Table 3: Summary Statistics (NLSY79; White Males; Aged 20-39)

Variable	No.Obs.	Mean	Std.Dev.	Median	Max	Min
(Panel 1. Initial conditions)						
Age at the first decision period (%)						
20	1916	0.627	-	-	1	0
21	1916	0.114	-	-	1	0
22	1916	0.112	-	-	1	0
23	1916	0.083	-	-	1	0
24	1916	0.042	-	-	1	0
25	1916	0.022	-	-	1	0
Educational attainment (%)						
Non college-educated	1916	62.58	-	-	1	0
College-educated	1916	37.42	-	-	1	0
Net worth at the initial age of decisions	387	11940.8	39499.7	3952	576000	-38308
(Panel 2. Pooled)						
Age	32166	29.03	5.29	29	20	39
Labor supply (%)						
Self-employed	31494	0.069	-	-	1	0
Paid-employed, full-time	31494	0.705	-	-	1	0
Paid-employed, part-time	31494	0.099	-	-	1	0
Non-employed	31494	0.101	-	-	1	0
SE & full-time PE	31494	0.013	-	-	1	0
SE & part-time PE	31494	0.012	-	-	1	0
Experience of paid-employed work (years)	32166	6.27	4.65	6	19	0
Annual Income from self-employment	2079	51350.8	56971.4	36900	884801	64
Annual Income from paid-employment						
Full-time	22295	32932.4	23900.2	28560	990057	184
Part-time	3417	14256.8	10885.6	11900	228000	143
Net worth	17169	57312.4	118703.6	20008	2673988	-72600

Note 1: "Non college-educated" individuals are highschool dropouts and highschool graduates, and "College-educated" are individuals with some college education and more.
Note 2: "Years of paid-employed work experience" counts 1-year experience if an individual works as a full-time as a full-time wage worker, and 0.5-year experience if he works as a part-time wage worker.
Note 3: Monetary values are in terms of year 2000 dollars.

or 23. With respect to net worth that each individual owns at his first age of decisions, the considerable difference between the mean and the median suggest the skewness of the wealth distribution even in early 20s. As is expected, the joint distribution of initial net worth and schooling (not shown), both the mean (13,062 versus 9,505 dollars) and the median (5,495 versus 1840 dollars) are higher for the college educated.

Panel 2 in Table 3 displays information on individual-period observations in the pooled data. The average (and the median) age is 29. As is mentioned in Introduction, of all the observations on labor supply decisions, 7 percent are provided as self-employed work while 80 percent are as either full- or part-time paid-employed work. The average accumulated years of experience as a wage worker is 6.3 (excluding years as a self-employer). The mean income from self-employment (51,351 dollars) is considerably higher (56 percent higher) than that from full-time paid-employment (32,932 dollars). The median difference is much smaller: the median income from self-employment is 29 percent higher than that from full-

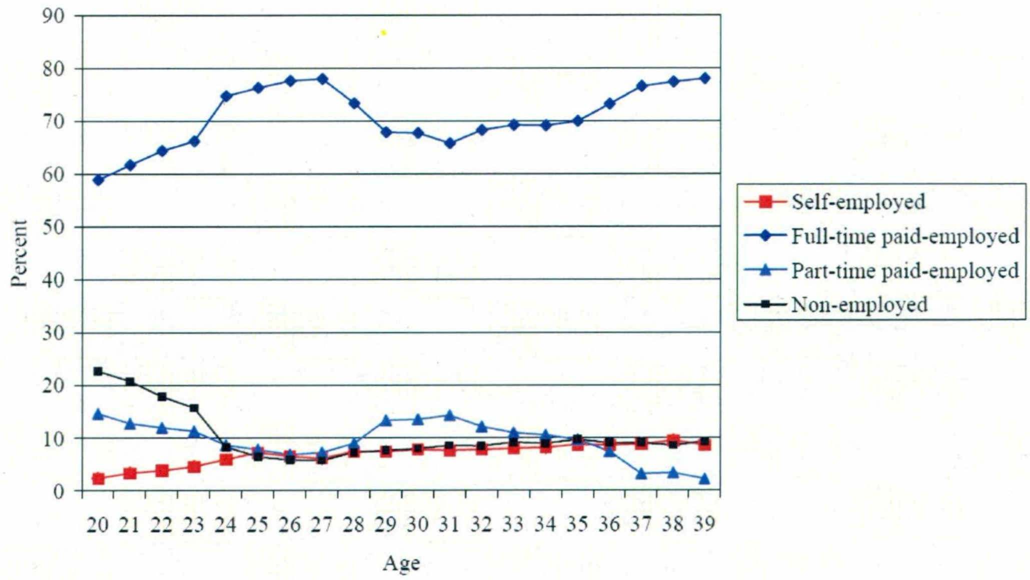

Figure 1: Distribution of Labor Supply Decisions by Age (White Males; NLSY79)

time paid-employment (36,900 versus 28,560 dollars). The mean income from part-time paid employment is 57 percent lower than that from full-time paid-employment. Lastly, the average net worth is 57,312 dollars while the median is 20,008 dollars.

5.2.2 Labor Supply Decisions: Age Profiles ($\{l^s_{i,t}, l^w_{i,t}\}$), Transitions, and Entry into and Exit from Self-Employment

Table 4 and Figure 1 show the marginal distribution of labor supply decisions by age. At age 20, only 2.4 percent of the white men are self-employed. Then, the rate increases rapidly until age 25 (7.3 percent). After that, it remains stable with a slight increase (9.5 percent at age 38). The rates of full-time paid employment are highest and stable over all the ages. Starting with 58.9 percent, the percentage grows to 77.9 percent at age 27. After that age, the number declines slightly (65.7 percent at age 31), and then it grows again. Corresponding to the slight decline in full-time paid employment, the rate of part-time paid-employment starts go up at age 27 after the decline since age 20, reaching 14.3 percent at age 31. Lastly, the percentage of the non-employed decreases rapidly in their early 20s: 22.8 percent at age 20 to 5.8 percent at age 27. Then, after age 28 the rates are stable with a slight increase (between 7.3 and 9.7).

Some key differences of self-employment by schooling have been already presented in Tables 1 and 2. In what follows, we look at details of life-cycle aspects of labor supply decisions. Table 5 shows the percentages of the individuals for the numbers of entries into self-employment. First, we find *self-employment experience is not rare*: 28.3 percent of individuals (543 out of 1916 individuals) have at least one year of self-employment experience. Second, we do not observe too many trials by the same young individual, however: 94.1 percent of them enters *only once or twice* in the data periods. As was already mentioned, the non-college educated is more likely to have self-employment experience than the college educated do.[45] Figure 2 shows an important difference in the timings of first entries into

[45] Remember that my data contains only nonprofessional white males in nonagricultural sectors. Excluded

Table 4: Marginal Distribution of Labor Supply Decisions by Age

Age (No.Obs.)	Self-employed		Paid-employed Full-time	Part-time	Non-employed		Dual-employed SE & Full-time PE	SE & Part-time PE
20 (1172)	2.4% 28		58.8% 689	14.6% 171	22.9% 268		0.9% 10	0.5% 6
21 (1593)	3.4% 47		61.7% 859	12.8% 178	20.8% 290		0.6% 9	0.7% 10
22 (1609)	3.9% 62		64.3% 1035	12.0% 193	17.9% 288		1.1% 18	0.8% 13
23 (1751)	4.6% 81		66.1% 1157	11.3% 197	15.9% 278		1.0% 18	1.1% 20
24 (1820)	6.0% 109		74.7% 1359	8.6% 157	8.4% 153		1.2% 22	1.1% 20
25 (1848)	7.3% 134		76.5% 1409	7.8% 144	6.5% 121		1.2% 23	0.9% 17
26 (1829)	6.6% 120		77.6% 1419	6.8% 125	5.9% 108		2.0% 37	1.1% 20
27 (1826)	6.1% 112		77.9% 1422	7.3% 133	5.8% 106		1.6% 30	1.3% 23
28 (1817)	7.5% 136		73.3% 1331	9.0% 164	7.3% 133		1.8% 32	1.2% 21
29 (1795)	7.5% 134		67.9% 1218	13.3% 239	7.7% 138		1.9% 35	1.7% 31
30 (1780)	7.8% 139		67.7% 1205	13.5% 240	8.0% 143		1.4% 25	1.6% 28
31 (1750)	7.7% 134		65.8% 1151	14.2% 249	8.6% 151		1.8% 31	1.9% 34
32 (1735)	7.8% 136		68.2% 1183	12.2% 211	8.5% 148		1.6% 28	1.7% 29
33 (1708)	8.0% 137		69.1% 1181	11.0% 188	9.3% 158		1.5% 25	1.1% 19
34 (1686)	8.2% 138		69.0% 1164	10.6% 178	9.0% 152		1.5% 25	1.7% 29
35 (1636)	8.7% 143		69.9% 1143	9.7% 159	9.8% 160		1.0% 16	0.9% 15
36 (1446)	8.6% 125		73.1% 1057	7.5% 108	9.1% 132		0.8% 11	0.9% 13
37 (1199)	8.8% 106		76.6% 918	3.2% 38	9.1% 109		1.1% 13	1.3% 15
38 (956)	9.6% 92		77.2% 738	3.5% 33	8.6% 82		0.6% 6	0.5% 5
39 (738)	8.8% 65		77.9% 575	2.2% 16	9.3% 69		0.8% 6	0.9% 7

Note: Percentages and number of observations.

Table 5: Distribution (percent) of the Number of Entries into Self-Employment

Number of entries into self-employment	All individuals	(Non-college)	(College)
0	69.8	68.2	72.5
1	19.5	20.8	17.4
2+	10.7	11.0	10.1
	100.0	100.0	100.0
(No.Obs.)	(1916)	(1199)	(717)

Note: Measured at the last periods observed in the data.

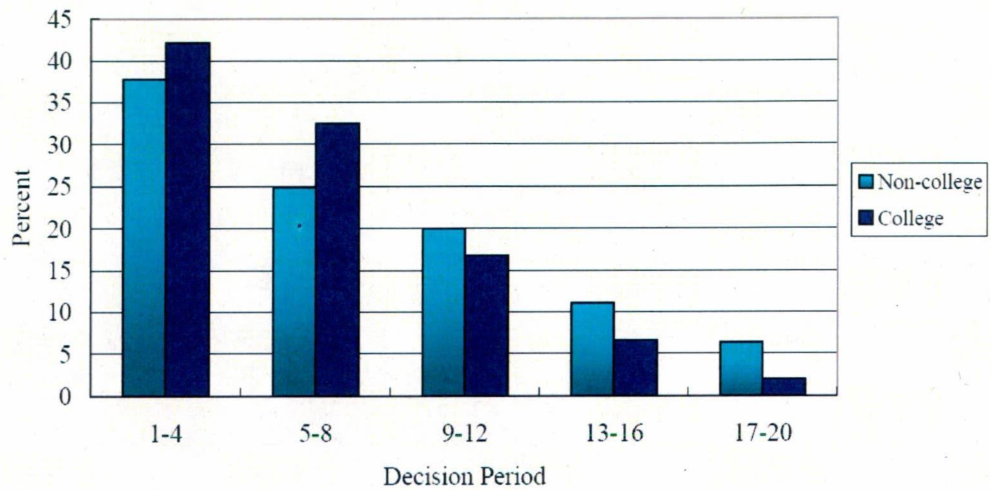

Figure 2: Distribution of Labor Supply Decisions by Age (White Males; NLSY79)

by schooling. Although the means and the medians of the first entries for both types of schooling are quite similar (8.2 (mean) and 7 (median) for the non-college educated, and 8.6 (mean) and 8 (median) for the college educated), the two distributions do not look similar: the highest percentage is attained at decision periods 5-8 for the college educated, while it is attained at decision periods 1-4 for the non-college educated.

The left panel of 6 shows one-period transition rates of labor supply decisions for both schooling levels.[46] The first number in each cell is the percentage of transitions from origin to destination (row %) while the second is the percentage in a particular destination who started from each origin (column %). The table shows *persistence in self-employment and in full-time paid-employment*: 75.4 (73.6) percent of the non-college (college) educated self-employers in one year do self-employment the next year, and 85.4 (89.5) percent of the

are 40 lawers/accountants and 23 doctors. This seems the reason of a low self-employment rate among category "College or higher" because college degree is necessary to be a professional of these kinds. If these 63 individuals are added to the self-employment cell, then the rate of self-employment rate for the college educated will be 31.4% (=(182+63)/(717+63)).

[46] I define year of *entry* into self-employment t by $l^s_{i,t} = SE$ and $l^s_{i,t-1} = Zero$, and define year of *exit* from self-employment t by $l^s_{i,t} = SE$ and $l^s_{i,t+1} = Zero$. The duration of a SE spell is defined by the difference between the exit year and the entry year.

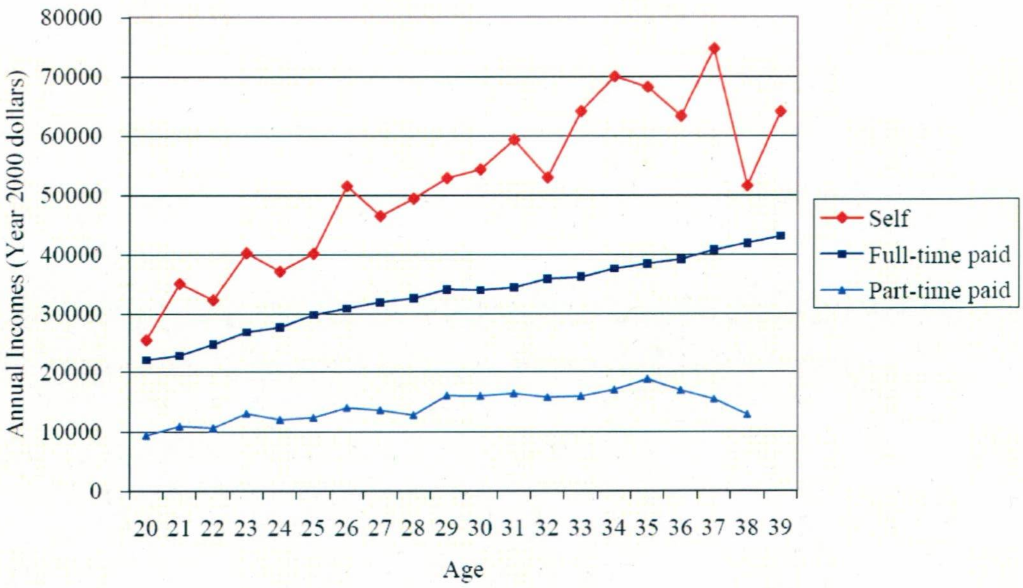

Figure 3: Age Profiles of Mean Annual Incomes

non-college (college) education who worked full-time as a wage worker in one year work as a full-time wage worker the next year. The age pattern of the self-employment and full-time paid employment is also worth attention. The left panel of 7 implies that self-employment in twenties is likely to end earlier than that in thirties: the transition rate of self-employment in twenties is 69 percent while that in thirties is 80 percent.

5.2.3 Age Profiles of Income ($\{y^s_{i,t}, y^w_{i,t}\}$) and of Net Worth ($\{a_{i,t}\}$)

As is already seen in Table 2, the self-employed earn more, on average, than the paid-employed do, and across the two groups of education levels, income from self-employment is higher than income from paid-employment (both for the mean and for the median). Table 8 and Figure 3 display age-specific mean real incomes from self-employment, from full-time and from part-time paid-employment. Real incomes rise with age in all the three modes of employment. The percentage difference between income and income from full-time paid-employment at early twenties is about 40 to 50 percent. It grows with age: at late thirties it becomes about 60 to 70 percent.

Table 9 and Figure 4 show the age profile of the mean and median net assets of all individuals. As is seen, the mean grows faster then the median does, and as a result, he mean net worth at late thirties is about 14 times larger than that at early twenties. The wealth distribution is thus more skewed in later ages.

6 Estimation Method

Using data X that is explained in the previous section, I estimate the parameters of the life-cycle model of employment mode decisions and wealth accumulation. Now, given the approximated values for $Emax_t$, it is possible to simulate individual behavior from the first decision period (one year after he finished schooling) to age 65, with an arbitrary pair of model parameters. I simulate individual choices (choice on labor and asset) and income

Table 6: Transition Matrices for Labor Supply Decisions (aged 20-39) by Schooling

Actual
Non-college

		Labor supply (t)			
		SE	PE Full-time	PE Part-time	NE
Labor supply (t-1)					
SE					
	Row %	75.4	7.2	2.6	6.2
	Column %	91.4	4.1	4.8	7.9
PE, Full-time					
	Row %	1.0	85.4	7.5	4.5
	Column %	1.2	49.2	14.1	5.7
PE, Part-time					
	Row %	1.7	51.1	28.0	18.4
	Column %	2.0	29.4	52.2	23.3
NE					
	Row %	4.4	29.9	15.5	49.7
	Column %	5.4	17.2	28.9	63.1

Predicted
Non-college

		Labor supply (t)			
		SE	PE Full-time	PE Part-time	NE
Labor supply (t-1)					
SE					
	Row %	83.0	10.3	0.9	5.8
	Column %	91.1	6.5	1.1	8.3
PE, Full-time					
	Row %	4.1	81.9	9.0	4.9
	Column %	4.5	52.3	11.0	7.1
PE, Part-time					
	Row %	2.2	49.0	43.3	5.5
	Column %	2.4	31.3	52.6	7.9
NE					
	Row %	1.8	15.5	29.0	53.7
	Column %	2.0	9.9	35.3	76.7

Actual
College

		Labor supply (t)			
		SE	PE Full-time	PE Part-time	NE
Labor supply (t-1)					
SE					
	Row %	73.6	8.4	3.3	4.2
	Column %	88.8	4.2	6.3	7.6
PE, Full-time					
	Row %	0.9	89.5	5.9	2.2
	Column %	1.1	45.5	11.3	4.0
PE, Part-time					
	Row %	2.9	56.0	27.8	12.5
	Column %	3.5	28.5	53.5	22.9
NE					
	Row %	5.5	42.7	15.0	35.7
	Column %	6.6	21.7	28.9	65.5

Predicted
College

		Labor supply (t)			
		SE	PE Full-time	PE Part-time	NE
Labor supply (t-1)					
SE					
	Row %	85.8	8.7	1.1	4.3
	Column %	89.7	4.3	3.2	6.5
PE, Full-time					
	Row %	4.3	91.6	2.8	1.2
	Column %	4.5	45.4	7.9	1.9
PE, Part-time					
	Row %	4.1	69.7	19.2	7.0
	Column %	4.3	34.5	54.0	10.5
NE					
	Row %	1.4	31.9	12.4	54.3
	Column %	1.5	15.8	34.9	81.1

Note 1: NE stands for non-employed, SE for self-employed, and PE for paid-employed.
Note 2: Rows labeled by "Row" contain the distribution of destinations (period t+1) conditional on origin (period t). Rows labeled by "Column" contain the distribution of origins conditional on destination.
conditional on destination.
Note 3: "SE and full-time PE" and 'SE and part-time PS" are omitted, so the sums of the numbers across row or column are not 100.0.

Table 7: Transition Matrices for Labor Supply Decisions by Age Group

Actual Aged 20-29

Labor supply (t-1)		Labor supply (t) SE	PE Full-time	PE Part-time	NE
SE	Row %	69.8	10.7	3.5	5.3
	Column %	89.8	5.8	6.3	7.8
PE, Full-time	Row %	1.3	85.5	7.1	4.5
	Column %	1.7	46.0	12.9	6.6
PE, Part-time	Row %	2.5	52.0	26.8	17.9
	Column %	3.2	27.9	48.9	26.5
NE	Row %	4.2	37.9	17.4	40.0
	Column %	5.4	20.4	31.8	59.1

Predicted Aged 20-29

Labor supply (t-1)		Labor supply (t) SE	PE Full-time	PE Part-time	NE
SE	Row %	87.3	9.4	2.3	1.1
	Column %	94.3	6.0	2.6	1.6
PE, Full-time	Row %	2.5	77.4	13.4	6.7
	Column %	2.7	50.0	15.4	10.2
PE, Part-time	Row %	2.1	50.4	47.1	0.4
	Column %	2.3	32.6	54.1	0.6
NE	Row %	0.7	17.6	24.4	57.4
	Column %	0.7	11.4	28.0	87.6

Actual Aged 30-39

Labor supply (t-1)		Labor supply (t) SE	PE Full-time	PE Part-time	NE
SE	Row %	79.4	4.7	2.2	5.8
	Column %	91.3	2.8	4.4	7.0
PE, Full-time	Row %	0.6	88.9	6.7	2.5
	Column %	0.6	52.2	13.4	3.1
PE, Part-time	Row %	1.6	53.4	29.3	14.9
	Column %	1.8	31.4	58.3	18.3
NE	Row %	5.4	23.4	12.0	58.5
	Column %	6.3	13.7	23.9	71.6

Predicted Aged 30-39

Labor supply (t-1)		Labor supply (t) SE	PE Full-time	PE Part-time	NE
SE	Row %	83.8	9.7	0.1	6.4
	Column %	82.2	3.9	0.4	32.3
PE, Full-time	Row %	5.6	92.3	1.1	1.0
	Column %	5.5	36.7	4.2	4.9
PE, Part-time	Row %	6.4	75.6	16.6	1.5
	Column %	6.3	75.6	61.4	7.5
NE	Row %	6.2	73.8	9.2	10.9
	Column %	6.0	29.4	34.0	55.3

Table 8: Age Profiles of Mean Incomes by Labor Supply Decisions

Age	Self-employed	(std.dev.)	(no.obs.)	Paid-employed Full-time	(std.dev.)	(no.obs.)	Part-time	(std.dev.)	(no.obs.)
20	25479.4	3346.0	38	22086.9	336.1	694	9302.1	354.7	171
21	35048.4	5636.7	55	22819.5	316.8	863	10891.8	417.9	183
22	32257.9	3008.8	78	24716.4	325.3	1044	10601.5	366.4	200
23	40238.2	3843.4	105	26791.4	582.8	1164	13016.0	1313.4	215
24	37131.3	2607.6	129	27602.3	355.0	1363	11992.7	1043.6	176
25	40122.7	2776.5	153	29703.4	624.2	1415	12313.6	683.4	158
26	51498.5	7828.1	155	30816.8	683.0	1435	14001.5	875.2	142
27	46444.7	3553.9	140	31865.1	779.3	1433	13582.5	964.9	151
28	49377.0	4034.2	163	32530.4	578.2	1344	12751.8	465.4	182
29	52852.2	4196.9	166	34036.2	1015.2	1230	16071.5	704.7	266
30	54313.3	8016.5	142	33911.9	780.0	1206	16020.7	591.6	265
31	59283.8	6854.9	141	34311.0	584.3	1160	16416.3	795.8	275
32	52942.5	6308.6	134	35868.1	671.1	1183	15775.6	622.7	234
33	64065.8	6837.5	100	36102.0	584.0	1180	15953.5	846.3	202
34	69952.1	7038.6	113	37554.4	716.2	1161	17069.6	903.0	202
35	68146.2	11395.2	71	38395.4	694.1	1143	18845.6	879.1	165
36	63237.1	7187.5	69	39146.6	714.6	1060	16963.7	1038.1	119
37	74635.8	11327.1	52	40691.1	864.4	917	15458.6	2032.3	51
38	51499.3	5752.5	38	41868.1	987.1	730	12833.2	1144.4	38
39	64036.2	7761.4	37	42990.4	1315.7	570	-	-	-

Note 1: Numbers are in year 2000 dollars.
Note 2: Mean part-time income for age 39 is not shown because the number of observations is small (22).

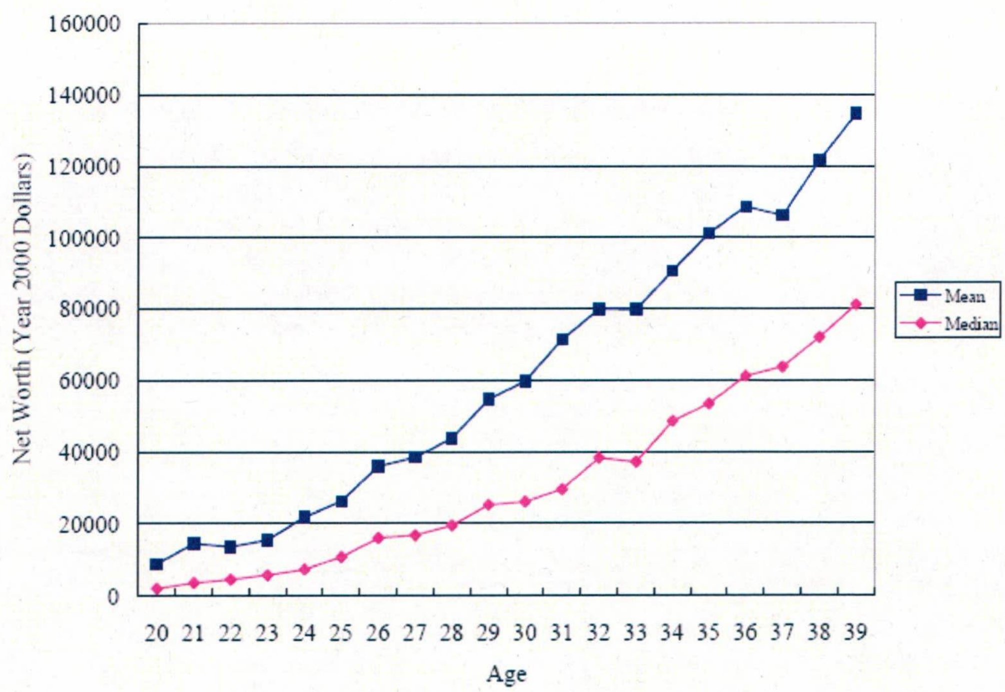

Figure 4: Actual Mean and Median of Net Worth

Table 9: Age Profile of Net Worth

Age (No.Obs.)	Mean	Median	25%	75%	Min	Max	Percent Negative
20 (138)	8829.1	2080	160	6840	-8480	184160	20.3
21 (311)	14437.0	3611	628	11200	-21038	576000	19.9
22 (588)	13556.3	4560	785	13860	-48165	769302	19.6
23 (834)	15453.4	5768	970	18240	-52560	364802	19.2
24 (1078)	21731.9	7300	1274	22338	-56836	814722	17.9
25 (1259)	26170.6	10640	2376	28576	-72336	679442	14.8
26 (1255)	35819.5	15985	3562	39672	-52820	742922	13.5
27 (1360)	38413.3	16800	3208	43916	-71438	912915	14.4
28 (1312)	43644.7	19382	4049	51778	-63510	1128144	13.0
29 (1327)	54481.7	25258	4620	61612	-60800	1905040	11.7
30 (1126)	59657.9	26101	5587	70702	-59796	1136710	12.1
31 (1123)	71103.3	29304	6838	73780	-59860	2594100	10.4
32 (953)	79519.8	38080	6991	87115	-56100	2231799	10.5
33 (925)	79702.4	37120	6100	93432	-59003	2579427	12.1
34 (836)	90289.1	48452	10681	111863	-69020	1217687	9.0
35 (842)	100622.3	52910	13807	118985	-63800	2023543	10.2
36 (651)	108198.7	60900	14160	141541	-49000	2673988	8.1
37 (516)	105425.2	62948	14329	143285	-56500	1421460	11.4
38 (436)	121347.6	71525	23723	160490	-55120	796098	6.7
39 (297)	134295.6	81000	20465	188400	-48760	816200	9.8

opportunities (including ones not chosen by the individual). The level of education and the initial amounts of net worth are taken as exogenous. At the initial decision period, any individual has no experience both for self-employment and for paid-employment.

Conditional on the deterministic part of the state space $\overline{S}_t$, the solution of the dynamic programming problem gives the conditional probability that an individual chooses option d, as the product of the type probabilities and a five-dimensional integral over the vector of shocks so that choice d is indeed optimal. If all variables in the state space were observed, then the conditional likelihood could be constructed as the the product, over time and individuals, of these probabilities.

However, a serious problem is that endogenous state variables in S_t are not always observed. In particular, as explained in Section 5, the NLSY79 started collecting information on asset in 1985, and since 1994 it has been collecting the asset information biannually.[47] Calculating the conditional choice probabilities would require one to integrate out all possible choices over the distribution of the unobserved elements. This would, however, be comutationally burdensome. I therefore adopt the method of *simulated maximum likelihood* developed by Keane and Wolpin (2001).[48] Notably, this method allows one to avoid computing the conditional probabilities, and only unconditional probabilities are used in estimation. The idea is that all observed outcomes are measured with error and model parameters are so chosen that the "distance" between simulated ("true") and observed outcomes is minimized.[49],[50]

Specifically, I first fix a trial vector of parameters $\theta \in \Theta$ and $type = 1,..,4$. In each sim-th simulation ($sim = 1,...,M$), a period-by-period random shock ϵ_t^{sim} is generated for each decision period t. As a solution of the dynamic choice problem, starting with the initial level of asset $\widetilde{a}_1^{sim}$ (see below), for each permanent state (except $type$) ($educ$, $\underline{age}$), I generate outcome histories of (i) choice realizations $\{(\widetilde{l^s}_{e,t}^{sim}, \widetilde{l^w}_{e,t}^{sim}), \widetilde{\Delta a}_{e,t+1}^{sim}\}_{t=1}^T$, and (ii) the resulting realizations of income $(\widetilde{y^s}_{e,t}^{sim}, \widetilde{y^w}_{e,t}^{sim})$, and asset realizations for the next period $\widetilde{a}_{e,t+1}^{sim}$.[51] I denote the sim-th simulated data (outcome history) for individual i in case his type is $type$ by

$$\widetilde{X}_{i,type}^{sim} = (\{(\widetilde{l^s}_{i,type,t}^{sim}, \widetilde{l^w}_{type,t}^{sim}), (\widetilde{y^s}_{i,type,t}^{sim}, \widetilde{y^w}_{i,type,t}^{sim}), \widetilde{a}_{i,type,t+1}^{sim}, \widetilde{k}_{i,type,t}^{sim}, age_{i,type.t}^{sim}\}_{t=1}^T,$$
$$\widetilde{a}_{i,1}^{sim}, educ_i),$$

[47] In addition, other endogenous variables (labor choice and income) are sometimes missing.

[48] See Keane and Sauer (2007) for technical issues of this method. In particular, they argue that the method is not only computationally practical but has good small sample properties. For an application of the method, see e.g. Keane and Sauer (2009).

[49] A byproduct of this method is that one does not have to discretize all continuous outcome variables. In this study, I do not have to discretize values for income. This is because in the presense of (normally distributed) measurement error any observed outcome history is able to be generated by any simulated outcome history with a nonzero probability.

[50] In constructing the log liklihood function, Rendon (2006) focuses only on the path of state variables afer the year 1985 (when collection on asset information started). In particular, his log likelihood function is constructed conditional on the observation in the year 1985. After obtaining the behavioral parameters, Rendon (2006) goes on to recover the initial asset distribution by using the data from the initial decision period to the year 1985. The way he does so is to update the uniform prior on initial assets by conditional on subsequent behavior.

[51] Notice here that the model components that have no counterpart in the actual data, realized income *opportunities* for the current period $\{\widetilde{f}_{e,t}^m, \widetilde{w}_{e,t}^m\}_{t=1}^T$ and the level of human capital in the next period $\widetilde{\Psi}_{e,t+1}^m$, are also generated by simulation.

where $age^{sim}_{i,type,t}$ is actually independent of sim or $type$ (determined by $\underline{age}$ and t). I assume that $educ_i$ and $\underline{age_i}$ (and hence $age_{i,t}$) are observed without error for $\underline{\text{any}}$ individual i.

Now, let the probability of the observed history of individual i conditional on the simulated history be $\Pr(X_i|\widetilde{X}^{sim}_{i,type})$.[52] The novel feature of the estimation method used in the present study is that the calculation of $\Pr(X_i|\widetilde{X}^{sim}_{i,type})$ does not depend on the state variables at any decision period t. This property enables me to construct the (unconditional) likelihood from the distributions of the measurement and classification errors (and the assumption that each error is independently distributed over individuals and time).

Specifically, I first obtain, by simulating M outcome histories, the unbiased simulator of the probability of X_i

$$\widehat{\Pr}(X_i|\theta) = \frac{1}{2M}\sum_{type=1}^{2}\sum_{sim=1}^{M}\Pr(X_i|\widetilde{X}^{sim}_{i,type})\frac{\Pr(type)}{M},$$

where $\Pr(type)/M$ is interpreted as the proportion of individuals with $type$ in all the simulated histories. The log likelihood is then given by

$$\log\mathcal{L}(\theta|\{X_i\}_{i=1}^{N}) = \sum_{i=1}^{N}\log(\widehat{\Pr}(X_i|\theta))$$

and the estimate for θ is so chosen that it maximizes the log likelihood.[53] Appendix C offers the actual functional form of $\log\mathcal{L}(\theta|\{X_i\}_{i=1}^{N})$. In the current implementation, I choose $M = 5N = 9580$. Standard errors are calculated using the outer product of numerical first derivatives.

7 Estimation Results

In this section, I discuss the fit of the estimated model to the key empirical moments as well as the interpretation of the estimated parameters.

7.1 Model Fit

To evaluate the fit of the estimated model, I artificially generated 9580 (5 times 1916) individual life-cycle paths to age 50 for each age of the first decision period (ages 20-26) using the estimated parameters.[54]

Table 10 compares the three key statistics about entry into and exit from self-employment in the actual data with those in the simulated data (the left part is a reproduction of Table 1). All the three characteristics are underpredicted both for the non-college and the college educated. In particular, entries into self-employment take place in later ages in the simulated

52 With the notation here, what is explained in Footnote 46 is now stated that for an arbitrary $\widetilde{X}^m_e$, $\Pr(X_i|\widetilde{X}^m_e) > 0$ for any X_i thanks to (adequately modeled) classification and measurement errors.

53 While some model parameters have their own structural relationships, thus are possible to be estimated independently from the other part of the model structure (e.g. the relationship between observed income and modeled income opportunities), the entire set pf model parameters enters the likelihood through the choice probabilities that are computed from the solution of the dynamic programming problem. Thus, I estimate all the parameters by maximixing the log likelihood function of probablities of outcome histories.

54 In obtaining any information, simulated data for each invidual is used up to his last period that was covered.

Table 10: Three Characteristics on Entry into and Exit from Self-Employment: Actual and Predicted

	Actual		Predicted	
	Non-college educated	College educated	Non-college educated	College educated
Ever experience of self-employment (%)	31.78	27.48	26.76	24.43
First entry into self-employment occurs in less than or equal to first eight decision years (%)	62.72	74.62	59.34	69.20
Exit from self-employment in a year (%)	32.28	28.57	28.09	23.61

data than in the actual data. It, however, seems to well capture the differences by schooling on entry into and exit from self-employment.

Figures 5-8 compare simulated age profiles of labor supply decisions (self-employed, full-time paid-employed, part-time paid-employed and non-employed) with actual ones. The model does a good job in replicating the age pattern of self-employment: the rate of the self-employed increases until age 25 and then it becomes moderately stable in the remaining ages. As for the other modes of employment, the simulated profiles resemble the actual profiles reasonably well, except few ages around early thirties. In the right panel of Table 1, the predicted one-period transition matrix is presented. The diagonal four transition rates of staying in the same mode of employment are reasonably replicated, though the one for part-time paid employment for the non-college educated and the one for non-employment for the college educated seem relatively overpredicted. The observation that the percentage from full-time paid-employment to self-employment is lower than that from non-employment is not well captured by the model. The right panel of Table 7 display the two transition matrices that correspond to age group 20-29 and to age group. The predicted numbers well capture the stronger persistence of self-employment for ages 30-39, though they show that the estimated model is less successful in explaining the transitions around part-time paid employment and non-employment.

Figures 9-14 display age profiles of annual income for each mode of employment. The model does a good job in replicating the age patterns of income as well. Figure 15 shows the age profile of the mean net worth. The model well captures the growth of the mean by age, though it is under predicted for most of ages, and is also less successful in replicating the skewness of the wealth distribution.

Overall, the estimated model reasonably fits the main features of the actual data, though there are some discrepancies between the empirical observations and the model predictions. More improvement is expected in future work.

7.2 Parameter Estimates

A full list of the model's estimated parameters is given in Appendix D. Here I discuss main characteristics of the estimates.

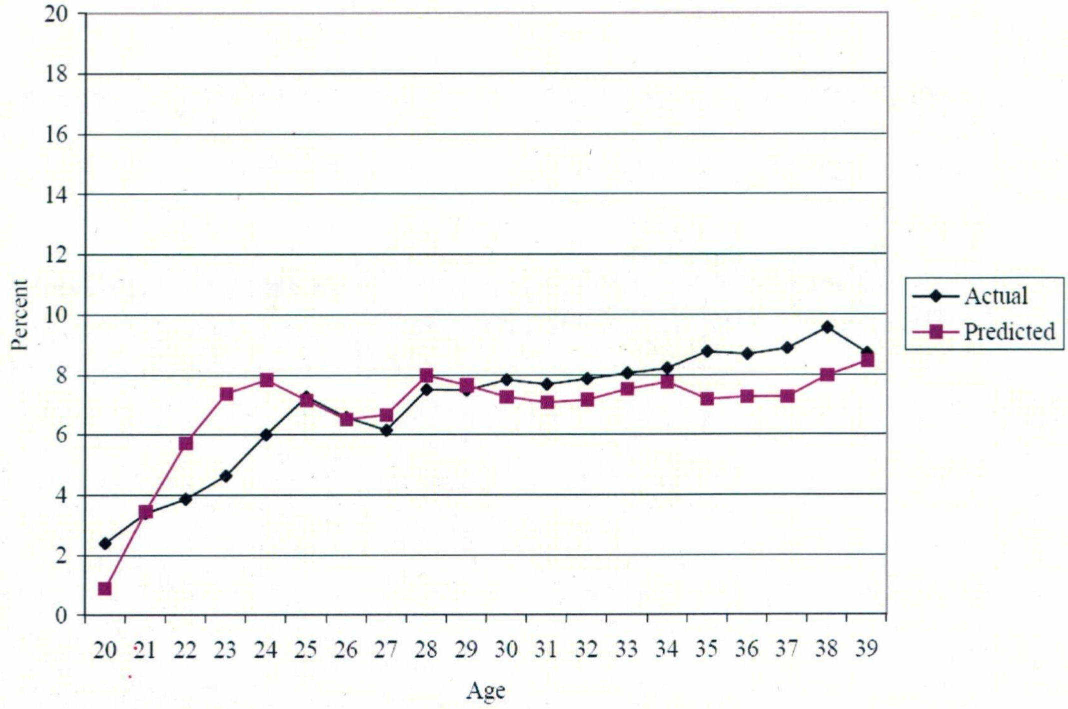

Figure 5: Age Profiles of the Self-Employed

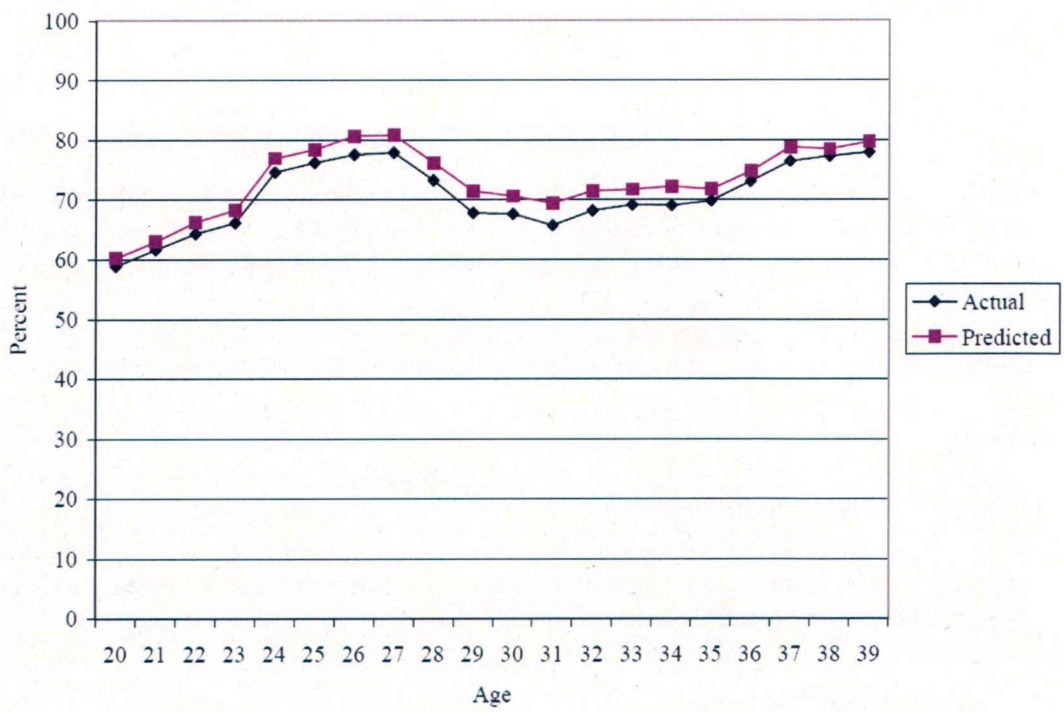

Figure 6: Age Profiles of the Full-Time Paid-Employed

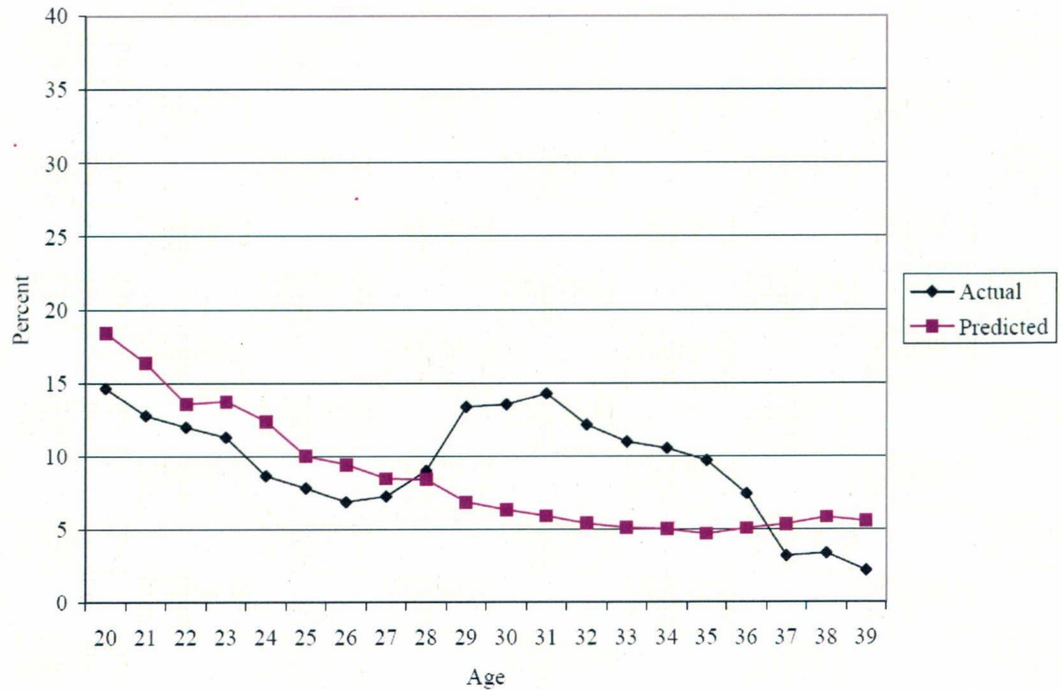

Figure 7: Age Profiles of the Full-Time Paid-Employed

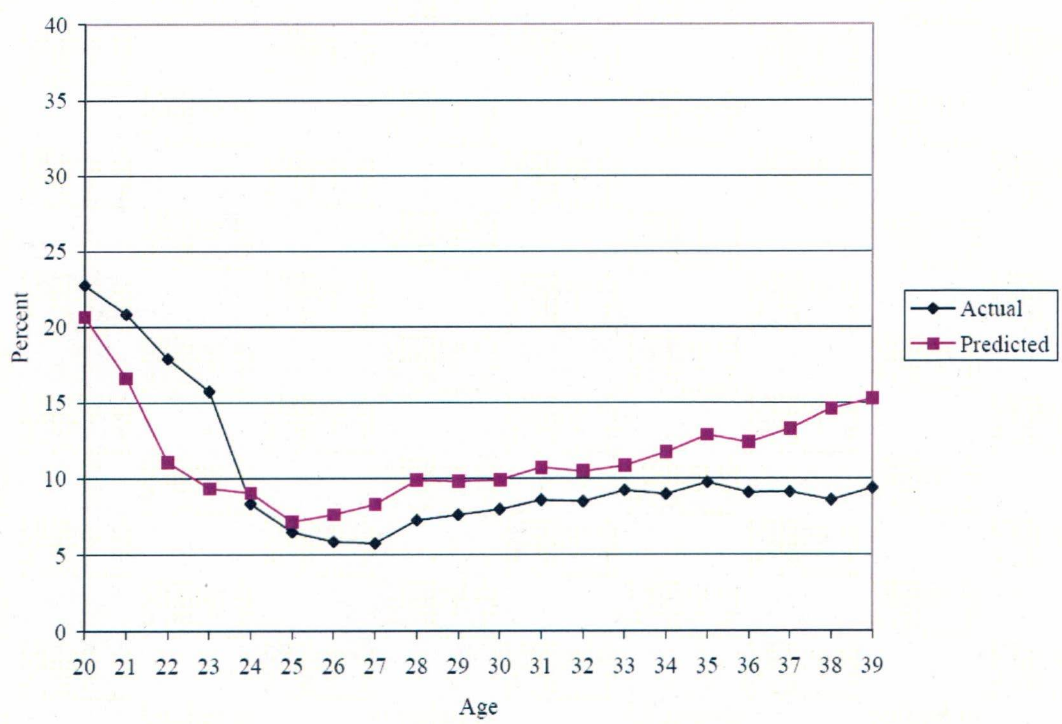

Figure 8: Age Profiles of the Non-Employed

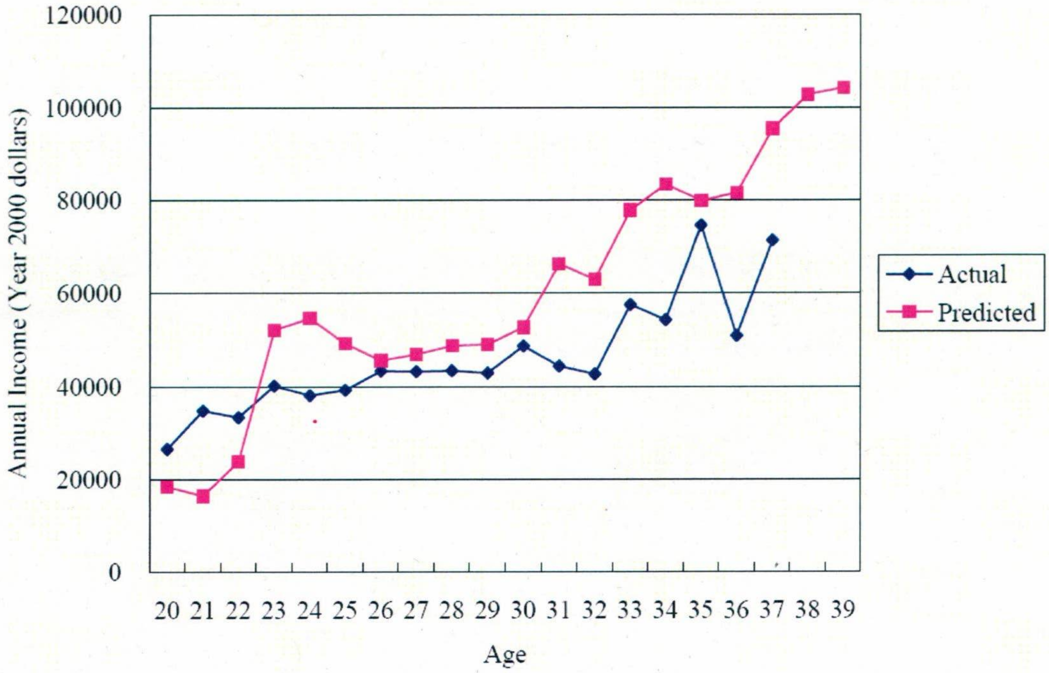

Figure 9: Age Profiles of the Mean Income from Self-Employment (Non-college)

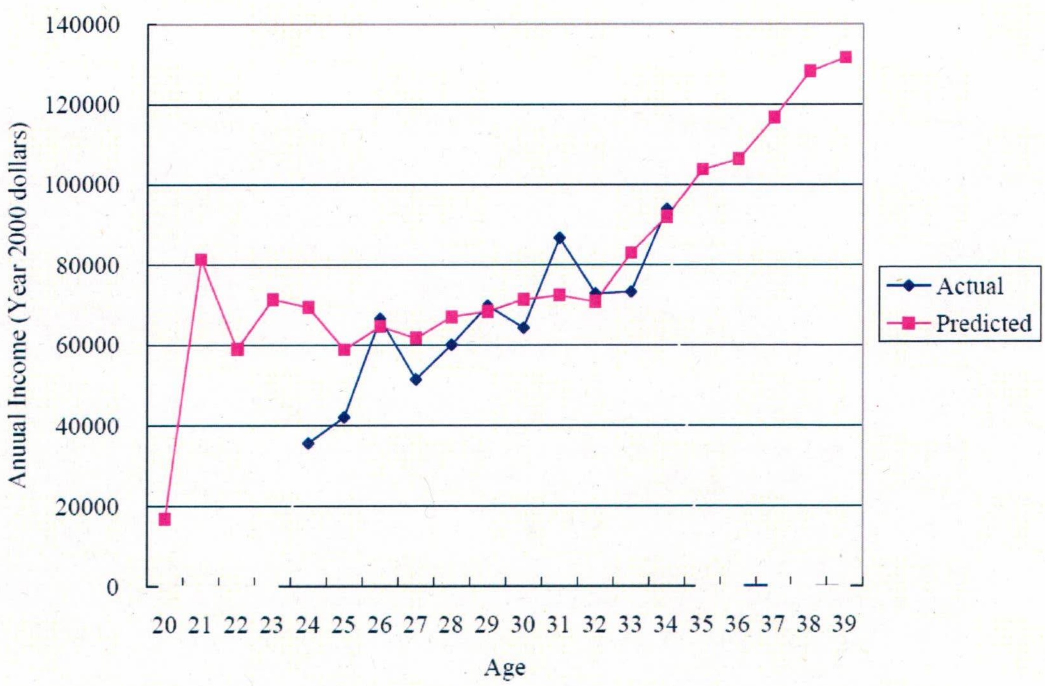

Figure 10: Age Profiles of the Mean Income from Self-Employment (College)

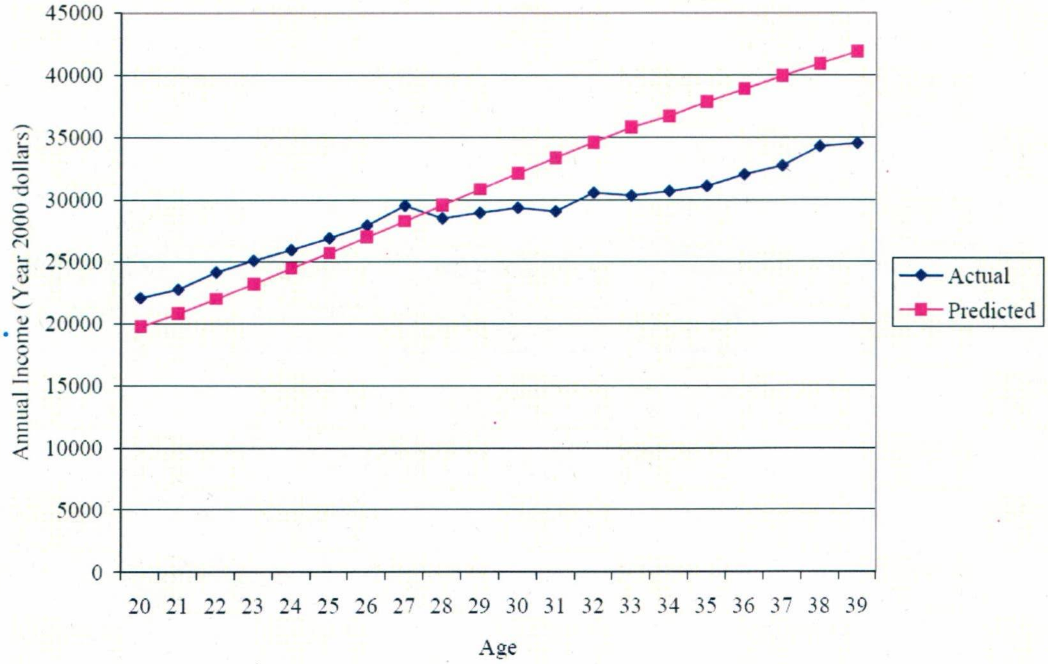

Figure 11: Age Profiles of the Mean Income from Full-time Paid-Employment (Non-college)

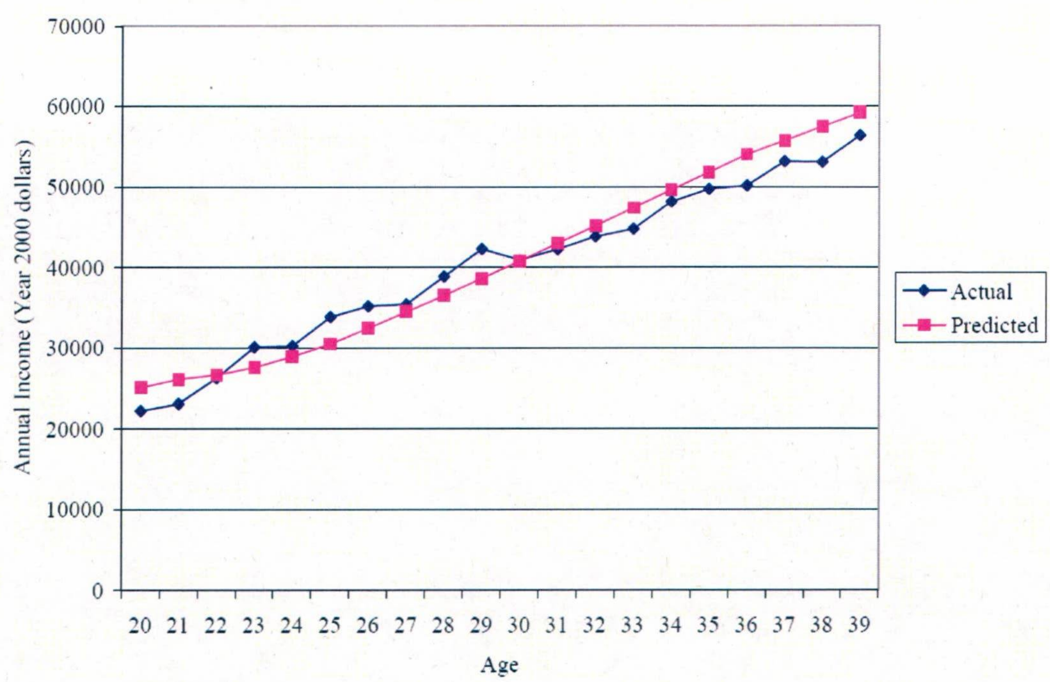

Figure 12: Age Profiles of the Mean Income from Full-time Paid-Employment (College)

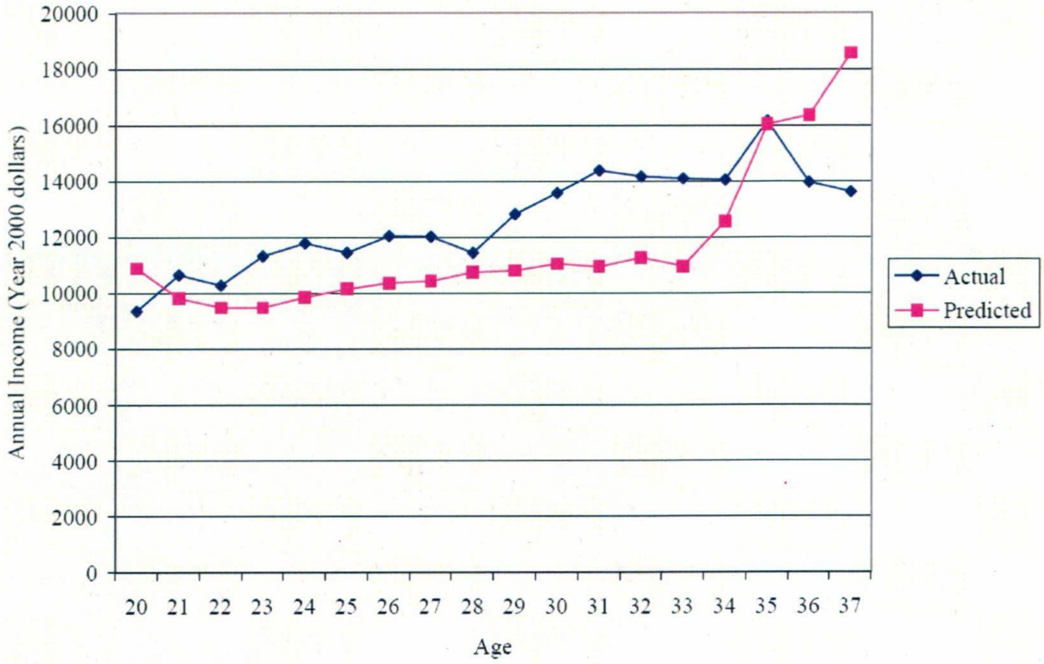

Figure 13: Age Profiles of the Mean Income from Part-time Paid-Employment (Non-college)

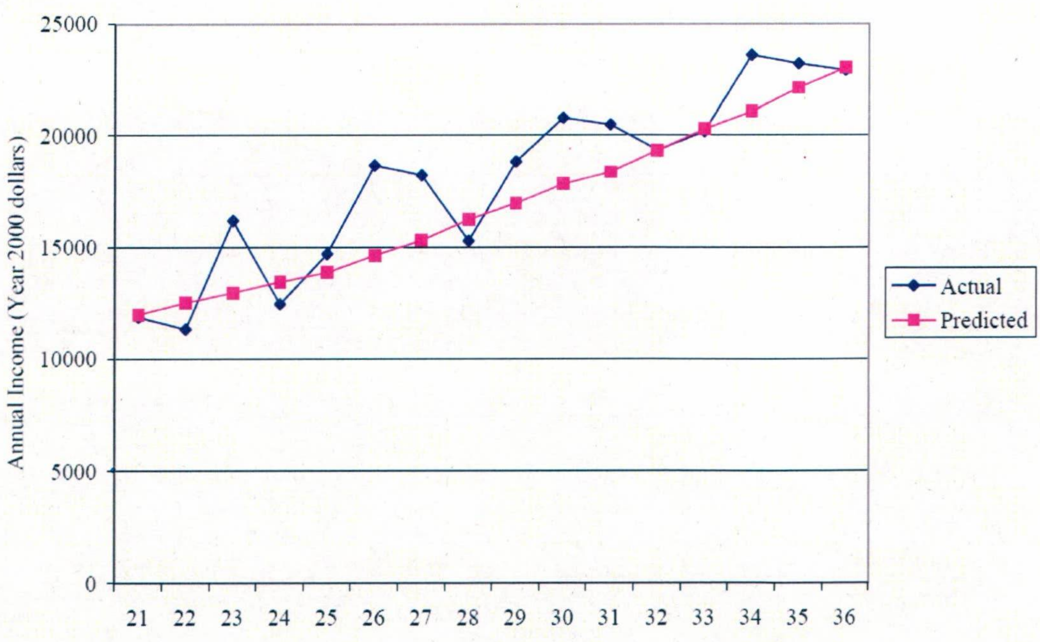

Figure 14: Age Profiles of the Mean Income from Part-time Paid-Employment (College)

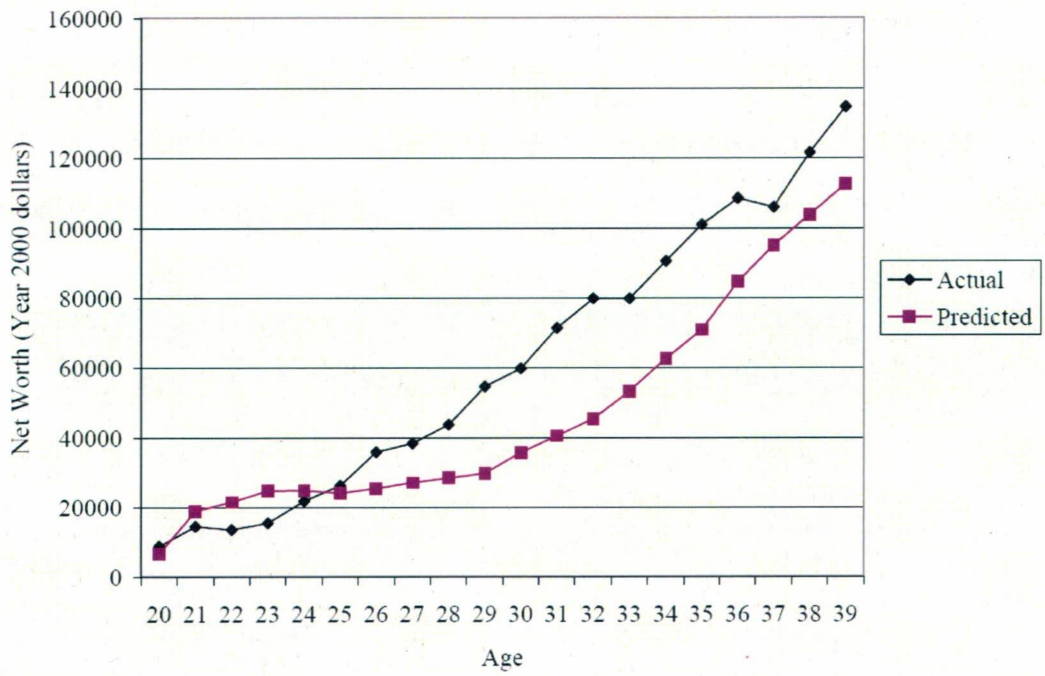

Figure 15: Age Profiles of the Mean Net Worth

7.2.1 Preference

The estimated rate with which all individuals discount utility values a year ahead is 97.56%. This means that the annual discount rate is 2.50%. Now, I turn attention to the CRRA coefficient.[55] With the CRRA form of utility, $u = c^{1-\mu_0}/(1-\mu_0)$, the coefficient of relative risk aversion is μ_0, the intertemporal elasticity of substitution in consumption is μ_0^{-1}. The typical estimated value for μ_0 in the literature is around -2. The estimated CRRA constants both for Type 1 and for Type 2 are much lower (0.483 and 0.472, respectively) than those in the macro literature, which is consistent with the recent studies that use micro data to estimate the parameter (e.g. Keane and Wolpin (2001), Gourinchas and Parker (2002), Keane and Imai (2004)). In these studies, the estimated values typically range between 0.5 and 2. Interestingly, this study's estimate for μ_0 is also close to Goeree, Holt, and Palfrey's (2002), who estimate the CRRA coefficient by laboratory experiments of generalized matching pennies games $\widehat{\mu}_0 = 0.440$. This low value for risk aversion also affects the individual's propensity to become a self-employer presumably because the estimated variance of income from self-employment is much higher than that from (full-time) paid-employment. If compared with the studies on entrepreneurship, my CRRA constant implies *less* risk averse individuals: In his estimation, Buera (2008a) does not estimate μ_0 (in his notation σ) and sets $\mu_0 = 1.50$ throughout.[56] Mondragon-Velez (2006) gives the estimate, $\widehat{\mu}_0 = 1.03$ (in his notation σ).[57]

My estimation results imply that *nonpecuniary* factors are important in explaining observed patterns of labor choice. The estimated value for disutility from self-employed work

[55] Evans and Jovanovic (1989) assume that individuals are risk neutral, while Buera (2008a,b) and Mondragon-Velez (2007) consider the CRRA utility. None of these papers takes into account labor disutility.

[56] In his study on effects of borrowing constraints on small manufacturing owner-firms in Ghana, Schündeln (2006) $\mu_1 = 0.50$.

[57] Mondragon-Velez (2007) does not consider heterogeneity in risk attitude.

in the first year of any spell (317.3 for Type 1 and 334.9 for Type 2) is twice as large as that from (full-time) paid work (164.9 for Type 1 and 179.9 for Type 2). Notice also that the estimated values for benefits from continuing self-employment are also high: they are as half as the values for labor disutility from self-employment. These large values are necessary to well replicate the observed persistence of self-employment. In the previous studies on self-employment, there were no estimates on nonpecuniary costs/benefits of entrepreneurship. Hamilton (2000) gives empirical findings that support the idea that self-employment offers significant nonpecuniary benefits. Specifically, in the data he uses (constructed from the 1984 panel of the Survey of Income and Program Participation (SIPP)), Hamilton (2000) finds that many self-employers experience lower earnings growth than wage workers do as well as lower earnings in initial periods of self-employment. He also finds little evidence that suggests that the earnings differential reflects the selection of low-ability individuals into self-employment. In the present study, I observe the higher mean and median incomes from self-employment than those from full-time paid-employment for each age in the age profiles of income. This finding is in contrast to Hamilton's (2000), though nonpecuniary benefits play important roles in replicating the age patterns of labor supply.[58] Mondragon-Velez 's (2006) unsatisfactory high estimates for entrepreneurial earnings may result from his exclusion of nonpecuniary factors. Without incorporating nonpecuniary costs/benefits of entrepreneurial work into a dynamic model, it may be very difficult to well capture dynamic aspects of self-employment in terms of both labor supply and income realization.

7.2.2 Entrepreneurial Production Function

My formulation allows for the coefficient of capital returns in the entrepreneurial production function to differ by schooling. The estimated value for the college educated is 0.16 ($= \widehat{\alpha}_0 + \widehat{\alpha}_1$) while that for the non-college educated is 0.17 ($= \widehat{\alpha}_0$). This finding is consistent with an observation is that college educated self-employers are more likely in the service industry while in non-college educated self-employers are more likely in the construction industry (Mondragon-Velez (2005)). The estimates for capital returns in the previous literature are much higher than those obtained here. This is presumably because I incorporate the component of human capital accumulation into the entrepreneurial production function. In contrast, Evans and Jovanovic (1989), Buera (2008a) and Mondragon-Velez (2006) estimate the following entrepreneurial production function:

$$y_t^s = A_t k_t^{\alpha}$$

where A_t is a compound component of nonstochastic and stochastic factors and human capital accumulation is not taken into account. The estimate of α by Evans and Jovanovic's (1989) is 0.22 (it is 0.23 in Xu's (1998) reestimation). As in the present study, Mondragon-Velez (2006) considers differences in capital returns by education (non-college and college). His estimates are: $\widehat{\alpha}$(non-college) $= 0.27$ and $\widehat{\alpha}$(college) $= 0.36$.

[58] This finding is also consistent with recent studies that show empirical evidence suggesting that self-employment may derive procedural utility (see e.g. Frey and Benz (2008) and Fuchs-Schündeln (2008)). The idea of procedural utility is that people may care not only about the outcomes but about the procedures that lead to them, and in this study's context, independent work in self-employment may give workers more satisfaction (the main difference of the two papers is that the latter allows for preference heterogeneity). Kawaguchi (2008), using job satisfactin scores in the NSLY79 and controlling for heterogeneity (in self-reporting one's own job satisfaction) at individual level, also finds evidence that self-employment gives workers more satisfaction than wage-employment does.

Table 11: Comparison with Evans and Leighton (1989, p.531)

	Evans and Leighton (1989)	**This study**
$\widehat{\gamma}_3^w$	0.0985	0.0868
$\widehat{\gamma}_4^w$	-0.2417	-0.2723
$\widehat{\gamma}_4^s$	0.1128	0.0967
$\widehat{\gamma}_5^s$	-0.4867	-0.1701
$\widehat{\gamma}_6^s + \widehat{\gamma}_7^s/50$	0.0212	0.0264

Note : In Evans and Leighton (1989), the composite of the coefficients, $\widehat{\gamma}_6^s + \widehat{\gamma}_7^s/50$, corresponds to the coefficient for the linear term for wage experience in the self-employment earnings equation.

7.2.3 Human Capital

Next, consider the estimated income opportunities. The contributions of college education and more to the human capital component are 25.2% for self-employed work ($= \widehat{\gamma}_1^s$) and 24.0% for wage work ($= \widehat{\gamma}_1^w$). These values lower estimates if compared with the literature on college premium in the Mincerian wage equation.[59] The difference between self-employment and paid-employment is small. The first one-year experience of full-time paid-employment increase the human capital component by 0.9 ($= \widehat{\gamma}_6^s - (\widehat{\gamma}_7^s/100)$) percent for self-employment and 8.4 ($= \widehat{\gamma}_6^w - (\widehat{\gamma}_7^w/100)$) percent for paid-employment. These two contrasting numbers are consistent with Kawaguchi's (2003) main finding that experience-earnings profiles were flatter in the human capital function for self-employment. Note, however, that Kawaguchi (2003) does not distinguish between experience of self-employment and that of wage employment. I distinguish these two, and the result is that in any spell, the first one-year of self-employment enhances the human capital component for self-employment by 7.5 ($= \widehat{\gamma}_4^s - \widehat{\gamma}_5^s/100$) percent. In contrast, ever experience of self-employment enhances the human capital component only by 0.8 ($= \widehat{\gamma}_3^s$) percent for self-employment and decreases the human capital component slightly for paid-employment (-0.3 ($= \widehat{\gamma}_5^w$) percent). Table 11 gives a comparison of the estimates of key parameters with Evans and Leighton's (1989,p.531). Except the estimate for the squared term of years in self-employment, the numbers seem close.

7.2.4 Lower Bound for Net Worth

Evans and Jovanovic (1989), Xu (1999), Buera (2008a) and Mondragon-Velez (2006) using the common notation in the literature $k_t \in [0, \lambda a_t]$ to express the borrowing constraints. The estimates of Evans and Jovanovic (1989), of Xu (1999) and of Buera (2008a) are $\widehat{\lambda} = 1.75$, $\widehat{\lambda} = 2.01$ and $\widehat{\lambda} = 1.01$, respectively. Mondragon-Velez (2006) does not estimate λ but compare various levels of λ ($\lambda = 1.0$, 1.25, 1.50, 1.75 and 2.0). In this study, λ is *not a*

[59] Evans and Leighton (1989) provide OLS estimates of log earnings equations for self-employers and wage workers. The variable for education is years of education. If we multiply these estimates by four, we obtain 41.1% for self-employment and 28.3% for paid-employment. For wage workers only, Heckman, Lochner and Todd (2008), for example, find, from the 1980 census, that the internal rate of returns for years 12-16 is 11%, so that the college premium is 44%.