Cyclical Earnings and Employment Transitions *

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Abstract

Recessions increase unemployment risk and decrease flows across employers and occupations. This paper explores the cyclical differences in the earnings change distribution—focusing on the more volatile tails. Because earnings changes are larger when workers change jobs and even larger when switching occupations, cyclicality in the incidence of flows directly affects the tails of the distribution of earnings changes. However, the business cycle also affects earnings outcomes conditional on a job, employment status and/or occupation change. Because job and occupation switching is endogenous, we introduce a business cycle model with on-the-job search and occupational mobility, which allows us to structurally decompose the contribution of flows and returns. Cyclical fluctuations in exogenous flows, along with worsening returns, drive dynamics in the bottom tail of earnings growth while returns affect changes in the top tail.

Keywords: Earnings, Unemployment, Business Cycle, Search, Occupational Mobility.
JEL: E24, E30, J62, J63, J64.

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1 Introduction

Labour markets are characterised by a large amount of churning. For example, in the US employed workers face a monthly probability of separating from their employers of about 6%. These separations typically lead to an employer change either directly or through a spell of unemployment. These separations are also accompanied by large positive and negative earnings changes. Crucially, the extent of these changes varies over the business cycle. During recessions we observe a larger proportion of negative earnings changes and a smaller proportion of positive earnings changes, implying that a key cyclical property of the earnings growth distribution is its countercyclical left-skewness (see Guvenen et al. 2013).[1] Although the cyclical relationship between earnings and employer changes has been well explored by a large literature (see e.g. Postel-Vinay and Robin, 2002; Bagger et al. 2014; Burdett et al., 2016), much less is known about the role of career changes in driving earnings growth over the business cycle. Do cyclical earnings changes respond more to changes in the type of job a worker performs or to changes in the employer in which the worker performs this job?

In this paper we investigate the movement of distribution of earnings changes, with especial focus on the high and low tails that move most over the business cycle. Our empirical and structural examinations show that career changes, which we observe as occupational mobility, are the main driver behind the cyclical patterns of the earnings change distribution and not employer churning. Moreover, it is occupational mobility due to workers' evolving idiosyncratic career prospects rather than occupation-wide productivity differences that makes occupational mobility the more important component. Indeed, we find that occupation-wide productivity differences play only a small part in determining cyclical earnings changes. This mirrors our finding about the cross-section: most of the dispersion in earnings changes is due to changes in the idiosyncratic match quality between worker and occupation or worker and firm. Recessions, then, affect the earnings distribution through these idiosyncratic effects, specifically the distribution of idiosyncratic occupational effects gets worse during recessions.

To motivate our approach we use the Survey of Income and Program Participation (SIPP) and establish the cyclical properties of the earnings change distribution in relation to occupational and employer change. Although this dataset is much smaller than typical administrative data sets, the advantage of the SIPP is that it is easily accessible, follows individuals for up to four years, records their employer and occupational changes and spell durations as well as it provides detailed information on their demographic and job characteristics. We find that in the cross-section the earnings growth distribution exhibits two key features: (i) The majority of workers do not change employers and experience relatively small (positive or negative) earnings changes across consecutive years/waves. (ii) Workers who experience large earnings changes across consecutive years/waves are typically those who had low previous-year earnings, *and* simultaneously changed employers and occupations. This occurs

[1] Storesletten et al. (2004), among others, argue instead that the key cyclical property of earnings growth is its countercyclical variance. This distinction is important as it has very different implications for our understanding of how recessions affect the career path of individuals, their consumption, savings and investment decisions, and ultimately inequality.

between and within demographic groups, suggesting that similar workers experience very different (and opposite) earnings changes from employer and/or occupation mobility. The findings motivates our focus on worker mobility across employers and occupations.

A particularly salient feature of the data is the importance of occupational mobility to the *dispersion* in earnings changes. Switchers have a much wider distribution and, in turn, the workers experiencing large earnings changes are disproportionately occupational switchers. Interestingly, this is a nearly symmetric feature so that the rate of occupational switching is V-shaped in the size of the earnings change.

Over the business cycle, we find that the earnings growth distribution exhibits a clear countercyclical left-skewness, but also a (albeit less strong) countercyclical variance. These two properties arise due to the asymmetric cyclical response of the tails of the distribution. The asymmetry arises as in recessions the left tail of the earnings growth distribution drops more than the right tail. This occurs because there is a much greater proportion of very large negative earnings changes relative to the decrease in large positive earnings. We show that although employer/occupational movers represent about 20% of our sample they are the main drivers of the cyclical behaviour of the earnings growth distribution over the business cycle.

This empirical evidence, however, could be driven by changes in the opportunities workers face or their endogeneous choices and hence, we provide a structural interpretation of this evidence. We propose an on-the-job search model with endogenous employer and occupational mobility. We model worker heterogeneity through idiosyncratic productivity shocks and distinguish between firm-worker match productivity and occupation-worker match productivity components. In addition, we consider accumulation of occupation-specific human capital acquired through a learning-by-doing process. Differences across occupations are driven by occupation-wide productivity shocks and fixed differences, while aggregate uncertainty is introduced through an economy-wide productivity shock. This aggregate shock also affects the exogenous flow rates: the cycle changes the opportunity to take a job, exogenous job loss and the ability to switch occupations in the process.

Given this structure, we show that workers' endogenous decisions to change employers and occupations with or without intervening spells of unemployment can reproduce the observed cyclical behaviour of the earnings growth distribution as well as the cyclical behaviour of worker mobility. Our approach provides a novel decomposition that allows us to disentangle the effects of idiosyncratic worker-employer and worker-occupation productivity shocks from aggregate and occupation-wide productivity shocks in explaining cyclical earnings growth.

We use this structure to understand the cyclicality of the distribution of earnings changes. Two major conclusions emerge about the two tails of the distribution. At the bottom, where the earnings losses are larger in recessions, cyclical changes in the job flow patterns drive almost all of the effect and very little of the loss comes from the cyclicality of the return to the flow. At the top, where recessions mean that earnings gains are dampened, the effect comes from both the decline in opportunities to make earnings gains and the potential returns to these gains. These results are intuitive and mirrored by statistical decompositions: exogenously caused job loss increases in recession and drives the larger losses whereas finding new jobs from unemployment or job-to-job is more rare in recession, hindering the ability to increase earnings, while those who do find work are less likely to find a very good match. We add to these dynamics the importance of occupational mobility: it is the job losses that also force an occupational switch that are most important to the downside losses in recession. At the same time, the top of the distribution is pulled in especially because occupational upgrades are more difficult: both fewer opportunities arise and those that do are less likely to draw a very good match quality.

The rest of this paper is organized as follows. First we present empirical work highlighting the role of occupational mobility in the dispersion of earnings changes and on the counter-cyclical skewness of earnings changes. Then we present the theoretical framework that will confront this data. We then show our estimation and model fit. The model is then used to decompose the change in the earnings growth distribution over the cycle. Finally we conclude.

2 The Earnings Growth Distribution

2.1 Data

We use data from the Survey of Income and Program Participation (SIPP) from the 1990 to 2008 panels, covering the 1990-2013 period. The advantage of using the SIPP is that each of its panels follows a large number of workers for up to four years. Within each panel individuals are divided into four rotation groups, where each group is interviewed in waves of four months. At the end of each wave individuals report information on their current and previous employment status, occupations, industries and earnings (hourly wages and hours worked), covering the last four months. Using this information, we define employer, occupation and earnings changes based on a worker's main job for each period.[2]

Labor market flows Within a panel we identify for each individual whether he/she experienced an employer and/or occupational transition. Employer changes that occurred without an intervening full month of unemployment are labeled EE transitions and those that occurred through unemployment are labeled EUE transitions. In the latter case, we include all transitions in which the worker returned to employment within the sample, even if the worker did not report actively searching. Since we only consider unemployment spells completed within the survey period, to minimize the potential under-representation of EUE relative to EE transitions we consider only transitions with at least 4 waves remaining in the panel. EUE transitions, however, would remain affected by our choice to exclude "temporary recalls", as these workers do not seem to face the same reallocation and search frictions as those workers who do not intent to return to their previous employers (see Fujita and Moscarini, 2017). We further detail our procedure in Appendix A.

To measure occupation changes we homogenise the occupation classification across SIPP panels using the crosswalk translation scheme created by IPUMS based on the 1990 Standard Occupational

[2]Since the SIPP records up to two jobs at a time for any individual, we define the main job as the one in which the worker spent the most hours, and break ties using earnings.

Classification (1990 SOC). We then aggregate the resulting three-digit occupational codes into four task-based occupational categories: non-routine cognitive, routine cognitive, non-routine manual and routine manual. We chose this coarse aggregation to focus on those changes in an individual's line of work that also involve a change in the main tasks performed. We then compare the task-based occupation for a given individual across waves.[3]

Using these two measures of change we label an individual to be an "employer/occupation mover" in a given wave when he/she reported a simultaneous employer and occupational change. As mentioned above we distinguish on whether the employer change takes the form of a EE or EUE transition. An individual is labelled as an "employer stayer / occupation mover" ("employer mover / occupation stayer") when we only observe a change in the occupation (employer). For an individual to be labelled an "employer/occupational stayer" in a given wave he/she should not have changed either of these dimensions in the previous or in the posterior year relative to this wave.[4] Under this categorisation we find that over 75% of the transitions are made up of employer/occupation stayers. The reminder observations contain at least one form of transition.

Earnings To study earnings we deflate nominal monthly earnings by the Personal Consumption Expenditure price index and then use the residual of a log earnings regression after controlling for a quadratic on potential experience, education, gender and race dummies, and month dummies. After this step we clean reporting errors in the residual earnings data by dropping the bottom and top 2% of the wave-frequency earnings sample and drop imputed earnings.[5] Following the literature we focus on year-to-year earnings growth. We construct annual earnings as the sum of all (residual) monthly earnings observed during the past 12 months. This measure therefore includes any zero earnings associated with the months in which an individual was unemployed.

For employed workers who do not change employers or occupation and are continually at work, earnings growth are computed by comparing the one year earnings to the next. In the case of employer and/or occupation movers, we compare earnings differences in the year prior to a transition to earnings in the year following the wave in which the transition occurred.[6] As mentioned above, some of

[3]Several studies, notably Moscarini and Thomsson (2007) and Kambourov and Manovskii (2008), have emphasized measurement error in occupation codes which create spurious mobility and can bias our results. 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. Carrillo-Tudela and Visschers (2021), however, show that among the latter 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. Given that we will compute earnings growth using earnings residuals (see below), we chose not to correct for coding errors among employer movers in the data analysis as this would require correcting occupational code at an individual level and running into small sample issues.

[4]See Card et al. (2013), Halvorsen et al. (2020) and Guvenen et al. (2021), for a similar definition of employer stayers.

[5]We utilize the top-code adjustment developed by the CEPR. 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. 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%. We check for such spurious earnings volatility at both monthly and wave frequency among workers not experiencing any job transitions.

[6]In this case earnings in the reference period are measured without the aforementioned stability restriction that the

these transitions include either an EU or a UE observation. Because some EU transitions entail re-employment after an unemployment spell that lasted for more than a year and hence these workers are associated with very low or zero earnings, we use the inverse hyperbolic sine differences

$$\Delta_{i,t+1} = \log(w_{i,t+1} + (w_{i,t+1}^2 + 1)^{1/2}) - \log(w_{i,t} + (w_{i,t}^2 + 1)^{1/2})$$

rather than log differences to compute annual earnings changes. The inverse hyperbolic sine differences are approximately the same as log differences except in the case of very low and zero earnings.[7]

2.2 The earnings distribution in the cross-section and over the cycle

Figure 1a depicts the distribution of annual earnings growth pooling all years in our sample. Guvenen et al. (2021) shows that a key feature of this distribution is that it is very leptokurtic, with approximately Pareto-distributed tails, hence we plot its log density to better visualize this latter property. Splitting the earnings growth distribution by the type of worker mobility and consistent with Guvenen et al. (2021), we observe that employer stayers (who represent the majority of workers in our sample) exhibit positive and negative earnings changes that are concentrated around zero. In contrast, employer movers have much more dispersed earnings changes and are primarily the ones behind the distribution's fat tails. The large negative earnings changes are mainly due to workers who experienced EUE transitions, while the large positive earnings changes are due to workers who experienced EE transitions or came back into employment to complete an EUE transition.[8]

Figure 1b depicts the cyclical changes of this distribution.[9] This graph is the main data pattern of our analysis. It shows how the earnings growth distribution changes over the cycle. Along the horizontal axis, we fix the quantile of the distribution and along the vertical we subtract the associated expansion from the recession earnings growth. A negative number on the horizontal axis means the q^{th} quantile has lower earnings growth in recessions than expansions. For example, at the 25th percentile of the earnings growth distribution recessions have an earnings loss that is about four percentage points higher than in expansions. The negative shift on both tails implies that earnings losses (the left of the distribution) are larger in recession and gains (the right of the distribution) are smaller in recession. This property was documented by Guvenen et al. (2014) and shows that the annual

respondent was at work every week of the reference period.

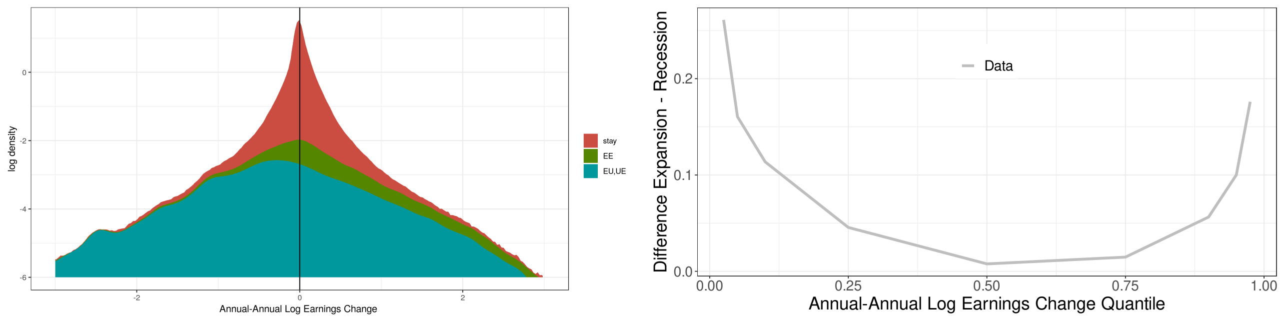
[7]With occasionally misreported earnings the variance of earnings changes will be biased upwards. This is especially a problem for job and occupation stayers because true earnings changes are smaller and so the measurement error may be relatively larger. A common method for cleaning earnings dynamics 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. Instead we follow a heuristic approach similar to Busch et al. (2021) who also study higher-order moments of earnings dynamics in survey data.

[8]In Appendix A we show that we arrive to a similar conclusion by analysing earnings growth conditional on previous earnings. The negative earnings/wage changes among workers who made an EE transitions have been documented previously in Jolivet et al. (2006) among others. Using the SIPP information on the reasons for leaving a job, we find that these changes are associated with both voluntary and involuntary transitions. Below we discuss this feature in the context of our model.

[9]Here recessions are defined as periods in which the HP-filtered unemployment rate is in the top 20% of realizations. In Appendix A we document the cyclicality of the earnings change distribution by defining recessions as periods defined by the NBER, without a meaningful change in our conclusions.

Figure 1: Earnings growth distribution in the cross-section and over the cycle

(a) Log-density of earnings changes (b) Quantile-wise cyclicality of earnings changes



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. Section 2.1 presents the details of the definition of earnings and worker transitions. Recessions are defined as periods in which the HP-filtered unemployment rate is in the top 20% of realizations. See Appendix A for robustness using the NBER definition of recessions and expansions.

earnings growth distribution is mainly characterised by its procyclical skewness. If recessions were to bring a level-change in the observed earnings growth distribution then we would observe a horizontal line at the average loss in earnings. If instead, recessions were characterized purely by countercyclical variance, we would observe a downward sloping curve crossing zero at the origin: losses in recessions would be worse meaning positive values below the 50th percentile, and gains in recessions would be higher meaning negative values above the 50th percentile.[10]

The key message from Figure 1 is therefore that the earnings growth distribution is characterized by long tails that exhibit very large fluctuations over the business cycle. These tails are disproportionately comprised of workers moving from one employer to another. Hence, to understand cyclical changes in the distribution, we need to understand its tails and the transitions that comprise it.

2.3 Implications of the canonical job ladder model

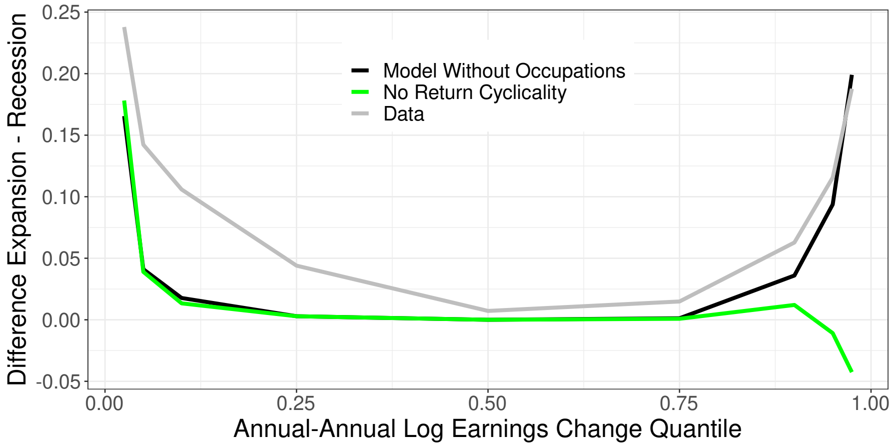
Given the prevalence of employer mobility on the tails of the earnings growth distribution, a natural place to start our investigation is to ask whether a simple extension to the canonical on-the-job search model originally proposed by Burdett (1979) is consistent with Figure 1. The canonical on-the-job search model is the backbone of many subsequent models that jointly study job transitions and non-trivial earnings/wage distributions.

To formalize the exercise, consider six transition probabilities: $\lambda_x^E, \lambda_x^U, \delta_x$ where x indexes the recession as $0, 1$. Workers lose their jobs and become unemployed with probability δ_x. They encounter job offers from unemployment with probability λ_x^U and draw a match-specific productivity ϵ from a known (and exogenous) distribution $\Gamma(.)$. The ϵ-productivity maps one-to-one to the earnings asso-

[10] Guvenen et al. (2014), Kurmann and McEntarfer (2018), Busch et al. (2021) and Harmenberg (2018), among many others, use administrative and survey data for the US, Germany, France, Sweden and Denmark, highlight that the main cyclical property of the aggregate annual earnings growth distribution is its procyclical skewness. Storesletten et al. (2004), using the PSID and after-tax earnings, imply that its countercyclical variance as the main property. Busch et al. (2021) and Busch and Ludwig (2020), however, show that the distribution of after-tax earnings growth exhibits procyclical skewness for both the US and Germany.

ciated with such a job offer. When employed, they draw a new ϵ with probability λ_x^E, such that with probability γ the worker decides whether to accept the new job or not; and with probability $1-\gamma$ he is forced to accept the new job, as long as it offers a payoff above the value of unemployment (see Jolivet et al., 2006, among others).[11] We structurally estimate this model by matching the average and the cyclical dynamics of the EE, EU and UE transition probabilities observed in the SIPP as well as the cross sectional earnings growth distribution depicted in Figure 1a, separately for EE employer movers, EUE employer movers and employer stayers. Appendix C provides all the details of the model, its estimation and fit to the data. In particular, it shows that the job ladder model is able to capture well the leptokurtosis of the earnings growth distribution, consistent with the results in Humber (2019) among others.[12] Here we present the cyclical properties of the implied earnings growth distribution. To do so, we simulate this model from 1990 to 2013 and change the recession cyclical indicator in periods in which the HP-filtered unemployment rate is in its highest 20%, the same definition used to construct Figure 1b.

Figure 2: Earnings growth distribution implied by the canonical job ladder model.



Note: The cyclical change of the earnings growth distribution is depicted as the difference between the expansion and recession annual earnings growth distribution. Recessions are defined as periods in which the HP-filtered unemployment rate is in the top 20% of realizations. Details of the estimation that generate the simulated earnings growth distributions can be found in Appendix C.

The green curve in Figure 2 shows the changes in the model's earnings growth distribution over the cycle. As above, we condition on a quantile of the earnings growth distribution and then subtract expansion from recession values. While the data shows that this distribution exhibits procyclical skewness as its main property, the job ladder model instead implies countercyclical variance. The intuition for these results focuses on unemployment transitions. The left tail falls in recessions because more workers transit into unemployment and have on average longer unemployment spells. However, note that the earnings associated with job loss are not large enough to fully capture the drop in the

[11]Our focus on match-specific shocks and not on worker and firm ex-ante heterogeneity is convenient since the unit of our analysis is the year-to-year difference in worker's earnings. Hence one would expect the effects of worker and firm fixed effects not to play a significant role in determining the cross-sectional distribution of earnings changes nor its cyclical behaviour.

[12]In essence the leptokurtosis arises because the nature of the job ladder is to have infrequent transitions, meaning that it generates significant density around zero earnings changes.

left tail. There is a very large gap between the simulated and the data distributions below the median. This arises as the model does not account for some of the large earnings losses observed among those individuals who had high pre-displacement earnings. The right tail exhibits two opposing effects. On the one hand, longer unemployment spells in recessions imply workers annual earnings fall. As these workers become re-employed their earnings then increase from a lower base and generate larger earnings growth. On the other hand, more opportunities to make EE transitions imply larger earnings growth in expansions. We find that the effect of workers moving out of unemployment dominates. Hence, flows in and out of unemployment dominate cyclical changes in the earnings growth distribution and predict both larger gains and losses in recessions.

A potential way for the job ladder model to generate procyclical skewness is to allow for cyclical changes in the returns to employer mobility, $\Gamma(.)$, in addition to cyclical changes in the mobility shocks, $\lambda_x^E, \lambda_x^U, \delta_x$. In order to identify cyclical changes in $\Gamma(.)$ we target the cyclicality of the earnings growth distribution as depicted in Figure 1b. Appendix C provides the details of this re-estimation. Figure 2 shows that this version of the model remains unable to generate larger earnings losses in recessions and hence does not improve the fit below the median. Earnings gains are now larger in expansions, creating procyclical skewness. However, the model consistently under-predicts the difference in the earnings gains between expansions and recessions, except at the very top end.

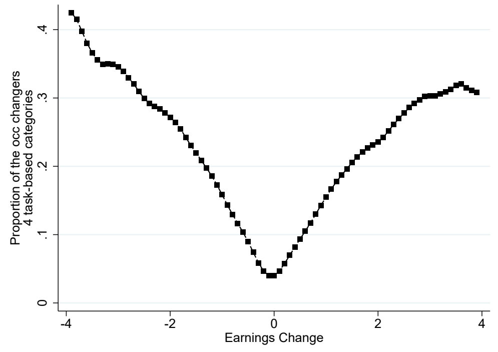
The lack of fit arises as the job ladder model (with cyclical mobility shocks and returns to mobility) remains unable to fully resolve the trade-off between reproducing the observed worker transitions flows and the earnings growth distribution over the cycle. The tension arises from the relationship between unemployment and earnings changes. By reproducing the observed UE transition probability in expansions and recessions, the model already implies a degree of cyclical change in the earnings losses through unemployment. This is, however, not sufficient to get the full dynamics of earnings changes, particularly among the larger earnings losses observed in recessions. In order to generate the latter the model either has to have (i) a steep ϵ job ladder, which comes into tension with the observed earnings changes associated with EE flows, or (ii) counterfactually long unemployment durations, which comes into tension with the cyclicality of UE flows.

A key contribution of the paper is to demonstrate that occupation switching and not employer switching is the main feature behind the tails of the earnings growth distribution in the cross-section and over the cycle. Further, when accounted for in a job ladder model it is able to replicate very closely the observe cyclical changes of the distribution of annual earnings growth.

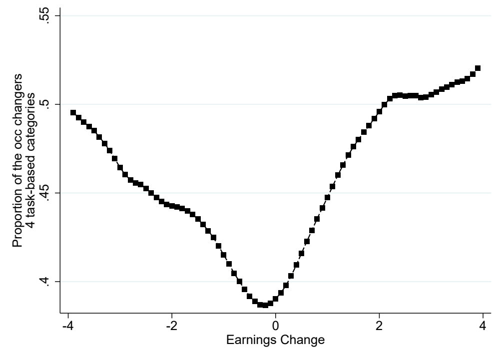
3 The importance of occupational mobility

Figure 3a depicts the overall probability of an occupational change associated with a given value of earnings growth. It shows that the fat tails of the earnings growth distribution depicted in Figure 1a are also associated with a high probability of an occupational change. Small earnings changes centred around zero, however, are associated with a much smaller probability of an occupational change.

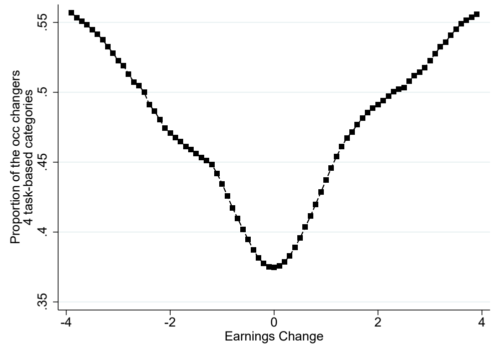
Although the large difference in the probability of an occupational move can be accounted for by the larger propensity to change occupations among employer movers (see Moscarini and Thompson, 2007, and Carrillo-Tudela and Visschers, 2021), Figure 3b show that the same pattern remains when only considering employer movers. Figures 3c and 3d further show that this pattern holds when analysing separately those individuals who changed employers through an EE or a EUE transition. This evidence thus shows that large negative or positive earnings changes are associated with a higher propensity to change occupations than smaller earnings changes.



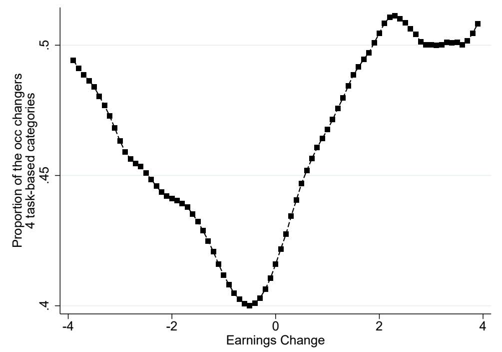
(a) All workers



(b) Employer movers



(c) EE movers



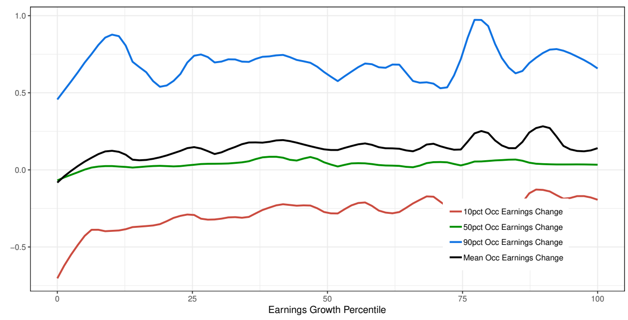
(d) EUE movers

Source: Survey of Income and Program Participation (SIPP).

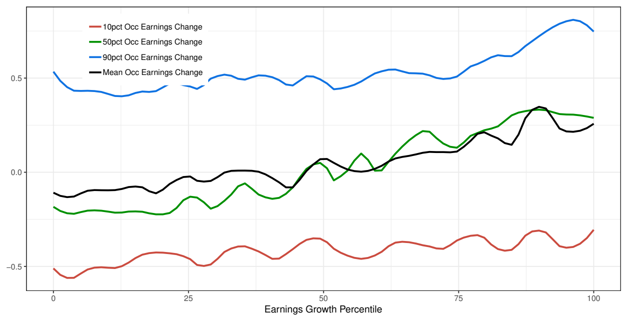
Figure 3: Earnings Growth Distribution by Occupation Mobility

To investigate further the role of occupational change on the the tails of the earnings growth distribution, we calculate the variance of this distribution as the proportion of the sum of squared deviations $\sum_K \sum_{o \in K} (\Delta w_o - E_{pop}[\Delta w])^2$ that originates from a group K of workers who share an occupation and employer transition (for example, the set of workers with an EE transition and an occupation switch), and divide it by the overall sum of squared deviations $\sum_{pop} (\Delta w_o - E_{pop}[\Delta w])^2$. We find that occupation movers contribute about 50% of the overall variance of earnings growth, even though the share of occupation movers in our sample is about 17%, where the biggest share of this contribution arises from EUE transitions. As we move away from the tails and consider progressively the variance between the 0.95-0.05, 0.9-0.1 and 0.75-0.25 percentiles, the contribution of occupation movers and employer movers diminishes, reaching 15% when considering the interquartile range.[13]

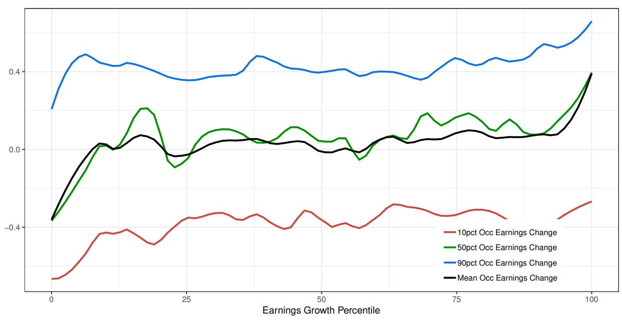
Earnings changes associated with occupational mobility can arise from workers moving from occupations with higher average earnings to occupations with lower average earnings, and vice versa, and from workers changing occupations due to idiosyncratic factors that can be related to their own careers. To investigate the extent of these two sources of earnings growth, we derive conditional occupational earnings averages by estimating an earnings regression, which includes a quadratic for potential experience, dummies for education, gender and race and a set of dummies for the task-based occupational categories. We treat the coefficients on these dummies as the occupation-specific earnings effect. For each occupational switcher we then calculate the difference between these coefficients at their source and destination occupation. Moving to occupations with a higher earnings effect can be considered as "climbing up the occupational ladder".



(a) Employer movers: EE



(b) Employer movers: EUE



(c) Employer stayers

Figure 4: Occupational ladder

Figure 4 then ranks occupational switchers by their earnings growth and relates these workers' rank to the distribution of the differences in occupational earnings effects. This is done for each type of labour market transition. Figure 4b shows an occupation ladder for EUE movers, where the mean, median, 90th and 10th percentiles are all upward sloping. This implies that workers with higher earnings growth are more likely to move to higher paying occupations. Figure 4c also shows a similar ladder for employer stayers. For EE movers, however, the estimates depicted in Figure 4a only

[13] Note that workers on average do seem to gain by switching occupations. In particular, employer stayers and EE movers who switched occupations gain on average about 4% and 26%, while employer stayers and EE movers gain on average about 1% and 16% when not switching occupations. For those workers who experienced EUE transitions, we find that occupation movers and stayers lose a very similar amount (around -34%).

show a noticeable occupational ladder at the mean and the 10th percentile. Although occupational ladders are visible, the key feature of these figures is that these ladders have a very subdued effect on the distribution of changes in the occupational earnings effect. That is, large earnings changes are associated with larger movements both up or down the occupational ladder across all types of labour market transitions, suggesting that a more important factor is the idiosyncratic motive for occupational change rather than average occupation-wide earnings differences.

Occupation switching and cyclical earnings growth To highlight the role of occupation mobility in the cyclical change of earnings growth, Figure 5 decomposes the difference in the earnings growth distribution between expansions and recessions by whether workers were occupational movers or stayers conditioning on employer change. As in Figure 1b we subtract the expansion from the recession earnings growth distribution.

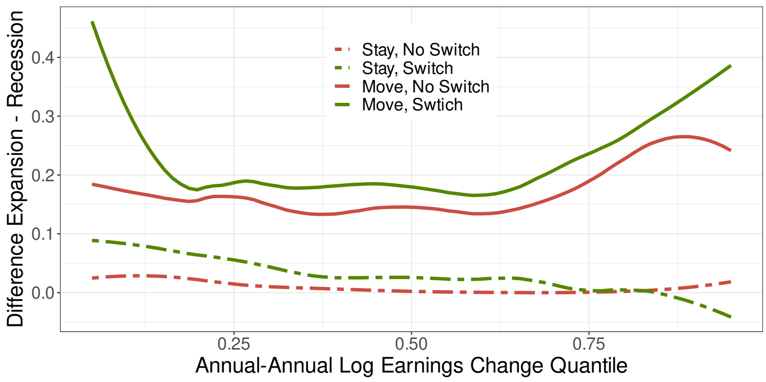
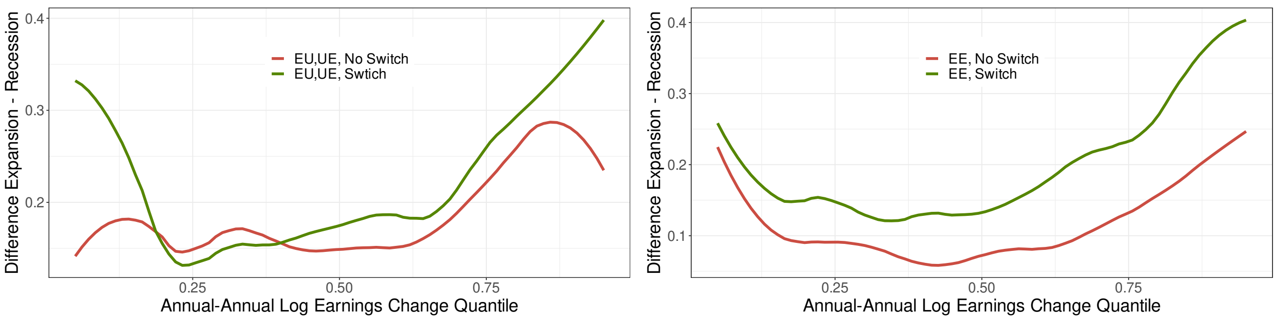


Figure 5: Cyclical Earnings Growth Distribution by Occupation Switching

Among employer stayers we observe that occupation movers have larger earnings losses during recessions than occupation stayers. However, these losses are modest, increasing only slightly towards the bottom of the distribution. Those who changed occupations within the same employer also exhibit larger but also modest earnings gains in expansions. However, at the very top of the distribution (above the third quartile) we observe the opposite behaviour. In recessions those who changed occupations within the same employer receive larger earnings gains relative to occupation stayers. Overall this leads to the earnings growth distribution of employer stayers/occupation movers to exhibit countercyclical variance. For occupational/employer stayers we instead observe a slight level-change between recession and expansions, whereby earnings losses in recessions are of similar magnitude as earnings gains in expansions.

When considering employer movers we observe larger earnings losses during recessions and larger earnings gains during expansions relative to employer stayers. However, those workers who at the same time changed their occupation exhibit much larger losses in recessions and these become even larger at the bottom end of the distribution. Further, they also exhibit much larger gains in expansions, which also become even larger at the top end of the distribution. These cyclical changes mimic quite closely that of the overall earnings growth distribution depicted in Figure 1b and implies that the earnings growth distribution of employer/occupation movers is characterised by its procyclical skewness. In contrast, among those who changed employers but did not change occupation we observe a nearly constant increase in earnings losses during recessions, while an increase in earnings gains during expansions. That is, these workers do not seem to experience an increase in the downside earnings risk of changing employers during recessions.



(a) Employer movers: occupational movers

(b) Employer movers: occupational stayers

Figure 6: The Cyclicality of the Earnings Growth - Employer movers and Occupation movers/stayers

To investigate these dynamics further Figure 6 decomposes the cyclicality of the earnings growth distribution among employer movers by their type of transition: EUE and EE. It is clear from this evidence that those who simultaneously changed their occupation and employer either through an EUE or EE transition exhibit earnings growth distributions characterised by their procyclical skewness. Perhaps unsurprisingly, during recessions the earnings losses among those occupation/EUE movers are more pronounced than among occupation/EE movers. During expansions, however, both type of transitions lead to similar increases in earnings gains. Among employer movers/occupation stayers only those who experienced an EE transition are the ones that exhibit an earnings growth distribution characterised by procyclical skewness. Those who changed employers through an EUE transitions exhibit a level-change in the their earnings losses during recessions, but an increase in earnings gains during expansions. Since we observe more EUE transitions during recessions, these pattern dominates the cyclical change of the downside earnings risk of the earnings growth distribution among employer movers/occupation stayers as depicted in Figure 5.

Taken together the above evidence then strongly suggests that the procyclical skewness observed in the overall earnings growth distribution depicted in Figure 1b mainly arises due to a combination of larger recessionary earnings losses among those occupation movers who changed employers through EUE (and to a lesser extent EE) transitions, and the larger earnings gains during expansions among those occupational movers who changed employers through either EUE or EE transitions.

4 Theoretical Framework

The empirical patterns documented above and the failure of the job ladder model to account for these patterns, highlight the need for incorporating occupational mobility to better explain the cyclicality of the earnings growth distribution. The empirical analysis, however, does not allow us to measure the relative importance of occupation relative to employer mobility, or to investigate whether the cyclical changes in the tails of the distribution are driven by changes in the expected returns to mobility or due to changes in the flow of workers reallocating along these two dimensions. To address these issues we now develop and structurally estimate a job search theory of occupational and employer mobility building on the framework presented in Section 2.3.

4.1 Environment

Time is discrete $t = 0, 1, 2, \ldots$ A mass of infinitely-lived, risk-neutral workers with common discount rate β is distributed over a finite number of occupations $o = 1, \ldots, O$. At any time t, workers within a given occupation can be either employed or unemployed and can differ in the following dimensions: an idiosyncratic firm-match productivity, ϵ_t, an idiosyncratic occupation-match productivity, z_t, and occupation-specific human capital, x_h.

The idiosyncratic ϵ-productivity determines how well the worker is doing with the employer he is currently working. This productivity follows a common and exogenous first-order stationary Markov process, with transition law $\Gamma(\epsilon_{t+1}|\epsilon_t)$. The ϵ-productivity realizations affect a worker only in employment and will allow us to generate employer-to-employer mobility. The idiosyncratic z-productivity represents a worker's "career match" and determines how well he is doing in the current occupation (see Neal, 1999). These productivities also follow a common and exogenous first-order stationary Markov process, with transition law $F(z_{t+1}|z_t)$. The z-productivity realizations affect workers both in employment and unemployment and will drive idiosyncratic occupational mobility and any earning growth associated with this type of occupational mobility. In addition, workers accumulate occupational-specific human capital through a learning-by-doing process. In period t an employed worker with human capital level x_h increases his human capital to x_{h+1} with probability $\chi_e(x_{h+1}|x_h)$, where $h = 1, \ldots, H$. A worker's occupational-specific human capital may also depreciate with unemployment. An unemployed worker with human capital level x_h decreases his human capital to x_{h-1} with probability $\chi_u(x_{h-1}|x_h)$ $h = 1, \ldots, H$.

Business cycles are modelled through fluctuations in the economy-wide productivity, where A_t denotes this aggregate productivity. We assume A_t follows a first-order stationary auto-regressive process. We also allow some occupations to be more attractive than others in terms of their occupation-wide productivities. Let $p_{o,t}$ denote the occupation-wide productivity of occupation o at time t and assume it follows an auto-regressive process. Let $\mathcal{P}_{O,t} = \{p_{o,t}\}_{o=1}^{O}$ denote the vector containing all the occupation-wide productivities at time t.

Production and earnings Firms are passive agents in our model. They only use labour in the production process under a constant return to scale technology and face no capacity constraints in hiring workers. The output of a worker characterised by (z_t, x_h, ϵ_t) in occupation o is given by $y(A_t, p_{o,t}, \epsilon_t, z_t, x_h)$. This production function is increasing and continuous in all of its arguments. To keep the analysis as parsimonious as possible we assume that workers' earnings are also represented by an exogenous function of their current productivities, $\hat{w}(A_t, p_{o,t}, \epsilon_t, z_t, x_h)$, which is strictly increasing and continuous in all of its arguments. This assumption implies that any change in hours worked and/or hourly wages are captured (in reduced form) through EE and EUE transitions and changes in workers' productivities.[14] Note, however, that the evolution of worker's output and earnings in the model remain endogenous as workers make employer and occupational transitions decisions that affect their productivities. When unemployed workers receive b each period.

Job destruction Jobs can break-up endogenously as workers may decide to quit to another employer in the same or in a different occupation. This can also occur if workers' productivities fall sufficiently such that they prefer to become unemployed within their occupation. Once unemployed, a worker can decide whether to change occupation or not. In addition, jobs can be destroyed due to exogenous reasons. We consider two sources of exogenous job destruction: one due to worker-firm idiosyncratic reasons and the other due to worker-occupation idiosyncratic reasons. Let $\delta_\epsilon(A_t)$ denote the probability that an employed worker loses his firm-match productivity and is forced to transit into unemployment within his occupation. Similarly, let $\delta_z(A_t)$ denote the probability that a worker loses his occupation-match productivity and is forced to change occupation through unemployment. In the spirit of Huckfeldt (2021) we interpret the latter as "obsolescence shocks".[15]

Searching within and across occupations Unemployed and employed workers face a probability $\lambda_u(A_t)$ and $\lambda_e(A_t)$ of meeting a firm when searching for jobs, respectively. Once a meeting takes place, a worker draws an initial firm-match productivity $\tilde{\epsilon}$ from $\Gamma_A(.)$, which we allow to shift according to the state of the business cycle to capture the possible cyclical changes in the quality of the worker-firm relationships and hence the returns to employer mobility. If the worker finds the firm-match productivity sufficiently attractive, production takes place until the match is destroyed. Otherwise, the worker remains in his current employment state.

Search across occupations is modelled following an imperfect directed search technology in the spirit of Fallick (1993). Occupation mobility entails the benefit of re-starting a worker's z-productivity process, but it comes at the loss of the accumulated occupational-specific human capital upon reallocation. Workers draw their initial career match in any occupation from $F_A(.)$, which we also allow to shift according to the state of the business cycle in order to capture possible cyclical changes in the quality of the worker-occupation relationships. Given differences in occupation-wide labour market conditions $p_{o,t}$, workers are not indifferent about which occupation to draw the new z-productivity.

[14] Di Nardi et al. (2019), Halvorsen et al. (2020) and Busch et al. (2021) using data from the Netherlands, Norway, Sweden and Germany, show the importance of both hourly wages and hours worked in driving the cyclical properties of the earnings growth distribution. Busch et al. (2021), for example, find that hourly wages and hours worked contribute equally to the procyclical skewness of the earnings growth distribution. Here we use a flexible functional form to match the earnings process observed in the data without assuming a particular wage/hours determination process.

[15] This type of job destruction shock allows the model to capture the large, negative earnings changes observed across individuals who were previously employed in high paying jobs, experienced an EUE transition with an occupational switch and ended up re-employed in a lower paying job. Huckfeldt (2021) uses "obsolescence shocks" to match a similar feature in his data. The key difference is that in our setting the obsolescence shock occurs during employment, rendering the worker unemployed and forcing him to change occupations; while in Huckfeldt (2021) this shock hits the worker during unemployed. Further, allowing the obsolescence shock to vary with the business cycle allows us to capture that during recessions we observe more frequent and larger earnings losses accompanied by occupational switching. Guvenen et al. (2015) also document large negative earnings shocks among those with high earnings and labels them "disaster" shocks.

We assume that within each period a worker can receive at most one z-productivity. The worker is endowed with a unit measure of search intensity which he must divide across occupations in order to maximise his chances of receiving such a z. In particular, a worker leaving occupation o has to decide which proportion $s^i_{\tilde{o}}$ of his time to devote to obtain a z-productivity from occupation $\tilde{o} =\neq o$, where $i = U, E$ denotes the worker's employment status. Let $\mathcal{S}^i$ denote a vector of $s^i_{\tilde{o}}$ for all $\tilde{o} \in O^-$, where O^- denotes the set of remaining occupations such that $\sum_{\tilde{o}\in O^-} s^i_{\tilde{o}} = 1$. The probability that a worker, currently in occupation o, receives a new z from an occupation $\tilde{o}$ is given by $\alpha(s^i_{\tilde{o}}, o)$, where $\alpha(., o)$ is a continuous, weakly increasing and weakly concave function with $\sum_{\tilde{o}\in O^-} \alpha(s^i_{\tilde{o}}, o) \leq 1$, for all $o \in O$. The latter implies that the probability of not receiving a new z is given by $1-\sum_{\tilde{o}\in O^-} \alpha(s^i_{\tilde{o}}, o)$.

In the case of receiving the new z-productivity and changing occupation, an unemployed worker starts with human capital x_1 and starts searching for jobs the same period in which reallocation takes place. If no meeting takes place, then the worker remains unemployed in the new occupation. An employed worker also starts with human capital x_1 and is able to search for jobs straight away. Once this worker meets a firm we assume that with probability γ he is able to decide whether to accept the new job or not; and with probability $1 - \gamma$ he is forced to accept the new job, as long as it offers a payoff above the value of unemployment. If no meeting takes place this worker then stays with his current employer but in the new occupation. The worker's idiosyncratic productivities and occupational human capital then evolve as described above. Workers can decide to reallocate once again, but they must sit out one period in their new employment state before doing so. In case the worker does not receive a z-productivity he retains his current occupation and employment status for the rest of the period and then starts the occupation mobility process once again.

Timing and state space The timing of the events is summarised as follows. At the beginning of the period the new values of A, $\mathcal{P}_O$, z, x and ϵ are realised. After these realisations, the period is subdivided into four stages: separation, reallocation, search and matching, and production. Let $\mathcal{G}$ denote the joint productivity distribution of unemployed and employed workers over all occupations. Let $\mathcal{G}^j$ denote this distribution at the beginning of stage j. At this point it is useful to define the vector $\Omega_t = \{A_t, \mathcal{P}_{O,t}, o, z_t, x_h\}$. To simplify notation we leave implicit the time subscripts, denoting the following period with a prime. We also leave implicit the dependence of output, wages and the exogenous match break-up and job finding probabilities on productivities as described above.

4.2 Worker's problem

Unemployed workers Consider an unemployed worker currently characterised by (z, x_h, o). The value function of this worker at the beginning of the production stage is given by

$$W^U(\Omega) = b + \beta \mathbb{E}_{\Omega'}\Big[(1-\delta'_z) \max_{m^U(\Omega')} \Big\{\rho^U(\Omega')R^U(\Omega') + (1-\rho^U(\Omega'))\Big[(1-\lambda'_U)W^U(\Omega') + \lambda'_U \int_{\underline{\epsilon}}^{\overline{\epsilon}} \max_{\phi^U(\Omega')} \Big\{\phi^U(\Omega')W^E(\tilde{\epsilon}, \Omega') + (1-\phi^U(\Omega'))W^U(\Omega')\Big\} d\Gamma_{A'}(\tilde{\epsilon})\Big]\Big\} + \delta'_z R^U(\Omega')\Big]. \tag{1}$$

The value of unemployment consists of the flow benefit of unemployment b, plus the discounted expected value of being unemployed at the beginning of next period's reallocation stage, where $\rho^U(\Omega)$

takes the value of one when the unemployed worker decides to search across occupations and zero otherwise. This decision is captured by the choice between the expected net gains from drawing a new $\tilde{z}$ in another occupation and the expected payoff of remaining in the current occupation. The latter entails meeting a firm with probability λ_U, drawing a firm-match productivity $\tilde{\epsilon}$ and deciding whether to accept it or not. The job acceptance decision is captured by $\phi^U(\Omega)$, which takes the value of one if the worker accepts the job and zero otherwise.

The expected net value for an unemployed worker of searching across occupations, $R^U(\Omega)$, is given by

$$\begin{aligned} R^U(\Omega) &= \max_{\mathcal{S}^U(\Omega)} \Bigg(\sum_{\tilde{o}\in O^-} \alpha^U(s^U_{\tilde{o}}(\Omega)) \int_{\underline{z}}^{\overline{z}} \Big[\lambda_U \int_{\underline{\epsilon}}^{\overline{\epsilon}} \max_{\phi^U(\tilde{\Omega}_1)} \Big\{\phi^U(\tilde{\Omega}_1)W^E(\tilde{\epsilon},\tilde{\Omega}_1) + (1-\phi^U(\tilde{\Omega}_1))W^U(\tilde{\Omega}_1)\Big\} d\Gamma_{A'}(\tilde{\epsilon}) \\ &+ (1-\lambda_U)W^U(\tilde{\Omega}_1)\Big] dF_{A'}(\tilde{z}) + \Bigg(1 - \sum_{\tilde{o}\in O^-} \alpha^U(s^U_{\tilde{o}}(\Omega))\Bigg) W^U(\Omega)\Bigg), \end{aligned} \tag{2}$$

where the maximization is subject to $s^U_{\tilde{o}} \in [0,1]$ and $\sum_{\tilde{o}\in O^-} s^U_{\tilde{o}} = 1$, such that $\tilde{\Omega}_1 = \{\tilde{z}, x_1, \tilde{o}, A, \mathcal{P}_O\}$. Note that this expression incorporates the value of immediately searching for an employer in the new occupation under the assumption that once a worker receives a new z in a new occupation, he will move to that occupation and enter the search and matching stage during the current period. It is only when the worker does not receive a new z that he remains unemployed in the old occupation and goes directly to the production stage.

Employed workers Now consider an employed worker currently characterised by (z, x, ϵ, o). The expected value of employment at the beginning of the production stage is described by

$$\begin{aligned} W^E(\epsilon,\Omega) &= w + \beta\mathbb{E}_{\epsilon',\Omega'}\Big[\delta'_z R^U(\Omega') + \delta'_\epsilon W^U(\Omega') + (1-\delta'_z-\delta'_\epsilon) \max_{d(\epsilon,\Omega)} \Big\{d(\epsilon',\Omega')W^U(\Omega') \\ &+ (1-d(\epsilon',\Omega')) \max_{\rho^E(\epsilon',\Omega')} \Big\{\rho^E(\epsilon',\Omega')R^E(\epsilon',\Omega') + (1-\rho^E(\epsilon',\Omega'))\hat{W}^E(\epsilon',\Omega')\Big\}\Big\}\Big]. \end{aligned} \tag{3}$$

The value of employment consists of the earnings, plus the discounted value of being employed at the beginning of next period's separation stage, where the worker faces exogenous job loss with probability $\delta_\epsilon + \delta_z$. Otherwise, $d(\epsilon,\Omega)$ takes the value of one if the worker decides to separate into unemployment and zero otherwise. If the worker remain employed, he enters the reallocation stage and must decide whether to search for jobs in a different occupation or not. This reallocation decision is summarised in $\rho^E(\epsilon,\Omega)$, such that it take the value of one when $R^E(\epsilon,\Omega) \geq \hat{W}^E(\epsilon,\Omega)$ and the value of zero otherwise.

In the case of no reallocation, the expected value of employment at the beginning of the search and matching stage in the current occupation is

$$\begin{aligned} \hat{W}^E(\epsilon,\Omega) &= \int_{\underline{\epsilon}}^{\overline{\epsilon}} \Big[\gamma\lambda_E \max_{\phi^E(\epsilon,\Omega)} \Big\{\phi^E(\epsilon,\Omega)W^E(\tilde{\epsilon},\Omega) + (1-\phi^E(\epsilon,\Omega))W^E(\epsilon,\Omega)\Big\} \\ &+ (1-\gamma)\lambda_E \max_{d(\tilde{\epsilon},\Omega)} \Big\{d(\tilde{\epsilon},\Omega)W^E(\tilde{\epsilon},\Omega) + (1-d(\tilde{\epsilon},\Omega))W^U(\Omega)\Big\}\Big] d\Gamma_{A'}(\tilde{\epsilon}) \\ &+ (1-\lambda_E)W^E(\epsilon,\Omega), \end{aligned} \tag{4}$$

where, with probability $\gamma\lambda_E$, the decision to accept or reject the new ϵ is captured by $\phi^E(\epsilon,\Omega)$ which takes the value of one if the worker accepts the job and zero otherwise. The job acceptance decision truncates the distribution of ϵ such that $W^E(\tilde{\epsilon},\Omega) > W^E(\epsilon,\Omega)$. Note that in this case the worker's fall back position is keeping his job with the current employer and value of ϵ. With probability $(1-\gamma)\lambda_E$, however, the worker is force to take the new ϵ' in a different employer, as long as this gives a value higher than unemployment. This allows us to capture within-occupation employer transitions that are associated with earnings cuts and rises. With probability $1-\lambda_E$ the worker does not meet a new employer and remains in his current state.

If instead the worker decides to reallocate, the expected net value of searching across occupations is given by

$$R^E(\epsilon,\Omega) = \max_{\mathcal{S}^E(\epsilon,\Omega)} \Bigg(\sum_{\tilde{o}\in O^-} \alpha^E(s^E_{\tilde{o}}(\epsilon,\Omega)) \int_{\underline{z}}^{\overline{z}} \Big[\int_{\underline{\epsilon}}^{\overline{\epsilon}} \Big[\gamma\lambda^c_E \max_{\phi^E(\epsilon,\Omega)} \Big\{ \phi^E(\epsilon,\Omega) W^E(\tilde{\epsilon},\tilde{\Omega}_1) + (1-\phi^E(\epsilon,\Omega)) W^E(\epsilon,\tilde{\Omega}_1) \Big\}$$
$$+ \ (1-\gamma)\lambda_E \max_{d(\tilde{\epsilon},\tilde{\Omega}_1)} \Big\{ d(\tilde{\epsilon},\tilde{\Omega}_1) W^E(\tilde{\epsilon},\tilde{\Omega}_1) + (1-d(\tilde{\epsilon},\tilde{\Omega}_1)) W^U(\tilde{\Omega}_1) \Big\} \Big] d\Gamma_{A'}(\tilde{\epsilon})$$
$$+ \ (1-\lambda_E) W^E(\epsilon,\tilde{\Omega}_1) \Big] dF_{A'}(\tilde{z}) + \Bigg(1 - \sum_{\tilde{o}\in O^-} \alpha^E(s^E_{\tilde{o}}(\epsilon,\Omega))\Bigg) W^E(\epsilon,\Omega) \Bigg), \tag{5}$$

where the maximization is subject to $s^E_{\tilde{o}} \in [0,1]$ and $\sum_{\tilde{o}\in O^-} s^E_{\tilde{o}} = 1$, and $\tilde{\Omega}_1 = \{\tilde{z}, x_1, \tilde{o}, A, \mathcal{P}_O\}$. Conditional on drawing a z-productivity from another occupation $\tilde{o}$, the worker meets a new employer with probability $\gamma\lambda_E$, draws a new value of ϵ and decides whether to accept it or not. If the offer is rejected, the worker remains with his current employer but switches to occupation $\tilde{o}$. With probability $(1-\gamma)\lambda^c_E$, however, the worker is forced to take the new value of ϵ' with a new employer in occupation $\tilde{o}$, as long as the value of this employment remains above the value of unemployment in the new occupation. Otherwise, the worker transits into unemployment in occupation $\tilde{o}$. With probability $1-\lambda_E$, the worker remains with his current employer, retains his current value of ϵ, but changes to occupation $\tilde{o}$. This formulation, then allows us to capture within and across employer occupational mobility, such that in both cases workers can end up with positive or negative earnings growth as observed in the data. The last term of equation (5) describes the case in which the worker does not receive a new value of z and hence remains with his current employer and occupation, retaining his start of the period values of ϵ and z.

4.3 Worker flows and the earnings distribution

The evolution of the distribution $\mathcal{G}$ 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 and λ_E coupled with workers' job separation and acceptance decisions $d(\epsilon,\Omega)$, $\phi^E(\epsilon,\Omega)$, $\phi^U(\epsilon,\Omega)$ and occupational mobility decisions $\rho^U(\Omega)$, $\rho^E(\epsilon,\Omega)$, $\mathcal{S}^E(\epsilon,\Omega)$ and $\mathcal{S}^U(\Omega)$ as described above. To obtain the laws of motions of unemployed and employed workers 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 $u^j_t(z, x_h, o)$ 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. As deriving these measures is cumbersome and they do not add much economic insight we relegate them to Appendix B.

These measures, however, are necessary to 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

$$G_t(w|A_t, \mathcal{P}_{O,t}) = \sum_{o \in O} \sum_{h \in H} \int_{\underline{z}}^{\overline{z}} \int_{\underline{\epsilon}}^{max\{\underline{\epsilon}, \tilde{\epsilon}=\hat{w}^{-1}(w,A,p_o,z,x_h)\}} \hat{w}(A, p_o, \epsilon, z, x_h) e_t^p(\epsilon, z, x_h, o) d\epsilon dz, \quad (6)$$

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 (6) 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. The key objective of the model is to allows us to decompose the variance of G and investigate the relative contributions of occupational shocks z and p_o, employer shocks ϵ and the aggregate shocks A. In addition, we want to use $G_t(w|A_t, \mathcal{P}_{O,t})$ to investigate the roles of changes in the shocks underlying worker mobility, δ_ϵ, δ_z, λ_U and λ_E, and in the returns to employer and occupational mobility as given by the shocks, p_o, z, ϵ, in determining the cyclical behaviour of G. We now turn to estimate the model using the patterns described in Section 2 and present the aforementioned decompositions.

5 Quantitative Analysis

We assume a period to be equal to a month and set the discount rate $\beta = 0.997$. We also set $O = 4$, consistent with the task-based categories (Non-Routine Cognitive, Routine Cognitive, Non-Routine Manual and Routine Manual) used to aggregate occupations in Section 2, such that $o \in \{NRC, RC, NRM, RM\}$. The following functional form assumptions yield a set of parameters that we jointly estimate on data from the SIPP based on the earnings growth patterns documented in Section 2 as well as on worker labour market flows across employers and occupations computed from the SIPP. We relegate to Appendix C all the details of the estimation procedure.

5.1 Parametrization

To solve the model we impose several convenient functional forms. Particularly important is how we design the function $\alpha(.)$, because they determine how workers switch and search across occupations. Further, the distributional assumptions on z and ϵ will be important because they essentially determine how the model will generate the earnings growth distributions conditional on previous labour market transition. Because we only observe accepted matches, these distributional assumption will be crucial for identification.

We let $\alpha^i(s_{\tilde{o}}) = \alpha_0 e^{\alpha_{\tilde{o}}\alpha_1^i} s_{\tilde{o}}^{1-\alpha_1^i}$, where occupation $\tilde{o} \in O^-$ denotes the search direction, i the worker's labour force status and $s_{\tilde{o}}$ denotes search intensity. This functional form is useful as the first order condition for $s_{\tilde{o}}^*$ is given by $\alpha'(s_{\tilde{o}}^*)\Big(\Psi^U(\tilde{\Omega}_1) - W^U(\Omega)\Big) = \mu$, where μ denotes the multiplier on $\sum_{\tilde{o}\in O^-} s_{\tilde{o}} = 1$. Together with the latter feasibility constraint, it implies that the search intensity takes a form similar to the Gumbel-distributed additive random utility model. 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

$$s_{\tilde{o}}^* = \frac{e^{\frac{1}{\alpha_1^i}\log\left(\Psi^U(\tilde{\Omega}_1) - W^U(\Omega)\right)}}{\sum_{\tilde{o}\in O^-} e^{\frac{1}{\alpha_1^i}\log\left(\Psi^U(\tilde{\Omega}_1) - W^U(\Omega)\right)}}, \tag{7}$$

for each $i = U, E$ and where $\tilde{\Omega}_1 = \{\tilde{z}, x_1, \tilde{o}, A, \mathcal{P}_O\}$ and

$$\begin{aligned}\Psi^U(\tilde{\Omega}_1) &= \int_{\underline{z}}^{\overline{z}} \Big[\lambda_U^c \int_{\underline{\epsilon}}^{\overline{\epsilon}} \max_{\phi^U(\tilde{\Omega}_1)} \Big\{\phi^U(\tilde{\Omega}_1) W^E(\tilde{\epsilon}, \tilde{\Omega}_1) + (1-\phi^U(\tilde{\Omega}_1)) W^U(\tilde{\Omega}_1)\Big\} d\Gamma(\tilde{\epsilon}) \\ &+ (1-\lambda_U^c) W^U(\tilde{\Omega}_1)\Big] dF(\tilde{z}).\end{aligned}$$

With a more general calibration, $\alpha_{\tilde{o}}$ differing across occupational directions in order to match the observed net flows, we end up with a multiplier that scales the search direction. Combined with the additive noise affecting the choice of ρ^U, ρ^E, which we use to smooth our approximate solution, this means the search direction problem takes a similar form to a nested, multinomial logit discrete choice model. In this setting, the parameter α_1^i helps determine the extent to which search is more or less directed, very similar to the variance of a Gumbel utility shock determines the dispersion of choices in the analogous logit model. A value closer to zero implies search becomes more directed as differences in the returns across occupations get amplified; while as α_1^i goes to infinity search becomes increasingly random, as workers weight all occupations more equally. The parameter α_0 is a scaling factor to guarantee the proper arrival rates, but does not play a role in the marginal choice of search direction. Similarly, the parameter $\alpha_{\tilde{o}}$ scales the probability of moving from occupation o to occupation $\tilde{o} \neq o \in \{NRC, RC, NRM, RM\}$. In Appendix C we provide a more detailed analysis of the relationship between our search across occupations technology and the Gumbel-distributed additive random utility model and well as a derivation of (7).

We parametrise the aggregate productivity shock, A, such that $A_{t+1} = \rho_A A_t + \upsilon_{t+1}$, where υ is assumed to be white noise with variance σ_A. We let A_I represent a cyclical indicator function which takes the value of one when the economy is in an expansion and zero otherwise.[16] The occupation-wide productivity shock, p_o, is parametrised such that $p_{o,t+1} = \tilde{p}_o + \rho_p p_{o,t} + \upsilon_{o,t+1}$ for all $o \in O$ where $\tilde{p}_o$ is a time-invariant occupation specific productivity and υ_o is assumed to be white noise with variance σ_p. Occupation-specific human capital accumulation follows a two state process, such that workers start with productivity x_1 and then move to x_2 with probability $\chi(x_2)$. To simplify we assume no occupational human capital depreciation while unemployed.

[16]To simplify computation we approximate the AR(1) process describing the dynamics of aggregate productivity by a two point distribution. Expansions are define when the aggregate productivity takes its high value, which in the estimation occurs in 80% of the times.

The occupation-match specific productivity shock is such that $E[z_{t+1}|z_t] = (1-\rho_z)z_t + \rho_z \upsilon_{z,t+1}$, where υ_z is distributed following $\tilde{F}(.)$, which we parametrize as a Weibull distribution with shape and scale parameters ν_z and σ_z. Upon a decision to switch occupations new values of z are then drawn from $F(z) = (1-A_I)\tilde{F}(z) + A_I[\omega_z \tilde{F}(z) + (1-\omega_z)(\frac{z_A - \underline{z}}{\bar{z}-\underline{z}})]$, where during recessions the reallocating worker draws z from a convolution between $\tilde{F}(.)$ and the uniform distribution $\frac{z_A-\underline{z}}{\bar{z}-\underline{z}}$. We assume that the firm-match specific productivity ϵ remains constant during the duration of the match and only changes upon a voluntary or involuntary employer-to-employer transition. This is motivated by the small variation in annual earning changes observed among employer stayers. Workers draw a new ϵ from $\Gamma(.)$, which is also allowed to shift during recessions in a similar way as $F(.)$. In this case, $\Gamma(\epsilon) = (1-A_I)\tilde{\Gamma}(\epsilon) + A_I[\omega_\epsilon \tilde{\Gamma}(\epsilon) + (1-\omega_\epsilon)(\frac{\epsilon_A - \underline{\epsilon}}{\bar{\epsilon}-\underline{\epsilon}})]$, where $\tilde{\Gamma}(.)$ is parametrized as a Double Exponentially-Modified Gaussian distribution (a normal distribution with exponential tails on both sides) with mean normalised to zero, central variance σ_ϵ and shape parameters lt_ϵ, rt_ϵ governing the exponential distributions describing the left and right tails, respectively. The mixtures $F(.)$ and $\Gamma(.)$ allows us to change the skewness during recessions through z_A and ϵ_A, and to change the variance through ω_z and ω_ϵ. The distributional choice for $\Gamma(.)$ allows for arbitrary skewness and kurtosis, which are both features of the earnings growth distribution in the data.

The job meeting probabilities are parametrised as $\lambda_i(A_I) = \lambda_0^i e^{\lambda_1^i A_I}$, where $i = U, E$ is the employment status indicator. For those who have just switched occupations, we allow for (potentially) different job meeting probabilities $\lambda_i^c(A_I) = \lambda_0^{c,i} e^{\lambda_1^{c,i} A_I}$. Recall that, conditional on meeting with a new employer and receiving a job offer, η denotes the probability with which the employed worker would not be able to refuse such a job offer (as long as its optimal to remain employed). The exogenous occupation obsolescence shock, δ_ϵ, and firm separation shock, δ_z, are given by $\delta_\epsilon(A_I) = \delta_0^\epsilon e^{\delta_1^\epsilon A_I}$ and $\delta_z(A_I) = \delta_0^z e^{\delta_1^z A_I}$. In addition, we deviate slightly and introduce a lowest value of z, z_0, which is tantamount to a forced separation from the occupation and the job. This helps us to match the rate of occupation switching through unemployment and the proper amount of downside earnings risk.

Finally, we assume that per period earnings follow a standard Mincer formulation,

$$\log w_{o,t} = \gamma_w \log w_{o,t-1} + (1-\gamma_w)(A_t + \tilde{p}_o + p_{o,t} + x_h + z_t + \epsilon_t), \tag{8}$$

where $\gamma_w \in [0,1]$ captures the extent of stickiness such that with probability γ_w the current earnings remains the same as last period's earnings. Annual earnings are then obtained by summing up monthly earnings, taking into account that during periods of unemployment the worker receives earnings of zero. Note, however, that the job acceptance and occupational mobility decisions of the unemployed depend on the per period payoff when unemployed b. We set the latter to match a 40% replacement ratio (see Shimer, 2005). It is worth noting that this is exactly the same set-up we use to estimate the job ladder model presented in Section 2.3, with the omission of occupational mobility.

5.2 Estimation

The above functional forms yield several parameters to estimate composed by the set that govern the arrival of job opportunities $\{\lambda_0^i, \lambda_1^i, \lambda_0^{c,i}, \lambda_1^{c,i}\}_{i=U,E}$. The set $\{\delta_0^z, \delta_1^z, \rho_z, \nu_z, \sigma_z, \omega_z, z_A\}$ that governs the idiosyncratic worker-occupation productivities. The set $\{\delta_0^\epsilon, \delta_1^\epsilon, \eta, \sigma_\epsilon, lt_\epsilon, rt_\epsilon, \omega_\epsilon, \epsilon_A\}$ 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 $\{\alpha_0, \alpha_1^U, \alpha_1^E, \alpha_{NRC}, \alpha_{NRM}, \alpha_{RM}, \alpha_{NRM}\}$. Finally, the set that governs the aggregate productivity process $\{\rho_A, \sigma_A\}$ and payments $\{\gamma_w, b\}$. To ease computational burden we 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 (2008).[17] The remaining parameters are jointly estimated through minimum distance and method of simulated moments by solving

$$\text{Min}(\mathbf{M^D} - \mathbf{M^S}(.))'\mathcal{W}(\mathbf{M^D} - \mathbf{M^S}(.)),$$

where $\mathbf{M^D}$ is a vector of data moments, $\mathbf{M^S}(.)$ is a vector of the same moments obtained from model simulations, which are a function of the parameters to estimate as described above, and $\mathcal{W}$ is a weighting matrix.[18]

Targeted moments Table 1 and Figure 7 present the set of data moments $\mathbf{M^D}$, which consist of 24 transition flows and productivity moments and 30 percentiles describing 6 (cross-sectional) earnings growth distributions. We now present some heuristic identification arguments that justify our choice of moments, keeping in mind that all parameters need to be estimated jointly.

The parameters governing the arrival rates of employment opportunities are informed by the observed transitions probabilities across employers and occupations. In particular, the arrival rates of job offers among occupational stayers, λ_0^U, λ_0^E and δ_0^ϵ are informed by the average UE, EE and EU transition rates during our observation period. The cyclical ratio of the UE, EE and EU rates inform the cyclical components of these offer arrival rates, λ_1^U, λ_1^E and δ_1^ϵ. Similarly, the arrival rate of offers among occupational movers, $\lambda_0^{c,U}$, $\lambda_0^{c,E}$, are informed by the average probabilities of an occupational change conditional on the worker's labour market transition, EE, EUE or employer stayer. The parameters $\lambda_1^{c,U}$, $\lambda_1^{c,E}$ are then informed by the cyclical ratios of the occupational change probability through a EE and EUE transition.

The directional parameters of the $\alpha(.)$ function, α_{NRC}, α_{RC}, α_{NRM} and α_{RM} are informed by the net flows to each of the four task-based occupations, where we target the relative contribution of

[17]The returns to occupational tenure correspond to the IV estimates of Kambourov and Manovskii (2008). Since we parametrise the returns to occupational human capital outside the simulation minimum distance procedure, we chose to target the IV estimates as they already control for the endogeneity bias present in the OLS returns.

[18]Our weighting matrix aims to accomplish two key features: (i) normalise to the same scale the transition probabilities and their ratios over the business cycle; (ii) emphasis the role of the earnings change distributions in the minimisation procedure.

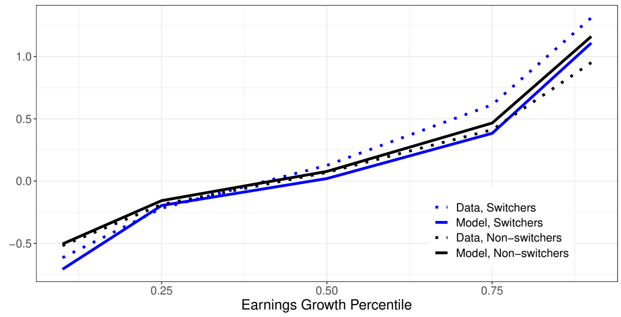
Table 1: Targeted moments in the estimation

Moment	Model	Data	Moment	Model	Data
Employment Switching					
EE transition rate	0.0296	0.0340	EE rate - expansion/recession ratio	1.1600	1.1846
UE transition rate	0.3492	0.3947	UE rate - expansion/recession ratio	1.0874	1.0876
EU transition rate	0.0236	0.0223	EU rate - expansion/recession ratio	0.7437	0.7460
Occupational Switching					
Prob (Occ. change | EE)	0.3107	0.2685	Prob (Occ. change | EE) - exp/rec ratio	1.1068	1.1068
Prob (Occ. change | EUE)	0.2867	0.2892	Prob (Occ. change | EUE) - exp/rec ratio	1.0670	1.0709
U duration - Occ. movers/stayers ratio	1.2280	1.2709	Prob (Occ. change | Stayer)	0.0101	0.0107
Variance (Occ. change | EE switch)	0.0293	0.0223	Variance (Occ. change | EUE switch)	0.0235	0.0218
Net flow to NRC	0.1849	0.1851	Net flow to RC	0.3395	0.3432
Net flow to NRM	0.2209	0.2201	Net flow to RM	0.2547	0.2516
Productivities					
Output per worker - AR (1) persistence	0.957	0.958	Output per worker - AR (1) variance	0.009	0.009
NRC wage fixed effect	1.000	1.000	RC wage fixed effect	0.767	0.767
NRM wage fixed effect	0.608	0.608	RM wage fixed effect	0.803	0.803

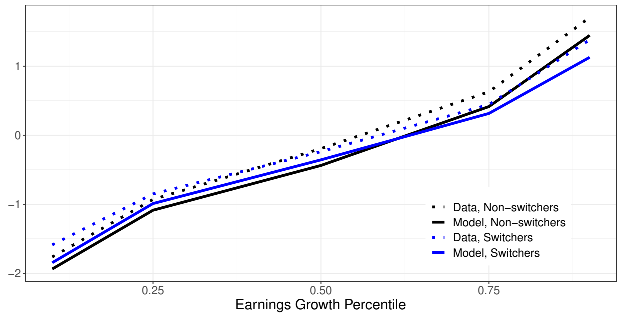
each occupation o on total net flows.[19] To inform the curvature parameters α_1^U, α_1^E, we instead use the variance of the distribution of these net flows conditioning on whether the occupation switch occurred through a EUE or EE transition. Since the functional form of $\alpha(.)$ implies that a higher (lower) value of α_1^i leads to workers searching more (less) randomly, one obtains a negative relationship between α_1^i and the differences in each occupation's net flows. We measure dispersion in the latter through the variance of the distribution of these net flows. In Appendix C we formally show that α_1^i directly determines the variance of a Gumbel distributed additive random utility that we obtain using the assumed functional form for $\alpha(.)$. The shift parameter α_0 helps determining the level of occupational mobility and hence it is informed by the average occupational change probabilities conditional on workers' employment transition.

To inform the idiosyncratic occupation-match productivity process we use the earnings growth distributions of occupational movers. These are separate by whether the workers made the occupational changes through a EE, EUE or within employer transition as depicted in Figure 7. For each of these distributions we target the 10th, 25th, 50th, 75th and 90th percentile. In particular, the earnings

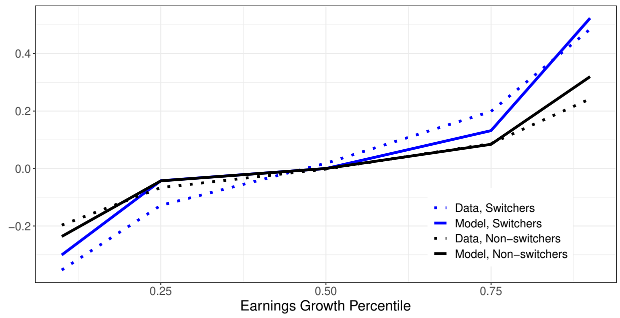
[19]Total net flows are calculated as the absolute value of the difference between inflows and outflows per occupation, summed up over all occupations, and divided by two as one person net inflow in some occupation is also counted as a net outflow some other occupation. Hence, the relative contribution of occupation o on total net flows is given by $\frac{|Inflow_o - Outflow_o|}{\sum_{o \in O} |Inflow_o - Outflow_o|}$.



(a) Earnings Growth Dist. EE movers



(b) Earnings Growth Dist. EUE movers



(c) Earnings Growth Dist. Emp stayers

Figure 7: Model fit for the earnings growth distributions

losses observed upon an occupational transition through unemployment help inform δ_0^z and δ_1^z, the obsolescence shock parameters governing job loss with a forced occupational move: very large earnings losses among occupational movers imply forced moves because they are driven by high z match individuals who otherwise are unlikely to search outside of their current occupation. The earnings losses of those who changed occupations within their employers or through a EE transition help to inform ω_z and z_A, the parameters that shift $F(.)$ during recessions. The shape and scale of this Weibull distribution, ν_z and σ_z, and the persistence of the z-productivity process, ρ_z, are then informed by the remaining percentiles of the conditional earnings growth distributions of occupational movers. We also use these earnings growth distributions to recover the parameters of the occupation-wide productivity processes, ρ_p and σ_p. In particular we use the earnings growth distribution of those workers who changed occupations within their employers. To inform, the productivity level $\bar{p}_o$ we estimate occupation fixed effects within the model and set each $\bar{p}_o \in O$ to match the corresponding regression fixed effect, where the regression is exactly the same as the one used to residualize earnings in Section 2.

For the parameters governing the idiosyncratic worker-firm productivities we use the earnings growth distributions of occupational stayers. The earnings losses among EUE employer movers inform ω_ϵ and ϵ_A, which shift $\Gamma(.)$ during recessions. The earnings losses of EE employer movers inform lt_ϵ, the left tail parameter of $\Gamma(.)$, and the rate at which employed workers are forced to move employers within their occupations, η. The earnings gains of EE and EUE employer movers then inform σ_ϵ and rt_ϵ, the variance and the shape of the upper tail of $\Gamma(.)$. To inform the wage

Table 2: Estimated parameter values

Job offer arrival				**Employer-match productivities**				**Occupation-match productivities**			
λ_0^U	0.9498	λ_0^E	0.0536	δ_0^ϵ	0.0055	lt_ϵ	4.3786	δ_0^z	0.0069	ν_z	4.4818
λ_1^U	-0.1700	λ_1^E	0.1605	δ_1^ϵ	-0.1409	rt_ϵ	0.6458	δ_1^z	-1.8336	σ_z	1.7784
$\lambda_0^{c,U}$	0.0671	$\lambda_0^{c,E}$	0.0001	η	0.4621	ω_ϵ	0.9990	ρ_z	0.0296	ω_z	0.7234
$\lambda_1^{c,U}$	1.0764	$\lambda_1^{c,E}$	2.9107	σ_ϵ	0.0750	ϵ_A	-0.9043			z_A	-0.1579
Search direction across occupations				**Occupation-wide productivities**				**Aggregate productivity and Payments**			
α_0	0.0403	α_{NRC}	-0.5406	ρ_p	0.6407	$\tilde{p}_{NRC}$	0 (normalize)	ρ_A	0.9580	γ_w	0.0911
α_1^U	0.7526	α_{RC}	0.5545	σ_p	0.0300	$\tilde{p}_{RC}$	-0.2658	σ_A	0.0090	b	0.4000
α_1^E	0.8560	α_{NRM}	-0.1777			$\tilde{p}_{NRM}$	-0.4976				
		α_{RM}	0.0253			$\tilde{p}_{RM}$	-0.2189				

stickiness parameter, γ_w, we rely on the earnings change distribution of those workers who did not change occupations or employers, especially the centre of this distribution. Finally, the aggregate productivity process parameters match the autocorrelation and unconditional variance of output per worker as observed in the US during the period of study, similar to Shimer (2005).[20] These data is available at a quarterly frequency from FRED, so we convert it to a monthly process, consistent with our simulation procedure.

Parameter estimates Table 2 reports the estimated parameter values. The estimated job offer arrival rates among workers searching for jobs in their current occupation, λ_0^U, λ_1^U, λ_0^E and λ_1^E, together with their job acceptance decisions, capture the behaviour of the UE and EE transitions rates among occupational stayers. If a worker decides to search across occupations, he faces a job arrival rate with parameters $\lambda_0^{c,U}$, $\lambda_1^{c,U}$ or $\lambda_0^{c,E}$, $\lambda_1^{c,E}$ until a job is found. These values together with workers' search direction and job acceptance choices determine the UE and EE transitions rates among occupational movers. Indeed, the reason why we find a stronger procyclicality of occupational movers' arrival rates is because they have to be scaled by the parameters of the α function, which are less than one, to match the observed transition rates. Overall, the model is consistent with the observed procyclical behaviour of the aggregate UE and EE transition rates and the occupational mobility rates observed along the four task-based occupational categories we consider.[21]

The top row of Figure 8 depicts the density of the $\Gamma(.)$ and $F(.)$ distributions implied by the

[20] Shimer (2005) uses the full post-war time period, which has the advantage of a longer time-series. While the process is different when considering the 80's onwards, using one or the other does not affect our conclusions.

[21] The estimated value of λ_1^U implies that the offer arrival probability of unemployed workers decreases in expansions among occupational stayers. This occurs as the estimation procedure uses this parameter to help match not only the cyclicality of the aggregate UE rate, but also to reproduce the cyclical change in the 2.5 percentile of the aggregate earnings growth distributions, which is largely affected by the cyclicality of the earnings distribution for EUE transitions. By setting this parameter to zero (i.e. no cyclical change in the job finding probability of occupational stayers), for example, we worsen the fit of the model in this dimension by a factor of five, generating much larger earnings losses than in the data during recessions.

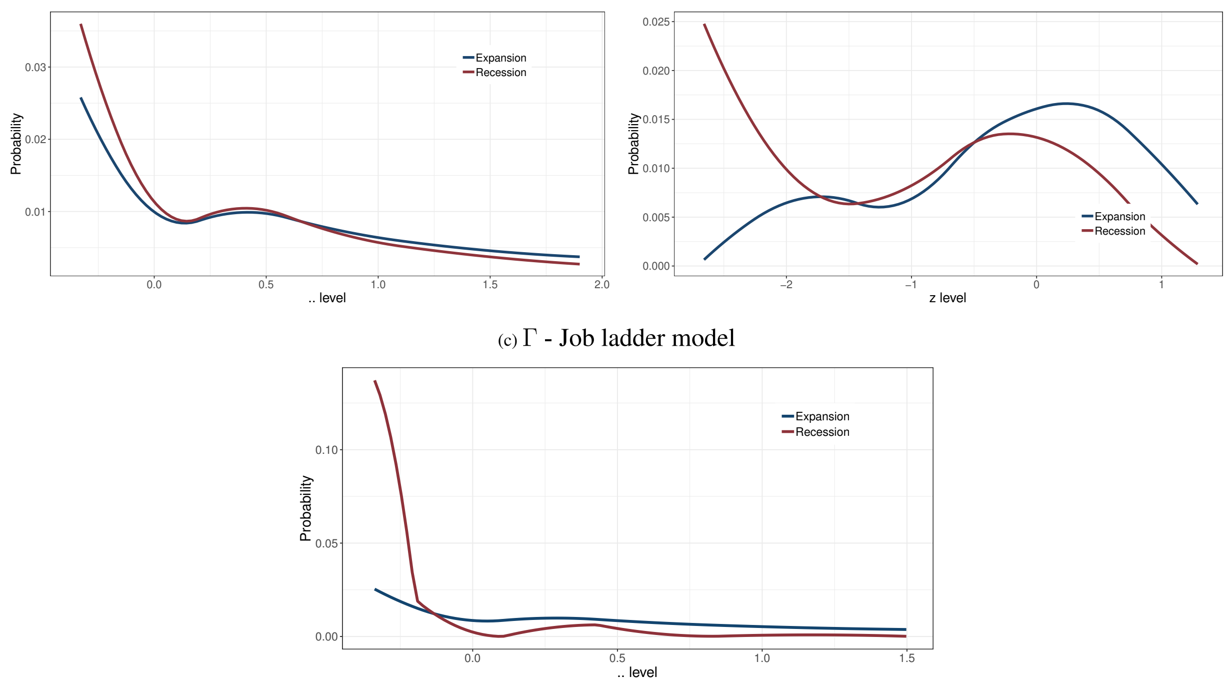
estimated parameters governing the worker-firm match productivity ϵ and worker-occupation match productivity z in expansions and recessions. During recessions workers are more likely to draw from worse match productivities when starting new jobs and occupations. During expansion, in contrast, workers are more likely to draw better match productivities. As we will demonstrate later, these cyclical changes in the productivities of new jobs contribute to the cyclical changes in the tails of the earnings growth distributions of employer/occupational movers as documented in Section 2. Another important characteristic of these distributions is that worker-occupation match productivities are estimated to be more dispersed than worker-firm match productivities, with variance of 1.041 and 0.585 expansions and of 1.085 and 0.540 in recessions, respectively, and an equal mean normalised to zero. This feature captures the increased earnings risk among occupational movers documented in Section 2.

To compare these results with the job ladder model discussed in Section 2.3, the bottom row depicts the density of the $\Gamma(.)$ distribution generated by the latter. The main difference is that during recessions workers in the job ladder model are about 5 times more likely to encounter very bad quality jobs (very low values of ϵ) relative to the occupational mobility model. Note that this difference does not arise from a much higher probability of drawing a very low z in the occupational mobility model. As shown below, the obsolescence shocks δ_z play an important role in generating the larger earnings losses observed in recessions through involuntary EUE occupational switches among some employed workers at the top of the earnings distribution. Table 2 shows that the probability of these job loss shocks, as well as δ_ϵ shocks, increase in recessions in order to generate countercyclical EU transitions.

Figure 8: The estimated Γ and F distributions

(a) Γ worker-firm match productivity ϵ

(b) F worker-occupation match productivity z



(c) Γ - Job ladder model

Recall that the parameters γ and ρ_z control how often workers move along the $\Gamma(.)$ and $F(.)$ distributions, such that with probability γ the worker is forced to change employer and draw a new ϵ and with probability ρ_z the worker draws a new z. Table 2 shows that re-draws of ϵ are about four times more likely than re-draws of z, suggesting that involuntary EE transitions are far more likely than changes in occupation match productivities.

The α function parameters imply that workers' search across occupations is not fully directed. As discussed in the previous sections, the value of α_1 controls the degree of directness such that a higher value implies that search is less directed. Table 2 shows that employed workers direct their search more than unemployed workers as $\alpha_1^U > \alpha_1^E$. An alternative way to evaluate the degree of directness is by using the effort exerted in searching for jobs in a given occupations, as this choice takes into account the frequency at which unemployed and employed workers encounter job opportunities. In this case, fully random search would arise when a worker targets all remaining occupations with an equal effort of $1/3$; while fully directed search occurs when the worker exert all his effort in targeted one occupation. A simple measure of directness based on search effort is therefore $(\max s_{\tilde{o}} - 1/3)/(1-1/3)$, where $\tilde{o} \in O^-$.[22] Using the latter we find that unemployed workers have a directness measure of 21.7%, once again lower than the one for employed workers of 22.6%. We also find that during recessions employed workers decrease their degree of search directness, while unemployed workers increase their search directness.[23]

Note that these measures suggest a mild degree of directness of search across occupations. This occurs due to the importance of the idiosyncratic occupation and firm match components in the overall payoff of new jobs. Since these productivities are randomly drawn from $F(.)$ and $\Gamma(.)$, workers do not differentiate as much between occupations. However, the extent to which individual occupations are targeted heavily depends on the occupation a worker is moving away from. In the estimated model both employed and unemployed workers that leave RM occupations have a directness measure of about 32.2% and 30.3%, while those that leave NRM occupations a measure of 27.4% and 26.0%. This occurs because RM and NRM workers mainly target RC occupations, which offer the highest chance of drawing a z-productivity due to the high estimated value of α_{RC} and offer a sufficiently high $\tilde{p}$. On the other hand, workers leaving RC and NRC do face a stronger trade-off between the α_o and $\tilde{p}_o$ and hence they tend to spreads more the search, particularly those workers leaving RC occupations who show a degree of directness of about 13%.

Finally, we find that occupation-wide productivity shocks are less persistent but more volatile than aggregate productivity shocks. We estimate (real) earnings also to be rather flexible with the stickiness parameter suggesting that earnings remain at their previous level with only a 5% probability every month.

[22] For unemployed workers we measure $\max s_{\tilde{o}}$ through the entire unemployment episode, while for employed workers we measure it just before the EE transition. In both cases we aggregate all data across the business cycle.

[23] However, the cyclicality on this measure is very mild. Employed workers increase their search directness from 22.5% to 22.6% from recessions to expansions, while unemployed worker decrease their search directness from 21.9% to 21.5%.

5.3 Model fit

The model fits the data very well, given the amount of over-identification. Table 1 shows that the model replicates the worker flow patterns among occupational movers and stayers as well as their search direction across occupations. Figure 7 shows quantile-by-quantile how well our minimum distance estimator does at bringing together the model and data on the earnings growth distributions of occupational movers and stayers among EUE, EE and employer stayers. Among the employer stayers, the model generally has difficulty capturing the inter-quartile range. To get enough earnings stickiness to satisfy other requirements of the model, the estimation tamps down these small variations in earnings slightly too much. Occupation switchers who do not change employers have slightly more upside than in the data. This is dictated by the distribution of z-productivity shocks which must be fairly wide to allow for the other large earnings differences we observe among employer switchers. However, that tends to overstate the earnings growth available to stayers. The model does reproduce correctly the relationship between EUE occupation movers and EUE occupations stayers. The steeper line among movers implies both more downside and upside risk for them. The model, however, generally does account well for the occasional, large earnings increases among EUE transitions.

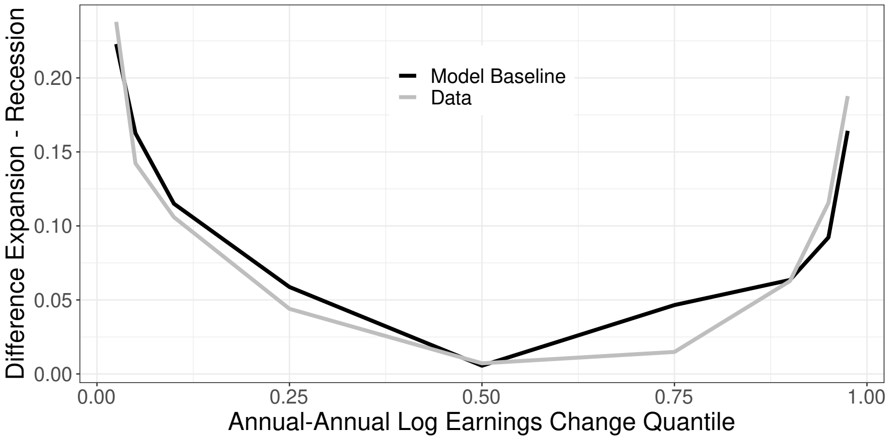
Taken together, the good fit of the conditional earnings growth distributions in recessions and expansions largely implies that the aggregate earnings growth distribution exhibits the observed cyclical properties as shown in Table **??**. The variance, measured by the median absolute deviation, of the simulated distribution is 0.080 in expansions and 0.082 in recessions, while in the data we obtain 0.134 in expansions and 0.150 in recessions. The expansion skewness, measured by the GM coefficient, is 0.141 and the recession one is -0.166; while in the data we obtain 0.106 and -0.020, respectively. Note that, although we generate a larger (smaller) skewness (variance), we do reproduce a stronger proportional change in the skewness relative to the variance over the business cycle.[24]

Figure 9 shows a graphical representation of these properties by comparing the implied changes in the earnings growth distribution over the cycle in the model and data. As in Figures 1b and 2 in Section 2, we condition on a quantile of the earnings growth distribution and then subtract expansion from recession values. The model produces a nearly perfect fit with some small misses in the upper-most tail and in the middle of the distribution. These small misses arise from the model largely resolving the following tension: in explaining the cyclicality of earnings growth, it needs earnings stickiness to be consistent with the overall kurtosis of the earnings growth distribution at the cost of dampening the cyclicality of median earnings. Nevertheless, our analysis shows that the occupational mobility model fits the data much better than the job ladder model.

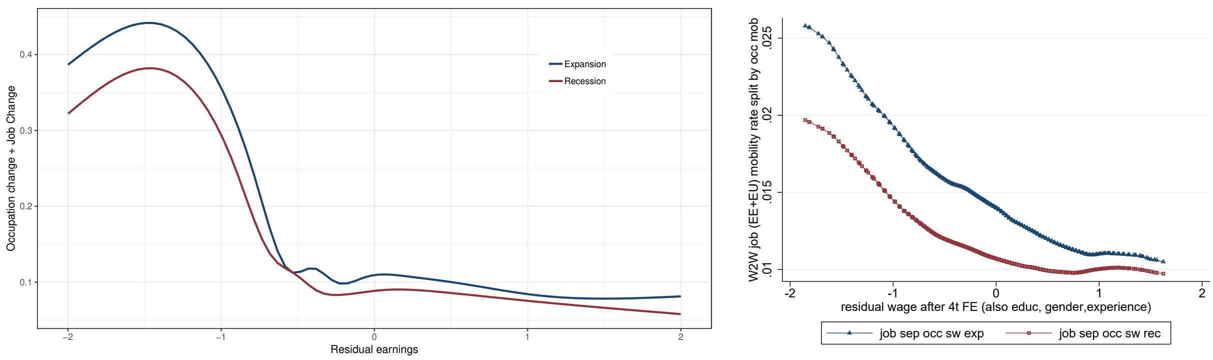
Our model not only captures the cyclical shifts of the earnings growth distributions among occupa-

[24]The model generates too much negative skewness essentially because it produces some very large earnings losses, even past the 2.5 percentile that are not present in the data. This can be because of the cleaning in the data: very large losses are difficult to distinguish from measurement error and also because in the data relatively few workers fall from the upper-most job rungs: unemployment tends to be more concentrated among those workers at the bottom of the earnings distribution than randomly arriving separation shocks.

Figure 9: Cyclical change in the earnings growth distribution - model and data



tional and employers movers, it also captures the (un-targeted) cyclical relationship between previous earnings and the probability of occupational mobility among employer movers. Figure 10 shows this relationship. In the model individuals who had low earnings immediately before changing employers, either through an EE or an EUE transition, exhibit the largest probability of occupational mobility. As previous earnings increase this probability decreases, initially fast and slowing down at higher earnings levels. During expansions this convex (towards the origin) relationship remains above that of recessions, showing that occupational mobility among employer movers is procyclical even when conditioning on previous earnings. The data shows a very similar relationship.[25]



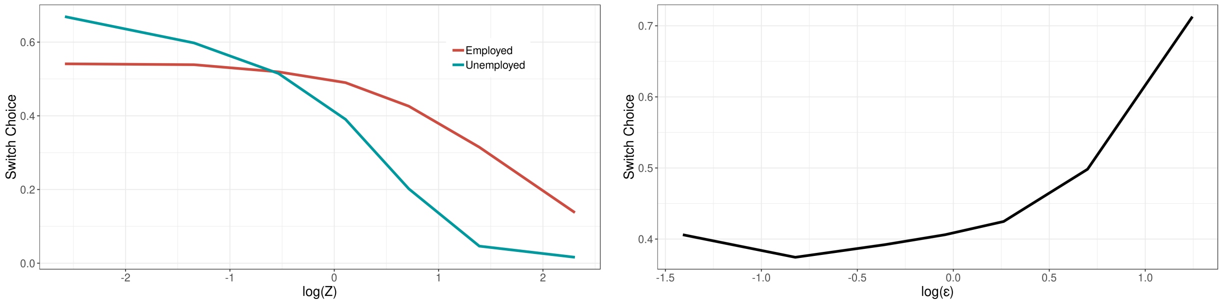
(a) Model

(b) Data

Figure 10: Occupational/employer mobility and previous earnings (untargeted)

Underlying the model's fit with the data lies workers' decisions to change employers and/or occupations. Figure 11 shows the probability of an occupational change as a function of the idiosyncratic firm- and occupation- match productivities. Figure 11.a shows that the probability of an occupational change decreases with the value of the z-productivity for both employed and unemployed workers.

[25]The more stark shape generated by the model in Figure 10.a could be smoothed if we added, for instance, random amenities. The small non-monotone section comes from our process of controlling for residual wages: some workers in high-paying occupations have relatively low z-productivities but also have sufficiently high ϵ that imply occupational mobility is not optimal.



(a) Worker-occupation match productivity z

(b) Worker-firm match productivity ϵ

Figure 11: Probabilities of changing occupations

Note that this probability decreases faster for unemployed workers. The reason for the latter is that the firm-match productivity also plays an important role in occupational switching among employed workers. Figure 11.b shows the relationship of ϵ and the probability of occupational switching for the employed. Here we find that a positive relationship, suggesting that z and ϵ can substitute each other. That is, workers with higher ϵ-productivities exhibit a higher probability of occupational switching when they also face a lower value of z and vice versa. This highlights that occupational mobility does not necessarily occur more often among those workers lower in the ϵ ladder.[26]

6 Structural Decomposition

What are the forces behind earnings inequality and what makes it fluctuate over the cycle? To answer these questions we first decompose the cross-sectional earnings growth distribution $G(.)$ as described in (6). The aim of this decomposition is to understand which productivity shocks are important at explaining earnings growth dispersion. Then we investigate how idiosyncratic productivity shocks as well as unemployment and employment mobility shocks, captured by the several job destruction and job finding probabilities, contribute to the change in earnings growth over the business cycle.

6.1 Decomposing earnings growth dispersion in the cross-section

To study the role of occupation- and firm-match specific shocks and aggregate and occupation-wide shocks we use a Shapley-Owen decomposition. This technique allows us to evaluate the contribution of each shock, taking into account that changes in one shock impacts the contribution of other shocks in the observed earnings growth distribution. In particular, we compute every combination of counterfactuals in which the variance of one shock is set to zero and the variance of the rest are set at their estimated baseline. The variance contribution of a given shock is then the average of its contribution across all these counterfactuals. Table 3 shows the results from this exercise, where the effects of the

[26] Although not shown here, a similar pattern occurs when relating the probability of employer change to ϵ and z. We obtain that this probability falls monotonically with ϵ, but increases with z. Thus, employer mobility does not necessarily occur more often among those workers lower in the z ladder.

job finding and job destruction probabilities are aggregated in the category "U/E mobility shocks".

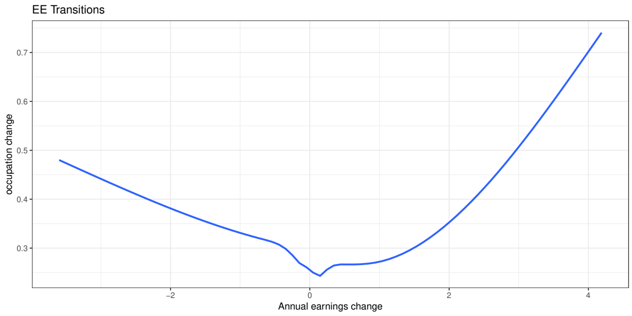
The Shapley-Owen decomposition shows that the largest single contributor to earnings growth dispersion in the cross-section is occupation-match productivity z. Dispersion in these shocks are identified from the increased dispersion in earnings growth among occupational switchers relative to non-switchers. This implies that the variance of z-productivities must replicate the fact that in the data occupational switchers' earnings are considerably larger than non-switchers. In interpreting the large role of these productivities, recall that they do not include fixed differences across occupation, which are part of the occupation-wide productivities p_o and contribute 2% to the variation of earnings growth. Instead, the importance of occupation-match productivities emphasizes the role of idiosyncratic match quality differences, where the dispersion of earnings growth is largely associated with individual-specific factors. Further this decomposition shows that although the firm-match productivity is important, it only represent about half the contribution of the z-productivity shocks. Thus, while employer transitions often coincide with occupational mobility, it is the latter that actually contributes more to earnings changes.

	Aggregate Shocks		Idiosyncratic Shocks		U/E Mobility shocks
	A	$\mathcal{P}_O$	ϵ	z	
Variance	0.14	0.02	0.28	0.56	0.20

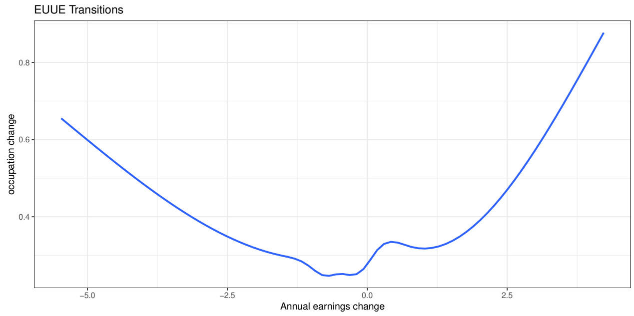
Table 3: Variance decomposition of annual earnings growth.

The importance of occupation-match productivity in the cross-sectional earnings growth distribution can also be observed when considering the model counterpart to Figure 3, Section 2, depicting the relationship between earnings growth and occupation mobility. This figure documents that occupational movers contribute disproportionately to the largest changes in earnings, both positive and negative. In the model the relationship between earnings growth and occupation mobility among all workers is partially a result of the relatively fixed wages of the majority of employer/occupation stayers. It is less clear, however, that the model will be able to obtain the higher probability of occupational switching among those with the largest earnings changes when conditioning on EE or EUE transitions. There, the effect of drawing a new z-productivity has to dominate the other shock processes that drive extreme earnings changes, such as job loss from high on the ϵ ladder. Figure 12 shows that this is indeed what happens, albeit with a more gradual increase in the probability of an occupational change among those with large earnings losses/gains relative to the data.

Conditional on EUE transitions the relationship between earnings growth and occupational mobility reaches its bottom near the mean of earnings growth, just below zero, as in the data. The same holds for the relationship between earnings growth and occupational mobility conditional on EE transitions, where the average worker makes an earnings gain of a few percentage points. As the earnings growth associated with a particular transition moves away from the middle of the distribution, the chance it involves an occupation switch increases. The workers who get above-average increases in earnings generally improved their z-productivity draw, whereas those who got below-average in-



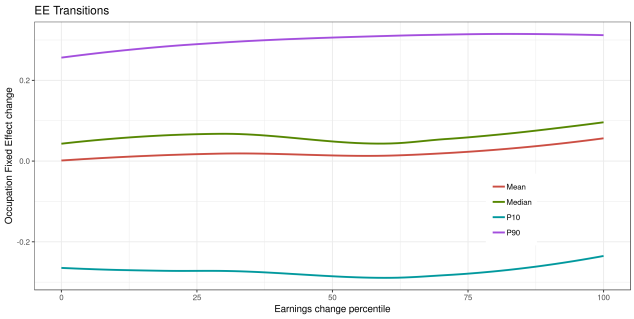
(a) Earnings Growth Dist. EE movers



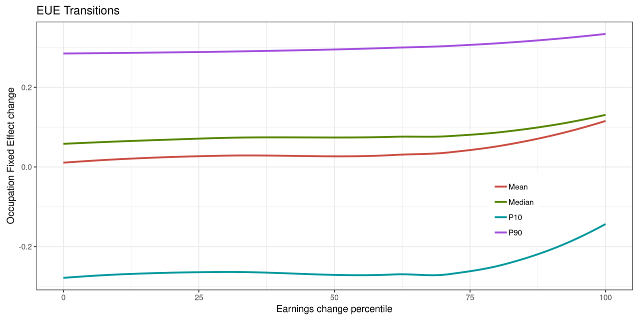
(b) Earnings Growth Dist. EUE movers

Figure 12: Model counter-part of earnings growth distributions

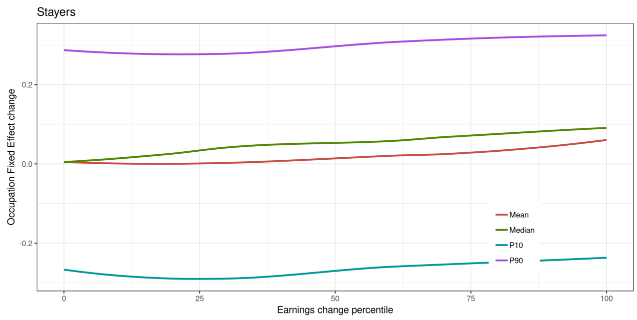
creases drew a worse z-productivity. The fact that these low values of z-draws remain acceptable shows that workers prefer large earnings declines to unemployment.



(a) Employer movers: EE



(b) Employer movers: EUE



(c) Employer stayers

Figure 13: Model implied occupational ladder

We can also observe the importance of the idiosyncratic z-productivity in the model by computing the relationship between occupation fixed effects (occupational ladder) and earnings changes. Figure 13 shows that the model is able to reproduce the large earnings changes associated with larger movements both up or down the occupational ladder, as documented in Figure 4, Section 2. As in our empirical analysis, we compute conditional occupation earnings averages by estimating an earnings regression on a set of dummies for the task-based occupational categories. We treat the coefficients on these dummies as the occupation-specific earnings effect and compute the distribution of the difference between these coefficients at their source and destination occupation at each percentile earnings growth. Occupation-wide productivity differences imply that the mean, median, 90th and 10th percentiles are upward sloping and that workers with higher earnings growth are more likely to move to higher paying occupations. However, as in the data, these slopes are very weak and imply that workers main motive to switch occupation arises from the idiosyncratic occupation-match productivity. Moreover, this pattern is present when we focus on employer movers, EE or EUE, or employer stayers.[27]

6.2 Decomposing earnings growth over the business cycle

We are now turn to investigate the driving forces that shifts earnings growth over the business cycles. Following from the cross-sectional decomposition, we first evaluate the importance of z and ϵ productivities in explaining the observed cyclical changes in the earnings growth distribution. Recall that the combined effect of these productivity shocks (including the much smaller effect of $\mathcal{P}_{O,t}$) directly determine earnings and workers' decisions to change employers and/or occupations, and hence capture the returns to mobility. Once again we employ the Shapley-Owen decomposition for this exercise.

6.2.1 Idiosyncratic productivity shocks

Figure 14 shows the data, the model's baseline fit and two counterfactuals, where the z or ϵ productivities are not allowed to vary with the business cycle. The latter is achieved by fixing the respective distributions to their expansions levels. The black line depicts the expansion/recession difference using the baseline model while the grey line depicts the data counterpart. The horizontal axis shows a set of quantiles of the earnings growth distribution and the vertical axis shows the difference in value at each quantile between expansion and recession as described in Section 2.

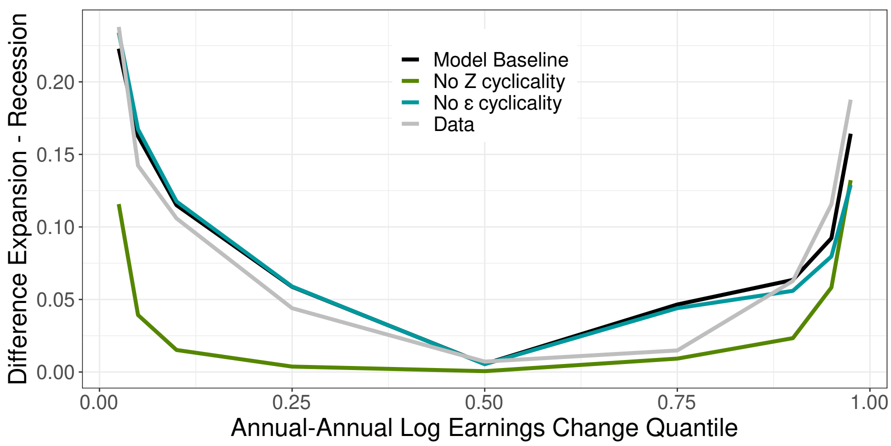


Figure 14: Cyclical change in the earnings growth distribution - The importance of z and ϵ

[27]Note the magnitudes of the occupation effects in the model, Figure 13, are slightly different compared with the data, Figure 4. This is because we allowed the occupation effects in the data to be relatively expansive, not only including the common average occupation earnings, but also the occupation-specific value of worker characteristics. In the model we use only the average earnings portion of the occupation effect because workers are not ex-ante heterogenous.

The counterfactual exercises demonstrate that occupation-match productivities are much more important in accounting for the cyclicality of the earnings growth distribution than firm-match productivities. Restricting the z-productivity distribution $F(.)$ to be constant over the cycle, significantly decreases the difference between the expansion and recessions earnings changes. Although this decrease is particularly pronounced at the left and right tails, we observe that cyclical changes in occupation-match productivities also play an important role in the interquartile range of the earnings growth distribution. In contrast, when restricting the ϵ-productivity distribution $\Gamma(.)$ to be constant over the cycle, the model does not suffer at all in its ability to generate the difference between the expansion and recessions earnings changes, except at the very top end of the distribution. This demonstrates that in the presence of occupation-match productivities, cyclical changes in firm-match productivities shocks contribute very little to the behaviour of earnings growth over the business cycle.

6.2.2 Mobility shocks

Note that the importance of the z-productivities in driving the cyclicality of the earnings change distribution does not mean that the unemployment and employment mobility shocks themselves are not important. The cyclical change of these mobility shocks is complementary to the cyclical change in the returns to mobility. The model has two unemployment (or job loss) shocks $\delta_z(A_I)$ and $\delta_\epsilon(A_I)$, and four employment (or job finding) shocks $\lambda_i(A_I)$ and $\lambda_i^c(A_I)$, where $i = U, E$ is the employment status indicator and A_I is the expansion indicator. To evaluate the importance of these mobility shocks in relation to the returns to mobility, we perform the counterfactual exercise in which all mobility shocks are set to their expansion levels but productivity shocks are set to their recession levels.

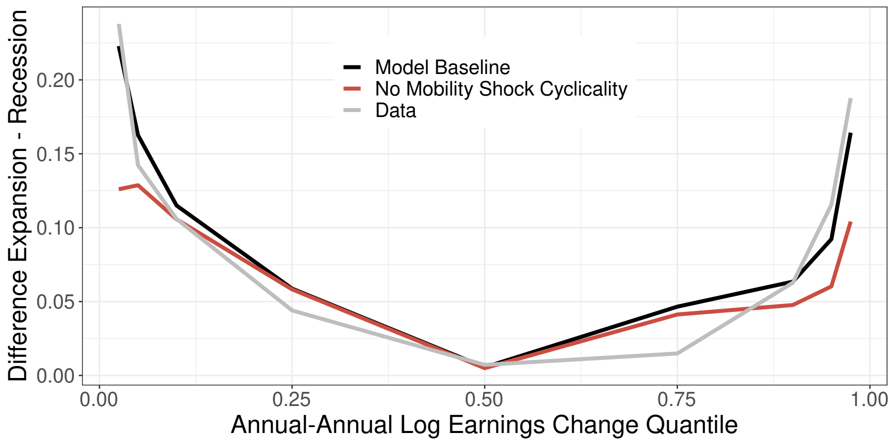


Figure 15: Cyclical change in the earnings growth distribution - The importance of mobility shocks

Figure 15 shows the result of this exercise. The red line shows the contribution of worse returns in recessions to the cyclical change in the earnings growth distribution. The residual, the gap between black and red, is then due to cyclical changes of the unemployment/employment mobility shock processes. Consider first the centre of the distribution. Here we observe that most of the changes in the center quartiles arise from cyclical changes in returns to mobility, while cyclical changes in the mobility shocks have relatively little effect. That is, workers whose earnings growth are around the median are not making employer/occupation transitions and so the cyclical changes in mobility shocks do not have a meaningful impact on their earnings. Instead, these earnings are affected by the productivity processes, which together with the stickiness parameter imply small changes.

At the left and right tails, however, the decomposition shows that mobility shocks have a more prominent role. At the left tail, the increase in earnings losses during recessions is largely due to the change in cyclicality of the mobility shock process. Worsening of the returns to mobility, however, still explains over 30% of the cyclical change in earnings growth, which as discussed above arises primarily due to cyclical changes in the occupation-match productivity. In contrast, the decline in earnings gains at the right tail arises mostly from worsening of the returns to mobility, explaining over 75% of the total reduction.

Job loss and job finding Given the importance of the mobility shocks in explaining the cyclicality of the tails of the earnings growth distribution, particularly the left tail, we evaluate which mobility shocks are the major contributors. If workers' choices played no role in determining the measure of workers across employers and occupations, $e_t^p(\epsilon, z, x_h, o)$, we could simply turn off the cyclical elasticity parameters of the mobility shocks one at a time and compare the earnings growth distributions G as described in (6) with and without them. Instead, however, since agents respond to the different unemployment/employment shocks, the outcomes of the model are not linear in the cyclicality of these shocks, but instead there are non-trivial interactions between each of them and the associated returns. Once again, the solution to this problem is to use a Shapley-Owen decomposition, in which we take every combination of turning on and off the cyclical elasticities and then attribute the average. In this decomposition we still allow cyclical changes in the ϵ and z-productivity distributions along with the aggregate and occupation-wide shocks.

With the six cyclical elasticities of the mobility shocks, there are a total of 61 combinations of counterfactuals we need to evaluate in which all but one element of the mobility shocks are set constant at their expansion values and the remainder is allowed to fluctuate with the business cycle. To make these experiments explicit, define $\Lambda(\mathbb{I})$ as a function that takes a vector of indicators and gives a vector of mobility shocks. If all elements of the vector of indicators are set to 0, the function $\Lambda(\mathbb{I})$ gives the values of the mobility shocks at their expansion values, thus not allowing the mobility shocks to change with the business cycle. However, if the i^{th} element of the vector of indicators is set to one, then $\Lambda(\mathbb{I})$ implies that the mobility shock associated with i is allowed to vary with the cycle. Slightly abusing the notion from earlier, let $\tilde{G}_R(w|\Lambda(\mathbb{I}))$ denote the distribution of earnings in all recession periods given $\Lambda(\mathbb{I})$ and $\tilde{G}_E(w|\Lambda(\mathbb{I}))$ denote the distribution pooling all expansion periods given $\Lambda(\mathbb{I})$. We then can evaluate counterfactuals with $\Lambda(\mathbb{I})$ for every combination of indicators, and each time storing $\tilde{G}_R(w|\Lambda), \tilde{G}_E(w|\Lambda)$ and computing their difference. Notice that these counterfactuals not only change the cyclicality of the mobility shocks, but also the value functions and hence the workers' mobility choices.

The top two rows of Table 4 present the difference between the expansion and recession earnings

Table 4: Contribution of cyclical mobility shocks in the tails

Percentile	0.025	0.05	0.10	0.90	0.95	0.975
Difference Exp-Rec.	0.179	0.079	0.15	0.11	0.024	0.034
Contribution of cyclical mobility shocks (%)						
Occupation loss, δ^z	103.56	102.48	64.17	-1.03	-38.91	-34.10
Employer loss, δ^ϵ	35.86	32.25	39.35	-2.02	-29.89	-29.78
Unemp. occ. movers job finding, $\lambda^{c,U}$	31.63	31.34	11.83	11.87	19.63	13.57
Unemp. occ. stayers job finding, λ^U	-36.22	-35.63	-5.01	43.02	30.04	25.79
Emp. occ. movers job finding, $\lambda^{c,E}$	-31.48	-26.04	-6.94	49.72	85.19	104.92
Emp. occ. stayers job finding, λ^E	-3.34	-4.40	-3.40	21.61	33.94	19.61

growth distributions that is attributed to all mobility shocks; i.e. the difference between the black and the red lines on Figure 15, focusing on the left and right tails. The remainder rows decompose this difference at each quartile, presenting individual contributions as a percentage such that for a given percentile all rows sum to 100%. The decomposition shows that cyclical changes in the probability of job loss is what makes the mobility shocks account for the majority of the cyclical change of the left tail. The lower job finding probabilities faced by the unemployed during recessions explains a much smaller proportion of these large earnings losses.[28] The job finding probabilities among employed workers, in contrast, contribute in a negative way to earnings losses, and to some extent offsets the effect of the unemployed job finding probabilities. This occurs as lower job finding probabilities among the employed during recessions lead to lower EE transitions and hence to less workers experiencing earnings losses.

Among the unemployment shocks, the obsolescence shocks, which forces employed workers to undergo and occupation switch through unemployment, is by far the most important shock. It can explain the entire contribution of the mobility shocks. In comparison, cyclical changes in job loss due to the loss of firm-match productivity can only explain about 36% of the contribution of the mobility shocks. Thus, large earnings losses during recessions arise in large part from occupations "shutting down" on some workers (particularly those with high earnings), forcing them into unemployment and to reallocate to another occupation. The decomposition depicted in Figure 14 shows that upon reallocation, these workers experience worse draws of z in the new occupation, further contributing to explain the large earnings losses observed in the data.

At the right tail we observe a very different behaviour. Although in this case the mobility shocks explain a much smaller proportion of cyclical earnings changes, we find that the majority of this effect arises from cyclical changes in the job finding probability among employed workers who decided to switch occupations. With lower job finding probabilities during recessions, workers have less opportunities to switch employers and occupations at the same time, contributing to the collapse of the right tail of the earnings growth distribution.

Taken together, the results of the cross-sectional and cyclical decomposition highlights the key

[28]The negative contribution of the job finding probability of unemployed workers searching in the pre-separation occupation arises from the fact that the estimate of λ_1^U is negative, increasing in recessions, as discussed in Section 4.2.

importance of idiosyncratic worker-occupation shocks in shaping the earnings growth distribution.

7 Conclusion

In this paper, we studied the root causes of the cyclicality of the earnings growth distribution. A series of important research has highlighted that higher-order moments of the earnings growth distribution are the most cyclical, that is, the tails of the distribution move the most over the cycle. Thus, crucial to understanding a recession is to understand why the bottom of the distribution experiences larger earnings losses and the top experiences smaller earnings gains. We demonstrate that a cyclical version of the canonical job ladder model is not able reproduce many important properties of the earnings growth distribution. Instead we document the importance of career changes, seen through occupational mobility, in understanding the tails of the earnings distribution. Workers who switch occupations have considerably more disparate outcomes, both to the upside and downside and whether through unemployment or directly through and EE transitions. This is easily seen by looking at the fraction of workers who had switched occupations at each quantile of earnings change. As we move out to larger earnings losses or larger earnings gains, the proportion of workers who switched occupations in that period is consistently increasing. Among the workers who saw large changes, most of them also switched occupations.

Recessions bring with them a change in the opportunity to find a new job or to switch careers but also potentially a change in the returns to such a transition. On the flip side, they bring a larger chance of job loss and a larger chance of job loss that displaces one from his career. These transitions, may also have different outcomes, for example, if the cost of job loss is considerably different in expansions or recessions as documented by Huckfeld (2021). To disentangle these forces: the change in the exogenous forces that cause job flows and the change in the return to these flows, we introduce a structural model of employer and occupation search. The structural model is necessary to isolate the exogenous changes in flow probability from returns, because agents choose their search differently when the returns change.

The decomposition through this model shows that almost all of the decline at the bottom tail comes because of the increase in job loss probability, but particularly job loss that also comes with career displacement. This is akin to the obsolescence or disaster shocks suggested by the work of Huckfeld (2021) and Guvenen et al. (2015). On the other hand, the top of the distribution moves inward because of a combination of worse outcomes and fewer opportunities. Again, career changes are particularly important because workers coming out of unemployment cannot switch occupations as easily during a recession and because workers making EE transitions cannot as easily climb the occupational match quality ladder.

This work has clear extensions, particularly during the Pandemic Recession. It is well placed to understand the relationship between workers' employment dynamics and the entire earnings growth distribution. This recession in particular, featured asymmetric shocks across occupations and the insight we present here is that displacement from one's occupation can be particularly damaging and account for much of the worst earnings losses in recession. Further, when workers have less opportunity to find a better job, as also occurred with a decline in EE mobility and occupational switching therein, this hinders the ability to increase one's earnings.

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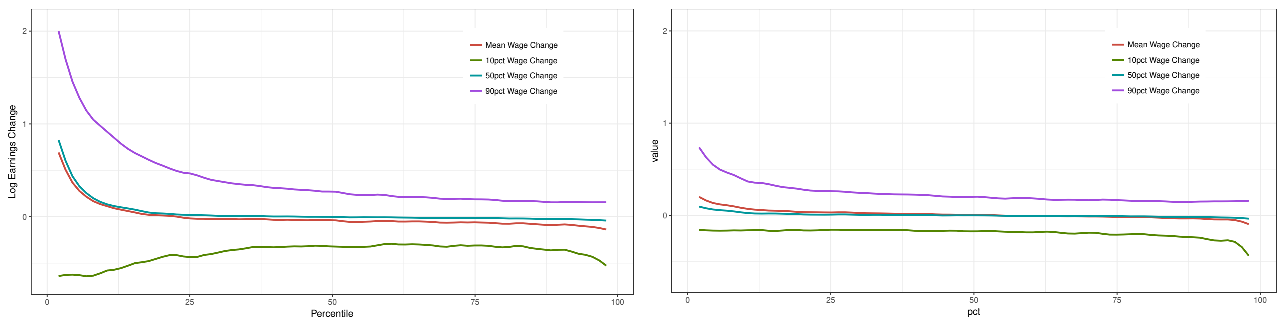
Appendix A

A Data

Description of dealing with censored spells, and other data construction issues.

To investigate how earnings growth depends on previous earnings, Figure 16a depicts the earnings growth distribution but now conditioning on the relative position of workers' previous year's residual earnings. It shows that workers with the larger earnings changes are also those who had the lowest earnings in the previous year, while those with progressively higher previous year earnings are associated with smaller changes.[29] The role of the underlying labor market flows can be gauged from Figure 16b, 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.



(a) Conditional on previous year earnings

(b) Conditional on previous year earnings and employer staying

Figure 16: Earnings Growth Distribution Conditional on Previous Earnings

This evidence then shows that those workers who experienced large earnings changes are also those who had low previous year earnings *and* changed employers. These patterns are broadly inline with the implications of standard "employer ladder" models (e.g. Burdett and Mortensen, 1998, and Postel-Vinay and Robin, 2002).[30]

[29]This message is consistent with Guvenen et al. (2014), who derive a similar graph using the earnings growth distribution as a function of previous five-year earnings percentile. They use the SSA data to analyse earnings changes among all workers in the US. One of the advantage of the SIPP relative to the SSA data is that the former provides better information about individuals' labor 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.

[30]Further, the 90th percentile curve in Figure 16a 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. This is also in line with the predictions of employer ladder models. The 10th percentile curve, however, shows two features: workers are also more likely to fall further when they are at the top of the earnings

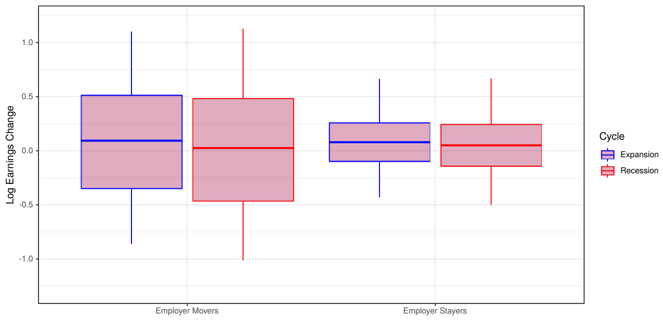
Table 5: Moments of Earnings Change Distribution over the Business Cycle

	Mean	Median	Med Abs Dev	GM coeff.	Moors coeff.
A. All workers					
Expansions	0.023	0.006	0.115	0.058	2.407
	(0.021,0.025)	(0.005,0.006)	(0.114,0.116)	(0.05,0.062)	(2.366,2.426)
Recessions	-0.017	-0.003	0.123	-0.044	2.461
	(-0.019,-0.014)	(-0.003,-0.002)	(0.123,0.125)	(-0.053,-0.038)	(2.423,2.493)
B. Employer transitions					
Employer Stayers					
Expansions	0.017	0.000	0.073	0.116	1.921
	(0.016,0.017)	(0.000,0.000)	(0.073,0.074)	(0.111,0.12)	(1.88,1.932)
Recessions	0.008	-0.004	0.077	0.082	1.983
	(0.007,0.01)	(-0.004,-0.003)	(0.076,0.077)	(0.076,0.087)	(1.942,2.016)
Employer Movers					
Expansions	0.037	0.071	0.391	-0.052	1.752
	(0.03,0.042)	(0.067,0.074)	(0.388,0.393)	(-0.06,-0.048)	(1.731,1.799)
Recessions	-0.075	0.011	0.439	-0.124	1.704
	(-0.084,-0.068)	(0.006,0.015)	(0.436,0.444)	(-0.134,-0.114)	(1.645,1.718)
C. Occupation mobility					
Occupation Stayers					
Employer Stayers					
Expansions	0.045	0.018	0.151	0.109	1.704
	(0.035,0.053)	(0.01,0.023)	(0.146,0.157)	(0.087,0.129)	(1.591,1.847)
Recessions	0.016	0	0.072	0.114	1.889
	(0.015,0.017)	(-0.001,0)	(0.072,0.073)	(0.108,0.119)	(1.865,1.942)
Employer Movers					
Expansions	-0.093	-0.017	0.525	-0.096	1.604
	(-0.104,-0.082)	(-0.031,-0.01)	(0.517,0.536)	(-0.108,-0.084)	(1.527,1.69)
Recessions	-0.046	-0.006	0.372	-0.066	1.646
	(-0.059,-0.033)	(-0.015,0.002)	(0.365,0.383)	(-0.081,-0.046)	(1.666,1.854)
Occupation Movers					
Employer Stayers					
Expansions	0.05	0.025	0.149	0.106	1.73
	(0.039,0.06)	(0.016,0.031)	(0.142,0.155)	(0.082,0.134)	(1.571,1.942)
Recessions	0.034	0.007	0.159	0.108	1.879
	(0.018,0.047)	(-0.001,0.016)	(0.147,0.166)	(0.065,0.154)	(1.381,1.953)
Employer Movers					
Expansions	-0.042	0.016	0.506	-0.076	1.569
	(-0.058,-0.026)	(0.005,0.027)	(0.497,0.52)	(-0.091,-0.06)	(1.568,1.747)
Recessions	-0.182	-0.079	0.558	-0.125	1.489
	(-0.209,-0.16)	(-0.1,-0.066)	(0.544,0.58)	(-0.145,-0.101)	(1.436,1.619)

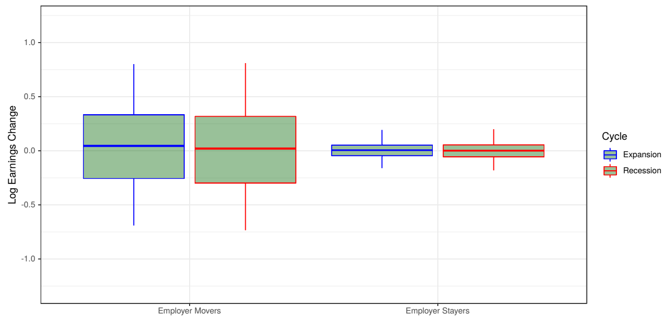
For EE transitions the wave-frequency change is the difference between the earnings observed in the wave before the one with the employer switch and the earnings in the wave that follows the

distribution, but also when they are at the bottom, which is consistent with a "slippery employer ladder" as in Pinheiro and Visschers (2016).

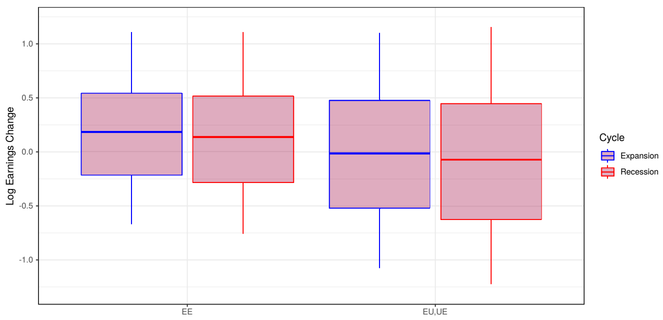
switch. We restrict ourselves to waves with continual employment at a single employer. We skip the wave in which the switch occurs because the transition may have occurred midway though the month. Annual earnings growth are computed as the earnings in the year prior to the EE transition compared to the year in which the EE transition occurred in the first wave.[31] For employer transitions through unemployment at the wave frequency, we compare earnings in the wave prior to separation with the first full wave of earnings after re-employment. As we did in EE transitions, we restrict ourselves to waves with continual employment at a single employer. If the worker was not at work for the entire wave strictly before or after the wave of transition, we exclude it from our computation.



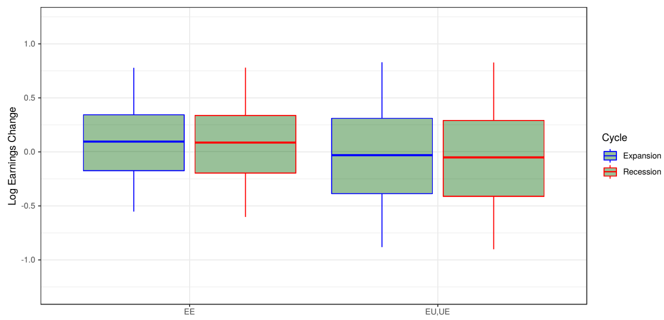
(a) Employer movers/stayers: occupational movers



(b) Employer movers/stayers: occupational stayers



(c) Employer movers : occupational movers



(d) Employer movers : occupational stayers

Figure 17: The Cyclicality of the Earnings Change Excluding Unemployment Periods - Occupation movers/stayers

[31] Alternatively, we could have chosen the year in which the EE transition was the first month, so we could observe earnings prior to and after the transition. Given the seam-bias in the SIPP, however, we opted for a measure that depends less on the exactness of the time of switching.

Appendix B

Flow Equations

Unemployed workers Given the initial conditions $(A_0, \mathcal{P}_{O,0}, \mathcal{G}^p_0)$, 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

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

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

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

where the first term denotes those unemployed workers at the beginning of the reallocation period who did not leave to another occupation. 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,

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

where $\tilde{\Omega} = \{\tilde{z}, x_{\tilde{h}}, \tilde{o}, A, \mathcal{P}_O\}$ and $\alpha^U_o(\tilde{\Omega}, \tilde{o})dF(z)$ 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 $\alpha^E_o(\tilde{\epsilon}, \tilde{\Omega}, \tilde{o})dF(z)$ 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 reseting 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

$$\begin{aligned} u^p_{t+1}(z,x_h,o)dz &= [(1-\lambda_U)+\lambda_U(1-\phi^U(\Omega))]u^r_{t+1}(z,x_h,o)dz \\ &+ (\mathbf{1}_{h=1})[(1-\lambda_U)+\lambda^c_U(1-\phi^U(\Omega))]\tilde{u}^r_{t+1}(z,x_1,o)dz \\ &+ \int_{\underline{\epsilon}}^{\overline{\epsilon}}[\delta_\epsilon+(1-\delta_\epsilon-\delta_z)(1-d(\tilde{\epsilon},\Omega))]e^s_{t+1}(\tilde{\epsilon},z,x_h,o)d\tilde{\epsilon}dz, \end{aligned} \tag{9}$$

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.

Employed workers Given the initial conditions $(A_0,\mathcal{P}_{O,0},\mathcal{G}^p_0)$, the measure of employed workers characterised by (ϵ,z,x_h) in occupation o at the beginning of next period's separation stage,

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

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

$$\begin{aligned} e^p_{t+1}(\epsilon,z,x_h,o)d\epsilon dz &= [1-\lambda_E\phi^E(\epsilon,\Omega)]e^m_{t+1}(\epsilon,z,x_h,o)d\epsilon dz + (\mathbf{1}_{h=1})\lambda^c_E\tilde{e}^m_{t+1}(\epsilon,z,x_h,o) \\ &+ \int_{\underline{\epsilon}}^{\overline{\epsilon}}\lambda_E[\gamma\phi^E(\hat{\epsilon},\hat{\Omega})+(1-\gamma)d(\hat{\epsilon},\Omega)]e^m_{t+1}(\hat{\epsilon},z,x_h,o)d\hat{\epsilon}dzd\Gamma(\epsilon) \\ &+ \lambda_U\phi^U(\Omega)u^r_{t+1}(z,x_h,o)dzd\Gamma(\epsilon) + (\mathbf{1}_{h=1})\lambda^c_U\phi^U(\Omega)\tilde{u}^r_{t+1}(z,x_1,o)dzd\Gamma(\epsilon), \end{aligned} \tag{10}$$

where $\Gamma(.)$ denotes the distribution of ϵ across the cycle and $e^m_{t+1}(\epsilon,z,x_h,o)d\epsilon dz = (1-\delta_z-\delta_\epsilon)(1-d(\epsilon,\Omega))(1-\rho(\epsilon,\Omega))e^s_{t+1}(\epsilon,z,x_h,o)d\epsilon dz$ 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 $[1-\lambda_E\phi^E(\epsilon,\Omega)]$ they did not change employers.

The second term in (10) 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 $\tilde{e}^m_{t+1}(\epsilon, z, x_h, o)$ is given by

$$\tilde{e}^m_{t+1}(\epsilon, z, x_h, o) = (1-\delta_\epsilon - \delta_z)\Bigg(\gamma\Bigg[\sum_{\tilde{o}\neq o}\sum_{\tilde{h}=1}^{H}\Big[\int_{\underline{z}}^{\overline{z}}\int_{\underline{\epsilon}}^{\overline{\epsilon}}\rho^E(\tilde{\epsilon},\tilde{\Omega})\alpha^E_o(\tilde{\epsilon},\tilde{\Omega},\tilde{o})\phi^E(\tilde{\epsilon},\tilde{\Omega})e^s_{t+1}(\tilde{\epsilon},\tilde{z},x_{\tilde{h}},\tilde{o})d\tilde{\epsilon}d\tilde{z}\Big]\Bigg]$$
$$+(1-\gamma)\Bigg[\sum_{\tilde{o}\neq o}\sum_{\tilde{h}=1}^{H}\Big[\int_{\underline{z}}^{\overline{z}}\int_{\underline{\epsilon}}^{\overline{\epsilon}}\rho^E(\tilde{\epsilon},\tilde{\Omega})\alpha^E_o(\tilde{\epsilon},\tilde{\Omega},\tilde{o})d(\tilde{\epsilon},\tilde{\Omega})e^s_{t+1}(\tilde{\epsilon},\tilde{z},x_{\tilde{h}},\tilde{o})d\tilde{\epsilon}d\tilde{z}\Big]\Bigg]\Bigg)dF(z)\Gamma(\epsilon).$$

The third term in (10) 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 (9).

APPENDIX C

Estimation of the job ladder model

A.1 Outcomes under no occupational mobility

To better understand the role of occupational mobility, we experiment in turning it off. We will find that without the additional risk from occupational mobility, it is very difficult for the model to match both flows and earnings growth tails. This makes sense because occupational mobility was an important feature of large deviations in earnings and by shutting those off, we require more flexibility from our employer effects than they can provide and still be compatibility with the flow rates across employers.

This implies flattening the permanent productivity differences across occupations, $\tilde{p}_i$, and eliminating the idiosyncratic match quality, z. This means that we have only two arrival rates out of unemployment, defined by $\lambda_0^U,\ \lambda_1^U$, and two for job-to-job transitions, $\lambda_0^E,\ \lambda_1^E$. The separation rates are also simplified, as there is no δ^z-shock, only δ_0^ϵ and δ_1^ϵ. We otherwise keep all of our functional and distributional forms the same, specifically the double-exponential distribution on ϵ and its updating.

Table 6: Targeted moments in the estimation, without occupations

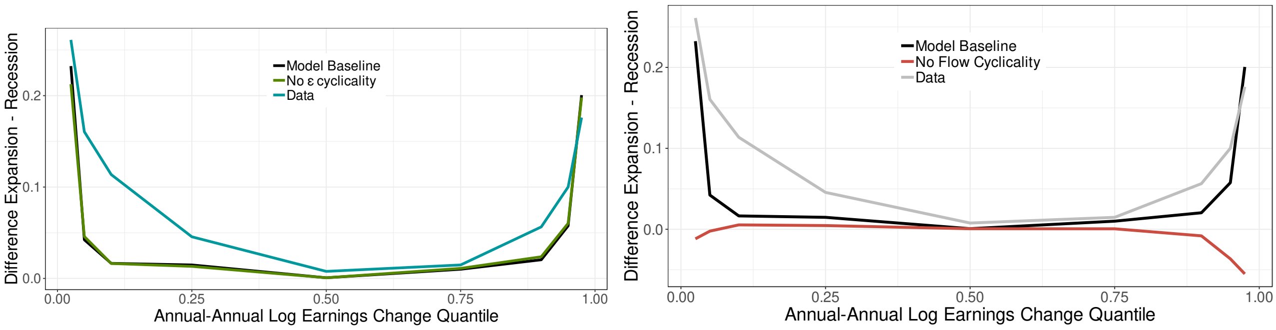
Moment	Model	Data	Moment	Model	Data
EE transition rate	0.034	0.034	UE ratio	1.078	1.088
UE transition rate	0.371	0.395	EU ratio	0.710	0.746
EU transition rate	0.023	0.022	EE ratio	1.173	1.185

We recalibrate the model just as before, matching the same set of targets but omitting those related to occupations. This means we try to match both the flows across employment, their cyclicality, the distribution of returns and the cyclicality of earnings changes, as in Figure 15. The first thing to note is that we cannot hit these targets as well: essentially within the model there is a trade off between hitting the flows and hitting the returns. The reason why is not simply that we did not allow enough flexibility in the distribution of ϵ. Rather, it is a tension coming from the relationship between unemployment and earnings changes. If we hit the UE finding rate in expansion and recession we are already implying some relationship between the change in earnings loss through unemployment. This is, however, not sufficient to get the full dynamics of earnings changes, and specifically it does not account for some of the very large earnings declines among those who fall off the occupational ladder, the δ^z shocks that were so important in our main calibration. The model without occupation shocks can create some very large earnings losses but to do that it either has to have a much steeper ϵ ladder—which comes into tension with the returns to EE flows—or longer unemployment durations—which comes into tension with the cyclicality of UE flows.

Table 7: Estimated parameter values

Job Offer Arrival				**Employer-match productivities**				**Aggregate productivity and Payments**			
λ_0^U	0.950	λ_0^E	0.137	δ_0^ϵ	0.003	lt_ϵ	3.998	ρ_A	0.958	γ_w	0.080
λ_1^U	0.001	λ_1^E	0.503	δ_1^ϵ	-0.564	rt_ϵ	0.600	σ_A	0.009	b	0.400
				η	0.237	ω_ϵ	0.490				
				σ_ϵ	0.001	ϵ_A	0.094				

Crucially, without occupations, the model does far worse at reproducing the left skewness of recessions. We see this in Figure 18 comparing the data to the occupation-less model baseline. In our full model, Figure 14 showed that ϵ cyclicality was doing little to move the distribution, which highlighted the importance of occupational mobility. Without that, flows do all of the work in this scenario to fit the cyclical change in earnings distribution.



(a) The effect of returns

(b) The effect of flows

Figure 18: Cyclicality of earnings in occupation-less restricted model. Cyclical flows account for all of the cyclicality

Machado Mata Decomposition of the Cyclicality Earnings Growth

B Statistically decomposing of earnings growth distribution over the cycle

The importance of employer and occupation movers in determining the cyclical pattern of earnings growth distribution motivates the main question of our paper. To what extent the above patterns are explained by cyclical changes in the returns to occupation/employer mobility relative to cyclical changes in the occupation/employer transitions rates? While the main results used a structural model to answer this question because of the relationship between mobility and the potential gains from moving, in this section we use a statistical method that does not adjust for this endogeneity. It is still, however a useful check on the sanity of our results.

It is well known that EE and UE transitions rates are strongly procyclical while EU transitions rates are strongly countercyclical. It is also known that occupational mobility rates are procyclical among workers who experienced EE or EUE transitions. In the appendix we verify the cyclicality of these time series in our data. Less is known about the cyclicality of the returns to employer and/or occupational mobility. In the next section we use a reduce form approach to decompose the relative importance of the returns to mobility from the associated transitions rates in determining the cyclicality of the earnings growth distribution.

We decompose the cyclical change in earnings growth into two components: (i) the cyclical changes in the frequency of employer/occupation transitions and (ii) the returns to these transitions. The basis for the decomposition is a regression that relates the change in earnings (or residual earnings after controlling for various observable traits) to indicators for unemployment and earnings changes. Thus, we partition the population into groups based on the transition they make, where sw and $no\ sw$ refers to occupation switching, UE, EU, EE refers to the different type of employer transitions and ST denotes no change in employer. The simplest form of this regression estimates the effects at the mean. Namely,

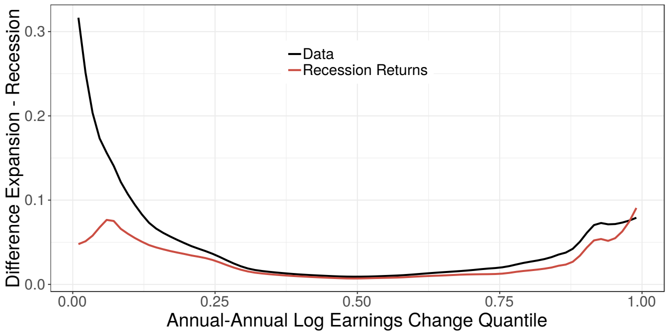
$$E[\Delta w|\mathbb{I}_s, \mathbb{I}_k, d, i] = \sum_{s\in\{sw,\ no\ sw\}} \mathbb{I}_s \times \left(\mathbb{I}_{UE}\beta^i_{s,UE} + \mathbb{I}_{EU}\beta^i_{s,EU} + \mathbb{I}_{EE}\beta^i_{s,EE} + \mathbb{I}_{stay}\beta^i_{s,ST}\right) + d\beta^i_d. \tag{11}$$

By separately estimating it for expansions ($i = E$) and recessions ($i = R$), we can obtain a Oaxaca-Blinder decomposition between changes in the mean return to a $k-$type transition, $\beta^i_{s,k}$, the changes in the average flow-rates, $E[\mathbb{I}_s \times \mathbb{I}_k]$, and changes in the average duration of unemployment transitions, d. The introduction is of unemployment durations as an explanatory variable is important as it allows us to further evaluate the importance of periods of zero earnings in our decomposition. Not controlling for duration implies that periods of zero earnings will be captured in our estimated returns to mobility.

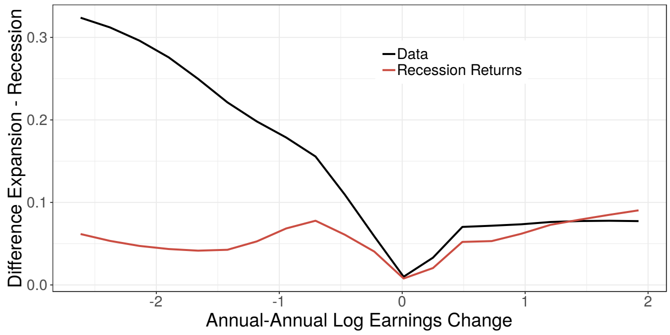
Since we are interested in the effects across the distribution, we also estimate equation (11) as a quantile regression separately for expansions and recessions. The resulting coefficients are the marginal effects of the conditional earnings growth distribution, because they are dummies of the type-k transition during recession and expansion. Again, these can be interpreted as the cycle-specific returns to a type-k transition. For example, at quantile τ, $\beta^i_{s,UE}(\tau)$ shows how the short-run cost of unemployment differs in recession and expansion, and how this varies by whether the worker switched occupations or not. Our decomposition, akin to the Oaxaca-Blinder decomposition at the mean, follows the method of Machado-Mata ((**?**) or (**?**)). Namely,

$$F^{-1}_{\Delta w}(\tau|\mathbb{I}_s, \mathbb{I}_k, d, i) = \sum_{s\in\{sw,\ no\ sw\}} \mathbb{I}_s \times \left(\mathbb{I}_{UE}\beta^i_{s,UE}(\tau) + \mathbb{I}_{EU}\beta^i_{s,EU}(\tau) + \mathbb{I}_{EE}\beta^i_{s,EE}(\tau) + \mathbb{I}_{stay}\beta^i_{s,ST}(\tau)\right) + d\beta^i_d(\tau) \tag{12}$$

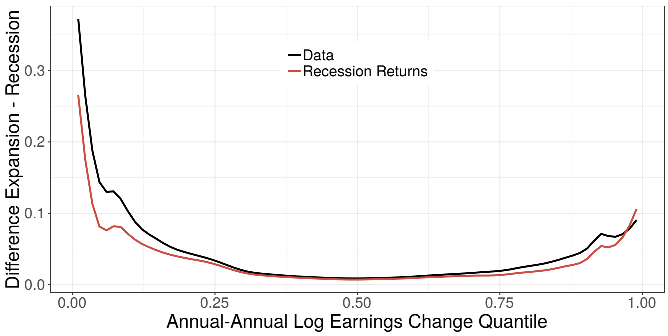
We estimate the above equations using annual earnings, as that is most comparable to the full distribution decomposition. The left column of Figure 19 plots (in black) the difference in the distributions between expansions and recessions at each quantile. The right column converts those quantiles to the corresponding earnings growth rate in the overall distribution. For example, median earnings



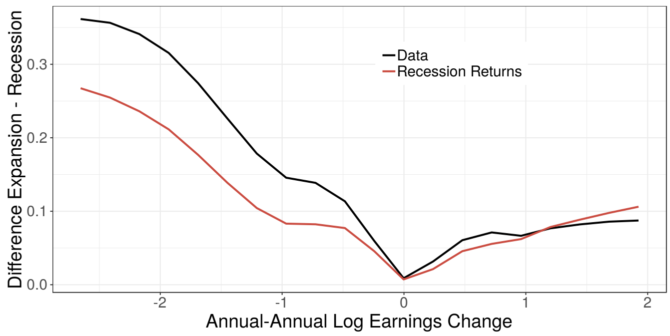
(a) Expansion - Recession at each quantile, with duration in counterfactual



(b) Expansion - Recession at the earnings growth rate, with duration in counterfactual



(c) Expansion - Recession at each quantile, no duration in counterfactual



(d) Expansion - Recession at the earnings growth rate, no duration in counterfactual

Figure 19: Expansion - Recession Annual Earnings Change

growth is about 1% more in expansions than recessions, and this is shown at 0.5 on the horizontal axis of the left column and approximately at 0 on the right column. The fact that for most of the interquartile range the difference between the distributions can be well approximated by a straight line that is above zero suggests that over the business cycle there is a uniform shift in earnings over that range. The overall downward sloping nature of the curve suggest that the variance of the earnings growth distribution is countercyclical, while its asymmetric U-shape suggests that the distribution becomes left-skewed in recessions.

The top row of Figure 19 considers the counterfactual results (in red) obtained from a regression that controls for unemployment duration as in equation (12), while the bottom row considers the counterfactual results without controlling for duration. To construct the counterfactual distributions we take the transition rates, $E[\mathbb{I}_s \times \mathbb{I}_k | i = E]$, from expansions and the estimated returns from recessions $\beta^R_{s,k}(\tau)\ \forall \tau \in (0,1)$. The red curve then shows how much of the recession effect can come from changes in the returns. The difference between the black and red curves then shows the contribution of the flow rates. At the median, the counterfactual distribution with recession returns accounts for the majority of the difference between the expansions and recessions distributions, predicting a decline of about 0.8% (relative to 1% as observed in the data) in median earnings during recessions. Further, over much of the quantiles the difference between expansion and recession is quite small and is mostly accounted by changes in returns.

As suggested by our previous analysis, it is in the tails of the distributions were we observe a more pronounced difference between expansion and recession. Below the 10th percentile, the bottom row figures show that when not controlling for unemployment duration changes in the returns are the ones that account for most of the difference between the distributions. In contrast, the top row shows that when controlling for unemployment duration the opposite conclusion arises. This discrepancy highlights once again the importance of the periods of zero earnings when constructing our annual earnings measure. The longer is the duration in unemployment, the more important periods of zero earnings become when measuring earnings changes and hence the costlier are unemployment spells when changing employers. When not controlling for duration, the effect of increased unemployment durations during recessions is included in the coefficients $\beta^R_{s,UE}$, $\beta^R_{s,EU}$ and hence returns become very important in explaining the difference in the left tail of the distribution. Computing the skewness by the GM-statistic, returns account for $\sim 80\%$ of the increased negative skewness in recessions when duration is omitted.

To further decompose the change in earnings distribution into the contributions of occupation and employer mobility, we focus the on the tails of the distribution. Table 8 considers the effect of each transition type on the right tail, $\geq 95\%$ and $\geq 97.5\%$ or the left tail, $\leq 5\%$ and $\leq 2.5\%$. To compute the contribution of each coefficient we use the flow rates from expansions and the contribution implied by using the coefficient set, $\{\beta^R_{s,k}, \beta^E_{-(s,k)}\}$, setting only that coefficient to its recessionary value, and the set of coefficients, $\{\beta^E_{s,k}, \beta^R_{-(s,k)}\}$, setting every other coefficient to its recessionary value.[32] The top panel considers the results without controlling for unemployment duration, while the lower panel considers the results when controlling for unemployment duration.

Table 8: Contribution to the cyclical change in the tails of the earnings growth distribution

	Employer movers							**Employer stayers**		
	$\beta_{sw,EE}$	$\beta_{sw,UE}$	$\beta_{sw,EU}$	$\beta_{no\ sw,EE}$	$\beta_{no\ sw,UE}$	$\beta_{no\ sw,EU}$	β_{dur}	$\beta_{no\ sw,ST}$	$\beta_{sw,ST}$	Total
Not controlling for Udur										
$\leq 2.5\%$	0.000	0.049	0.427	0.000	0.041	0.168		0.000	0.000	0.685
$\leq 5.0\%$	0.006	0.033	0.388	0.010	0.044	0.178		-0.001	-0.015	0.642
$\geq 95.0\%$	0.223	0.200	0.136	0.152	0.254	0.146		0.007	-0.062	1.057
$\geq 97.5\%$	0.293	0.230	0.095	0.141	0.270	0.109		0.006	0.000	1.145
Controlling for Udur										
$\leq 2.5\%$	0.000	0.029	0.031	0.000	0.034	0.008	0.089	0.000	0.000	0.192
$\leq 5.0\%$	0.008	0.021	0.065	0.015	0.042	0.024	0.119	0.000	0.010	0.305
$\geq 95.0\%$	0.225	0.059	0.081	0.156	0.115	0.130	0.458	0.005	-0.080	1.149
$\geq 97.5\%$	0.325	0.000	0.068	0.165	0.111	0.108	0.523	-0.000	0.000	1.301

Both set of results confirm our previous results that employer and occupational changes are the key transitions that account for most of the cyclical variation of the tails of the earnings growth distribution. In particular, we observe that the declines in the returns to EE transitions accompanied by an occupational switch are the main driving force in explaining the downward shift of the right tail of the earnings growth distribution in recessions. The top panel shows that the decline in the returns

[32]This is essentially the same as a Shapely-Owen decomposition but with a slightly lower computational cost because we do not compute every perturbation of coefficient combinations.

at re-employment with an occupational change are also important in explaining the downward shift of the right tail during recessions. Further, the top panel shows that the lower tail is mostly affected by the declines in the returns of job losers, EU transitions, who end up switching occupations. Their worst outcomes account for about 40% of the change in the very bottom tail, the lowest 2.5%. The key implication of the bottom panel is to show that a large part of the cost of an EU and a UE during recessions comes from the duration of the unemployment spell experience by occupational movers. Indeed, Carrillo-Tudela and Visschers (2019) show that occupational movers take about a month and a half longer than occupational stayers to regain employment during recessions. The analysis here shows the importance of this observation for the earnings growth distribution.

Up to now we have shown the importance of sectoral mobility and unemployment risk in determining the cyclical behaviour of the earnings change distribution. In particular, we have explored the role of occupations switching. The next step is to propose a job search model that can explain these changes to explore the causality.