at a full-time job. The reason that this mainly affects those who attend school on a part-time basis, is because these are also the individuals who suffer the most from liquidity constraint.

In Figures 11a and 11b we see the average accumulated years of education in the general and basic schooling categories, respectively. Note that while we match the shape of the pattern quite closely for both groups we are underpredicting the accumulation of general human capital by about 1/2 year, while overpredicting the accumulation of basic human capital, early in one's life cycle by about 1/2 year as well.

In terms of matching accumulated experiences in the four occupations we do quite well over all, although not as well as one might have liked for at least the expert occupation. This is seen in Figures 12a–12d. For the technical and managerial occupations we predict the accumulation of experience quite well. For the laborer we do a good job early on in one's life cycle, but do relatively poorly toward the end of the sample year, as is the case for the accumulated experience in the expert occupation.

As Figures 13a–13d show we do a much better job in matching accumulated experiences in the various industries that in the four occupations. In particular in the first years (up to age 30), where most of the data are available we do a remarkable job in matching the model predictions against the actual data across all industries. For the service and professional industries we match the data very well throughout the sample period, while for the production and trade industries we systematically underpredicted the level of accumulated experience for at least the last few age groups from 31 through 35.

Finally, in Figures 14a–c we present the predictions of the model regarding the fraction of working men (Figure 14a), the fraction of men working part-time (Figure 14b), and the fraction of men working full-time (Figure 14c). Admittedly, the prediction of these aspects of the model are not very good and need to be dramatically improved. Yet, the general patterns observed in the data generally match those predicted by the model.

5 Summary and Conclusions

In this paper we revisit the results previously obtained in the literature regarding the career choices of individuals early in their life cycle, particularly Keane and Wolpin (1997). The literature is well aware of the fact that the choices one makes, particularly at young ages, are dynamic in nature. Nevertheless, constrained by computer capabilities some of the models that are currently available are somewhat abstract in nature and do not allow for too many choices to be made.

In this paper we expand on the influential paper of Keane and Wolpin (1997) and examine the career choices of young men, using data from the 1979 National Longitudinal Survey of Youth (NLSY). We expand their model allowing for several important new features that empirically are found to be quite important. One particularly important extension is that we allow individuals to choose between two alternative educational paths, which we term *general schooling* and *basic schooling*. Another feature that is important for individuals who try to obtain more human capital through studies in some formal school is that there is a large fraction of them that have liquidity constraints. Thus, they are not able to attend school without being engaged in at least some work. We therefore allow in our model for choice of schooling not to be mutually exclusive. That is, in general, an individual can also work while at school. This is particularly important in explaining schooling attendance in two-year colleges, as well as other post-secondary schools that are not the traditional four-year colleges.

These two types of schooling have different consequences for individuals employed in different occupations and industries. We therefore consider here four different occupations and four different industries, thus allowing for 16 different occupation-industry combinations.

The results obtained, even though they are preliminary ,are quite encouraging and shed new light on understanding the career choices of young men. We find that indeed the two channels of education are different in nature, leading individuals to choosing very different career paths after completion of their schooling. Moreover, we find that the return to these two types of schooling are very different across the various occupations. We also find that experience accumulated in one occupation generally yields the highest return in the occupation in which it has been acquired. The return to experience declines dramatically when it is used in a different occupation.

The model performs generally very well matching most of the general patterns observed in the data. Nevertheless, more fine tuning is required before it would be useful for the examination of some alternative policy measures and in performing some welfare evaluations.

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Table 1: Number of Observations by Year and Age

	Year															
Age	1979	1980	1981	1982	1983	1984	1985	1986	1987	1988	1989	1990	1991	1992	1993	Total
16	687	727	525	—	—	—	—	—	—	—	—	—	—	—	—	1,939
17	659	687	727	525	—	—	—	—	—	—	—	—	—	—	—	2,598
18	694	659	687	727	525	—	—	—	—	—	—	—	—	—	—	3,292
19	644	694	659	687	727	524	—	—	—	—	—	—	—	—	—	3,935
20	649	644	694	659	687	700	516	—	—	—	—	—	—	—	—	4,549
21	638	649	644	694	659	666	682	505	—	—	—	—	—	—	—	5,137
22	58	638	649	644	694	631	648	656	484	—	—	—	—	—	—	5,102
23	—	58	638	649	644	627	616	626	628	473	—	—	—	—	—	4,959
24	—	—	58	638	649	548	601	590	597	612	456	—	—	—	—	4,749
25	—	—	—	58	638	545	532	577	563	581	592	404	—	—	—	4,490
26	—	—	—	—	58	507	526	522	545	553	558	499	394	—	—	4,162
27	—	—	—	—	—	48	490	508	501	531	532	496	490	387	—	3,983
28	—	—	—	—	—	—	47	472	483	487	512	464	486	474	373	3,798
29	—	—	—	—	—	—	—	45	448	466	467	465	454	475	468	3,288
30	—	—	—	—	—	—	—	—	43	440	449	389	449	444	462	2,676
31	—	—	—	—	—	—	—	—	—	43	428	371	379	445	431	2,097
32	—	—	—	—	—	—	—	—	—	—	38	352	362	376	437	1,565
33	—	—	—	—	—	—	—	—	—	—	—	32	351	351	362	1,096
34	—	—	—	—	—	—	—	—	—	—	—	—	31	346	340	717
35	—	—	—	—	—	—	—	—	—	—	—	—	—	30	343	373
36	—	—	—	—	—	—	—	—	—	—	—	—	—	—	29	29
Total	4,029	4,756	5,281	5,281	5,281	4,796	4,658	4,501	4,292	4,186	4,032	3,472	3,396	3,328	3,245	64,534

Table 2: Number of Observations by Activity and Age

	Work		School		Work & School		Home		Total
Age	Obs.	%	Obs.	%	Obs.	%	Obs.	%	Obs.
16	107	5.58	878	45.75	841	43.82	93	4.85	1,919
17	297	11.89	865	34.64	1,138	45.57	197	7.89	2,497
18	905	29.88	689	22.75	1,053	34.76	382	12.61	3,029
19	1,614	45.43	542	15.25	856	24.09	541	15.23	3,553
20	2,227	54.18	502	12.21	834	20.29	547	13.31	4,110
21	2,787	58.71	410	8.64	967	20.37	583	12.28	4,747
22	3,123	65.61	292	6.13	781	16.41	564	11.85	4,760
23	3,391	72.49	204	4.36	613	13.10	470	10.05	4,678
24	3,419	75.52	138	3.05	492	10.87	478	10.56	4,527
25	3,379	78.40	89	2.06	426	9.88	416	9.65	4,310
26	3,191	79.56	80	1.99	355	8.85	385	9.60	4,011
27	3,102	80.07	60	1.55	320	8.26	392	10.12	3,874
28	3,048	82.00	55	1.48	258	6.94	356	9.58	3,717
29	2,640	81.89	39	1.21	219	6.79	326	10.11	3,224
30	2,199	83.90	19	0.72	155	5.91	248	9.46	2,621
31	1,727	84.33	20	0.98	108	5.27	193	9.42	2,048
32	1,286	84.22	12	0.79	76	4.98	153	10.02	1,527
33	914	84.71	9	0.83	40	3.71	116	10.75	1,079
34	603	85.65	7	0.99	32	4.55	62	8.81	704
35	308	84.38	3	0.82	16	4.38	38	10.41	365

Table 3: Number of Observations by Schooling Type and Age

Age	General Schooling					Basic Schooling					Total
	Part-Time		Full-Time			Part-Time		Full-Time			
	Obs.	%	Obs.	%	Total	Obs.	%	Obs.	%	Total	
16	0	0.00	0	0.00	0	3	0.17	1,716	99.83	1,719	1,719
17	6	0.30	10	0.50	16	9	0.45	1,978	98.75	1,987	2,003
18	97	5.57	333	19.12	430	111	6.37	1,201	68.94	1,312	1,742
19	169	12.09	536	38.34	705	200	14.31	493	35.26	693	1,398
20	230	17.22	645	48.28	875	193	14.45	268	20.06	461	1,336
21	347	25.20	657	47.71	1,004	180	13.07	193	14.02	373	1,377
22	270	25.09	496	46.10	766	166	15.43	144	13.38	310	1,076
23	233	28.55	326	39.95	559	125	15.32	132	16.18	257	816
24	174	27.75	259	41.31	433	96	15.31	98	15.63	194	627
25	157	30.60	201	39.18	358	75	14.62	80	15.59	155	513
26	127	29.33	177	40.88	304	61	14.09	68	15.70	129	433
27	112	29.71	132	35.01	244	69	18.30	64	16.98	133	377
28	96	30.97	119	38.39	215	39	12.58	56	18.06	95	310
29	86	33.46	81	31.52	167	41	15.95	49	19.07	90	257
30	45	26.01	60	34.68	105	32	18.50	36	20.81	68	173
31	33	25.78	47	36.72	80	22	17.19	26	20.31	48	128
32	31	35.23	21	23.86	52	14	15.91	22	25.00	36	88
33	9	18.37	13	26.53	22	8	16.33	19	38.78	27	49
34	10	25.64	9	23.08	19	12	30.77	8	20.51	20	39
35	9	47.37	3	15.79	12	1	5.26	6	31.58	7	19

Table 4: Transition Probabilities between Activities, by Age

Activity at $t-1$	Activity at t				
	Work	**School**	**Home**	**Work & School**	**Total**
A. Age group 16-25					
Work	18,053	131	1387	773	20,344
% of row	88.74	0.64	6.82	3.80	100.00
% of column	78.94	4.06	33.17	12.11	55.49
School	540	2,110	419	1,380	4,449
% of row	12.14	47.43	9.42	31.02	100.00
% of column	2.36	65.41	10.02	21.61	12.14
Home	1,718	162	2,133	88	4,101
% of row	41.89	3.95	52.01	2.15	100.00
% of column	7.51	5.02	51.02	1.38	11.19
Work & School	2,559	823	242	4,144	7,768
% of row	32.94	10.59	3.12	53.35	100.00
% of column	11.19	25.51	5.79	64.90	21.19
Total	22,870	3,226	4,181	6,385	36,662
% of row	62.38	8.80	11.40	17.42	100.00
% of column	100.00	100.00	100.00	100.00	100.00
B. Age group 26-35					
Work	9,470	40	741	408	10,659
% of row	88.85	0.38	6.95	3.83	100.00
% of column	87.64	18.02	40.01	33.69	75.65
School	45	84	52	77	258
% of row	17.44	32.56	20.16	29.84	100.00
% of column	0.42	37.84	2.81	6.36	1.83
Home	716	48	1,023	17	1,804
% of row	39.69	2.66	56.71	0.94	100.00
% of column	6.63	21.62	55.24	1.40	12.80
Work & School	574	50	36	709	1,369
% of row	41.93	3.65	2.63	51.79	100.00
% of column	5.31	22.52	1.94	58.55	9.72
Total	10,805	222	1,852	1,211	14,090
% of row	76.69	1.58	13.14	8.59	100.00
% of column	100.00	100.00	100.00	100.00	100.00

Table 5: Number of Observations in Each Industry by Schooling Type and Age

	Basic Schooling					General Schooling				
Age	Prod.	Trade	Services	Prof.	Total	Prod.	Trade	Services	Prof.	Total
16	1	0	1	0	2	0	0	0	0	0
17	8	1	12	7	28	5	0	3	1	9
18	161	30	343	99	633	114	11	109	13	247
19	319	56	648	230	1,253	218	24	198	31	471
20	364	87	817	322	1,590	300	53	261	63	677
21	437	97	922	452	1,908	466	91	334	93	984
22	438	126	932	441	1,937	553	131	327	104	1,115
23	446	129	910	462	1,947	537	164	320	112	1,133
24	458	152	823	459	1,892	528	161	275	119	1,083
25	414	164	805	445	1,828	488	187	262	120	1,057
26	362	158	728	411	1,659	437	194	268	107	1,006
27	336	172	680	419	1,607	427	190	234	101	952
28	326	176	673	373	1,548	417	193	219	109	938
29	306	145	559	321	1,331	349	192	179	84	804
30	265	141	449	249	1,104	273	160	159	77	669
31	192	116	354	201	863	215	144	111	67	537
32	142	99	268	151	660	178	98	77	42	395
33	106	61	200	102	469	111	69	57	30	267
34	70	45	121	63	299	80	45	37	22	184
35	31	20	69	36	156	33	31	18	14	96

Table 6: Joint Distribution of Industry-Occupation by Age Group

A. 16-25 Age Group

Occupation	Industry				
	Prod.	**Trade**	**Services**	**Prof.**	**Total**
Technical	1,407	2,776	2,033	2,469	8,685
% of row	16.20	31.96	23.41	28.43	100.00
% of column	10.75	37.49	41.69	63.60	29.69
Managerial	439	971	354	136	1,900
% of row	23.11	51.11	18.63	7.16	100.00
% of column	3.35	13.11	7.26	3.50	6.50
Laborers	7,668	3,007	1,497	1,068	13,240
% of row	57.92	22.71	11.31	8.07	100.00
% of column	58.59	40.61	30.70	27.51	45.26
Expert Workers	3,573	651	992	209	5,425
% of row	65.86	12.00	18.29	3.85	100.00
% of column	27.30	8.79	20.34	5.38	18.55
Total	13,087	7,405	4,876	3,882	29,250
% of row	44.74	25.32	16.67	13.27	100.00
% of column	100.00	100.00	100.00	100.00	100.00

B. 26-35 Age Group

Occupation	Industry				
	Prod.	**Trade**	**Services**	**Prof.**	**Total**
Technical	1,430	1025	1,431	2,431	6,317
% of row	22.64	16.23	22.65	38.48	100.00
% of column	14.04	30.12	41.12	68.93	30.67
Managerial	1,059	980	593	305	2,937
% of row	36.06	33.37	20.19	10.38	100.00
% of column	10.40	28.80	17.04	8.65	14.26
Laborers	4,800	1012	837	611	7,260
% of row	66.12	13.94	11.53	8.42	100.00
% of column	47.12	29.74	24.05	17.32	35.25
Expert workers	2,898	386	619	180	4,083
% of row	70.98	9.45	15.16	4.41	100.00
% of column	28.45	11.34	17.79	5.10	19.82
Total	10,187	3403	3,480	3,527	20,597
% of row	49.46	16.52	16.90	17.12	100.00
% of column	100.00	100.00	100.00	100.00	100.00

Table 7: Occupational Transition by Age Group

A. 16-25 Age Group

	Occupation at t				
Occupation at $t-1$	**Technical**	**Managerial**	**Laborers**	**Expert**	**Total**
Technical	5,113	544	1,424	459	7,540
% of row	67.81	7.21	18.89	6.09	100.00
% of column	69.10	26.19	12.95	9.08	29.54
Managerial	389	880	349	149	1,767
% of row	22.01	49.80	19.75	8.43	100.00
% of column	5.26	42.37	3.17	2.95	6.92
Laborers	1,499	460	7,885	1,548	11,392
% of row	13.16	4.04	69.22	13.59	100.00
% of column	20.26	22.15	71.69	30.63	44.62
Expert	398	193	1,341	2,898	4,830
% of row	8.24	4.00	27.76	60.00	100.00
% of column	5.38	9.29	12.19	57.34	18.92
Total	7,399	2,077	10,999	5,054	25,529
% of row	28.98	8.14	43.08	19.80	100.00
% of column	100.00	100.00	100.00	100.00	100.00

B. 26-35 Age Group

	Occupation at t				
Occupation at $t-1$	**Technical**	**Managerial**	**Laborers**	**Expert**	**Total**
Technical	3,839	428	500	191	4,958
% of row	77.43	8.63	10.08	3.85	100.00
% of column	77.13	17.41	9.11	6.10	30.88
Managerial	409	1,478	260	182	2,329
% of row	17.56	63.46	11.16	7.81	100.00
% of column	8.22	60.13	4.74	5.81	14.51
Laborers	534	331	4,062	696	5,623
% of row	9.50	5.89	72.24	12.38	100.00
% of column	10.73	13.47	74.02	22.23	35.03
Expert	195	221	666	2,062	3,144
% of row	6.20	7.03	21.18	65.59	100.00
% of column	3.92	8.99	12.14	65.86	19.58
Total	4,977	2,458	5,488	3,131	16,054
% of row	31.00	15.31	34.18	19.50	100.00
% of column	100.00	100.00	100.00	100.00	100.00

Table 8: Industrial Transition by Age Group

A. 16-25 Age Group

	Industry at t				
Industry at $t-1$	**Prod.**	**Trade**	**Services**	**Prof.**	**Total**
Prod.	9,277	1,033	815	404	11,529
% of row	80.47	8.96	7.07	3.50	100.00
% of column	77.46	17.41	19.07	12.08	45.16
Trade	1,320	4,115	692	291	6,418
% of row	20.57	64.12	10.78	4.53	100.00
% of column	11.02	69.33	16.19	8.70	25.14
Services	940	551	2,443	331	4,265
% of row	22.04	12.92	57.28	7.76	100.00
% of column	7.85	9.28	57.17	9.90	16.71
Prof.	439	236	323	2319	3,317
% of row	13.23	7.11	9.74	69.91	100.00
% of column	3.67	3.98	7.56	69.33	12.99
Total	11,976	5,935	4,273	3,345	25,529
% of row	46.91	23.25	16.74	13.10	100.00
% of column	100.00	100.00	100.00	100.00	100.00

B. 26-35 Age Group

	Industry at t				
Industry at $t-1$	**Prod.**	**Trade**	**Services**	**Prof.**	**Total**
Prod.	6,799	458	433	238	7,928
% of row	85.76	5.78	5.46	3.00	100.00
% of column	85.57	17.48	16.16	8.48	49.38
Trade	506	1,891	212	94	2,703
% of row	18.72	69.96	7.84	3.48	100.00
% of column	6.37	72.18	7.91	3.35	16.84
Services	405	215	1,849	182	2,651
% of row	15.28	8.11	69.75	6.87	100.00
% of column	5.10	8.21	68.99	6.48	16.51
Prof.	236	56	186	2,294	2,772
% of row	8.51	2.02	6.71	82.76	100.00
% of column	2.97	2.14	6.94	81.70	17.27
Total	7,946	2,620	2,680	2,808	16,054
% of row	49.50	16.32	16.69	17.49	100.00
% of column	100.00	100.00	100.00	100.00	100.00

Table 9: Multinomial Logistic Regression for Industry Allocation

Variable	Industry 2	Industry 3	Industry 4
Constant	0.6527	-1.7507	-3.5323
	(0.1698)	(0.1824)	(0.2154)
Experience in:			
Occupation 1	0.0166	0.0347	0.2015
	(0.0123)	(0.0106)	(0.0098)
Occupation 2	0.0522	0.0063	0.1259
	(0.0148)	(0.0142)	(0.0167)
Occupation 3	0.0056	0.0121	0.1903
	(0.0127)	(0.0113)	(0.0108)
Occupation 4	-0.0129	0.0019	0.1634
	(0.0135)	(0.0120)	(0.0125)
Industry 1	-0.0806	-0.1235	-0.2878
	(0.0126)	(0.0111)	(0.0107)
Industry 2	0.1439	0.0136	-0.1647
	(0.0124)	(0.0114)	(0.0114)
Industry 3	0.0434	0.1363	-0.1690
	(0.0140)	(0.0117)	(0.0128)
Dummy variable for being at $t-1$ in:			
Industry 1	-1.2198	-1.0522	-1.5774
	(0.0471)	(0.0520)	(0.0639)
Industry 2	1.1876	0.0678	-0.5897
	(0.0466)	(0.0601)	(0.0754)
Industry 3	-0.0963	1.3981	-0.1049
	(0.0627)	(0.0541)	(0.0752)
Industry 4	-0.2185	0.4256	1.8966
	(0.0871)	(0.0789)	(0.0666)
Age	-0.0650	0.0154	0.0168
	(0.0071)	(0.0072)	(0.0086)
Years of Education:			
General	-0.0010	0.0188	0.0763
	(0.0047)	(0.0050)	(0.0061)
Low	-0.0003	0.0154	0.0761
	(0.0058)	(0.0062)	(0.0078)
Part-time	0.8553	0.7244	1.1983
	(0.0398)	(0.0437)	(0.0475)

Table 10: Utility Function

	Parameter estimate	**Standard error**
Consumption (α_c)	0.560	(0.021)
Leisure (α_l)	0.767	(0.312)
General education		
Constant (γ_{11})	0.507	(0.011)
Slope (γ_{12})	0.122	(0.010)
Low education		
Constant (γ_{21})	-0.051	(0.061)
Slope (γ_{22})	0.175	(0.009)
Min. Consumption	962.4	(188.7)

Table 11: Wage Functions by Occupation

	Occupation 1		Occupation 2		Occupation 3		Occupation 4	
Variable	Est.	St. err.	Est.	St. err.	Est.	St. err.	Est.	St. err.
Constant	0.4120	(.0811)	0.2923	(.0551)	0.7706	(.0818)	0.8063	(.0719)
Experience in occupation:								
1. Technical	0.0556	(.0092)	0.0479	(.0081)	0.0434	(.0011)	0.0357	(.0055)
2. Managerial	0.0166	(.0011)	0.0547	(.0172)	0.0496	(.0072)	0.0015	(.0005)
3. Laborer	0.0276	(.0071)	0.0465	(.0094)	0.0743	(.0083)	0.0168	(.0022)
4. Experts	0.0117	(.0033)	0.0566	(.0082)	0.0521	(.0094)	0.0677	(.0066)
Experience in industry:								
1. Production	0.0045	(.0007)	0.0043	(.0063)	0.0004	(.0002)	0.0286	(.0031)
2. Trade	0.0000	(.0000)	-0.0001	(.0000)	-0.0003	(.0000)	-0.0006	(.0002)
3. Services	0.0075	(.0021)	0.0172	(.0021)	-0.0165	(.0011)	-0.0060	(.0016)
Education:								
General	0.0740	(.0023)	0.0755	(.0032)	0.0348	(.0045)	0.0313	(.0042)
Low	0.0706	(.0311)	0.0705	(.0291)	0.0404	(.0067)	0.0370	(.0034)

Table 12: Cost of Schooling

Variable	**Est.**	**St. err.**
Pecuniary cost of schooling:		
Basic (2-year college)	2,559	(514.3)
General (college)	2,420	(481.2)
General (graduate)	2,701	(389.9)
Hours cost of schooling:		
Additional Hours after dropping out (basic)	350.7	(112.1)
Additional Hours after dropping out (general)	400.0	(123.4)

Table 13: Stochastic Terms

Parameter	**Est.**	**St. err.**
Occupation:		
σ_1^O	0.2203	(.0812)
σ_2^O	0.2000	(.0801)
σ_3^O	0.2255	(.0891)
σ_4^O	0.1988	(.0798)
Industry:		
σ_1^I	0.5227	(.1232)
σ_2^I	0.6578	(.1343)
σ_3^I	0.5889	(.1256)
σ_4^I	0.8016	(.1378)
Education:		
σ^G	3061.3	(409.1)
τ_{PT}^G	0.5551	(.1113)
σ^B	2475.3	(367.4)
τ_{PT}^B	0.5642	(.2110)

Table 14: Stochastic Terms—Correlations

Param.er	Est.	St. err.	Param.	Est.	St. err.	Param.	Est.	St. err.
$\rho_{1,2}^{OO}$	0.0000	(0.0000)	$\rho_{3,1}^{OI}$	0.0000	(0.0000)	$\rho_{G,1}^{O}$	0.0000	(0.0000)
$\rho_{1,3}^{OO}$	0.0000	(0.0000)	$\rho_{3,2}^{OI}$	0.0000	(0.0000)	$\rho_{G,2}^{O}$	0.0500	(0.0221)
$\rho_{1,4}^{OO}$	0.0000	(0.0000)	$\rho_{3,3}^{OI}$	0.0000	(0.0000)	$\rho_{G,3}^{O}$	-0.0281	(0.0189)
$\rho_{1,1}^{OI}$	-0.0231	(0.0110)	$\rho_{3,4}^{OI}$	0.1100	(0.0000)	$\rho_{G,4}^{O}$	0.0028	(0.0013)
$\rho_{1,2}^{OI}$	0.0000	(0.0000)	$\rho_{4,1}^{OI}$	0.0275	(0.0113)	$\rho_{G,1}^{I}$	0.0000	(0.0000)
$\rho_{1,3}^{OI}$	0.0247	(0.0101)	$\rho_{4,2}^{OI}$	0.0000	(0.0000)	$\rho_{G,2}^{I}$	0.0000	(0.0000)
$\rho_{1,4}^{OI}$	0.0250	(0.0109)	$\rho_{4,3}^{OI}$	0.0000	(0.0000)	$\rho_{G,3}^{I}$	0.0000	(0.0000)
$\rho_{2,3}^{OO}$	0.0000	(0.0000)	$\rho_{4,4}^{OI}$	0.0000	(0.0000)	$\rho_{G,4}^{I}$	0.0000	(0.0000)
$\rho_{2,4}^{OO}$	0.0000	(0.0000)	$\rho_{1,2}^{II}$	0.1238	(0.0334)	$\rho_{B,1}^{O}$	-0.0923	(0.0413)
$\rho_{2,1}^{OI}$	0.0000	(0.0000)	$\rho_{1,3}^{II}$	0.0000	(0.0000)	$\rho_{B,2}^{O}$	0.0212	(0.0157)
$\rho_{2,2}^{OI}$	0.0000	(0.0000)	$\rho_{1,4}^{II}$	0.1107	(0.0344)	$\rho_{B,3}^{O}$	0.0000	(0.0000)
$\rho_{2,3}^{OI}$	0.0000	(0.0000)	$\rho_{2,3}^{II}$	0.0000	(0.0000)	$\rho_{B,4}^{O}$	-0.0033	(0.0016)
$\rho_{2,4}^{OI}$	0.0000	(0.0000)	$\rho_{2,4}^{II}$	-0.0063	(0.0412)	$\rho_{B,1}^{I}$	0.0000	(0.0000)
$\rho_{3,4}^{OO}$	0.0000	(0.0000)	$\rho_{3,4}^{II}$	0.0000	(0.0000)	$\rho_{B,2}^{I}$	-0.0031	(0.0021)
						$\rho_{B,3}^{I}$	0.0000	(0.0000)
ρ_{GB}	0.1186	(0.0331)				$\rho_{B,4}^{I}$	-0.0993	(0.0313)

Figure 1: Fractions in Each Activity

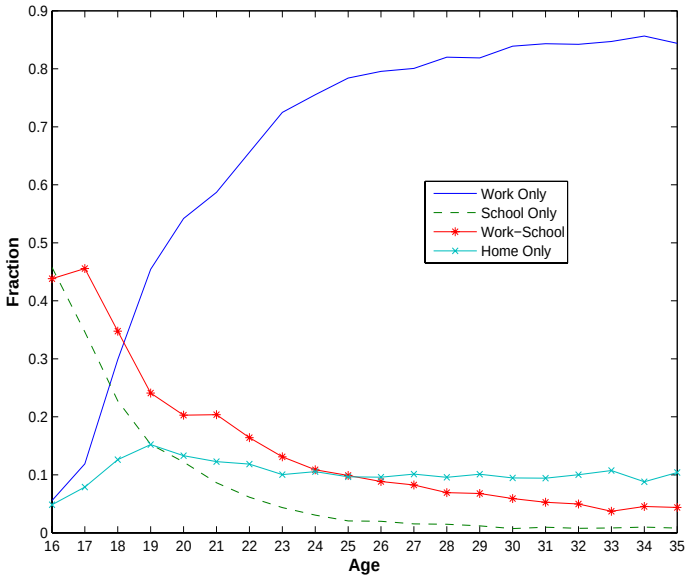


Figure 2a: Fractions in General and Basic Schooling All Population

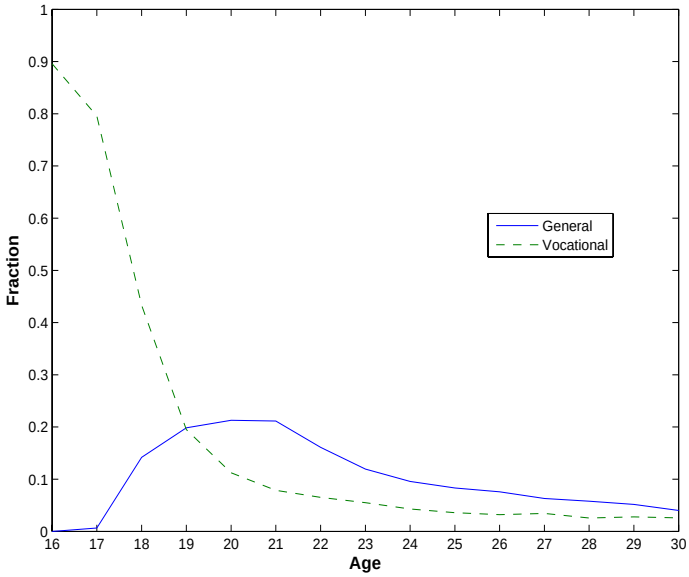


Figure 2b: Fractions in General and Basic Schooling For Individuals Attending School

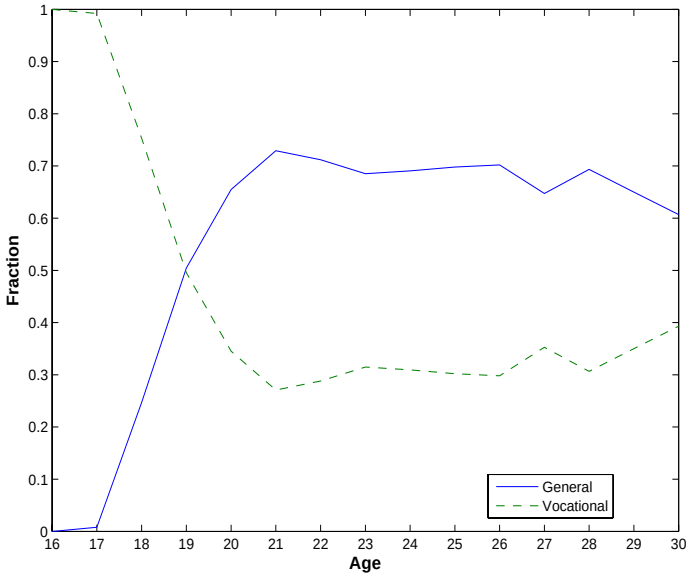


Figure 2c: Fractions in General and Basic Schooling For Individuals with More than 12 Years of education

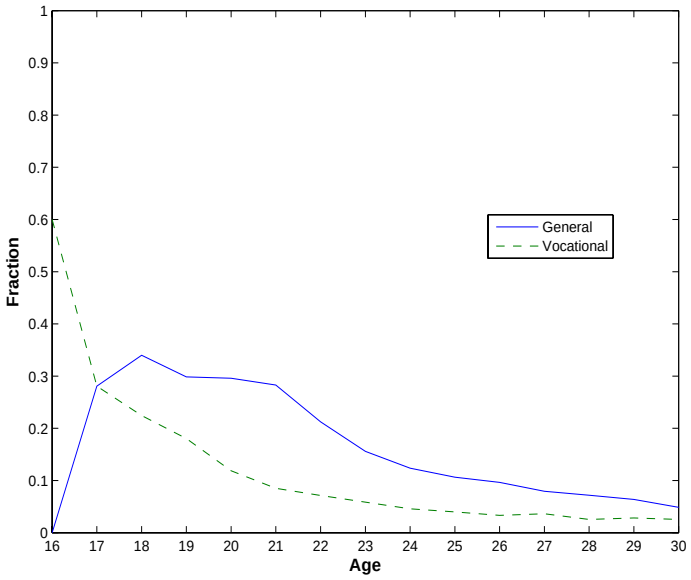


Figure 3: General and Basic Schooling by Part- and Full-Time Status

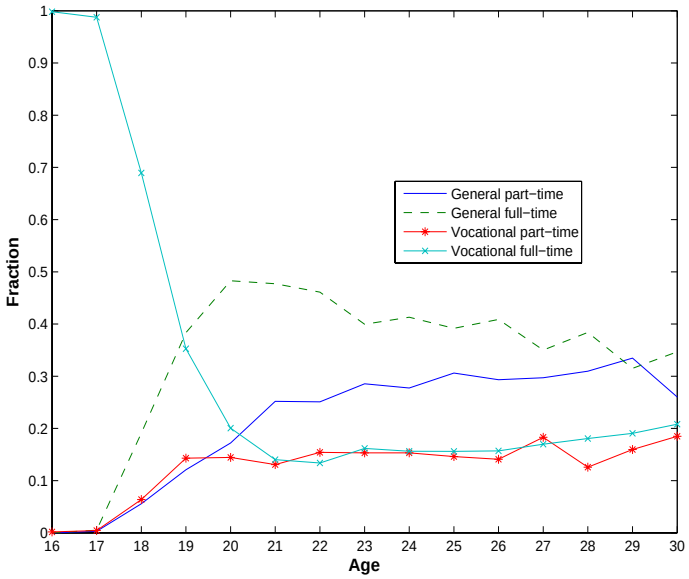


Figure 4: Work by Part- and Full-Time Status

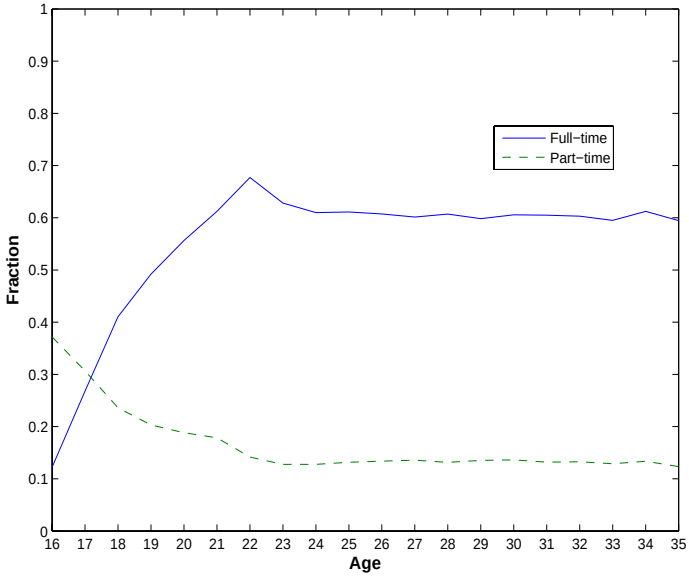


Figure 5: Real Average Hourly Wages by Type of Schooling

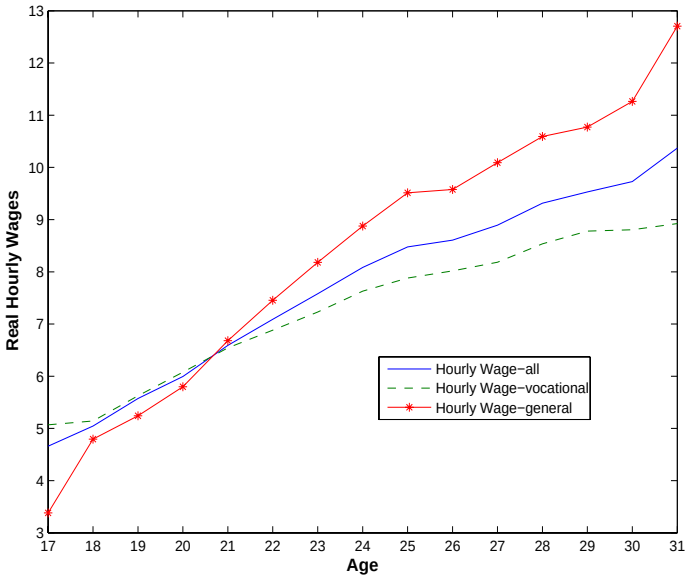


Figure 6a: Distribution Across Industries by Type of Schooling All

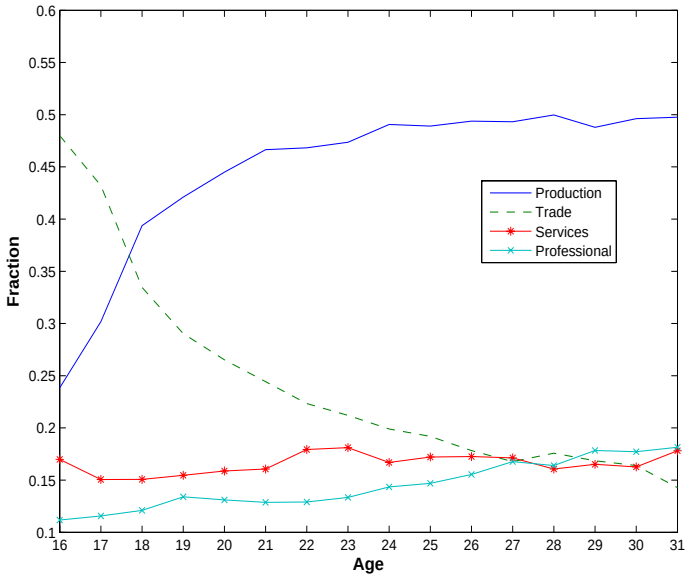


Figure 6b: Distribution Across Industries by Type of Schooling General

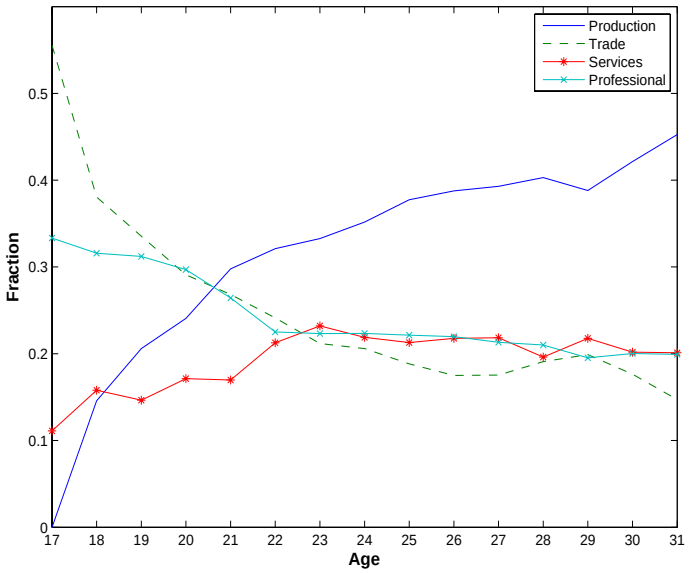


Figure 6c: Distribution Across Industries by Type of Schooling Basic

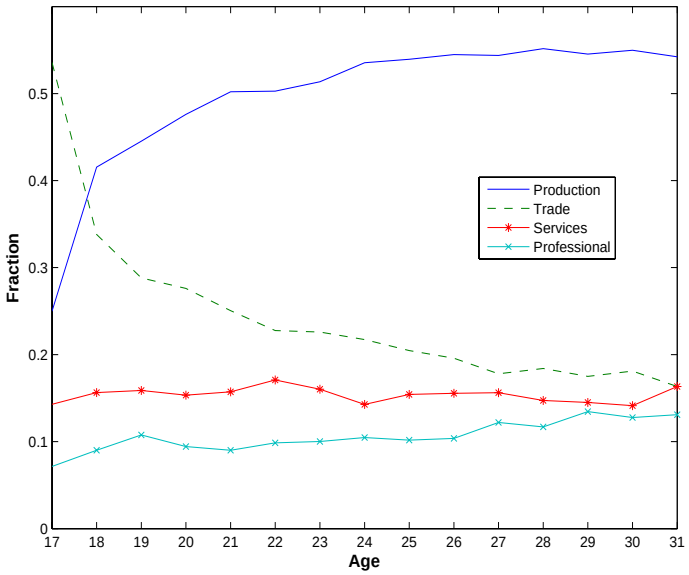


Figure 7a: Distribution Across Occupations by Type of Schooling All

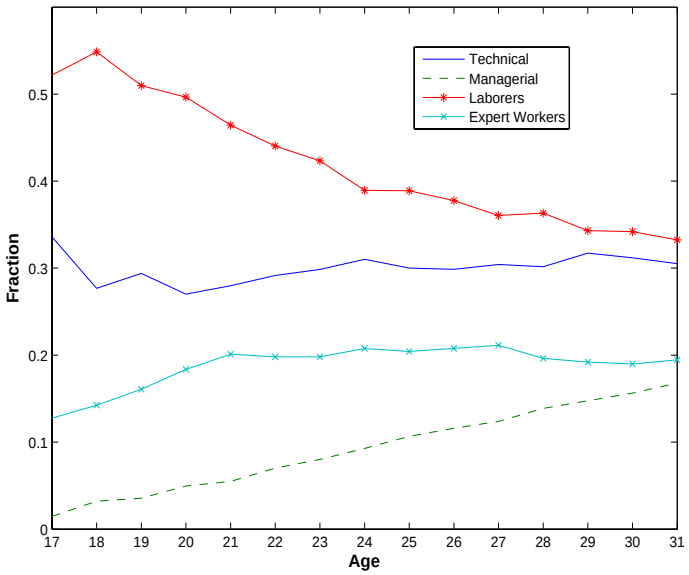


Figure 7b: Distribution Across Occupations by Type of Schooling General

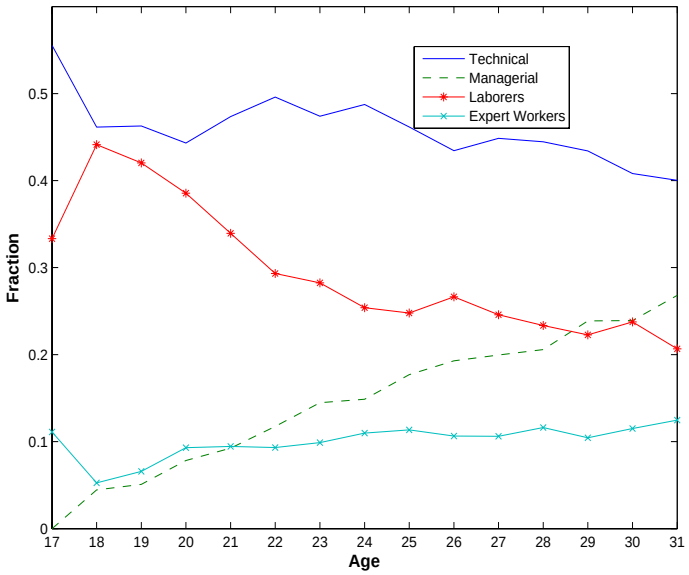


Figure 7c: Distribution Across Occupations by Type of Schooling Basic

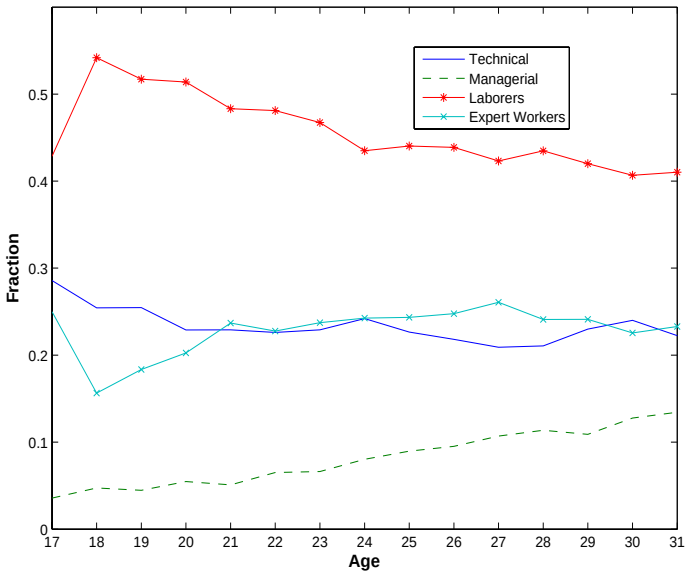


Figure 8a

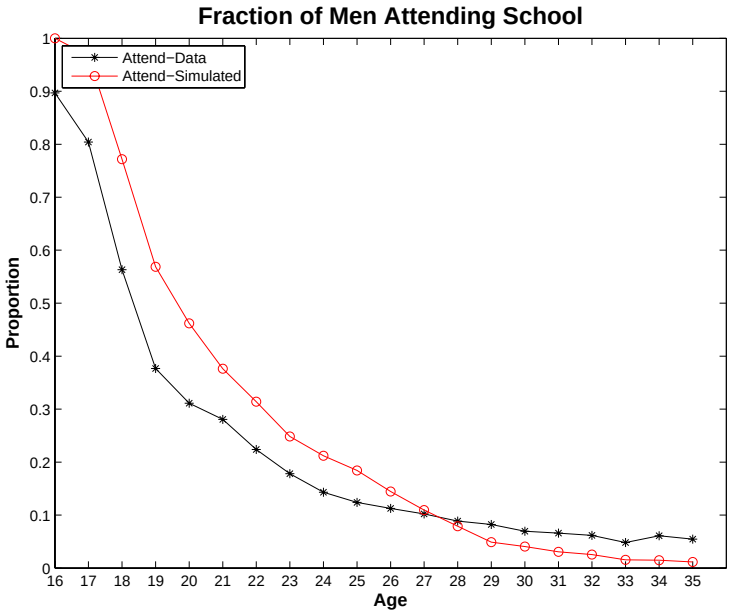


Figure 8b

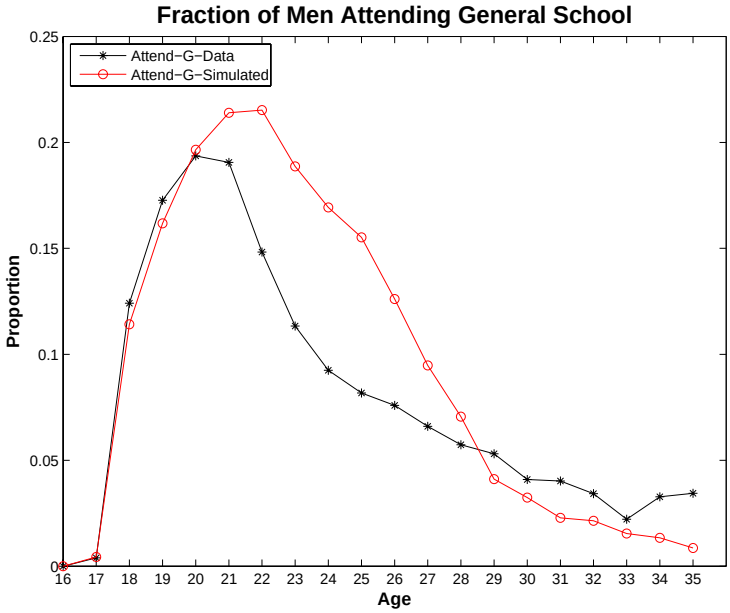


Figure 8c

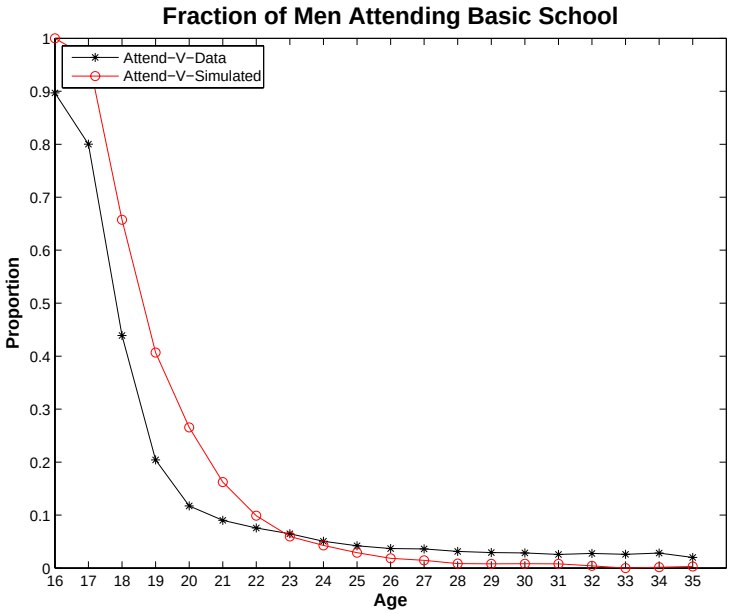


Figure 9a

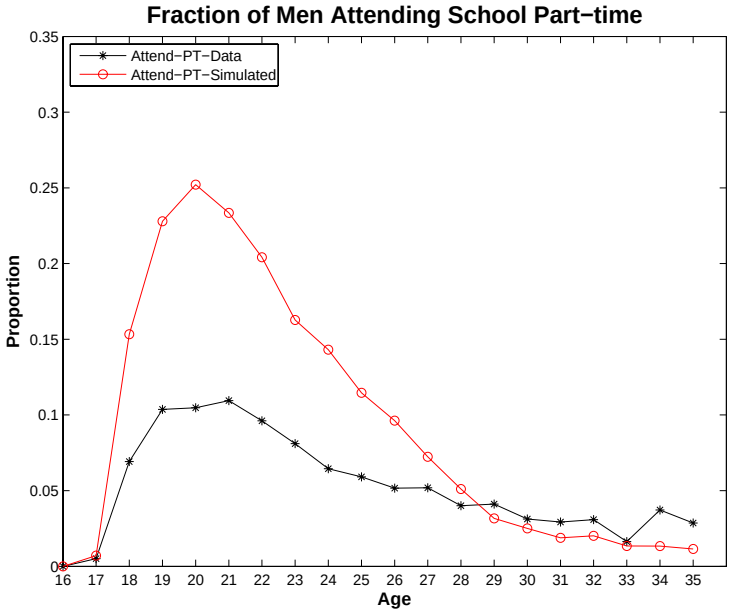


Figure 9b

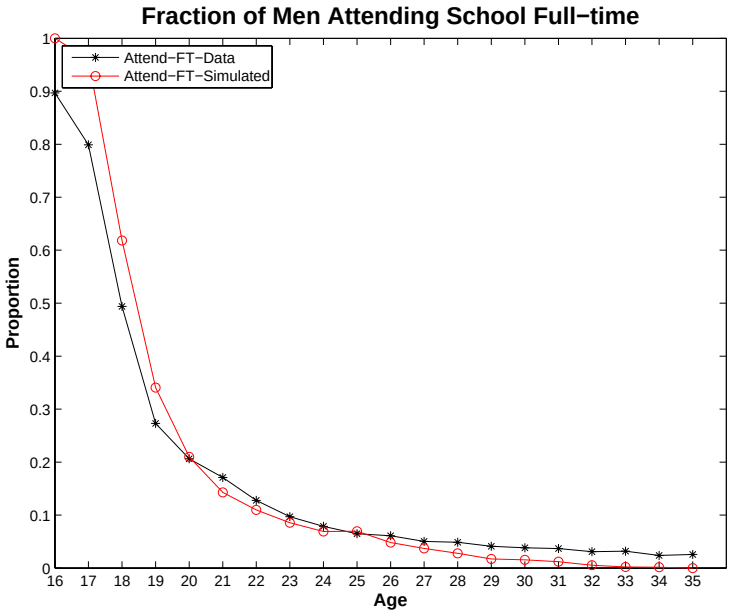


Figure 10

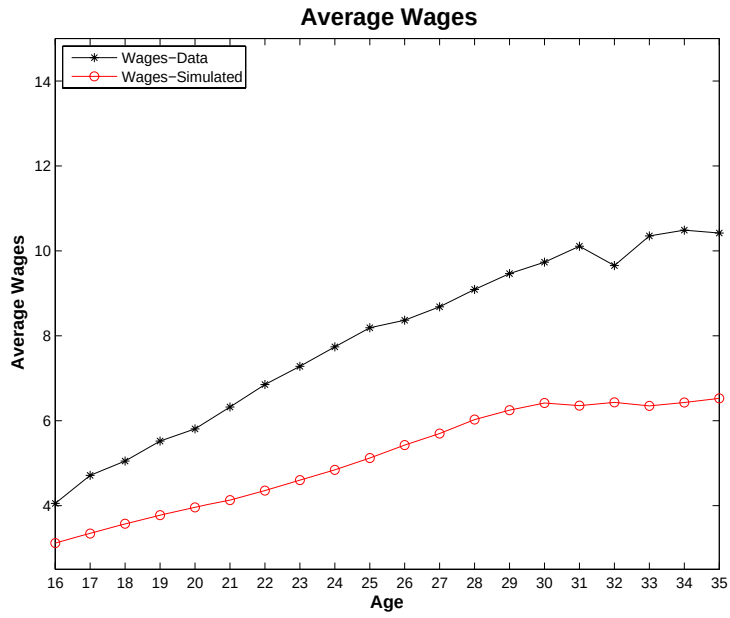


Figure 11a

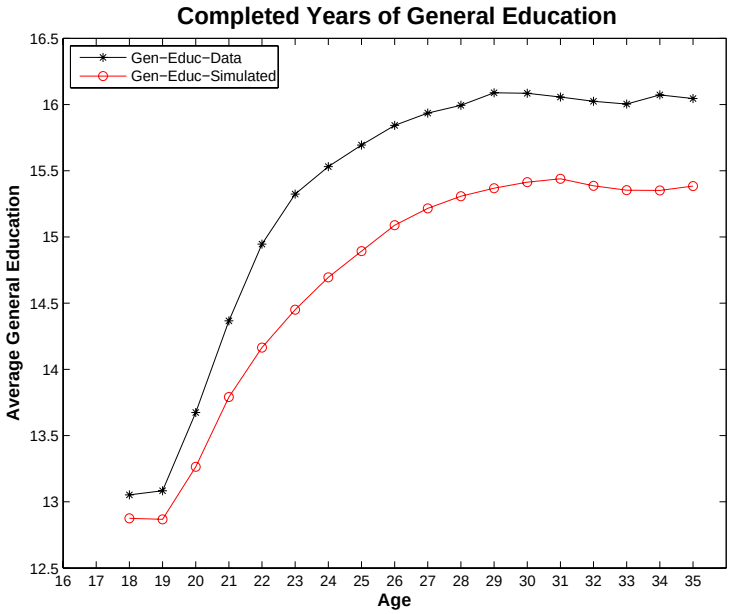


Figure 11b

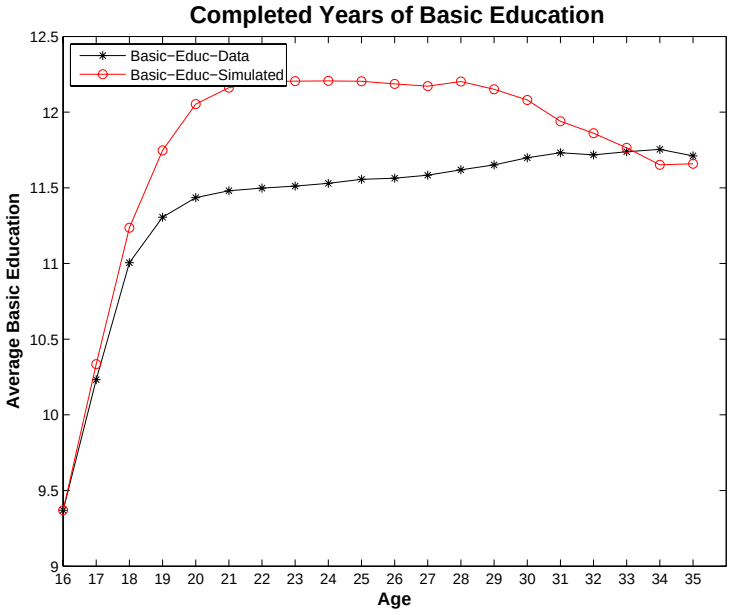


Figure 12a

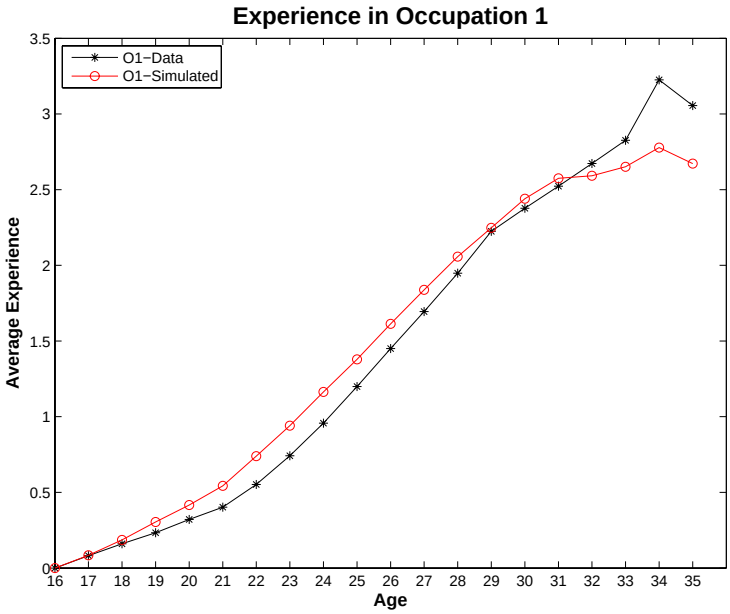


Figure 12b

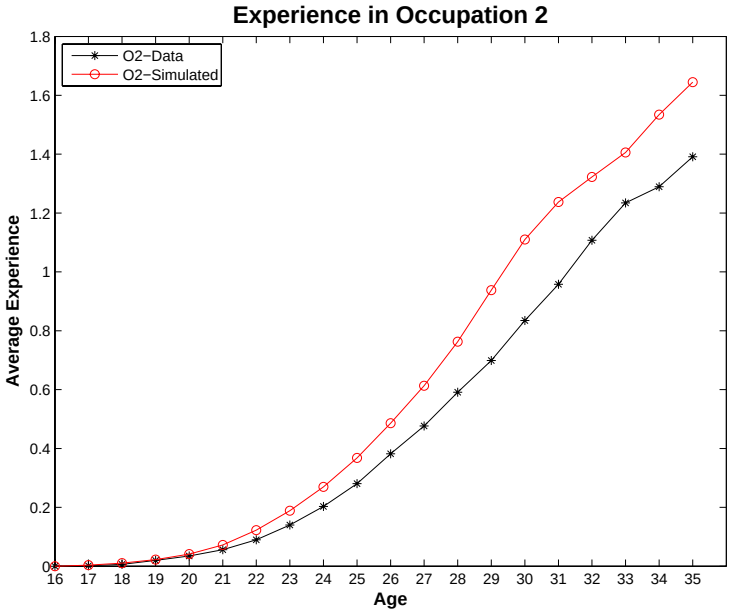


Figure 12c

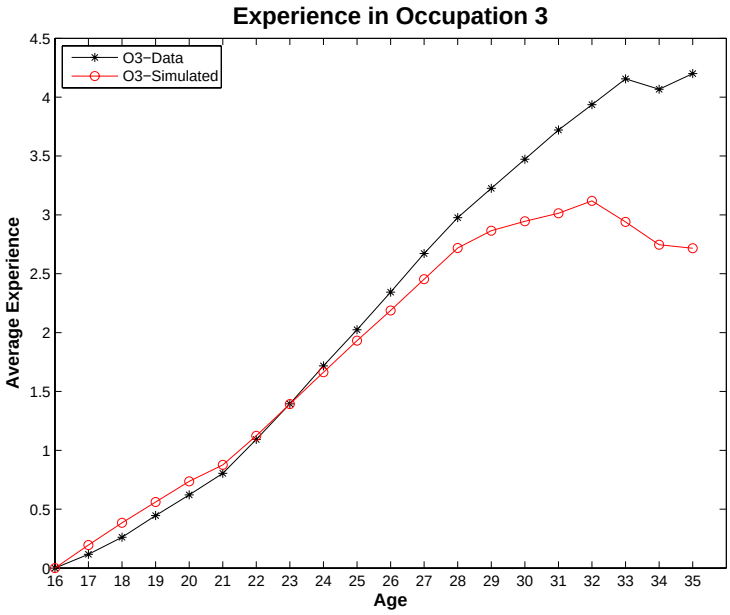


Figure 12d

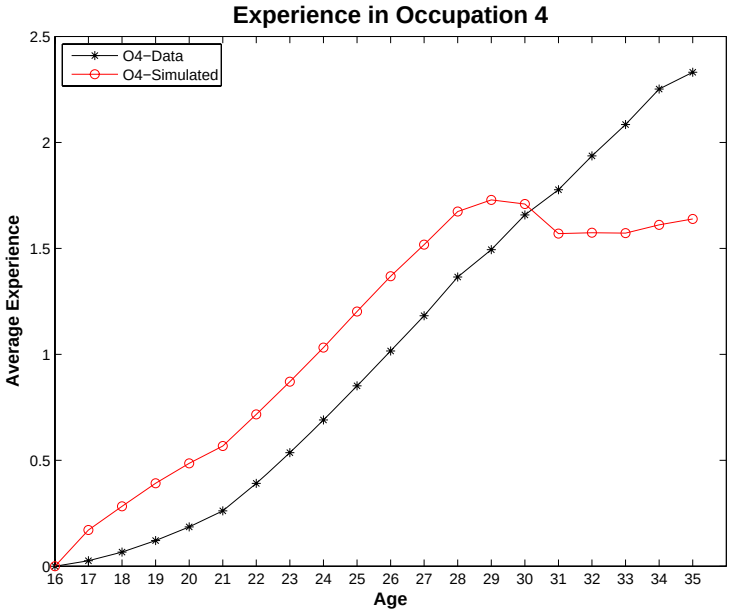


Figure 13a

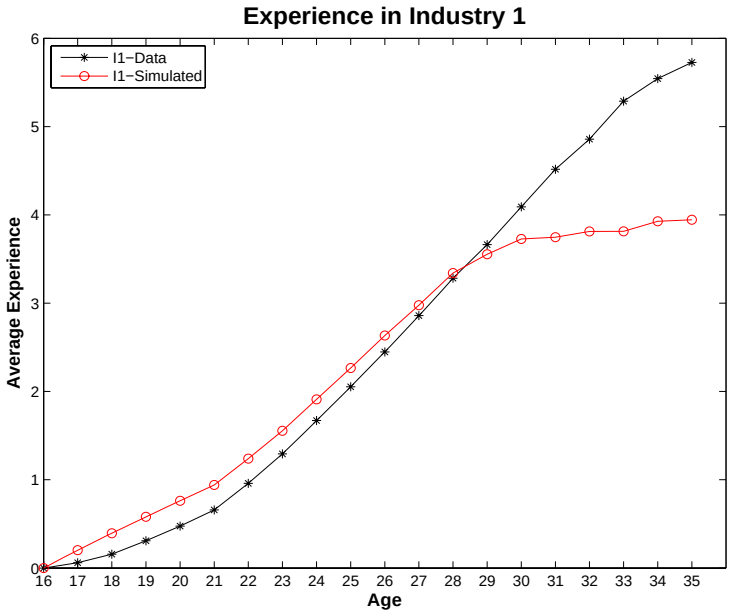


Figure 13b

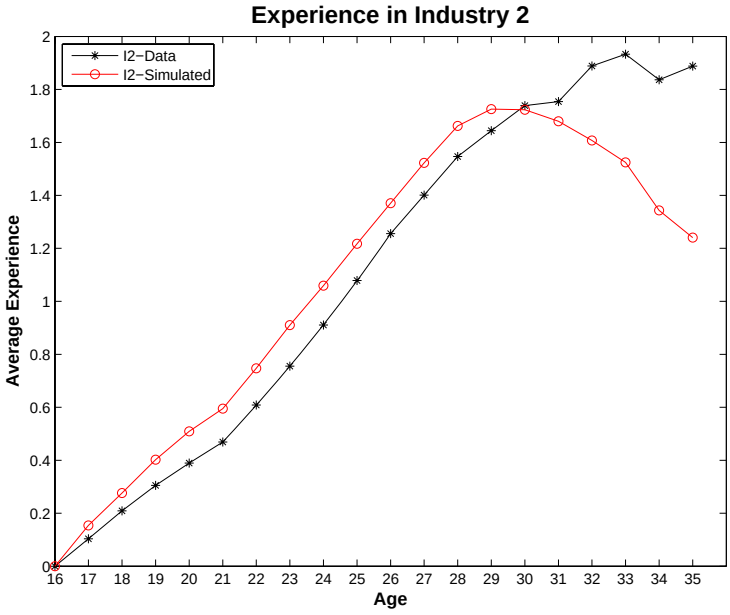


Figure 13c

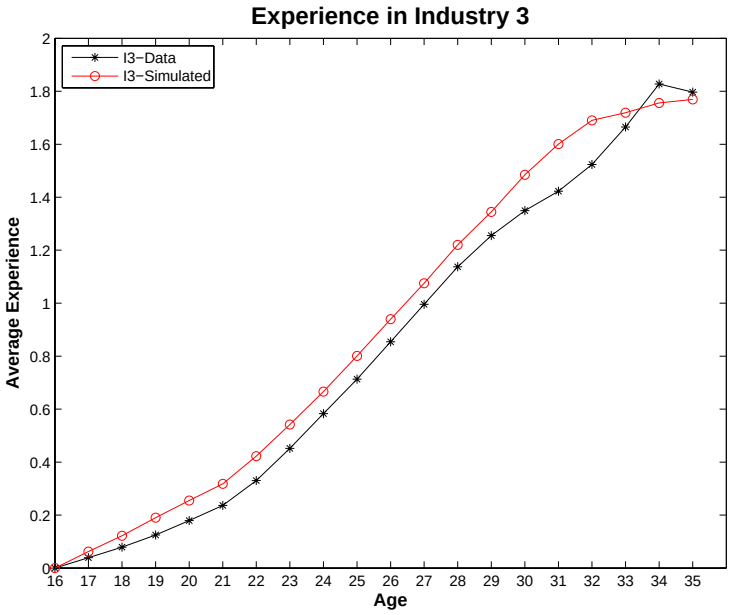


Figure 13d

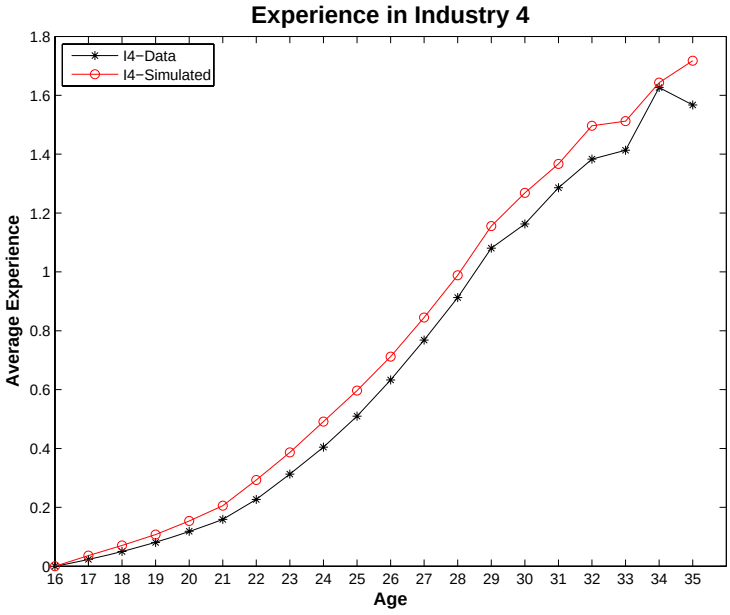


Figure 14a

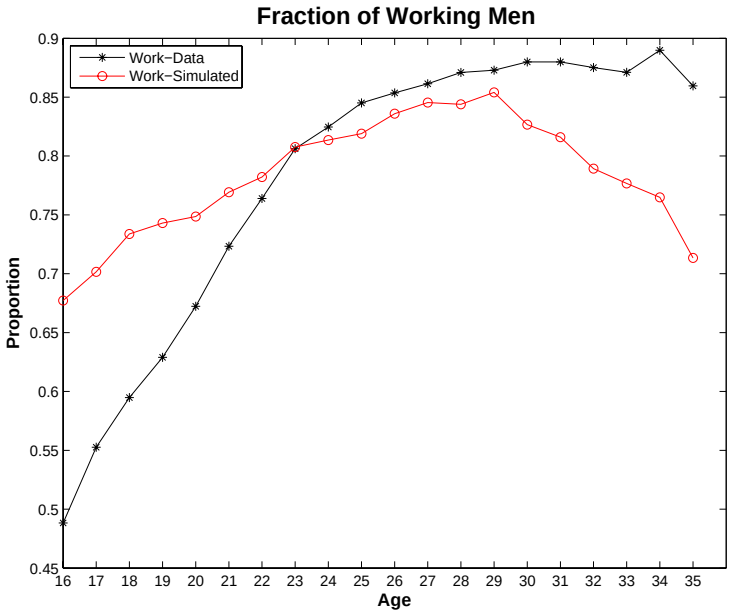


Figure 14b

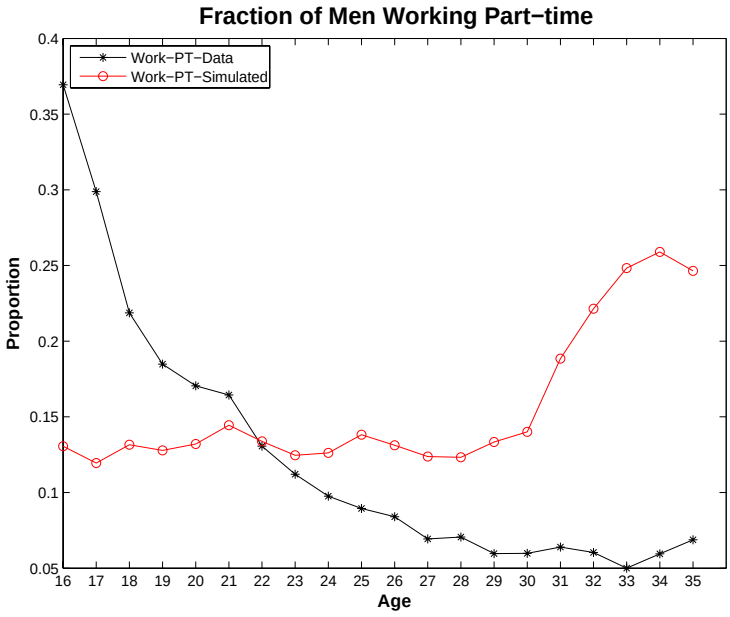
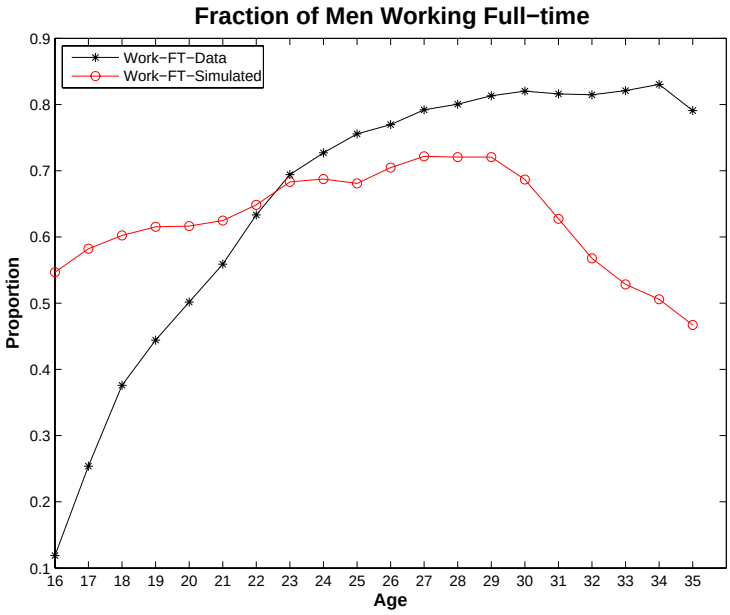


Figure 14c


Fraction of Men Working Full−time
Work−FT−Data
Work−FT−Simulated
Proportion
Age
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
16 17 18 19 20 21 22 23 24 25 26 27 28 29 30 31 32 33 34 35