Sources of Inequality in Earnings Growth Over the Life Cycle *

Fatih Karahan† Serdar Ozkan‡ Jae Song§

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Abstract

Individuals that rank at the top of the lifetime earnings (LE) distribution experience almost an 8-fold increase in their annual earnings between age 30 and 55, whereas median earners only see a 50% increase. If all workers have had experienced the same earnings growth, the difference in LE between the top and the 10th percentiles of LE distribution would be 85% smaller. What explains the vast heterogeneity in lifetime earnings growth? We study both empirically and theoretically the career paths across the LE distribution. Using administrative data, we document large dispersion in job switching patterns, incidence of unemployment, and wage growth for stayers and switchers across the LE distribution. To interpret these facts, we estimate a job-ladder model featuring heterogeneity in unemployment risk, job finding rate and contact rate for employed workers, as well as returns to experience. The estimated model matches a rich set of facts including the dispersion in the career paths over the LE distribution, as well as the distribution of annual earnings changes. We use the estimated model to decompose lifetime earnings growth differences into i) ex-ante heterogeneity in unemployment risk, and offer arrival rate both on and off the job, ii) returns to experience, and iii) ex-post idiosyncratic risk.

Keywords: Job ladder, search frictions, life-cycle earnings risk, inequality

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†FRB of New York; fatih.karahan@ny.frb.org; sites.google.com/site/yfatihkarahan/

‡University of Toronto; serdar.ozkan@utoronto.ca; www.serdarozkan.me

§Social Security Administration; jae.song@ssa.gov

1 Introduction

People differ greatly in their lifetime earnings (LE).[1] For example, people at the top 10% (2%) percent of the lifetime earnings distribution earn about 4 (15) times more than those at the 10th percentile. Even though earnings inequality starts early in life, differences in earnings growth rates are key for the level of lifetime earnings inequality. In fact, if everyone had experienced the same earnings growth, the 90/10 (98/10) ratio of LE earnings would have been 50% (85%) lower.

What explains the vast heterogeneity in lifetime earnings growth? Individuals can differ in their ability to accumulate human capital (e.g. Huggett *et al.* (2011)). They may also differ in their ability to climb up the job ladder, because of ex-ante differences in unemployment risk, job finding rate, or job-to-job transition rate (e.g. Bagger *et al.* (2014)). Some differences also arise due to differences in ex-post realizations of idiosyncratic risk. The goal of this paper is to quantify the importance of each of these factors by studying both empirically and theoretically the differences in career paths across LE groups.

In our empirical analysis, we use a large confidential employer-employee matched panel of earnings histories of U.S. male workers from the Social Security Administration (SSA). This data set allows us to measure, with little error, total annual earnings for each individual, long-term unemployment spells, and changes in employers. We document large dispersion in job switching patterns, incidence of unemployment and wage growth for job stayers and switchers across the LE distribution. We document two broad sets of facts.

First, people at the bottom of the LE distribution work for about 12 different employers between the ages of 25 and 60; about twice as many as those at the top. Moreover, the likelihood of going through a full-year unemployment spell in a given year decreases from around 10 percent at the bottom of the LE distribution to 2.5 percent at the median and to 1.5 percent at the top.[2]

Second, we document patterns of annual earnings growth for job stayers and switchers across the LE distribution. We further break down switchers into a group of individuals that are more likely to have made direct employment to employment switches (EE-switchers) and another group of workers that possibly have gone through a period of unemployment (EUE-

[1] Lifetime earnings is computed by summing workers' labor earnings from ages 25 through 60 using administrative data (see Guvenen *et al.* (2014)). See section 2 for more details.

[2] We find similar facts for short-term unemployment using data from the Survey of Income and Program Participation (SIPP).

switchers).[3] We find that most stayers experience similar annual earnings growth regardless of their rank in the LE distribution, except for those at the top 10-20% depending on their age. Furthermore, higher LE workers are more likely to stay with the same employer. For switchers, there is a strong, monotonic, increasing relationship between annual earnings growth and the rank of the worker in the LE distribution. This pattern is due to differences in the composition of switchers: Looking at EE- and EUE-switchers separately, we find that their annual earnings growth does not vary as much over the LE distribution, with the exception of the top and the bottom end. However, the share of EE-switchers increases strongly over the LE distribution, which generates larger annual earnings growth for high-LE switchers.

A better understanding of the determinants of lifetime earnings requires us to uncover the underlying heterogeneity behind these patterns across the LE distribution. To this end, we develop and estimate a job ladder model in the spirit of Jarosch (2015), Cahuc *et al.* (2006) and Bagger *et al.* (2014). In particular, the model features heterogeneity in worker and firm fixed effects, on the job search, employer competition, and idiosyncratic shocks to worker productivity. We also allow for worker heterogeneity in unemployment risk, job finding rate and the contact rate for employed workers, as well as returns to experience that captures differences in ability to accumulate human capital. Finally, the model features recalls for unemployed workers by their last employers.

We estimate this model by targeting a rich set of moments from the SSA data. The first set of moments are about the cross-sectional distribution of earnings changes. Specifically, we target the second-, third-, and fourth-order moments of annual earnings changes for various age and income groups. Second, we target the same moments separately for job stayers and switchers. The third and fourth moments are about the fraction and wage growth of job stayers, EE-switchers, and EUE-switchers by lifetime earnings percentiles. And finally, we also target the life cycle income profile of median LE group.

The estimated model fits the targeted moments fairly well. The fit is particularly good for the cross-sectional moments of the earnings change distribution. The model does not only account for the variation in higher-order moments over the income distribution, but also matches the heterogeneity between stayers and switchers. Moreover, the model also provides a decent fit to the remaining sets of moments as well as some nontargeted moments such as the incidence of long-term unemployment. We find that a key feature of the model behind its success in fitting the data is the heterogeneity in unemployment risk, job finding rate and the

[3] The construction of these groups are explained in detail in section 2.

contact rate for employed workers. Without this heterogeneity, the model cannot account for the variation in the fraction of stayers, EE- and EUE-switchers over the LE distribution.

Finally, we use the estimated model to decompose inequality in lifetime earnings growth into its sources. We find that a substantial portion of earnings growth heterogeneity is driven by the heterogeneity in the returns to experience, while the job finding and separation rates also matter to some extent.

The rest of the paper is organized as follows. Section 2 presents the data and the stylized facts. Section 3 describes the model, section 4 discusses its structural estimation and presents the preliminary results. Section 7 concludes.

2 Empirical Analysis

In this section, we document several stylized facts that motivate and guide our analysis of lifetime earnings inequality. Most of our analysis is based on administrative data from the Social Security Administration (SSA), but we also use data from the Survey of Income and Program Participation.

2.1 SSA

Our data is drawn from the Master Earnings File (MEF) of the U.S. Social Security Administration records. The MEF is the main source of earnings data for the SSA and contains information for every individual in the United States who was ever issued a Social Security number. Basic demographic variables, such as date of birth, place of birth, sex, and race, are available in the MEF along with several other variables. The earnings data in the MEF are derived from the employee's W-2 forms, which U.S. employers have been legally required to send to the SSA since 1978. The measure of labor earnings is annual and includes all wages and salaries, bonuses, and exercised stock options as reported on the W-2 form (Box 1). Furthermore, the data are uncapped (no top coding) since 1978. We convert nominal earnings records into real values using the personal consumption expenditure (PCE) deflator, taking 2005 as the base year. W-2 forms contain another crucial information for our purpose, a unique employer identification number (EIN) for each W-2 earnings record. This allows us to follow each worker's career path at an annual frequency. For background information and detailed documentation of the MEF, see Panis *et al.* (2000) and Olsen and Hudson (2009).

Constructing a nationally representative panel of males from the MEF is relatively straightforward. The last four digits of the SSN are randomly assigned, which allows us to pick a number for the last digit and select all individuals in 1978 whose SSN ends with that number.[4] This process yields a 10% random sample of all SSNs issued in the United States in or before 1978. Using SSA death records, we drop individuals who are deceased in or before 1978 and further restrict the sample to those between ages 25 and 60. In 1979, we continue with this process of selecting the same last digit of the SSN. Individuals who survived from 1978 and who did not turn 61 continue to be present in the sample, whereas 10% of new individuals who just turn 25 are automatically added (because they will have the same last digit we pre-selected), and those who died in or before 1979 are dropped. Continuing with this process yields a 10% representative sample of U.S. males in every year from 1978 to 2013. Finally, the MEF has a small number of extremely high earnings observations. In each year, we cap (winsorize) observations above the 99.999th percentile in order to avoid potential problems with these outliers.

Sample selection and the construction of lifetime incomes Our sample consists of males between the ages of 25 and 60, which we refer to as a worker's lifetime.[5] We require that each individual has at least 36 years of data. This leaves us with the cohorts born between 1951 and 1957. Given the focus of the paper on labor market frictions, we want to obtain a sample of individuals with a high labor market attachment. One issue with the SSA data is that, unlike survey data, it doesn't have direct measures for this dimension. We circumvent this problem by further restricting our sample to individuals, who (i) have earnings above a time-varying minimum earnings threshold, $Y_{\min,t}$, for at least three fourths of their working life, (ii) do not fall below the minimum income for more than two consecutive years, (iii) are not self employed for more than one eigth of their working life, and (iv) are not self employed in more than two consecutive years.[6] We classify a worker as self employed, if he has self employment income above both $Y_{\min,t}$ and 10% of his wage and salary income. Table I provides the breakdown of the sample selection. Our initial sample consists of 1,497,661 individuals. Of these individuals, about 17% are self employed in at least one fourth of their working life. Then, about 400,000 individuals are eliminated from the sample, because they do not satisfy the minimum years of employment criterion. We throw out close to 180,000 individuals due to

[4]In reality, each individual is assigned a transformation of their SSN number for privacy reasons, but the same method applies.

[5]We acknowledge that some individuals enter the labor market and start their careers earlier, likely due to differences in educational attainment. The SSA data does not contain any information on education. To focus on a sample of workers that are most probably not enrolled at any educational institution, we require individuals to be older than 25.

[6]$Y_{\min,t}$ is defined as one-fourth of a full-year full-time (13 weeks at 40 hours per week) salary at half of the minimum wage, which amounts to annual earnings of approximately $1,885 in 2010.

consecutive nonemployment in the third stage, and about 42,000 individuals due to consecutive self employment in the last stage. This procedure leaves us with a final sample of 611,126 individuals for which we have at least 33 years of wage data.

We compute lifetime earnings (LE) as the sum of individuals' W-2 earnings from 25 to 60. This measure is then used to assign workers into 50 equally sized lifetime earnings quantiles.

TABLE I – Sample selection

	# individuals dropped	Size after selection
Initial sample		1,497,661
# yrs self employed	259,009	1,238,652
# yrs employed	404,882	833,770
consecutive nonemployment	179,823	653,947
consecutive self employment	42,821	611,126

Identifying job stayers The SSA data set contains a unique employer identification number (EIN) for each job that a worker holds in a given year, which makes our analysis feasible. At the same time, the annual frequency of the data, together with the fact that some workers may hold multiple jobs concurrently, poses a challenge for a precise identification of job stayers and job switchers. We call a worker a "job stayer" between years t and $t+1$ if i) he has income from the same employer in years $t-1$, t, $t+1$, and $t+2$, ii) his income in years t and $t+1$ is above the minimum income threshold for that year, and iii) this employer accounts for at least 90% of his total labor income in years t and $t+1$. This definition ensures that the main employer was the same in years t and $t+1$, and that he had at least some employment with this firm in a 4-year window. All other individuals are classified as nonstayers between t and $t+1$ (sometimes referred to as switchers). Note that according to this definition, nonstayers encompass a lot of heterogeneity. This group contains people that make job-to-job transitions (EE-switchers), that transition to a different employer after an unemployment spell (EUE-switcher), and those that spend most of year $t+1$ as unemployed and earn below minimum income (nonemployed). To obtain more disaggregated results and understand nonstayers better, we define EE-switchers and EUE-switchers as follows: A nonstayer in year t is classified as an EE-switcher if his earnings in year $t+1$ is no less than 75% of his earnings in year t. All other nonstayers are classified as EUE switchers. Behind this 75% rule is our belief that someone who makes a direct job-to-job transition would not take a pay cut in excess of 25 percent. Thus, we believe our classification of EUE switchers is accurate. However, the EE-switchers may contain some individuals that have a short unemployment spell and start working for a different employer.[7] Later, we examine the robustness of our main findings with respect to these choices.

Identifying unemployment spells There are two issues with the SSA data when it comes to identifying unemployment spells. First, we do not observe the participation margin, which means we cannot distinguish nonparticipants from the unemployed. Second, due to the annual frequency of earnings observations, we cannot identify short unemployment spells. Nevertheless, we identify long unemployment spells that cause an individual's earnings to fall below the minimum income threshold. We explore several measures. Our baseline definition classifies an individual as unemployed in year t, if his earnings record below the minimum income $Y_{\min,t+1}$. We also entertain alternative definitions that call individuals unemployed if they experience a large cut in earnings between years t and $t+1$ (larger than 75% or 50%). We use the terms unemployed and nonemployed interchangeably and note that the use of the term "unemployed" involves an abuse of notation.

2.2 Stylized facts on lifetime earnings growth

Workers differ greatly in their lifetime earnings. Comparing the top quantile (top two percentiles) to the bottom quantile (bottom two percentiles), we find a striking ratio of 28 in lifetime incomes. An important share of this difference comes from the large inequality at the very top: The top quantile earns about 4 times more than the 45th quantile (90th percentile). Lastly, there are also sizable differences at the bottom of the distribution: 10th percentile (LE5) earns almost twice as the bottom quantile.

TABLE II – Selected statistics from the earnings distribution

Statistic	Total LE	Age 25	Age 40	Age 55
LE50/LE1	28.2	2.99	23.95	46.34
LE50/LE5	15.1	1.92	12.17	24.6
LE50/LE45	3.9	0.99	3.3	5.17
LE45/LE5	3.85	1.93	3.69	4.66
LE38/LE13	1.97	1.40	1.94	2.2
LE5/LE1	1.87	1.56	1.97	1.88

[7] For example, someone has an unemployment spell shorter than 3 months in year t and finds a job with a different employer at the same monthly wage, working full year, would be classified as an EE switcher. The estimation of the model in section 3 deals with this issue by defining these groups in the simulated data in the same way.

While the large differences in lifetime earnings levels are well documented, something that is perhaps less well known is the amount of fanning out in earnings during the working life of a cohort. In fact, the second to fourth columns of table II show similar inequality measures at different ages. If there was no fanning out of earnings over the life cycle, then inequality in lifetime earnings would be the same as inequality at the age of 25. A quick look at the second column of table II shows that this is far from the truth, especially for top income earners.

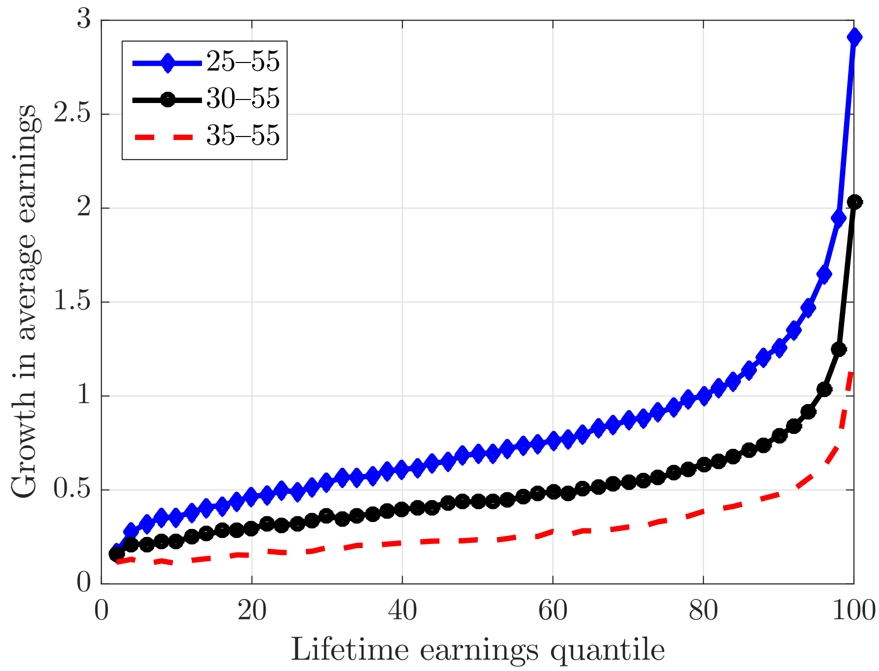
To better illustrate this point, figure 1 shows how earnings growth over the career of a cohort is related to lifetime earnings. Not surprisingly, earnings growth is positively related to the level of lifetime earnings: All else the same, one should expect the higher growth individuals to rank at the top of the distribution. However, the quantitative magnitudes are striking: The top LE earners see their earnings rise by more than 20-fold between the ages of 25 and 55, median workers experience a two-fold increase, whereas those at the bottom see little to no earnings growth. These large differences in earnings growth have an unmistakable contribution to the level of lifetime earnings inequality. In other words, while there are initial differences in the earnings of a cohort when they enter the labor market, the fanning out that occurs over the next 30 years or so is at least as important for lifetime inequality. In fact, a simple accounting exercise suggests that inequality of lifetime incomes would have been about one third of its current level, had everyone experienced the same level of earnings growth. It is possible that some of this steep rise in earnings growth at the top might be simply due to transition from school enrollment around the age of 25 to employment in the labor market.[8] Figure 1 also plots earnings growth focusing on the period between the ages of 30 and 55 and 35 to 55. While the magnitudes change, we find that the shape of the earnings growth profile remains intact, implying that inequality in earnings growth is indeed an important factor determining the level of lifetime earnings inequality. An immediate question is what accounts these large differences in earnings growth, which we now turn to.

Given our focus on the role of labor market in generating inequality in lifetime incomes, we investigate the differences in labor market experiences by LE percentile. More specifically, we are interested in i) unemployment rates, ii) the number of distinct employers over the working life, iii) frequency of job switches, iv) wage growth for job stayers, and v) wage growth for EE and EUE switchers. These cuts of the data allow us to see which margin accounts for most of the dispersion in earnings growth.

We start by investigating the frequency of unemployment by LE quantile. To that end, we

[8] Top LE individuals are likely pursuing graduate degrees around these ages.

FIGURE 1 – Heterogeneity in lifetime earnings growth



first count up the number of years that each individual falls below the minimum income (or experiences more than 75% or 50% decline in annual earnings) as a share of his working life. This measure is then averaged over all workers in a given LE quantile. This measures the fraction of lifetime an average individual in a given LE quantile spends unemployed. Figure 2 plots this measure against LE quantile. According to our baseline measure based on minimum income threshold, we find that workers at the bottom of the LE distribution spend as much as 10% of their working life (3.6 years) in serious (i.e. long term) unemployment. This fraction decreases rapidly with lifetime earnings and plateaus around 1.5% for the top two deciles of the LE distribution. The other two measures based on declines in annual earnings point to a qualitatively similar pattern.

A consequence of the large unemployment rates at the bottom is that these individuals end up working for many different employers. Figure 3 shows the number of different employers an individual works for during his working life. Individuals at the bottom of the LE distribution work for about 12 different employees on average. Given the 36 year window that we are looking at, this implies that about one third of this group switches employers in any given year. Or, put in another way, a given worker changes employer once every three years.

FIGURE 2 – Long-term unemployment

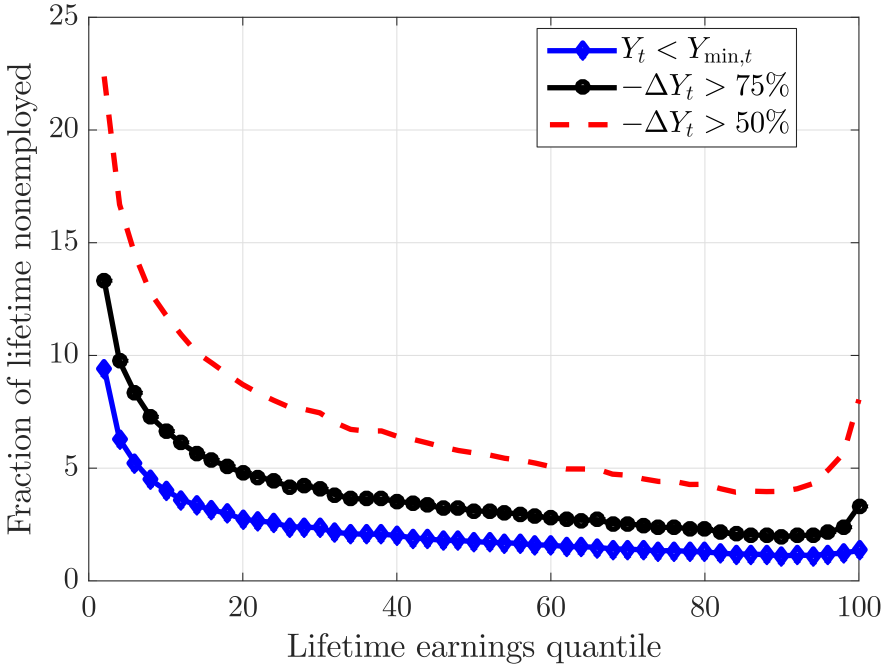
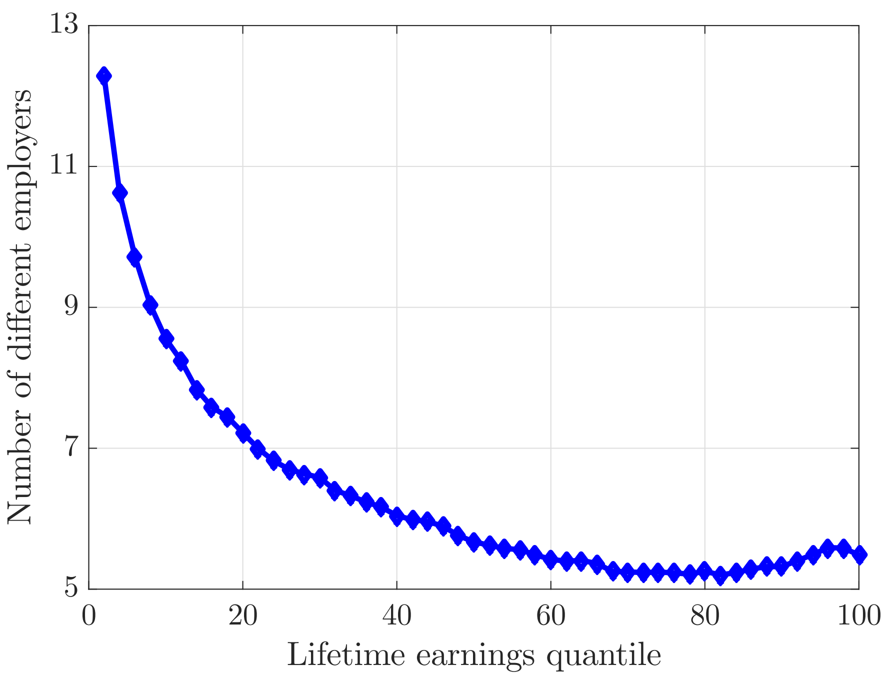


FIGURE 3 – Number of Employers during Working Life



So far, we have shown that bottom LE workers work for many different firms and this is caused by frequent spells of (long-term) unemployment. We now turn to earnings and investigate how wage growth for job stayers and nonstayers depends on the LE quantile, where the latter is a broad category and includes EE-switchers, EUE-switchers as well as those that transition into long-term unemployment. The left panels on figure 4 show the probability of being a stayer and a nonstayer. Two facts stand out. First, individuals at higher LE quantiles are more likely to be stay with the same firm in two consecutive years. Second, the probability of staying with the same firm displays a hump-shaped profile over the life cycle.

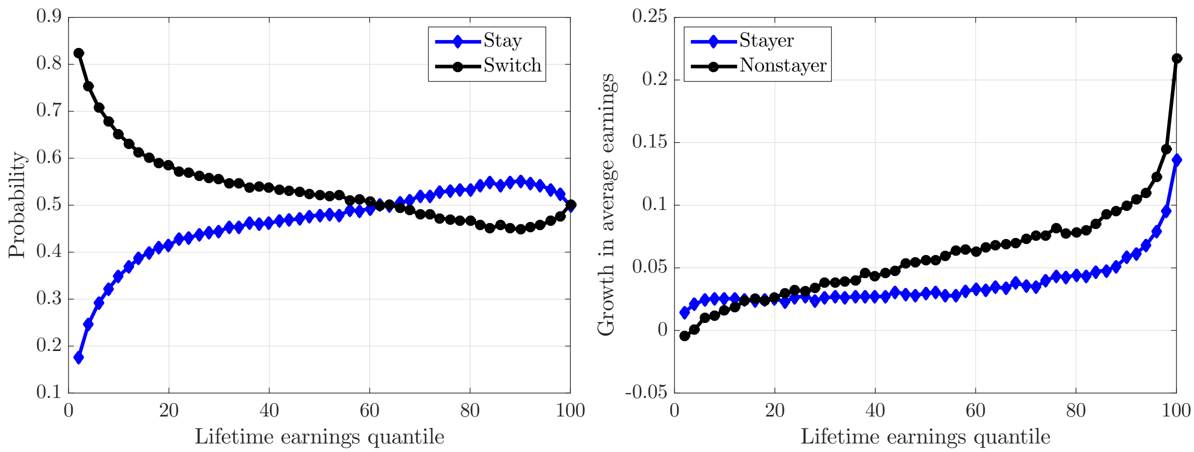
The right panels figure 4 show the average wage growth for stayers and nonstayers over the LE distribution. Several remarks are in order. First, wage growth for nonstayers (shown on the black line) increases monotonically with lifetime earnings up to the 95th percentile, and accelerates at the top. Turning to job stayers (shown on the blue dotted line), we find much less heterogeneity in the first 80th percentiles of the LE distribution: Staying with the same employer entails a wage growth of about 3 percent. Interestingly, staying entails an increasingly larger wage growth as we go up in the LE distribution, reaching a maximum of about 15 percent for top earners.[9] Thus, the heterogeneity in earnings growth of nonstayers dwarfs the heterogeneity among the stayers, except for the top end of the LE distribution.

To some extent, this heterogeneity in the wage growth of nonstayers is to be expected. After all, this group includes individuals that make direct job-to-job transitions as well as those that switch employer due to an unemployment spell. We will now further decompose the heterogeneity in lifetime income growth into these groups. Figure 5 shows the probability of being an EE-switcher conditional on being a nonstayer and their average income growth over the life cycle. We find that nonstayers in higher LE quantiles are more likely to be EE-switchers. Among the EE-switchers, those at the top and the bottom end of the LE distribution experience the largest earnings growth when switching, whereas the average earnings growth for non-EE switchers displays almost a flat profile over the LE distribution, except for young individuals between the ages of 25 and 35.

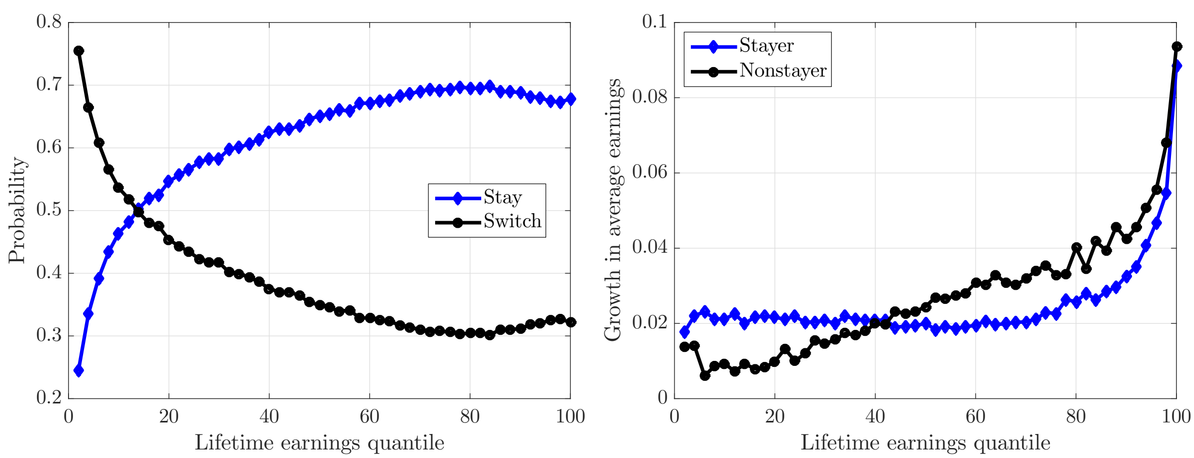
[9]Between ages 25 and 35 there is some heterogeneity among stayers but almost non after age 35, except for the top end of the LE distribution.

FIGURE 4 – Wage Growth of Stayers vs. Non-Stayers

(C) Between Age 25-35



(F) Between Age 36-45



(I) Between Age 46-55

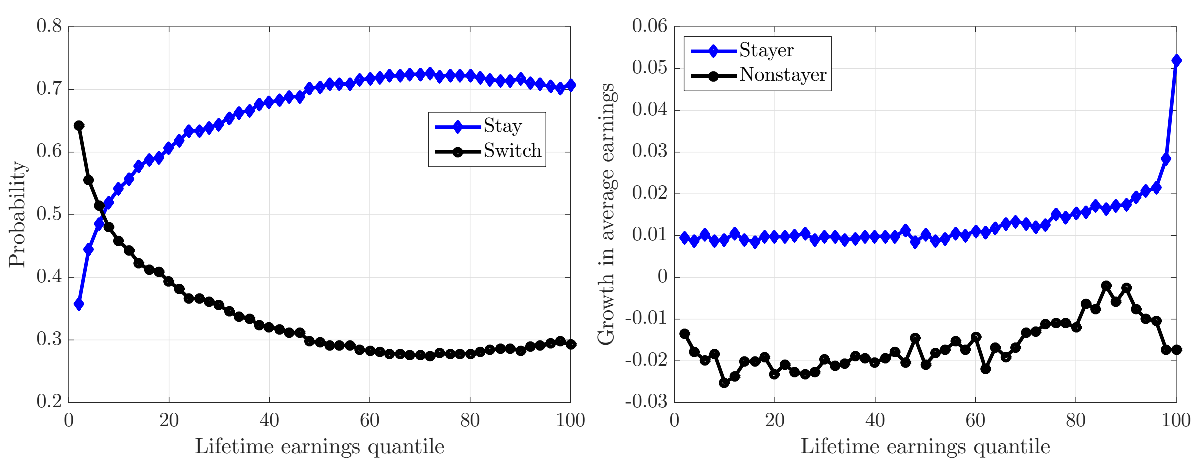
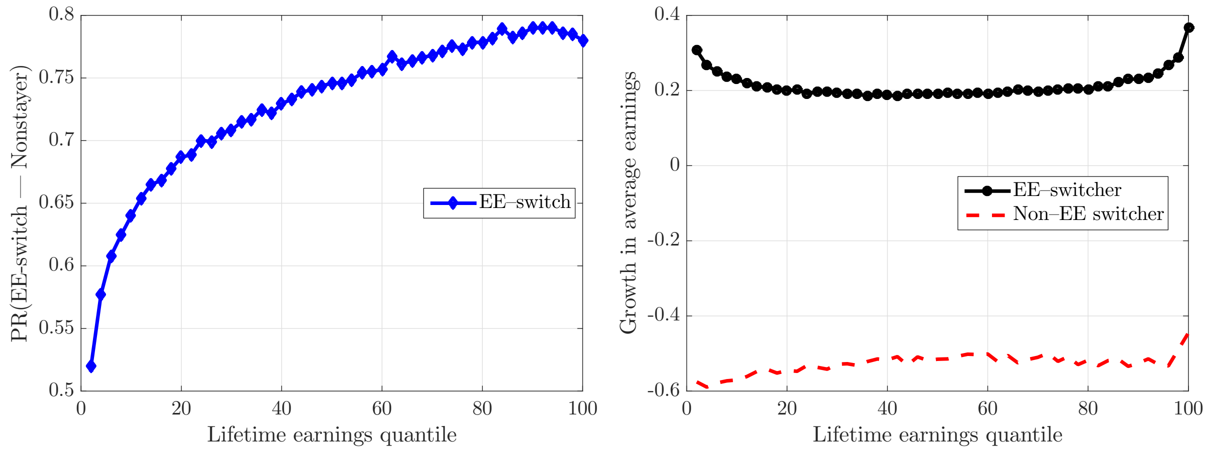
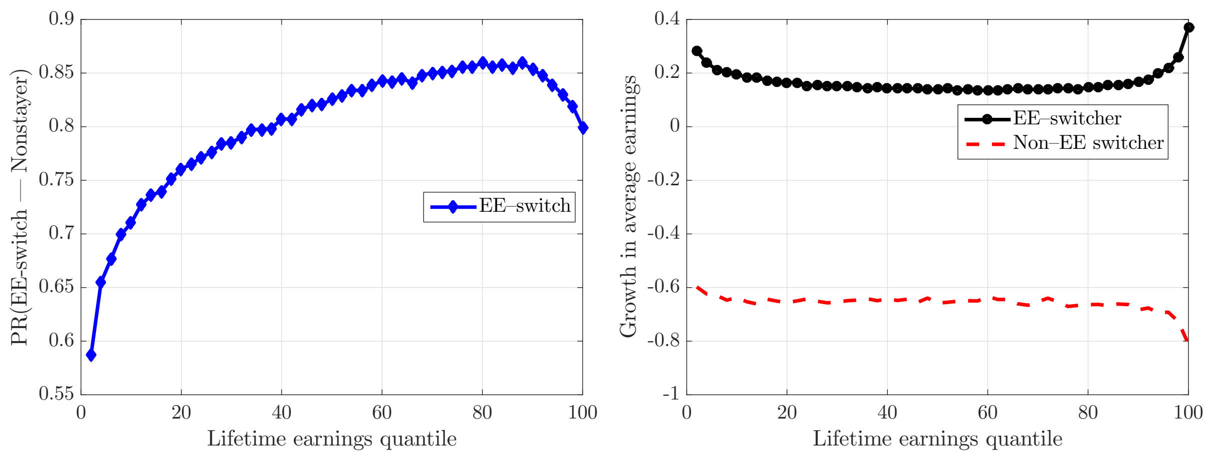


FIGURE 5 – Wage Growth of EE- and non-EE-Switchers

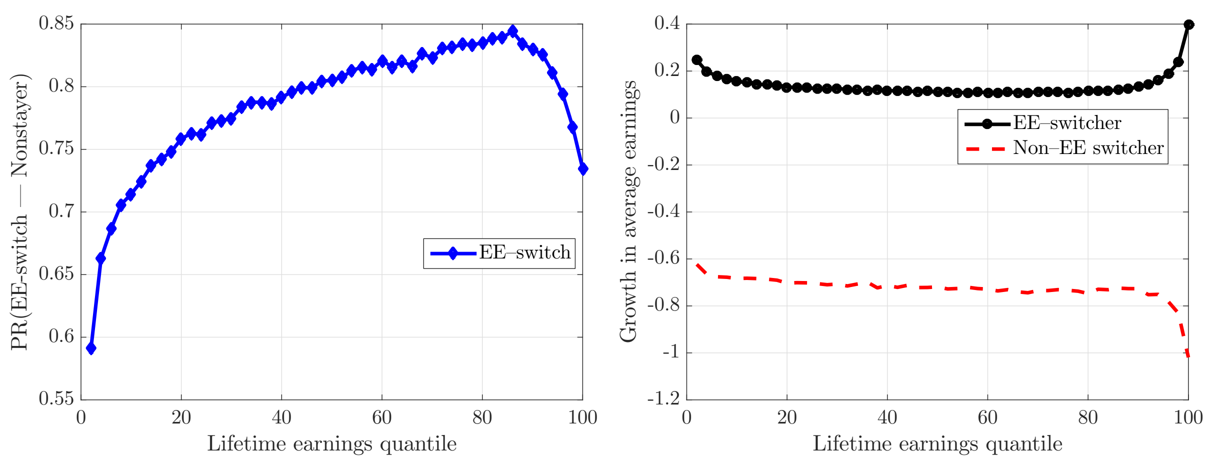
(C) Between Ages 25-35



(F) Between Ages 36-45



(I) Between Ages 46-55



These facts already shed some light on the nature of earnings growth heterogeneity and points to the importance of labor market frictions in the form on unemployment and job-to-job switches. Some workers have careers that are frequently interrupted with long-term unemployment spells, who then have to switch employers and end up earning less each time this happens. As a consequence, these workers are more likely to rank at the bottom of the LE distribution. In comparison, some other workers have fewer unemployment spells, which implies they can climb the job ladder without being interrupted. These individuals also tend to experience somewhat larger earnings growth both they stay with the same employer and when they switch. Consequently, these individuals end up at higher ranks of the lifetime earnings distribution.

While these facts are useful for describing the different components of earnings growth heterogeneity, they do not offer a structural interpretation to the *sources* of those differences. We now turn to a job ladder model to fulfill this remaining task.

3 Model

The model follows closely to that in Bagger *et al.* (2014). We study a labor market populated by heterogeneous workers and firms that produce a single consumption good. Workers can be employed or unemployed, and search for jobs, both when unemployed and employed, in a frictional labor market. Workers are infinitely lived and have preferences with log per-period utility, and discount future periods at rate ρ, that is,

$$U(\{c_t\}_{t=0}^{\infty}) = \sum_{t=0}^{\infty} \rho^t \log c_t$$

Endowment Let t denote the actual experience of a worker, i.e. the number of periods he has worked until t. The efficiency units of a worker with experience t is given by

$$h_t := g(t) + \alpha + \beta t + \varepsilon_t, \tag{1}$$

where $g(t)$ is the common component modeled as a quadratic function of experience (in units of years) that reflects human capital accumulation while working. α is an individual-specific fixed component that reflects permanent differences in individual productive ability, β captures heterogeneity in the returns to experience. We assume that α and $\log \beta$ are jointly normally distributed, $(\alpha, \log \beta - 1) \sim \mathcal{N}(0, \Sigma)$. Finally, ε_t is an idiosyncratic component, which is modeled as a linear $AR(1)$ process with innovations drawn from a mixture of normal distributions. In particular, $\varepsilon_t = \rho\varepsilon_{t-1} + \varepsilon_t$, where with probability π, $\varepsilon_t \sim \mathcal{N}\left(0, \sigma_\varepsilon^2\right)$ and with probability $1-\pi$, $\varepsilon_t = 0$.

Meeting and production technology Unemployed workers search for jobs and meet firms with probability λ_0. A meeting turns into a match if a positive surplus can be extracted. Once in a match, the worker produces a single divisible good sold in a perfectly competitive market. Firms differ in their (log-) productivity p, a fixed firm heterogeneity parameter that is distributed according to cdf F. We assume a Pareto distribution for F with a shape parameter of ψ_F and a scale parameter of ς_F. The log-output per period of a match, y_t, is given by

$$y_t = p + h_t.$$

While employed, workers search for better jobs and meet potential poachers at contact rate λ_1. This contact triggers a renegotiation between the worker, the incumbent firm and the poaching firm that we explain below.

The timing of events is as follows: At the beginning of each period, ε_t is revealed to employed workers and human capital is updated according to equation 1. Next, employed workers can experience one of two events: (1) the match dissolves with probability δ, (2) the worker receives an outside offer with probability λ_1. We assume that unemployed workers do not accumulate experience. Unemployed workers meet with a firm with probability λ_0. Regardless of the employment status or the human capital of the worker, the worker draws the productivity p of the firm from the same distribution F.

The model allows for various channels to account for the heterogeneity in the data: Lifetime earnings can differ due to the variation in realized idiosyncratic shocks, ε, and due to the differences in realized unemployment and job-to-job transition rates for otherwise similar individuals. To capture the heterogeneity in the data, we also allow λ_0, λ_1 and δ to be functions of the individual-specific fixed effect α. More specifically, we model the probability of any given rate, p, as

$$p = \frac{\exp\left(c_{p,0} + c_{p,1}\alpha\right)}{1 + \exp\left(c_{p,0} + c_{p,1}\alpha\right)},$$

where $p \in \{\lambda_0, \lambda_1, \delta\}$. We assume that unemployed workers are recalled by their last employer with a type-invariant probability of ξ.

There is no inter-temporal savings device; in other words workers are assumed to be hand-to-mouth consumers.

Poaching and wage determination We borrow the wage determination protocol from Bagger *et al.* (2014). Here, we provide an overview of the wage determination and refer the interested reader to that paper for a more detailed technical description.

Wages are specified as piece-rate contracts. If a worker with h_t efficiency units of labor works for a firm with productivity p at a piece rate of $R = e^r \leq 1$, he receives a log wage w_t of $w_t = r + p + h$. Here, R is the endogenous contractual piece rate. Upon meeting with firms, both employed and unemployed workers bargain with the firm (potential poacher, in the case of already employed workers) over this piece rate. We start by describing the negotiation process for an employed worker.

Consider a worker with experience t, employed at a firm of type p at a piece rate R. Let $V(r, h_t, p)$ denote the lifetime utility of this worker. Suppose that this worker meets with a firm with productivity p'. The poacher and the incumbent firm bargain to obtain the services of the worker. We assume that at the time of this bargaining, the idosyncratic shock ε_{t+1}, thus the level of human capital of the worker h_{t+1}, is not known. The protocol is such that the firm that values the worker more eventually hires (or retains) the services of the worker. In this case, this party is the firm with a higher productivity.

There are several cases to consider. First, let's suppose that the poacher has higher productivity; $p' > p$. The poacher secures the services of the worker, by offering a piece rate r' that solves the following equation:

$$E_t V\left(r', h_{t+1}, p'\right) = E_t \left\{ V\left(0.h_{t+1}, p\right) + \beta \left[V\left(0, h_{t+1}, p'\right) - V\left(0, h_{t+1}, p\right) \right] \right\}. \qquad (2)$$

Here, the expectation is with respect to the only unresolved uncertainty; that is ε_{t+1}. Equation (2) implies that the poacher hires the worker, by offering the value of the worker's existing match as well as a share β of the additional surplus generated by this outside offer. β captures the worker's "bargaining power."

Second, let's consider a case in which the poacher has lower productivity than the current employer. The bargaining protocol implies that the incumbent firm retains the worker by adjusting the worker's piece rate. This new piece rate offers the worker the entire value he could possibly obtain while working at firm p', i.e. the value associated with $r = 0$, and a β-share of the additional surplus generated by the offer. In this case, the new piece rate r' solves the following equation:

$$E_tV\left(r',h_{t+1},p\right)=E_t\left\{V\left(0.h_{t+1},p'\right)+\beta\left[V\left(0,h_{t+1},p\right)-V\left(0,h_{t+1},p'\right)\right]\right\}. \tag{3}$$

In some cases, the productivity of the poacher may be so low that the new contact does not entail any increase in the piece rate. Let q denote the threshold firm productivity that falls short of generating any additional surplus to the worker. Whenever an employed worker meets a potential poacher with $p'\leq q$, the offer gets discarded. q solves

$$E_tV\left(r,h_{t+1},p\right)=E_t\left\{V\left(0.h_{t+1},q\right)+\beta\left[V\left(0,h_{t+1},p\right)-V\left(0,h_{t+1},q\right)\right]\right\}. \tag{4}$$

We now consider an unemployed worker who finds a job at an employer type p. These workers receive a share β of the expected match surplus. Let r_0 denote the initial piece rate of a newly-hired worker. r_0 solves

$$E_tV\left(r_0,h_{t+1},p\right)=V_0\left(h_t\right)+\beta E_t\left[V\left(0,h_{t+1},p\right)-V_0\left(h_t\right)\right], \tag{5}$$

where $V_0\left(h_t\right)$ is the lifetime utility of unemployment for a worker with experience t. Following Bagger *et al.* (2014), we assume that unemployment is equivalent to employment in the least productive firm of type $p_{\min}$. This assumption simplifies the problem and implies that an unemployed worker accepts any job offer.

4 Estimation

We now take this model to the data and estimate it by simulated method of moments. We simulate monthly data and create a model-based matched employer-employee panel mimicking the SSA sample, which is then used for computing the model counterparts of our targets. In particular, given the parameters of the model, we simulate a monthly panel of 100,000 individuals. Each individual starts his life as unemployed at the age of 23 and remains in the labor force until the age of 60. We discard the first two years of the simulated panel and use ages 25 to 60 and aggregate monthly data to annual observations. Importantly, we subject the model to the same sample selection criteria used to select our SSA sample and use the final simulated sample to compute the model counterparts of our targets, which we now describe in detail.

4.1 Targeted moments

We target five sets of moments. The first two sets of moments are about the cross-sectional distribution of earnings changes. The third and fourth moments are about the fraction and wage growth of job stayers, EE-switchers, and EUE-switchers by lifetime earnings percentiles. And finally, we also target the life cycle income profile of median LE group. We now explain these moments in detail.

4.1.1 Cross-sectional moments of earning growth

We target the standard deviation, skewness and kurtosis of annual earnings changes. In constructing these moments, we follow Guvenen *et al.* (2015) closely. In particular, we focus on how these moments vary by age and by the level of earnings. We briefly explain the methodology, and refer the readers for more details to Guvenen *et al.* (2015).

Accounting for zero incomes For the estimation of the search model, we would like to capture the patterns of "zero earnings" (or very low earnings observations due to long term unemployment), given that they clearly contain valuable information about the importance of search frictions. Targeting higher order moments of changes of log annual earnings does not allow us to include such observations in our estimation unless we transform these observations by arbitrarily mapping them into earnings values that are above some minimum level. We rather follow a different approach and focus on arc percent changes defined as follows:

$$\frac{y_{t+k} - y_t}{(y_{t+k} - y_t)/2},$$

where y_t is the annual earnings.[10]

Grouping workers We first group workers into three age bins (25–34, 35–44, 45–55). Then, within each age group, we rank individuals by a measure of what we call "recent earnings" and assign them into percentile groups (1-4, 5–10, 11--20, ..., 81–90, 91–96, 97–100). This measure is defined as follows. For a given individual i, who is h years old, his recent earnings, $\bar{Y}^i_{h-1}$, is an average of his past earnings taken over $h-1$ through $h-5$. When constructing $\bar{Y}^i_{h-1}$, we control for age effects by normalizing individual earnings using average earnings at each age. Our first set of targets constitutes the standard deviation, skewness and kurtosis of annual arc-percent earnings changes within each age and recent earnings group.

[10] Obviously, even the arc percent changes cannot capture zero earnings observations if they occur for two consecutive years. However, the probability of having zero earnings for two consecutive years is quite small in our sample.

In addition, we further divide workers in a given age and recent earnings group into job stayers and switchers. We call a worker a "job-stayer" between years t and $t+1$ if he works for the same firm in years $t-1$ through $t+2$, and if this job provides at least 90% of his total annual earnings in t and $t+1$. All other workers are labeled as "job-switchers".[11] Our second set of moments is composed of the standard deviation, skewness and kurtosis of annual arc-percent earnings changes within each age and recent earnings group for job stayers and switchers separately.

4.1.2 Average income growth moments

The remaining sets of targets are about the heterogeneity in income growth over the life cycle across 12 different groups, which are defined by the following lifetime earnings percentiles: 1–4, 5–10, 11–20, ..., 81–90, 91–96, 97–100.

In the third set of moments, we target the life cycle earnings profile of workers by LE groups at ages 25, 30, 35, 40, 45, 50, 55, and 60.

Next, we target the fraction and average income growth of stayers, EE-switchers, and EUE-switchers by three age groups (25–34, 35–44, 45–55) and LE groups. These moments are presented in section 2.2 and shown in figures 5 and 4.

The model counterparts of our targets are calculated by following the same steps that are applied on SSA data.

4.2 Estimation methodology

Let m_n for $n = 1, ..., N$ denote a generic empirical moment, and let $d_n(\theta)$ be the corresponding model moment that is simulated for a given vector of model parameters, θ. When computing the model moments, we apply precisely the same sample selection criteria and employ the same methodology to the simulated data as we did with the actual data. To deal with potential issues that could arise from the large variation in the scales of the moments, we minimize the *scaled* deviation between each data target and the corresponding simulated model moment. For each moment n, define

$$F_n(\theta) = \frac{d_n(\theta) - m_n}{|m_n| + \gamma_n},$$

where $\gamma_n > 0$ is an adjustment factor. When $\gamma_n = 0$ and m_n is positive, F_n is simply the percentage deviation between data and model moments.

[11] This classification is similar to the one in Guvenen *et al.* (2015).

The MSM estimator is

$$\hat{\theta} = \arg\min_{\theta} F(\theta)' W F(\theta), \tag{6}$$

where $F(\theta)$ is a column vector in which all moment conditions are stacked, that is,

$$F(\theta) = [F_1(\theta), ..., F_N(\theta)]^T .$$

The weighting matrix, W, is chosen such that each set of moment receives a relative weight of 25%. We target a total of 636 moments to estimate 18 parameters.

Numerical method for estimation We minimize the objective value as follows. We first generate 10,000 uniform Sobol (quasi-random) points and compute the objective value for each of these. Then, we select the best 1,000 Sobol points (i.e., ranked by objective value), each of which is used as an initial guess for the local minimization stage. This stage is performed with a mixture of Nelder-Mead's downhill simplex algorithm (which is slow but performs well on difficult objectives) and the DFNLS algorithm of Zhang *et al.* (2010), which is much faster but has a higher tendency to be stuck at local minima. We have found that the combination balances speed with reliability and provides good results. In the end, we pick the best parameter estimates out of 1,000 local minima. This procedure takes around 5 full days using a cluster of 75 parallel cores.

5 Model's fit to the data

In this section, we present and discuss our model's performance in fitting the targeted moments. In doing so, we also discuss the economic forces behind these patterns. This helps us understand what features of the data inform the various pieces in the model.

5.1 Cross-sectional moments

Figure 6 shows the fit of the model to cross-sectional moments. The left panel shows the moments for the entire group, whereas the right panel shows the moments for job stayers and switchers separately. For the clarity of exposition, we suppress the life cycle variation in these moments by plotting their averages over three age groups.

We start with the standard deviation shown on the top panel. Overall, the model does a fairly good job of capturing both the level of standard deviation and its variation across recent earnings groups (shown on the left panel). Both in the data and the model, the standard

TABLE III – Parameter values

Parameter	Value
g_t, constant	-0.33
g_t, linear	0.12
g_t, quadratic	-0.02
σ_α	0.55
σ_β	0.01
$\sigma_{\alpha\beta}$	0.90
ρ_ε	0.42
π_ε	0.32
σ_ε	0.36
$c_{\lambda_0,0}$	-0.66
$c_{\lambda_0,1}$	2.70
$c_{\lambda_1,0}$	-5.50
$c_{\lambda_1,1}$	-1.6
$c_{\delta,0}$	-3.2
$c_{\delta,1}$	-0.06
ψ_F	6.83
ς_F	1.36
ξ	0.21

deviation of annual earnings changes declines with the level of earnings except for the top end. This declining pattern is due to the fact that higher income workers are more likely to be stayers (both in the data and the model; top left panel of figure 7) and that stayers face a lower dispersion of earnings growth (see the right panel). Furthermore, the model also generates a declining pattern of standard deviation for switchers, albeit more pronounced than the data. This feature is also due to the variation in the composition switchers. Specifically, as shown on the bottom two panels of figure 7, the share of EE-switchers, who have lower standard deviations of earnings growth, increases with income.

Next, we turn to the centralized third moment. The model generates negative skewness, consistent with the data. However, the top end of the recent earnings distribution faces a much larger negative skewness compared to the data (middle panel of figure 6). Note that the model does a fairly good job of generating a realistic skewness for job switchers. Though, for stayers skewness declines sharply with recent earnings, in contrast to what we observe in the data (see the right panel). This happens for two reasons. First, as workers climb up the job ladder, the skewness declines due to the compression of the right tail of the earnings change distribution, driven by a declining probability of an outside offer better than the worker's current wage.

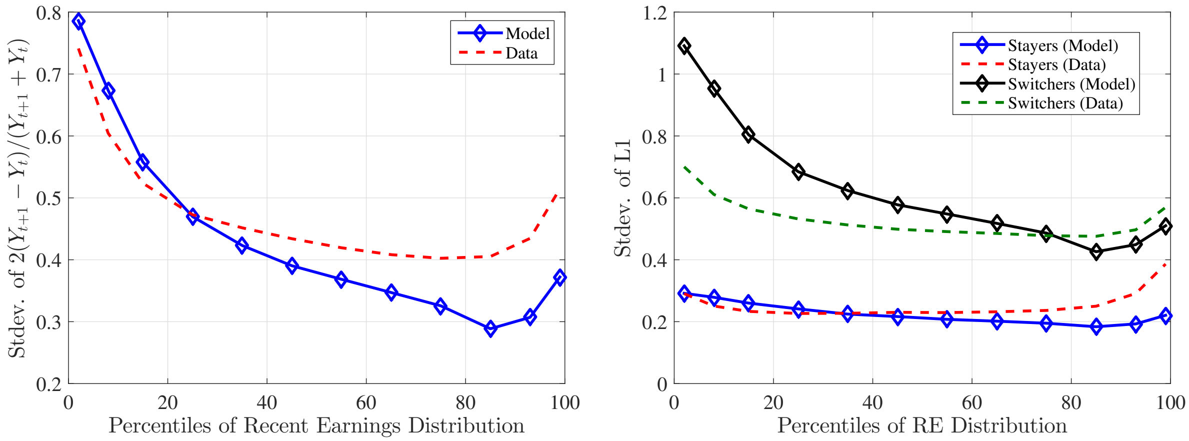
Second, as we show in the middle panel of figure 8, the contact rate declines with α. Since LE is an increasing function of α (see the left panel of figure 9), high recent earnings individuals have fewer outside offers, thus face a shorter right tail.

How does the model generate a negative skewness for some groups of stayers? The recall feature of the model is key for this result. In a model without recalls, the distribution of earnings changes for stayers is always strongly right skewed. This is because most of the time stayers experience small changes in their earnings due to idiosyncratic shocks, and every once in a while see their wages increase significantly due to outside offers. Recalled workers show up as job stayers, however they have earnings changes similar to EUE-switchers, who experience large drops in their earnings.

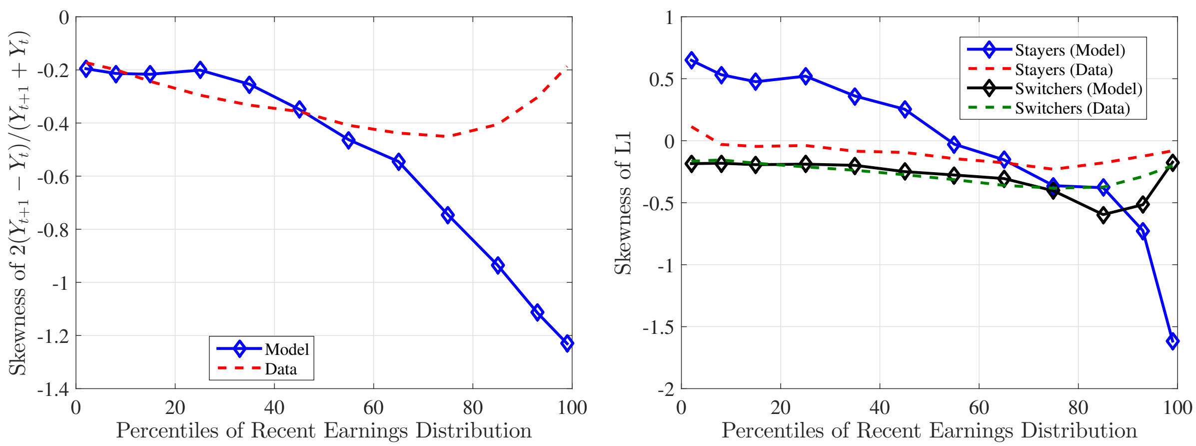
Finally, the bottom panel shows the kurtosis. The model is quite successful matching the level of kurtosis as well as its variation with recent earnings. We also find that the model generates a higher kurtosis for stayers, consistent with the data.

FIGURE 6 – Model's fit to cross-sectional moments

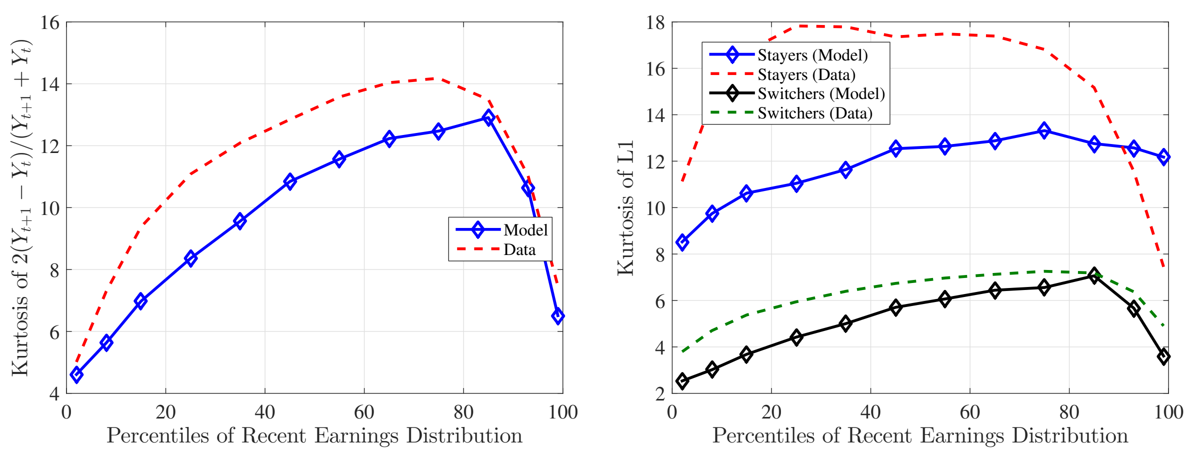
(C) Standard deviation



(F) Skewness



(I) Kurtosis



5.2 Income growth moments

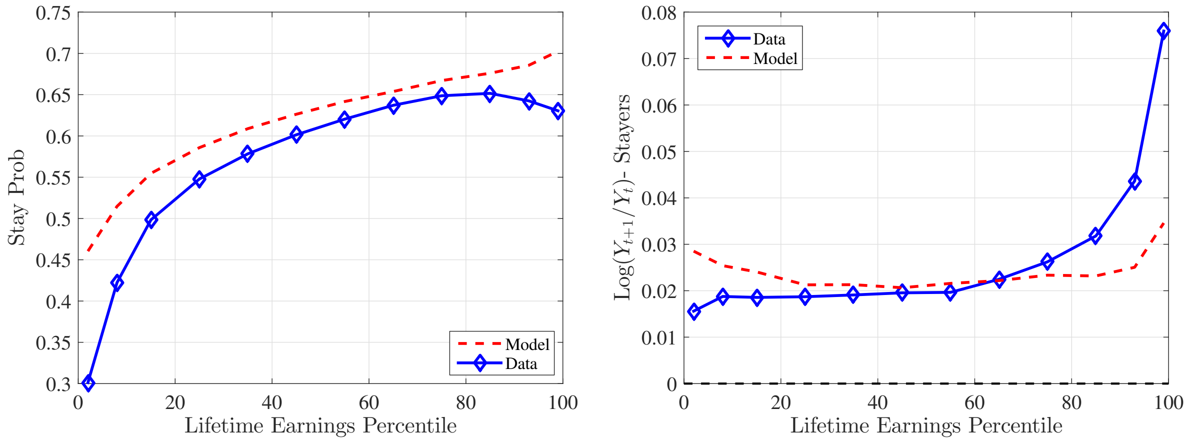
The left panel of figure 7 compares the model's predictions for the fraction of stayers, EE-switchers, and EUE-switchers against the data. A couple of remarks are in order. First, the model matches quite well not only the level but also the shape of the probability of being a stayer and EUE-switcher over the LE distribution. As we plot in 8, both the contact rate p_1 and the unemployment risk δ decline by α (thus, by LE). This explains the rise in the probability of being a stayer and the EUE-switcher.

The model does a relatively worse job in matching the probability profile of being an EE-switcher over the LE distribution (see the left middle panel). On the one hand, the contact rate decreases with α, implying a decreasing pattern of EE probability. On the other hand, the job finding rate is increasing in α (see the top panel of figure 8), which in turn classifies an increasing share of EUE-switches erroneously as EE-switches. These two forces cancel out each other, generating an almost flat profile of EE probability.

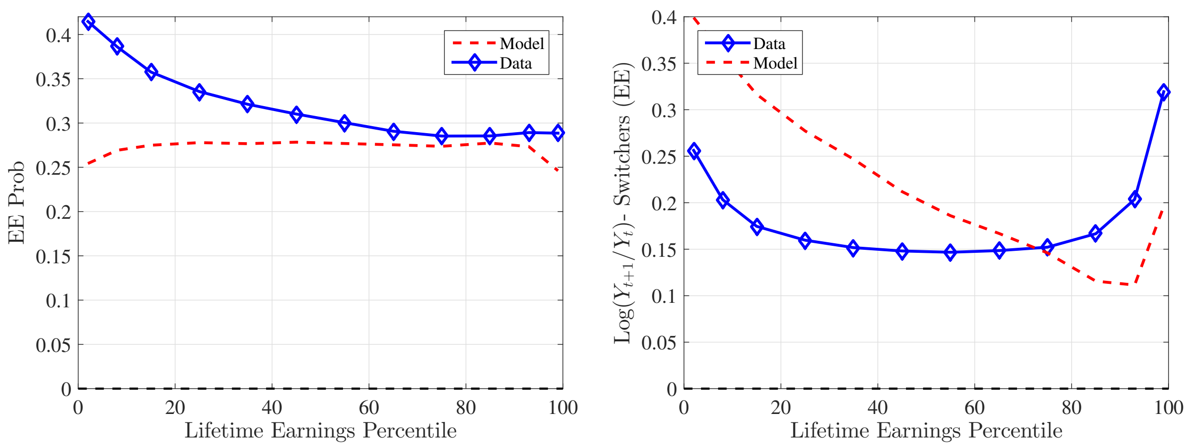
Turning to the right panel of figure 7, we find that the model generates plausible growth rates on average for job stayers, EE-switchers and EUE-switchers. As for how these vary over the LE distribution, the model is not as successful as in the previous moments. Specifically, at the top end of the LE distribution, stayers experience much smaller earnings gains in the model relative to the data. Moreover, for the EE-switchers, the model overstates the income growth in the lower end of the LE distribution.

FIGURE 7 – Model's fit to income growth moments

(C) Stayers



(F) EE-Switchers



(I) EUE-Switchers

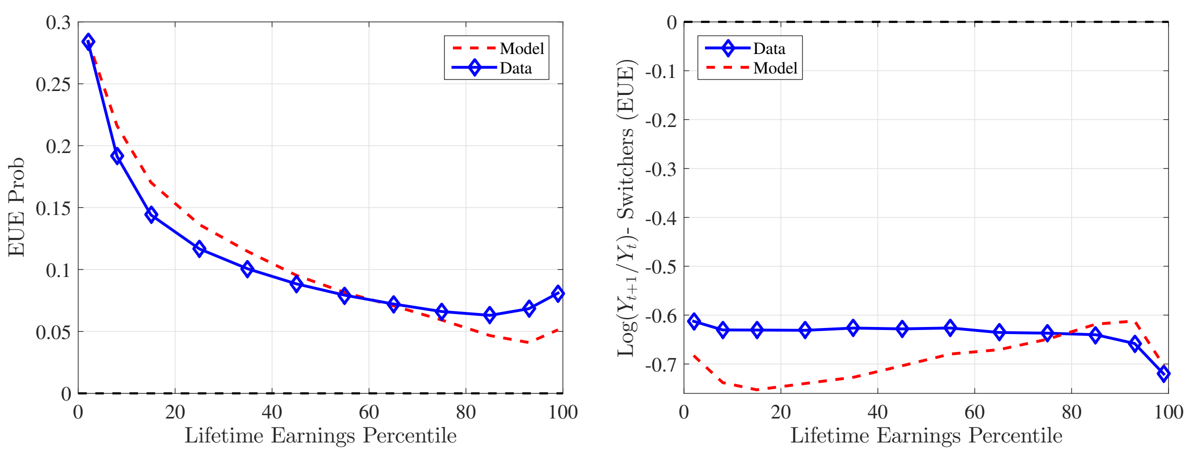


FIGURE 8 – Flow rate functions

(A) $p_0(\alpha)$ (B) $p_1(\alpha)$ (C) $\delta(\alpha)$

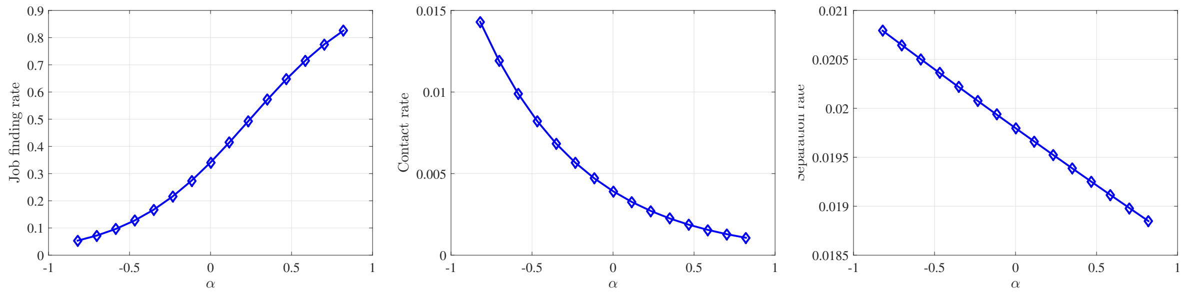
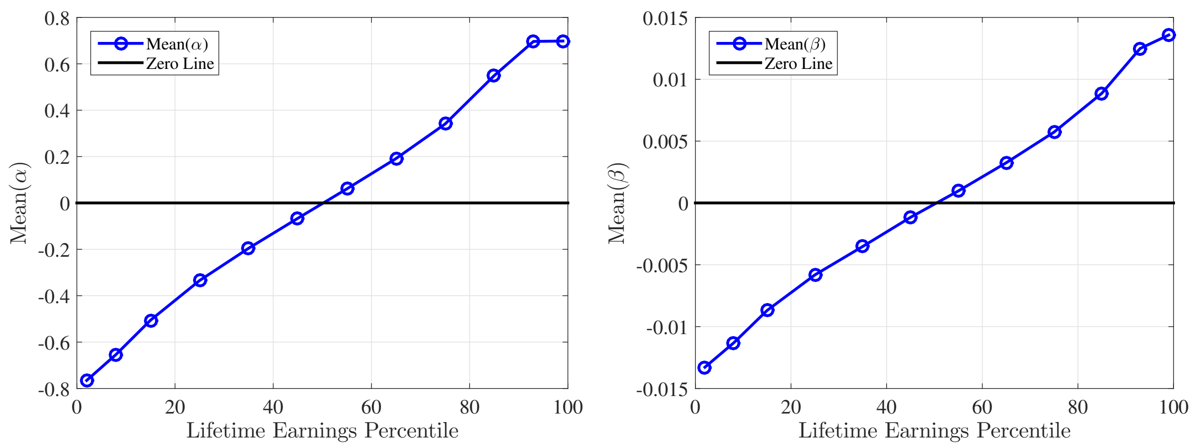


FIGURE 9 – Average fixed effects of LE groups

(A) α (B) β

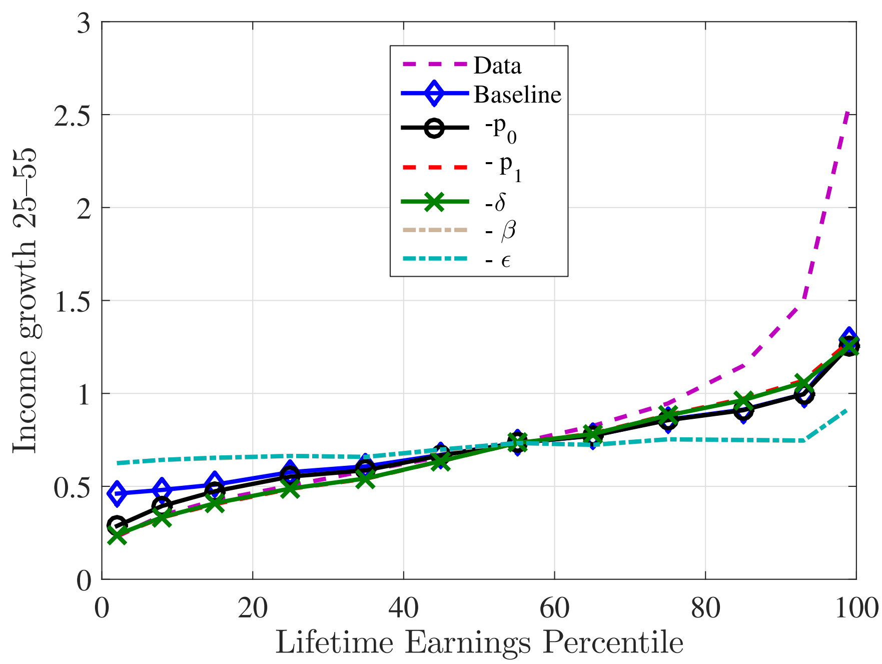


6 Decomposing life cycle income growth

Finally, we are ready to use the model as a laboratory for measuring the contribution of various factors to the inequality in lifetime earnings growth. To do so, we first start by discussing the fit of the moment along this dimension. Figure 10 plots lifetime earnings growth from the estimated model (labeled as "baseline") and compares it to the data. Overall, the model generates a quite substantial dispersion in income growth rates: While the bottom LE earners experience close to 50% earnings growth in 30 years, top earners experience an almost 4-fold increase. In terms of matching the entire profile, the model provides a good account of the income growth of individuals up until the 75th LE percentile. However, we understate the income growth of individuals above this group.

How much of this heterogeneity is driven by the various features of the model? Specifically, we are interested in the contributions of the heterogeneity in the returns to experience, heterogeneity in the job finding, separation and job-to-job transition rates, and idiosyncratic shocks. For this purpose, we simulate individuals in each LE group by consecutively shutting down a component of the model. We keep the random numbers fixed across simulations to ensure the results are not driven by different draws of luck. We shut down the heterogeneity in the returns to experience by setting σ_β to zero. To turn off the heterogeneity in the job finding and separation rates, and the employer contact rate of employed workers, we suppress their dependence on α. Lastly, we turn off the idiosyncratic shocks completely by setting their standard deviation to zero ($\sigma_\varepsilon = 0$). The resulting profile of lifetime earnings for each simulation is plotted in figure 10. Overall, we find that a substantial portion of earnings growth heterogeneity is driven by the heterogeneity in the returns to experience, while the job finding and separation rates also matter to some extent.

FIGURE 10 – Decomposing income growth



In figure 11, we show how heterogeneity in various parameters of the model affect the fraction and wage growth of stayers, EE-switchers and EUE-switchers. This allows us to understand what is driving the result in figure 10. The variation in fraction of stayers across the LE distribution is mainly determined by the variation in the job finding and contact rates.

Though, even when we shut down the heterogeneity in δ, p_0, and p_1, the realized fraction of stayers is increasing over the LE distribution. This declining pattern is due to the fact that it's hard to poach workers that are closer to the top of the job ladder. However, this economic force falls short of generating an empirically plausible variation in the realized fraction of stayers. Therefore, we conclude that it is critical to allow for heterogeneity in these probabilities.

The reason that the baseline model generates a flat profile for the wage growth of stayers (except for the top end of the LE distribution) is due to two opposing forces that cancel each other to a large extent. On the one hand, the contact rate, p_1, declines over the LE distribution. As a result, higher LE individuals get fewer outside offers and in turn experience lower wage growth on the job. On the other hand, higher LE groups tend to have higher returns to experience, β, causing higher wage growth on the job.

7 Conclusion

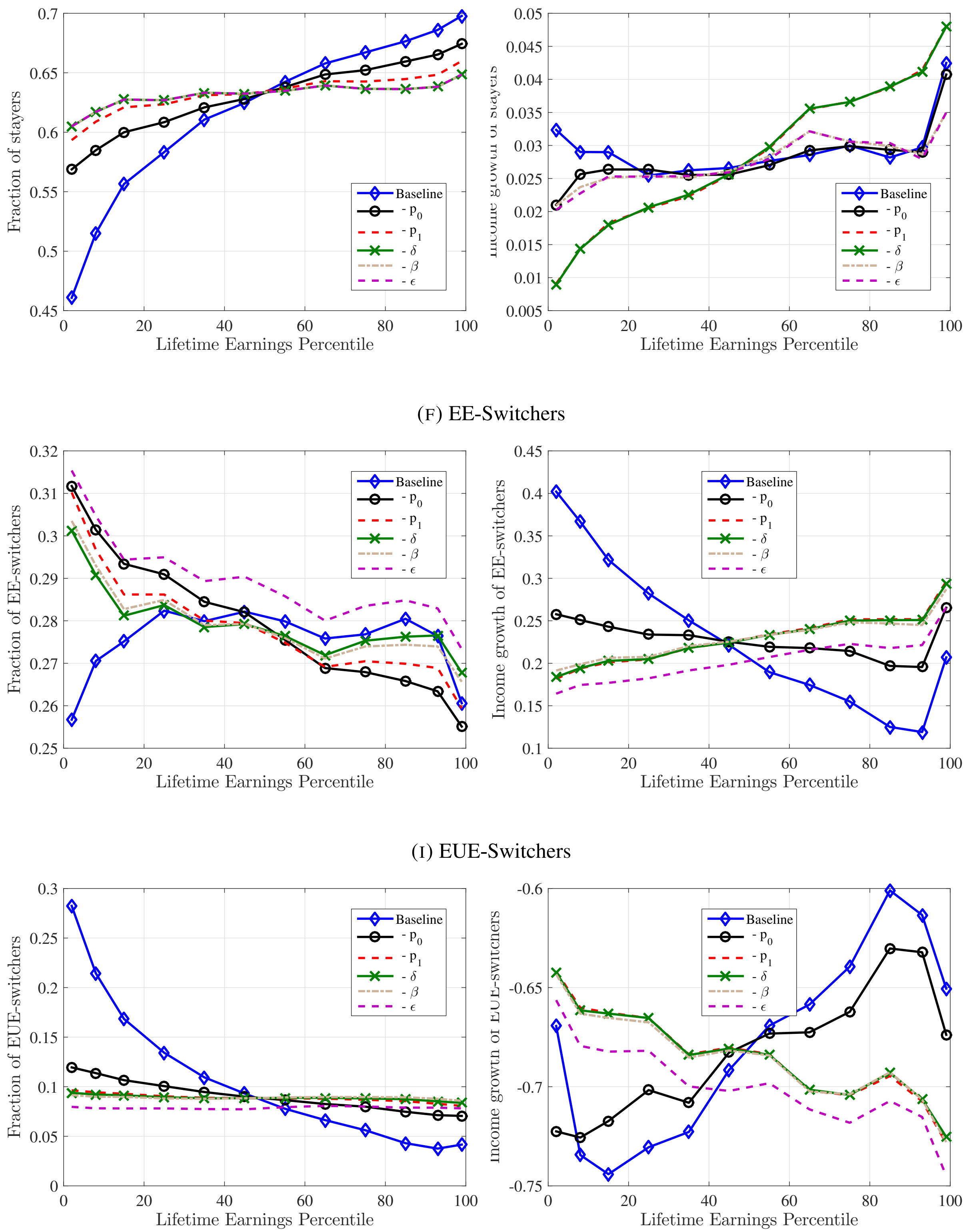
This paper investigates the causes of the large heterogeneity in earnings growth. Earnings growth during one's career is an important contribution to overall lifetime inequality. More specifically, we focus on the role of search frictions. Our empirical work suggests there is substantial heterogeneity in labor market flow rates. Estimating a search model using these new findings, we conduct experiments to understand the effects of search frictions on earnings growth over the lifetime.

FIGURE 11 – Income growth for stayers, EE- and EUE-switchers

(C) Stayers

(F) EE-Switchers

(I) EUE-Switchers



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A SIPP

There are two important drawbacks of the SSA data. The first is its annual frequency, which doesn't allow us to see higher frequency movements in earnings. The second is that it doesn't allow us to condition the outcomes on the labor market status of workers. To supplement the facts documented in the previous section, we use data from the Survey of Income and Program Participation (SIPP), a nationally representative sample of U.S. households. The data consists of monthly observations in overlapping panels with length between 2.5 and 4 years, with the first panel conducted in 1984. Each SIPP panel is conducted in waves, interviewing households every four months about the prior four months. Using data on labor force status, employment rates and labor market transition rates can be computed at a monthly frequency from the SIPP. Similarly, using individual income data, we are able to investigate how these flow rates vary with the level of earnings.[12] We also use the SIPP to compute labor market flow rates for individuals by educational attainment.

A.1 Sample

The SIPP sample is selected in a way that mirrors the SSA sample construction; we select males between the ages of 25 and 60. To construct previous income quintiles, we first keep observations which have at least 12 months of prior data. We then compute total wage earned in the the last year and sort individuals into quintiles (deciles) based on this value. We apply a further refinement to the sample selection when computing the share of individuals never unemployed for the duration of a panel (discussed in Section A.2); specifically, we drop individuals who had questionnaire responses in <75% of the panel length. We also drop individuals who report Not in the Labor Force as their employment status for >20% of their responses over the course of a panel.

A.2 Heterogeneity in Labor Market Flows

In this section, we document heterogeneity in labor market events (job separations, job finding, etc..) using the sample described above.

Figure 12 displays 4-month flow rates. These show significant heterogeneity across previous year wage quintiles (deciles for some plots) for all age categories displayed. The top left panel shows that the 4-month job finding probabilities are strongly increasing with the level

[12] We cannot rank people by their lifetime earnings, since in the SIPP we don't observe the entire earnings history of individuals. Therefore, we condition workers by their average past wages.

of past earnings. This rate is around 30% for young workers (25-34) with low earnings, and increases monotonically up to 85%. The top right panel plots the transition rates into unemployment, and finds substantial variation. More specifically, 4-month E-U flow rates are as high as 5% for young workers and decline steadily with past earnings, reaching a low of 1% for the top quintile. Moving to job-to-job transition rates (shown on the bottom left panel), we find that these are as high as 10% for young workers with low earnings, decline with recent earnings and are about 4% for the top quintile. Finally, we also compute the fraction of individuals always employed (shown on the bottom right panel). This fraction is increasing as we move from the lowest income quintile to the highest; at the bottom, 62% of individuals are never observed to be unemployed over the duration of the panel, while at the top, it is nearly 90%.

If labor market risks were homogeneous across workers, there would be no relationship between flow rates and past income, other than what can be attributed to sampling variation. Thus, any sizable systematic differences that we document should therefore point to heterogeneity in labor market prospects.[13]

We suspect that the heterogeneity in labor market experience observed in the SIPP and the SSA contribute to lifetime earnings inequality: A group of workers experience much fewer unemployment spells, find jobs faster when they are unemployed, and experience faster wage growth when switching employers. The next goal of our paper is to quantify the importance of this heterogeneity. In the next section, we describe a model that we use as a measurement device for understanding the contribution of various margins (U-E, E-U, E-E) to wage growth inequality.

[13] It is important to note that we rank people by *past* earnings. Therefore, there is no mechanical link between what we sort people on and *future* labor market outcomes.

FIGURE 12 – Labor market flow rates across the income distribution