Determinants of Downward Risk in Labor Income *

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Abstract

This paper uses the PSID to estimate empirical Markov transition matrices for each year of the survey for the probability of transitioning from one quartile of the labor income distribution to any of the other quartiles of the labor distribution. We merge in crime rate, high school dropout rate, and inequality level data associated with the geography of each PSID respondent because these variables have shown to be significant predictors of intergenerational mobility. We show that age, gender, and these location-specific factors also predict high frequency transition probabilities in labor income. We are currently applying for access to the zip code level data from the PSID, and we will also apply for access to the IRS panel of earnings transitions.

JEL classification: put codes here

*This research benefited from support from the Open Source Economics Laboratory (OSE Lab) at the University of Chicago. All Python code and documentation for the computational model is available at https://github.com/OpenSourceEcon/IncomeTrans [currently a private repository].

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1 Introduction

Outline of paper

- Question: What are the key determinants of downward income mobility?
  - Contributions
    - We add geographic variables as in Chetty, et al (?)
    - Focusing on downward mobility addresses asymmetry in Markov transition matrices. Stochastic income regression models imply symmetric effects of upward and downward shocks.
  - Link to stochastic income literature and to intergenerational mobility literature
- Data: PSID, NLSY79, Census
  - Get zip code data from PSID and NLSY79 via IRB request
- Markov Matrices
- Logistic regression with cross validation
- Conclusion
  - Policy implications
  - Further questions
  - Use in stochastic models

Recent work has focused on estimating the stochastic income processes faced by different households. The accuracy of these processes are an essential input to modeling household behavior. The expected riskiness of labor income varies by earner personal and location characteristics. Precautionary savings and labor supply behavior is influenced by the perceived riskiness of future income streams. This paper describes how downward income risk changes based on individual characteristics (age and gender) as well as some location specific characteristics shown to be important in the literature (crime rate, dropout rate, and inequality).

Guvenen et al. (2014) study how labor earnings transition probabilities change over the business cycle. Their main findings are that the skewness of the shock process shifts from expansion to recession. They also find that the earnings process for top earners is significantly different from that of the rest of the distribution and that the downside earnings risk for top earners increases disproportionately during a recession.

DeBacker and Ramnath (2019) estimate these transition probabilities for narrow quantiles of the U.S. population using administrative panel data from the Internal Revenue Service.

2 Data: PSID, NLSY79, and U.S. Census

2.1 PSID Sample

The PSID data is a longitudinal survey of individuals and families starting from 1968. It consists of over 5000 families when first interviewed. The PSID also interviewed members who were from the original main family in 1968 and built new families in later years, which are termed as "split family" in the PSID. There are 31228 families that have at least one record of the variables we focus on.

Income: When not considering gender, we use the total taxable family income variable in the Family Public Data Section in PSID as the measure of family income, which includes taxable income and total transfers of head, wife and others in the family. When considering gender, we use the total labor income variable instead as the measure of individual income.

Age: The respondents in the PSID were aged 15-104 in the survey years. The average age of respondents in most interview years was between 40 to 45.

Race: In PSID, around 55%-65% of the respondents are white, and 32%-38% are black. We compare income transition matrices between white and black people only as the data of other races are not large enough for constructing a large number of markov matrices. When estimating the logistic regressions, we can take all races into consideration.

Geography: The PSID data have information about the state respondents lived in each interview year, which allows us to link the commuting zone data provided by Chetty et al. (2014) and to measure the influence of environments on downward mobility.

2.2 NLSY Sample

The NLSY79 is a longitudinal survey of 12,686 American people who were born between 1957-1964. Unlike the PSID, it did not include new families that were built by members from the original family.

Income: We use the total net family income variable as the measure of respondents' family income, which composites incomes from family members that related to the interviewer by blood or marriage [1].

Age: The respondents were aged 14-22 when first interviewed in 1979, and aged 51-60 in 2016, the last year of records so far. Since the NLSY does not add new respondents after 1979, the average age of the respondents increases by one year per year.

Education: This paper uses the highest grade completed as the measure of one's educational attainment, which ranges from 0 to 20. In particular, the value 13 of this variable means the first year of college, so whether a person's highest grade completed is 13 or greater indicates whether the person has attended to college. The largest possible value 20 means the 8th year of college or more. The maximal educational level a person records is considered.

Race: The variable "Race" in the NLSY79 has three values: Black, Hispanic, and Non-Black, Non-Hispanic. 15.8% of the respondents are hispanic, 25.0% are black,

[1]The respondents whose total family income is above 100,001, the traditional truncation level, were recorded as truncated income, which is equal to the average value of U.S. citzens who have total family income greater than the truncation level. This does not influence the analysis in our paper since we only measure a person's income quartile.

and 59.2% are non-black, non-Hispanic. We compare the Markov transition matrices across these three groups.

Number of Children: The NLSY records the number of biological children for each female from 2000 to 2016, and the number of biological, step, and adopted children before 2000. The median and the mode of this variable are 2 in most years.

Health Limitations: The NLSY records whether the respondents have health limitations that impact the type or amount of work they can do in each interview year. The percentage of people who have health limitations increase from 9.6% in 1996 to 27.7% in 2016. This might because the average age of the respondents increases.

Geography: The NLSY data have variables that show whether an individual is living in urban or rural areas in each interview year. Around 78% of the respondents lived in urban area in each year.

3 Conditional Markov Transition Matrices

In this section, we provide the estimations of the Markov transition matrices:

$$\begin{bmatrix} p_{11} & p_{12} & p_{13} & p_{14} \\ p_{21} & p_{22} & p_{23} & p_{24} \\ p_{31} & p_{32} & p_{33} & p_{34} \\ p_{41} & p_{42} & p_{43} & p_{44} \end{bmatrix}$$

where p_{ij} refers to the probability that an individual whose income is in the i_{th} quartile in year t will be in the j_{th} quartile in year $t + 2$. [2] The process of calculating the Markov transition matrices is as follows: (1) create M empty 4×4 matrices, where M represents the number of categories we care about (e.g., if we hope to estimate two income transition matrices, one for urban residents, one for rural residents, then M=2). (2) We identify the type of movement (i.e., from the i_{th} quartile to the j_{th} quartile, i, j=1, 2, 3, 4) for every two consecutive interview year for each individual, and add one in the corresponding entry in the corresponding matrix. After reading

[2]The NLSY interviews respondents biennially in 1996-2016.

the whole dataset, we will get M matrices, each of which records the number of each type's movement n_{ij} for the category $m \in M$. (3) For each matrix, calculate $p_{ij} = \frac{n_{ij}}{\Sigma_{j=1}^{4} n_{ij}}$

3.1 NLSY

The Baseline Markov Transition Matrix: First, we calculate the baseline Markov transition matrix for the whole individuals in the NLSY data. The result is shown in Table 1:

Table 1: The Baseline Matrix Transition Matrix for All Records

	Q1	Q2	Q3	Q4
Q1	0.745 (9873)	0.195 (2587)	0.038 (509)	0.021 (284)
Q2	0.172 (2402)	0.605 (8442)	0.187 (2609)	0.036 (507)
Q3	0.040 (569)	0.162 (2324)	0.626 (8966)	0.172 (2456)
Q4	0.023 (326)	0.043 (611)	0.156 (2239)	0.778 (11159)

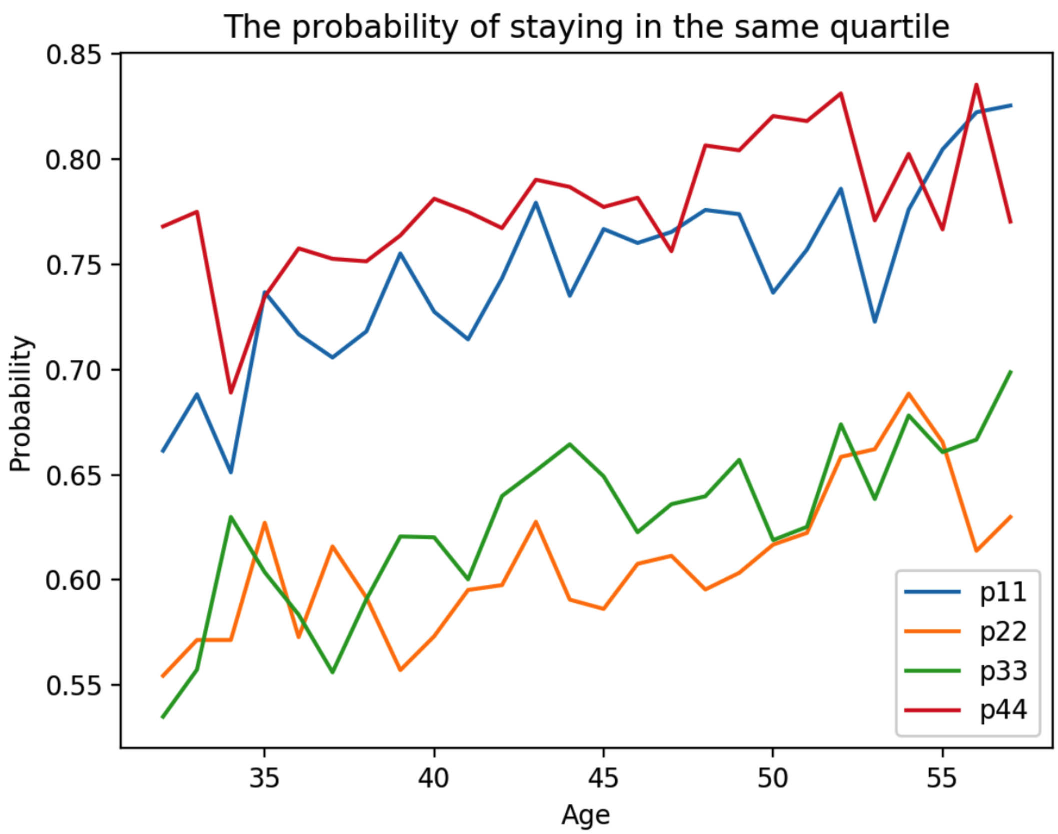
* This table shows the Markov transition matrix for all records. The first number in each box represents the transition probability while the number in the parenthesis represents the number of records.

There are some findings worth mentioning. First, the people whose income level is in the lowest or the highest quartile are more stable than those who have income level in the second or the third quartile. Second, Higher income people tend to be more stable than lower income people, which is reflected as $p_{44} > p_{11}, p_{33} > p_{22}$, $p_{34} < p_{23} < p_{12}$, and $p_{43} < p_{32} < p_{21}$, etc. Third, most one quartile upward movement probabilities are higher than the corresponding one quartile downward movement probabilities (i.e., $p_{12} > p_{21}$, $p_{23} > p_{32}$, $p_{34} > p_{43}$, and also $p_{23} > p_{21}$, $p_{34} > p_{32}$). Fourth, for more than one quartile movement, the upward probabilities are slightly lower than the corresponding downward probabilities (i.e., $p_{13} < p_{31}$, $p_{14} < p_{41}$, $p_{24} < p_{42}$).

Markov Transition Matrices conditional on Age:

In this part, we calculate 26 markov transition matrices, each representing an age.

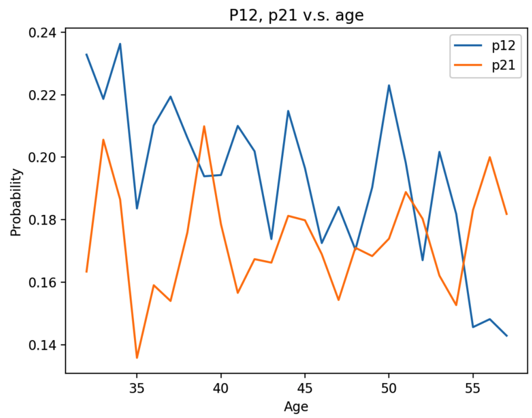
Figure 1: The probability of staying in the same quartile



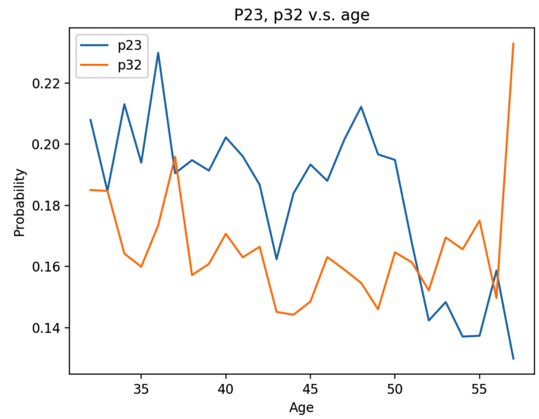
Notes: This figure shows the relationships between staying in the same quartiles and age.

The Figure 1 shows the relationships between staying in the same quartiles and age. We could find that (1) $p_{44} > p_{11} > p_{33} > p_{22}$ for nearly all ages, which is consistent to the baseline estimation. (2) All p_{ii} increase in age, indicating that as people get older, their income becomes more stable. The probability p_{ii} could increase around 10% from 32 to 57 years old.

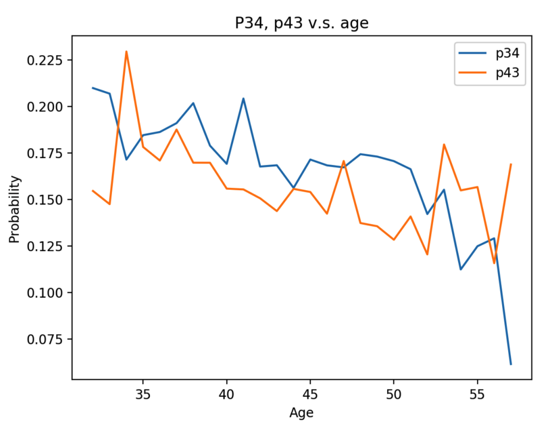
The Figure 2a to 3b confirm the finding that upward mobility is higher than the corresponding downward mobility, which is shown in the baseline estimation. Also, we find that downward probabilities do not show a clear decreasing or increasing pattern with age as p_{21} and p_{32} remain roughly constant across all ages, although p_{43} presents a minor decreasing trend, and the overall downward probabilities is around



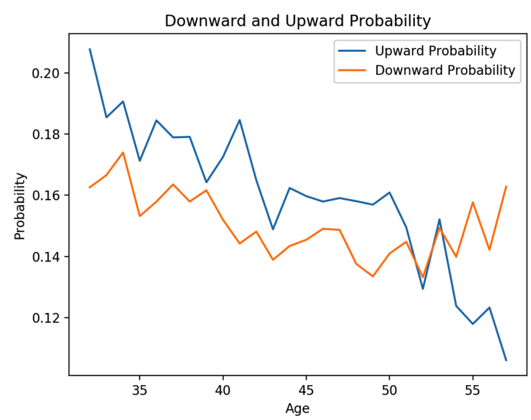
(a) p12, p21 v.s. age



(b) p23, p32 v.s. age



(a) p34, p43 v.s. age



(b) Upward and Downward Probability v.s. age

16% at age 32, falling to lowest 14% at age 52, and returns to about 16% at age 57. However, upward probabilities decrease dramatically as nearly all upward probabilities decrease around 10% from age 32 to age 57, which means that the decreasing chance of upward movement is the main source of the increasing stability of a person's income as people get older. The findings indicate that individuals' downward risks will not decrease significantly as aged, but they have less upward chances as becoming older.

Race: We construct Markov transition matrices for different races. The Table 2 to 4 show the Markov transition matrices for blacks, Hispanics, and people of other races, respectively. The outcomes indicate that (1) blacks are more likely to have lower income than to have higher income, while people of other races are more likely to have higher income, and Hispanics' pattern is between the two, and more importantly, (2) blacks have much higher downward probabilities than non-black and non-Hispanic people, and blacks' downward probabilities are also higher than their corresponding upward probabilities, which is inconsistent with the patterns for all people. (3) In contrast, individuals of other races have higher upward probabilities than their corresponding downward probabilities. Hispanics do not show clear differences between downward and upward probabilities. The results indicate that, even black and people of other races have the same income quantile today, blacks are more likely to have lower income than people of other races in the next time.

The Figure 4a show the relationship between age and downward probability for each race. From the figure, we could see that the people of other races' downward probabilities decrease slightly from age 32 to age 50, and increase slightly after age 50, which is consistent with the findings in Figure 3b. The patterns for blacks and Hispanics are less obvious, but it is clear that the gaps in downward probability between the three races do not change dramatically with age.

The patterns for upward probability are not the same as shown in Figure 4b. The decrease in upward probability is much more dramatic for people of other races than for blacks and Hispanics. At age 32, people of other races could have up to 10%

higher upward chances than blacks, but the differences decrease to around 5% at age 52.

Table 2: The Matrix Transition Matrix for Blacks

	Q1	Q2	Q3	Q4
Q1	0.796 (4908)	0.169 (1041)	0.026 (161)	0.009 (57)
Q2	0.216 (955)	0.603 (2662)	0.154 (679)	0.026 (116)
Q3	0.053 (164)	0.204 (626)	0.593 (1821)	0.149 (458)
Q4	0.033 (75)	0.061 (137)	0.190 (427)	0.716 (1609)

* This table shows the Markov transition matrix for black people. The first number in each box represent the transition probability while the number in the parenthesis represent the number of records.

Table 3: The Matrix Transition Matrix for Hispanics

	Q1	Q2	Q3	Q4
Q1	0.740 (2058)	0.199 (554)	0.040 (112)	0.020 (57)
Q2	0.163 (492)	0.619 (1864)	0.188 (565)	0.030 (90)
Q3	0.046 (116)	0.178 (452)	0.614 (1563)	0.162 (413)
Q4	0.031 (67)	0.056 (119)	0.179 (382)	0.733 (1561)

* This table shows the Markov transition matrix for Hispanic people. The first number in each box represents the transition probability while the number in the parenthesis represent the number of records.

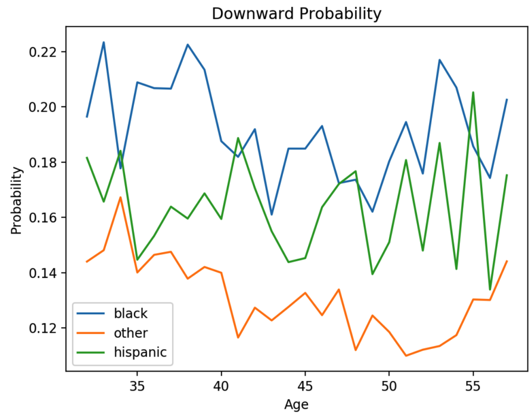
Table 4: The Matrix Transition Matrix for Non-Black Non-Hispanic people

	Q1	Q2	Q3	Q4
Q1	0.675 (2907)	0.230 (992)	0.055 (236)	0.039 (170)
Q2	0.146 (955)	0.599 (3916)	0.209 (1365)	0.046 (301)
Q3	0.033 (289)	0.143 (5582)	0.641 (5582)	0.182 (1585)
Q4	0.018 (184)	0.036 (1430)	0.144 (1430)	0.802 (7989)

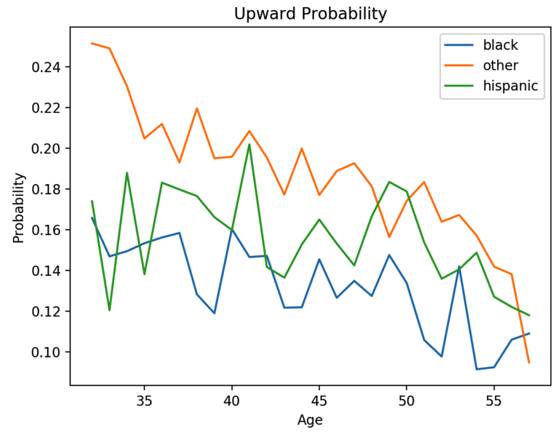
* This table shows the Markov transition matrix for Non-Black Non-Hispanic people. The first number in each box represents the transition probability while the number in the parenthesis represents the number of records.

Education:

In this part, we construct Markov Transition Matrices conditional on whether the individual has attended college. The Table 5 and 6 show the markov transition



(a) Downward Probability v.s. Age Conditional on Race



(b) Upward Probability v.s. Age Conditional on Race

matrices for the two groups. The probabilities of downward movements are much higher for people who never attend college compared to those who have some college education. The differences are especially large for high income individuals as p_{44} for people have no college education is 15.6% lower than those who attend college, meaning that the income for people without college education is much more likely to fall even if it is high today. Upward probabilities show similar patterns as the people who have attended college but is in the first quartile have 35.5% probability to enter into higher quartile, while this number for no college educated people is only 20.8%.

The Figure 5a and 5b show that the gap in downward probability (upward probability) between college educated and no college educated people remain roughly constant with age. Compare the figures for races, we find that college educated people have roughly similar downward probability with people of other races and no college educated individuals have similar downward probability with blacks in all ages. However, for upward probabilities, college educated individuals have similar upward probability with people of other races when they are relatively young, but have higher upward probability than people of other races at older ages. In contrast, no college educated people's upward mobility is lower than blacks in older ages. These might indicate that whether people could move upward might more depend on whether

Table 5: The Matrix Transition Matrix for People Who Have College Education

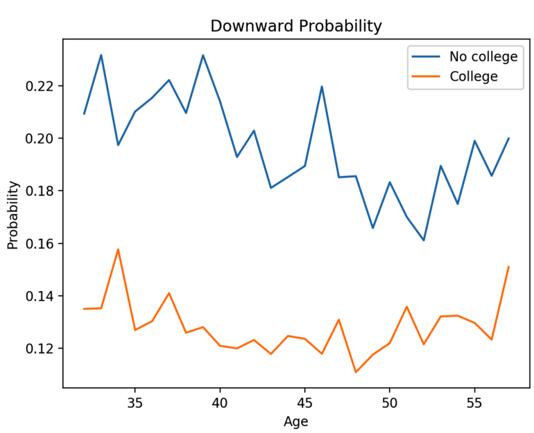
	Q1	Q2	Q3	Q4
Q1	0.645 (2703)	0.253 (1061)	0.060 (252)	0.042 (174)
Q2	0.141 (935)	0.600 (3993)	0.213 (1416)	0.046 (307)
Q3	0.032 (271)	0.147 (1224)	0.627 (5239)	0.194 (1618)
Q4	0.018 (195)	0.031 (334)	0.135 (1458)	0.816 (8797)

* This table shows the Markov transition matrix for people who have some college education. The first number in each box represents the transition probability while the number in the parenthesis represents the number of records.

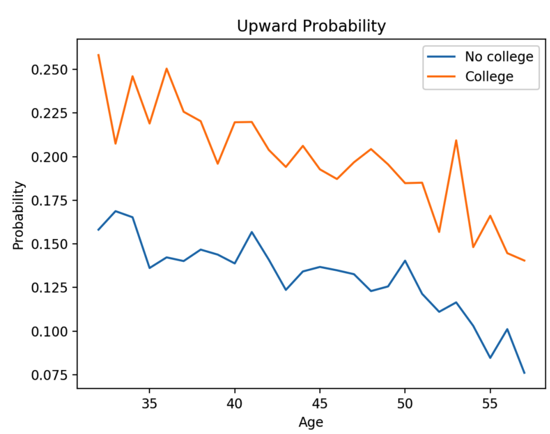
Table 6: The Matrix Transition Matrix for People Who Have no College Education

	Q1	Q2	Q3	Q4
Q1	0.792 (6822)	0.169 (1459)	0.028 (238)	0.011 (99)
Q2	0.200 (1395)	0.610 (4249)	0.163 (1138)	0.026 (183)
Q3	0.049 (280)	0.185 (1052)	0.629 (3585)	0.137 (780)
Q4	0.038 (120)	0.081 (259)	0.231 (736)	0.650 (2067)

* This table shows the Markov transition matrix for individuals who have never attended college. The first number in each box represents the transition probability while the number in the parenthesis represents the number of records.



(a) Downward Probability v.s. Age Conditional on Whether Having College Education



(b) Upward Probability v.s. Age Conditional on Whether Having College Education having college education, rather than race.

Living in Urban or Rural Areas:

Table 7: The Matrix Transition Matrix for People Living in Urban Area

	Q1	Q2	Q3	Q4
Q1	0.745 (7230)	0.195 (1891)	0.039 (375)	0.021 (205)
Q2	0.171 (1736)	0.611 (6209)	0.181 (1838)	0.036 (369)
Q3	0.042 (415)	0.162 (1596)	0.620 (6127)	0.176 (1742)
Q4	0.022 (229)	0.043 (446)	0.151 (1576)	0.785 (8206)

* This table shows the Markov transition matrix for people who are living in urban areas at the time of interview. The first number in each box represents the transition probability while the number in the parenthesis represents the number of records.

Table 8: The Matrix Transition Matrix for People Living in Rural Area

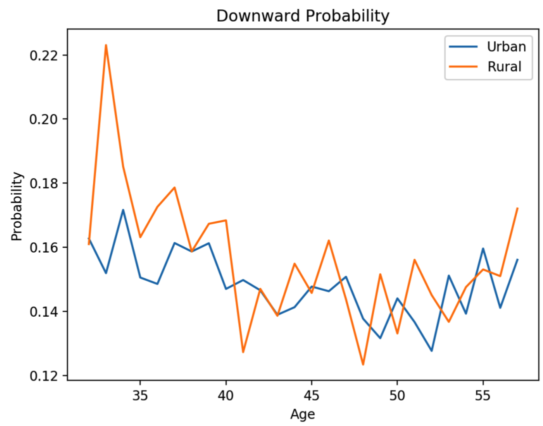
	Q1	Q2	Q3	Q4
Q1	0.744 (2168)	0.196 (571)	0.038 (112)	0.022 (64)
Q2	0.175 (565)	0.591 (1910)	0.199 (644)	0.034 (111)
Q3	0.035 (133)	0.162 (623)	0.649 (2489)	0.155 (593)
Q4	0.027 (88)	0.045 (144)	0.171 (552)	0.757 (2436)

* This table shows the Markov transition matrix for individuals who are living in rural areas at the time of interview. The first number in each box represents the transition probability while the number in the parenthesis represents the number of records.

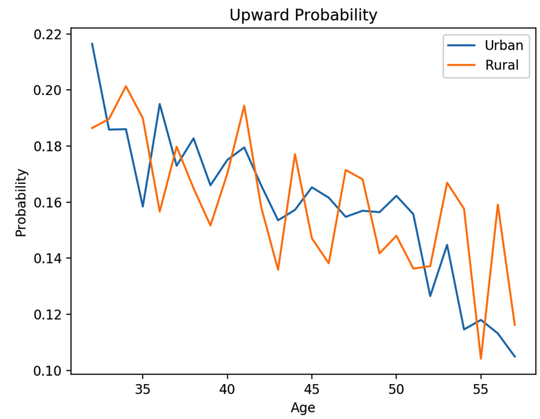
Both the Markov transition matrices for all ages and the patterns of movement probabilities with ages show that there is no obvious difference in income transition probabilities between people living in urban areas and those living in rural areas. The probabilities for each entry in Table 7 and 8 are very close, as most of the probabilities are within 3%. The Figure 6a and 6b indicate the trend of upward and downward probabilities with age are also similar between citizens living in urban and rural areas.

Number of Children:

The income transition probabilities are also similar between people who have at most one child and those who have more than one child. The probabilities for each entry in Table 9 and 10 are very close, as most of the probabilities are within 4% (p_{23} for people who have more than one child is 3.2% higher than the p_{23} for people who



(a) Downward Probability v.s. Age Conditional on Whether Living in Urban or Rural Area



(b) Upward Probability v.s. Age Conditional on Whether Living in Urban or Rural Area

have at most one child). The Figure 7a and 7b also indicate the trend of upward and downward probabilities with age are similar between the two groups.

Table 9: The Matrix Transition Matrix for People Who Have No More Than One Child

	Q1	Q2	Q3	Q4
Q1	0.742 (2476)	0.194 (647)	0.043 (144)	0.021 (69)
Q2	0.165 (588)	0.629 (2239)	0.164 (583)	0.042 (150)
Q3	0.044 (135)	0.165 (505)	0.618 (1887)	0.172 (525)
Q4	0.030 (85)	0.053 (150)	0.176 (459)	0.740 (2076)

* This table shows the Markov transition matrix for people who have no more than one child. The first number in each box represents the transition probability while the number in the parenthesis represents the number of records.

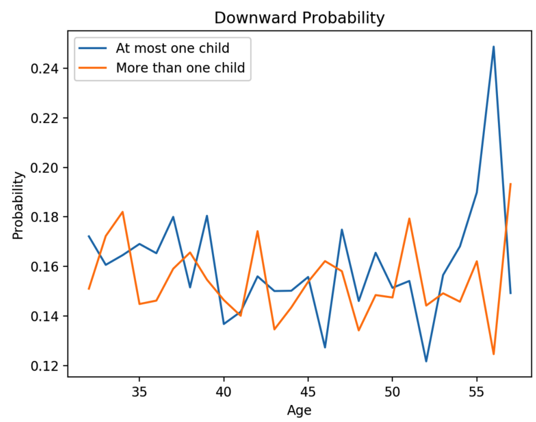
Whether Having Health Limitations:

The Table 11 and 12 show the Markov transition matrix for people who have and who do not have health limitations respectively. The differences among this two groups are very large. For example, those in the fourth quartile but have health limitations have 16.9 % higher probability of downward movements than those who have no health limitations, comprising of 6.3% higher in p_{41}, 6.4% higher in p_{42}, and 4.2% higher p_{43}.

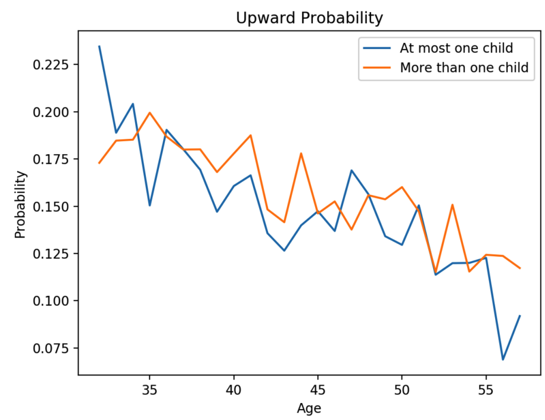
Table 10: **The Matrix Transition Matrix for People Who Have More Than One Child**

	Q1	Q2	Q3	Q4
Q1	0.758 (4077)	0.186 (1002)	0.038 (203)	0.018 (97)
Q2	0.182 (921)	0.589 (2986)	0.196 (992)	0.034 (174)
Q3	0.042 (227)	0.166 (908)	0.622 (3401)	0.171 (933)
Q4	0.022 (121)	0.044 (238)	0.161 (866)	0.773 (4166)

* This table shows the Markov transition matrix for individuals who have more than one child The first number in each box represents the transition probability while the number in the parenthesis represents the number of records.



(a) Downward Probability v.s. Age Conditional on Whether Having More than One Child



(b) Upward Probability v.s. Age Conditional on Whether Having More than One Child

Table 11: **The Matrix Transition Matrix for People Who Have No Health Limitations**

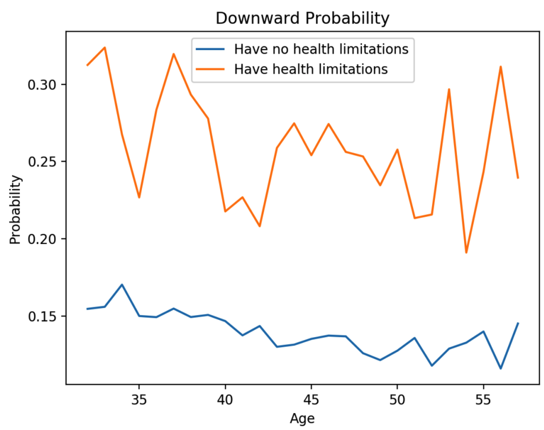
	Q1	Q2	Q3	Q4
Q1	0.688 (6004)	0.239 (2083)	0.048 (415)	0.025 (219)
Q2	0.152 (1854)	0.618 (7549)	0.194 (2368)	0.036 (440)
Q3	0.034 (445)	0.159 (2098)	0.633 (8373)	0.174 (2305)
Q4	0.019 (262)	0.039 (531)	0.154 (2086)	0.788 (10675)

* This table shows the Markov transition matrix for people who have no health limitations. The first number in each box represents the transition probability while the number in the parenthesis represents the number of records.

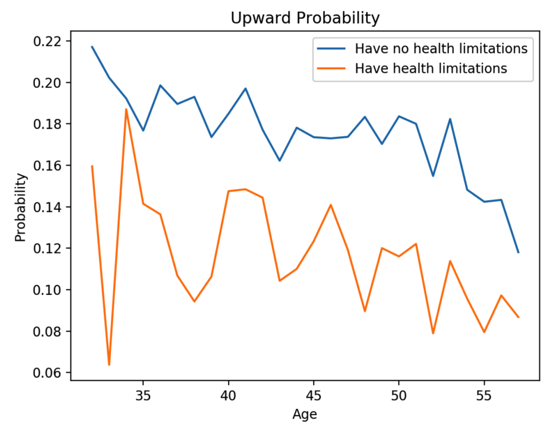
Table 12: The Matrix Transition Matrix for People Who Have Health Limitations

	Q1	Q2	Q3	Q4
Q1	0.855 (3857)	0.112 (503)	0.020 (91)	0.013 (60)
Q2	0.314 (548)	0.511 (893)	0.137 (240)	0.038 (67)
Q3	0.113 (123)	0.207 (226)	0.543 (593)	0.138 (151)
Q4	0.082 (64)	0.103 (80)	0.196 (53)	0.619 (483)

* This table shows the Markov transition matrix for individuals who have health limitations. The first number in each box represents the transition probability while the number in the parenthesis represents the number of records.



(a) Downward Probability v.s. Age Conditional on Whether Having Health Limitations



(b) Upward Probability v.s. Age Conditional on Whether Having Health Limitations

In conclusion, income transition (both upward and downward) probabilities are largely correlated with a person's race, educational level, and health condition, and among them, health conditions result in the highest difference. The income transition probabilities do not show clear correlation with whether living in urban or rural areas, and whether having more than one child.

4 Logistic Regressions with Cross Validation

In this part, we create binary variables representing which movements (i.e., $p_{11}, p_{12}, ..., p_{43}, p_{44}$) an individual experiences in each year and whether each individual experiences downward or upward movement in that year, then we conduct logistic regressions in which the dependent variable is one of the binary variables. Note since advantaged people may be more likely to have higher income at all time, which means that they have higher chance of experiencing downward movements just because their starting point is higher. Thus, to eliminate this influence, for regression analysis, we need to limit the observations to those who have the same quantiles.

Table 13: Logistic Regressions for Downward Movements with Bootstrap

	Dependent Variable: Multiple Downward Movements						
	downward	p_{43}	p_{42}	p_{41}	p_{32}	p_{31}	p_{21}
const	0.363**	1.304***	1.173*	0.726	0.049	−0.130	0.292
	(0.156)	(0.342)	(0.634)	(0.888)	(0.310)	(0.525)	(0.382)
age	−0.009***	−0.011*	−0.009	−0.016	0.001	−0.037***	−0.008*
	(0.003)	(0.006)	(0.010)	(0.016)	(0.005)	(0.010)	(0.005)
black	0.367***	0.334***	0.641***	0.284	0.469***	0.466***	0.442***
	(0.049)	(0.066)	(0.137)	(0.246)	(0.084)	(0.129)	(0.091)
hispanic	0.104	0.147	0.340**	0.232	0.172*	0.095	0.040
	(0.064)	(0.093)	(0.137)	(0.263)	(0.093)	(0.182)	(0.095)
education	−0.098***	−0.136***	−0.197***	−0.167***	−0.107***	−0.106***	−0.125***
	(0.009)	(0.013)	(0.024)	(0.036)	(0.016)	(0.027)	(0.017)
urban	−0.047	−0.089	−0.047	−0.324*	−0.084	0.125	−0.106
	(0.038)	(0.071)	(0.117)	(0.184)	(0.091)	(0.146)	(0.094)
num of children	0.013	0.007	−0.010	−0.015	0.018	0.140**	0.091***
	(0.018)	(0.029)	(0.063)	(0.097)	(0.025)	(0.056)	(0.026)
healthlimits	0.571***	0.412***	0.679***	1.018***	0.260**	1.193***	0.802***
	(0.069)	(0.121)	(0.194)	(0.195)	(0.113)	(0.141)	(0.090)
married	−0.143***	−0.491**	−1.222***	−1.433***	−0.371***	−0.812***	−0.461***
	(0.042)	(0.198)	(0.307)	(0.315)	(0.118)	(0.218)	(0.110)
Pseudo R^2	0.021	0.025	0.051	0.049	0.016	0.043	0.038
Num of obs	19,397	7,373	7,373	7,373	6,969	6,969	5,055
Replications	50	50	50	50	50	50	50

* This table shows the logistic regressions of downward movements on covariates. The dependent variables are multiple downward movements, shown in the first row.

The regression analysis shows that even if we hold all factors considered in the paper constant, those factors that have been shown could make a difference in downward and upward movements are still significant here. The findings are: (1) the factors that have a significant positive relationship with downward movements are: health limitations, blacks (compared to non-black non-Hispanic). (2) The factors that have a significant negative relationship with downward movements are age, education, and

Table 14: Logistic Regression for Upward Movements with Bootstrap

	Dependent Variable: Multiple Upward Movements						
	upward	p_{12}	p_{13}	p_{14}	p_{23}	p_{24}	p_{34}
const	-2.007^{***}	-2.551^{***}	-4.114^{***}	-8.171^{***}	-3.185^{***}	-4.250^{***}	-3.167^{***}
	(0.192)	(0.327)	(0.511)	(1.058)	(0.373)	(0.690)	(0.361)
age	-0.016^{***}	-0.002	-0.024^{**}	-0.009	-0.010^{*}	-0.026^{**}	-0.016^{***}
	(0.003)	(0.006)	(0.011)	(0.019)	(0.006)	(0.011)	(0.006)
black	-0.149^{***}	-0.215^{***}	-0.618^{***}	-1.527^{***}	-0.208^{**}	-0.371^{**}	-0.257^{***}
	(0.046)	(0.108)	(0.221)	(0.426)	(0.090)	(0.176)	(0.086)
hispanic	-0.041	-0.095	-0.197	-0.675^{**}	-0.077	-0.253	-0.141
	(0.051)	(0.132)	(0.196)	(0.342)	(0.099)	(0.191)	(0.091)
education	0.084^{***}	0.104^{***}	0.170^{***}	0.301^{***}	0.117^{***}	0.128^{***}	0.123^{***}
	(0.008)	(0.020)	(0.029)	(0.052)	(0.018)	(0.036)	(0.015)
urban	0.090^{**}	0.057	0.064	0.256	0.103	0.260	0.152^{**}
	(0.039)	(0.100)	(0.169)	(0.210)	(0.082)	(0.159)	(0.073)
num of children	-0.009	-0.027	-0.048	0.028	-0.019	-0.079	-0.001
	(0.015)	(0.027)	(0.060)	(0.079)	(0.026)	(0.072)	(0.026)
healthlimits	-0.337^{***}	-0.999^{***}	-0.642^{***}	-1.392^{***}	-0.507^{***}	0.252	-0.243^{*}
	(0.064)	(0.098)	(0.174)	(0.431)	(0.119)	(0.207)	(0.126)
married	0.517^{***}	0.929^{***}	1.197^{***}	2.328^{***}	1.180^{***}	0.618^{***}	0.593^{***}
	(0.048)	(0.099)	(0.190)	(0.350)	(0.107)	(0.177)	(0.125)
Pseudo R^2	0.023	0.073	0.100	0.265	0.049	0.027	0.021
Num of obs	15,890	3,866	3,866	3,866	5,055	5,055	6,969
Replications	50	50	50	50	50	50	50

[*] This table shows the logistic regressions of upward movements on covariates. The dependent variables are mutiple upward movements, shown in the first row.

already married. (3) According to the absolute number of the z-values, educational level has the largest impacts on downward movements, the second, third, fourth, and fifth most important determinants are health limitations, whether the race of the individual is black, whether already married, and age, respectively. (4) For upward movements, consistent with the findings in section 3, the z-value of *age* is larger than that for regressions for downward probabilities, and whether already married seems to play a more important role in upward probabilities than in downward probabilities.

5 Conclusion

Put conclusion here.

6 Appendix

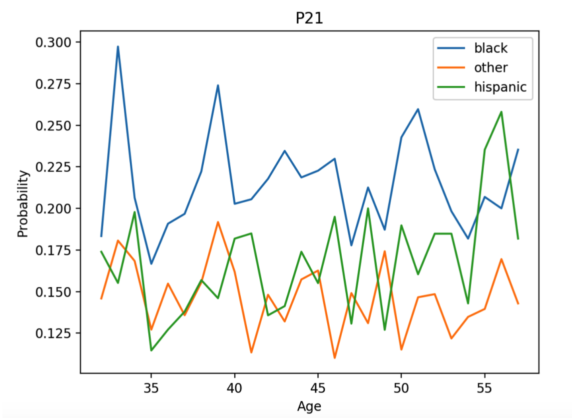
Table 15: Logistic Regression of Downward Movement on Interaction and Quadratic Terms with Bootstrap

	Dependent Variable: Downward Movement				
	–	*age*	*black*	*hispanic*	*education*
age	-0.119^{**}	0.001^{*}	0.004	0.013^{*}	0.002^{**}
	(0.046)	(0.000)	(0.007)	(0.007)	(0.001)
black	0.066	–	–	–	-0.009
	(0.411)	–	–	–	(0.021)
hispanic	-0.659^{*}	–	–	–	0.029
	(0.395)	–	–	–	(0.021)
education	-0.235^{***}	–	–	–	0.002
	(0.070)	–	–	–	(0.002)
urban	-0.575	–	–	–	–
	(0.399)	–	–	–	–
num of children	0.286^{**}	–	–	–	–
	(0.137)	–	–	–	–
healthlimits	1.074^{*}	–	–	–	–
	(0.064)	–	–	–	–
married	-0.932^{**}	–	–	–	–
	(0.048)	–	–	–	–

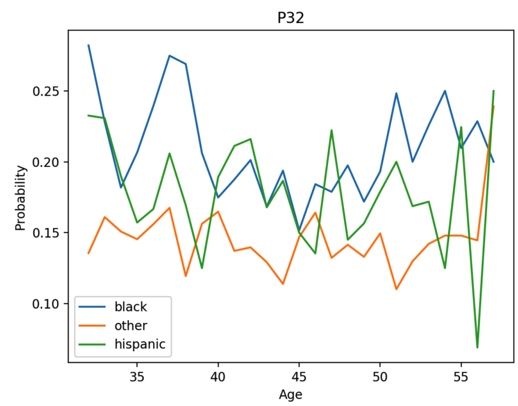
	urban	*num of children*	*healthlimits*	*married*
age	-0.001	-0.006^{**}	-0.010	0.017^{**}
	(0.006)	(0.002)	(0.009)	(0.007)
black	0.142	0.044	0.018	0.097
	(0.114)	(0.045)	(0.134)	(0.152)
hispanic	-0.071	0.093^{*}	0.001	-0.369^{**}
	(0.109)	(0.054)	(0.197)	(0.157)
education	0.014	-0.004	0.005	0.001
	(0.018)	(0.007)	(0.030)	(0.025)
urban	–	0.019	0.267^{**}	0.315^{**}
	–	(0.035)	(0.116)	(0.151)
num of children	–	0.017^{**}	0.025	-0.113
	–	(0.007)	(0.061)	(0.046)
healthlimits	–	–	–	-0.434^{**}
	–	–	–	(0.189)
married	–	–	–	–
	–	–	–	–

$Pseudo\ R^2$: 0.024
$Num\ of\ obs$: $19,397$
$Replications$: 50

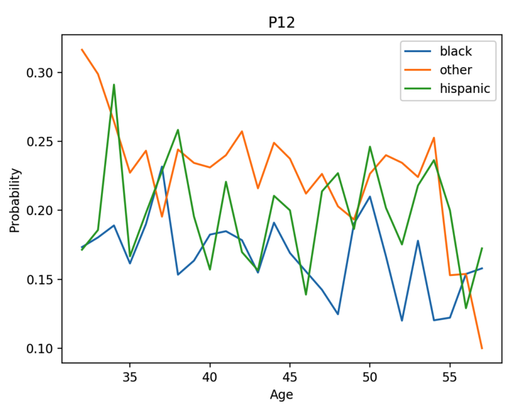
[*] This table shows the logistic regressions of the downward movement on covariates with interaction effect and quadratic terms.



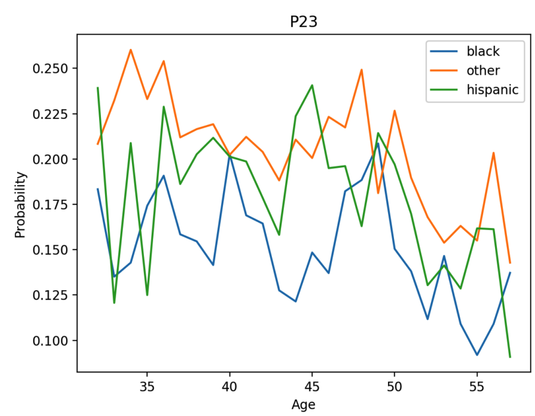
(a) P_{21} v.s. Age Conditional on Race



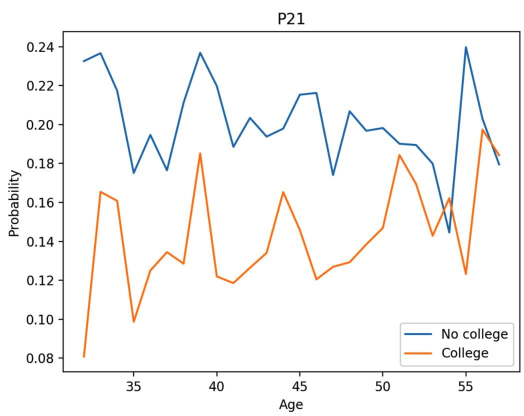
(b) P_{32} v.s. Age Conditional on Race



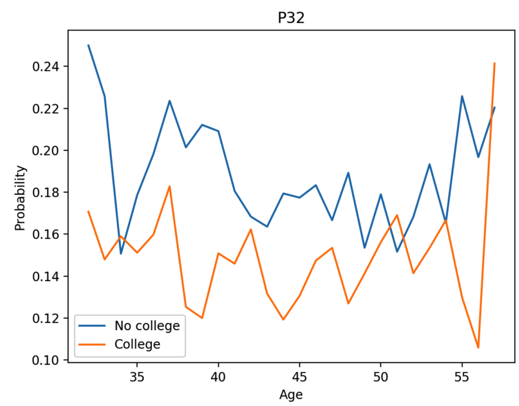
(c) P_{12} v.s. Age Conditional on Race



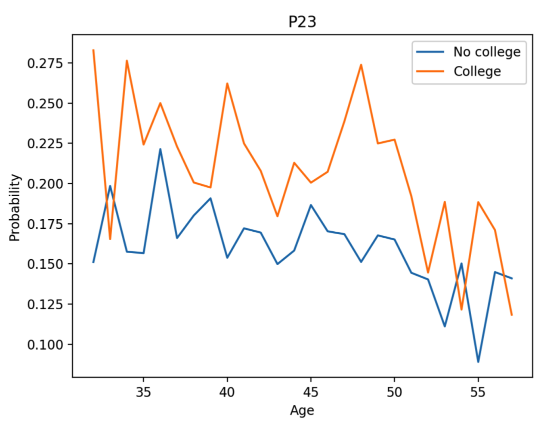
(d) P_{23} v.s. Age Conditional on Race



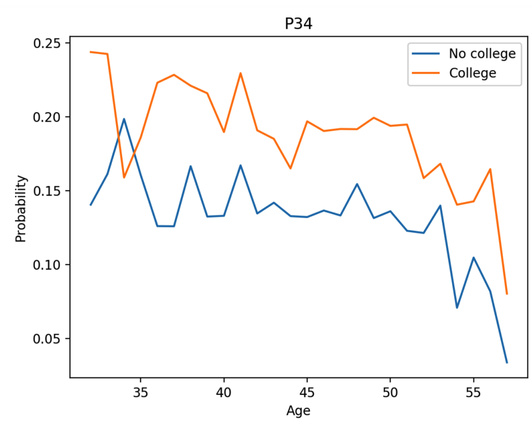
(a) P_{21} v.s. Age Conditional on Whether Having College Education



(b) P_{32} v.s. Age Conditional on Whether Having College Education



(c) P_{23} v.s. Age Conditional on Whether Having College Education



(d) P_{34} v.s. Age Conditional on Whether Having College Education

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