Occupational Switching, Tasks, and Wage Dynamics*

Christopher Busch†

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Abstract

Observed wage dynamics are the result of both exogenous factors, such as productivity shocks, and workers' choices. Using data from administrative German social security records, I document that the extent of occupational switching upon changing jobs is high, and that the choice to change occupations is of major relevance for realized wage changes. I develop a structural model in which workers optimally switch occupations in response to idiosyncratic productivity shocks. In the model, switching occupations entails a cost, because workers can only imperfectly transfer human capital. The degree of transferability depends on the distance in the task space. Disentangling the role of choices and shocks, I find that the endogenous choice of occupations accounts for 26% of the dispersion of wage changes after controlling for human capital changes.

JEL Codes: J24, J31, J62

Keywords: Occupational Choice, Occupational Mobility, Human Capital, Wage Dynamics

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†Universitat Autònoma de Barcelona, MOVE, and Barcelona GSE; www.chrisbusch.eu; chris.busch@movebarcelona.eu

1 Introduction

Many economic decisions hinge on labor income risk faced by individuals: among others, savings behavior and portfolio choice (e.g. Carroll, 1997; Guvenen, 2007), or fertility decisions (e.g. Ejrnæs and Jørgensen, 2020). Accordingly, understanding idiosyncratic labor income risk is important for a number of economic phenomena—ranging from the wealth distribution (Aiyagari, 1994), over asset prices (Constantinides and Duffie, 1996), to the welfare costs of idiosyncratic risk (Storesletten *et al.*, 2001).

The traditional approach to evaluate the extent of labor income risk is to analyze labor income data (see, e.g. Moffitt and Gottschalk, 2002; Guvenen, 2009; Guvenen *et al.*, 2014). However, income dynamics observed in the data are the result of an interplay between risk and decisions made by individuals—where these decisions are partly in reaction to risk faced. One decision that plays a key role for realized wage dynamics of workers is the one to change jobs (Topel and Ward, 1992; Low *et al.*, 2010).

In this paper, I zoom in on job-to-job changes and study the role of occupational switching decisions for wage dynamics. Based on panel data from German social security records, I show that a large share of workers switch to different occupations when changing jobs.[1] It turns out that workers tend to switch to occupations that have similar task requirements as their old one.[2] Furthermore, staying in the current occupation or moving to another is of large quantitative relevance for the wage changes realized upon the job change: both high wage gains and severe wage cuts are realized more frequently by job changers who also switch occupations.

By its very nature, the switching decision is endogenous. Therefore, I set up a structural model of occupational switching that allows me to dissect the realized wage change into its *shock* and *choice* components. In the model, the realized wage dynamics result from an interplay between underlying risk and the choice to switch occupations or not. This choice enables workers to react to shocks and thereby potentially mitigate negative realizations—or to realize high wage gains related to a move to a different occupation. The model allows me to evaluate the magnitude and distribution of underlying productivity shocks necessary to generate a distribution of realized wage changes in line with what is observed in the data.

A key component of my analysis is the notion that any job can be characterized by task requirements, and that human capital is to some extent linked to tasks. Thus, when a worker changes jobs, how well the requirements of the new job are met will in part depend on how similar the new job is to the old. If the task requirements differ between the old and the new job, the part of human capital that is linked to tasks in the old job is not relevant anymore, while

[1]While I document this observation for the German labor market, it appears to be a common feature of labor markets with very different institutional settings: see Carrillo-Tudela and Visschers (2014) for the US, or Carrillo-Tudela *et al.* (2016) for the UK.

[2]The quantitative meaning of *similar* or *different* is pinned down using a metric based on a collection of task requirements.

new human capital needed to be productive in the tasks of the new job is yet to be accumulated. In this context, occupations can be understood as a combination of certain typical tasks (e.g., Autor, 2013; Gathmann and Schoenberg, 2010), and thus, some of the requirements of a specific job do systematically depend on its occupation.[3] In other words, workers that change jobs within their occupation will typically face similar task requirements in their new job, while workers that switch occupations will face different requirements. In my anlysis, I explore the consequences of these moves in the task space for individual outcomes of workers that switch.

The main data source of my analysis is the *Survey of Integrated Labour Market Biographies* (SIAB), a large sample of labor market histories of workers drawn from administrative German social security records. Due to the administrative nature of the data set, I cannot directly observe the tasks performed by a worker in a given employment spell. Instead, I use information from survey data by the Federal Institute for Vocational Education and Training (BiBB). In these surveys, workers report their occupation and which tasks they perform regularly. I aggregate this information to the occupation level and calculate the distance between each pair of occupations. I then merge this distance measure to the occupational switches observed in the SIAB data.

I document that, first, conditional on changing jobs, the probability to switch occupations is about 40% on average. Second, this switching probability depends negatively on the wage of a worker relative to all workers in the same occupation before changing jobs. This is to say that low ranked workers switch more frequently. Third, the cumulative share of switchers by distance obeys a concave relationship: workers that switch tend to switch to occupations that have similar task requirements as their old one. Fourth, switches are more likely after an unemployment period: about 55% of all job changes that go through unemployment involve a switch of occupations, while this is true for 35% of direct job-to-job changes. The declining pattern of the switching probability by relative wage holds for both job changes through unemployment and direct job-to-job transitions. Directly related, I find that the probability to switch occupations upon re-entering employment increases strictly with the duration of unemployment. Turning to individual outcomes related to the job change, I find that, fifth, workers that switch occupations face a wider distribution of wage changes than those who change jobs within their current occupation. Those workers who transition through unemployment face negative wage changes that are both more common, and more severe.

My model builds on the tradition of island economies a la Lucas and Prescott (1974), and is closely related to Carrillo-Tudela and Visschers (2014). As in their model, idiosyncratic productivity shocks are the driver of worker movements across occupations.[4] Different to their

[3]This is true regardless of the occupational classification system: if information about task contents of jobs exists, it can be aggregated to some level of the occupational classification, thus characterizing occupations by their typical task contents.

[4]This is one key difference of my model or the model of Carrillo-Tudela and Visschers (2014) to, e.g., Alvarez and Shimer (2011), or Wiczer (2015), where reallocation is driven by occupation-specific shocks.

model, reallocation is not necessarily through unemployment. The economy is characterized by occupational islands, each of which is populated by a continuum of workers. Workers stochastically accumulate human capital, i.e., they stochastically move up a human capital ladder. In addition, workers receive persistent shocks to their idiosyncratic productivity, that are orthogonal to human capital. Each period, workers randomly select an alternative occupation, costlessly search on-the-job for alternative jobs, and receive a job offer with some probability. The offer comes as a productivity shock. Given this offer and a productivity shock related to their current occupation, workers decide whether to take the offer or to stay. The draws of the two shocks come from two different distributions, related to staying or switching. The decision of the worker determines which of the two shocks materializes, i.e., becomes relevant for their idiosyncratic productivity. Switching entails a cost for workers, because human capital is only imperfectly transferable. This is modelled as workers "falling down" some rungs of the human capital ladder. The degree of transferability, i.e., how many rungs workers fall down, depends on the distance of the new occupation to the old. The interplay between shocks and the resulting switching decision (and the implied moves along the human capital ladder) allows the model to generate different distributions of realized wage changes for stayers and switchers. Workers face an exogenous separation shock, and unemployed workers face a search friction. When finding a job, workers have all bargaining power such that wages correspond to marginal productivity.

In a calibrated version of the model that is consistent with the documented patterns of occupational switching and wage changes, I find that the variance of productivity changes realized by switchers is 69% of the variance of the underlying shocks. Thus, if one were to equate the *observed* distribution with the *underlying* distribution, one would make an error of 31% in terms of the dispersion. For stayers, the variance of realized productivity changes amounts to 96% of the variance of underlying shocks. Considering the distribution of wage changes for switchers and stayers together, the endogenous choice of switching generates about 26% of the variance of realized productivity changes. For this calculation, I compare the actual dispersion of productivity changes in the model to the dispersion of a counterfactual distribution, where workers are randomly selected to be switchers or stayers—keeping the overall level of occupational switching constant. Given that the switching decision turns out to have large relevance for wage changes, I use the calibrated model to calculate the utility gain derived from the possibility to switch: the gain for the average worker corresponds to 0.78% of per-period consumption.

Relation to Literature

This paper is closely related to Low *et al.* (2010), who also argue that realized income dynamics result from an interaction of underlying risk and worker decisions. They focus on the decision of workers to change jobs and differentiate productivity risk from employment risk, and evaluate the welfare consequences of the different risks using a life cycle consumption-savings model, which features a rich set of government insurance policies. Regarding the analysis of wage dynamics, there are two main differences between this paper and their analysis. First, they do not address the occupational choice of workers; I show this to be of major importance for realized wage outcomes. Second, they do not explicitly model the job changing decision of workers; instead they estimate a reduced form income process, in which the selection of workers to change jobs is captured by a first-stage probit regression. The focus of my paper is the switching decision itself.

By emphasizing the importance of analyzing economic choices for the understanding of labor income risk, this paper is related to Guvenen and Smith (2014). Using data on labor earnings and consumption, they estimate a consumption-savings model and infer the amount of risk faced by agents and the degree of insurance against this risk. In the sense that I am interested in the extent to which occupational switching—or its twin, occupational attachment—can help us to understand aggregate phenomena, my analysis is in the spirit of Kambourov and Manovskii (2008), who consider a channel through which occupational mobility relates to income inequality, as well as Wiczer (2015), and Carrillo-Tudela and Visschers (2014).[5] Focusing on the reallocation decision of unemployed, Carrillo-Tudela and Visschers (2014) use data from the Survey of Income and Program Participation (SIPP) to analyze the role of occupational switching upon finding employment for aggregate unemployment fluctuations and the distribution of unemployment duration. They develop a search and matching model that accounts for the observed patterns. On the empirical side, they document that the likelihood of switching the occupation upon reemployment increases with the unemployment duration. Their framework is closely related to Wiczer (2015), who builds a model in which unemployed workers are attached to their recent occupation due to specific human capital.

The first empirical paper that emphasizes the importance of performed tasks in the context of specific human capital and its partial transferability across occupations is Gathmann and Schoenberg (2010). Using an earlier version of the administrative data analyzed in this paper and the same data on task measures, they construct a measure of 'task-tenure' and show that it significantly correlates with wages. While they estimate the average returns to task-tenure in a reduced form Mincer-regression framework, I link differences in task requirements to costs of switching occupations, and explicitly analyze the switching decision of workers. I then link the distance of an occupational switch to the whole distribution of wage dynamics.

Empirically, Wiczer (2015) constructs a distance measure between occupations based on occupational task measures of the O*NET project. In this regard, his analysis is close to this paper. However, while his focus is on the role of occupational attachment of the unemployed

[5] In terms of analyzing effects of occupational matching on wages, the paper is also related to Guvenen *et al.* (2020) and Lise and Postel-Vinay (2020), who analyze how (multidimensional) match quality affects wage growth. However, these papers explicitly focus on a life cycle perspective.

for long-term unemployment, I focus on the transferability of specific human capital across occupations by rank of workers. This connects this paper to Groes *et al.* (2015), who, using Danish administrative data, analyze how the rank of a worker within the occupation-specific wage distribution affects the observed occupational switching behavior. They document that, first, both workers with a relatively low wage and those with a relatively high wage appear to be more likely to leave the occupation compared to workers closer to the mean wage. Second, the farther up (down) a switcher ranks in the wage distribution of her origin occupation, the more likely she switches to an occupation that pays on average higher (lower) wages than the origin distribution. They rationalize these two facts with a model of vertical sorting across occupations based on absolute advantage.[6]

Huckfeldt (2016) relates occupational switching to the dynamics of earnings and, using data from the Panel Study of Income Dynamics, documents that average earnings losses upon losing a job are concentrated among workers who re-enter employment in lower lanked occupations. His analysis posits an occupational ladder and focusses on negative implications for the average worker of moving down this ladder. My analysis is complementary to his in that I consider occupational switching in the context of movements in the task-space, which I relate to the distribution of wage changes. In line with this, in my model, there is no vertical ranking of occupations: occupations matter only insofar as a change of occupations informs about changes in the task requirements workers face.

The remainder of the paper is structured as follows. Section 2 describes the data used in the analysis. Section 3 analyzes the empirical relevance of occupational switching and its role for realized wage changes. Section 4 introduces a model of occupational switching. Section 5 discusses the calibration of the model, and analyzes, first, the interplay between switching and wage changes, and, second, the utility gain from the availability to switch occupations. Section 6 concludes.

2 Data and Measurement

2.1 Data Sets and Sample Selection

The main data set is the SIAB, which has been used for the analysis of earnings and wage dynamics in, e.g., Busch *et al.* (2020), Card *et al.* (2013), or Gathmann and Schoenberg (2010). The BiBB surveys have been used to characterize occupations in, e.g., Gathmann and Schoenberg (2010), or recently by Becker and Muendler (2015).

[6] Their model features learning of workers about their own skills. In my model, there is no ex ante heterogeneity of workers, and thus learning about the own type does not play a role for the analyzed mechanism. An overview of papers that model worker learning about skills or talent can be found in Sanders and Taber (2012).

The SIAB data

The analysis is based on a sample from social security records provided by the Institute of Employment Research (IAB) of the German federal unemployment agency. The data set covers 2% of all workers who are employed and subject to social security contributions from 1976 to 2010, implying that civil servants and students are not covered. Throughout the analysis, the focus is on males working in West Germany. After applying the usual selection criteria, the sample comprises on average 55,000 individuals per year, with about 430,000 individuals in total. For a detailed description of the data, see vom Berge *et al.* (2013).

Sample Selection

While East German employment spells since unification are observed in the data, the analysis focuses on West Germany. East Germany went through a transition period from a planned economy to a market economy and hence the economic forces governing wages, and, of prime importance for this paper, occupational choices, were very different than those in West Germany. I consider full-time employment spells only and focus on those employment relationships that have some minimum stability, which I define as a minimum duration of two months. I drop observations for ages below 25 or above 54. All reported results are for males.

The BiBB data

Information on the skill and task content of occupations is taken from a set of surveys conducted by the Federal Institute for Vocational Education and Training (BiBB) with wave-specific co-operation partners. The waves are 1979, 1986, 1992, 1999, 2006, and 2012. The cross-sectional surveys cover representative samples of about 30,000 respondents each, and contain information on the tasks performed by workers and on the skills required by their job. Importantly for the present analysis, respondents report their occupations, which allows the aggregation of task and skill measures to the level of occupations. I use data from the first five waves and merge the generated occupation-level information to the SIAB sample. A comprehensive description of the data can be found in Gathmann and Schoenberg (2010).

Definition of Occupations

Occupations are defined by the *KldB88* – the 1988 version of the German employment agency's classification of occupations, which is consistently available in the data. I use the classification at the level of *occupation segments*, which comprises 30 groups of occupations. At this level of aggregation, potential problems of misclassification can be expected to be small. Examples for the groups are "Painter and similar", "Carpenter, model makers", "Organization-, Administration-, Office- related", or "Physicist, Engineer, Chemist, Mathematician". Appendix D shows all 30 groups.

2.2 Switching Distance and Ranking of Workers

Measurement of Tasks and the Distance Between Occupations

I measure the *distance* of an occupational switch in the dimension of tasks, building on the concept of an occupation as a combination of tasks (cf. Autor, 2013; Acemoglu and Autor, 2011). To the extent that human capital is task-specific (as argued, among others, by Gathmann and Schoenberg, 2010), the economic implications of switching occupations vary with the *distance* in the task dimension between old and new occupation.[7]

Due to the lack of direct information on tasks performed by the workers observed in the SIAB, I use external information on task usage at the level of occupations. Task data comes from representative surveys by the BiBB (see above). I follow Becker and Muendler (2015) and define 15 time-consistent task categories and then calculate the share of workers in each occupation that performs any given task.[8]

Based on this measure, I calculate the distance between any two occupations o and o'. Following the literature (cf. Gathmann and Schoenberg, 2010), my preferred measure of distance is

$$d_{oo'} \equiv 1 - \frac{\sum_{j=1}^{J} (q_{jo} \times q_{jo'})}{\left[\left(\sum_{j=1}^{J} q_{jo}^2\right) \times \left(\sum_{j=1}^{J} q_{jo'}^2\right)\right]^{1/2}}, \tag{1}$$

where q_{jo} denotes the share of workers in occupation o who perform task j. The fraction on the right-hand side is the angular separation, which in the given context as a measure of proximity takes only differences in the *relative mix* of tasks into account. Consider an example with two tasks and two occupations, where both occupations are characterized by the same overall mix of tasks. In occupation 1, all workers perform both tasks, while in occupation 2, half of the workers performs task 1 exclusively and the other half performs task 2 exclusively. The distance as measured by (1) between the two occupations is zero. The measure is long-established in the literature on R&D spillovers, where research intensity of firms in different technologies is used to characterize the proximity of firms (cf. Jaffe, 1986).

[7] An alternative to the task based characterization of occupations is to resort to measures of skills required to perform the tasks (e.g., Guvenen *et al.*, 2020). Because I do not analyze the matching of skill requirements of occupations to the skills of workers, but rather use the occupation level information to measure the distance between occupations, the two approaches can be expected to yield similar results if similarity of occupations in terms of performed tasks correlates positively with similarity of skill requirements. Given that some of the task categories used in the analysis are explicitly based on skill requirements, the applied distance measure reflects differences along the lines of applied skills.

[8] I thank Sascha Becker for providing details on the task imputation procedure developed in Becker and Muendler (2015).

I calculate the distance measure for all pairs of occupation segments in each cross-section of the BIBB and then merge the distance measure to the SIAB sample of worker histories.[9] Across the five waves, details of the measurement of tasks varies. Thus, there is no clear interpretation of time-variation of the distance measures. I therefore consider the distance between a pair of occupations in any given wave relative to the wave-specific standard deviation across all occupation-pairs.

The Relative Wage of Workers

One key concept throughout the analysis is the one of the *rank* of a worker within his occupation. I base the rank of a worker i of age a within the occupation-specific wage distribution in a given month t on age-adjusted (log) wages, $w_{i,a,t}$. The age adjustment removes the economy-wide average age profile, however, it does not remove potential heterogeneity of age profiles across occupations. Let $\tilde{w}_{i,a,t}$ be the raw (log) wage. I achieve the age adjustment by subtracting from $\tilde{w}_{i,a,t}$ the (adjusted) coefficient on the relevant age dummy, d_a, from a regression of raw (log) wages on age and cohort dummies, as well as a constant:

$$\tilde{w}_{i,a,t} = \beta_0 + \sum_{j=2}^{A} \tilde{d}_j^{age} \mathbb{1}\left\{a = j\right\} + \sum_{k=2}^{C} \tilde{d}_k^{cohort} \mathbb{1}\left\{c = k\right\}. \quad (2)$$

I rescale the coefficients on the age dummies to the mean wage at the youngest age: $d_1 = \beta_0$ and $d_{a\epsilon[2,A]} = \beta_0 + \tilde{d}_a^{age}$, which then gives $w_{i,a,t} = \tilde{w}_{i,a,t} - d_a$. Based on this age-adjusted wage, workers are ranked cross-sectionally into 20 groups relative to other workers in their occupation. The monthly ranking considers all workers who work in a full-time employment spell that lasts for at least three months, and at least two weeks lie in the given month.

3 Occupational Switching and Wage Changes

In this section, I first document the degree of occupational switching, and important regularities in terms of *who* switches, and to *where*. I then link the occupational switching patterns to individual outcomes in terms of wage changes.

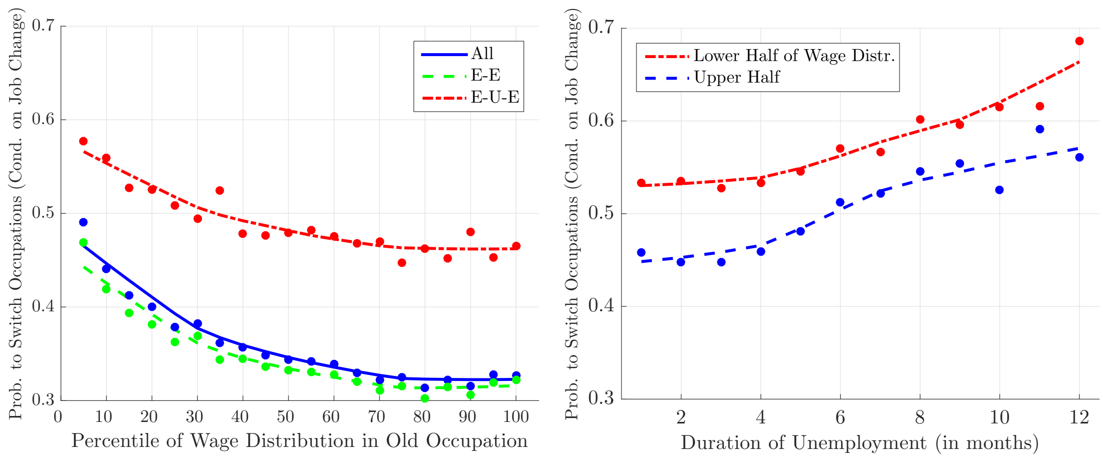
3.1 The Extent of Occupational Switching

Probability of Occupational Switching The probabilities of switching occupations across quantiles of the occupation-specific wage distribution are shown in Figure 1. The population used to estimate the monthly switching probabilities comprises all workers that, after having

[9] I merge the distance measure from the 1979 BiBB wave to switches in the SIAB which occur between 1980 and 1982, from the 1986 wave to switches in 1983–1988, from the 1992 wave to switches in 1989–1994, from the 1999 wave to switches in 1995–2001, and from the 2006 wave to switches in 2002–2010.

Figure 1: Probability of Switching Occupations

(a) Switching by Rank (b) Switching by Unemployment Duration



Note: Non-parametric probabilities. Smoothed using locally weighted regressions with a 1st degree polynomial. Only workers with unemployment duration up to one year are considered.

worked in full-time employment previously, start a new employment spell in month t. I estimate the probability of switching occupation o for a worker i ranked at rank r, conditional on starting a new job, non-parametrically as[10]

$$Pr\left\{Switch^i | job_{i,new} \neq job_{i,old} \wedge rank_{i,old} = r\right\} = \frac{\sum_j \mathbb{1}\left\{o_{i,new} \neq o_{i,old} \wedge rank_{i,old} = r\right\}}{\sum_j \mathbb{1}\left\{job_{i,new} \neq job_{i,old} \wedge rank_{i,old} = r\right\}}. \quad (3)$$

The blue scatters (and smoothed line) in Figure 1(a) show that across wage ranks, the probability of leaving the occupation upon changing jobs is high. Among the workers coming from the bottom five percent of the wage distribution in their old occupation, the share of workers leaving their job for another occupation is highest at about 50%. Up to the 80^{th} percentile, the switching probability displays a declining pattern, which then flattens out at about 37%.[11]

I then differentiate direct job changes, which I refer to as Employer-to-Employer transitions (E-E), and job changes which go through unemployment (E-U-E). I consider unemployment spells of up to one year, and treat a transition to be a direct job change when the unemployment spell is shorter than one month. Figure 1(a) reveals that, across ranks, it is less likely for workers to switch occupations when they directly switch employers (green): on average, about 35% switch occupations. This is true for 46% of workers from the bottom and just above 30% from the higher ranks. Out of all workers who experience a period of unemployment (red): on

[10]In the quantitative model analysis, I estimate switching probabilities using a parametric linear probability model, in which I also control for age. The parametric estimation captures well the patterns discussed here.

[11]Note that Groes *et al.* (2015) analyze a similar switching pattern for Denmark. However, they analyze annual earnings data (while I look at monthly wage data) and find a pronounced U-shape of the switching probability by rank.

average, about 55% of the job changers that went through unemployment switch occupations. Again, the pattern across ranks is declining from about 60% for workers coming from the bottom five percent to around 48% for the highly ranked workers.

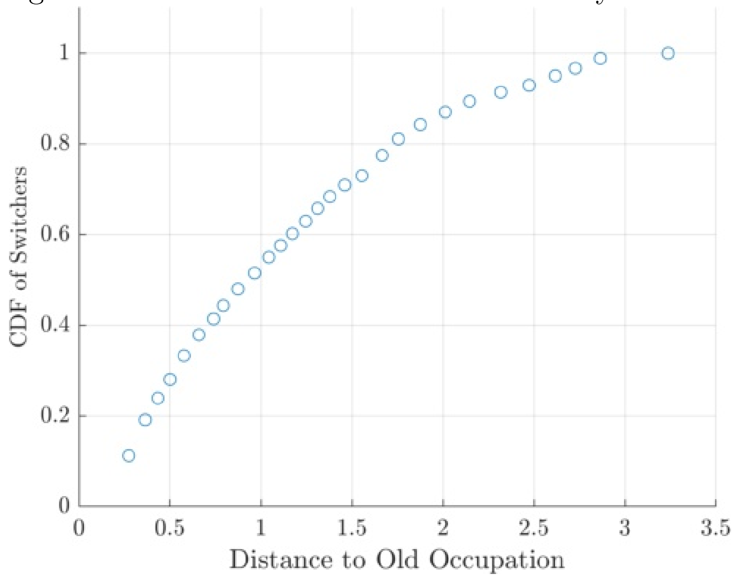
Furthermore, it turns out that the share of workers switching occupations increases with the duration of unemployment, shown in Figure 1(b). For workers from the lower half of the occupation-specific wage distribution before entering unemployment, it stays constant at around 55% for the first five months, after which it increases in a roughly linear fashion up to just below 70% for workers leaving unemployment in the 12^{th} month. The switching probability for workers from the upper half of the occupational wage distribution displays a similar pattern, with a constant probability of about 45% in the first four months, increasing to about 55%.[12]

Moves through the Task Space I next explore where workers switch to when they switch occupations. For this I use the distance measure between occupations introduced in Section 2.2. Recall that a short distance between any two occupations implies that they require a similar composition of tasks in terms of the relative importance of those tasks. It turns out that the observed switches are not random moves through the task space. In Figure 2 I plot the cummulative share of occupational switches by distance in the task space. The concave pattern implies that switches to some target occupation become more unlikely the farther away it is to the origin occupation of a worker. In other words, workers tend to switch to occupations that are relatively similar in terms of their task requirements.

Moves across Ranks Now consider again the rank of a worker in the occupation-specific wage distribution before changing jobs. Where do workers end up to rank in the occupation they move to? In order to answer this question I consider all workers that change jobs and rank them in their new occupation. In Figure 3(a), I then plot the median rank of workers coming from any of the 20 ranks in the old occupation, separately by workers that switch occupations and those that stay in their occupation. The other panels in Figure 3 are constructed in the same way. Figures 3(a) and 3(b) show that, for both E-E and E-U-E transitions, a worker from higher wage ranks tends to rank relatively lower in the (new) occupational wage distribution when switching occupations. The drop in rank is more pronounced for moves through unemployment. On top of that, Figures 3(c) and 3(d) show that, among the occupation switchers, a worker tends to rank relatively lower in the new occupation when the switch covers a greater distance through the task space. This is especially true for transitions through unemployment. The three groups of switches ("close", "medium", and "far") are based on grouping all workers that switch occupations into terciles by the distance they cover.

[12]Controlling for the role of age for switching, I estimate a linear probability model of a switching dummy on a full set of dummies for age, rank, transition type (unemployment dummy), and year fixed effects. The profile is decreasing in age.

Figure 2: Cummulative Share of Swichers by Distance



Note: For occupation switches, the figure shows the cummulative share of workers switching to another occupation, where those target occupations are ordered ascendingly by distance to the origin occupation.

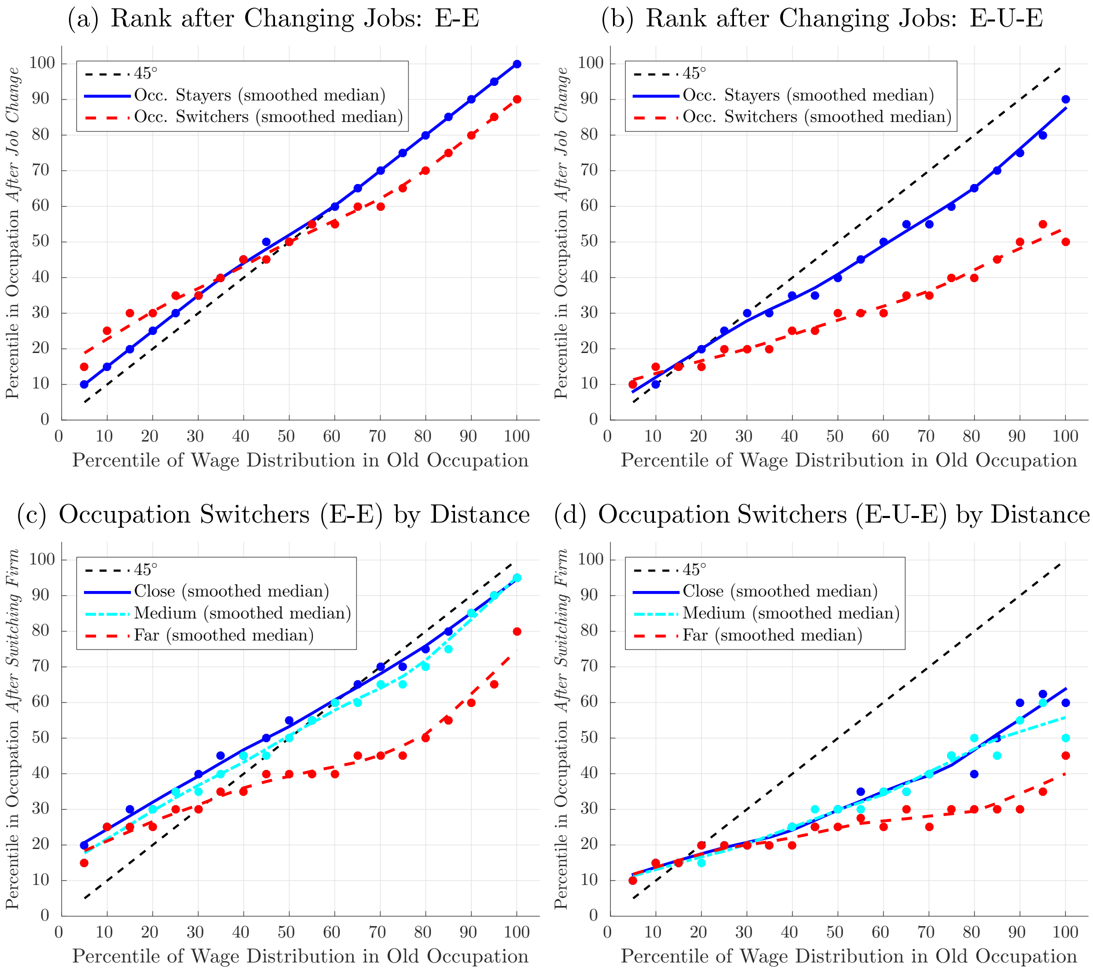
3.2 *Realized* Wage Changes Upon Switching Occupations

I now turn to the actual ex-post implications at the individual level of changing to a job in a different occupation, i.e., to a job with different task requirements. To this end, I compare workers that stay within their occupation upon changing jobs to workers that switch occupations and thus move across the task-space. Following up on the discussion in the previous section, I differentiate direct job changes (E-E), and job changes which go through unemployment (E-U-E).

A First Look at the Distribution of Wage Changes

Figure 4(a) shows the smoothed log-density function of wage changes upon changing jobs for four groups: stayers vs. switchers and E-E vs. E-U-E transitions. The individual wage change is calculated as the difference between the logs of the wage at the new job and at the old job. From the four groups, the distribution of wage changes for workers that transition directly and stay within their occupation displays the smallest dispersion. Figure 4(b) directly shows the differences. Upon changing jobs directly, occupation switchers realize both higher wage losses and higher wage gains more frequently. Overall, their distribution is more skewed to the right, with the right arm of the density shifting farther out than the left arm relative to occupation stayers. Turning to the transitions through unemployment, as would be expected, a big share of the workers reentering the labor market faces a wage loss relative to the pre-unemployment

Figure 3: Relative Position of Job Changers



Note: The scatters show the position of the median worker from the respective group, the lines are smoothed using a locally weighted regression with span 0.5.

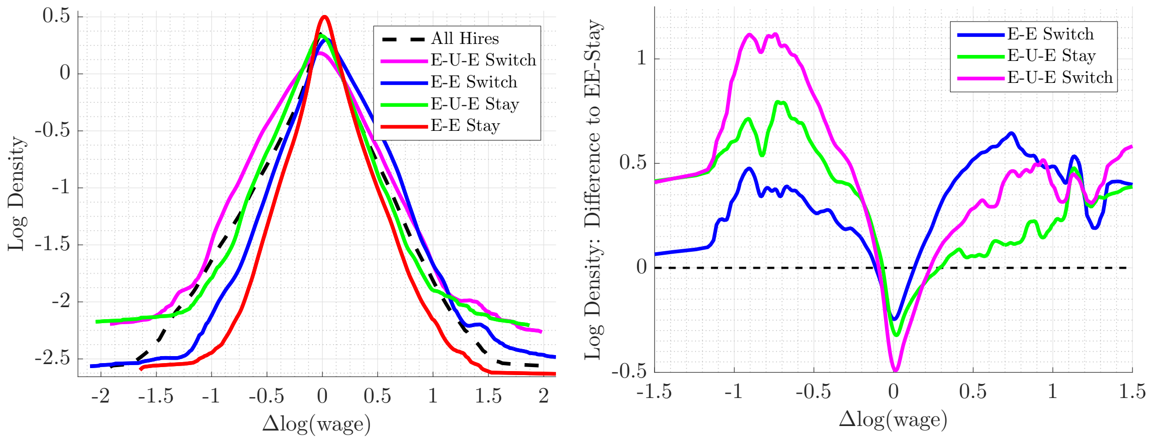
job. Comparing the distribution of wage changes of occupation switchers to the one for stayers that go through unemployment, I find higher losses for switchers.

Quantile Regression Analysis

While the preceding look at wage changes by means of the log density plots can deliver a good first intuition, it cannot shed light on the role of continuos variables for wage changes, such as the distance of a switch or the rank before changing jobs. I address this by fitting a set of quantile regressions, which are a useful tool to analyze how different parts of the conditional distribution of wage changes differ with a set of observable characteristics Koenker and Hallock (2001). Overall, these regressions confirm and quantify the intuitive insights from above.

Figure 4: Wage Changes for Different Switches

(a) Distribution of Wage Changes (b) Difference to E-E Stayers



Note: Panel a plots the log-density of wage changes upon changing jobs based on a pooled sample. The non-parametric estimates are smoothed using a locally weighted regression with span 0.05. Panel b shows the difference of the distribution for three groups of job changes relative to E-E stayers.

The regressions take the following form:

$$quan_{\tau}\left(\triangle\log\left(wage_{i,t}\right)\right) = \beta_0\left(\tau\right) + \beta_1\left(\tau\right) Rank_{i,t} + \beta_2\left(\tau\right)\mathbb{1}\left\{Unemp_{i,t}\right\} + ...$$
$$\mathbb{1}\left\{Switch_{i,t}\right\} \times \left(\beta_3\left(\tau\right) + \beta_4\left(\tau\right) Rank_{i,t} + \beta_5\left(\tau\right)\mathbb{1}\left\{Unemp_{i,t}\right\} + \beta_6\left(\tau\right) Distance_{i,t}\right) + \ldots$$
$$\sum_{\tilde{t}=2}^{T}\gamma_{\tilde{t}}\left(\tau\right)\mathbb{1}\left\{t=\tilde{t}\right\} + u_{i,\tilde{t}}, \quad (4)$$

where $quan_{\tau}\left(\triangle\log\left(wage\right)\right)$ is the τ's quantile of the distribution of (log) wage changes conditional on the explanatory variables:[13] $\mathbb{1}\{Unemp\}$is a dummy variable that takes on value one if the transition is through unemployment and zero otherwise; $\mathbb{1}\left\{Switch\right\}$ is a dummy variable for occupational switching; $Rank$ measures the rank in the last job in vintiles; $Distance$ measures the distance between the old and the new occupation; $\mathbb{1}\left(year = t\right)$ represents year dummies; and u is an error term.

Before turning to the discussion of the coefficients in more detail, let me first briefly discuss the quantiles of the wage change distribution implied by a set of the quantile regressions that does not include rank nor the distance of the switch. It thus gives first quantification of the distributions shown in Figure 4(a). Table 1 shows the quantiles evaluated with the average of the year fixed effects. Each entry is a quantile of log wage changes multiplied by 100. For

[13]It might be helpful to think about the quantile regression models relative to a "standard" linear regression model: coefficients of the quantile regression model for quantile τ predict the τ^{th} quantile of the conditional distribution, while coefficients of the linear regression model predict the conditional mean. Estimation is performed by maximum likelihood, where the objective function is (minus) the sum of weighted absolute deviations from the predicted value, with quantile-specific weights for positive and negative deviations.

Table 1: Quantiles Implied by Quantile Regression

	Wage Change upon hiring (log points):				
quantiles:	10%	25%	50%	75%	90%
E-E Stay	–11.30	–2.17	2.12	10.43	21.84
E-E Switch	–19.10	–4.81	4.44	18.04	34.33
E-U-E Stay	–27.64	–12.42	–0.36	10.88	25.10
E-U-E Switch	–37.01	–18.73	–1.93	13.45	31.01

Note: Table shows quantiles of the distribution of wage changes implied by a set of quantile regression for four different groups. Each row shows quantiles of the conditional distribution of wage changes for different groups of workers. The wage changes are expressed in log points. For details on the fitted quantile regressions see text.

example, the first entry indicates that the worker at the 10^{th} percentile of the distribution of wage changes conditional on staying in the occupation realizes a log income change of -0.1130, or -11.30 log points. Consider first workers that directly change employers: the log 90-10 differential is about 60% wider for occupation switchers than for occupation stayers. Similarly, for workers going through an unemployment period, switchers realize a distribution of wage changes that is about 30

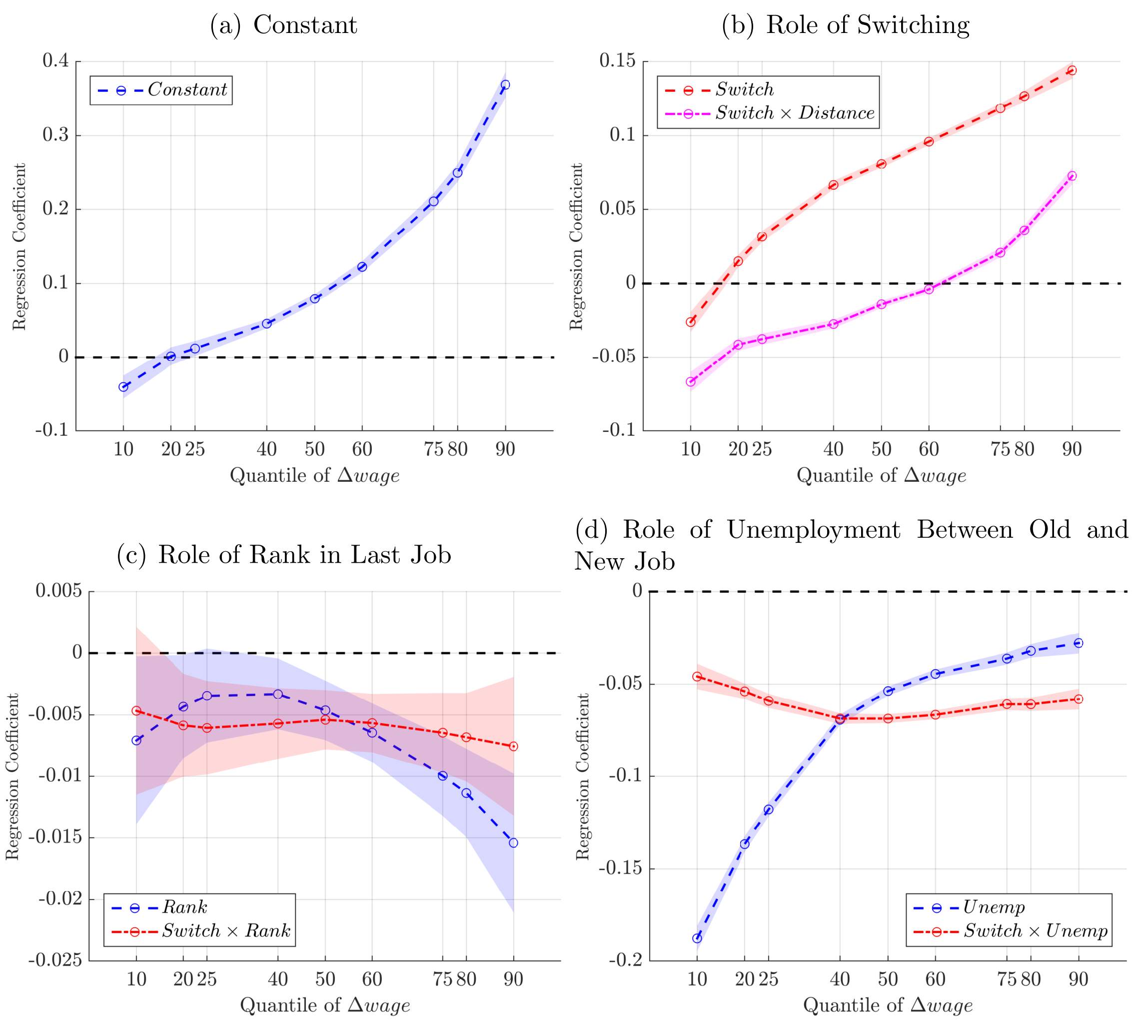
The coefficients of the full set of quantile regressions including rank and distance as covariates are plotted in Figure 5 along with 95% confidence bands.[14] The reported coefficients for the constant are normalized by the average year fixed effect. Consider first the coefficients on the rank in the last job, which are negative for all quantiles: the higher a worker is ranked relative to other workers in the same occupation, the more severe (relatively) are the adverse implications for wage changes of a job change. The point estimates imply that the median worker that changes the job within the same occupation faces a distribution of wage changes with an about 0.07 lower 10^{th} percentile and an about 0.15 lower 90^{th} percentile than the worker from the lowest rank.[15] Workers that go through unemployment realize a distribution of wage changes that is shifted down relative to job changers that do not experience an unemployment spell: the workers at the 10^{th} percentile of wage changes realize an about18 log points bigger wage cut than those at the 10^{th} percentile among the direct job changers. At the 90^{th} percentile, the wage cut is larger by about 3 log points.

Turning to the occupation switchers, the positive slope of the coefficients on the switching dummy by quantile confirm that the distribution of wage changes is wider than for job changers within the same occupation. Considering the distance of the switch, the coefficients imply that

[14]Confidence bands are based on the standard deviation of the coefficients from 200 bootstrap repetitions. Bootstrap samples are clustered at the individual level in order to preserve the auto-correlation structure of wages present in the original sample.

[15]The rank is measured in vintiles, so the median worker is in rank 10.

Figure 5: Coefficients of Quantile Regressions



Note: Each plot shows the coefficients from quantile regressions for log wage change for several quantiles; the regression includes a constant and year fixed effects as specified in (4). Rank can take on values 1-20, and the distance is between 0 and 1. 374,139 observations (sample of job changers).

the distribution is the wider, the farther the switch. Regarding job changers within the same occupation, the wage gains are lower if the worker ranked higher. Last, relative to a direct job changer, a worker who switches occupations after an unemployment spell faces a penalty for the unemployment period that is more pronounced than the unemployment penalty for the workers that stay in their occupation.

4 A Model of Occupational Switching

4.1 Overview of the Model Economy

I now build a stationary model of the labor market in which workers discretely choose their sector of employment—in reaction to productivity shocks. The model allows me to shed light on the relative roles of occupational choices and of productivity shocks for realized income changes. More precisely, using the model, I calibrate the distributions of shocks consistent with observed wage changes. This allows me to analyze occupational switching as an insurance device against income risk that is related to the occupation of current employment.

Time is discrete and the labor market is characterized by a finite number of sectors, or "islands", which resemble occupations. This island structure of the labor market is similar to Pilossoph (2014) and Carrillo-Tudela and Visschers (2014), which are versions of the Lucas and Prescott (1974) framework. Each island is populated by a continuum of firms, which use effective labor as an input in a linear production technology. Unemployed workers searching for a job face a search friction on each island, which implies that a worker-job match generates quasi-rents. I assume that workers have all the bargaining power and thus are paid according to their marginal product. Focussing on a partial equilibrium analysis, I keep the firm side as simple as possible, and do not endogenize the job finding probability. Each pair of occupations is characterized by an exogenous distance, which reflects the concept of an occupation as a certain combination of tasks.

While employed in an occupation, workers move up a ladder of occupation specific human capital at a stochastic rate. On top of this experience profile, workers receive persistent stochastic shocks to idiosyncratic productivity, that are orthogonal to human capital. Workers randomly select an alternative occupation, costlessly search on-the-job for alternative jobs, and receive a job offer with some probability. Given an offer, workers decide whether to accept the offer from the other occupation or to stay in their current occupation, for which they draw another productivity shock. Human capital is imperfectly transferable across occupation islands.

Workers lose their job with an exogenously given probability and become unemployed. Unemployed workers randomly search for employment in one alternative occupation and their current one. As for employed workers, the job finding probability is exogenously given and the same across all islands. While unemployed, the stochastic component of idiosyncratic productivity does not change, and each period, an unemployed worker steps down a rung of the ladder of occupation specifc human capital with some probability.

The decision of both employed and unemployed workers whether to stay on their current island or move to the (randomly selected) alternative island depends on both wage-related and non-pecuniary aspects. The wage-related aspects are that, when starting a new job, both human capital and the stochastic productivity component are affected by the choice of the worker. First, when switching to another occupation, the worker enters it at a lower human capital level—the more distant the occupations are, the more steps on the ladder the worker climbs down. Second, given the implications of their choice for human capital, workers weigh the stochastic skill shocks they received for staying or moving against one another. The non-pecuniary aspect affecting the decision of where to search for a job is a worker's *taste* for the different occupations: I assume that, each period, each worker draws a vector of tastes for all islands from distributions that are independent and identical over workers, islands, and over time.[16]

My model is a model of gross flows across occupations and in this respect similar to Carrillo-Tudela and Visschers (2014). This implies that the occupational employment shares are constant over time. The reason for this modelling choice is that I am interested in the reallocation across occupations in the individual decision problem and its relation to the wage process. In order to analyze this decision, I do not need any correlation of shocks across workers.

4.2 The Environment

There is a discrete number of occupational islands. The set of these islands is denoted by O, and each is populated by firms offering one job each, operating a production technology that is linear in idiosyncratic worker productivity. Each pair (o_i, o_j) of occupations is characterized by a distance $d(o_i, o_j)$. A period is divided into three stages: a pre-production stage, a production stage, and a post-production stage.

Stochastic Productivity Stochastic idiosyncratic productivity is denoted by $x_{i,t}$ and follows an $AR(1)$ in logs. A worker enters the pre-production stage with productivity $x_{i,t}$ and draws two shocks, $\boldsymbol{\eta}_{i,t} = \left\{\eta_{i,t}^{stay}, \eta_{i,t}^{move}\right\}$, where $\eta_{i,t}^{stay} \sim F_{\eta,t}^{stay}$ and $\eta_{i,t}^{move} \sim F_{\eta,t}^{move}$. If the worker works

[16] Recent examples of models that use taste shocks in the context of occupational switching are Wiczer (2015) and Pilossoph (2014). The taste shocks over occupations are a shortcut to achieving worker heterogeneity beyond skill heterogeneity in the cross-section. There is also some direct empirical evidence that non-penuniary job characteristics are a relevant component affecting the occupational switching decision. In an analysis of the effects of occupational switching on outcomes of workers, Longhi and Brynin (2010) document in survey data of the British Household Panel Survey and the German Socioeconomic Panel, that a large share of occupation switchers report an improvement in job satisfaction.

during the production stage, the stochastic productivity component is given by

$$\log(x_{i,t+1}) = g^e(x_{i,t}, o_{i,t}, o_{i,t+1}; \boldsymbol{\eta}_{i,t}) \equiv \rho \log(x_{i,t}) + \mathbb{1}\{o_{i,t+1} = o_{i,t}\}\, \eta_{i,t}^{stay} + \mathbb{1}\{o_{i,t+1} \neq o_{i,t}\}\, \eta_{i,t}^{move}, \tag{5}$$

where $\mathbb{1}\{*\}$ is an indicator function taking the value 1 if $*$ is true and the value 0 otherwise: only one of the two shocks is relevant for productivity. If the worker is unemployed during the production stage, $x_{i,t}$ does not change.

Human Capital Human capital of a worker i evolves stochastically and can take on H discrete values $h_{i,t} \in \{h_1, ..., h_H\}$, where $h_1 < h_2 < ... < h_H$. A worker who enters period t in the pre-production stage with human capital level $h_{i,t} = h_j$ in occupation $o_{i,t}$ and who ends up working in occupation $o_{i,t+1}$, has human capital level $\tilde{h}_{i,t+1}$ during the production stage, where

$$\tilde{h}_{i,t+1} = h_{j-k}, \text{ with } k = f(d(o_{i,t}, o_{i,t+1})), \tag{6}$$

where $f(d(o_{i,t}, o_{i,t+1}))$ pins down how many steps of the human capital ladder the worker moves down depending on the distance, where $f(0) = 1$ and $f(1) = \kappa$, where $\kappa < H - 1$ denotes the number of steps a worker moves when switching to the most different occupation. This captures that the degree of transferability of skills across occupations depends *systematically* on the distance between occupations. If a worker is employed in the production stage with human capital level $\tilde{h}_{i,t+1} = h_k$, then, during the post-production stage,

$$h_{i,t+1} = \begin{cases} h_{k+1} & \text{with probability } \psi_k^{hup} \\ h_k & \text{with probability } 1 - \psi_k^{hup} \end{cases}. \tag{7}$$

The probability of stepping up depends on the current position on the ladder, and $\psi_k^{hup} > \psi_{k+1}^{hup} \forall k$, i.e., the probability of stepping up the ladder decreases with the current position. This notion of steps that become steeper allows the model to generate a profile of the switching probability that is decreasing in human capital. Once at the highest level, h_H, a worker stays there with probability 1—unless he switches occupations or becomes unemployed.

If a worker is unemployed during the production stage and the human capital level is $\tilde{h}_{i,t+1} = h_k$, then, during the post-production stage, the worker moves down one step with probability ψ^{hdown}:

$$h_{i,t+1} = \begin{cases} h_{k-1} & \text{with probability } \psi^{hdown} \\ h_k & \text{with probability } 1 - \psi^{hdown} \end{cases}. \tag{8}$$

Separation and Job-Finding In the pre-production stage, a worker is separated exogenously with probability $1-\phi$. A separated worker is unemployed during the production stage and enters the next period as unemployed. Both employed and unemployed workers receive job offers, with probabilities ψ^e and ψ^u, respectively. There is no congestion in the labor market, and workers have all bargaining power, resulting in marginal product wages.

Life Span I focus on the stationary equilibrium of the economy and in order to ensure a realisitc equilibrium distribution over wages and human capital, agents leave the economy with a constant probability of death, $1-\pi<1$. For each worker who dies, a new worker enters the economy, generating a perpetual youth structure a la Blanchard (1985) and Yaari (1965), such that the population is of constant size. Newborns enter the economy as unemployed at the lowest human capital level, with average stochastic productivity, and randomly attached to one of the occupations.

4.3 The Decision Problem of Workers

Employed Workers Workers maximize their expected discounted lifetime utility. When employed at the beginning of the period t, a worker i is characterized by his occupation $o_{i,t}$, his level of human capital $h_{i,t}$, and his stochastic idiosyncratic productivity $x_{i,t}$. Also, workers enter the period with a vector $\mathbb{O}_{i,t}$ of tastes for occupations. If not separated, the worker randomly chooses in which alternative occupation to search for a job. Then the worker draws two idiosyncratic productivity shocks, $\boldsymbol{\eta}_{i,t}=\left\{\eta_{i,t}^{stay},\eta_{i,t}^{move}\right\}$ from distributions $F_{\eta,t}^{stay}$ and $F_{\eta,t}^{move}$. Search is costless, and with probability ψ^e an offer arrives and the worker chooses whether to stay in the current occupation or move to the other. The human capital level at the production stage depends on this choice according to (6). If no offer is received, the worker stays with his current job (and occupation). The worker receives wages according to the total productivity and consumes all income, i.e., $c_{i,t+1}=x_{i,t+1}\times\tilde{h}_{i,t+1}$. I assume a linear utility function and hence per-period utility at the production stage is given by

$$\widetilde{u}^{empl}\left(x_{i,t+1},o_{i,t+1},\tilde{h}_{i,t+1}\right)=x_{i,t+1}\times\tilde{h}_{i,t+1}. \tag{9}$$

The recursive problem is given by

$$\begin{aligned}V^{empl}\left(x_{i,t},\boldsymbol{\eta}_{i,t},h_{i,t},o_{i,t}\right)=\phi\times\Bigg(&\psi^e\times V^{offer}\left(x_{i,t},\boldsymbol{\eta}_{i,t},h_{i,t},o_{i,t}\right)+\dots\\&(1-\psi^e)\times V^{stay}\left(x_{i,t},\boldsymbol{\eta}_{i,t},h_{i,t},o_{i,t}\right)\Bigg)+\dots\\&(1-\phi)\times\left(\widetilde{u}^{unempl}+\widetilde{\beta}E\left[V^{unempl}\left(x_{i,t+1},\boldsymbol{\eta}_{i,t+1},h_{i,t+1},o_{i,t}\right)\right]\right)\end{aligned} \tag{10}$$

$$
\begin{aligned}
& s.t. \\
x_{i,t+1} &= x_{i,t} \\
h_{i,t+1} & \text{ acc. to } (8)
\end{aligned}
$$

where I express the value function with the adjusted discount factor $\widetilde{\beta} = \beta\pi$, with β denoting the pure discount factor and π the probability of survival. If the worker loses the job in the pre-production stage, he stays unemployed in period t and enters the next period unemployed with $o_{i,t}$ indicating the occupation of his last employment, while idiosyncratic productivity remains constant. If the worker does not lose his job, and receives no alternative job offer, he stays with the current job; when receiving a job offer, he can choose whether to stay with the current job or to move to another occupation.

The sub value functions are given by $V^{stay}(\bullet)$ and $V^{offer}(\bullet)$ as follows.

$$
\begin{aligned}
V^{stay}(x_{i,t}, \boldsymbol{\eta}_{i,t}, h_{i,t}, o_{i,t}) = \widetilde{u}^{empl}\left(x_{i,t+1}, o_{i,t}, \tilde{h}_{i,t+1}\right) + \ldots \\
\widetilde{\beta} E\left[V^{empl}(x_{i,t+1}, \boldsymbol{\eta}_{i,t+1}, h_{i,t+1}, o_{i,t}) + \mathbb{O}_{i,t+1}(o_{i,t})\right]
\end{aligned}
\tag{11}
$$

$$
\begin{aligned}
& s.t. \\
x_{i,t+1} &= g^{e}(x_{i,t}, o_{i,t}, o_{i,t}; \boldsymbol{\eta}_{i,t}) \\
\tilde{h}_{i,t+1} &= h_{i,t} \\
h_{i,t+1} & \text{ acc. to } (7)
\end{aligned}
$$

and

$$
\begin{aligned}
& V^{offer}(x_{i,t}, \boldsymbol{\eta}_{i,t}, h_{i,t}, o_{i,t}) = \\
& \widetilde{\beta} \times \sum_{j \neq o_{i,t}} \pi_j \times \max\left(\tilde{v}(j|\bullet) + E_{\mathbb{O}}\mathbb{O}_{i,t+1}(j), \tilde{v}(o_{i,t}|\bullet) + E_{\mathbb{O}}\mathbb{O}_{i,t+1}(o_{i,t})\right)
\end{aligned}
\tag{12}
$$

where π_j is the probability that the worker randomly chooses occupation j in the pre-production stage and $\tilde{v}(j|\bullet)$ is given by:[17]

$$
\begin{aligned}
& \tilde{v}(j|\bullet) = \widetilde{v}(j|x_{i,t}, \boldsymbol{\eta}_{i,t}, h_{i,t}, o_{i,t}) \equiv \\
& \frac{1}{\widetilde{\beta}}\widetilde{u}^{empl}\left(x_{i,t+1}, j, \tilde{h}_{i,t+1}\right) + E_{\boldsymbol{\eta}, \psi^{hup}} V^{empl}(x_{i,t+1}, \boldsymbol{\eta}_{i,t+1}, h_{i,t+1}, j).
\end{aligned}
$$

[17] I make use here of the independence of taste shocks and productivity (and human capital) shocks.

$$
\begin{aligned}
&s.t. \\
&x_{i,t+1} \quad = \quad g^{e}\left(x_{i,t}, o_{i,t}, o_{i,t+1}; \boldsymbol{\eta}_{i,t}\right) \\
&\tilde{h}_{i,t+1} \quad \text{acc. to} \quad (6) \\
&h_{i,t+1} \quad \text{acc. to} \quad (7).
\end{aligned}
$$

Unemployed Workers A worker entering the period unemployed is characterized by a state vector collecting his last occupation, $o_{i,t}$, his level of human capital, $h_{i,t}$, his stochastic idiosyncratic productivity, $x_{i,t}$, and his preferences over occupations, $\mathbb{O}_{i,t}$. He randomly chooses one alternative occupation $o_{i,t+1}$ in which to costlessly search for a job, while also searching in the old occupation. The unemployed worker then draws two idiosyncratic productivity shocks, $\boldsymbol{\eta}_{i,t} = \left\{\eta_{i,t}^{stay}, \eta_{i,t}^{move}\right\}$ from the same distributions $F_{\eta,t}^{stay}$ and $F_{\eta,t}^{move}$ as employed workers. With probability ψ^{u} the worker receives a job offer and when staying unemployed at the production stage, the worker receives $\widetilde{u}^{unempl}$. The recursive problem is given by

$$
\begin{aligned}
V^{unempl}\left(x_{i,t}, \boldsymbol{\eta}_{i,t}, h_{i,t}, o_{i,t}\right) = \psi^{u} \times V^{offer}\left(x_{i,t}, \boldsymbol{\eta}_{i,t}, h_{i,t}, o_{i,t}\right) + \ldots \\
(1-\psi^{u}) \times \left(\widetilde{u}^{unempl} + \widetilde{\beta} E V^{unempl}\left(x_{i,t}, \boldsymbol{\eta}_{i,t+1}, h_{i,t+1}, o_{i,t}\right)\right) \quad (13)
\end{aligned}
$$

$$
\begin{aligned}
&s.t. \\
&h_{i,t+1} \quad \text{acc. to} \quad (8)
\end{aligned}
$$

The Conditional Choice Probabilities

Note that, conditional on receiving an offer, the choice problem of employed and unemployed workers is the same. The introduction of the taste shocks implies that the value function is smooth in the state space $(x_{i,t}, \boldsymbol{\eta}_{i,t}, h_{i,t}, o_{i,t})$, and that from a group of workers who are at the same position in the state space, every occupation is chosen by some members of the group, because they differ in their tastes. The policy function is thus a set of choice probabilities for each occupation.

I assume $F_{\mathbb{O}}$ to be a Gumbel distribution, which allows me to exploit results from discrete choice theory, as also done recently in, e.g., Pilossoph (2014) or Iskhakov *et al.* (2015):[18] they yield analytical expressions for the conditional choice probabilities, which for occupation $o_{i,t+1}$

[18] Iskhakov *et al.* (2015) provide a detailed discussion of taste shocks as a smoothing device in the solution of discrete choice problems. I denote the scale parameter by $\sigma_{\mathbb{O}}$ and normalize the location parameter as $-\sigma_{\mathbb{O}}\gamma$, where γ is Euler's constant. The normalization is such that the (unconditional) expected value of each taste shock is zero.

is given by

$$P\left(o_{i,t+1}=j|x_{i,t},\boldsymbol{\eta}_{i,t},h_{i,t},o_{i,t},(\psi^e=1\vee\psi^u=1)\right)=$$
$$\pi_j\times\frac{1}{1+\exp\left(\frac{\widetilde{v}(o_{i,t}|x_{i,t},\boldsymbol{\eta}_{i,t},h_{i,t},o_{i,t})-\widetilde{v}(j|x_{i,t},\boldsymbol{\eta}_{i,t},h_{i,t},o_{i,t})}{\sigma_O}\right)},\quad(14)$$

where π_j is the exogenous sampling probability of occupation j.

5 Quantitative Analysis

In this section, I analyze a calibrated version of the model. The calibration has two goals. First, it allows me to quantify the relative role of different components of wage changes, i.e., human capital changes and changes of the stochastic productivity. For direct job changers that stay in their occupation, productivity shocks account for about 66% of wage changes, for occupation switchers this number is 49%. Ignoring selection of workers into switching and staying, one would underestimate the variance of productivity shocks for occupation movers by 31% and for stayers by 4%. Second, given that workers choose to switch occupations in response to underlying productivity shocks, I calculate the option value that workers assign to the availability of the switching channel. To this end, I ask workers in a counterfactual world without the option of switching, before the realization of productivity shocks, how much they gain in expectation from the option. As a share of per-period consumption, the answer to the question is 0.78.

5.1 Calibration of the Model

Model Elements Calibrated Exogenously

In the calibrated version of the model, I choose a period to be one month and set the number of (horizontally differentiated) occupations to six. Given symmetry in terms of productivity, having six occupations allows me to define the distance $d_{oo'}$ from one occupation o to any other occupation o' as either 1/3 ("close"), 2/3 ("medium"), or 1 ("far").[19]

Table 2 lists the exogenous parameters that are set outside the model. I choose the survival probability π such that the expected duration of a career is 40 years. The monthly probabilities to lose a job when employed and to find a job when unemployed, respectively, are set in line with the average transition rates as documented by Jung and Kuhn (2013). Taking the probablity of death into account, I choose the monthly discount factor to comply with a 4% annual interest

[19]Visualize the occupations to be distributed equidistantly on a circle. The shortest way to get to another occupation along the circle gives the distance, which I normalize such that the maximum distance is 1.

Table 2: Pre-Calibrated Parameters

Parameter	Description	Value	Informed by
π	Probability to survive to next period	.9979	Implied expected duration of career: 40 years (25-64)
ψ^e	Monthly probability of job offer when employed	.01	Average monthly E-E, E-U, and U-E transition rates
$(1-\phi)$	Monthly probability to loose job	.0005	
ψ^u	Monthly probability of job offer when unemployed	.0062	
β	Monthly discounting factor	.9988	4% annual interest rate

Note: Table shows parameters calibrated exogenously. E and U denote Employment and Unemployment, respectively. Transition rates from Jung and Kuhn (2013). β takes the survival probability into account.

rate. Finally, I set the per-period utility of unemployment, $\tilde{u}^{unempl}$, to 80% of the lowest per-period utility level received by an employed worker.

Identification of the Remaining Model Elements

Productivity Shocks A key element of the model is its take on the nature of idiosyncratic shocks. In the data, I can only observe the distributions of realized wage changes for workers that endogenously decide either to stay in their occupation or to switch to a different one. The model's key identifying assumption for the underlying shock distributions is that workers make a utility-maximizing choice.

The mechanism can be understood directly in a stripped-down version of the decision problem. Disregarding the human capiral element of the model, just consider the two shocks, η^{stay} and η^{move}, and assume that these directly translate into wage changes depending on the choice of the worker to stay or to move. Given any distributions $F^{stay}_{\eta,t}$ and $F^{move}_{\eta,t}$, the utility maximization of the workers implies that η^{stay} is observed as a wage change whenever the draws are such that $\eta^{stay} > \eta^{move}$ and vice versa. Thus, the probability to observe realization n of the move shock, $\eta^{move} = n$, is a combination of the probabilities that $\eta^{move} = n$ is actually drawn from $F^{move}_{\eta,t}$ and that the realization of the stay-shock is worse, i.e., $\eta^{stay} \leq n$. In other words, the share of realization n in the distribution of wage changes realized by occupation switchers is informative about the lower tail of the distribution of stay-shocks, and vice versa.

$F^{stay}_{\eta,t}$ and $F^{move}_{\eta,t}$ are assumed to be Normal distributions, with means and standard deviations denoted by μ^{stay}_{η}, σ^{stay}_{η}, μ^{move}_{η} and σ^{move}_{η}.

Human Capital Ladder In terms of the human capital ladder, the following elements are not yet fixed: the number of steps, H, the step size of the ladder, Δh, the probabilities to step up, ψ_k^{hup}, or down, ψ^{hdown}, and the number of steps down depending on the distance of an occupation switch, $f(d(\cdot))$.

I set the number of steps on the human capital ladder to $H = 11$. Consider the implications of an occupational switch. According to Equation (6), a worker moves down the ladder when switching occupations, which implies a wage cut. Above, I defined the distance between occupations to be 1/3, 2/3, and 1. I set the implied number of steps down on the human capital ladder to be 1, 2, and 3, respectively. The main empirical motivation for workers stepping down the human capital ladder when switching is the rank-rank relationship shown in Figure 3 above.

I calibrate the probability to step up the ladder, ψ_k^{hup}, as a piecewise linear function of the current state k. In the calibration procedure, I set the probability for $k = 1$, $k = 6$, and $k = 10$, and linearly interpolate between these nodes. Why does the probability to step up depend on where you are on the ladder? Other things equal, a higher human capital level implies a higher wage. Now assume that $\psi_k^{hup} = \psi^{hup} \forall k$. In this scenario, the higher a worker is on the ladder, the less relevant is the temporary wage cut from stepping down the ladder: workers with higher wages are willing to accept the wage cut and switch occupations more frequently. To see this, consider the inverse of the probability to choose a given occupation j in Equation (14):

$$P\left(o_{i,t+1} = j|\bullet\right)^{-1} = \left(1 + \exp\left(\frac{\widetilde{v}\left(o_{i,t}|x_{i,t}, \boldsymbol{\eta}_{i,t}, h_{i,t}, o_{i,t}\right) - \widetilde{v}\left(j|x_{i,t}, \boldsymbol{\eta}_{i,t}, h_{i,t}, o_{i,t}\right)}{\sigma_{\mathbb{O}}}\right)\right) \times \frac{1}{\pi_j}$$

The expected value of occupation j relative to the alternative of staying in the current occupation $o_{i,t}$, weighted by the scale of the taste shocks, is relevant for the choice. Now consider a worker i, currently in some occupation o with human capital level h_k, who has the option to switch to occupation $o' \neq o$. At the production stage, the human capital level of that worker is $\tilde{h}_i = h_k$ when choosing to stay in occupation o, and $\tilde{h}_i = h_{k-d(o,o')}$ when choosing to switch to occupation o'. As the worker gets closer to the top of the ladder, keeping the level of the stochastic component and the productivity shocks constant, $\widetilde{v}(o|\bullet) - \widetilde{v}(o'|\bullet)$ decreases with the level of human capital h_k (the step down is compensated quicker, because the end of the ladder is reached earlier when choosing to stay). Thus, for the same stochastic productivity levels and shocks, the probability to stay in occupation o decreases with human capital if the probability to step up the ladder is constant.

However, the empirical analysis in Section 3.1 showed that higher ranked workers are less likely to switch. In order to allow the model to generate this, I let the probability to step up vary with the step on the ladder. If the ladder becomes *steeper* as one climbs up (in the sense that the probabiltiy of stepping up decreases), then this has a positive effect on $\widetilde{v}(o|\bullet) - \widetilde{v}(o'|\bullet)$ as a function of the level of human capital. The probabilities to climb up are hence identified by the probability of switching as a function of the rank.[20] Unemployed workers move down the human capital ladder one rung each period with probability ψ^{hdown}. I documented above that the probability of switching occuaptions increases with the duration of unemployment. This is what identifies this parameter.

The step size of the ladder, Δh, is identified by the right tail of the distribution of wage changes realized by job changers within an occupation. Consider equation (7): when staying in the occupation, a share of workers moves up the ladder one step, thus experiencing an increase of human capital by Δh. Similarly, the lower part of the distribution of wage changes realized by occupation switchers is informative for Δh: upon switching occupations, a worker moves down the ladder by at least Δh. The other tails of the respective distributions are governed by the mean parameters of the productivity shocks.

Taste Shocks The scaling factor of the taste shocks, $\sigma_{\mathbb{O}}$, affects the probability of workers to switch occupations. A higher $\sigma_{\mathbb{O}}$ implies that differences of the expected value of being in either occupation are less relevant; in the present model, workers are more willing to accept the human capital loss that comes with switching and switch more frequently. Along these lines, Wiczer (2015) and Pilossoph (2014) argue that the switching rate pins down the scale of the taste shocks. In my model, the switching rates are driven by productivity shocks and taste shocks. The productivity shocks are pinned down by moments of wage changes, and hence there is scope for the taste shocks.

Less obvious, the scaling factor also affects the elasticity of the switching probability with respect to changes of the relative payoffs of staying and switching. To see this, consider again the probability to choose occupation j in Equation (14). As discussed above, the probability of switching occupations varies with the level of human capital. If the taste shocks are more dispersed, then a (marginal) change of the relative value of j matters less for the choice (because the difference of expected payoffs is scaled with the inverse of $\sigma_{\mathbb{O}}$). Thus, the pattern of switching by rank is also informative for the scaling of taste shocks.

One important implication of the model featuring taste shocks is that those shocks smooth the discrete decision problem. In particular, the choice probabilities in Equation 14 are a smooth function over the state space (net taste shocks). This allows for interpolation when simulating the model. The reason this is crucial for my analysis is that I need to evaluate quantiles of the distribution of wage changes. While I need to discretize the state space (and thus the $\boldsymbol{\eta}$-

[20]Note that, in the model, the rank of a worker within the occupation-specific wage distribution is not the same as his human capital level: wages are a combination of human capital and the stochastic idiosyncratic component. Given that the ladder gets steeper when climbing up, there is a selection process of workers with lower levels of stochastic productivity: workers with higher levels of human capital are willing to accept worse stochastic productivity shocks, because they weigh this against a loss of human capital upon switching from which they (in expectation) recover less quickly.

Table 3: Moments–Data vs. Calibrated Model

Moment	Data		Model		Informs
Distribution of (log) wage changes of E-E transitions					
	stayers	switchers	stayers	switchers	
10^{th} percentile	-.11	-.19	-.10	-.23	Productivity shocks; step size of human capital ladder
50^{th} percentile	.02	.04	.03	.05	
90^{th} percentile	.22	.34	.17	.26	
Probability to switch					
Avg. (E-E)	.30		.22		Scaling of taste shocks
By rank (E-E)	(.43, .27, .24)		(.25, .22, .26)		Prob. to step up human capital ladder
increase over 1 year of unemp.	.29		.22		Prob. to step down during unemployment

Note: The table shows data moments that are targeted in the calibration and model counterparts with the calibrated parameters.

productivity shocks) when solving for the policy and value functions, I can then use a much finer grid of shocks in the simulation.

Wage Changes and Switching Probability

Table 3 summarizes the targeted moments and their counterparts in the calibrated model. I calculate the model-implied moments in the stationary distribution of the model economy.[21] As empirical counterpart for these moments, I choose long-run averages.

Specifically, for the percentiles of wage changes, I use the fitted percentiles from a set of quantile regressions, similar to the ones outlined in Equation (4) in Section 3.2. I do not use rank and distance of switch as control variables here, because I target the *average percentiles* of direct job changers for the current calibration. Given the estimates, I add the average of the year-dummy coefficients to the constant, and calculate the fitted percentiles of wage changes for switchers and stayers, respectively.

For the switching probability on average and by rank, I use the predicted probabilities from a linear probability model. The linear probability model regresses a switching dummy on a constant, a set of dummies for the rank, a dummy for the type of switch (1 if E-U-E, 0 if E-E), the unemployment duration (interacted with the unemployment dummy), a full set of year dummies, and dummies for age group; I choose three age groups: 25—34, 35—44, and 45—54.

[21] Appendix C describes the model solution and the calculation of moments in the stationary distribution.

Table 4: Calibrated Parameters

Parameter	Value	Parameter	Value
μ_η^{stay}	-.0075	ψ^{hdown}	24.23%
μ_η^{move}	.0237	ψ_{lo}^{hup}	22.57%
σ_η^{stay}	.0934	ψ_{med}^{hup}	9.97%
σ_η^{move}	.1829	ψ_{high}^{hup}	.52%
Δh	.7795	$\sigma_{\mathbb{O}}$	.2710

Note: The table shows parameters calibrated using the model.

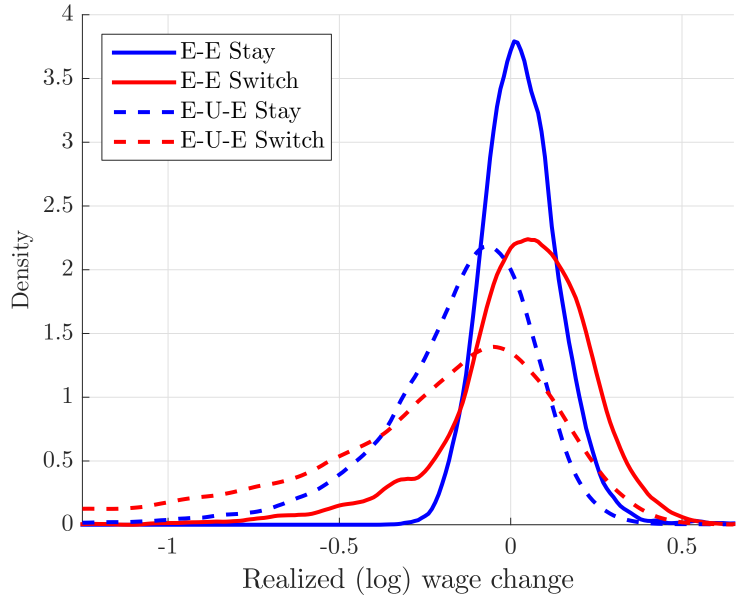
Given that the model does not feature an age dimension,[22] I use the predicted switching profile for the second age group as target. In order to generate long-run average switching probabilites, I add the average of the year-dummy coefficients. The last target is the average increase of the switching probability over one year of unemployment. For this, I use the predicted average switching profile from a linear probability model of switching on a constant, year dummies, and the unemployment duration (interacted with the unemployment dummy).

Table 4 lists the calibrated parameters. The calibrated model does a good job in matching the pattern of the targeted percentiles of wage changes—the key focus of the analysis. Specifically, the median for switchers and stayers, and the 90^{th} percentile for switchers are fit well (1 log point difference). This is also true for the 10^{th} percentile of wage changes for stayers. For switchers, the 10^{th} percentile is 4 log points worse in the model than in the data. The 90^{th} percentile of wage changes is five log points too low for stayers and eight log points for switchers.

The average switching probability in the model is 22% for the direct job changers, compared to 30% in the data. However, given that the model features six occupations, whereas the data moment is based on 30 occupational groups, this seems a minor issue of the calibration. Turning to the slope of the switching profile by unemployment duration, the probability to switch increases by about 22% in the model, compared to 29% in the data. The relationship is generated, because the switching probability decreases with human capital, as discussed above. The model has difficulties in matching the switching pattern by rank in the calibration: it exhibits a u-shape, compared to the monotonically decreasing pattern in the data. The reason for this is a negative correlation between beginning of period human capital and idiosyncratic productivity (the correlation coefficient is $-.07$; see footnote 20).

[22] The model does have a perpetual youth structure, but the probability of death is the same for every worker. Therefore, the model does not generate an horizon effect, in the sense that younger workers would switch more often because they can profit from an investment element of the switching decision longer than older workers. A channel like this can be introduced in the model by having two age groups living at the same time: a young worker then ages with an exogenous probability, and an old worker dies with an exogenous probability.

Figure 6: Distribution of Wage Changes in Calibrated Model

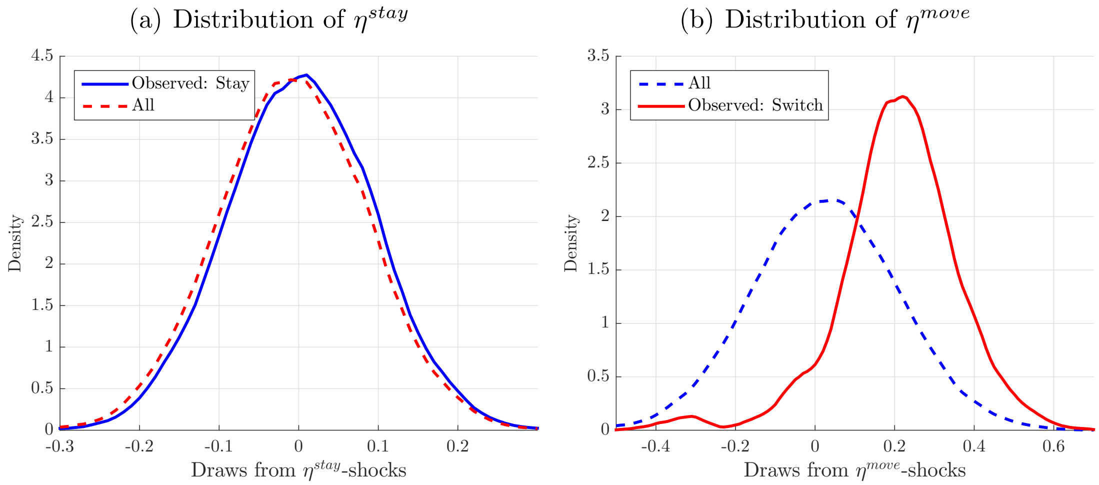


Note: Density functions of observed wage changes in the model.

Figure 6 shows the overall distribution of realized wage changes for the four subgroups defined by direct job change (E-E) vs. job change through unemployment (E-U-E), and staying in the occupation vs. switching occupations. Consider direct job changers that stay at their occupation. Their distribution of wage changes is driven by two elements: first, their draws of η^{stay}-shocks, and second, a share of these workers moves up the human capital ladder by one step, which slightly bends the right tail outwards. Job Changers that switch occupations realize more negative wage realizations because they move down the human capital ladder. Similarly, a larger share realizes high wage gains: these workers find a particularly productive match in a different occupation (they draw from a wider distribution of productivity shocks), and thus they are willing to move down the human capital ladder.

Now, consider the distribution of wage changes realized in the model by workers that spend up to one year in unemployment. We see in Figure 6 that these workers move down the human capital ladder and thus the left arm of the distribution of wage changes is heavier. Compared to the data, the calibrated model overemphasizes the negative wage changes for the job changers through unemployment. In the data, the 10^{th}, 50^{th}, and 90^{th} percentiles of wage changes for the stayers and switchers are $(-.28, -.00, .25)$ and $(-.37, -.02, .31)$, respectively. The model generates 10^{th}, 50^{th}, and 90^{th} percentiles of wage changes of $(-.45, -.12, .09)$ and $(-.83, -.16, .15)$, respectively.

Figure 7: Distribution of Underlying Shocks and of Realized Shocks



Note: Density functions of η^{stay}-shocks and η^{move}-shocks received by workers that decide to stay or to switch; solid lines are *observable* shocks, dashed lines are *all* shocks.

5.2 Choice vs. Shock and the Option Value of Switching

Roles of Underlying Productivity Shocks and Occupational Choice

Figure 7 shows the distribution of stochastic productivity shocks together with the distribution of the shocks that can be observed; "observed" referring to the *stay*-shocks realized by *stayers* and the *move*-shocks realized by *switchers*. Considering stayers, the distribution of observed realizations from the distribution is more skewed to the right than the distribution of η^{stay}-shocks in the population: left-tail (right-tail) events are less (more) likely to be observed than they are realized. For the distribution of η^{move}-shocks this is even more apparent. Compared to the distribution of draws from the underlying distribution, in the observed distribution the left tail collapses almost completely: switchers face the (indirect) cost of moving down the human capital ladder and thus only draws that compensate for the implied wage loss are accepted. The mass points in the left tail are the result of workers accepting a more severe human capital cut when moving to an occupation that is more distant.

Comparing the role of changes of the stochastic productivity component relative to movements along the human capital ladder, it turns out that the stochastic component is more important for switchers than for stayers. For direct job changers that stay in their occupation, the overall variance of wage changes in the calibrated model is .0128, out of which .0044 are generated by changes in human capital; for switchers these numbers are .0469 and .0284, respectively. Now, what is the role of the occupational *choice relative to underlying shocks*? To evaluate this, I disregard changes of human capital for now. Assume that one can directly observe the realized distributions of productivity shocks for switchers and stayers as displayed in figure 7. The variances of realized shocks turn out to be $\left(\tilde{\sigma}_{\eta}^{move}\right)^2 = .0231$ and $\left(\tilde{\sigma}_{\eta}^{stay}\right)^2 = .0084$, where tilde denotes realized changes. Compare these to the variance of underlying shocks, $\left(\sigma_{\eta}^{move}\right)^2 = .0335$ and $\left(\sigma_{\eta}^{stay}\right)^2 = .0087$. If one were to ignore selection of workers into switching and staying, and equate the observed realizations of productivity shocks to the underlying distribution, one would underestimate the variance of productivity shocks for movers by 31.0% and for stayers by 3.7%.

A second way of pinning down the importance of the selection process for the distribution of productivity changes is to calculate its role for the distribution of wage changes for *all job changers* (E-E). Assume that one knew the true dispersion of the productivity shocks and the correct share of switchers (implied by the model), p_{switch}. If selection into either group was random, one could express the distribution of productivity shocks as a mixture of Normal distributions: with probability p_{switch} a worker draws from $\mathcal{N}\left(\mu_{eta}^{move}, \left(\sigma_{\eta}^{move}\right)^2\right)$, and with probability $(1 - p_{switch})$, a worker draws from $\mathcal{N}\left(\mu_{eta}^{stay}, \left(\sigma_{\eta}^{stay}\right)^2\right)$. The implied counterfactual distribution of productivity shocks has a variance of $\left(\sigma_{\eta}^{counterfact}\right)^2 = .0137$. Compare this to the distribution of productivity shocks actually realized in the model: $\left(\sigma_{\eta}^{actual}\right)^2 = .0186$. Thus, the counterfactual distribution understates the dipersion by 26%. Put differently, the endogenous choice accounts for 26% of realized productivity changes.

The counterfactual scenario differs from the actual distribution on two ends: some workers would decide to switch but are forced to stay; and some workers would decide to stay but are forced to switch. For the forced stayers, switching would imply a better outcome, i.e., either a smaller negative change of productivity, or a larger positive change. Given that the dispersion is larger once workers endogenously choose the occupation, the second channel is quantitatively more important; this channel can be interpreted as career progression. The first channel can be interpreted as an informal insurance character of occupational switching: the switcher still realizes a negative productivity change, but the counterfactual would be worse. Thus, workers can react to bad luck that affects them in their current occupation: think, for example, of a construction worker who after an accident cannot continue to work as a construction worker, but is able to switch to a physically less demanding occupation.

The Option Value of Occupational Switching

Given that the endogenous switching decision appears to be of major relevance for realized dispersion of productivity changes, I now evaluate how much workers do prefer a world in which they can switch occupations to a world where they are exposed to occupation-related shocks? In other words, what is the utility gain that workers get from the *option of switching* in expectation of productivity shocks? I evaluate this by calculating the Compensating Variation in a counterfactual world without the option to switch occupations that is necessary to make these workers indifferent to living in the actual (model) world–while workers are facing the same shock processes for exogenous job separations, job finding, stochastic productivity, human capital accumulation, and occupational tastes.

Consider a worker who enters the period employed in occupation $o_{i,t}$, with human capital level $h_{i,t}$, and stochastic productivity $x_{i,t}$. The worker receives two productivity shocks, $\boldsymbol{\eta}_{i,t}$, and his value function is given in equation (10) as $V^{empl}(x_{i,t}, \boldsymbol{\eta}_{i,t}, h_{i,t}, o_{i,t})$. In the counterfactual world, the worker always stays in occupation $o_{i,t}$. The value functions for employed and unemployed workers are denoted by $V^{count}(x_{i,t}, \boldsymbol{\eta}_{i,t}, h_{i,t}, o_{i,t})$ and $V^{count-ue}(x_{i,t}, \boldsymbol{\eta}_{i,t}, h_{i,t}, o_{i,t})$, and shown in appendix Appendix B. The ex ante expected value of being employed in state $(x_{i,t}, h_{i,t}, o_{i,t})$, i.e., before the realization of the $\boldsymbol{\eta}$-shocks, is given in the two worlds by

$$\widetilde{V}^{empl}(x_{i,t}, h_{i,t}, o_{i,t}) \equiv E_{\boldsymbol{\eta}} V^{empl}(x_{i,t}, \boldsymbol{\eta}_{i,t}, h_{i,t}, o_{i,t})$$

and

$$\widetilde{V}^{counter}(x_{i,t}, h_{i,t}, o_{i,t}) \equiv E_{\boldsymbol{\eta}} V^{counter}(x_{i,t}, \boldsymbol{\eta}_{i,t}, h_{i,t}, o_{i,t}).$$

I now calculate the per-period Consumption Compensating Variation (CCV), λ, that makes the average worker in the world without switching indifferent to the world where he can switch. Denote the state vector $(x_{i,t}, h_{i,t}, o_{i,t})$ by $s_{i,t}$. Using the stationary distribution of workers over states $s_{i,t}$ in the model with occupational switching, λ is defined implicitly by

$$\sum_j \omega_j \widetilde{V}^{empl}(s_{i,t} = j) \stackrel{!}{=} \sum_j \omega_j \widetilde{V}^{counter}(s_{i,t} = j; \lambda), \tag{15}$$

where $\widetilde{V}^{counter}(\bullet; \lambda)$ reflects the expected present value utility when consumption is adjusted by the factor $(1 + \lambda)$ in every state, and ω_j denotes the share of workers in state $s_{i,t} = j$ in the stationary distribution. Given the homotheticity of the per-period utility function (utility is linear), λ can be calculated in closed form as

$$\lambda = \left(\frac{\sum_j \omega_j \widetilde{V}^{empl}(s_{i,t} = j)}{\sum_j \omega_j \widetilde{V}^{counter}(s_{i,t} = j)} \right) - 1.$$

Table 5 shows the value that workers assign to the option of switching.[23] Ex ante, workers have a utility gain from the option to switch that amounts to about 0.78% of their expected per-period consumption. Conditioning on employment state, those that enter the period as unemployed, assign a higher value of about 1.25% of per-perid consumption to the availability of switching–which is to be expected, given that unemployed workers switch more often. The Compensating Consumption Variation for employed workers is 0.73%.

[23]The calculation for unemployed workers follows the same procedure as the one for employed workers described in the text.

Table 5: The Option Value of Occupational Switching

	λ
Overall	0.78%
Unemployed Workers	1.25%
Employed Workers	0.73%

Note: The table shows the utility gain from switching expressed as a share of per-period Consumption, λ.

6 Conclusion

In this paper, I take a step in disentangling the role played by productivity *shocks* and occupational *choices* for observed wage dynamics. I first document several regularities regarding occupational switching in German administrative data from social security records. I find that, (i.), switching occupations is an empirically relevant phenomenon among job changers, (ii.), the switching probability correlates negatively with relative wage in the old occupation, (iii.), the switching probability increases with the duration of unemployment, (iv.), switches are more frequently observed to occupations that share similar tasks, and (v.), upon switching workers tend to rank lower in the new occupation and this downgrade is more pronounced for switches to occupations farther away in the task space. I then show that the distribution of *realized* individual wage changes varies systematically between occupation switchers and stayers. In the second part of the analysis, I set up a structural model of the labor market featuring multiple occupations, in which workers accumulate human capital that is only partly transferable across occupations. This implies a cost for workers to switch occupations, which they do in reaction to productivity shocks. The calibrated model is consistent with the documented patterns of occupational switching and wage changes and serves two purposes. First, it allows me to evaluate the relative role of occupational choice for productivity changes. In the model, if one were to mistake the observed distribution of productivity changes (after controlling for human capital in the model) realized by switchers (stayers) for the underlying shock distributions, one would make an error of 31% (4%) in terms of the variance. Overall, the endogenous choice of occupations accounts for about 26% of realized productivity changes of workers that change jobs without experiencing an unemployment spell. Second, workers value the option of switching occupations, because it allows them to react to negative shocks in the current occupation and to realize good offers related to a different career. The utility gain from the option to switch occupations corresponds to 0.78% of per-period consumption for the average worker; given that unemployed workers utilize the option to switch more often, their utility gain is higher (1.25%) than the gain for employed workers (0.73%).

Appendix A Simplifying the Value Functions

An implication of the taste shocks is that it simplifies the value functions–relative to a version of the model without these shocks. Technically speaking, I get rid of kinks in the value functions V^{stay}, V^{offer}, and V^{unempl} that are induced by the discrete choices and am left with continuous value functions. I impose $F_{\mathbb{O}}$ to be a Gumbel distribution with scale parameter $\sigma_{\mathbb{O}}$ and location parameter $-\sigma_{\mathbb{O}}\gamma$, where γ is Euler's constant. The location parameter is a normalization such that the unconditional expected value of each taste shock is zero. Using Gumbel iid taste shocks allows me to exploit results from discrete choice theory, as also done in, e.g., Pilossoph (2014) or Iskhakov *et al.* (2015). Gumbel distributed taste shocks yield analytical expressions for the continuation values conditional on the state vector $(x_{i,t}, \boldsymbol{\eta}_{i,t}, h_{i,t}, o_{i,t})$.

First, consider the (expected) continuation values in equations (10) and (11): the worker does not control $o_{i,t}$, which is a state. The expected value of the taste shock is thus the unconditional expected value of $F_{\mathbb{O}}$, which is normalized to zero. By independence of the productivity and taste shocks, this gives

$$\begin{aligned} V^{empl}\left(x_{i,t}, \boldsymbol{\eta}_{i,t}, h_{i,t}, o_{i,t}\right) = \phi \times \Bigg(& \psi^{e} \times V^{offer}\left(x_{i,t}, \boldsymbol{\eta}_{i,t}, h_{i,t}, o_{i,t}\right) + \ldots \\ & (1-\psi^{e}) \times V^{stay}\left(x_{i,t}, \boldsymbol{\eta}_{i,t}, h_{i,t}, o_{i,t}\right) \Bigg) + \ldots \\ & (1-\phi) \times \left(\widetilde{u}^{unempl} + \widetilde{\beta} E V^{unempl}\left(x_{i,t+1}, \boldsymbol{\eta}_{i,t+1}, h_{i,t+1}, o_{i,t}\right)\right) \end{aligned} \tag{16}$$

and

$$\begin{aligned} V^{stay}\left(x_{i,t}, \boldsymbol{\eta}_{i,t}, h_{i,t}, o_{i,t}\right) \quad = \quad & \widetilde{u}^{empl}\left(x_{i,t+1}, o_{i,t}, \tilde{h}_{i,t+1}\right) + \ldots \\ & \widetilde{\beta} E V^{empl}\left(x_{i,t+1}, \boldsymbol{\eta}_{i,t+1}, h_{i,t+1}, o_{i,t}\right). \end{aligned} \tag{17}$$

In the following, I only explicitly state the state variables η and o for readability. The expected continuation value of entering next period as an employed worker is

$$\begin{aligned} EV^{empl}\left(\boldsymbol{\eta}_{i,t+1}, o_{i,t}\right) = \phi \times \Bigg(& \psi^{e} \times E_{\boldsymbol{\eta}} V^{offer}\left(\boldsymbol{\eta}_{i,t+1}, o_{i,t+1}\right) + \ldots \\ & (1-\psi^{e}) \times E_{\boldsymbol{\eta}} V^{stay}\left(\boldsymbol{\eta}_{i,t+1}, o_{i,t+1}\right) \Bigg) + \ldots \\ & (1-\phi) \times \left(\widetilde{u}^{unempl} + \widetilde{\beta} E_{\boldsymbol{\eta}} V^{unempl}\left(\boldsymbol{\eta}_{i,t+1}, o_{i,t+1}\right)\right) \end{aligned} \tag{18}$$

Next, consider the sub value function $V^{offer}(\bullet)$, which in the two value functions (10) and (13) represents situations in which the worker chooses a target occupation $o_{i,t+1}$. Conditional on sampling occupation j as alternative occupation, the worker chooses to either stay in occupation $o_{i,t}$ or to take the offer from j, maximizing

$$\max\left(\tilde{v}\left(j|\bullet\right)+E_{\mathbb{O}}\mathbb{O}_{i,t+1}\left(j\right),\tilde{v}\left(o_{i,t}|\bullet\right)+E_{\mathbb{O}}\mathbb{O}_{i,t+1}\left(o_{i,t}\right)\right). \tag{19}$$

The expectation over taste shocks $\mathbb{O}$ is the expected value of the maximum of the expression. The taste shock can be integrated out to get

$$E_{\mathbb{O}}\left[\max\left(\tilde{v}\left(j|\bullet\right)+\mathbb{O}_{i,t+1}\left(j\right),\tilde{v}\left(o_{i,t}|\bullet\right)+\mathbb{O}_{i,t+1}\left(o_{i,t}\right)\right)\right].$$

McFadden (1978) shows that the integral over $\mathbb{O}$ can be analytically solved; using his derivation, I write the above expected value as

$$\begin{aligned}
&E_{\mathbb{O}}\left[\max\left(\tilde{v}\left(j|\bullet\right)+\mathbb{O}_{i,t+1}\left(j\right),\tilde{v}\left(o_{i,t}|\bullet\right)+\mathbb{O}_{i,t+1}\left(o_{i,t}\right)\right)\right]\\
&\qquad=\sigma_{\mathbb{O}}\log\left(\exp\left[\frac{\tilde{v}\left(o_{i,t}|\bullet\right)}{\sigma_{\mathbb{O}}}\right]+\exp\left[\frac{\tilde{v}\left(j|\bullet\right)}{\sigma_{\mathbb{O}}}\right]+\frac{-\sigma_{\mathbb{O}}\gamma}{\sigma_{\mathbb{O}}}+\gamma\right)\\
&\qquad=\sigma_{\mathbb{O}}\log\left(\exp\left[\frac{\tilde{v}\left(o_{i,t}|\bullet\right)}{\sigma_{\mathbb{O}}}\right]+\exp\left[\frac{\tilde{v}\left(j|\bullet\right)}{\sigma_{\mathbb{O}}}\right]\right)\\
&\qquad=\sigma_{\mathbb{O}}\left(\frac{\tilde{v}\left(o_{i,t}|\bullet\right)}{\sigma_{\mathbb{O}}}+\log\left(1+\exp\left[\frac{\tilde{v}\left(j|\bullet\right)-\tilde{v}\left(o_{i,t}|\bullet\right)}{\sigma_{\mathbb{O}}}\right]\right)\right)
\end{aligned}$$

where γ is Euler's constant. This gives the simplified sub value funciton $V^{offer}\left(\bullet\right)$ as:

$$V^{offer}\left(\bullet\right)\;=\;\widetilde{\beta}\times\sum_{j\neq o_{i,t}}\pi_j\times\sigma_{\mathbb{O}}\left(\frac{\tilde{v}\left(o_{i,t}|\bullet\right)}{\sigma_{\mathbb{O}}}+\log\left(1+\exp\left[\frac{\tilde{v}\left(j|\bullet\right)-\tilde{v}\left(o_{i,t}|\bullet\right)}{\sigma_{\mathbb{O}}}\right]\right)\right), \tag{20}$$

in which the taste shocks are integrated out and the conditional expectation over the taste shocks has an analytical solution, leaving us with smooth value functions in which only the expectation operator over productivity shocks remains.

Appendix B Value Functions for Counterfactual

Consider the welfare experiment in section 5.2. Along the lines of equations (10), (11), and (13), the value functions of employed and unemployed workers in the counterfactual world are given by

$$V^{count}\left(x_{i,t},\boldsymbol{\eta}_{i,t},h_{i,t},o_{i,t}\right)=\phi\times\Bigg(\widetilde{u}^{empl}\left(x_{i,t+1},o_{i,t},h_{i,t}\right)+\ldots$$
$$\widetilde{\beta}E\left[V^{count}\left(x_{i,t+1},\boldsymbol{\eta}_{i,t+1},h_{i,t+1},o_{i,t}\right)+\mathbb{O}_{i,t+1}\left(o_{i,t}\right)\right]+\ldots$$
$$(1-\phi)\times\left(\widetilde{u}^{unempl}+\widetilde{\beta}E\left[V^{count-ue}\left(x_{i,t+1},\boldsymbol{\eta}_{i,t+1},h_{i,t+1},o_{i,t}\right)+\mathbb{O}_{i,t+1}\left(o_{i,t}\right)\right]\right)\quad(21)$$

$$\begin{aligned}&s.t.\\ x_{i,t+1}\quad &=\quad g^{e}\left(x_{i,t},o_{i,t},o_{i,t};\boldsymbol{\eta}_{i,t}\right)\\ h_{i,t+1}\quad &\text{acc. to}\quad (7)\end{aligned}$$

$$V^{count-ue}\left(x_{i,t},\boldsymbol{\eta}_{i,t},h_{i,t},o_{i,t}\right)=\psi^{u}\times\Bigg(\widetilde{u}^{empl}\left(x_{i,t+1},o_{i,t},\tilde{h}_{i,t+1}\right)+\ldots$$
$$\widetilde{\beta}E\left[V^{count}\left(x_{i,t+1},\boldsymbol{\eta}_{i,t+1},h_{i,t+1},o_{i,t}\right)+\mathbb{O}_{i,t+1}\left(o_{i,t}\right)\right]\Bigg)+\ldots$$
$$(1-\psi^{u})\times\left(\widetilde{u}^{unempl}+\widetilde{\beta}E\left[V^{count-ue}\left(x_{i,t+1},\boldsymbol{\eta}_{i,t+1},h_{i,t+1},o_{i,t}\right)+\mathbb{O}_{i,t+1}\left(o_{i,t}\right)\right]\right)\quad(22)$$

$$\begin{aligned}&s.t.\\ x_{i,t+1}\quad &=\quad \begin{cases} g^{e}\left(x_{i,t},o_{i,t},o_{i,t};\boldsymbol{\eta}_{i,t}\right) & \text{if empl. in prod. stage of } t\\ x_{i,t} & \text{else}\end{cases}\\ h_{i,t+1}\quad &\text{acc. to}\quad \begin{cases}(7) & \text{if empl. in prod. stage}\\ (8) & \text{else}\end{cases}\end{aligned}$$

Appendix C Numerical Solution and Simulation

I solve the model on a discretized state space using global methods. Given a vector of parameters, I use Gaussian quadrature to pick the nodes and weights of the grid for the Normal productivity shocks. For the grid of stochastic productivity, I select the lower (upper) bound to receiving the worst (best) productivity shock five times in a row. I then distribute the grid points with a higher mass of points around the mid-point between lower and upper bound. The grid for human capital is normalized to start at zero and has equidistant grid points; the step size is a parameter.

At every point in the state space, each choice of $o_{i,t+1}$ implies a value of human capital, and a value of idiosyncratic productivity. I locate the point on the grid for idiosyncratic productivity and calculate the linear interpolation weights corresponding to the two surrounding grid points. Together with the exogenous transition probabilities, these weights give an $o_{i,t+1}$–choice specific transition matrix on the whole state space. Given a guess for the value functions, I use the simplified Bellman equations from Appendix A to update the value functions. During the calibration stage I iterate until convergence of the policy functions (i.e., the probability to choose any occupation, which is calculated analytically for a given guess of the value functions).

Given the converged policy functions, I combine the policy function with the exogenous transition matrix, which gives a transition matrix over the whole state space as a solution to the model. To get the stationary distribution, I extract (and normalize) the eigenvector with eigenvalue 1 from this transition matrix. To calculate the moments implied by the model in the long run, I directly use the policy functions, which I weight with the stationary distribution over the discrete state space, to calculate the average switching probability and the switching probability as a function of the unemployment duration.

The discretization of the state space implies that I cannot directly use the wage changes implied by the moves on the grid to calculate percentiles of the distribution of wage changes: the calculation of central moments is unproblematic, but there are too few realizations to meaningfully calculate percentiles. I thus distribute N individuals over the discrete state space according to stationary distribution and draw continuous shocks for this sample of workers. One implication of the taste shocks is that the choice probabilities become a smooth function over the state space (net the taste shocks). Thus, I can interpolate the choice probabilities using the policy functions on the discrete grid. Then, I can calculate the wage change for each worker as implied by the choice. Similarly for EUE-transitions, where in addition I take into account that workers transition over the state space during unemployment. I choose a number of N=30,000 individuals for the simulation, repeat the simulation M=3 times, and take the average of the implied moments over the M simulations.

For the calibration, I solve the model at 1,000 parameter combinations, which I choose from a Sobol sequence over the ten-dimensional parameter space. I then calculate the distance as the sum of squared deviations between the model implied moments and the data moments for the selected targets. I choose an identity weighting matrix (reflecting insights in Altonji and Segal (1996), on small sample performance of GMM estimators). I then use the best ten parameter vectors as initial guesses for a simplex downhill minimization algorithm a la Nelder and Mead (1965) to find a minimum.

Appendix D Classification of Occupations

The empirical measures of occupational switching are based on occupational segments as defined in the KldB88. The 30 groups are outlined below.

Table D.1: Classification of Occupations

Segment	SIAB group	Description
100	1	Farmers until animal keepers and related occupations
	2	Gardeners, garden workers until forest workers, forest cultivators
200	3	Miners until shaped brick/concrete block makers
301	4	Ceramics workers until glass processors, glass finishers
302	5	Chemical plant operatives
	6	Chemical laboratory workers until vulcanisers
	7	Plastics processors
303	8	Paper, cellulose makers until other paper products makers
	9	Type setters, compositors until printers (flat, gravure)
	10	Special printers, screeners until printer assistants
304	11	Wood preparers until basket and wicker products makers
305	12	Iron, metal producers, melters until semi-finished product fettlers and other mould casting occupations
	13	Sheet metal pressers, drawers, stampers until other metal moulders (non-cutting deformation)
	14	Turners
	15	Drillers until borers
	16	Metal grinders until other metal-cutting occupations
	17	Metal polishers until metal bonders and other metal connectors
	18	Welders, oxy-acetylene cutters
306	19	Steel smiths until pipe, tubing fitters
	20	Sheet metal workers
	21	Plumbers
	22	Locksmiths, not specified until sheet metal, plas-tics fitters
	23	Engine fitters
	24	Plant fitters, maintenance fitters until steel struc-ture fitters, metal shipbuilders
	25	Motor vehicle repairers
	26	Agricultural machinery repairers until precision mechanics

	27	Other mechanics until watch-, clockmakers
	28	Toolmakers until precious metal smiths
	29	Dental technicians until doll makers, model mak-ers, taxidermists
307	30	Electrical fitters, mechanics
	31	Telecommunications mechanics, craftsmen until radio, sound equipment mechanics
	32	Electrical appliance fitters
308	33	Electrical appliance, electrical parts assemblers
	34	Other assemblers
	35	Metal workers (no further specification)
309	36	Spinners, fibre preparers until skin processing operatives
	37	Cutters until textile finishers
310	38	Bakery goods makers until confectioners (pastry)
	39	Butchers until fish processing operatives
	40	Cooks until ready-to-serve meals, fruit, vegetable preservers, preparers
	41	Wine coopers until sugar, sweets, ice-cream makers
311	42	Bricklayers until concrete workers
	43	Carpenters until scaffolders
	44	Roofers
	45	Paviors until road makers
	46	Tracklayers until other civil engineering workers
	47	Building labourer, general until other building labourers, building assistants, n.e.c.
312	48	Stucco workers, plasterers, rough casters until insulators, proofers
	49	Tile setters until screed, terrazzo layers
	50	Room equippers until other wood and sports equipment makers
313	51	Carpenters
314	52	Painters, lacquerers (construction)
	53	Goods painters, lacquerers until ceramics/glass painters
315	54	Goods examiners, sorters, n.e.c.
	55	Packagers, goods receivers, despatchers
316	56	Assistants (no further specification)
317	57	Generator machinists until construction machine attendants
	58	Machine attendants, machinists helpers until ma-chine setters (no further specification)
401	59	Mechanical, motor engineers
	60	Electrical engineers

	61	Architects, civil engineers
	62	Survey engineers until other engineers
	63	Chemists, chemical engineers until physicists, physics engineers, mathematicians
402	64	Mechanical engineering technicians
	65	Electrical engineering technicians until building technicians
	66	Measurement technicians until remaining manu-facturing technicians
	67	Other technicians
	68	Foremen, master mechanics
	69	Biological specialists until physical and mathemat-ical specialists
	70	Chemical laboratory assistants until photo labora-tory assistants
	71	Technical draughtspersons
501	72	Wholesale and retail trade buyers, buyers
	73	Salespersons
	74	Publishing house dealers, booksellers until ser-vice-station attendants
	75	Commercial agents, travellers until mobile traders
502	76	Bank specialists until building society specialists
	77	Health insurance specialists (not social security) until life, property insurance specialists
	78	Forwarding business dealers
	79	Tourism specialists until cash collectors, cashiers, ticket sellers, inspectors
503	80	Railway engine drivers until street attendants
	81	Motor vehicle drivers
	82	Navigating ships officers until air transport occupations
	83	Post masters until telephonists
	84	Warehouse managers, warehousemen
	85	Transportation equipment drivers
	86	Stowers, furniture packers until stores/transport workers
504	87	Entrepreneurs, managing directors, divisional managers
	88	Management consultants, organisors until char-tered accountants, tax advisers
	89	Members of Parliament, Ministers, elected offi-cials until association leaders, officials
	90	Cost accountants, valuers until accountants
	91	Cashiers
	92	Data processing specialists
	93	Office specialists
	94	Stenographers, shorthand-typists, typists until data typists

	95	Office auxiliary workers
505	96	Factory guards, detectives until watchmen, custo-dians
	97	Doormen, caretakers until domestic and non-domestic servants
	98	Soldiers, border guards, police officers until judi-cial enforcers
506	99	Journalists until librarians, archivists, museum specialists
	100	Musicians until scenery/sign painters
	101	Artistic and assisting occupations (stage, video and audio) until performers, professional sports-men, auxiliary artistic occupations
507	102	Physicians until Pharmacists
	103	Non-medical practitioners until masseurs, physio-therapists and related occupations
	104	Nurses, midwives
	105	Nursing assistants
	106	Dietary assistants, pharmaceutical assistants until medical laboratory assistants
	107	Medical receptionists
508	108	Social workers, care workers until religious care helpers
	109	Home wardens, social work teachers
	110	Nursery teachers, child nurses
	111	University teachers, lecturers at higher technical schools and academies until technical, vocational, factory instructors
	112	Music teachers, n.e.c. until other teachers
	113	Economic and social scientists, statisticians until scientists n.e.c.
509	114	Hairdressers until other body care occupations
	115	Restaurant, inn, bar keepers, hotel proprietors, catering trade dealers until waiters, stewards
	116	Others attending on guests
	117	Housekeeping managers until employees by household cheque procedure
	118	Laundry workers, pressers until textile cleaners, dyers and dry cleaners
	119	Household cleaners until glass, buildings cleaners
	120	Street cleaners, refuse disposers until machinery, container cleaners and related occupations

Note: Table shows the occupation groups. The 120 "SIAB groups" are provided in the data set. The First column denotes the 30 aggregated occupational segments (Berufsgruppen) used in the analysis.

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