Abstract

Recessions increase unemployment risk and decrease job and occupation flows. This paper connects cyclical differences in the earnings change distribution with cyclical differences in workers flows. Earnings changes are typically larger when workers change jobs and even larger when switching occupation. This implies that the incidence of flows directly affects earnings changes. However, the business cycle also affects earnings outcomes conditional on a job, employment status and/or occupation change. We formally decompose cyclical movements in the earnings change distribution into worker-flow components and “returns” components. Then, because job and occupation switching are endogenous, we look through the lens of a business cycle model with on-the-job search and occupational mobility to rationalize observed behaviour, thereby distinguishing who moves and why, and how this relates to the underlying risks workers face.

Keywords: Earnings, Unemployment, Business Cycle, Search, Occupational Mobility.

JEL: E24, E30, J62, J63, J64.
1 Introduction

From expansion to recession, the distribution of earnings changes skews to the left; during a recession there are more and deeper earnings losses than in an expansion. Recessions also increase unemployment, slow job-to-job flows and change how workers climb their career ladders. Guvenen et al. (2013, JPE) demonstrates the change in earnings growth distribution during a recession, but not its relationship to the concurrent change in employment flows. In this paper we investigate to what extent (i) the cyclical change in the number of workers reallocating across jobs and (ii) the cyclical changes in the returns to this reallocation can explain the observed earnings dynamics over the business cycle. We quantify their relative contributions, using cross-sectoral worker flows to estimate the effects on reallocation across occupations and industries.

To do so, we proceed in three steps. First, we document in the data how different types of labor market flows are associated with different wage change distributions, and how these distributions are affected by the business cycle. Second, over the business cycle not only these distributions change, but also the frequencies of the flows. We use a statistical decomposition, the Machado-Mata decomposition, to gauge the contribution of the change in labor market flows and the role of changes of the associated earnings change distributions in the cyclical shift of the earnings change distribution. Third, addressing that labor market flows and observed earnings changes endogenously respond to underlying cyclical changes, we build a structural model to lay bare the changes in the economic environment over the business cycle that workers face.

At this stage, our main findings are confined to the first steps. We find that sectoral mobility is particularly important for pulling down the top of the earnings change distribution in recessions and particularly the decline in the returns to switching diminish the potential for large earnings gains. At the bottom of the distribution, we study whether the increased incidence of unemployment during recession or the increase in the cost of an unemployment spell, is responsible for the increase in observed earnings losses and again find that the cost of an unemployment spell is the larger contributor. As recessions pull left the distribution, causing a more negative skewness, about 80% comes from a change in the return to transitions rather than a change in the rate of these transitions. The single largest force is that job losers who switch occupations have larger losses in recessions than expansions.

Finally, we discuss the economic model that we plan to use to uncover the impact of the cycle on the economic environment in which workers choose to switch employer and occupation, and the earning changes that result from these (or the absence of these).

Related Literature  To be written
2 The earnings change distribution

2.1 Data

We use data from the Survey of Income and Program Participation (SIPP) from the 1990 through 2008 panels, covering the 1990-2013 period. The advantage of using the SIPP is that each of its panels follow 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 covering the last four months on their current and previous employment status, occupations, industries and earnings (hourly wages and hours worked). Using this information, we define employer, occupation and earnings changes based on a worker’s main job for each period.\textsuperscript{1}

Our analysis of earnings focuses on two measures. (i) The $EU, UE$ measure: a year-to-year earnings change measure that includes the zero earnings associated with the months in which an individual does not work; and (ii) the $EUE$ measure: a wave-to-wave earnings mobility measure that only considers periods of positive earnings. In the latter measure, employer transitions through unemployment are still included, by comparing the last full wave of earnings before unemployment with the first full wave of earnings afterwards. When putting these two perspectives next to each other, we hope to capture the role of zero earnings periods in earnings mobility, together with impact of unemployment periods on subsequent earnings.

**Labor Market Flows** Let us first look at how we distill employer and occupational transitions from the data. We code these transitions month-to-month. Employer changes that occurred without an intervening full month of non-employment are labeled as $EE$ transitions and those that occurred through non-employment as $EU$ and $UE$ transitions. In the latter case, we include all transitions in which worker the worker returned to employment within the sample, even if the worker did not report actively searching, which is consistent with evidence from \textsuperscript{7} that re-employment is quite common among recently employed nonparticipants. Because we only consider non-employment spells completed within the survey period, our non-employment durations are potentially biased downwards, affecting mostly the tail of the distribution.\textsuperscript{2} Were we only to lose non-employment spells at the end of a panel due to this truncation, we would under-represent $EU, UE$ transitions relative to $EE$ transitions, thus we consider only transitions with at least 4 waves remaining. Our $EUE$ transitions are also affected by our choice to exclude “temporary recalls”. Fujita and Moscarini (2017) thoroughly documents that many times unemployed workers return to their initial employer shortly after their

\textsuperscript{1}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. Further, because interviews are conducted at 4-month intervals the data suffers from “seam-bias” at the interview months and so we consider observations at the wave frequency. Nevertheless we revisit its potential effects in the appendix.

\textsuperscript{2}In particular, we find that the median unemployment duration in our data is of 2 months and 2.49 months in the Current Population Survey (CPS) data. At the same time, the average unemployment duration in our data is about 2.1 months, compared with 4.7 months in the CPS data. The calculation based on the CPS is obtained for the 1996-2012 period.
separation. We do not count these recalls as job-status transitions because they almost never entail
an occupational switch and they are not comparable to $EE$ changes because they do not involve a
change of employer. We further detail our procedure in the Appendix.

To analyse occupational change, we homogenise the occupation classification across panels us-
ing the crosswalk translation scheme created by IPUMS based on the 1990 Standard Occupational
Classification (1990 SOC). We aggregate the resulting occupational codes into 2-digit occupation
groups and measure occupational change by comparing the occupation groups for a given individual
across interviews. 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. This, however, still remains an
issue for employer movers. Carrillo-Tudela and Visschers (2018) provide a in-depth analysis of this
issue and show that the same coding errors translate differently among employer movers and stayers,
affecting much more, in relative terms, the occupational mobility rates of employer stayers. In what
follows we will not correct for coding errors among employer movers in the data sections, but pro-
vide robustness checks based on simultaneous occupational and industry changes, and address it in
the structural analysis by incorporating measurement error in our quantitative model.

Earnings (mobility) To study earnings, we deflate nominal earnings by the PCE; then we estimate
the earnings changes as the changes in the residual of regression log of earnings after controlling for:
quadratic on potential experience, education, gender and race dummies, and month dummies.

As mentioned above, earnings changes are computed at wave and annual frequency. For employed
workers who do not change employers and are continually at work, we simply compute the wave-to-
wave earnings changes by comparing consecutive waves and annual earnings changes as growth from
one year to the next.

For $EE$ transitions, the wave-frequency change is the difference in earnings in the wave before the
one with the employer switch with earnings in the wave that follows the switch. We skip the wave in
which the switch occurs because the transition may have occurred midway though the month. Annual
earnings changes 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.

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3 The relative impact of coding errors on measured transition is much more important for employer stayers, under
independent interviewing. They find that the occupational mobility rate of the latter is inflated by around 50% (which
should be drastically reduced dependent interviewing procedure of the SIPP). However, employer changers exhibit high
true occupational mobility rates, and hence the scope for creation of a coded occupational transition while workers remain
in reality in their previous occupation, is more limited. The occupational mobility rate of employer movers is inflated
by around 20%. The impact of these coding errors is likely to attenuate any actual differences between occupational
movers and stayers – the fact that we find meaningful differences even with attenuation implies that these differences are
potentially even larger.

4 Carrillo-Tudela and Visschers (2018) show that the simultaneous occupational and industry mobility measure pro-
vides a good lower bound for the error-corrected occupational mobility rate of employer movers.

5 Alternatively, we could chose the year in which the $EE$ transition was the first month, so we could see earnings prior
For employer transitions through unemployment, \( EUE \), at the wave frequency, we compare earnings in the wave prior to separation with re-employment earnings in the wave following. We restrict ourselves to waves with continual employment at a single employer. As we did in \( EE \) transitions, 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 of average earnings.

For annual earnings changes, we again compare earnings changes in the year prior to a transition to earnings in the year following the wave in which the transition occurred.\(^6\) These transitions can include either an \( EU \) or a \( UE \) observation. Because there are some separations, \( EU \) transitions in which the worker matches but after more than a year of non-employment duration, we will use inverse hyperbolic sine differences, rather than log differences. These are approximately the same as log differences except in the case of very low and zero earnings. Namely,

\[
\Delta_{i,t+1} = \log(w_{i,t+1} + \sqrt{1 + \frac{w_{i,t+1}^2 + 1}{2}}) - \log(w_i + \sqrt{1 + \frac{w_{i,t}^2 + 1}{2}})
\]

To clean reporting errors in the earnings data, we take a light touch. We windsorize the bottom and top 2% of the wave-frequency earnings sample and drop imputed earnings. 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.

Using these data, we study the distribution of changes in earnings both non-parametrically and through quantile regressions.

### 2.2 Earnings changes: Long-run patterns

Figure 1 depicts the distribution of annual earnings changes pooling all years in our sample, in four panels. The upper row refers to annual earnings change distribution, taking into account periods of zero earnings, while the lower row displays the in-work wave-by-wave earnings changes (excluding periods of zero earnings). The left-hand picture shows the log density, while the right-hand picture displays the vertically truncated density.

These figures all imply that the aggregate earnings change distribution is characterised by two important features: (i) most of its mass is centred around zero, meaning that the majority of workers exhibit relatively small (positive or negative) earnings changes across consecutive years. However, (ii) a relatively large mass of workers exhibit large (positive or negative) earnings changes, which generate tails that are approximate linear in logs and hence well approximated by a Pareto distribution, in Figures 1a and 8c.

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\(^6\) Here, earnings in the reference period are measured without the aforementioned stability restriction that the respondent was at work every week of the reference period.
FIGURE 1: EARNINGS CHANGE DISTRIBUTION, 1990-2013

Earnings Mobility and Labor Market Flows Importantly, these features relate to the underlying labor market flows. To visualize this, we decompose the earnings change distribution by the labor market mobility of the worker. Specifically, we look (in red) at whether the worker stayed with the same employer, and if the worker changed employer, whether this change involved unemployment (EUE, in turquoise), or was a direct employer-to-employer move (EE, in green). Figures 1a and 8c shows that employer stayers (who represent the majority of workers in our sample, around 75%) have earnings changes that are less dispersed and more concentrated around zero. In contrast, employer movers have much more dispersed earnings changes and are primarily the ones behind the distribution’s fat tails. Perhaps unsurprisingly, 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 came back into employment as to complete an EUE transition or experienced EE transitions. In the lower row, the ‘in-work’ earnings changes for EUE transitions (which, as above, refer to earnings strictly before losing the job compared to earnings strictly after regaining employment) are still responsible for most of the earnings changes in the tails.

The Role of Labor Market Flows in Earnings Mobility across the Earnings Distribution Figure 2a plots the same earnings change 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. This figure conveys a rather similar message to the one in Guvenen et al. (2014), which displays the earnings change distribution as a function of
previous five-year earnings percentile.\(^7\)

The role of labor market flows behind Figure 2a can be gauged from Figure 2b, which presents plots the same relation but for a sample restricted to only employer stayers. Here we find that the earnings changes of employer stayers are not only much less dispersed (as shown in Figure ??), but the probability of an earnings change (positive or negative) is much less sensitive to these workers’ previous year earnings. In fact, the \textit{earnings change} distribution does not change much across the earnings distribution, apart from the probability of larger improvements at the low-earnings end, and the probability of earnings losses at the very high-earnings end. Together this evidence then suggests that those workers who experienced the large earnings changes depicted in Figure ?? are also those who had low previous year earnings \textit{and} changed employers.

These patterns are inline with the implications of standard job ladder models. In these models, workers typically move to better paying employers, but once in a while they lose their jobs and either become unemployed or get immediately re-employed possibly receiving a pay cut. What we see at the 90th percentile line is that workers who are low on the job ladder climb the most and the slow decline reflects the job ladder’s concavity. The 10th percentile, however, shows two features: workers are also more likely to to fall further when they are at the top of the earnings distribution, which is consistent with every job ladder model, but also when they are at the bottom, which is consistent with a “slippery job ladder.”

The Role of Occupational Mobility in Earnings Mobility A substantial body of work has suggested that occupational changes play an important role in determining workers’ earnings dynamics (more recently e.g. Kambourov and Manovskii (2008, 2009), Moscarini and Thomsson, Lise and Postel-Vinay, Guvenen...). Figures 3a and 3b condition the earnings change distribution by whether workers switched occupations and/or employers across consecutive years. The boxes depict the density within the interquartile range and the whiskers the density within the 90-10 percentiles. The thick

\(^7\)Note that Figure 2a is very similar to the one obtained by Guvenen et al. (2014), who uses 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.
Figure 3: Earnings Change Distribution, 1990-2013

line within the boxes depicts the mean of the distribution. These figures show a large role of occupational mobility in earnings changes: when switching occupation, earnings changes are more dispersed for both employer stayers and movers. Occupational change thus seems to add an additional source of to workers’ earnings changes.

EE occupation switchers seem to gain on average, relative to the EE occupation stayers. This also appears the case for employer stayers, but the difference is smaller. For EUE movers the mean is slightly higher for those that change occupations. Across every type of transition, occupational mobility has a relation not only with mean earnings changes, but also with a noticeably increased dispersion of earnings changes.

To give a quantitative overview of the role of employer and occupation transitions (or the absence thereof) in the earnings change distribution, not only for the variance, but also for skewness and kurtosis, we display the contributions of the cross-product of labor market (non)transition in the tables below. For each subset \( K \) of workers that share occupation and (type of) job (im)mobility, e.g. the set of workers with EE-job move that is accompanied by an occupational switch, we calculate the proportion of the sum of squared deviations \( \sum_K \sum_{o \in K} (\Delta w_o - E_{pop}[\Delta w])^2 \) that originates in this group, and divide it by the overall sum of squared deviations \( \sum_{pop}(\Delta w_o - E_{pop}[\Delta w])^2 \). (Similar calculations are then done for the third and fourth central moment below.)

Tables 1 and 2 report the contribution of occupational stayers/movers and employer stayers/movers to the variance of the earnings change distribution. They show that occupational movers contribute about 50% of the overall variance even though the share of occupational movers in our sample is
Table 1: Decomposition of annual earnings change dispersion, by mobility
(earnings changes include periods of zero earnings)

<table>
<thead>
<tr>
<th>Occupation Stayers</th>
<th>Occupation Movers</th>
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<tr>
<td>Employer Stayers</td>
<td>Employer Mover</td>
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<tr>
<td></td>
<td>EE</td>
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<tr>
<td></td>
<td>EU,UE</td>
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<tr>
<td>Entire distribution</td>
<td>0.119</td>
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<td>0.944</td>
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<td>EU,UE</td>
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<tr>
<td>Entire distribution</td>
<td>-0.008</td>
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<td>0.010</td>
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Table 2: Decomposition of ‘in work’, wave-wave earnings change dispersion, by mobility

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<td>Employer Stayers</td>
<td>Employer Mover</td>
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<td></td>
<td>EU,UE</td>
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<td>Entire distribution</td>
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<td>0.813</td>
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<tr>
<td>Truncated: 0.9-0.1 ptiles</td>
<td>0.883</td>
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<tr>
<td>Truncated: 0.75-0.25 ptiles</td>
<td>0.950</td>
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<td>EE</td>
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<td></td>
<td>EU,UE</td>
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<td>Truncated: 0.9-0.1 ptiles</td>
<td>0.883</td>
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<tr>
<td>Truncated: 0.75-0.25 ptiles</td>
<td>0.950</td>
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about $\frac{1}{6}$. Further, the biggest share of this contribution arises from those workers who changed employers through unemployment. 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 occupational and employer movers diminishes, reaching 15% and 4% when considering the interquartile range, respectively. Note that workers on average do seem to gain by switching occupations. In particular, employer stayers and EE movers who switched occupations gain about 4% and 26%, while employer stayers and EE movers gain 1% and 16% when not switching occupations. For those workers who experienced EUE transitions, we find that occupational switchers lose a very similar amount (around -34%) as those who did not switch occupations.

We can do a similar exercise with the third central moment, telling us the ‘contribution’ of each category of labor market transition (or absence thereof) contributes to the skewness of the wage change distribution. Looking first at our annual earning change measure, transitions through unemployment are 103% of the negative skewness in the distribution overall. This is to say, the over-
all distribution is slightly negatively skewed, and only EU,UE transitions are themselves negatively skewed. The transitions that involve an occupation move are slightly more negatively skewed and therefore contribute more than non-move transitions. The EE transitions and employer stayers are both positively skewed and therefore contribute negatively to the negative skewness.

This is flipped when we look at earnings “in work,” when the distribution as a whole is slightly positively skewed. In this case transitions through unemployment are actually quite symmetric and therefore contribute little positively or negatively to the moment overall. EE transitions, on the other hand, bring large, immediate earnings gains that are positively skewed. The occupation movers, while representing about half of the EE transitions, are even more positively skewed and therefore contribute more to the overall third moment.

**The occupational ladder and worker earnings mobility**  
Given the importance of occupational mobility in the earnings change distribution, we now investigate whether earnings changes are associated with movements from occupations that on average earn more to those that earn on average less, and vice versa. To do so, we derive conditional occupational earnings averages by running a simple earnings regression, including a quadratic for potential experience, dummies for education, gender and race and a set of dummies for the 2-digit occupations. We treat the coefficients on these dummies as the occupational earnings effect. Moving to occupations with a higher earnings effect is considered ‘climbing up the occupational ladder’.

We calculate the change in occupational earnings effect for each worker, and group these by employer stayers, and EE or EUE movers. In Figure 4 we rank transitions by the size of the earnings change (on the x-axis) and, within a quantile of earnings change, look at the distribution of occupational earnings effect changes. This procedure then allows us to analyse whether most of the workers whose employer transition resulted in an earnings gain also moved to an occupation with higher average earnings. Figure 4a shows the median, 90th and 10th percentiles of growth in average occupational earnings at each percentile of earnings growth for EE transitions. Figure 4b shows the same for EUE transitions.

In addition, in both figures we have overlaid the inverse pdf of the aggregate earnings change distribution, i.e. for each quantile we plot the associated earnings change on the y-axis. It follows immediately from comparing these that the distribution of changes in occupational earnings effect does not drive the wage change distribution, in the sense that large earnings changes are associated with larger movements up or down the occupational ladder. In fact, for both EE and EUE employer movers the median growth in occupational earnings is nearly the same for those who lost earnings as those who gained earnings. That is, workers whose earnings grew in a (EE or EUE) transition were almost as likely to move to a higher pay occupation than one whose earnings shrunk.
2.3 Earnings changes: Business cycle patterns

We now turn to explore the cyclicality of the earnings change distribution. Figure 5 shows the earnings change distribution for all workers in expansions and recessions.\(^8\) When considering \(EU, UE\) earnings changes, Figure 5a shows that the earnings change distribution shifts downwards during recessions, exhibiting smaller gains and larger loses. The top panel of Table 3 summarises the cyclicality of the moments of this distribution. It shows that the median and variance (measured by the median absolute deviation) are essentially acyclical. In contrast, the earnings change distribution exhibits countercyclical left-skewness (measured by the Groeneveld and Meeden’s (GM) coefficient), whereby during a recession, relative to expansions, the right tail of the earnings change distribution becomes thinner and the left tail becomes fatter.\(^9\) This behaviour is similar to the one documented by Guvenen et al. (2014), Busch and Ludwig (2018) and Harmenberg (2018) for the earnings change distribution using administrative data for the US, Germany and Denmark, respectively.

When considering \(EUE\) earnings changes, Figure 5b shows a much more subdued cyclical behaviour. During recessions, it is only the left tail of the distribution which reacts, showing larger earnings losses and pulling down the distribution. The bottom panel of Table 3 shows that this translates into a lower degree of countercyclicality in our skewness measure.

An important advantage of using the SIPP is that we can compute the cyclical properties of the

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\(^8\)Here recessions are defined as periods in which the HP-filtered unemployment rate. In the Appendix we document the cyclicality of the earnings change distribution by defining recessions as periods defined by the NBER.

\(^9\)The GM coefficient is given by \((\mu - \nu)/E[X - \nu]\), where \(\mu\) is the sample mean and \(\nu\) the sample median.
Table 3: Moments of earnings change distribution - All workers

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<tr>
<td>Expansions</td>
<td>0.023</td>
<td>0.006</td>
<td>0.115</td>
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<td>2.407</td>
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<tr>
<td></td>
<td>(0.021, 0.025)</td>
<td>(0.005, 0.006)</td>
<td>(0.114, 0.116)</td>
<td>(0.05, 0.062)</td>
<td>(2.366, 2.426)</td>
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<td>-0.003</td>
<td>0.123</td>
<td>-0.044</td>
<td>2.461</td>
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<td></td>
<td>(-0.019, -0.014)</td>
<td>(-0.003, -0.002)</td>
<td>(0.123, 0.125)</td>
<td>(-0.053, -0.038)</td>
<td>(2.423, 2.493)</td>
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<td>0.085</td>
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<td>(0.077, 0.09)</td>
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<td>0.054</td>
<td>2.680</td>
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<td></td>
<td>(0.003, 0.005)</td>
<td>(-0.005, -0.005)</td>
<td>(0.065, 0.065)</td>
<td>(0.046, 0.06)</td>
<td>(2.587, 2.682)</td>
</tr>
</tbody>
</table>

2.3.1 The role of employer mobility

We now turn to analyse the role of employer mobility in accounting for the cyclical changes of the earnings change distribution. Figure 6a considers the case of \( EU, UE \) earnings changes, while Figure 6b considers \( EUE \) earnings changes. These graphs show that the cyclical behaviour of the earnings change distributions documented in the previous section, is mainly driven by the cyclicality of the earnings change distribution of employer movers. For the \( EU, UE \) case, our results show that during recessions the right tail of the distribution exhibits less earnings gains, while the left tail exhibits larger earnings losses. In contrast, the earnings change distribution of employer stayers shows a more subdued cyclical pattern.

Table 4 shows the moments of the earnings change distributions of employer movers and employer stayers. Here we can observe a stronger countercyclicality in the skewness of \( EU, UE \) earn-
Figure 6: The Cyclicality of the Earnings Change Distribution - employer movers/stayers, 1990-2013

Table 4: Moments of earnings change distribution - Employer movers/stayers

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>Median</th>
<th>Med Abs Dev</th>
<th>GM coeff</th>
<th>Moors coeff</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Including period of no earnings zeros</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Employer Stayers</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Expansions</td>
<td>0.017</td>
<td>0.000</td>
<td>0.073</td>
<td>0.116</td>
<td>1.921</td>
</tr>
<tr>
<td></td>
<td>(0.016,0.017)</td>
<td>(0.000,0.000)</td>
<td>(0.073,0.074)</td>
<td>(0.111,0.12)</td>
<td>(1.88,1.932)</td>
</tr>
<tr>
<td>Recessions</td>
<td>0.008</td>
<td>-0.004</td>
<td>0.077</td>
<td>0.082</td>
<td>1.983</td>
</tr>
<tr>
<td></td>
<td>(0.007,0.01)</td>
<td>(-0.004,-0.003)</td>
<td>(0.076,0.077)</td>
<td>(0.076,0.087)</td>
<td>(1.942,2.016)</td>
</tr>
<tr>
<td><strong>Employer Movers</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Expansions</td>
<td>0.037</td>
<td>0.071</td>
<td>0.391</td>
<td>-0.052</td>
<td>1.752</td>
</tr>
<tr>
<td></td>
<td>(0.03,0.042)</td>
<td>(0.067,0.074)</td>
<td>(0.388,0.393)</td>
<td>(-0.06,-0.048)</td>
<td>(1.731,1.799)</td>
</tr>
<tr>
<td>Recessions</td>
<td>-0.075</td>
<td>0.011</td>
<td>0.439</td>
<td>-0.124</td>
<td>1.704</td>
</tr>
<tr>
<td></td>
<td>(-0.084,-0.068)</td>
<td>(0.006,0.015)</td>
<td>(0.436,0.444)</td>
<td>(-0.134,-0.114)</td>
<td>(1.645,1.718)</td>
</tr>
<tr>
<td><strong>Excluding period of no earnings zeros</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Employer Stayers</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Expansions</td>
<td>0.010</td>
<td>-0.002</td>
<td>0.049</td>
<td>0.093</td>
<td>2.516</td>
</tr>
<tr>
<td></td>
<td>(0.009,0.01)</td>
<td>(-0.003,-0.002)</td>
<td>(0.049,0.05)</td>
<td>(0.088,0.097)</td>
<td>(2.53,2.609)</td>
</tr>
<tr>
<td>Recessions</td>
<td>0.004</td>
<td>-0.005</td>
<td>0.056</td>
<td>0.069</td>
<td>2.488</td>
</tr>
<tr>
<td></td>
<td>(0.003,0.005)</td>
<td>(-0.005,-0.005)</td>
<td>(0.056,0.057)</td>
<td>(0.061,0.074)</td>
<td>(2.441,2.516)</td>
</tr>
<tr>
<td><strong>Employer Movers</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Expansions</td>
<td>0.037</td>
<td>0.014</td>
<td>0.351</td>
<td>0.042</td>
<td>1.752</td>
</tr>
<tr>
<td></td>
<td>(0.026,0.048)</td>
<td>(0.008,0.021)</td>
<td>(0.346,0.359)</td>
<td>(0.028,0.054)</td>
<td>(1.639,1.783)</td>
</tr>
<tr>
<td>Recessions</td>
<td>0.002</td>
<td>-0.017</td>
<td>0.372</td>
<td>0.033</td>
<td>1.757</td>
</tr>
<tr>
<td></td>
<td>(-0.012,0.013)</td>
<td>(-0.023,-0.008)</td>
<td>(0.363,0.384)</td>
<td>(0.014,0.048)</td>
<td>(1.586,1.795)</td>
</tr>
</tbody>
</table>

ings changes distribution among employer movers relative to employer stayers. In contrast, when considering the EUE earnings change distribution we observe similar cyclical patterns across the moments of the earnings change distribution of employer stayers and movers.

2.3.2 The role of occupational mobility

Just as the earnings change of those changing employer is more cyclical volatile, the earnings change of occupation switchers among any type of transition. This is particularly stark among workers tran-
sitting through unemployment. As we have established, occupational mobility increases dispersion among every type of transition. In Figures 7 and 8 we show the earnings change of workers going from one occupation to another are both more dispersed and more cyclical.

The different cyclicality between occupation switchers and non-switchers does not appear at the center of the distribution. For instance, using the measure of annual earnings changes including unemployment spells among employer movers both occupation stayers and switchers have a mean decline of about 15 percentage points and a median decline of about 10 percentage points in recessions.

The large difference, however occurs at the bottom of the distribution. For the lowest decile of employer changers, recessions bring earnings declines of 40% more (8 percentage points) for occupational switchers than non-switchers. This is driven almost entirely by workers switching occupations through unemployment as shown in panels (c) and (d) of Figures 7 and 8. The difference in earnings lost at the bottom decile of occupation switchers is twice that of non-occupation switchers: the bottom decile of non-switchers lose 12 percentage points more earnings in recessions than expansions but for occupations switchers, earnings losses are 25 percentage points larger.

Interestingly, this earnings decline among switchers does not occur as starkly at the top tail. Among job-to-job transitions, neither occupation switchers nor non-switchers see much decline at the top decile of their earnings growth distribution. Among EE transitions, occupation switchers at the 90th percentile gain about 110% in recession or expansion while non-switchers gain about 75%. Important to note with this observation, however is that the overall distribution of earnings changes may still change at the top of the earnings growth distribution if fewer workers in recessions make EE transitions or EE transitions with occupation switches then there is less of an upside to the overall earnings change distribution. Decomposing the effect of changes in the conditional earnings growth distributions, which we have explored so far, and the transition rates, is exactly what we explore in Section 2.4.

### 2.4 A decomposition of earnings changes

We now present preliminary results from our attempt to systematically separate whether the top end of earnings changes comes down because the potential gains from a sectoral switch are lower or because fewer people make these transitions. We also ask the opposite of the effect of unemployment. To put structure onto our analysis, we can consider a simple 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. The simplest form of this regression estimates the effects at the mean. If we run it twice, for \( i \in \{ E, R \} \) for expansions and recessions, we can do a Oaxaca decomposition between changes in the mean return to a \( k \)-type transition, \( \beta_{s,k}^i \), and the average flow-rates associated with the cycle phase, \( E[\Pi_s \times \Pi_k] \).

\[
E[\Delta w | \Pi_s, \Pi_k, i] = \sum_{s \in \{ sw, no\ sw \}} \Pi_s \times (\Pi_{UE}s,UE \beta_{s,UE}^i + \Pi_{EU}s,EU \beta_{s,EU}^i + \Pi_{EE}s,EE + \Pi_{stay}s,ST \beta_{s,ST}^i)
\]
Figure 7: The Cyclicality of the Earnings Change Including Unemployment Periods- occupation movers/stayers, 1990-2013

Figure 8: The Cyclicality of the Earnings Change Excluding Unemployment Periods- occupation movers/stayers, 1990-2013
Since we are also interested in the effects across the distribution, we run a quantile regression on earnings changes, as in equation 1. We estimate this separately in expansions and in recessions, indexed $i$. The resulting coefficients are the marginal effects or the conditional distribution, because they are dummies of the type-$k$ transition during recession and expansion. Again, these can be interpreted as the sector-specific returns to a type-$k$ transition. For example, at quantile $\tau$, $\beta_{s,UE}^i(\tau)$ shows how the short-run cost of unemployment differs in recession and expansion, $i \in \{R, E\}$, and how this varies whether the worker switched sectors with $s \in \{sw, no sw\}$. Now our decomposition, akin to the Oaxaca blinder decomposition at the mean, follows the method of Machado Mata (or ?).

$$F_{\Delta w}(\tau|\Pi_s, \Pi_k, i) = \sum_{s \in \{sw, no sw\}} \Pi_s \times \left( \Pi_{UE} \beta_{s,UE}^i(\tau) + \Pi_{EU} \beta_{s,EU}^i(\tau) + \Pi_{EE} \beta_{s,EE}^i(\tau) + \Pi_{stay} \beta_{s,ST}^i(\tau) \right)$$

We first look at earnings change at an annual basis, as that is most comparable to the full distribution decomposition. Figure 9 plots the difference in distribution between expansions and recessions at each quantile (Left), then converts those quantiles to the corresponding earnings growth rate in the overall distribution (Right). This is to say, that at the median, earnings growth is about 1% more in expansions than recessions, shown on the black line at 0.5 on the horizontal axis of the left panel and approximately 0 on the right panel. The U-shape of the black line demonstrates that the distribution becomes left-skewed: a straight line above 0 would mean a uniform shift in income, a downward sloping line would be a counter-cyclical variance and the U-shape means the bad outcomes become worse and fewer good outcomes.

In this decomposition, the red line takes the transition rates, $E[\Pi_s \times \Pi_k|i = E]$, from expansions and return distributions from recessions $\beta_{s,k}^R(\tau) \forall \tau \in (0, 1)$. To interpret this, the red line shows us how much of the recession-effect can come purely from the change in returns and the remainder comes from changes in the flow rates.

At the median, where the difference in earnings is about 1%, the counter-factual distribution with returns accounts for the majority, predicting a decline of about 0.8% in median income during recessions. Over much of the earnings change distribution the difference between expansion and recession is quite small and is mostly accounted by changes in returns. At the 25th and 75th percentiles, for instance, the gap between the data and counter-factual is less than 1 percentage point.

The change in the tails between expansion and recession is quite a bit more pronounced. The
counter-factual distribution also captures much of, thought not all of the shifting in the tails, and thus the increased negative skewness. Computing the skewness by the GM-statistic, returns account for $\sim 80\%$ of the increased negative skewness in recessions. Some of the reason for the importance of returns to skewness comes because the extreme right side of the distribution, the top 2.5 percent, where the upside-risk is actually over-accounted by the returns. This portion of the distribution is particularly the workers finding jobs from unemployment and job-to-job transitions, the top of whose distributions are not particularly adverse in recessions, though there are fewer of them.

To further decompose the change in earnings distribution into contributions of individual transition-types, we will focus particularly on the tails. Table 5 considers the effect of each transition type on the top tail, $\geq 95\%$ and $\geq 97.5\%$ or the bottom 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, $\{ \beta_{s,k}^R , \beta_{-(s,k)}^E \}$, setting only that coefficient to its recessionary value, and the set of coefficients, $\{ \beta_{s,k}^E , \beta_{-(s,k)}^R \}$, setting every other coefficient to its recessionary value.$^{10}$

<table>
<thead>
<tr>
<th></th>
<th>$\beta_{sw,EE}$</th>
<th>$\beta_{sw,UE}$</th>
<th>$\beta_{sw,EU}$</th>
<th>$\beta_{no sw,EE}$</th>
<th>$\beta_{no sw,UE}$</th>
<th>$\beta_{no sw,EU}$</th>
<th>$\beta_{no sw,ST}$</th>
<th>$\beta_{sw,ST}$</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\leq 2.5%$</td>
<td>0.000</td>
<td>0.050</td>
<td>0.428</td>
<td>0.000</td>
<td>0.043</td>
<td>0.182</td>
<td>0.000</td>
<td>0.000</td>
<td>0.703</td>
</tr>
<tr>
<td>$\leq 5.0%$</td>
<td>-0.002</td>
<td>0.035</td>
<td>0.383</td>
<td>0.005</td>
<td>0.045</td>
<td>0.183</td>
<td>0.000</td>
<td>-0.007</td>
<td>0.643</td>
</tr>
<tr>
<td>$\geq 95.0%$</td>
<td>0.141</td>
<td>0.185</td>
<td>0.129</td>
<td>0.180</td>
<td>0.206</td>
<td>0.148</td>
<td>0.009</td>
<td>0.043</td>
<td>1.042</td>
</tr>
<tr>
<td>$\geq 97.5%$</td>
<td>0.253</td>
<td>0.231</td>
<td>0.097</td>
<td>0.209</td>
<td>0.216</td>
<td>0.126</td>
<td>0.003</td>
<td>0.000</td>
<td>1.133</td>
</tr>
</tbody>
</table>

Table 5: Contribution to the cyclical change in the tails of the earnings growth distribution.

Notice that the lower tail is particularly effected by the returns of job losers, $EU$ transitions, who end up switching occupations. Their worse outcomes account for about 40% of the change in the very bottom tail, the lowest 2.5%. The workers staying in the same employer have almost no effect on the lower tail. On the other hand, a small set of occupation switchers affect the top tail: less than $\frac{1}{20}$ of the decline in the top 5% comes from worse earnings growth among employer stayers who switch occupations. Job-to-job, $EE$ transitions have less of an effect on either end of the distribution: they have almost no effect on the bottom tail, as they are scarcely represented in that section of the distribution but worse outcomes for $EE$ transitions in recession contribute about $\frac{1}{3}$ to $\frac{1}{2}$ of the change in the right tail.

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 simple model that can explain these changes to explore the causality.

---

$^{10}$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.
3 Theoretical Framework

We now develop and estimate a theory of occupational mobility to explain the above empirical results. Our model incorporates aggregate uncertainty, occupational-wide productivity differences, job-specific match wage differences and worker heterogeneity.

3.1 Environment

Time is discrete $t = 0, 1, 2, \ldots$ A mass of infinitely-lived, risk-neutral workers 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: general human capital, $x_{ht}$, occupation-specific human capital, $x_{ot}$, an idiosyncratic occupation-match productivity, $z_{t}$, and an idiosyncratic firm-match productivity, $\theta_{t}$.

Workers’ accumulate general and occupational-specific human capital through a learning-by-doing process. In period $t$ an employed worker with human capital level $x_{ht}$ increases his human capital to $x_{ht+1}$ with probability $\chi_{t}(x_{ht+1} | x_{ht})$, where $\chi_{t}(x_{ht+1} | x_{ht}) = 1 - \chi_{t}(x_{ht} | x_{ht})$, $x_{ht} < x_{ht+1}$, $h = 1, \ldots, H$ and $x_{ht} \in \mathbb{R}_{+}$. A worker’s general or occupational-specific human capital may also depreciate with unemployment. An unemployed worker with human capital level $x_{ht}$ decreases his human capital to $x_{ht-1}$ with probability $\chi_{u}(x_{ht-1} | x_{ht})$, where $\chi_{u}(x_{ht-1} | x_{ht}) = 1 - \chi_{u}(x_{ht} | x_{ht})$, $x_{ht} > x_{ht-1}$, $h = 1, \ldots, H$ and $x_{ht} \in \mathbb{R}_{+}$.

We interpret the $z$-productivity as a “career match” which captures how well the worker is doing in the occupation he is currently attached to (see Neal, 1999). Workers’ $z$-productivities follow a common and exogenous first-order stationary Markov process, with transition law $F(z_{t+1} | z_{t})$ and $z_{t}, z_{t+1} \in [\underline{z}, \overline{z}]$, $\underline{z} > 0$ and $\overline{z} < \infty$. The $z$-productivity realizations affect a worker both in employment and in unemployment and will drive excess occupational mobility in our model.

We further assume that workers differ with respect to an idiosyncratic firm-match productivity, $\theta_{t}$. This productivities follow a common and exogenous first-order stationary Markov process, with transition law $G(\theta_{t+1} | \theta_{t})$ and $\theta_{t}, \theta_{t+1} \in [\underline{\theta}, \overline{\theta}]$, $\underline{\theta} > 0$ and $\overline{\theta} < \infty$. The $\theta$-productivity realizations affect a worker only in employment and will allow our model to generate employer-to-employer mobility that are accompanied by wage rises and wage cuts.

We model the business cycle through fluctuations in the economy-wide productivity and let $A_{t}$ denote this aggregate productivity. We assume $A_{t}$ follows a first-order stationary auto-regressive process with $A_{t} = \phi_{A}A_{t-1} + \sigma_{A} e_{A}$. To generate net occupational mobility we allow some occupations to be more attractive than others in terms of their occupation-wide productivities. Let $p_{ot}$ denote the occupation-wide productivity of occupation $o$ at time $t$. We assume $p_{ot}$ also follows an auto-regressive process, depending on aggregate productivity $A_{t}$ through its loading $\zeta_{o}$. Thus, $p_{ot} = \phi_{p}p_{ot-1} + \zeta_{o} A_{t} + \sigma_{p} e_{p,t}$. Let $P_{O,t} = \{p_{ot}\}_{o=1}^{O}$ denote the vector that contains all the occupation-wide

---

11The difference with Neal (1999) is that the $z$-productivities evolve over time. This could be due to, for example, industry, location or employer productivity shocks that are orthogonal to occupational human capital.
productivities at time $t$.

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 with current productivity $z_t$ and human capital $x_i$ for $j = g, s$, employed with firm-match productivity $\theta_t$ in occupation $o$ is given by $y(A_t, p_0, z_t, \theta_t, x_i)$. This production function is strictly increasing and continuous in all of its arguments and differentiable in the first four. To keep the analysis as parsimonious as possible we assume that in each period the wages of employed workers are equal to their marginal product $y(.)$. Any unemployed worker receives $b$ each period. At this point it is useful to define $\Omega_t = \{A_t, P_{o,t}, o, z_t, x_i\}$.

All agents discount the future at rate $\beta$. Workers retire stochastically and afterwards receive a fixed utility flow normalized to zero. They are replaced by inexperienced workers entering the labour force. Without loss of generality, we can rescale $\beta$ to incorporate this risk.

**Searching within an occupation**  Both employed and unemployed workers search for job opportunities. We assume that unemployed workers face an exogenous probability $\lambda_u(\Omega_t)$ of meeting a firm, while employed workers face an exogenous probability $\lambda_e(\Omega_t)$ of meeting a new firm. Once a meeting takes place, a worker draws an initial firm-match specific productivity $\tilde{\theta}$ from $G(.)$, which we take it to be the ergodic distribution of the Markov process $G(\theta_{t+1}|\theta_t)$. Once in the new job, production takes place until the match is destroyed. Match break-up can occur with an exogenous probability $\delta(\Omega_t)$, but can also occur if the worker quits to another employer.

**Searching across occupations** Instead of searching for jobs in their own occupation, workers can decide to search for jobs in different occupations. This comes at a per-period cost $c$ and entails restarting their $z$-productivity process. In line with Neal (1999), workers draw their initial career match in any occupation from $F(.)$, which we take to be the ergodic distribution associated with the Markov process $F(z_{t+1}|z_t)$.

Given differences in occupation-wide labor market conditions $p_{0,t}$, workers are not indifferent from which occupation to draw their new $z$-productivity. To capture that in the data excess mobility is much larger than net mobility, we model search across occupations in the spirit of Fallick (1993). In particular, a worker who is considering moving away from his current occupation has a limited amount of time (and resources) to investigate his employment prospects in different occupations. The worker with employment status $i = U, E$ has to decide which proportion $s_i$ of his time to devote to obtain a $z$-productivity from occupation $\tilde{o}$. Let $S^d$ 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 $o \in O$. We will show that this formulation allows us to go from fully directed search (only net mobility) across occupations to fully random search (only excess mobility) across occupations.

After observing the new $z$-productivity, an unemployed worker sits out one period unemployed before deciding whether or not to sample another $z$-productivity from a different occupation. If the
worker decides to sample another \( z \)-productivity, the above process is repeated. If the worker decides to accept the \( z \)-productivity, he starts unemployed with human capital \( x_1 \) in the new occupation. The worker’s \( z \)-productivity and occupational human capital then evolve as described above. In the case of an employed worker, after observing the new \( z \)-productivity, he faces an exogenous probability \( \lambda_m(\Omega_t) \) of meeting a firm. If a meeting takes place, the worker draws an initial firm-match specific productivity \( \tilde{\theta} \) from \( G(\cdot) \). If no meeting takes place, however, the worker retains his previous value of \( \theta \) at the old employer.

**Timing and state space** The timing of the events is summarised as follows. At the beginning of the period the new values of \( A, P_O, z, x^g, x^s \) and \( \theta \) are realised. After these realisations, the period is subdivided into four stages: separation, reallocation, search and matching, and production. Let \( G \) denote the joint productivity distribution of unemployed and employed workers over all occupations. Let \( G^j \) denote this distribution at the beginning of stage \( j \). To simplify notation we leave implicit the time subscripts, denoting the following period with a prime.

### 3.2 Worker’s Problem

**Unemployed workers** Consider an unemployed worker currently characterised by \((z, x^g, x^s, o)\).

The value function of this worker at the beginning of the production stage is given by

\[
W^U(\Omega) = b + \beta E_{\Omega'} \left[ \max_{m^U(\Omega')} \left\{ m^U(\Omega') R^U(\Omega') + (1 - m^U(\Omega')) \left[ (1 - \lambda_u(\Omega')) W^U(\Omega') \right] \right\} 
+ \lambda_u(\Omega') \int_{\tilde{\theta}} \max \left\{ W^E(\tilde{\theta}, \Omega'), W^U(\Omega') \right\} dG(\tilde{\theta}) \right].
\]

(2)

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 \( m^U(\Omega) \) takes the value of one when the unemployed worker decides to search across occupations and zero otherwise. The term \( R^U(\Omega) \) denotes the expected net value for an unemployed worker of searching across occupations and is given by

\[
R^U(\Omega) = \max_{s^U(\Omega)} \left( \sum_{\tilde{o} \in O^-} \alpha^U(s^U_\tilde{o}(\Omega)) \int_{\tilde{z}} W^U(\tilde{z}, x_1^g, \tilde{o}, x^g, A, P_O) dF(\tilde{z}) + \left( 1 - \sum_{\tilde{o} \in O^-} \alpha^U(s^U_\tilde{o}(\Omega)) \right) W^U(\Omega) - \kappa \right),
\]

(3)

where the maximization is subject to \( s^U_\tilde{o} \in [0, 1] \) and \( \sum_{\tilde{o} \in O^-} s^U_\tilde{o} = 1 \). It is through this term that expected labor market conditions in other occupations affect the value of unemployment, and indirectly the value of employment, in the worker’s current occupation. The worker’s decision to search across occupations 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 \( \lambda_u(\Omega) \), drawing a firm-match productivity \( \tilde{\theta} \) and deciding whether to accept it or not. In equation (2) the job acceptance decision is captured by \( \sigma^U(\Omega) \), which takes the value of one if the worker accepts the job and zero otherwise.
Employed workers  Now consider an employed worker currently characterised by \((z, x^g, x^s, \theta, o)\).
The expected value of employment at the beginning of the production stage is described by
\[
W^E(\theta, \Omega) = w(\theta, \Omega) + \beta_\theta\mathbb{E}_{\theta', \Omega'} \left[ \delta(\Omega') W^U(\Omega') + (1 - \delta(\theta', \Omega')) W^{Er}(\theta', \Omega') \right].
\] (4)
The value of employment consists of the wage \(w(\theta, \Omega)\), plus the discounted value of being employed or separating into nonemployment for the next period.
\[
W^{Er}(\theta, \Omega) = \max_{m^E(\theta', \Omega)} \left\{ m^E(\theta', \Omega') R^E(\theta, \Omega') + (1 - m^E(\theta', \Omega')) W^{Em}(\theta', \Omega') \right\}
\]
denotes the value of employment at the beginning of the reallocation stage. If the worker remains employed, he must decide whether to search for jobs in a different occupation or not. This reallocation decision is summarised in \(m^E(\theta, \Omega)\), such that it takes the value of one when \(R^E(\theta, \Omega) \geq W^{Em}(\theta, \Omega)\) and the value of zero otherwise. \(R^E(\theta, \Omega)\) denotes the expected net value for an employed worker with current \(\theta\) and \(\Omega\) of searching across occupations and is given by
\[
R^E(\theta, \Omega) = \max_{s^E(\theta, \Omega)} \left( \sum_{\tilde{\theta} \in O^-} \alpha^E(s^E_\theta(\theta, \Omega)) \int_{\tilde{\theta}}^\theta [\lambda_m(\Omega) \int_{\tilde{\theta}}^\theta W^E(\tilde{\theta}, \tilde{z}, x^s, \tilde{o}, x^g, A, \mathcal{P}_O) dG(\tilde{\theta}) + (1 - \lambda_m(\Omega)) W^E(\tilde{\theta}, \tilde{\Omega})] + \left(1 - \sum_{\tilde{\theta} \in O^-} \alpha^E(s^E_\theta(\theta, \Omega)) \right) W^E(\theta, \Omega) - \kappa \right),
\] (5)
where the maximization is subject to \(s^E_\theta \in [0, 1]\) and \(\sum_{\tilde{\theta} \in O^-} s^E_\theta = 1\). Conditional on drawing a \(z\)-productivity from another occupation, the worker meets a new employer with probability \(\lambda_m(\Omega)\) and then draws a new value of \(\theta\). With probability \(1 - \lambda_m(\Omega)\), the worker remains with his current employer, retains his current value of \(\theta\) and takes as given the new value of \(z\). The former represents an occupational change involving an employer transition, while the latter represents an occupational change within the same employer. In both cases the worker takes the new values of \(z\) and/or \(\theta\) as given, even though they might imply worse employment conditions. This allows us to capture the fact that many occupational changes that do not involve an intervening spell of unemployment are associated with wage cuts. 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 with his current occupation and \(\theta\).

If the worker decides to stay in his current occupation, however, the value of employment at the beginning of the search and matching stage is given by
\[
W^{Em}(\theta, \Omega) = \gamma \lambda_s(\Omega) \int_{\tilde{\theta}}^\theta \max \left[ W^E(\tilde{\theta}, \Omega), W^E(\theta, \Omega) \right] dG(\tilde{\theta})
\] (6)
+ \(1 - \gamma \lambda_s(\Omega) \int_{\tilde{\theta}}^\theta W^E(\tilde{\theta}, \Omega) dG(\tilde{\theta}) + (1 - \lambda_s(\Omega)) W^E(\theta, \Omega)\).

In this case the worker meets a new potential employer with probability \(\lambda^e(\Omega)\). We further assume that with probability \(\gamma\) the meeting is “voluntary” and entails a decision to accept or reject the new \(\theta\). The job acceptance decision truncates the distribution of \(\theta\) such that \(W^E(\tilde{\theta}, \Omega) > W^E(\theta, \Omega)\). With probability \(1 - \gamma\), however, the meeting is “involuntary” and the worker is forced to take the new \(\theta\).
This allows us to capture within occupation employer transitions that are associated with wage cuts and wage rises (see also Jolivet et al, 2006).

### 3.3 Implementation

Imposing $\alpha(x) = \frac{\alpha_0}{1 - \alpha_1} x^{1 - \alpha_1}$ and the feasibility constraint that $\sum_{\delta \in O^-} s_\delta = 1$, it can be shown that the choice probabilities take a form similar to a Gumbel-distributed additive random utility model. This is because the first-order condition on $s_d$ is

$$
\alpha'(s_d) \left( \int_{z} W^U(\tilde{z}, x^s, o_d, x^g, P_O) dF(\tilde{z}) - W^U(\Omega) \right) = \mu
$$

where $\mu$ is the multiplier on $\sum_{\delta \in O^-} s_\delta = 1$. Using the functional form assumption we get

$$
s_d = \left( \frac{\alpha_0}{\mu} \right)^{1/\alpha_1} \left( \int_{z} W^U(\tilde{z}, x^s, o_d, x^g, P_O) dF(\tilde{z}) - W^U(\Omega) \right)^{1/\alpha_1}. \tag{7}
$$

This is the case for all directions $d \in O^-$, so we can use our equality constraint $\sum_{\delta \in O^-} s_\delta = 1$ and divide the left side by 1 and the right side by $\sum_{\delta \in O^-} s_\delta$, but substitute $s_\delta$ with its optimality condition, Equation 7, to get:

$$
s_d = \frac{\left( \frac{\alpha_0}{\mu} \right)^{1/\alpha_1} \left( \int_{z} W^U(\tilde{z}, x^s, o_d, x^g, P_O) dF(\tilde{z}) - W^U(\Omega) \right)^{1/\alpha_1}}{\sum_{\delta \in O^-} \left( \frac{\alpha_0}{\mu} \right)^{1/\alpha_1} \left( \int_{z} W^U(\tilde{z}, x^s, o_d, x^g, P_O) dF(\tilde{z}) - W^U(\Omega) \right)^{1/\alpha_1}}.
$$

Of course, $\left( \frac{\alpha_0}{\mu} \right)^{1/\alpha_1}$ cancels from numerator and denominator. Thus, we have the form

$$
s_d = \frac{\left( \int_{z} W^U(\tilde{z}, x^s, o_d, x^g, P_O) dF(\tilde{z}) - W^U(\Omega) \right)^{1/\alpha_1}}{\sum_{\delta \in O^-} \left( \int_{z} W^U(\tilde{z}, x^s, o_d, x^g, P_O) dF(\tilde{z}) - W^U(\Omega) \right)^{1/\alpha_1}}
$$

or equivalently, by transforming $X_{\alpha_1} = e^{\frac{1}{\alpha_1} \log(X)}$

$$
s_d = \frac{e^{\frac{1}{\alpha_1} \log\left( \int_{z} W^U(\tilde{z}, x^s, o_d, x^g, P_O) dF(\tilde{z}) - W^U(\Omega) \right)}}{\sum_{\delta \in O^-} e^{\frac{1}{\alpha_1} \log\left( \int_{z} W^U(\tilde{z}, x^s, o_d, x^g, P_O) dF(\tilde{z}) - W^U(\Omega) \right)}}. \tag{8}
$$

Combined with the additive noise affecting the choice of $m^U$, which we use to smooth our approximate solution, this means the search direction takes the a form similar to a nested, multinomial logit discrete choice. $\alpha_1$ plays the role of how “directed” search is, where sending it to 0 will lead $s_\delta$ to its corners at $\{0, 1\}$ and raising it makes search more random. $\alpha_0$ is a scaling factor to guarantee the proper arrival rates, but does not play a role in the marginal choice of search direction.

The separation shock $\delta$ and finding rates, $\lambda_k$ are assumed to depend upon $A_d$ and $p_{at}$, allowing separations to be cyclical. Separation rates are linear, $\delta(\Omega) = \zeta A + \phi_\delta p_\delta + \delta_0$, as are finding rates $\lambda_k(\Omega) = \lambda_{k0} + \zeta_k A + \phi_k p_0$ for $k = \{m, s, u\}$.

Finally, we let wages take the form $w = \frac{e^{(1-\gamma)(A+p_\delta+x^g+x^s+x^s)}}{1-\gamma} + w_0$. This implies each of the shocks have multipliclicative complementarity, while $\gamma$ determines its overall curvature. $w_0$ ensures wages are positive. Clearly, we cannot determine $\gamma$ purely from observations on earnings because we could equally scale any of the shocks themselves. It will, however, help to determine the interaction
between occupation switching and levels of the other shocks.

### 3.4 Characterization

Though we are still in the process of estimating our model parameters, we can see it already behaves reasonably.

To characterize the solution to our model, we first look at the occupational switching behavior. This is important to consider as endogenous because it leads to a concentration of workers with good matches. While the draw distribution of $z$ was taken as symmetric and workers cannot select the $z$ before they accept a job, workers endogenous switching behavior selects for higher $z$ because they switch more frequently from low $z$ matches. Figure 10 shows the 4-month switching probability among unemployed and employed workers. The sorting leaves about 70% of workers matched with an occupation for which their realized $z$ is greater than $\bar{z} = \int z dF(z)$.

![Figure 10: Switching probability by occupation match quality $z$.](image)

Interestingly, however, $\theta$ acts differently than $z$, in that workers with relatively high $\theta$ are more likely to switch. Figure 11 shows the difference in occupational switching propensity as a function of $\theta$. Higher levels of theta allow a worker to take on more risk, as associated with an occupational switch. The effect is attenuated compared to the effect from $z$, as seen in the scale on the y-axis.

As in the data, switching occupations bring a considerably wider distribution of earnings outcomes. In Figure 12, we show the earnings change distribution among job-to-job transitions in the model. To match the data, the distribution of earnings outcomes among job-changers who also switch occupations is much wider because they also are taking on risk in $z$ match. Again, just as in the data, the tail of the earnings growth distribution is dominated by workers with low earnings to begin with: here they have low $z$ and low $\theta$, therefore switching more frequently and taking on additional risk.

### 4 Structural Decomposition

[To be written...]
Figure 11: Switching probability by job match quality $\theta$.

Figure 12: Earnings change distribution among occupation switchers and stayers.

**APPENDIX**

A Data

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