ONLINE APPENDIX

Appendix A - Data

The Survey of Income and Programme Participation (SIPP) is a longitudinal data set based on a representative sample of the US civilian non-institutionalized population. It is divided into multi-year panels. Each panel comprise a new sample of individuals and is subdivided into four rotation groups. Individuals in a given rotation group are interviewed every four months such that information for each rotation group is collected for each month. At each interview individuals are asked, among other things, about their employment status as well as their occupations, industrial sectors and monthly earnings during employment in the last four months.[31]

The SIPP offers a high frequency interview schedule and aims explicitly at collecting information on worker turnover. Further, its panel dimension allows us to follow workers over time and construct uninterrupted spells of unemployment (or non-employment) that started with an employment to unemployment transitions and ended in a transition to employment. Its panel dimension also allows us to analyse these workers' occupational mobility patterns conditional on unemployment (or non-employment) duration and their post occupational mobility outcomes as outlined in Section 2 in the main text.

Survey design and use of data

We consider the period 1990 - 2013. To cover this period we use the 1990-1993, 1996, 2001, 2004 and 2008 panels. For the 1990-1993 panels we have used the Full Panel files as the basic data sets, but appended the monthly weights obtained from the individual waves (sometimes referred to as core wave data). Until the 1993 panel we use the occupational information from the core waves. We do this for two reasons: (i) the full panel files do not always have an imputation flag for occupations; and (ii) between the 1990 and 1993 panels firm identities were retrospectively recoded, based on core wave firm identifiers. For the 1996, 2001, 2004 and 2008 panels there is no longer a Full Panel file nor a need for one. One can simply append the individual wave information using the individual identifier "lgtkey" and merge in the person weights of those workers for whom we have information from the entire panel (or an entire year). In this case, the job identifier information is also clearly specified.

The SIPP's sample design implies that in *all* panels the first and last three months have less than four rotation groups and hence a smaller sample size. For this reason we only consider months that have information for all four rotation groups. For individual-level histories, to match occupations after a separation we need to observe re-employment. In unemployment spells, if the separation occurs too close to the end of the panel, we will non-randomly select short unemployment spells. For this reason, we also exclude periods with less than 2 waves remaining until the end of the panel. This restriction is

[31] See http://www.census.gov/sipp/ for a detailed description of the data set.

also necessary for us to compute annual earnings growth. Of the remaining observations, we weight them according to the SIPP's person weights, "wpfinwgt".

The data also shows the presence of seams effects between waves, where transitions are more likely to occur at a seam (i.e. between waves, and therefore at 4,8, 12 ... months) than based on other characteristics, e.g. duration. When we consider time series and given the above restrictions, there is always one rotation at the seam in every month we consider which effectively smooths out the clustering at the seam. In the case of the duration statistics for which the seam effect matters, we consider observations in 4 months bins (e.g. survival at 4, 8, 12, 16 months of unemployment).

Sample selection, labour market status and transitions

For the 1990-2008 panels, we consider all workers between 18 and 65 years of age who are not in self-employment or in the armed forces. We measure an individual's employment transitions in the SIPP using two sources of information. The first one relies on the monthly employment status recode. Using the SIPP 2001 wording as an example, we consider a worker to be employed during a month if the individual reported in the monthly employment status recode variable that he/she was "with a job entire month, worked all weeks", but also when "with a job all month, absent from work without pay 1+ weeks, absences not due to layoff", or "with a job all month, absent from work without pay 1+ weeks, absences due to layoff". If workers have spent part of the month in employment and part of the month in unemployment, workers are nonemployed only if they are nonemployed in week 2 *and* have been nonemployed for at least four weeks in total. That is, those who have less than a month of nonemployment in week 2 are still counted as employed. If the worker is "no job/business - looking for work or on layoff" during one of the weeks in nonemployment (i.e. in the "no job/business") state, we consider the worker to be unemployed. We have chosen this classification, because we want entry into unemployment to capture the serious weakening of the link with the previous firm of employment, rather than to be a definite period of nonproduction after which the worker would return to the previous employer. The restriction of nonemployment for at least four weeks is meant to further limit the role of short-term absences from the same firm and temporary layoffs. This is motivated by the analysis of Fujita and Moscarini (2017), who document that many workers with very short unemployment spells return to their previous employer. We want to focus on those unemployed who at least *consider* employment in other firms and possibly other occupations.

To measure job-to-job transitions we use the second source of information, start and end dates and job numbers. While each employer presumably gets a unique number, the month the job number changes does not necessarily correspond to the timing of the job-to-job change. Further, there are spurious job number changes. So, we corroborate these job number changes with employment end dates. So we require that the individual is fully employed in both adjoining months, but that one of the employment relationships ended and the job number switched in that wave.

Assigning "source"/"destination" - occupations to unemployed workers

The SIPP collects information on a maximum of two jobs an individual might hold simultaneously. For each of these jobs we have information on, among other things, hours worked, total earnings, 3-digit occupation and 3-digit industry codes. We drop all observations with imputed occupations (and industries). If the individual held two jobs simultaneously, we consider the main job as the one in which the worker spent more hours. We break a possible tie in hours by using total earnings. The job with the highest total earnings will then be considered the main job, though this type of tie is exceedingly rare. Once the main job is identified, the worker is assigned the corresponding two, three or four digit occupation.

Each unemployment spell that is started and finished inside the panel can be assigned a "source"-occupation (main occupation right before the start of the unemployment spell), and a "destination"-occupation (main occupation right after becoming employed again). If the occupation code is missing just before the unemployment spell (e.g. due to imputation) and an occupation code is reported in a previous wave, while employment is continuous from the time that the occupation was reported until the start of the unemployment spell under consideration, we carry the latter occupation forward as source occupation. A worker is an occupation mover if source and destination occupations do not coincide. We thus conservatively count the following situation also as an occupational stay: the worker is simultaneously employed in two firms at the moment the worker becomes unemployed, and finds a job afterwards in an occupation that matches the occupation in one of the two previous jobs, even when it matches the job with less hours. The effect on the occupational mobility statistics of counting as occupational stays the unemployment spells with two simultaneous jobs at either side is small.

We construct the occupational mobility statistics from transitions of the form: at least a month in employment (with a non-imputed occupational code), followed by an unemployment spell which has a duration of at least a month, followed by at least a month in employment (with a non-imputed occupational code). We label these transitions as EUE transitions. We also consider transitions of the form: at least a month in employment (with a non-imputed occupational code), followed by a non-employment spell which has a duration of at least a month and involved at least one month of unemployment. We call these E-NUN-E transitions, or NUN-spells of nonemployment. Further convexifying the space between EUE and E-NUN-E, we also consider spells that started with a EU transition, i.e. employment directly followed by unemployment (though later the worker can report to stop looking for work), and those that ended with UE transition. We label these transitions as E-UN-E, E-NU-E, and if both restrictions apply, E-UNU-E transitions. We also tried other versions of the latter in which the full jobless spell was non-employed (ENE).

Occupational Classifications The SIPP uses the Census of Population Occupational System, which relates closely to the Standard Occupational Code (SOC). The 1984-1991 panels use the 1980 Census Occupational classification, while the 1992-1996 and 2001 panels use the 1990 Census Occupational classifications. These two classifications differ only slightly between them. The 2004 and 2008 panels

use the 2000 Census occupational classification, which differs more substantially from the previous classifications. We use the IPUMS recoding of the 1980 and 2000 Census Occupational Classification (very similar to David Dorn's from Dorn, 2009, and Autor and Dorn, 2013) into the 1990 Census Occupational Classification to have a uniform, 3-digit coding system.[32]

From these 3-digit, consistent occupational codes, we aggregate further into two usable groupings, a 2-digit and a 1-digit version. The 2-digit occupational codes correspond to the 22 Standard Occupation Codes, the system that is the federal statistical standard. For our 1-digit codes, we further combine the codes into 4 task-based categories defined by combinations of routine/non-routine and cognitive/non-cognitive. It is well-known that measurement error in occupational codes might give rise to spurious transitions, as discussed for example in Kambourov and Manovskii (2008) and Moscarini and Thomsson (2007). Since 1986 the SIPP interviewing procedure has implied that if the worker declared he/she did not change type of job and employer in a given interview, the occupational code recorded in the previous interview was carried forward. This form of "dependent interviewing" reduces spurious occupational transitions among employer stayers, but coding errors still remain among employer movers. Because we need a particular occupational code to determine an individual observation of an earnings change, we do not use the probabilistic correction methods as in Kambourov and Manovskii (2008). Rather, we use a high degree of aggregation to minimize this coding error. Carrillo-Tudela and Visschers (2021) show that among the employer movers correcting for coding errors when using the four task-based categories will decrease the observed gross occupational mobility rate by about 5 percentage points. Hence the high levels of occupational mobility we observe in the data will remain after correction. Further, to the extent that misclassification bias does not change much over the cycle (as shown in Carrillo-Tudela and Visschers, 2021), coding error will introduce a downward bias to the effect of occupational mobility in explaining the procyclical skewness of the earnings growth distribution. This is because the earnings changes of observed occupational stayers (which are individuals who are very likely to be true stayer) exhibit weak procyclical skewness relative to observed occupational movers. As it is likely that among the latter group there are true occupational stayers due to misclassification, the extent of procyclical skewness among true occupational movers should be higher than the one observed among observe occupational movers.

Earnings and wages construction

Using the above panels of the SIPP we construct the earnings growth distribution for our sample period. As described in the main text we deflate nominal monthly earnings in the SIPP by the Personal Consumption Expenditure price index. Our measure of earnings is based on the residuals obtained from regressing log real earnings on a quadratic on potential experience, education, and month dummies. In terms of measurement error, note that with occasionally misreported earnings the variance of

[32] In any of these classifications we have not included the Armed Forces. The 1980 and 1990 classifications can be found at https://www.census.gov/people/io/files/techpaper2000.pdf. The 2000 classification can be found in http://www.bls.gov/soc/socguide.htm. Additional information about these classifications can be found at http://www.census.gov/hhes/www/ioindex/faqs.html.

earnings changes will be biased upwards. This is especially a problem for employer/occupation stayers because true earnings changes are smaller and so the measurement error may be relatively larger. A common method for cleaning earnings dynamics applies time-series break-detection methods, as in Gottschalk (2005) to reject small transitory changes in earnings. The trouble with that method is that it will itself make our earnings process leptokurtic and evidence from administrative data (Kurmann and McEntarfer, 2018) suggest that these small changes are not just erroneous measurement error. Among those workers with interrupted careers, Hudomiet (2015) finds even bigger annual earnings changes in administrative data relative to survey data. This result suggests that the annual earnings changes of EUE occupation/employer movers we derive from the SIPP *underestimate* the true scale of earnings changes among this group of individuals.

Given this evidence and following Busch et al. (2021), to clean reporting errors in the residual earnings data we drop the bottom and top 2% of the wave-frequency earnings sample as well as imputed earnings. In less than 1% of the sample, earnings seem to be unrealistically reported in one period because they increase or decrease rapidly and then revert without any other transitions, suggesting a shifted decimal or entry error. We drop these periods, which we define as a change exceeding 200% but which reverts such that the two-period change is less than 10%. When checking for these spurious earnings changes, we allow them if there is an employment status change at either monthly or wave frequency. For both earnings and wages, we aggregate earnings within a wave. This is because seam effects are quite large and so changes are often mistimed within waves. If a worker is non-employed for one of these months, we count that as zero earnings. To construct annual earnings growth, we take the sum of all (residual) monthly earnings observed during the past 3 waves and next two waves from the reference wave. We drop observations in which either the full year prior or the next has earnings below $1040.

Appendix B - Additional graphs

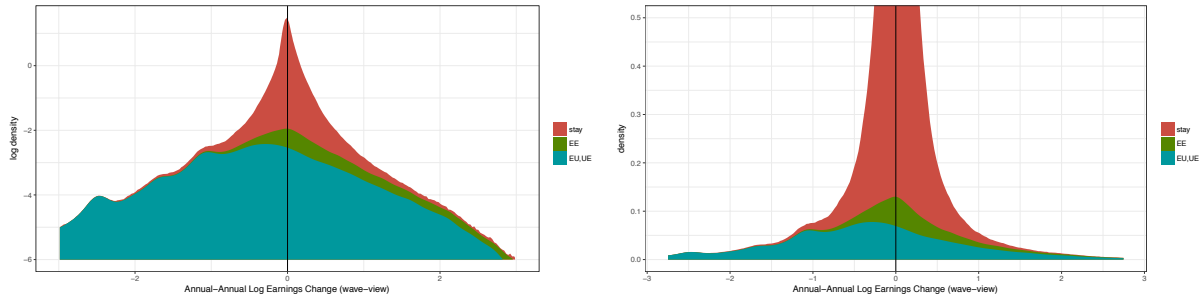
Earnings growth distribution

Figure 1a, Section 2.2 of the main text depicts the derived cross-sectional earnings growth distribution. It shows that this distribution has the well documented properties: left-skewed and leptokurtic. There we present the log density of the earnings growth distribution to highlight its Pareto tails. Figure 1a below depicts the same distribution but instead it stacks the distributions associated with EUE, EE transitions and employer stayers on top of each other to show the role of each of these transitions in shaping the earnings growth density. Figure 1b shows the same stacked graph but instead using the density level to highlight its kurtosis. To show the role of EE and EUE transitions on the tails of the distribution, we only depict part of the density around zero earnings changes.

Figure 2a shows that the SIPP data is also consistent with the relationship between earnings growth and previous earnings documented by Guvenen et al. (2014), who use the previous five-year earnings percentile based on SSA data for all US. Although here we only use the previous year earnings,

Figure 1: Earnings growth distribution

(a) Log Density (b) Level Density



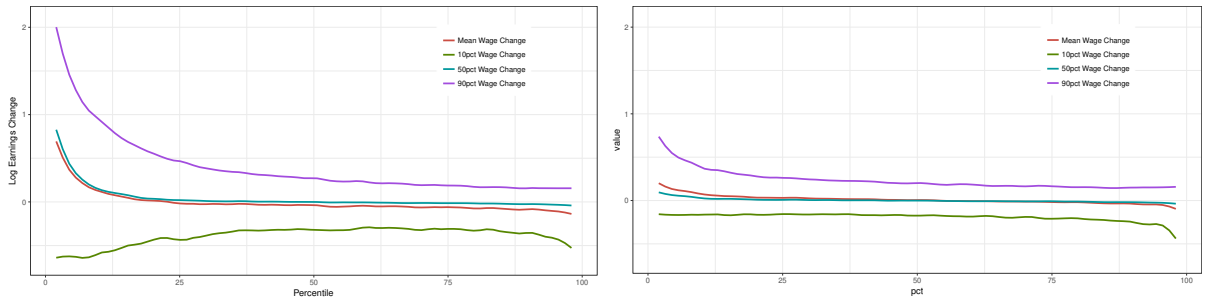
Note: The annual earnings growth distribution is constructed for the sample period 1990-2013. It is based on residual earnings after controlling for potential experience, education, gender, race and month dummies.

the figure shows that workers with the larger earnings changes are also those who had the lowest earnings, while those with progressively higher previous year earnings are associated with smaller changes. One of the advantage of the SIPP relative to the SSA data is that the former provides better information about individuals' labour market histories and demographic characteristics. These characteristics are the ones we exploit in this paper and it is reassuring that, despite the much smaller number of observations, the SIPP and the SSA data present consistent pictures of the earnings change distribution.

The role of the underlying labour market flows can be gauged from Figure 2b, which presents the same relation but for a sample restricted to only employer stayers. The earnings growth of employer stayers are not only much less dispersed, but the probability of an earnings changes (positive or negative) is much less sensitive to these workers' previous year earnings. In fact, the earnings growth distribution does not change much across the previous year's earnings distribution, apart from the probability of relatively larger improvements among the very low-earners, and the probability of earnings losses among very high earners.

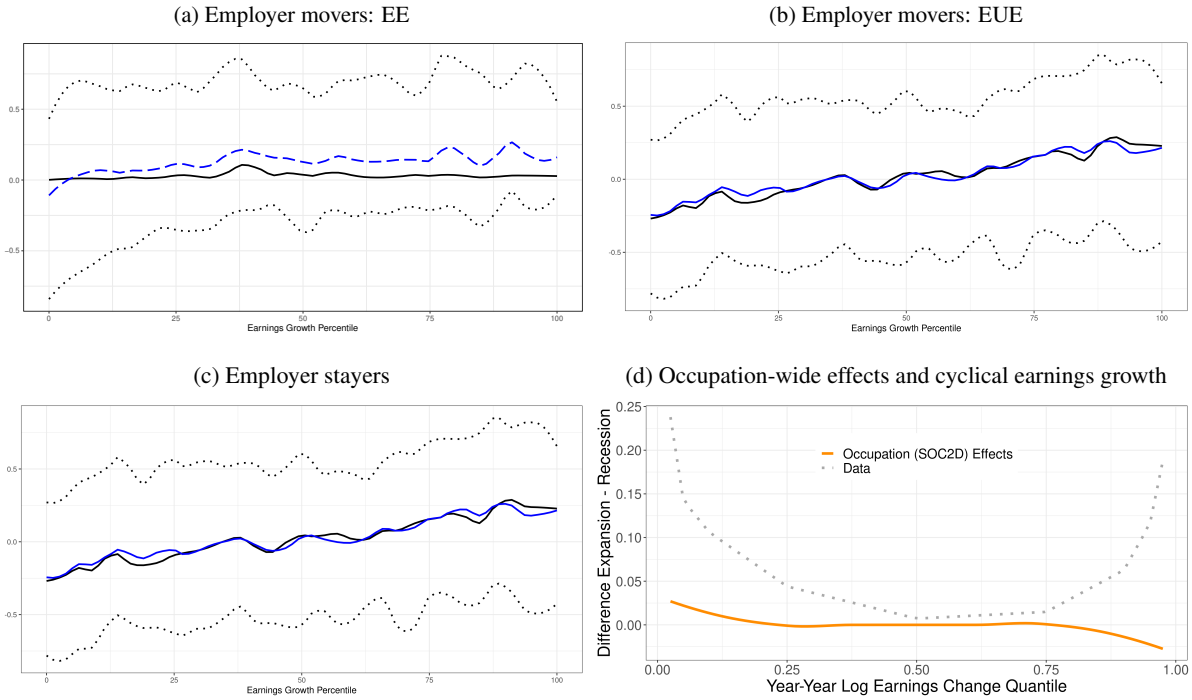
Figure 2: Earnings growth distribution conditional on previous earnings

(a) Conditional on previous year earnings (b) Conditional on previous year earnings and employer staying



This evidence then shows that those workers who experienced large earnings changes are also those who had low previous year earnings *and* changed employers. Further, the 90th percentile curve

Figure 3: Occupational Ladder with 22 2-digit SOC Codes



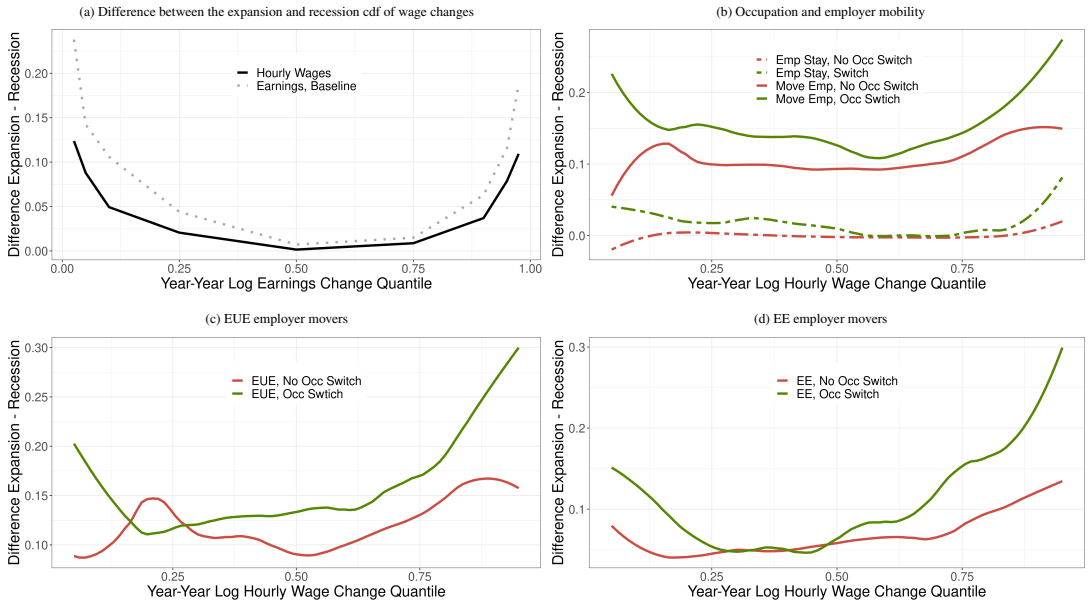
Note: Occupational switchers are ranked by their earnings growth in the horizontal axis. For each rank the vertical axis depicts the mean, median, 90th and 10th percentiles of the distribution of the differences in occupational earnings effects. Occupations defined at the 2-digit level of aggregation

in Figure 2a shows that workers who were at the bottom of the earnings distribution climb the most, while the slow decline of the curve reflects that the larger is a worker's earnings the lower is his/her gain from changing employer. These patterns are broadly inline with the implications of standard job ladder models.

Earnings growth and the occupational job ladder

In Figure 3, Section 2.3 of the main text we highlighted the role of occupational mobility due to workers' *idiosyncratic* career concerns as the main underlying force behind the cross-sectional earnings growth distribution. To emphasize the idiosyncratic nature of these effects, we depicted the relationship between the distribution of the change between the source and destination occupation fixed effects (obtained from an earnings regression) and the percentile of these workers' earnings change in the cross-sectional earnings growth distribution. We presented the results using our baseline 4 task-based occupational categories. Here, Figure 3 now shows that the same patterns holds in our 22 occupation categories of the 2-digit 1990 SOC to highlight that our conclusions were not driven by aggregation into the 4 task-based categories.

Figure 4: Wage growth distribution over the cycle and the importance of occupational movers



Note: The annual wage growth distribution is constructed for the sample period 1990-2013. It is based on residual wages after controlling for potential experience, education and month dummies. Recessions are defined as periods in which the HP-filtered unemployment rate is in the top 20% of realizations.

Cyclical changes in wage growth

In this section, we replicate our principle figures using wages instead of earnings. As described, we accumulate average hourly wages over the prior and posterior year following a transition, just as we did for earnings. When the worker is nonemployed, we assign a wage rate of zero. Hence, we isolate out changes along the intensive margin of hours. Particularly because we are focusing on workers who have large earnings changes one might be concern that these reflect occupation transitions that are accompanied by movements in and out of part-time work and/or changes in work habits. Including periods of unemployment here is fully consistent with our theoretical framework as our proposed job ladder model also include these periods. We observe that wage changes have remarkably similar patterns as earnings changes. We first replicate Figure 1d with wages rather than earnings: establishing the basic cyclical skewness in not only a feature on changes in hours worked. Then we show that occupation changes are the primary drivers of this skewness by replicating Figures 4a, 5a, and 5b again using wages rather than earnings. These hourly wage versions are in Figure 4.

Skewness decomposition of cyclical earnings changes

As discussed in Section 2 of the main text, Table 4 presents a linear decomposition of the change in the skewness of the earnings growth distribution along the business cycle. This decomposition follows the method proposed by Halvorsen et al. (2020). The main implication of the exercise is that those workers who change occupations and employers at the same time contribute 59.2% to the observed

Table 4: Linear decomposition of third central moment of skewness

	No Occ Switch			Occ Switch		
	Emp Stay	EE	EUE	Emp Stay	EE	EUE
Skewness Contrib	0.031	0.087	0.281	0.008	0.123	0.469
Fraction of Observations	0.865	0.027	0.051	0.012	0.014	0.031
N (thous)	402.281	12.423	23.946	5.412	6.495	14.442

Note: Decomposition of cyclical change in third central moment following Halvorsen et al. (2020). Weights across groups held constant over the cycle. Annual earnings change based on residual wages after controlling for potential experience, education and month dummies. Recessions are defined as periods in which the HP-filtered unemployment rate is in the top 20% of realizations.

increase in the left-skewness of the earnings growth distribution during recessions. This happens even though occupation/employer movers represent 4.5% of all observations in our sample. This table also shows that the large contribution of this group mainly arises from EUE occupation movers.

Appendix C - Model derivations

Worker flows and the earnings distribution

The evolution of the earnings distribution G of workers across occupations and employment status is a result of the dynamics of the exogenous job separation and job finding probabilities δ_ϵ, δ_z, λ_U, λ_U^c, λ_E and λ_E^c coupled with workers' job separation, job acceptance and occupational mobility decisions as described in the main text. Therefore to derive such a distribution we need to first derive the laws of motions of unemployed and employed workers. For this purpose it is useful to derive the measure of unemployed and employed workers at each stage j within a period, where $j = s, r, m, p$ represent separations, reallocations, search and matching and production. Let $u_t^j(z, x_h, o)$ denote the measure of unemployed workers with idiosyncratic productivity z and human capital x_h in occupation o at the beginning of stage j in period t. Similarly, let $e_t^j(\epsilon, z, x_h, o)$ denote the measure of employed workers in labor market with idiosyncratic productivities ϵ and z and human capital x_h in occupations o at the beginning of stage j in period t. Finally let $\mathcal{G}$ denote the joint productivity distribution of unemployed and employed workers over all occupations, and $\mathcal{G}^j$ denote this distribution at the beginning of stage j.

Unemployed workers Given the initial conditions $(A_0, \mathcal{P}_{O,0}, \mathcal{G}_0^p)$, the measure of unemployed workers characterised by z and x_h in occupation o at the beginning of next period's separation stage is given by

$$u_{t+1}^s(z, x_h, o)dz = \chi^u(x_h|x_h)\int_{\underline{z}}^{\overline{z}} u_t^p(\tilde{z}, x_h, o)dF(z|\tilde{z})d\tilde{z} + \chi^u(x_h|x_{h+1})\int_{\underline{z}}^{\overline{z}} u_t^p(\tilde{z}, x_{h+1}, o)dF(z|\tilde{z})d\tilde{z},$$

where the two terms capture the measure of unemployed workers characterised by $(\tilde{z}, x_h, o)$ and $(\tilde{z}, x_{h+1}, o)$ in the previous period's production stage who will be characterised by (z, x_h, o) immediately after the z and x_h shocks occur. During the separation stage some employed workers will become unemployed within their own occupation with probability δ_ϵ. Since by assumption these newly

unemployed workers do not participate in the current period's reallocation or search and matching stages, we count them at the production stage. This implies that $u^r_{t+1}(z, x_h, o)dz = u^s_{t+1}(z, x_h, o)dz$. Since with probability δ_z some of the unemployed at the beginning of the reallocation will be forced to change occupation, the previous arguments imply that the measure of unemployed workers characterised by (z, x_h) in occupation o at the beginning of the search and matching stage is given by

$$u^m_{t+1}(z, x_h, o)dz = (1-\delta_z)(1-\rho^U(.)u^r_{t+1}(z, x_h, o)dz + (\mathbf{1}_{h=1})\tilde{u}^r_{t+1}(z, x_1, o)dz,$$

where the first term denotes those unemployed workers at the beginning of the reallocation period who did not leave to another occupation and $\rho^U(z, x_h, o, A, \mathcal{P}_O)$ is an indicator function taking the value of one if the unemployed worker reallocates and zero otherwise. The second term corresponds to all those unemployed workers in other occupations who voluntarily or involuntarily reallocated and ended up in occupation o with productivity z, plus all those employed workers at the beginning of the separation stage in other occupations who involuntarily reallocated and also ended up in occupation o with productivity z. Namely,

$$\begin{aligned}\tilde{u}^r_{t+1}(z, x_1, o)dz &= \left[\sum_{\tilde{o}\neq o}\sum_{\tilde{h}=1}^{H}\Big[\int_{\underline{z}}^{\overline{z}}[(1-\delta_z)\rho^U(.)+\delta_z]\alpha^U_o(., \tilde{o})u^r_{t+1}(\tilde{z}, x_{\tilde{h}}, \tilde{o})d\tilde{z}\right]dF(z)\\ &+ \left[\sum_{\tilde{o}\neq o}\sum_{\tilde{h}=1}^{H}\Big[\int_{\underline{z}}^{\overline{z}}\int_{\underline{\epsilon}}^{\overline{\epsilon}}\delta_z\alpha^E_o(., \tilde{o})e^s_{t+1}(\tilde{\epsilon}, \tilde{z}, x_{\tilde{h}}, \tilde{o})d\tilde{\epsilon}d\tilde{z}\right]dF(z),\end{aligned}$$

where $\alpha^U_o(\tilde{z}, x_{\tilde{h}}, A, \mathcal{P}_O, \tilde{o})dF(z)$ denotes the probability that an unemployed worker characterised by $(\tilde{z}, x_{\tilde{h}})$ in occupation $\tilde{o}$, received idiosyncratic productivity z from occupation o at the moment of reallocation; while $\alpha^E_o(\tilde{\epsilon}, \tilde{z}, x_{\tilde{h}}, A, \mathcal{P}_O, \tilde{o})dF(z)$ denotes the probability that an employed worker characterised by $(\tilde{\epsilon}, \tilde{z}, x_{\tilde{h}})$ in occupation $\tilde{o}$, received productivity z from occupation o when reallocating. Given that reallocation involves resetting any accumulated human capital, the indicator function $\mathbf{1}_{h=1}$ in the expression for $u^m_{t+1}(z, x_h, o)$ takes the value of one when we are considering the measure $u^m_{t+1}(z, x_1, o)$ and zero otherwise.

The measure of unemployed workers characterised by (z, x_h) in occupation o during the production stage is then given by

$$\begin{aligned}u^p_{t+1}(z, x_h, o)dz &= [(1-\lambda_U)+\lambda_U(1-\phi^U(.))]u^r_{t+1}(z, x_h, o)dz \\ &+ (\mathbf{1}_{h=1})[(1-\lambda^c_U)+\lambda^c_U(1-\phi^U(.))]\tilde{u}^r_{t+1}(z, x_1, o)dz \\ &+ \int_{\underline{\epsilon}}^{\overline{\epsilon}}[\delta_\epsilon+(1-\delta_\epsilon-\delta_z)(1-d(\tilde{\epsilon}, .))]e^s_{t+1}(\tilde{\epsilon}, z, x_h, o)d\tilde{\epsilon}dz,\end{aligned} \tag{8}$$

where first two terms denote those $u^m_{t+1}(z, x_h, o)dz$ workers who did not manage to get re-employed, while the third term denote the measure of all those employed workers with occupation-match productivity equal to z, who separated into unemployment and stayed in occupation o. In these terms, $\phi^U(z, x_h, o, A, \mathcal{P}_O)$ is an indicator function that take the value of one if the unemployed worker accepts a firm's job offer and zero otherwise, while $d(\tilde{\epsilon}, z, x_h, o, A, \mathcal{P}_O))$ is another indicator function that takes the value of one if the worker decides to quit into unemployment and zero otherwise.

Employed workers Given the initial conditions $(A_0, \mathcal{P}_{O,0}, \mathcal{G}_0^p)$, the measure of employed workers characterised by (ϵ, z, x_h) in occupation o at the beginning of next period's separation stage,

$$\begin{aligned} e_{t+1}^s(\epsilon, z, x_h, o)d\epsilon dz &= \chi^e(x_h|x_h)\int_{\underline{z}}^{\overline{z}}\int_{\underline{\epsilon}}^{\overline{\epsilon}} e_t^p(\hat{\epsilon}, \hat{z}, x_h, o)d\Gamma(\epsilon|\hat{\epsilon})d\hat{\epsilon}dF(z|\hat{z})d\hat{z} \\ &+ (\mathbf{1}_{h>1})\chi^e(x_h|x_{h-1})\int_{\underline{z}}^{\overline{z}}\int_{\underline{\epsilon}}^{\overline{\epsilon}} e_t^p(\hat{\epsilon}, \hat{z}, x_{h+1}, o)d\Gamma(\epsilon|\hat{\epsilon})d\hat{\epsilon}dF(z|\hat{z})d\hat{z}, \end{aligned}$$

where the two terms show the probability that employed workers characterised by $(\hat{\epsilon}, \hat{z}, x_h, o)$ and $(\hat{\epsilon}, \hat{z}, x_{h-1}, o)$ in the previous period's production stage will be characterised by (ϵ, z, x_h, o) immediately after the ϵ, z and x_h shocks occur. The indicator function $\mathbf{1}_{h>1}$ takes the value of one when the level of human capital is associated with a value of $x_h > x_1$ and zero otherwise.

The same arguments used in the case of unemployed workers imply that the measure of employed workers at the beginning of the production stage is given by

$$\begin{aligned} e_{t+1}^p(\epsilon, z, x_h, o)d\epsilon dz &= [1 - \lambda_E\phi^E(\epsilon, .)]e_{t+1}^m(\epsilon, z, x_h, o)d\epsilon dz + (\mathbf{1}_{h=1})\lambda_E^c\tilde{e}_{t+1}^m(\epsilon, z, x_h, o) \\ &+ \int_{\underline{\epsilon}}^{\overline{\epsilon}} \lambda_E[\gamma\phi^E(\hat{\epsilon}, .) + (1-\gamma)d(\hat{\epsilon}, .)]e_{t+1}^m(\hat{\epsilon}, z, x_h, o)d\hat{\epsilon}dzd\Gamma(\epsilon) \\ &+ \lambda_U\phi^U(.)u_{t+1}^r(z, x_h, o)dzd\Gamma(\epsilon) + (\mathbf{1}_{h=1})\lambda_U^c\phi^U(.)\tilde{u}_{t+1}^r(z, x_1, o)dzd\Gamma(\epsilon), \end{aligned} \tag{9}$$

where $\Gamma(.)$ denotes the distribution of ϵ across the cycle and $e_{t+1}^m(\epsilon, z, x_h, o)d\epsilon dz = (1-\delta_z-\delta_\epsilon)(1-d(\epsilon, z, x_h, o, A, \mathcal{P}_O))(1-\rho(\epsilon, z, x_h, o, A, \mathcal{P}_O))e_{t+1}^s(\epsilon, z, x_h, o)d\epsilon dz$ denotes the measure of employed workers characterised by (ϵ, z, x_h) who remained in the occupation and entered the search and matching stage, such that with probability $[1-\lambda_E\phi^E(\epsilon, z, x_h, o, A, \mathcal{P}_O)]$ they did not change employers, and $\phi^E(\epsilon, z, x_h, o, A, \mathcal{P}_O)$ is an indicator function that take the value of one when the employed worker accepts the firm's job offer and zero otherwise.

The second term in (9) denotes the measure of employed workers from other occupations who reallocate to occupation o arriving with idiosyncratic productivity z and drew idiosyncratic productivity ϵ when meeting an employer. In this case, we need to take into account only of employed workers who voluntarily decided to change occupations. Some of these workers will be able (with probability γ) to decide whether to change occupations within or across employers; while others (with probability $1-\gamma$) will have to take the position in a new employer, as long as it is above their expected value of unemployment. These arguments then imply that $\tilde{e}_{t+1}^m(\epsilon, z, x_h, o)$ is given by

$$\begin{aligned} \tilde{e}_{t+1}^m(\epsilon, z, x_h, o) = (1-\delta_\epsilon-\delta_z)\Bigg(&\gamma\Bigg[\sum_{\tilde{o}\neq o}\sum_{\tilde{h}=1}^{H}\Big[\int_{\underline{z}}^{\overline{z}}\int_{\underline{\epsilon}}^{\overline{\epsilon}}\rho^E(.)\alpha_o^E(., \tilde{o})\phi^E(.)e_{t+1}^s(\tilde{\epsilon}, \tilde{z}, x_{\tilde{h}}, \tilde{o})d\tilde{\epsilon}d\tilde{z}\Big]\Bigg] \\ &+ (1-\gamma)\Bigg[\sum_{\tilde{o}\neq o}\sum_{\tilde{h}=1}^{H}\Big[\int_{\underline{z}}^{\overline{z}}\int_{\underline{\epsilon}}^{\overline{\epsilon}}\rho^E(.)\alpha_o^E(\tilde{\epsilon}, \tilde{\Omega}, \tilde{o})d(\tilde{\epsilon}, \tilde{\Omega})e_{t+1}^s(\tilde{\epsilon}, \tilde{z}, x_{\tilde{h}}, \tilde{o})d\tilde{\epsilon}d\tilde{z}\Big]\Bigg]\Bigg)dF(z)\Gamma(\epsilon), \end{aligned}$$

where $\rho^E(\tilde{\epsilon}, \tilde{z}, x_{\tilde{h}}, A, \mathcal{P}_O, \tilde{o})$ is an indicator function taking the value of one if the employed worker reallocates and zero otherwise. The third term in (9) denotes the measure of employed workers within the same occupation o who found a new job with idiosyncratic productivity ϵ. The last two terms denote the measure of unemployed workers who got re-employed in occupation o with idiosyncratic

productivities z and ϵ, as implied by (8).

Earnings distribution Given the above measures we can now derive the earnings distribution. Given that $\hat{w}(A, p_o, \epsilon, z, x_h)$ is increasing in all of its arguments and that $e_t^p(\epsilon, z, x_h, o)$ can be equal to zero for some combinations of (ϵ, z, x_h, o) as workers might prefer unemployment than remaining employed, the probability of observing earnings $w' \leq w$ at time t is given by

$$G_t(w|A_t, \mathcal{P}_{O,t}) = \sum_{o \in O} \sum_{h \in H} \int_{\underline{z}}^{\bar{z}} \int_{\underline{\epsilon}}^{max\{\underline{\epsilon}, \tilde{\epsilon} = \hat{w}^{-1}(w, A, p_o, z, x_h)\}} \hat{w}(A, p_o, \epsilon, z, x_h) e_t^p(\epsilon, z, x_h, o) d\epsilon dz, \quad (10)$$

where $\hat{w}^{-1}(w, A, p_o, z, x_h)$ denotes the inverse of $\hat{w}$, such that the value of ϵ solves $\hat{w}$ for earnings equal to w. Aggregating (10) across p_o, A and t, then yields the cross sectional earnings distribution, G. Note that both $e_t^p(\epsilon, z, x_h, o)$ and current earnings $w = \hat{w}(.)$ are endogenous objects as they depend on worker's employer and occupational mobility decisions.

Appendix D - Estimation

Simulation procedure

The parametric assumptions made in Section 4.1 imply that we need to recover 48 parameters which can be divided into several sets. The set that governs the arrival of job opportunities $\{\lambda_0^i, \lambda_1^i, \lambda_0^{c,i}, \lambda_1^{c,i}\}_{i=U,E}$. The set $\{\delta_0^z, \delta_1^z, \rho_z, \nu_z, \sigma_z, \omega_z, z_A, \bar{z}, \underline{z}\}$ that governs the idiosyncratic worker-occupation productivities. The set $\{\delta_0^\epsilon, \delta_1^\epsilon, \eta, \sigma_\epsilon, lt_\epsilon, rt_\epsilon, \omega_\epsilon, \epsilon_A, \bar{\epsilon}, \underline{\epsilon}\}$ that governs the idiosyncratic worker-employer productivities, the set $\{\rho_p, \sigma_p, \tilde{p}_{NRC}, \tilde{p}_{RC}, \tilde{p}_{NRM}, \tilde{p}_{RM}\}$ that governs the occupation-wide productivities, the set of occupational human capital accumulation $\{x_1, x_2, \chi(x_2)\}$ and the set of directional parameters across occupations $\{\alpha_0, \alpha_1^U, \alpha_1^E, \alpha_{NRC}, \alpha_{NRM}, \alpha_{RM}, \alpha_{NRM}\}$. The set that governs the aggregate productivity process $\{\rho_A, \sigma_A\}$, payments $\{\gamma_w, b\}$ and the discount rate $\beta = 0.997$.

As mentioned in the main text we fix $\beta = 0.997$, normalise x_1 to one, set $\chi(x_2)$ such that human capital accumulation occurs on average after 5 years of occupational tenure and choose x_2 to match the 12% 5-year returns to occupational tenure reported by Kambourov and Manovskii (2009). We also set $b = 0.4$ to match a 40% replacement ratio (see Shimer, 2005). The aggregate productivity process parameters are set to the values of the autocorrelation and unconditional variance of output per worker as observed in the US during the period of study, similar to Shimer (2005), such that $\rho_A = 0.9580$ and $\sigma_A = 0.0090$. To generate the idiosyncratic productivity grid, we apply an evenly spaced grid based on the deciles of the distributions F and Γ. These procedure then leads to $\bar{z} = \bar{\epsilon} = 3$ and $\underline{z} = \underline{\epsilon} = -3$.

Given these pre-set parameters, we estimate the model following a two-step procedure in which we split all remaining parameters between an inner and outer loop. Given values for the outer loop parameters, we can directly calibrate those in the inner loop such that their values match *exactly* the targeted moments. The inner loop contains the productivity levels $\bar{p}_o$ and the directional parameters of the $\alpha(.)$ function, α_{NRC}, α_{RC}, α_{NRM} and α_{RM}. We then iterate on the values of the outer loop

parameters using simulated method moments, adjusting the inner loop parameters at each iteration.

To simulate the model, we first solve it by value function iteration using global methods. Local methods would be unsuitable for our purpose as they truncate some of the variation in earnings changes in response to the shock (see Petrosky-Nadeau and Zhang, 2021). This is particularly important for our estimation as we want to investigate cyclical changes in the tails of the earnings growth distribution. Using global methods allows for unstructured changes in earnings as response to shocks. To solve the model around a set of outer loop parameters we re-set all of the grids for shocks and the distributions thereon. Because we are solving this using global methods, we use value function iteration until the convergence. Because of the discrete choices that imply value functions intersect, this can cause non-concave portions of the state space and long (or infinite) converge lengths. Hence, we smooth over the discrete choice to move occupations using a logit-type function with a very steep slope parameter.

We then draw 64 13-year histories of 10,000 agents each. We parallelize it on 64 labour market histories to match a multiple of the number of cores using in our cluster. Each history has its own draw of aggregate shocks, though on average 20% of periods are in recession and we preserve that auto-correlation structure of the cycle as well. The simulations are on the shocks grids, rather than interpolating between. To begin the history, workers in the first period have the ergodic distribution of x_h and occupations. Once the histories are simulated we convert them into a four monthly frequency as in the SIPP and average over histories to compute the moments in $M^S(\cdot)$, discussed in the text. This procedure is followed until convergences.

Search across occupations and its relationship with the Gumbel-type shocks

In Section 4.1 we parametrised the probability of obtaining a z from a given occupation as $\alpha^i(s_{\tilde{o}}) = \alpha_0 e^{\alpha_{\tilde{o}}\alpha_1^i} s_{\tilde{o}}^{1-\alpha_1^i}$, where occupation $\tilde{o} \in O^-$ denotes the search direction, i the worker's labour force status, $i = U, E$, and $s_{\tilde{o}}$ denotes search intensity. Workers have to chose a $s_{\tilde{o}}$ for each $\tilde{o} \in O^-$ to maximise the probability of receiving a z given that $\sum_{\tilde{o}\in O^-} s_{\tilde{o}} = 1$. The first order condition for such maximisation is given by $\alpha'(s^*_{\tilde{o}})\Phi^i(\tilde{\Omega}_1) = \mu$, where μ denotes the multiplier on the constraint $\sum_{\tilde{o}\in O^-} s_{\tilde{o}} = 1$, $\tilde{\Omega}_1 = \{\tilde{z}, x_1, \tilde{o}, A, \mathcal{P}_O\}$ and $\Phi^i(\tilde{\Omega}_1)$ denotes the net conditional return to searching in direction $\tilde{o}$ such that $\Phi^U(\tilde{\Omega}_1) \equiv \Psi^U(\tilde{z}, x_1, \tilde{o}, \Omega) - W^U(z, x_h, o, \Omega)$ with

$$\begin{aligned}\Psi^U(\tilde{z}, x_1, \tilde{o}, \Omega) &= \int_{\underline{z}}^{\overline{z}} \Big[\lambda_U^c(A) \int_{\underline{\epsilon}}^{\overline{\epsilon}} \max\Big\{W^E(\tilde{\epsilon}, \tilde{z}, x_1, \tilde{o}, \Omega), W^U(\tilde{z}, x_1, \tilde{o}, \Omega)\Big\} d\Gamma(\tilde{\epsilon}) \\ &+ (1 - \lambda_U^c(A)) W^U(\tilde{z}, x_1, \tilde{o}, \Omega)\Big] dF(\tilde{z});\end{aligned}$$

and $\Phi^E(\tilde{\Omega}_1) \equiv \Psi^E(\epsilon, \tilde{z}, x_1, \tilde{o}, \Omega) - W^E(\epsilon, z, x_h, o, \Omega)$ with

$$\begin{aligned}\Psi^E(\epsilon, \tilde{z}, x_1, \tilde{o}, \Omega) &= \Bigg(\int_{\underline{z}}^{\overline{z}}\Bigg[\int_{\underline{\epsilon}}^{\overline{\epsilon}}\Bigg(\gamma\lambda_E^c(A)\max\Big\{W^E(\tilde{\epsilon}, x_1, \tilde{z}, \tilde{o}, \Omega), W^E(\epsilon, x_1, \tilde{z}, \tilde{o}, \Omega)\Big\} \\ &+ (1-\gamma)\lambda_E^c(A)\max\Big\{W^E(\tilde{\epsilon}, x_1, \tilde{z}, \tilde{o}, \Omega), W^U(x_1, \tilde{z}, \tilde{o}, \Omega)\Big\}\Bigg)d\Gamma(\tilde{\epsilon}, A) \\ &+ (1-\lambda_E^c(A))W^E(\epsilon, x_1, \tilde{z}, \tilde{o}, \Omega)\Bigg]dF(\tilde{z}, A)\Bigg),\end{aligned}$$

and $\Omega = \{A, \mathcal{P}_O\}$. Substituting the assumed functional form for $\alpha(.)$ in the first-order condition yields,

$$s_{\tilde{o}}^* = \left(\frac{(1-\alpha_1^i)\alpha_0 e^{\alpha_{\tilde{o}}\alpha_1^i}}{\mu}\right)^{1/\alpha_1^i}\left(\Phi^i(\tilde{\Omega}_1)\right)^{1/\alpha_1^U}.$$

Since this holds for all directions $\tilde{o} \in O^-$, we can use the equality constraint $\sum_{\tilde{o}\in O^-} s_{\tilde{o}} = 1$ to obtain:

$$s_{\tilde{o}}^* = \frac{\left(\frac{(1-\alpha_1^i)\alpha_0 e^{\alpha_{\tilde{o}}\alpha_1^i}}{\mu}\right)^{1/\alpha_1^i}\left(\Phi^i(\tilde{\Omega}_1)\right)^{1/\alpha_1^i}}{\sum_{\tilde{o}\in O^-}\left(\frac{(1-\alpha_1^i)\alpha_0 e^{\alpha_{\tilde{o}}\alpha_1^i}}{\mu}\right)^{1/\alpha_1^i}\left(\Phi^i(\tilde{\Omega}_1)\right)^{1/\alpha_1^i}}.$$

Noting that $(\frac{(1-\alpha_1^i)\alpha_0}{\mu})^{1/\alpha_1^i}$ cancels from the numerator and denominator, and using the transformation $X^{\frac{1}{\alpha_1^i}} = e^{\frac{1}{\alpha_1^i}\log(X)}$ one obtains

$$s_{\tilde{o}}^* = \frac{e^{\alpha_{\tilde{o}} + \frac{1}{\alpha_1^i}\log\left(\Phi^i(\tilde{\Omega}_1)\right)}}{\sum_{\tilde{o}\in O^-} e^{\alpha_{\tilde{o}} + \frac{1}{\alpha_1^i}\log\left(\Phi^i(\tilde{\Omega}_1)\right)}}.$$

If the directional terms $\alpha_{\tilde{o}}$ are all equal, this takes a very convenient form, such that the optimal value of $s_{\tilde{o}}$ is given by

$$s_{\tilde{o}}^* = \frac{e^{\frac{1}{\alpha_1^i}\log\left(\Phi^i(\tilde{\Omega}_1)\right)}}{\sum_{\tilde{o}\in O^-} e^{\frac{1}{\alpha_1^i}\log\left(\Phi^i(\tilde{\Omega}_1)\right)}}, \tag{11}$$

Equation (11) is convenient because it allows more flexibility in matching net mobility across occupations. It does so by breaking the symmetry that the random utility model, which is the one typically used to model occupational mobility, imposes. Nevertheless, our approach has a direct counterpart in the random utility model where the utility shocks follow a Gumbel distribution. To shows this suppose the worker obtains a vector of shocks ϖ whose elements are the shocks associated with each of the occupations in O^-. Each element of ϖ is Gumbel-distributed with dispersion parameter α_1 and are realised when the worker chooses to search across occupations. The slight difference from the usual random utility model is that here we require ϖ to enter in a multiplicative way (rather than additively) such that searching in direction $\tilde{o}$ yields expected payoff $\Phi(\tilde{\Omega}_1)e^{\tilde{\varpi}}$. To identify one occupation from another, we will introduce the notation o^j and $\Phi(\Omega_1^j)$ and to save notation we leave implicit the index $i = U, E$.

The probability that a worker chooses occupation o^j over o^k, is then given by $v_{o^j} = \Pr[\Phi(\Omega_1^j)e^{\varpi^j} >$

$\Phi(\Omega_1^k)e^{\varpi^k}]$, which is equivalent to the monotonic transformation $v_{oj} = \Pr[\log\Phi(\Omega_1^j)+\varpi^j > \log\Phi(\Omega_1^k)+\varpi^k]$, and hence $v_{oj} = \Pr[\log\Phi(\Omega_1^j) - \log\Phi(\Omega_1^k) + \varpi^j > \varpi^k]$ for any occupations j and k. Integrating over ϖ^j means that we are now considering the expected choice for the population, rather than the probability that an individual goes in given occupational direction. The population-level probability is written as:

$$v_{oj} = \int \prod_{k\neq j} F(\log\Phi(\Omega_1^j) - \log\Phi(\Omega_1^k) + \varpi^j) f(\varpi^j) d\varpi^j,$$

where $F(.)$ and $f(.)$ are the CDF and PDF of the Gumbel distribution with location parameter 0 and dispersion α_1. Using the Gumbel functional form gives us

$$v_{oj} = \int \prod_{k} \exp\left(-\exp\left(-\alpha_1\left\{\log\Phi(\Omega_1^j) - \log\Phi(\Omega_1^k) + \varpi^j\right\}\right)\right)\exp(-\varpi^j)\exp(-\exp(-\varpi^j))d\varpi^j.$$

After some tedious algebra this yields the well-known form for the choice probability:

$$v_{oj} = \frac{e^{\frac{1}{\alpha_1}\log\Phi(\Omega_1^j)}}{\sum_{k\in O^-} e^{\frac{1}{\alpha_1}\log\Phi(\Omega_1^k)}}.$$

To normalize this probability by any outside option $\log\Phi^0$, we simply multiply both top and bottom of this equation by $\log(W^U(.))$ or $\log(W^E(.))$. Note that $\tilde{v}$ is exactly $s_{\tilde{o}}$ as derived in (11). To incorporate the parameters α_k, one just needs to multiply the e^{α_k} by the return to occupation k, $\Phi(\Omega_1^k)$ in the previous expression.

Finally, a comparison with the canonical on-the-job search model with endogenous search intensity developed from Burdett (1978) is also useful to further clarify our search across occupation technology. In such a model, for example, an unemployed worker receives with per-period probability $\lambda \leq 1$ a wage draw (from a known stationary distribution) and with probability $1-\lambda$ he does not and remains unemployed. A similar process occurs when the worker becomes employed. With endogenous search intensity, λ is typically a continuous, weakly increasing and weakly concave function of search effort, s. Unemployed workers need to chose s in order to maximise the probability of receiving a wage offer subject to a convex search cost. Our set up builds on this structure. We assume that a worker (leaving o) has one unit of search intensity, s, per period. With probability $\sum_{\tilde{o}\in O^-}\alpha(s_{\tilde{o}};o) \leq 1$ the worker receives a z and with complementary probability $1-\sum_{\tilde{o}\in O^-}\alpha(s_{\tilde{o}};o)$ he does not and remains unemployed. The key difference with our technology is that the draw of z (w in the one-sided search model) can come from one of several occupations (all occupations sharing the same known stationary distribution, F) and the worker has to choose how to allocate s across the remaining occupations in order to maximise the probability of receiving a z, knowing that α is a continuous, weakly increasing and weakly concave function of s and $\sum_{\tilde{o}\in O^-} s_{\tilde{o}} = 1$.

Standard errors of the conditional earnings growth distributions

To complement the standard errors of the targeted moments described in Table 1 in the main text, Table 5 now presents the bootstrapped standard errors of the quantiles of the earnings growth distribution depicted in Figure 6 in the main text.

Table 5: Bootstrapped standard errors of earnings growth distributions

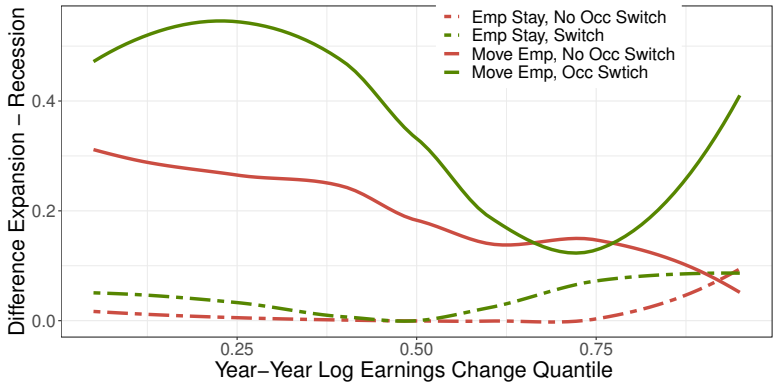
	Employer stayers		EUE movers		EE movers	
	Occ. movers	Occ. stayers	Occ. movers	Occ. stayers	Occ. movers	Occ. stayers
Percentile						
10th	0.0007	0.0109	0.0108	0.0193	0.0207	0.0235
25th	0.0002	0.0046	0.0059	0.0090	0.0079	0.0147
50th			0.0046	0.0094	0.0076	0.0124
75th	0.0005	0.0068	0.0072	0.0138	0.0121	0.0174
90th	0.0007	0.0076	0.0153	0.0236	0.0280	0.0253

In addition, we target the 2.5^{th}, 5th, 10th, 25th, 50th, 75th, 90th, 95th, 97.5^{th} cyclical change in the earnings growth distribution depicted in Figure 9b. The bootstrapped standard errors for these percentiles are 0.0265, 0.0128, 0.0076, 0.0026, 0.0024, 0.0079, 0.0138, 0.0260, respectively.

Cyclical changes in the earnings growth distribution

In Section 4.3 of the main text we presented the fit of the model in relation to the cyclical change of the earnings growth distribution (see Figure 9a). Figure 5 presents the model counterpart of Figure 4a in Section 2, which conditions the cyclical shift of the earnings growth distribution by whether workers changed employers and/or occupations. The model does not match fully the exact shape of each of the curves relative to the data, but it does match its key features. In particular, it shows that both in the data and model the procyclical skewness of the earnings growth distribution is due to those workers who change occupations and employers simultaneously. The model is also consistent with the fact that among employer mover/ occupation stayers the cyclical change in the earnings growth distribution is below that of employer and occupation movers. Further, the model shows that among employer stayers /occupation movers or stayers the cyclical change in the earnings growth distribution is even lower.

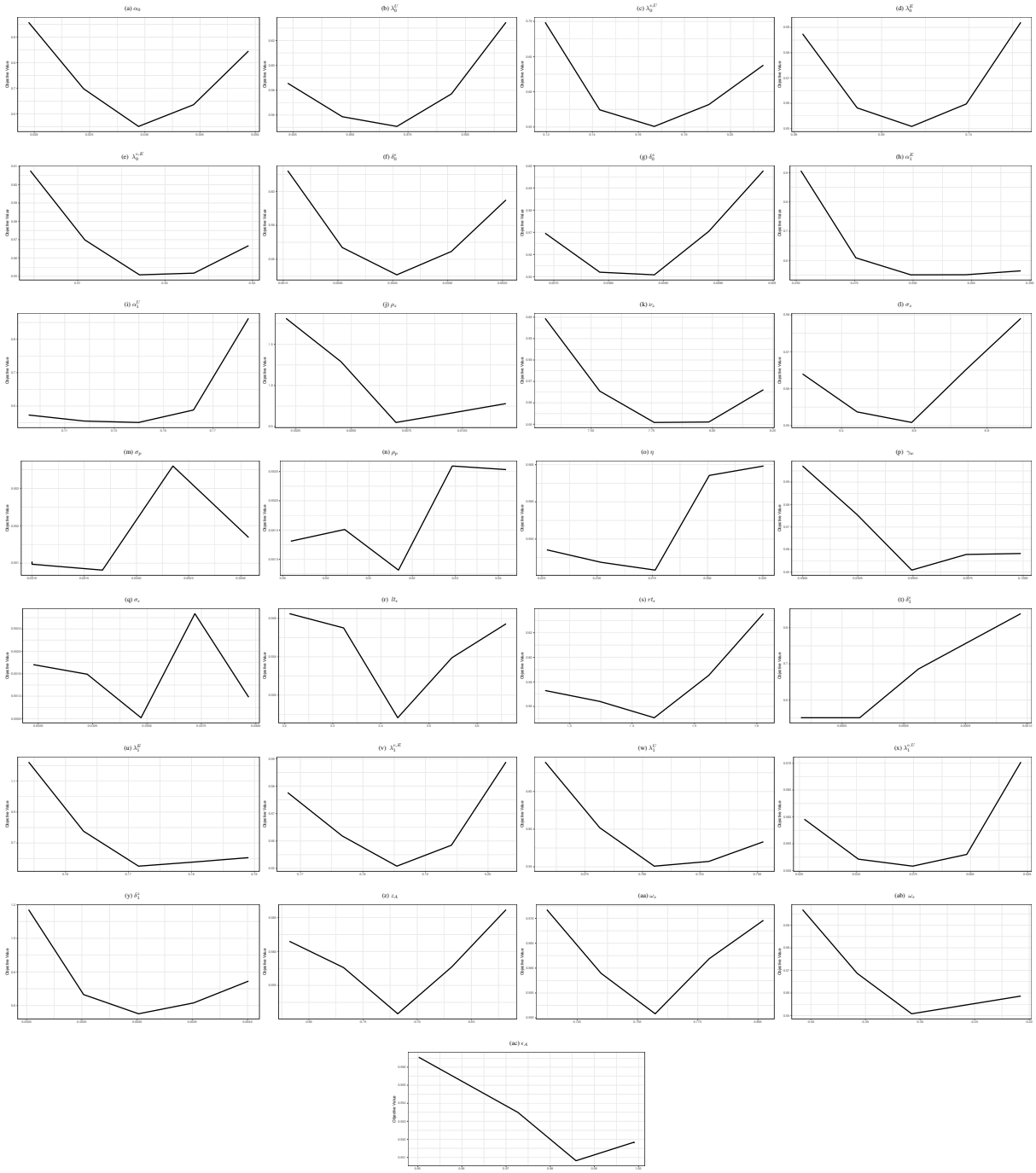
Figure 5: Cyclicalty of the earnings growth distribution by occupation/employer change - Model



Note: This figure present the difference between earnings growth distribution in expansion and recessions periods generated by the model. It conditions these distributions by whether workers changed occupations and employers at the same time, did not experience any of these changes or only experienced one of them. To construct these distributions we follow the same procedure as we did using the SIPP and depicted in Figure 4 in the main text.

Identification graphs

Figure 6: Global Identification



Note: Each graph shows the re-optimized value of the loss function $(\mathbf{M^D} - \mathbf{M^S}(.))'\mathcal{W}(\mathbf{M^D} - \mathbf{M^S}(.))$. after perturbating each parameter in turn from its estimated value by $\pm 2.5\%$ and the $\pm 5\%$.

To show identification of the outer loop parameters we perturb each parameter from its estimated value by $\pm 2.5\%$ and the $\pm 5\%$, similar to that shown in Bilal et al. (2021). We then compute the loss

function $(\mathbf{M^D} - \mathbf{M^S}(.))'\mathcal{W}(\mathbf{M^D} - \mathbf{M^S}(.))$, where $\mathbf{M^D}$ denote the vector of data moments and $\mathbf{M^S}$ the vector of simulated moments. Identification is achieved if the value of the loss function plotted against the perturbed values of each parameter traces a steep U shape relationship with a minimum at the estimated parameter values, described in Table 2 in the main text. Figure 6 depicts these U shape relationships and shows that the parameters are indeed identified.

No occupation mobility model

In Section 6 of the main text we discuss the implications of a version of our model in which workers are not allowed to change occupations. We structurally estimate such a model using the same moments presented in Section 4 of the main text, except for those pertaining to occupational mobility. The estimated parameter values in this case are $\lambda_{0,U} = 0.950$, $\lambda_{1,U} = 0.001$, $\lambda_{0,E} = 0.137$, $\lambda_{1,E} = 0.503$, $\eta = 0.237$, $\delta_{0,\epsilon} = 0.003$, $\delta_{1,\epsilon} = -0.564$, $\sigma_\epsilon = 0.001$, $rt_\epsilon = 0.600$, $lt_\epsilon = 3.998$, $\omega_\epsilon = 0.490$, $\epsilon_A = 0.094$, and $\gamma_w = 0.080$. Table 6 shows that this version is able to replicate very well the targeted average EE, EU and UE transition probabilities as well as their expansion/recessions ratios.

Table 6: Targeted moments in the estimation, without occupations

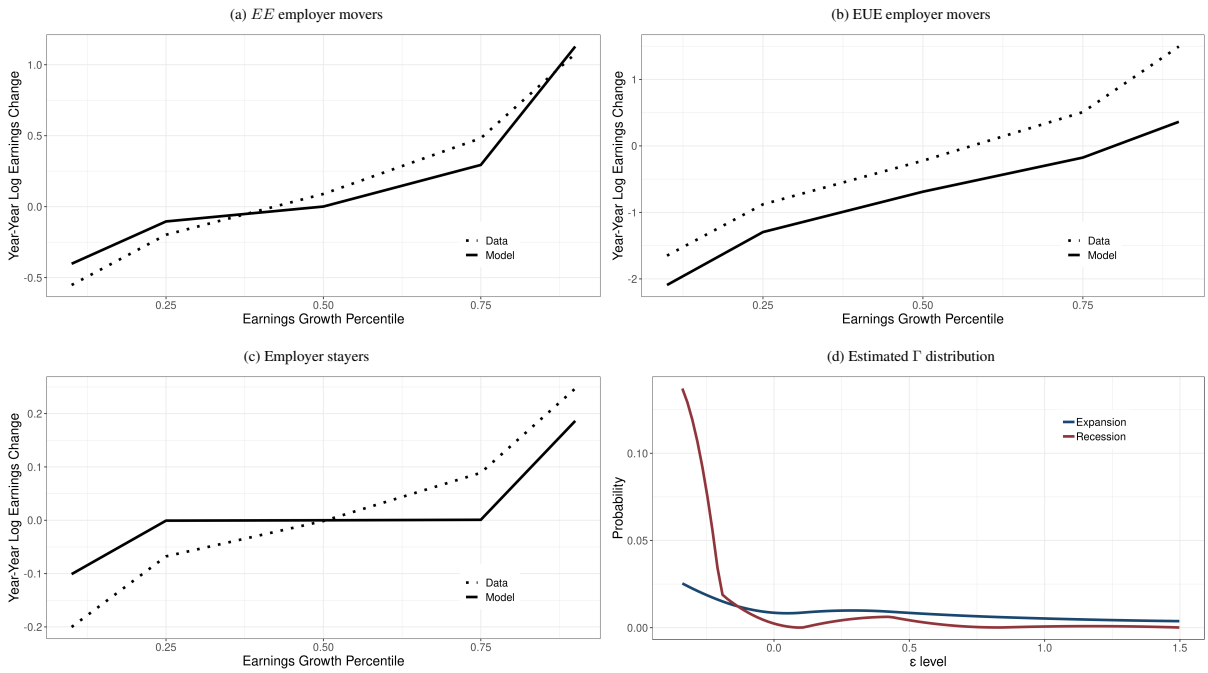
Moment	Model	Data	Moment	Model	Data
EE transition prob	0.034	0.034	EE rate - expansion/recession ratio	1.173	1.185
		(0.0003)			(0.0469)
UE transition prob	0.371	0.395	UE rate - expansion/recession ratio	1.078	1.088
		(0.0025)			(0.0244)
EU transition prob	0.023	0.022	EU rate - expansion/recession ratio	0.710	0.746
		(0.0002)			(0.0333)

Note: Bootstrapped standard errors in parenthesis.

Figure 13a in the main text shows that the model is also able to replicate the cross-sectional earnings growth distribution, capturing well its skewness and leptokurtosis, consistent with the results in Hubmer (2018) and Karahan et al. (2020). Underlying this fit, however, Figures 7a, 7b and 7c reveal that the model fails to capture the targeted earnings growth distributions conditional on employer transitions, particularly the ones for EUE employer movers. Among the latter, the model generates not only larger earnings losses relative to the data, but it hardly generates any earnings gains. It is only close to the 90th percentile that we observe these earnings gains, while in the data earnings gains from EUE transition starts occurring much closer to median. This is a consequence of the shape of the estimated $\Gamma_A(.)$, depicted in Figure 7d. Its long right tail implies that employed workers can climb the job ladder and achieve high values of ϵ relatively fast. Figure 7a and the estimated transition probabilities show that this makes the model consistent with the earnings growth distribution of EE movers. However, when these workers fall into unemployment, the estimated $\Gamma_A(.)$ implies that at

re-employment workers are more likely to draw low values of ϵ. Even though these workers might not accept the lowest ϵ draws (particularly during recessions), they will still face a higher probability of becoming re-employed in jobs associated with a low ϵ. The initial large drop in earnings due to job loss coupled with low re-employment earnings then leads to larger earnings loses and smaller earnings gains among EUE workers relative to the data.

Figure 7: Job ladder model - earnings growth distribution (cdf)



Note: The first three panels show that targeted earnings growth distribution, computed separately for EE and EUE employer movers and employer stayers. Each of these graphs presents the corresponding distribution be showing the annual earnings growth value and the corresponding percentile. The estimation targets the 10th, 25th, 50th, 75th and 90th percentiles of each of these distributions. The last panel shows the estimated Γ distribution in expansions and recessions.

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