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Job Separations, Heterogeneity, and Earnings Inequality

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Changes in the fraction of workers experiencing job separations can account for most of the increase in earnings dispersion that occurred both between, as well as within educational groups in the United States from the mid-1970s to the mid-1980s. This is not true of changes in average earnings losses following job separations. A search model with exogenous human capital accumulation calibrated to match some selected moments of the U.S. labor market is used to measure the effects of changes in the fraction of workers experiencing job separations (extensive margin) versus changes in average earnings losses following job separations (intensive margin). While both margins do well in accounting for the increase in the college premium, only the changes in the extensive margin do well in accounting for the increases in the variance of both the permanent and transitory components of earnings.

Key words: Job Separations, Inequality, Human Capital.

JEL codes: E24, J24, J31.

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1 Introduction

From the mid-1970s to the mid-1980s there was an increase in wage earnings inequality in the United States.[1] This increase occurred not only across different educational groups, but also within these groups.[2] Moreover, this increase in inequality within educational groups was not entirely persistent in nature. Gottschalk and Moffit (1994) argue that an important fraction was due to increases in the variance of the temporary component.

I investigate whether changes in earnings involving job separations can quantitatively account for the increase in inequality in its various dimensions. Why is this an investigation worthwhile pursuing? Because understanding the *proximate* source of the increase in inequality (changes in earnings involving separations versus changes in earnings that do not) is crucial for researchers who want to build models of the *ultimate* cause of the increase in inequality. To illustrate this point, while Kambourov and Manovskii (2004) consider a mechanism that leads to increases in inequality and operates through occupational changes (associated with job separations), Guvenen and Kuruscu (2006) suggest that the observed increase in inequality can result from a mechanism that operates exclusively through earnings changes within jobs.

This analysis allows for an even finer distinction. Changes in inequality due to changes in earnings associated with separations can come about because the fraction of people separating (*extensive margin*) is changing, or because the changes in earnings following separations are themselves changing (*intensive margin*). Again, to illustrate the point, the mechanism in Kambourov and Manovskii (2004) targets the former, while Ljungqvist and Sargent (1998) emphasize the latter, which they term changes in *turbulence*.

The Ljungqvist and Sargent (1998) world – a search model with exogenous skill accumulation – is extended to include ex-ante heterogeneity. This is done in order to make inequality between groups of people with different characteristics meaningful. Individuals are indexed by their skill accumulation dynamics. Anybody who has sat on a school bench is aware of the fact that different people learn at different speeds. Some people are able to master new skills very quickly, while it takes others a long time to do so. Moreover, skills that are acquired but not exercised often tend to depreciate. I focus on the differences in skill accumulation between workers with and without a college degree as a potentially crucial factor in understanding changes in inequality.

After building the model economy, I parameterize it such as to replicate key moments of the U.S. labor market in the mid-1970s period. The first experiment involves changing the

[1] For analyses of the evolution of wage earnings in the United States see, for example, Levy and Murnane (1992), Katz and Murphy (1992), and Gottschalk and Moffit (1994).

[2] See Juhn, Murphy, and Pierce (1993) and section 3.

fraction of people separating from what it was in the mid-1970s to waht it was in the mid-1980s. This allows me to assess the contribution of the extensive margin. The second experiment involves replicating the observed change in average earnings following a separation (while keeping constant the fraction of separations). This allows me to assess the contribution of the intensive margin. Finally, I put the two together, which allows me to assess any interactions between the two margins, as well as the contribution of changes in earnings that involve a separation versus changes in earnings that do not.

I find that the observed changes in the extensive margin can account for over 80% of the increase in the college premium, as well as for all the increase in the variance of the temporary component of earnings, but only for about half of the changes in the variance of the permanent component of earnings. Changes to the intensive margin can account for all of the increase in the college premium, but account for little of the changes in the variance of both the permanent and transitory component of earnings. Putting the changes in both margins together is not enough to account for the changes in the variance of the permanent component of earnings.

The simplest way to think about this analysis is as an exercise in finding out what observed features in the evolution of earnings and labor market outcomes does a theory aiming at explaining the increases in inequality need to be consistent with. As with all models, the one I use conditions the (simulated) data obtained. However, the model is simple enough that such biases are very transparent. Skill accumulation within each group is exogenous and agents cannot change groups (college versus non-college). The flip side to this simplicity is that general equilibrium effects that change incentives towards acquiring a college degree, for example, are absent. Also, changes in returns to skill accumulation (within each category) only affect agents through their reservation wage setting decision.

Ultimately, this exercise is only useful if it provides researchers with clues of what are and how to model the the ultimate causes of the increase in inequality. The results suggest that in order to be successful in all the dimensions considered, any possible explanation should result in increases in the fraction of people separating. Also, since changes involving separations cannot account for all the changes in the variance of permanent earnings, there seems to be a role in this dimension for explanations that emphasize changes in earnings within the same job.

Ljungqvist and Sargent (1998) coined the term turbulence when referring to changes in wage earnings following a job loss. This is not to be confused with its meaning in the Industrial Organization literature: volatility in firm-level performance, or in the Labor literature, where it is sometimes taken to be synonymous with job security or job stability. Ljungqvist and Sargent's work suggests it is possible to quantify how much of the increases in within-group wage earnings inequality can be accounted for by changes in wage earnings following a job loss.[3] In this framework, explicit technological shocks to the firms' production functions are absent. This contrasts with most of the existing literature.[4] Such a departure from the usual mechanisms used in the literature begs further investigation. I find that the claim that turbulence is behind the increase in earnings inequality does not withstand close quantitative scrutiny.

The focus of Ljungqvist and Sargent (1998) is not, however, the increase in within-group inequality. They are interested in how the effect of increased turbulence on unemployment rates varies according to whether unemployment benefits are present or absent. They use the increase in inequality as subsidiary evidence for the presence of turbulence. The authors argue that the values they use to calibrate turbulence give rise to changes in inequality that resemble (in some dimensions) the ones found by Gottschalk and Moffit (1994). This conclusion is unwarranted, as it depends on the rest of their calibration, which has counterfactual implications for the earnings distribution, for example.

The literature devoted to the study of the increase in earnings inequality in the United States in the last three decades can, for the most part, be divided into two broad groups: one emphasizing changes in institutions like the decline in unionization rates or the decline in the minimum wage,[5] the other emphasizing technological change. In the second group, some authors have addressed the increase in inequality between educational groups,[6] others have addressed the increase in residual inequality,[7] while others still have addressed both kinds of increases.[8]

The approach I follow falls in this last group but exploits a simpler mechanism, and should therefore be regarded as complementary to this literature. In Guvenen and Kuruscu (2006), to illustrate my point, shocks to a skill-biased technological production function interact with endogenous human capital accumulation decisions in trying to account for the data features described above. In contrast, here, changes in wage losses following job separations, or changes in the fraction of people separating, are taken as given, and interact with exogenous human

[3]Throughout the paper, the term "separations" is taken to mean the sum of quits and job losses, while job losses are the sum of firings and displacements (no-fault dismissals.)

[4]See, for example, Acemoglu (1999), Lloyd-Ellis (1999), Galor and Moav (2000), Kambourov and Manovskii (2004), Shi (2002), Violante (2002), and Guvenen and Kuruscu (2006).

[5]See, for example, DiNardo, Fortin, and Lemieux (1996) and Fortin and Lemieux (1997).

[6]Contributions in this area include, among others, Katz and Murphy (1992), Caselli (1999), Krusell, Ohanian, Ríos-Rull, and Violante (2000), and Beaudry and Green (2002).

[7]See, for example, Kambourov and Manovskii (2004), Violante (2002), and Huggett, Ventura, and Yaron (2006). Within-group inequality is also referred to as residual inequality in the literature.

[8]See, for example, Acemoglu (1999), Lloyd-Ellis (1999), Galor and Moav (2000), Shi (2002), and Guvenen and Kuruscu (2006).

capital accumulation. In fact, as far as the model is concerned, the changes in wage losses could be the result of skill-biased technological change, as the losses following separations increased more for those without a college education than for those with one.

The spirit of the exercise is to ask what are the minimum features necessary to do a good job in quantitatively addressing not only the increase in the college premium (which accounts for roughly a third of the overall increase in inequality), but also the increases in within-group wage inequality of both the permanent and transitory earnings components.

The paper proceeds as follows. The next section describes the model economy. Section 2.1 describes the equilibrium. Section 3 presents the data used as well as the calibration. Section 4 describes the experiments conducted and presents the results, and section 5 concludes.

2 The Economy

At any point in time there is a measure one of individuals in the economy. The lifetime of an individual is entirely spent in the labor force. Each period an individual faces a probability α of dying and not remaining in the labor force for next period. This means an individual's age (time since entering the labor force) is geometrically distributed, with average $(1-\alpha)/\alpha$. To keep the population constant, a measure α of people enter the labor force every period. Moreover, the

At any point in time an individual has skill level $h \in H$, a finite set. Let the minimal and maximal elements in H be denoted by h_{min} and h_{max} respectively.

There are 2 types of individuals indexed by $i \in I \equiv \{c, nc\}$, college educated or non-college educated. Individuals do not choose their type, meaning the measure of each type is time invariant and their sum is one.

A *wage offer* is a number $w \in \mathcal{W}$, where $\mathcal{W} \subseteq \mathbb{R}_+$, $0 \in \mathcal{W}$, and $\mathcal{W} \setminus \{0\}$ is compact and convex. Let the minimal and maximal elements in $\mathcal{W} \setminus \{0\}$ be denoted w_{min} and w_{max} respectively.

When faced with a wage offer, individuals can either accept it, in which case they are said to be *employed*, or reject it, in which case they are said to be *unemployed*. In the particular case when the wage offer is $w = 0$, individuals are said to be unemployed.[9] Unemployed agents can spend part of their time, $s_i(h)$, searching for new wage offers. They draw wage offers for next period, w', with a probability that depends on the amount of time they devote to search, $p(s_i(h))$. The wage offer is drawn from a distribution function that depends on their type, $\Phi_i(w) = \Pr\,(w' \leq w)$, defined on $\mathcal{W} \setminus \{0\}$. Henceforth, let ϕ_i be the unique

[9] In this case the accept/reject decision will turn out to be irrelevant.

probability measure associated with Φ_i. An accepted wage offer becomes a wage rate. The surplus generated by an individual with skill level h, matched with wage w is $e = wh$.

Individual skills evolve according to Markov chains. The transition probabilities for these Markov chains depend on the individual's skill level, employment status, as well as type. It is precisely the difference in the laws of motion governing skill accumulation that distinguishes types.

While employed, the probability, for an individual of type i, of going from skill level h this period to skill level h' next period is given by $\pi_i^e(h, h')$. If the individual is unemployed, this probability is given by $\pi_i^u(h, h')$. The job match may cease to exist for one of two reasons: the worker loses her job, which happens with probability λ_i^l, or quits, which happens with probability λ_i^q.[10] In these cases, the transition probabilities are given, respectively, by $\pi_i^l(h, h')$ and $\pi_i^q(h, h')$. It is important to distinguish between the two sorts of job loss because the data suggests they imply very different subsequent earnings behavior as discussed in section 3.

The evolution of the individual state variables is as follows. At the beginning of the period, an individual has state (i, h, w). If $w = 0$, the individual does not enter a job match and obtains earnings equal to zero. Next period's skill level is h' with probability $\pi_i^u(h, h')$, while next period's wage offer is $w' \in W' \subseteq \mathcal{W} \setminus \{0\}$ with probability $p_i(s_i(h))\phi_i(W')$, or $w' = 0$ with probability $(1 - p(s_i(h)))$. If $w > 0$, the individual decides whether to accept or reject this wage offer. In the case where the individual rejects w, she does not enter a job match and obtains earnings equal to zero. Next period's skill level is h' with probability $\pi_i^u(h, h')$, while next period's wage offer is $w' \in W' \subseteq \mathcal{W} \setminus \{0\}$ with probability $p(s_i(h))\phi_i(W')$, or $w' = 0$ with probability $(1 - p(s_i(h)))$. In the case where the individual accepts w, she enters a job match and obtains earnings equal to wh. If this match dies because a job loss occurs, which happens with probability λ_i^l, next period's skill level is h' with probability $\pi_i^l(h, h')$, while if the match dies because the worker quit, which occurs with probability λ_i^q, next period's skill level is h' with probability $\pi_i^q(h, h')$. In both cases, next period's wage offer is $w' = 0$. If this match survives, which occurs with probability $(1 - \lambda_i^l - \lambda_i^q)$, next period's skill level is h' with probability $\pi_i^e(h, h')$, while next period's wage is $w' = w$. By assumption, after a match dies, the individual is unemployed for at least one period.[11]

Below are some assumptions regarding the individual transition probabilities.

Assumption 1. *Laws of motion for employed:* $\pi_i^e(h, h') = 0$ *for all* $h' < h$, *and* $i \in I$.

Skill level evolution is weakly increasing for employed individuals.[12] This implies that once

[10] The fraction of quits is exogenous.

[11] This assumption is made for convenience and bears no influence on the results.

[12] Topel (1991) finds evidence in support of the view that the accumulation of specific capital is an important ingredient in determining life-cycle earnings.

an individual reaches the maximum skill level, h_{max}, she will remain there while employed.

Assumption 2. *Laws of motion for unemployed:* $\pi_i^u(h, h') = 0$ *for all* $h' < h$, *and* $i \in I$.

Skill level evolution is weakly decreasing for unemployed individuals. This implies that once an individual reaches the minimum skill level, h_{min}, she will remain there while unemployed.

Assumption 3. *Laws of motion in case of separation:*

1. *Laws of motion for job losers:* $\pi_i^u(h, h') = 0$ *for all* $h' < h$, *and* $i \in I$;

2. *Laws of motion for quitters:* $\pi_i^q(h, h') = 0$ *for all* $h' < h$, *and* $i \in I$.

Job losers (displaced or fired) face wage losses, workers who quit enjoy wage gains. This assumption is suggested by the data[13].

Individuals' period utility is linear in consumption, and they maximize future expected discounted utility. Their objective is:

$$E_t \sum_{j=0}^{\infty} \beta^j (1-\alpha)^j c_{t+j}, \tag{1}$$

where c is consumption and β is the discount factor. The linear utility assumption means the private bonds market can be ignored. Without loss of generality this market can be shut down, which simplifies the computation considerably as consumption equals earnings every period.

There is an ongoing debate in the literature on whether human capital accumulation is more job (or firm, or occupation) specific, or more general (individual specific). To distinguish between the two it is crucial to disentangle returns to tenure from returns to experience.[14] In this model, individuals only accumulate skills while on the job, but when a separation occurs they do not lose all their accumulated skills. In this sense, skill accumulation encompasses both job specific skills as well as more general skills (that do not get lost once a job ends.)

Finally, note that the modeling of the firm side is kept to the bare minimum. Wages are simply drawn from an exogenous distribution. This is within the spirit of the paper: understanding how far one can go in answering the question at hand using a simple search model where all that matters are differences in the laws of motion governing individual skill accumulation.

[13] See Polsky (1999) and section 3.

[14] For the debate on this issue see Topel (1991) and Altonji and Williams (2004).

2.1 Equilibrium

Let $V_i^u(h)$ denote the discounted expected utility of an unemployed agent of type i, with skill level h. It is given by:

$$V_i^u(h) = \max_s \left\{ -d_i(s) + \beta(1-\alpha) \left\{ \sum_{h'} \pi_i^u(h,h') \left[p_i(s) \int V_i(h',x)\, d\Phi_i(x) + (1-p_i(s)) V_i^u(h') \right] \right\} \right\}, \tag{2}$$

for $i \in I$, where $d_i(s)$ is the cost of searching. $V_i(h,w)$ denotes the discounted expected utility of an individual of type i, with skill h, that has a wage offer $w > 0$, and is given by:

$$\begin{aligned} V_i(h,w) \quad = \quad & \max \Big\{ V_i^u(h), \quad wh + \beta(1-\alpha) \Big[(1-\lambda_i^l - \lambda_i^q) \sum_{h'} \pi_i^e(h,h') V_i(h',w) \\ + \quad & \Big(\lambda_i^l \sum_{h'} \pi_i^l(h,h') + \lambda_i^q \sum_{h'} \pi_i^q(h,h') \Big) V_i^u(h') \Big] \Big\}, \quad \text{for } i \in I. \end{aligned} \tag{3}$$

An individual who receives a wage offer $w > 0$, can accept it or reject it. In case of rejection, the individual is unemployed this period, and the value of that is $V_i^u(h)$. In case of acceptance, earnings this period are wh. Next period, with probability $(1 - \lambda_i^l - \lambda_i^q)$, the same wage is offered, so the expected value is taken only over all possible skill levels. With probability λ_i^l there is a job loss, or a quit with probability λ_i^q, either way, the individual is unemployed next period, which has a value of $V_i^u(h')$.

The following proposition states that the optimal policy associated with equation 3 exists and is unique. All the proofs are standard and appear in Amaral (2002).[15]

Proposition 4. *The solution to equation 3 exists and is unique but for a set of measure zero.*

The next proposition states that the optimal policy associated with equation 3 is of the reservation wage type and characterizes the solution to (3).

Proposition 5. *The optimal policy associated with equation 3 is of the reservation wage form. For any $h \in H$ there exist numbers $\underline{w}_i(h)$, $i \in I$, such that an agent of type i with skill h, will accept wage offer w if $w \geq \underline{w}_i(h)$, and reject it otherwise. Furthermore, the solution to (3) is a nondecreasing, continuous, piecewise linear function of w.*

Given the individuals' optimal policies, $\underline{w}_i(h)$, the next step is to make explicit the laws of motion governing the transitions between different states. Let $\mu_t(i,h,W)$, where $W \subseteq \mathcal{W} \backslash \{0\}$,

[15]The proofs are also posted at http://www.econ.umn.edu/ pamaral/

denote the period t measure of individuals of type i, with skill level h, and a strictly positive wage offer $w \in W$, while $\mu_t(i,h,0)$ denotes those individuals with wage offer $w=0$. For every period t,

$$\sum_i \sum_h \left[\mu_t(i,h,0) + \int_{w_{min}}^{w_{max}} \mu_t(i,h,x)\,dx \right] = 1. \tag{4}$$

For this equation to hold over time, the measure of individuals entering the labor force has to equal the measure leaving it, given by α. I assume that those people entering the labor force do so with a skill level of $h = h_{min}$ and a wage offer $w = 0$.

Letting $\mu_{t+1}(i,h',W')$ denote next period's measure:

$$\begin{aligned} \mu_{t+1}(i,h',W') &= (1-\alpha)\Bigg\{(1-\lambda_i^l-\lambda_i^q)\sum_h \pi_i^e(h,h')\mu_t(i,h,W')\chi_{(w'\geq \underline{w}_i(h))} \\ &+ \phi_i(W')\sum_h p_i(s_i(h))\pi_i^u(h,h')\mu_t(i,h,0) \\ &+ \phi_i(W')\sum_h p_i(s_i(h))\pi_i^u(h,h')\int_{w_{min}}^{\underline{w}_i(h)} \mu_t(i,h,x)\,dx\Bigg\}. \end{aligned} \tag{5}$$

The three lines in equation 5 highlight the fact that individuals have three possible origins regarding their previous period's state. The first line refers to those individuals that were employed the previous period at wage $w' \in W'$ and evolved to skill level h'.[16] Only a fraction $(1-\lambda_i^l-\lambda_i^q)$ actually gets the same wage offer. The second line refers to those individuals that had wage offer $w=0$ the previous period and evolved to skill level h'. Only a fraction $\phi_i(W')$ will have an offer of $w' \in W'$. Finally, the third line captures all those that had a strictly positive wage offer the previous period, but rejected it and evolved to skill level h'. Again, only a fraction $\phi_i(W')$ will have an offer of $w' \in W'$.

Some individuals lose their job, while others simply do not get a job offer after rejecting one, or after having lost their job. These are the people that have $w=0$. The evolution of the measure of these individuals is given by:

[16] $\chi_{(w'\geq \underline{w}_i(h))}$ is an indicator function that equals one when the wage is above the reservation wage, otherwise it is zero. This captures the employed only.

$$
\begin{aligned}
\mu_{t+1}(i,h',0) &= \alpha\chi_{(h'=h_{min})} + (1-\alpha)\Bigg\{\Big(\lambda_i^l \sum_h \pi_i^l(h,h') + \lambda_i^q \sum_h \pi_i^q(h,h')\Big) \int_{\underline{w}_i(h)}^{w_{max}} \mu_t(i,h,x)\,dx \\
&+ \sum_h (1-p_i(s_i(h)))\pi_i^u(h,h')\mu_t(i,h,0) \\
&+ \sum_h (1-p_i(s_i(h)))\pi_i^u(h,h') \int_{w_{min}}^{\underline{w}_i(h)} \mu_t(i,h,x)\,dx \Bigg\}. \qquad (6)
\end{aligned}
$$

The first term on the right-hand-side of equation 6, $\alpha\chi_{(h'=h_{min})}$, is the measure of people entering the labor force for the first time. The first line inside the curly brackets includes all individuals that were employed in the previous period but lost their job and evolved to skill level h'. The second line refers to those individuals that had wage offer $w = 0$ the previous period and evolved to skill level h'. Finally, the summation in the third line captures all those that had a wage offer $w > 0$ the previous period but rejected it and evolved to skill level h'.

Definition 6. *A* ***steady-state equilibrium*** *is reservation wage policies, $\underline{\mathrm{w}}_i(h)$, and associated invariant probability measures, $\mu(i,h,W)$, $W \subseteq \mathcal{W} \setminus \{0\}$, and $\mu(i,h,0)$, such that:*

1. *$\underline{\mathrm{w}}_i(h)$ are the optimal policies for (3), for each type i, and each skill level h;*

2. *given $\bar{w}_i(h)$, $\mu(i,h,W)$ and $\mu(i,h,0)$ solve (4), (5) and (6).*

The measures $\mu(i,h,W)$ and $\mu(i,h,0)$ are the invariant measures associated with equations 5 and 6.

The next proposition shows existence and uniqueness of the above equilibrium.

Proposition 7. *Under assumptions 1, 2, and 3, a steady-state equilibrium exists and is unique.*

This framework will now be used to conduct experiments that will help determine whether:

1. changes in the fraction of individuals facing job losses and quits; or

2. changes in the average rate of skill depreciation following job losses and in the average rate of skill appreciation following quits; or

3. both of the above,

can help us understand the observed increase in wage earnings dispersion both between, and within the two groups.

3 Data

This section uses data for two purposes. The first one is to establish a benchmark against which to compare the results of the experiments involving the model economy and the second one is to parameterize the model economy. The latter is postponed to subsection 3.1 and here the data and statistics used are described.

I use the Panel Study of Income Dynamics (PSID) between 1974-79 and 1980-85.[17] The universe consists of white males between 20 and 60 years of age that are household heads. Only full time workers that are not self employed are considered.[18] This is meant to avoid biases caused by workers that are heterogeneous in dimensions that the model economy was not designed to capture.

Earnings data and statistics

The measure of earnings I use is the log of weekly wages. The yearly wage earnings from the PSID are divided by the number of weeks worked and deflated by the 2000 price index for personal consumption expenditures published by the Bureau of Economic Analysis. This is the most common measure of wage earnings in the literature. The sample is divided into two distinct populations, those with a college degree and those without one.[19]

As a measure of relative wage earnings I take the college differential, the difference in average log weekly wages between college educated individuals and those without a college education. This measure approximates the college premium (defined as the ratio of average weekly wages minus one) for small enough premia. Between 1974 and 1979, the college differential averaged 0.361, while between 1980 and 1985 it averaged 0.401.

With respect to the dispersion of earnings within groups, I use the standard deviation of log weekly wage earnings. Because the model economy does not distinguish between more and less educated people within each group, I regress the log weekly wage earnings on years of education for each group and then compute the standard deviation of the residuals of this regression. Between 1974 and 1979, the average standard deviation was 0.405 for those without a college degree and 0.387 for those with one. These numbers are used below to parameterize the model economy. The cumulative earnings distributions calculated from the PSID are shown as solid lined in figures 1 and 2.

[17] The analysis starts in 1974 because before that the college premium was actually declining. Guvenen and Kuruscu (2006) propose an explanation for the fall and subsequent rise in the premium.

[18] A full time worker works more than 40 weekly hours. The appendix provides a more detailed description of the data.

[19] A college degree means having completed at least a BA, AB, or BS.

An important dimension in which residual dispersion increased was first reported by Gottschalk and Moffit (1994). By decomposing wage earnings into a permanent and a transitory component they argued that a substantial part of the increase in residual dispersion was due to increases in the variance of the temporary component.[20]

After decomposing weekly log earnings into the sum of a permanent and a temporary component: $y_{jt} = \mu_j + \nu_{jt}$, I compute the variance (across individuals) of the permanent component, as well as the average (across individuals) variance (over time) of the temporary component for the two periods. Unlike what happens with the statistics presented in Gottschalk and Moffit (1994), I do not regress earnings on age. This is because the model economy includes an age structure. Letting the data reflect life-cycle effects provides another dimension over which to test the model. Figure 3 presents the distribution of permanent earnings in the top two panels, as well as the distribution of the dispersion of transitory earnings, in the bottom two panels. The top panels illustrate that for both groups, the dispersion of the permanent component of earnings increased from the first to the second period. The bottom two panels make this point for the transitory component of earnings.

Table 1 presents the earnings statistics for the sample described above over the two periods considered. In section 3.1 the model economy is parameterized to match some of the statistics in the first period. The results of the experiment will then be compared to the statistics in the second period.

Job separations data and statistics

The mapping of a job separation in the model to its data counterpart is very important in the context of this investigation. There are two types of job separations in the model: quits (which occur with probability λ^q) and job losses (which occur with probability λ^l.) The exercise ahead will be based on changing either the rate at which these separations occur, or the way workers' skills evolve after these separations, or both.

The strategy is to identify job losses in the model with permanent layoffs (because a job ended or a plant closed) and firings data, and to identify quits in the model with quits in the data.[21]

I use the PSID to identify both sorts of separations, but there are some caveats. There are no employer codes associated with each worker in the PSID, so one has to extract information

[20] These results are subject to the criticism in Baker and Solon (2003) regarding the imposition of (possibly) false restrictions on the earnings function due to lack of data.

[21] Temporary layoffs are not of interest in the context of the model, as they are not associated with a subsequent (costly) job search.

from the survey questions.[22] In the interview, the workers are asked the "reason for separation from previous employer". If the answer to this question is "Company folded/changed hands/moved out of town; employer died/went out of business", or "Laid off; fired", a job loss is recorded. If the answer to this question is "Quit; resigned", a quit is recorded. This is done regardless of whether the respondent is employed or unemployed (considering only unemployed workers would mean missing the workers that are reemployed between consecutive interviews and yields too little observations to make any significant inference.)[23]

For those workers who report strictly positive earnings in the year the separation is recorded, as well as in the following one, I compute the difference in log weekly wage earnings between the current and the following year. In the context of the model, this is an indicator of the skill change workers face when they lose their job or when they quit. I also compute job loss rates and quitting rates for each year. They all appear in table 2. Wage earnings losses following job separations increase for both groups, while earnings gains following quits increase for college workers but decrease for non-college workers. The incidence of job losses and quits increases across the board. These data are used below to parameterize the model economy as well as to discipline the experiments.

3.1 Parameterizing the model economy

The parameterization strategy involves not only choosing values for the model's parameters so as to replicate key features of the U.S. economy, but also specifying some functional forms.

The model period is set to one week. Both firms and workers make very frequent decisions about hiring and looking for jobs. Also, most of the literature reports either hourly wages or weekly wages, therefore, having a period be a week makes the results directly comparable.

The value for α is set such that the average life of a worker in the model is the same as the average years of experience in the PSID sample, 16.6 years.[24] The discount factor, β, is set such that the annual interest rate would be 4 percent if a bond market existed.

[22] The Displaced Workers Survey, a supplement to the CPS, was especially created to deal with permanent layoffs. There are two problems with using it in this context though: (i) it disregards firings and (ii) it only started in 1981 so it can only be used for the second period.

[23] The wording of the question changed slightly over the years, but more importantly, before 1984 the question was only asked if the respondent reported that they had been in their present position for less than 12 months. After 1984 the question was only asked if the respondent reported that they had been in their present position at least since January of the previous year. The universe of people asked the question was thus larger after 1984 possibly biasing comparisons. Since the sample period here ends in 1985, any possible biases are likely to be very small.

[24] This number is the worker's age minus 22 (for the college educated) or minus 18 (for the remainder). It actually differs between college and non-college workers. I took the average of the whole sample because I did not want the probability of survival to be a source of heterogeneity.

The values for the parameters indexing the job loss rates and quitting rates: λ_i^l and λ_i^q, respectively, are set so as to match the corresponding data moments found in table 2 in the first period.

The set H_i contains 21 points evenly spaced between 1 (h_{min}) and 3 (h_{max}). The set $\mathcal{W}\backslash\{0\}$ is discretized to contain 100 points, evenly distributed between 10 (w_{min}) and 1000 (w_{max}). This was done so that the maximum weekly earnings in the model $h_{max}w_{max} = 3000$, which is the maximum weekly earnings observed in the data.

For the remaining model parameters, a one-to-one mapping between the parameter and the (data) moment of interest does not exist, so a set of parameter values is assigned jointly to match a corresponding set of moments using the method of moments.

The distributions from which the workers draw wages, ϕ_i, are constructed from a normal distribution with mean μ_i^w and standard deviation σ_i^w. Since the support of these distributions is the finite set $\{10, ..., 1000\}$, they are discretized and rescaled so that they integrate to one. The parameters μ_i^w and σ_i^w are set below.

Let the probability of obtaining a wage offer as a function of the search intensity be given by: $p_i(s) = s^{n_i}$, where n_i is calibrated below. Let the search cost be linear: $d_i(s) = d_i s$, where d_i is also set below.

Regarding the laws of motion for skills in each state, while unemployed, and also following a job loss, skill evolution is weakly decreasing. The probabilities of moving from skill level h to skill level $h' \leq h$, $\pi_i^u(h, h')$, and $\pi_i^l(h, h')$, are distributed according to the left-side of a normal distribution with mean h that is discretized and rescaled to the support $\{h_{min}, ..., h\}$. Following Ljungqvist and Sargent (1998), these distributions are indexed by their variance: p_i^u and p_i^l. In these cases, increasing the variance decreases the expected skill level.

Following a quit, skill evolution is weakly increasing. The probability of moving from skill level h to skill level $h' \geq h$, $\pi_i^q(h, h')$, is distributed according to the right-side of a normal distribution with mean h that is discretized and rescaled to the support $\{h, ..., h_{max}\}$. This distributions is indexed by its variance: p_i^q. In this case, increasing the variance also increases the expected skill level.

To mimic the concave profile of earnings while employed there is one extra twist. The goal is to make the probability of moving from h_j to h_{j+1} higher than that of moving from h_{j+1} to h_{j+2}, for example. Because the points in H are equally spaced, then, under the functional forms above, these probabilities would be the same, therefore, transform the set H into set $G = \{g_j\}_{j=1}^{21}$, according to:

$$g(j) = h_{min} + [h_{max} - h_{min}]] \left[\frac{h(j) - h_{min}}{h_{max} - h_{min}}\right]^{\frac{1}{m}},$$

where $m < 1$ is set below. The endpoints are the same, but at the lower end of the interval, the points are closer together than at the upper end. Then, let the probability of moving from skill level h_j to skill level $h' \geq h_j$, $\pi_i^e(h_j, h')$ be distributed according to the right-side of a normal distribution with mean $g(j)$ that is discretized and rescaled to the support $\{g_j, ..., g_{max}\}$. This distributions is indexed by its variance, p_i^e. Increasing it also increases the expected skill level.

The task now is to find values for the following nine pairs of parameters:

$$\theta_i = \left(\mu_i^w, \sigma_i^w, p_i^u, p_i^l, p_i^q, n_i, d_i, p_i^e, m_i\right)_{i \in \{c,nc\}}.$$

A given set of parameter values, θ_i, generates model moments, call them $m^m(\theta_i)$, that have data counterparts, m_i^d. Some of the moments used can be directly obtained from the model's invariant distribution, while others can only be obtained by simulating the model over a certain number of periods. Regardless, since I will have the same number of moments as parameters, I use a simple method of moments estimator, $m^m(\hat{\theta}_i) = m_i^d$.

I first describe the moments whose model counterpart can be computed directly from the invariant distribution. Since the model is going to be used to make inference on how the earnings distribution changed from one period to the next, it is important that the parameterization yields an initial earnings distribution that resembles the one observed in the 1974-79 period. The first pair of moments is the average log weekly earnings. Using the PSID data sample described above for the first period, I get $m_{nc}^d(1) = 6.576$ and $m_c^d(1) = 6.937$. The average residual standard deviation of log weekly earnings for each group in the first period is the second pair of moments: $m_{nc}^d(2) = 0.405$ and $m_c^d(2) = 0.387$.

The third pair of moments was chosen to reflect skill depreciation following unemployment spells. Keane and Wolpin (1997) estimate that workers lose between 10 percent (blue collar) and 30 percent (white collar) of their wage earnings following a one year spell of unemployment. The PSID allows one to distinguish between blue and white collar workers. 95.5% of college workers in the sample are white collar workers, while this number is 31.5% for non-college workers. This implies that the earnings losses following a year of unemployment are $-0.3 \times 0.955 - 0.1 \times (1 - 0.955) = -0.291$ for college workers and $-0.3 \times 0.315 - 0.1 \times (1 - 0.315) = -0.163$ for non-college. Accordingly, I set $m_{nc}^d(3) = -0.163$ and $m_c^d(3) = -0.291$.

The wage earnings changes following a job loss in the first period were computed in the previous section and are shown in table 2. The data moments to be matched are $m_{nc}^d(4) = -0.09$, and $m_c^d(4) = -0.01$. The wage earnings changes following a quit in the first period are also in table 2: $m_{nc}^d(5) = 0.079$, and $m_c^d(5) = 0.078$.

Since the reservation wage in the model has important implications for the minimum earnings observed and the amount of unemployment in the economy, the sixth moment is the log earnings of the 10th percentile for each group in the first period: $m^d_{nc}(6) = 6.03$ and $m_c(6) = 6.44$, while the seventh moment is the unemployment rate for each group: $m^d_{nc}(7) = 0.031$ and $m^d_c(7) = 0.013$, both computed from the PSID sample described above.

The last two pairs of moments capture how fast earnings grow for each group. A natural question to ask of a model of skill accumulation is how well does it match features of each group's earnings profile. There is evidence that college workers have steeper wage income profiles than non-college workers, and this is also what I found.[25] Using the PSID sample from 1970 to 1987, let n_i be the first year earnings are reported for an individual. I computed the ratio of earnings at $n_i + 7$ (if in the sample) to n_i for each individual.[26] On average, this ratio is 1.61 for college workers and 1.56 for non-college workers. Accordingly, I set the eighth pair of data moments to $m^d_{nc}(8) = 1.56$ and $m^d_c(8) = 1.61$. Finally, because I want the model to capture the concavity in the earnings profile, I also computed the 15th to 1st year ratio, to get the last pair of moments: $m^d_{nc}(8) = 1.81$ and $m^d_c(8) = 2.03$.

Unlike the previous pairs of moments, the last two cannot be computed directly from the invariant distribution of earnings. In order to generate them, a panel of 50,000 individuals (for each group) is constructed from the model's invariant distribution. I simulate their first 15 years of work life using the laws of motion described in section 2.1 and compute the last two moments.

Table 3 lists all the parameter values that set the model moments equal to their data counterpart. The dashed lines in figures 1 and 2 show the resulting initial distributions of earnings are very close to their data (full line) analogues.

4 Experiments

This section presents 3 experiments motivated by the data. Starting with the benchmark economy, I ask what the model predicts would have happened to the college differential and the measures of dispersion in table 1 if (i) only the fraction of workers experimenting separations had changed like in the data; (ii) only the earnings changes following separations had changed like in the data and; (iii) both (i) and (ii) happened. The first experiment captures what I termed here the extensive margin, the second captures the intensive one, while the third one captures any potential interactions.

[25]See, for example, Heckman, Lochner, and Taber (1998).

[26]I excluded the top and bottom 1% weekly earnings in each year-education cell and demeaned them

4.1 Changing the extensive margin

As the last two rows of table 2 indicate, from the first to the second period, separation rates increased across the board. These increases were sizable. Job losses increased by about 39% for non-college and 75% for college, while quits increased by about 13% for non-college and 28% for college. This experiment aims to capture such increases. Table 4 contains the parameterization detailing these changes, all other parameters remain unchanged.

Relative to the benchmark steady-state, separations occur more often for both types. Since I did not adjust the parameters governing the loses after separations, average earnings changes after separations are not kept constant, but they do not change a lot.[27]

The results from this experiment appear in table 5. Changes to the extensive margin are able to capture more than 80% of the fall in the college differential.[28] The average earnings for both groups fall. The college differential increases because this fall is higher for the non-college educated people (7%) than for the college educated ones (3.7%). This is a consequence of the concave earnings profiles. Loosely, in the original steady-state, college educated workers are (on average) on a higher, and flatter, part of their earnings profiles, than their non-college counterparts. As both types slide down, the relative losses are higher for the non-college types.[29]

To obtain the permanent and transitory components of earnings I simulate a 6-year panel of 50,000 individuals of each type distributed in terms of their skill level, wage, and employment status according to the invariant distribution. Individuals evolve according to the laws of motion detailed above. A (randomly chosen) fraction α dies every period and is replaced by others with the lowest skill level, a (randomly chosen) fraction λ_i^l of those employed loses their job, etc. I simulate one panel starting with the invariant distribution associated with the benchmark and another starting with the invariant distribution associated with the economy where I changed the extensive margin.

Even though the initial variances of the permanent and transitory components were not moments the method of moments attempted to match, the model has no problem in generating the sort of magnitudes observed in the data. It falls short with respect to the variance of the permanent component for the college type (0.158 versus 0.254). The extensive margin

[27] For the non-college group they go from -9% to -9.2% following a job loss and from 7.9% to 8.2% following a quit. For the college educated they go from -1% to -1.1% following a job loss and from 7.8% to 7.9% following a quit. When I adjust the parameters governing earnings changes following a separation, to keep earnings changes constant, the results do not differ in any significative way.

[28] If the comparison was being made with the change in the college differential between 1974 and 1985 (as opposed to the 6-year averages) this number would be more modest.

[29] Also, the reservation wage profile in the new steady state is about 10% below the original one for the non-college types, and only 8.8% below the original one for the college types.

mechanism on its own does surprisingly well in accounting for all of the increase in the variance of the transitory component of earnings. It also accounts for around half of the increase in the variance of the permanent component. Figures 3 and 4 show that not only does the extensive margin mechanism succeed in accounting for the change in the means of the variances, it also does well in terms of the change in the whole distribution of the two earnings components. The top panels in the two figures plot the distribution of the permanent component relative to its mean. Just like in the data, there is some weight being shifted from the center of the support to both tails. The distribution of the standard deviation of the temporary component shifts to the right, just like in the data.

Changes to the extensive margin are not only able to capture the overall increases in earnings dispersion for each group, but also do a good job in capturing changes across percentiles of the earnings distribution. As in the data, following increases in the fraction of job separations, the workers in the lower percentiles see their earnings deteriorate, while those in the upper percentiles experience the opposite. This is true of both groups, as seen in figures 5 and 6.

The fact that this mechanism is able to generate the observed increase in the variance of transitory earnings, but cannot quite match the increase in the variance of permanent earnings is reminiscent of what happens in Kambourov and Manovskii (2004). Like in their model, the channel emphasized is one that privileges the extensive margin, and just like in their model, this channel falls short when it comes to accounting for the increased dispersion of permanent earnings, while doing very well on the transitory earnings side. Why? In order for the model here to be able to generate enough dispersion in the permanent component of earnings, it has to be that the shock either increases skill dispersion (within each group) by enough, or decreases reservation wages by enough, or both, as the underlying distribution wages are being drawn from is not changing. What happens here is that the standard deviation of skills actually declines for the non-college type from 0.312 to 0.304 and it increases only nominally, from 0.51 to 0.52 for the college type. The action is all coming from the fall in the reservation wage profile of each type. Improvements in this dimension can be made by having the shock affecting the underlying wage distribution.

4.2 Changing the intensive margin

Looking at the first two rows in table 2, the behavior of earnings changes following separations is mixed. While for both groups, the earnings losses following job losses increased significatively, the earnings gains following quits only increased for the college group, for the non-college they actually decreased. This asymmetry will be reflected below in the experiment's results.[30]

In this experiment, only the parameters indexing the variance of the distribution of the skill evolution following a job loss, p_i^l, or a quit, p_i^q, change. Such parameter changes are presented in table 6. The results are in table 7. While the changes in the extensive margin are more than capable of accounting for the change in the skill premium, they come short of accounting for the changes in the variance of both the permanent and transitory earnings components. The variance of the permanent component for the non-college actually decreases (this being a result of the asymmetry in the earnings changes following quits.)

This results stands in sharp contrast to the findings of Ljungqvist and Sargent (1998) (LS). They argue that increases in turbulence, here termed the intensive margin, can give rise to changes in the variance of both the permanent and transitory earnings components that are very similar to what Gottschalk and Moffit (1994) obtain. The reason for this difference lies in the different benchmark economies we consider. The LS benchmark economy is not calibrated to match the mean and variance of earnings in the data. As a result, their distribution is wildly different from the data, as can be seen in figure 7, that replicates the LS Laissez-Faire economy for the different levels of turbulence they consider. Not only are earnings much more concentrated than in the data to start with, but they are concentrated at the top of the support.[31] In the economy with no turbulence, the average skill level is 1.88 (out of a maximum of 2). When LS increase turbulence, which means increasing the variance of skill losses after separations, agents fall down the skill ladder and the dispersion increases naturally as figure 7 shows.

In fairness, it should be said that the point of the LS paper is not that turbulence can give rise to increases in the dispersion of permanent and transitory earnings. Their point is that as turbulence increases, economies with unemployment insurance based on past earnings, compared to those without, will experience much higher levels of unemployment. The fact that increases in turbulence can give rise to increases in the dispersion of permanent and transitory earnings of the kind seen in the data is presented as subsidiary evidence for the argument that what changed from the 1970s to the 1980s was something that can be thought of as an increase in turbulence. I argue that one should look elsewhere for such evidence.

[30] Using different periods, 1976-81 and 1986-91, and a different sample, Polsky (1999) finds that changes in real wages increased from 7.5% to 19.3%. He does not distinguish between education types.

[31] In the economy with no turbulence, for example, the bottom 1% makes, on average, around 38% less than the mean, while the top 1% makes, on average, around 17% more than the mean.

4.3 Changing both margins

The last experiment uses changes in both margins to investigate whether there is some complementarity between the two. The parameterization for the second period in this experiment is in table 8, and the results appear in table 9. Indeed, when we compare these results to the results from the changes in the extensive margin alone, we notice some amplification in the changes of all variables except for the variance of the permanent component of earnings for the non-college type. This is puzzling, as it is evidence of some asymmetry between the two types. One important piece of this puzzle is to understand why did the earnings changes following quits evolved differently for the two types. This task is out of the scope of this model, as it requires a model where quits are endogenous, but it seems interesting enough to warrant some further investigation.

4.4 Discussion

The purpose of this paper is to inform future research. So what is future research to do with these results? Suppose one wants to investigate if and how technological change gave rise to increases in inequality along the dimensions discussed here. Consider two types of technological advancements, the first kind is embodied in capital goods that are already in use, and therefore does not necessarily give rise to more job separations (like a better Xerox machine.) The second kind is of the sort that makes existing production processes, or skill sets, obsolete. The results obtained here suggest that, if they are to account for the observed changes in inequality, most of the advances must be of the latter kind. Given the asymmetry observed above regarding the changes in permanent components, whatever shocks of the former kind there are, they should increase the variance of the permanent component of earnings more so among the non-college types than among the college type.

It is important to understand that even though the exercises here are motivated by changes associated with job separations, to the extent that these changes move individuals up and down their skill profiles, they also affect the evolution of earnings within jobs. But this is different from shocks to the skill profiles themselves. What I argue is that shocks of this second sort are less likely to be behind the bulk of the changes in inequality.

Some of the assumptions used in the name of simplicity and tractability in this model are very restrictive, like linear utility, fixed supply of both types, and exogenous skill evolution and returns. The question is whether they make a difference for the main findings or not.[32]

[32] Some shortcomings of the restriction imposed on the model are actually obvious, but are somewhat orthogonal to the point of the paper. For example, a model with exogenous skill accumulation, like this one, will not be able to account for the decrease in the skill premium before 1974 and its subsequent increase.

The main point of the paper is that earnings changes involving job separations seem more important than those that occur within jobs when it comes to accounting for the different dimensions in which inequality increased. Moreover, unlike changes along the extensive margin that can account for large fractions of both the changes in inequality across groups as well as within groups, changes along the intensive margin have problems in accounting for the latter. The impact of intensive margin changes would certainly be different if agents were able to endogenously devote off-market time to improving their skills. Suppose that average earnings changes after job losses fall. Then, agents would invest less in acquiring skills. If to this we add some concavity to the skill schedule as a function of time invested, this effect would be stronger for people that already have a low skill level, increasing skill dispersion within the group.

The paper also sheds some light on the *general* versus *specific* skills discussion. There are many dimensions where one can look for clues as to whether human capital has more of a general or a (firm, industry, job) specific component. A part of the literature looks at how well can shocks to models with general versus specific skills account for the increases in inequality in its various dimensions. For purposes of illustration, let me characterize the extremes of this debate using two papers: on the general skills side, the work of Guvenen and Kuruscu (2006), and on the specific skills side, the work of Kambourov and Manovskii (2004). Relative to these two poles, this paper is somewhere in between. Skills have a specific component, to the extent that upon a job loss there is an expected skill loss, but because not all skills are lost, there is also a general component.

In Guvenen and Kuruscu (2006), skill biased technological shocks can account for the changes in the skill premium, as well as for the increases in overall and residual inequality. They do not present results for the changes in the temporary and permanent components, but my conjecture, given the results here, is that they would fall short with respect to the increases in the temporary component, which is where the specific component of skills seems to matter the most. On the other hand, in Kambourov and Manovskii (2004), occupational shifts can account for the increase in overall inequality as well as in the variance of the temporary component of earnings, but fall very short with respect to increases in the variance of permanent earnings. The model presented here highlights the fact that a general component to skills goes a long way in improving the results regarding the changes in the permanent component of earnings.

5 Conclusion

Changes in earnings associated with job separations that occurred from the mid 1970s to the mid 1980s in the US are important in accounting for the contemporaneous increase in inequality between educational groups, as well as within these groups. While changes in the fraction of people separating (extensive margin) can account for the increase in both the variance of the temporary component of earnings as well in the variance of the permanent component (to a less extent), movements in the earnings changes following separations have a harder time in accounting for these sorts of increases in inequality.

The fact that most of the changes in inequality can be accounted for by changes in the fraction of people separating lends support to models who emphasize explanations that operate through this channel, and highlights the importance of the (job) specific component of skills.

6 Appendix

6.1 Data

The basic income dataset uses 12 waves of the Panel Study of Income Dynamics (PSID) from 1974 to 1985. The sample includes white males head of households between 20 and 60 years old, who are not self-employed. The low income oversample is excluded and only those who work between 40 and 60 hours per week are included. Each year, the sample is divided between college and non-college workers, according to whether the individual reports having completed at least a college BA. Only those individuals that report at least one instance of non-zero yearly wages and have a positive PSID weight are included. All the statistics computed across individuals use the PSID weights.

To compute log weekly wages, yearly wages are divided by weeks worked and adjusted according to the 2000 price index for personal consumption expenditures published by the Bureau of Economic Analysis. In each year-education cell, the top and bottom 1% are excluded. To avoid year to year fluctuations, I construct an index of each year's mean log weekly wages relative to the 6-year average in each period. Log weekly wages are then adjusted by this index. The averages by education appear in table 3 as $m_i^d(1)$, and their difference as the college differential in table 1.

Within each group, individuals differ in years of education. Therefore, in each period, and for each group, log weekly wages are regressed on years of education. The standard deviation of the residuals from this regression in the first period appears in table 3 as $m_i^d(2)$.

These residual earnings are also used to compute the dispersion in the permanent and transitory components. For each of the two periods, the permanent component of log yearly earnings is simply the average of strictly positive earnings over that period for each individual: $\mu_j = \sum_{t=1}^{6} \frac{y_{jy}}{6}$. The transitory component is then $\nu_{jt} = y_{jt} - \mu_j$. The top two panels in figure 3 show the distributions of the permanent components for each group, in each period. For each individual, over each period, the standard deviation of the transitory component is computed and their distribution is shown on the two bottom panels of figure 3. Table 1 also shows the mean of the variance of the permanent component, as well as the mean of the variance of the transitory component for each group, in each period.

Regarding job separations, up until 1983, unemployed individuals or those whose job tenure was less than 12 months were asked "What happened to the job you had before?". If the answer to this question was: "Company folded/changed hands/moved out of town; employer died/went out of business" or "Laid off; fired", a job loss is registered. If the answer to the question was: "Quit; resigned; retired; pregnant; needed more money; just wanted a change in jobs", a quit is registered. Starting in 1984 this question is asked of unemployed and those whose tenure started after January 1st of that year, so there is a slight difference in the sample that gets asked this question, but since the last year of my sample is 1985, the bias described in Polsky (1999), if present, is likely to have very little effect. This sample differs slightly from the one described above in that workers are not restricted to 40 to 60 weekly hours of work. Without relaxing this requirement sample sizes would be too small to be able to make any meaningful inference.

The values λ_i^l and λ_i^q are simply the average (from 1974 to 1979) fraction of the sample of individuals that report either a job loss or a quit. For each of these individuals (regardless of whether they are employed or unemployed), if they report positive earnings in the year they report a job loss or a quit as well as in the following year, the percentage loss (or gain) is computed and then averaged across individuals in each group and for each period. For those who report quits I excluded those that report increases above 100%, and for those that report a job loss, increases above 50%. These average appear as $m_i^d(4)$ and $m_i^d(5)$.

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Table 1: **Selected earnings statistics**

Variable	1974-79	1980-85	% Change
College differential	0.3608	0.4006	**11.03**
	(0.0021)	(0.0022)	
Var(permanent component) (Coll.)	0.1420	0.1652	**16.34**
	(0.0019)	(0.0019)	
Var(temporary component) (Coll.)	0.0254	0.0294	**15.75**
	(0.0005)	(0.0006)	
Var(permanent component) (Non-coll)	0.1442	0.1770	**22.75**
	(0.0012)	(0.0013)	
Var(temporary component) (Non-coll.)	0.0332	0.0411	**23.80**
	(0.0003)	(0.0005)	

Source: Author's calculations from the PSID. See data appendix.
Note: Bootstrapped standard deviations in parenthesis.

Table 2: **Post-separation changes**

	Job losses		*Quits*	
	Non-college	College	Non-college	College
Earnings changes (74-79)	-0.090	-0.010	0.079	0.078
	(0.003)	(0.007)	(0.003)	(0.005)
Earnings changes (80-85)	-0.130	-0.070	0.042	0.113
	(0.003)	(0.006)	(0.003)	(0.004)
Separation rates (74-79)	0.067	0.020	0.092	0.084
	(0.001)	(0.001)	(0.001)	(0.002)
Separation rates (80-85)	0.093	0.035	0.104	0.108
	(0.001)	(0.001)	(0.001)	(0.002)

Source: Author's calculations from the PSID. See data appendix
Note: Standard deviations in parenthesis.

Table 3: **Parameterization: benchmark**

Parameter	Value	Moment matched
$\alpha_s = \alpha_f$	0.000468823	Average worklife = 16.6 years
β	0.999246040	Annual interest rate = 0.040
λ_{nc}^l	0.001336884	Job loss rate = 0.067
λ_c^l	0.000392362	Job loss rate = 0.020
λ_{nc}^q	0.001850030	Quit rate = 0.092
λ_c^q	0.001694249	Quit rate = 0.084
μ_{nc}^w	310.0120063	$m_{nc}^d(1) = 6.576$
μ_c^w	371.6594568	$m_c^d(1) = 6.937$
σ_{nc}^w	84878.88774	$m_{nc}^d(2) = 0.405$
σ_c^w	71120.17527	$m_c^d(2) = 0.387$
p_{nc}^u	0.000855674	$m_{nc}^d(3) = -0.163$
p_c^u	0.001561576	$m_c^d(3) = -0.291$
p_{nc}^l	0.038957447	$m_{nc}^d(4) = -0.090$
p_c^l	0.002130563	$m_c^d(4) = -0.010$
p_{nc}^q	0.023460113	$m_{nc}^d(5) = 0.079$
p_c^q	0.036840932	$m_c^d(5) = 0.078$
n_{nc}	0.523437489	$m_{nc}^d(6) = 6.030$
n_c	0.238054032	$m_c^d(6) = 6.440$
d_{nc}	189012.5500	$m_{nc}^d(7) = 0.031$
d_c	422303.0867	$m_c^d(7) = 0.013$
m_{nc}	0.910000000	$m_{nc}^d(8) = 1.560$
m_c	0.920000000	$m_c^d(8) = 1.610$
p_{nc}^e	0.000270000	$m_{nc}^d(9) = 1.810$
p_c^e	0.000370000	$m_c^d(9) = 2.030$

Note: For the moments' definition see section 3.1.

Table 4: **Parameterization: extensive margin**

Parameter	Value	Moment matched
λ^l_{nc}	0.001873293	Job loss rate = 0.093
λ^l_c	0.000692871	Job loss rate = 0.035
λ^q_{nc}	0.002105313	Quit rate = 0.104
λ^q_c	0.002184702	Quit rate = 0.108

Note: For the moments' definition see section 3.1.

Table 5: **Results: extensive margin**

	Model turbulence		
Variable	Low	High	% Change
College differential	0.3608	0.3938	**9.1**
Var(permanent component) (Coll.)	0.1519	0.1666	**9.7**
Var(transitory component) (Coll.)	0.0158	0.0214	**35.4**
Var(permanent component) (Non-coll.)	0.1406	0.1545	**9.9**
Var(transitory component) (Non-coll.)	0.0309	0.0423	**36.9**

Table 6: **Parameterization: intensive margin**

Parameter	Value	Moment matched
p^l_{nc}	0.097393618	$m^d_{nc}(4) = -0.130$
p^l_c	0.036219571	$m^d_c(4) = -0.070$
p^q_{nc}	0.008445641	$m^d_{nc}(5) = 0.042$
p^q_c	0.073681864	$m^d_c(5) = 0.113$

Note: For the moments' definition see section 3.1.

Table 7: **Results: intensive margin**

	Model turbulence		
Variable	Low	High	% Change
College differential	0.3608	0.4248	**17.7**
Var(permanent component) (Coll.)	0.1519	0.1583	**4.2**
Var(transitory component) (Coll.)	0.0158	0.0167	**5.7**
Var(permanent component) (Non-coll.)	0.1406	0.1296	**-7.8**
Var(transitory component) (Non-coll.)	0.0309	0.0322	**4.2**

Table 8: **Parameterization: both margins**

Parameter	Value	Moment matched
λ^l_{nc}	0.001873293	Job loss rate = 0.093
λ^l_c	0.000692871	Job loss rate = 0.035
λ^q_{nc}	0.002105313	Quit rate = 0.104
λ^q_c	0.002184702	Quit rate = 0.108
p^l_{nc}	0.087654256	$m^d_{nc}(4) = -0.130$
p^l_c	0.034089008	$m^d_c(4) = -0.070$
p^q_{nc}	0.007976438	$m^d_{nc}(5) = 0.042$
p^q_c	0.071102998	$m^d_c(5) = 0.113$

Note: For the moments' definition see section 3.1.

Table 9: **Results: both margins**

	Model turbulence		
Variable	Low	High	% Change
College differential	0.3608	0.4558	**26.3**
Var(permanent component) (Coll.)	0.1519	0.1711	**12.6**
Var(transitory component) (Coll.)	0.0158	0.0225	**42.4**
Var(permanent component) (Non-coll.)	0.1406	0.1428	**1.6**
Var(transitory component) (Non-coll.)	0.0309	0.0447	**44.7**

Figure 1: **Earnings distribution: non-college**

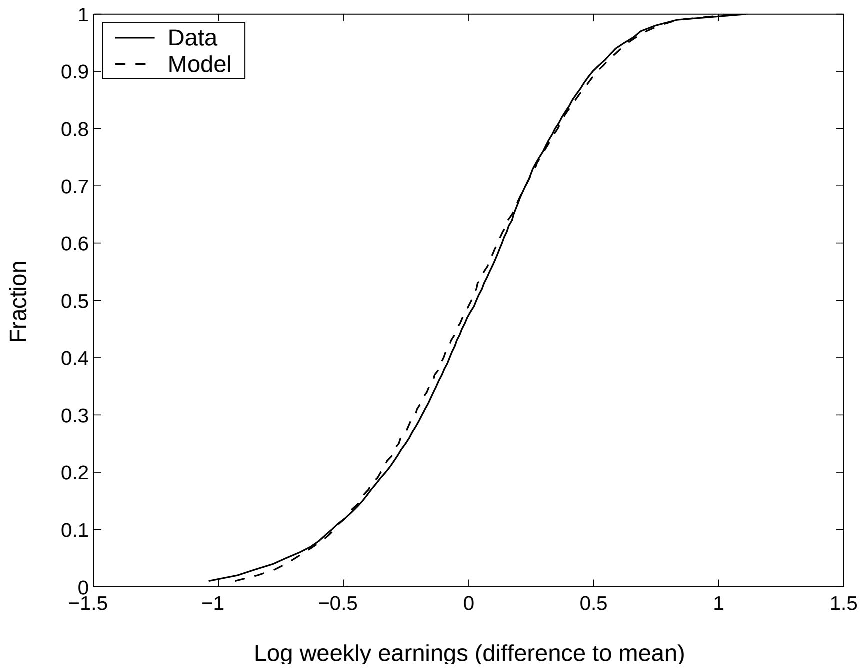

Figure 2: **Earnings distribution: college**

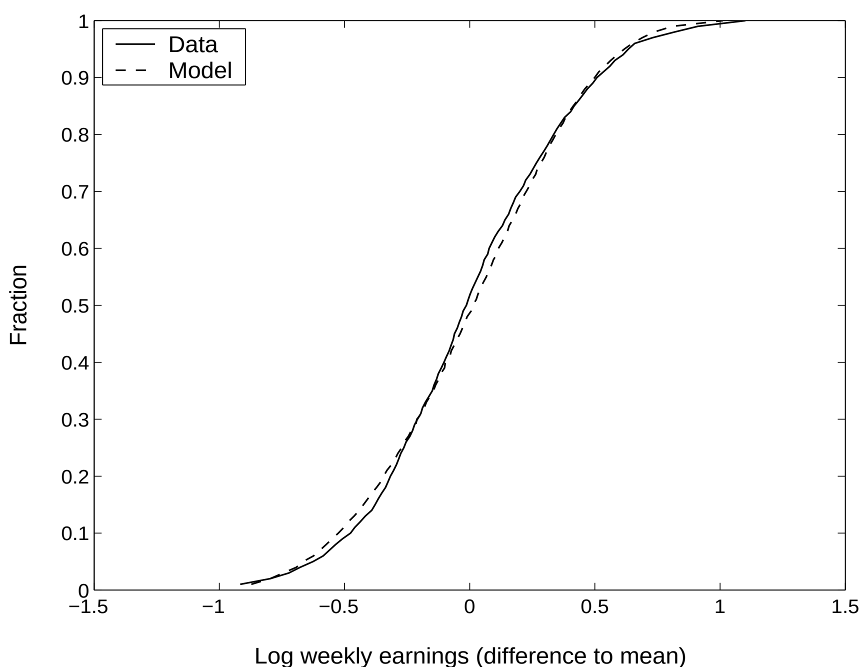

Figure 3: **Earnings components distributions: data**

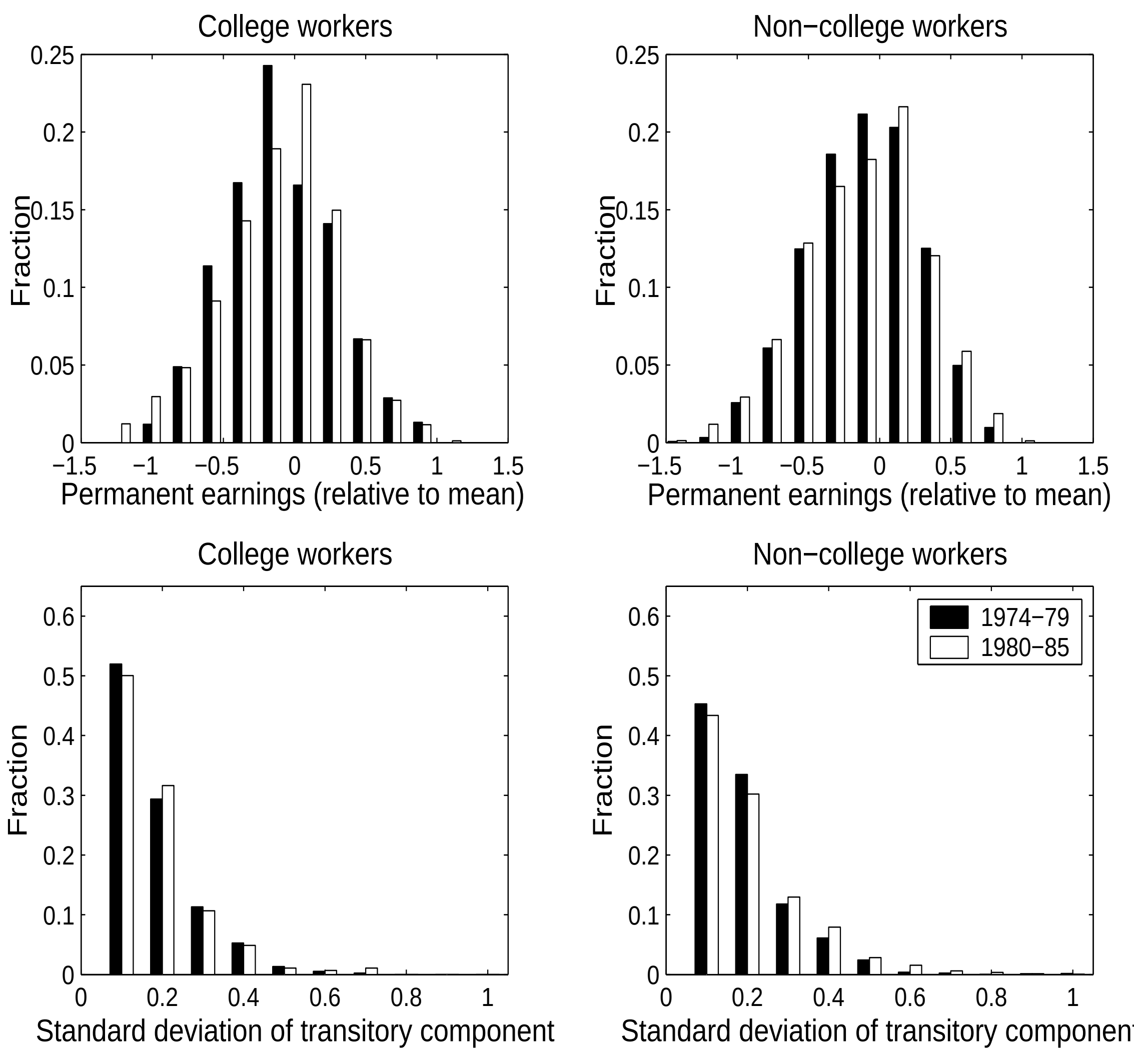

Figure 4: **Earnings components distributions: extensive margin**

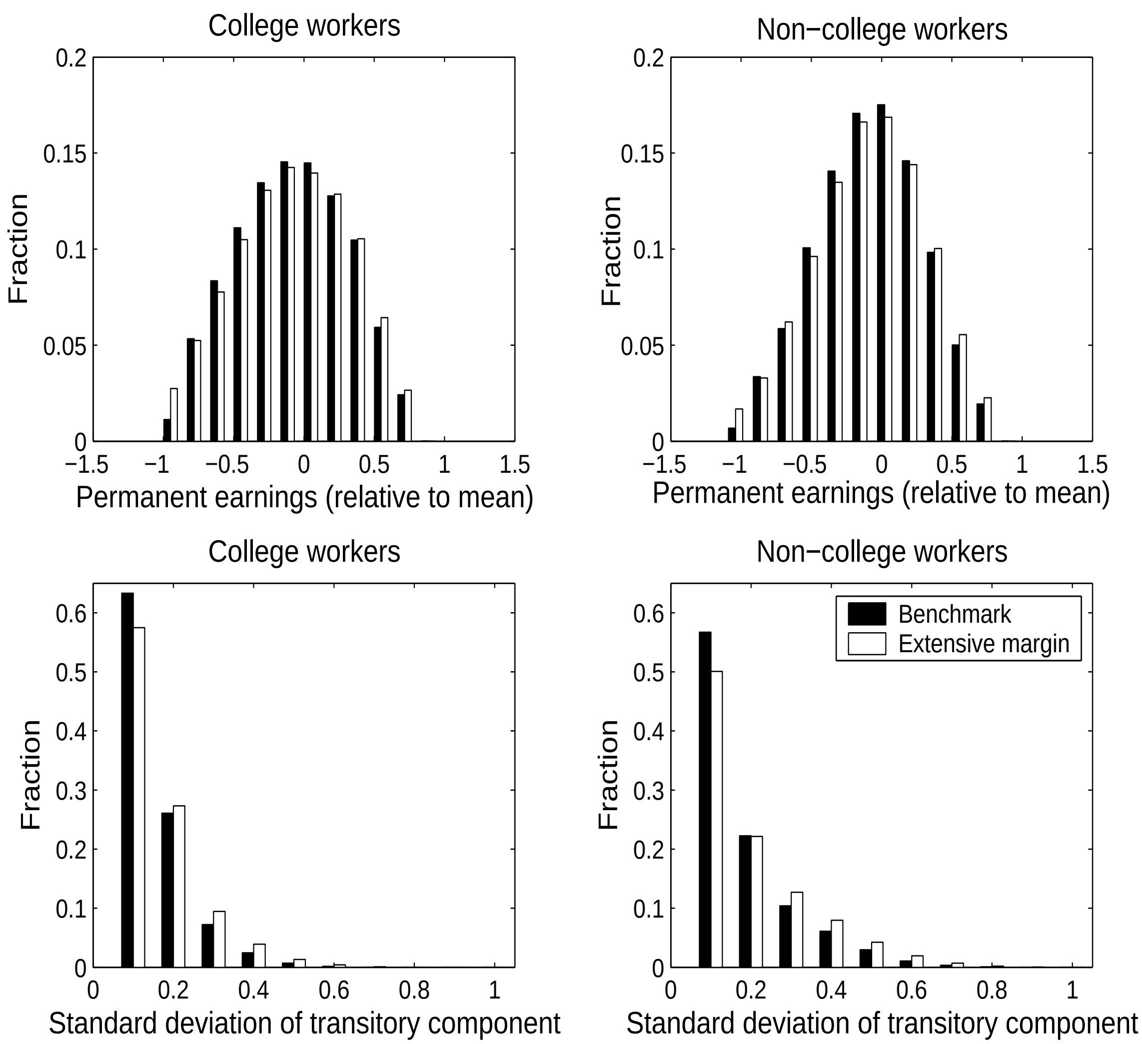

Figure 5: **Change in earnings by percentile: non-college**

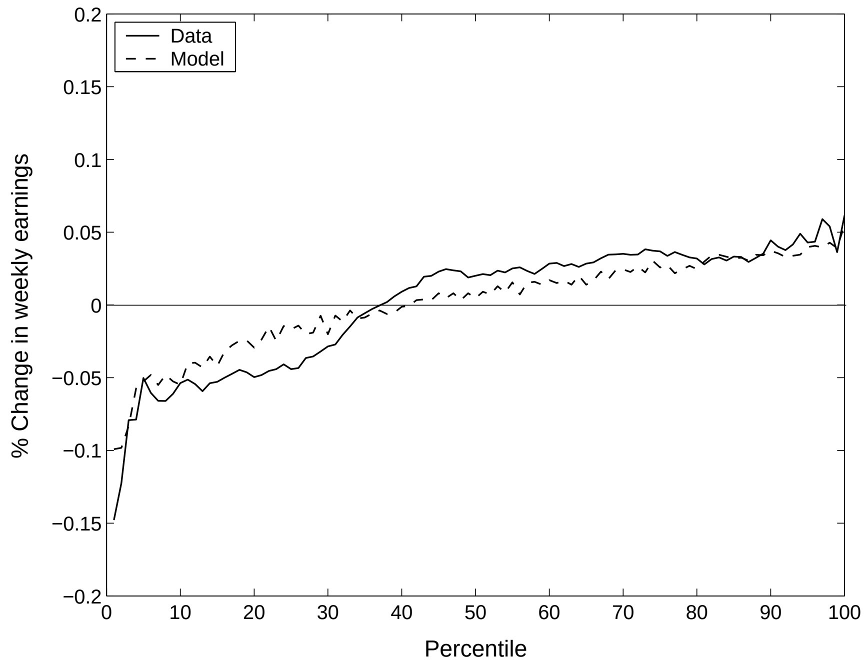

Figure 6: **Change in earnings by percentile: college**

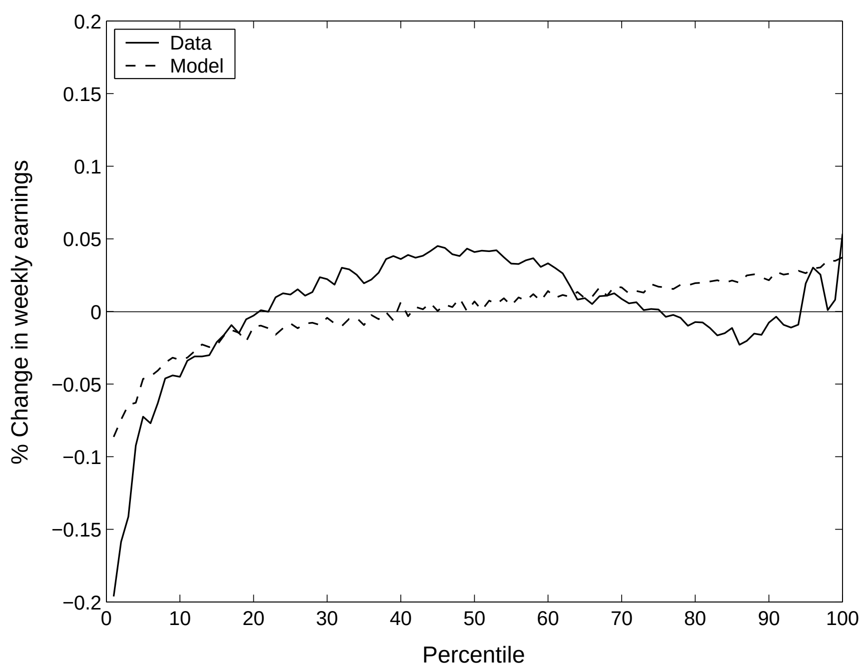

Figure 7: **Earnings distributions: Ljungqvist and Sargent (1998)**