Institute for Employment Research

The Research Institute of the Federal Employment Agency

IAB

IAB-Discussion Paper 26/2015

Articles on labour market issues

Reallocation patterns across occupations

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ISSN 2195-2663

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Abstract

Using high-quality administrative data, I analyze workers' opportunity costs of reallocation across occupations by measuring the additional time spent in unemployment before being hired in a new occupation. Furthermore, I inspect the wage changes after reallocation and find that workers who change occupations through unemployment face wage losses. Interpreted through the lens of islands models in the spirit of Lucas/Prescott (1974), these findings are counterintuitive because workers would only reallocate when they can recoup the costs of reallocation through wage gains. To shed some light on the question of what other factors may drive reallocation, I further investigate whether other economic conditions of an occupation might be more important in the worker's decision to reallocate. I assess whether the workers direct their search across markets with respect to job finding rates and job separation rates and labor market tightness, finding that they play no decisive role.

Zusammenfassung

Diese Studie untersucht mit Hilfe administrativer Daten die Opportunitätskosten von Arbeitnehmern, die den Beruf aus Arbeitslosigkeit heraus wechseln. Die Opportunitätskosten werden dabei durch die durchschnittliche Arbeitslosigkeitsdauer abgebildet. Anschließend werden diese Kosten den potentiellen Lohngewinnen gegenübergestellt. Weiterhin wird gezeigt, dass der Lohnunterschied, der sich nach einem Wechsel des Berufs durch Arbeitslosigkeit ergibt, negativ ist. Das Zusammenspiel dieser Ergebnisse steht im Gegensatz zu sog. islands-Modellen (Lucas/Prescott, 1974), in welchen Reallokation von Arbeitnehmern nur dann stattfindet, wenn diese einen Lohn erzielen, der ausreicht um die Kosten der Reallokation zu decken. Daher wird untersucht, ob andere ökonomische Größen innerhalb eines Berufes einen größeren Einfluss darauf haben, wohin Arbeitnehmer wechseln. Als ökonomische Größen werden dabei die Abgangsrate aus Arbeitslosigkeit, der Zufluss in Arbeitslosigkeit und das Verhältnis von Vakanzen zu Arbeitslosen (Arbeitsmarktanspannung) innerhalb der Berufe herangezogen. Allerdings zeigt sich auch hier, dass Arbeitnehmer diese Größen in ihrer Entscheidung den Beruf zu wechseln nicht berücksichtigen.

JEL classification: E24, J62, J64

Keywords: reallocation, transition, employment, unemployment, training costs, move unemployment

Acknowledgements: I gratefully acknowledge financial support by the Graduate Program of the IAB and the School of Business and Economics of the University of Erlangen-Nuremberg (GradAB).

1 Introduction

The Great Recession triggered a high unemployment rate in the US that is characterized, on the one hand, by high unemployment duration and, on the other hand, by unevenly concentrated unemployment incidence across occupations and industries (high job losses in construction and manufacturing). The standard search and matching model (Pissarides, 2000) is able (at least qualitatively) to explain the first fact, but it is unable to explain the second one because it lacks a multi-market structure. Thus, recent studies in the macro-labor literature advance models based on a Lucas/Prescott (1974) island-matching framework that offers such a multi-market structure (e.g., Alvarez/Shimer (2011); Wong (2011); Pilossoph (2012); Wiczer (2013); Carrillo-Tudela/Visschers (2013)). In particular, these models give rise to the question of the relative contribution of reallocation vs. wait unemployment (or, in the words of Alvarez/Shimer (2011), search vs. rest unemployment) to (fluctuations in) the aggregate unemployment rate. In other words, in light of the recent crisis, these models explore what induces steel workers and assemblers to wait in unemployment (thus boosting long-term unemployment) instead of reallocating to an occupation with better job prospects.

Generally speaking, in these models, reallocation is determined by workers' decisions to move to another "island" instead of remaining on their respective "island". The worker's choice is based on a comparison of the net present value of search across different islands to the net present value of search within an island. However, as it is costly to move, the net present value across islands is reduced by the costs to enter a particular island. Because, in these models, a worker typically reallocates through unemployment (nearly all of the models abstract from job-to-job transitions), these reallocation costs refer to the time a worker spends in unemployment while s/he is searching across islands. Summarizing, worker reallocation is pinned down by the variables that either influence the net present value of search or the costs of moving to a different island. However, little is known about the reallocation of workers out of unemployment. Thus, the contribution of my paper is 1) to shed light on the question of how high reallocation costs, measured in terms of unemployment duration, may be. Using comprehensive German administrative data, I asses how much time is spent on average in unemployment between two spells of employment conditioned on an occupational switch; 2) I analyze the patterns of switching occupations with respect to individual and aggregate labor market outcomes by examining the wage changes after the switch and the direction of switching.

From an empirical perspective, the paper contributes a different angle to the literature on labor mobility. A paper that is closely related to my study is from Carrillo-Tudela et al. (2014). In addition to examining whether recessions have a cleansing or "sullying" effect, they also present some general facts concerning reallocation out of unemployment in the UK, which are in line with the Lucas/Prescott (1974) island model. They find that that 50 percent of workers who were hired out of unemployment change their occupation. Furthermore, in the UK, the rate of switching is independent of whether the worker faces a spell of unemployment before switching employers and that switching is generally beneficial in terms of wage gains, especially when the workers earn a low wage.

However, my results suggest that in Germany, the data are at odds with the classical Lucas/Prescott (1974) island model. Workers who reallocate through unemployment bear the opportunity costs of being unemployed for at least two months longer than otherwise equal workers (who return to the same occupation after unemployment). However, reallocating workers cannot compensate for these costs, as they further lose up to 2.3 percent of their wage upon moving. This result holds even when I consider changes in the average occupational wage (despite the effects being smaller) instead of the individual wage changes.

The remainder of the paper is organized as follows. Section 2 gives a brief introduction to the theoretical background. Section 3 describes the preparation of the data. In Section 4, I examine reallocation costs in terms of unemployment duration and gains in terms of wage changes. Thereafter, I discuss the implications of my results for Lucas/Prescott (1974) island models and how the findings contrast with those of other empirical studies.

2 Theoretical background

In the basic Lucas/Prescott (1974) island-matching model, there is a continuum of competitive labor markets, and initially, each labor market is characterized by a certain number of workers and a given productivity. When a productivity shock hits the labor market, workers can choose to work for the equilibrium wage or to search for employment in a different labor market. The workers face reallocation frictions because it is costly to move across labor markets. While searching, the worker gives up a period of wage earnings and is considered unemployed. In this context, search unemployment is a result of workers reallocating across labor markets. As search unemployment is the only type of unemployment in the model, it predicts a procyclical unemployment rate (relative to GDP). To overcome this problem, the model is augmented by wait unemployment, which slightly affects the worker's decision (Jovanovic, 1987; Hamilton, 1988; King, 1990; Gouge/King, 1997). After the break-up of a match, the worker decides either to remain unemployed in the labor market in which s/he was previously employed (and to collect unemployment benefits) or to reallocate to another labor market. Recent models in the literature (Pilossoph, 2012; Wiczer, 2013; Carrillo-Tudela/Visschers, 2013) assume that the within-labor-market structure follows the DMP framework. Hence, in addition to reallocation frictions that cause unemployment across markets, matching frictions exist that cause unemployment within markets. A prominent feature of recent studies is that they allow gross flows to exceed net flows, which facilitates studying the impact (and the interaction effects) of these flows on aggregate outcomes.

In addition to the expected profit stream in another labor market, the costs of moving play an influential role in the worker's decision to move across labor markets (King, 1990). In essence, the unemployed worker compares the expected present value of remaining in a certain island to the expected present value of search, i.e., the profit stream at another island minus the costs of reallocating to that island.

Essentially, this implies the following:

1. The worker has an incentive to reallocate to another labor market whenever the net present value of search in another market is higher than in the current market.

2. The gain from moving has to compensate for the costs of moving.

In a simplistic environment that features only two separate labor markets, the first implication can be pinned down by a comparison of the values of unemployment in these two labor markets. As the value of unemployment in the canonical search and matching model (e.g., Pissarides (2000), chapter 1)[1] captures the probability-weighted income stream in future periods in these two labor markets, it is beneficial for the worker to move from labor market 1 to labor market 2 if the value of search is expected to be larger in sector 2 than in sector 1. Abstracting from the costs the worker has to pay to move, that implies:

$$U_{1,t} < U_{2,t} \tag{1}$$

$$b + E_t\beta\Big(f_{1,t}W_{1,t+1} + [1 - f_{1,t}]U_{1,t+1}\Big) < b + E_t\beta\Big(f_{2,t}W_{2,t+1} + [1 - f_{2,t}]U_{2,t+1}\Big) \tag{2}$$

As the value of unemployment benefits b and the discount factor β are the same across all markets, this expression only depends on the probability of finding a job in the respective labor market $f_{i,t}$ for $i = 1, 2$ and the values of being unemployed $U_{i,t+1}$ or employed $W_{i,t+1}$. Let us assume that hiring in each market is subject to matching frictions. For illustration purposes, I use a Cobb-Douglas matching function with constant returns to scale that has the same weight on vacancies for all markets. The probability of finding a job $f_{i,t}$ depends on the market tightness $\theta_{i,t}$ in labor market i and the matching elasticity α. The value of being employed depends on the wage $w_{i,t}$ and the values of employment in the next period, provided that the match is sustained, which occurs with the probability $[1 - s_{i,t}]$, and the value of unemployment in the next period, provided that the worker is separated with probability $s_{i,t}$ (which is the (exogenous) separation rate).

$$f_{i,t} = \frac{m(U_{i,t}, V_{i,t})}{U_{i,t}} = \Phi_i \theta_{i,t}^{1-\alpha} \tag{3}$$

$$W_{i,t} = w_i + E_t\beta\Big([1 - s_{i,t}]W_{i,t+1} + s_{i,t}U_{i,t+1}\Big) \tag{4}$$

The following steady state equations express the values of employment and unemployment for a worker who remains within market i for his entire life span:

$$U_i = \frac{b + \beta f_i W_i}{1 - \beta(1 - f_i)} \tag{5}$$

[1] Pissarides (2000) outlines a continuous time model, whereas I use a discrete time version of the model. Nonetheless, the same implications can be shown using equations (1.12) and (1.13) from Pissarides (2000).

$$W_i = \frac{w_i + \beta s_i U_i}{1 - \beta(1 - s_i)} \tag{6}$$

Plugging in the steady state values and rearranging, equation 2 simplifies to[2]:

$$U_1^{ss} < U_2^{ss} \tag{7}$$

$$\frac{b(1 - \beta(1 - s_1)) + \beta f_1 w_1}{(1 - \beta) + \beta(s_1 + f_1)} < \frac{b(1 - \beta(1 - s_2)) + \beta f_2 w_2}{(1 - \beta) + \beta(s_2 + f_2)} \tag{8}$$

It follows that:

$$\frac{\partial U_i^{ss}}{\partial w_i} = \frac{\beta f_i}{(1 - \beta)\beta s_i + f_i} > 0 \tag{9}$$

$$\frac{\partial U_i^{ss}}{\partial f_i} = \frac{(1 - \beta(1 - s_i))\beta(w - b)}{((1 - \beta) + \beta(s_i + f_i))^2} > 0 \qquad \text{if} \quad w_i > b \tag{10}$$

$$\frac{\partial U_i^{ss}}{\partial s_i} = \frac{\beta^2 f_i(b - w_i)}{((1 - \beta) + \beta(s_i + f_i))^2} < 0 \qquad \text{if} \quad w_i > b \tag{11}$$

Thus, moving from labor market 1 to labor market 2 is beneficial for the worker, provided that either s/he receives a higher wage $w_1 < w_2$, it is easier to find a job in the other market $f_1 < f_2$ (which indirectly means that $\theta_1 < \theta_2$, and hence the destination labor market is tighter, implying that there is less competition among unemployed) or the probability of separating from the match is lower, $s_1 > s_2$.

As these equations determine the gain from moving, the second implication states that:

$$\frac{b(1 - \beta(1 - s_2)) + \beta f_2 w_2}{(1 - \beta) + \beta(s_2 + f_2)} - \frac{b(1 - \beta(1 - s_1)) + \beta f_1 w_1}{(1 - \beta) + \beta(s_1 + f_1)} > c \tag{12}$$

Given this relationship, the higher the costs of switching to another labor market are, the more attractive it is to remain in the current island, and the less reallocation is observed. Typically, the costs c are interpreted as the time a worker spends in unemployment while retraining (Pilossoph, 2012: e.g. p. 8) (and sometimes also other/direct costs related to the training). To calibrate these models, c is set to match either certain mobility rates or the average unemployment duration in the economy. The rationale behind this calibration is that the costs of switching must be low when the observed mobility rates are high and vice versa. Equivalently, when unemployment duration is high, the higher the reallocation costs must be.

However, empirically, little is known about the reallocation of unemployed or about the time spent in unemployment before reallocating. Most studies that are concerned with the reallocation of workers or, worker mobility more generally, examine the movement of employed

[2] See Appendix A for details.

workers (Kambourov/Manovskii, 2008, 2009a,b). The main type of mobility measured by these mobility rates is job-to-job mobility, which is not a feature of the model. Thus, whenever the model is calibrated to target mobility rates that include job-to-job-transitions, the problem is that the model needs to have low moving costs to generate this high mobility. If the mobility rates of the unemployed are in fact lower, then reallocation costs are understated. The same holds true when the average unemployment duration is used. The average unemployment duration also includes very short durations that might occur because of frictions within a labor market but are not related to reallocation. Whenever unemployed workers who reallocate, systematically face longer unemployment durations than the average, then the reallocation costs are again understated[3].

3 Data

To assess whether the model is in line with the data, I first edit a sample of German administrative data to properly match the model's mechanism. The so-called Sample of Integrated Labour Market Biographies (SIAB), provided by the Institute of Labor Market Research, represents the employment biographies (i.e., employment and unemployment episodes) of approximately 2 percent of the German workforce from 1979 onwards. In the following, I assume that a labor market is represented by occupations and analyze the period from 2000 to 2010. For a detailed description of the data set, see Appendix B.

3.1 Movers vs. stayers and the role of occupations

I identify movers and stayers across occupations to capture the workers who reallocate and those who stay according to the model. Because the workers in the model necessarily move with an intervening spell of unemployment, I distinguish movers based upon their labor market status before the move.

As the occupation information in the data set is the most reliable for spells of employment, I complete the occupation information by transcribing the occupation of an employment spell to the proceeding spells of unemployment. Thus, I assume that workers search for jobs in the occupation in which they were last employed and identify a switch in the occupation upon being hired again.[4] Doing this before restricting the sample to the period 2000-2010 has the advantage that I do not lose information at the beginning of the sample period (otherwise, I would lose all the spells until the first occurrence of an employment spell) and thus can observe all occupation switches during the observation window. The occupation information is provided by the employer and is available at the 3-digit level (according to the

[3] This generates some problems in the model. For instance, Alvarez/Shimer (2011: p. 103 ff.) find "that search costs must be high if wages are persistent," and "to match the empirical persistence and variance [...] the search cost has to be very large." In other words, in their calibration, which sets the reallocation costs (as they term them, search costs) to the average unemployment duration, the reallocation costs are too low to generate persistence. Considering the unemployment duration or the mobility rates from workers that face a spell of unemployment between moving across labor markets might alleviate this problem, as doing so better aligns the model with the data. Given that the search costs would then be higher, this does not only generate persistence but also raises the relative contribution of wait unemployment in explaining total unemployment because reallocation would be lower.

[4] However, performing the procedure other way around makes no major difference.

German classification scheme KldB88), whereby the 3-digit level depicts over 300 different occupations.

As my study focuses not only on the movement across occupations but also across the states of employment and unemployment, I categorize workers in the following way:

Table 1: Worker types

occupation switch	status in t	status in $t+1$	
		E	U
yes	E	*EE-mover*	–
	U	*UE-mover*	–
no	E	*E-stayer*	*Separation*
	U	*UE-stayer*	*U-stayer*

A "UE mover" is defined as a worker who moves from unemployment to employment and switches occupation contemporaneously. Without the occupational switch, I would consider him a "UE-stayer". I consider a worker who switches occupation without an intervening spell of unemployment, an "EE-mover". Whenever a person maintains his/her employment status and does not switch occupation, I consider this person to be a stayer. Being categorized as an EE-stayer is independent of being employed in the same establishment, i.e., even when the individual moves to another firm, without an intervening spell of unemployment, and performs the same occupation, I term him an EE-stayer. By construction, the possibility of being unemployed and switching occupations or switching occupations while unemployed is excluded[5]. This categorization allows me to compare individuals who differ in their decision to switch occupations but were hired out of unemployment (UE-stayers vs. UE-movers) or remained in employment (E-stayers vs. EE-movers) or to compare individuals who both switched their occupation but had a different labor market status before(EE-movers vs. UE-movers). According to that categorization, the data companion to the reallocating workers in the model are UE-movers and the data companion to workers who stay in the model are UE-stayers.

Concerning the question of the definition of an occupation, I begin with the German 2-digit classification of occupations (KldB88[6]), which includes 86 different occupations (e.g., teacher, banker & insurance broker, electrician, etc.). Table 2 shows the distribution of worker types according to this categorization based on the German 2-digit occupation classification:

[5] Recall that I transcribed the occupation information of the last employment spell to the proceeding spells of unemployment.

[6] See http://metadaten.bibb.de/klassifikation/5 for details.

Table 2: Distribution of worker types

	Observations	Percent	Individuals	Percent
EE-mover	180,841	2.94	125,342	19,56
UE-mover	185,756	3.02	111,295	17.36
UE-stayer	131,177	2.13	77,289	12.06
E-stayer	4,455,628	72.51	–	–
U-stayer	956,561	15.57	–	–
Separation	234,500	3.82	–	–
Total	6,144,463	100.00	640,979	

In approximately 70 percent of the spells, the individual remains employed in the same occupation (E-stayer) and in approximately 15 percent of the spells, the individual remains unemployed (U-stayer). In 6 percent of the spells, people switch occupations, whereby switching through unemployment (UE-mover) happens somewhat more often than switching without unemployment (EE-mover). This pattern also holds for other (higher aggregated) occupation classification, although switching in general becomes less pronounced (see Appendix D). As spells are less informative, I calculated how many of the individuals are an EE-mover, an UE-mover or an UE-stayer at least once in the observation period. Approximately 20 percent of the people in the sample switch their occupation at least once by an employment-to-employment transition, and approximately 17 percent do so by an unemployment-to-employment transition. Approximately 12 percent of the individuals return at least once to their previous occupation after being hired out of unemployment[7]. In total, 63 percent of the UE-movers and 70 percent of the EE-movers move only once during the observation period[8]. This implies that approximately 30 percent of the people that switched occupations once are likely to switch occupations again.

3.2 Duration

As, in theory, the relevant measure of the costs of reallocation is unemployment duration, I assess unemployment duration for UE-stayers and UE-movers. Given the categorization, unemployment duration is always enclosed by employment spells such that my quantitative analysis does not have to address truncation. The unemployment duration is measured as the sum of days in unemployment between two employment spells, where unemployment is captured via spells that contain information on whether the worker is registered at the local employment agency as "available and searching for a job". Although I use high-quality

[7] Note that the categorization into EU-mover, EE-mover and UE-stayer is not exclusive, i.e., people who are UE-movers might be UE-stayers at another point in time.

[8] 66 percent of UE-stayers return to the same occupation once.

administrative data, this unemployment duration measure might be biased because it neglects individuals who are searching for a job but are not registered at a local employment agency or whose registration is delayed, which causes gaps in their biographies. To capture at least the latter bias, I repeat my analysis using the entire duration between two employment spells conditioned on observing at least one spell of unemployment. While the first measure provides a lower bound on the duration of unemployment, the latter provides an upper bound because it might label spells of part-time work, marginal work, self-employment, or participation in active labor market measures as unemployment. I refer to the latter measure as 'nonemployment'[9]. As I have fuzzy margins (on the left and right) because unemployment spells are overlapping the observation window of 01.01.2000 to 31.12.2010, I set the spells that begin before or end later to these dates. This is necessary because the unemployment spells in the data can last for several years, while employment spells last for at most one year[10]. Otherwise, unemployment duration would be overstated. For the groups of interest (UE-movers vs. UE-stayers), the distribution of unemployment duration, shown in Figure **??**, indicates that UE-stayers have a lower average duration of unemployment before being hired.

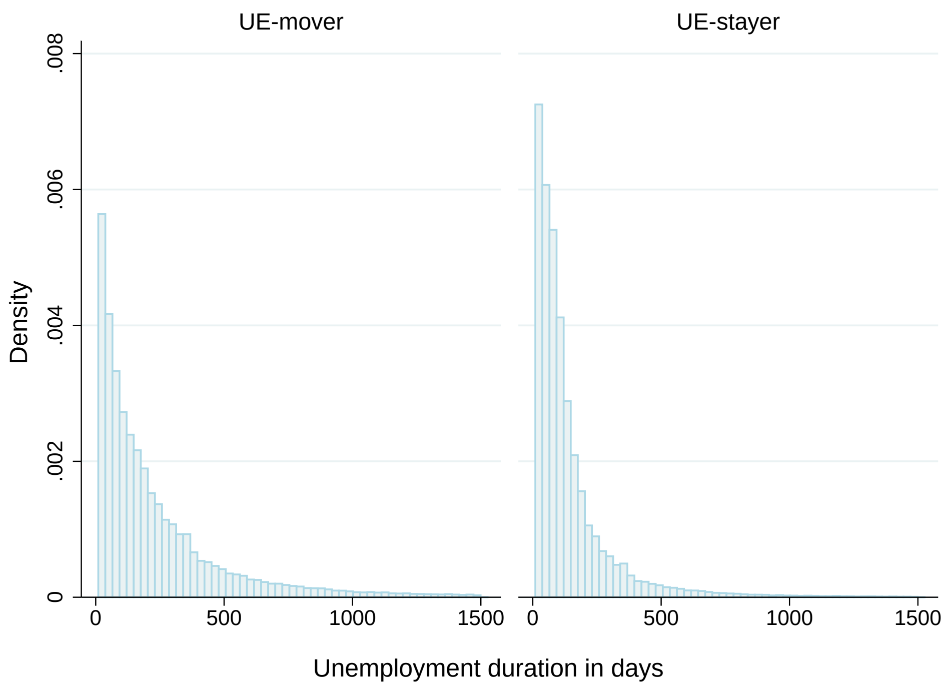

Figure 1: Distribution of unemployment duration for UE-mover and UE-stayer

9 In principal, I could also label gaps between two consecutive employment spells (i.e., unconditioned on observing at least one unemployment spell) as 'nonemployment'. However, if I do not observe any unemployment spell, I neglect that duration because this consideration would alter my categorization of being an UE-mover or UE-stayer. Moreover, the duration between two employment spells, where I do not observe unemployment in between is quite short (8 days on average), which indicates that this duration is simply due to delays in the processing of the hiring.

10 For instance, the status information for a person who is unemployed from September 1998 to May 2011 is captured by only one spell in the data, while the information for a person who is employed throughout the same period is captured by 14 spells because the information is renewed each year. For the unemployed person, I trim the spell to begin in January 2000 and end in December 2010, and for the employed person, I only use the 11 spells from January 2000 to December 2010.

3.3 Wages

Turning to the gains from reallocation, the first measure under consideration is the worker's individual wage. The wage information measures the average daily wage of the employment spell and is highly reliable because it is the basis for the calculation of social security contributions. I deflate wages using the German consumer price index to the 2000 wage level and use the logarithm throughout. In Germany, there is a limit on social security taxes that causes wages to be censored. I infer these wages using an imputation procedure based on interval regressions. The imputation is performed separately for women and men, for East and West Germany and by year. The underlying interval regression includes worker and firm characteristics[11]. Further, I delete spells for which the wage exhibits values below the marginal wage level[12], as these mainly reflect resting employment relations (e.g., maternity leave).

Based on this wage, I calculate wage differences from one employment spell to the previous one. The wage difference thus provides information on the percentage loss or gain in comparison to the previous employment spell. I also construct the worker's rank in the wage distribution within the occupation s/he currently performs in a given year. To do so, I extract residual wages from an OLS regression of the worker's wage on worker and firm characteristics (i.e., the same regressors as in the interval regression), which I estimate separately for every occupation. Thereafter, I rank the worker based on the residual wage within his/her occupation in a given year.

3.4 Job finding and separation rates

Other variables that influence reallocation are job finding and separation rates. I take both measures from Bauer (2013), who uses the same database but a larger sample. The job finding rate is measured as transitions from unemployment to employment divided by the last period's stock of unemployed within an occupation. The separation rate measures transitions from employment to unemployment relative to the last period's stock of employed within an occupation. The rates are constructed such that they reflect the job finding and separation rates of stayers and thus do not take the impact of switching into account. I average the data over the period and merge them by occupation with my data. In that way, the measure reflects overall differences in job finding and separation rates but cannot capture different evolutions of occupations over time. However, due to data limitations, the measure is available for only 60 of the 86 occupations under consideration. Similarly, I also compute the average market tightness using these data, which reflects the relationship between vacancies and unemployed within an occupation, and merge it with my data.

[11] In detail, it includes the worker's age (and its square), the education, firm and occupation tenure (and its square), general labor market experience (and its square), occupational status, industry, the shares of high- and of medium-qualified persons, of females and of full-time employees in the firm, the median wage and the firm's wage at the 25th and 75th percentile.

[12] This limit amounted to 325 Euros monthly until 2003 and to 400 Euros monthly afterwards.

4 Determinants of reallocation

Through the lens of the model, the best way to assess the costs of moving[13] is to compare the average duration of unemployment for a UE-mover compared with a UE-stayer while controlling for a wide range of observable characteristics. The average unemployment duration of a UE-stayer would reflect unemployment due to search frictions within the market. Thus the relative difference of the duration in unemployment for a UE-mover compared with a UE-stayer captures the additional time in unemployment due to reallocation frictions across markets. Thereafter, I assess the "gains" in the net present value of workers by estimating the potential wage gains upon moving to a different occupation. I compare the average difference in individual wages of UE-movers, EE-movers and UE-stayers compared with the average difference of EE-stayers (which is virtually zero). After controlling for the duration of unemployment, UE-stayers are expected to face neither gains nor losses, as their re-employment wage should be approximately the same as before. EE-movers should also gain from moving; however, because they do not bear the costs of unemployment, the gains might be smaller than for UE-movers. Consequently, UE-movers are expected to have the highest gains, as they bear the highest costs. As the wage is not the only influential parameter in the net present value, I perform the same comparison for changes in the job finding and separation rates (and in labor market tightness).

4.1 Costs in terms of duration

I estimate a simple OLS regression for the duration of unemployment and an AFT (accelerated failure time) model in log-normal form[14]. The main effect is absorbed by a dummy variable that indicates whether individual i is a UE-mover in a given spell s. The reference group consists of UE-stayers. As covariates, I include a comprehensive set worker characteristics: age and its square, the occupation the individual switches to, general labor market experience (measured as days in employment) and its square[15], the spell number and its square, schooling, sex, nationality, and calendar year dummies.

$$duration_{i,s} = \beta_0 + \beta_1 UE\text{-}mover_{i,s} + covariates + \epsilon_{i,s} \tag{13}$$

The regressions yield the following results:

[13] The identification of moving costs in the empirical literature typically relies on exploring the wage gains and losses upon moving (Kambourov/Manovskii, 2009b,a). Another approach is to measure the task difference between two jobs, which underlies the assumption that moving costs are higher, the higher the distance in the task composition of occupations is(Cortes/Gallipoli, 2014; Gathmann/Schönberg, 2010; Autor/Levy/Murnane, 2003).

[14] For the accelerated failure time model, I take the log of unemployment duration.

[15] This variable is constructed before the observation period is set and reflects the labor market experience from 1979 onwards.

Table 3: Average unemployment duration of UE-mover (in comparison to UE-stayer)

	unemployment	nonemployment
OLS		
UE-mover	93.9416^{***}	171.8017^{***}
R^2	0.1438	0.1727
AFT		
UE-mover	0.3904^{***}	0.5085^{***}
R^2	0.1423	0.1703

Standard errors are clustered by person id; the dependent variable is un-/nonemployment duration measured in days; the reference group is UE-stayer; full table of coefficients available on request; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$;

The OLS regression indicates that workers who switch occupation upon hiring tend to have remained in unemployment (nonemployment) for approximately 3 (5.5) months longer (c.p. on average) than workers that have not switched occupation[16]. The AFT model implies that UE-movers spend approximately 40 (50) percent more time in unemployment (nonemployment) than UE-stayers. All values are highly significant at the 1-percent level.

Robustness

Although I control for a wide range of observable characteristics, my regressions may be biased by systematic differences between UE-movers and UE-stayers in unobservable characteristics. To assess whether this is influential, I estimate fixed-effects (FE) regressions to control for time-constant unobservables.[17]

The regressions yield the following results:

[16] A between-effects model, which uses averages across individuals delivers very similar results; thus, interpreting the pooled OLS-estimate as differences in persons appears appropriate.

[17] A Breusch and Pagan Lagrangian multiplier test indicates that the individual-specific component matters in my regression. A Hausman test of whether fixed or random effects is more appropriate indicates the use of FE regression.

Table 4: Average unemployment duration of UE-mover (in comparison to UE-stayer)

	unemployment	nonemployment
FE		
UE-mover	58.1328^{***}	99.1134^{***}
R^2	0.1806	0.2823
FE-AFT		
UE-mover	0.2702^{***}	0.3447^{***}
R^2	0.1351	0.1911

Standard errors are clustered by person id; the dependent variable is un-/nonemployment duration measured in days; the reference group is UE-stayer; R^2 refers to within-variation; full table of coefficients available on request; $^{*}\ p < 0.05$, $^{**}\ p < 0.01$, $^{***}\ p < 0.001$;

The FE regression shows that the coefficient in the OLS estimation is upward biased[18]. Under the FE specification, a UE-mover spends approximately 2 (3) additional months in unemployment (nonemployment) compared with a UE-stayer. However, the identification strategy of the FE regression relies on within-differences of persons who have been UE-stayers and UE-movers at some point in time and thus might refer to a very special group[19].

4.2 Wage changes

To recoup the opportunity costs of switching occupations, the model postulates that workers move to an occupation where they earn higher wages. To determine whether this is in line with the data, I again estimate OLS and FE regressions for the change in individual log-wages.

[18] Even though the FE regression control for time-constant unobservables, the results may be biased by time-varying unobservables. Another issue is, that both regressions, OLS and FE, cannot account for the reverse causality. This issue addressed in Appendix C.

[19] The regressions use the information on approximately $\frac{1}{4}$ of all individuals.

Table 5: Difference in log-wages from 2000-2010

	OLS	FE
E-stayer	reference	reference
UE-mover	-0.0521^{***}	-0.0472^{***}
EE-mover	0.0542^{***}	0.0541^{***}
UE-stayer	-0.0198^{***}	-0.0181^{***}
R^2	0.4924	0.5289

The dependent variable: difference in log-wages; covariates: lagged occupation-year residual wages (squared), difference in year-occupation residual wage percentiles (squared), age (squared), nationality, sex, schooling, (difference in) occupational status, general labor market experience (squared), spell (squared), destination occupation and calendar year dummies, firm characteristics of current employment (number of employees, share of females, share of part-time workers, share of managers, share of high/medium/low skilled, median daily wage), tenure (occupation, industry) and industry (3-digit); * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$;

Table 6 shows that UE-movers and UE-stayers face losses, while EE-movers exhibit wage gains (of approximately 5 percent). For UE-stayers, the wage loss is smaller than for UE-movers, who lose up to 5 percent of their wage after the switch. The negative effect for UE-stayers might be due to the occurrence, i.e., scarring effects, of unemployment (Arulampalam/Gregg/Gregory, 2001; Arulampalam, 2001). Moreover, not only the occurrence but also the duration of unemployment might be influential for the wage losses of UE-movers and UE-stayers. Therefore, I estimate OLS and FE regressions that include unemployment duration. Additionally, I estimate OLS and FE regressions that include an interaction term of unemployment duration and the dummy variable for being a UE-mover to account for the fact that UE-movers have longer unemployment duration. This interaction term is significant and negative in all regressions but small in magnitude. Thus, the wage effects for UE-movers reported in Table 6 represent lower bounds.

Table 15 shows that the change for UE-stayers is ambiguous and very small. The effect for EE-movers is unaffected and displays a 5 percent wage increase (c.p. on average). The negative effects for UE-movers remain even after controlling for their longer duration in unemployment compared with UE-stayers. However, the wage loss amounts to between 1.3 and 2.3 percent, which is considerably smaller than before without controlling for unemployment duration.

Table 6: Difference in log-wages from 2000-2010 - controlling for unemployment duration

	(1)	(2a)	(3a)	(2b)	(3b)
OLS					
UE-mover	-0.0521^{***}	-0.0162^{***}	-0.0232^{***}	-0.0158^{***}	-0.0222^{***}
EE-mover	0.0542^{***}	0.0541^{***}	0.0542^{***}	0.0541^{***}	0.0542^{***}
UE-stayer	-0.0198^{***}	0.0028^{***}	-0.0026^{***}	0.0018^{**}	-0.0043^{***}
Fixed-effects					
UE-mover	-0.0472^{***}	-0.0136^{***}	-0.0212^{***}	-0.0131^{***}	-0.0202^{***}
EE-mover	0.0541^{***}	0.0545^{***}	0.0543^{***}	0.0545^{***}	0.0543^{***}
UE-stayer	-0.0181^{***}	0.0038^{***}	-0.0020^{**}	0.0028^{**}	-0.0038^{***}

The dependent variable: difference in log-wages; covariates: lagged occupation-year residual wages (squared), difference in year-occupation residual wage percentiles (squared), age (squared), nationality, sex, schooling, (difference in) occupational status, general labor market experience (squared), spell (squared), destination occupation and calendar year dummies, firm characteristics of current employment (number of employees, share of females, share of part-time workers, share of managers, share of high/medium/low skilled, median daily wage), tenure (occupation, industry) and industry (3-digit); * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; Column (1) without additional controls. Column (2a) includes unemployment duration. Column (3a) includes unemployment duration and an interaction of unemployment duration and the UE-mover dummy. Column (2b) includes nonemployment duration. Column (3b) includes nonemployment duration and an interaction of nonemployment duration and the UE-mover dummy.

Improvement and deterioration within individual wage changes

The regressions reflect averages across individuals. Nonetheless, there are "winners" and "losers" within the groups of UE-movers and EE-movers. A plot of the difference in (log)wages against the rank of the residual wage in the origin occupation (see Figure 2) shows that the effects are unequally distributed across the worker's rank in the residual wage distribution of the previous job. UE-movers (left panel) experience wage increases when they were below the 20th residual wage percentile in their previous occupation, whereas EE-movers (right panel) experience wage increases when they were below the 80th residual wage percentile in their previous occupation[20].

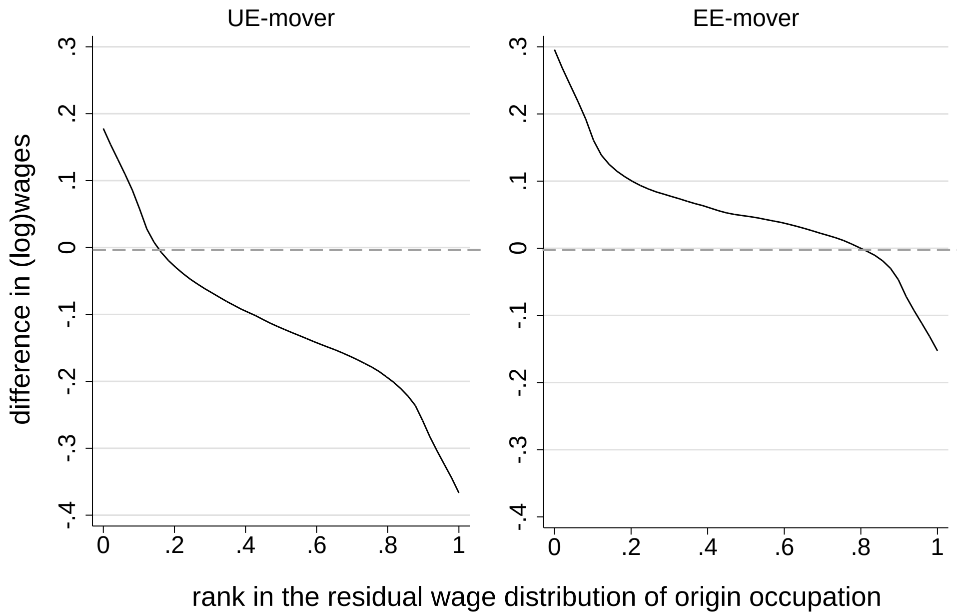

Figure 2: Difference in (log)wages against rank in origin occupation

Average wage

At a first glance, this result appears to be at odds with the theoretical model, as people who reallocate across occupations face losses in terms of unemployment duration and, simultaneously, cannot compensate for these costs because they face wage losses. However, a study by Groes/Kircher/Manovskii (2014) using Danish data shows that workers at the lower end of the (residual) wage distribution tend to switch to occupations that have a lower *average wage*, whereas workers in the upper part of the distribution tend to switch to occupations with higher average wages. This suggests that unemployed workers direct their search with respect to the average occupational wage, not their individual wage. Thus, I compute the average wage within an occupation for a given year and run the same regressions as above.

[20] Note that, in general, people experience improvements in their relative position in the wage distribution when they were in the lower half of the wage distribution in their origin occupation and a deterioration of they were in the upper half.

Table 7: Difference in average occupational log-wages
from 2000-2010

	OLS-estimate	Fixed-effects
E-stayer	reference	reference
UE-mover	-0.0032^{***}	-0.0020^{**}
EE-mover	0.0260^{***}	0.0247^{***}
UE-stayer	0.0021^{***}	0.0027^{***}
R^2	0.1461	0.0706

The dependent variable: difference in mean log-wages per occupation; covariates: lagged occupation-year residual wages (squared), difference in year-occupation residual wage percentiles (squared), age (squared), nationality, sex, schooling, (difference in) occupational status, general labor market experience (squared), spell (squared), destination occupation and calendar year dummies, firm characteristics of current employment (number of employees, share of females, share of part-time workers, share of managers, share of high/medium/low skilled, median daily wage), occupational tenure and industry (3-digit); * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$;

The regression results show that the negative effects remain, and although they are statistically significant, they are small in magnitude. However, the results still do not show a wage gain. In conclusion, it appears that unemployed workers also do not direct their search with respect to the average wage. UE-movers move on average to occupations with a slightly lower average wage, whereas EE-movers move to occupations with (substantially) higher average wages.

Improvement and deterioration within average occupational wage changes

Figure 3 displays a plot of the average occupational wage change conditional on the rank of the wage distribution in the origin occupation. Apparently, the picture here contrasts with that in Figure 2, as the average occupational wage is increasing in the rank of the residual wage distribution. That means that UE-movers move to occupations with a higher average wage given that they were above the 80th percentile, while EE-movers move to occupations with higher average wages when they were above the 20th percentile in the previous occupation.

4.3 Aggregate conditions

According to theory, the only possible explanation in line with these observations would be that occupations with a high job finding rate (or high labor market tightness, respectively), or a low separation rate attract workers. Thus, I perform similar regressions for the (percentage) change in the job finding rate, the separation rate and labor market tightness. I

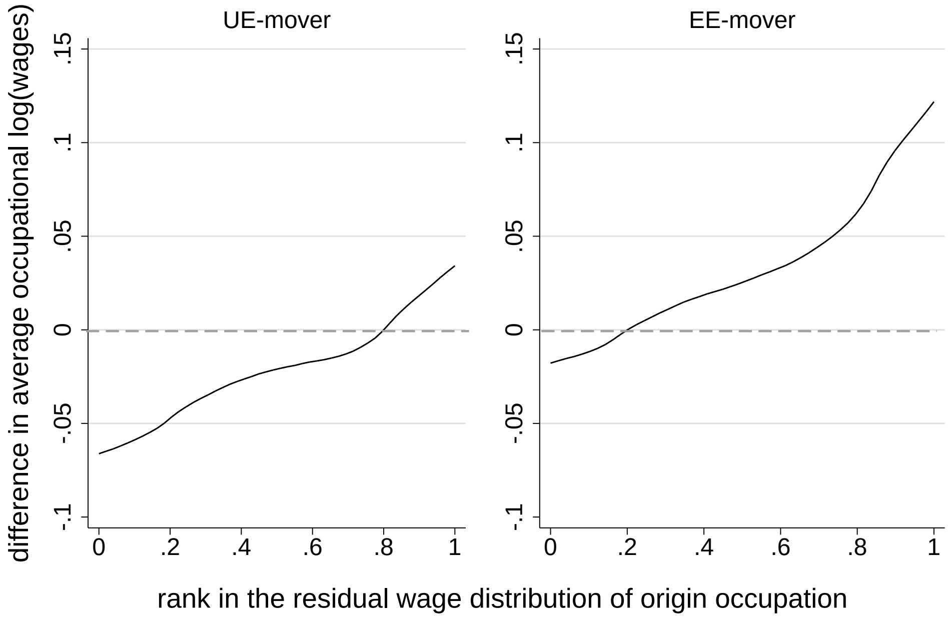

Figure 3: Difference in (log)wages against rank in origin occupation

take the logs of the job finding rate, the separation rates and labor market tightness and regress them on the dummies indicating the worker type, on observable worker characteristics, occupation and year dummies, and the (log) difference in average wages[21]. As job finding, separation rates and labor market tightness are connected via the matching function, I control for their influence in the regressions. In the regression for the difference in job finding rates, I include differences in labor market tightness and separation rates, in the regression for the difference in separation rates, I include differences in the job finding rate and labor market tightness and, in the regression for labor market tightness, I include the difference in job finding and separation rates.

[21] In detail, I use exactly the same set of variables as in the wage regression without firm characteristics. As aggregate variables such as the job finding rate are not substantially influenced by the firm characteristics (often insignificant effects), I exclude them from the regression to reduce the influence of multicollinearity.

Table 8: Difference in aggregate conditions from 2000-2010

	job finding rate	separation rate	labor market tightness
OLS			
UE-mover	-0.0111^{***}	0.0007	-0.0121^{***}
EE-mover	-0.0077^{***}	0.0009	-0.0245^{***}
UE-stayer	-0.0002^{*}	-0.0009^{***}	0.0031^{***}
Fixed-effects			
UE-mover	-0.0030^{*}	0.0006	-0.0030^{*}
EE-mover	0.0004	-0.0013	-0.0015
UE-stayer	0.0003	-0.0007	-0.0007

The dependent variable: difference in average job finding rate, separation rate and labor market tightness across occupations; covariates: lagged occupation-year residual wages (squared), difference in year-occupation residual wage percentiles (squared), age (squared), migrant, sex, schooling, (difference in) occupational status, general labor market experience (squared), spell (squared), destination occupation and calendar year dummies, tenure (occupational group, industry) and industry (3-digit); * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$;

Although there are some significant effects in the OLS and FE regression, they are rather small and negative. For instance, according to the FE regressions, UE-movers move to occupations in which the job finding rate and labor market tightness is on average 0.3 percent lower. In principle, this is in contrast with theory, but as the effects are not substantial (close to zero), I conclude that workers do not direct their search with respect to aggregate conditions.

5 Discussion

I have shown that reallocation costs in terms of unemployment duration are high and that wage changes upon switching occupation out of unemployment cannot offset these costs. These two findings cast doubt on the model mechanism of so-called Lucas/Prescott (1974) islands models, as given these findings, workers would have no incentive to switch occupations.

Regarding the first result, I find that workers who switch occupations by moving from unemployment to employment spend approximately 2 to 5.5 additional months in unemployment compared with stayers. In other words, workers who switch occupations spend 27 to 50 percent more time in unemployment than workers who return to the same occupation upon reemployment.[22] To the best of my knowledge, this is the first study that explicitly analyzes

[22] A back-of-the-envelope calculation illustrates how substantial these costs are: Given that the average daily

the costs of reallocation by estimating the additional time spent in unemployment. In the existing literature, the costs of switching occupations (or industries) are usually approximated by estimating the differences in tasks (e.g., Gathmann/Schönberg (2010); Cortes/Gallipoli (2014)) or wages (Kambourov/Manovskii, 2009a). While the first approach rests on the assumption that the greater the distance in tasks, the higher the costs of moving, the latter approach assumes that the wage gains (exactly) compensate for the moving costs. The advantage of my approach is that it provides a direct measure of the costs of switching that is used in the class of island matching models. Intuitively, occupational switching can have two opposing effects on unemployment duration. On the one hand, it might shorten the unemployment spell because the individual searches within a tighter market, which raises the matching probability. On the other hand, switching occupations might prolong the unemployment spell because the individual loses human capital. As Kambourov/Manovskii (2009b) show, human capital is largely occupation-specific; thus, movers who lose this occupation-specific human capital are in a worse position compared with stayers within the new occupation. In Germany, the latter effects appear to prevail, which might be due to the strongly occupation-oriented apprenticeship system.

Regarding the second result, I find that switching occupations without an intervening spell of unemployment leads to a wage *increase* of approximately 5.4 percent, whereas switching through unemployment leads to a *decrease* of approximately 1.3 to 2.3 percent. For direct moves from employment to employment, my finding is in line with theories of job-shopping (e.g., Johnson (1978)) or on-the-job search (e.g. (Burdett, 1978)). For moves through unemployment, my findings are at odds with the theory of Lucas/Prescott (1974) models, in which reallocation through unemployment is the key mechanism. Similarly, search and matching theory also predict positive wage gains, as a longer spell in unemployment might positively affect match quality (Bowlus, 1995). My finding implies that occupational mobility through unemployment appears to be in line with human capital (Becker, 1962) or signaling theories Gibbons/Katz (1991). According to the first mentioned theory, occupation-specific human capital is lost and general human capital depreciates (especially because unemployment duration is longer for movers than for stayers), which would result in wage losses. In the latter theory, mobility via unemployment might have negative wage effects, as the spell of unemployment would signal low productivity relative to EE-movers. However, this theory would also predict wage losses for UE-stayers, which are found to be very small in my analysis.

From an empirical perspective, my findings are in contrast to a recent study by Carrillo-Tudela et al. (2014), who find that moving tends to be beneficial independent of whether an individual switches occupations out of employment or unemployment (in the UK). Studies for Germany confirm my results. Burda/Mertens (2001) estimate the "wage losses of displaced workers in Germany" and find that displaced workers show substantially higher occupational mobility rates and that the wage loss amounts to 2 to 3 percent in the 1980s. They also document that the wage loss is unequally distributed across the wage distribution. Whereas workers in the lower part of the wage distribution slightly gain, workers at

real wage in my sample is 90 Euros and that the average unemployment duration of an UE-stayer is 148 days and assuming that the replacement rate is 60 percent, the additional costs of unemployment lie between 1439 and 2664 Euros, i.e., 4 to 8 percent of the average annual wage.

the higher end of the distribution face losses of up to 17 percent. I can confirm this result by showing that moving through unemployment is beneficial provided that the worker is below the 20th wage percentile in his origin occupation (see Figure 2). Inversely, for EE-movers, it is not beneficial to move when the worker is above the 80th wage percentile. Schmelzer (2012) estimates wage changes upon switching employers and distinguishes between moves out of unemployment and employment, finding wage losses of approximately 8 to 9.6 percent, which are quite high. Fitzenberger/Licklederer/Zwiener (2015) find wage losses for graduates who simultaneously switch occupations and employers of approximately 3 to 4 percent[23].

One might argue that the individual wage change does not matter for reallocation because it is subject to uncertainty or information frictions. Thus, I also analyzed whether workers direct their search towards occupations with higher average wages because the average wage of an occupation is observable. However, I find (qualitatively) similar patterns as for the individual wage changes. UE-movers tend to switch to occupations with slightly lower average wages, whereas EE-movers switch to occupations with higher average wages (c.p. on average). Similarly, with respect to the average occupational wage, the gains and losses are distributed differently across the (origin) wage distribution. UE-movers above the 80th wage percentile switch to occupations with higher average wages and EE-movers above the 20th wage percentile switch to occupations with higher average wages. Nonetheless, the bottom line of this analysis is that, on average, it is not beneficial for workers to switch occupations out of unemployment.

A potential explanation for why workers do not direct their search with respect to average wages might be that other factors under consideration in a reallocation decision, such as job finding and separation rates or labor market tightness, have a larger impact. However, I could not find any (economically) significant influence of these variables on the direction of moving.

In summary, it remains puzzling why workers appear to neither direct search across occupations with respect to individual wages nor with respect to aggregate conditions (average wage, job finding rate, separation rate, labor market tightness of the occupation). Conceivably, people experience difficulties in finding a job in their respective occupation (e.g., because of regional preferences or the like) and prefer to search for a different occupation, even if this entails a wage loss and increases the time spent in unemployment searching for a new job, rather than remaining unemployed. Moreover, there are also non-monetary occupation characteristics (such as giving up shift work) or occupational standardization that affect the decision to change occupation. On the one hand, non-monetary occupation characteristics could also offset the costs of switching, but on the other hand, standardization could increase these costs. Whether these factors play a role, and the extent to which they influence the workers' decision, can only be answered through additional empirical studies. Similarly, an extension of the time period under consideration could give rise

[23] That the findings of Fitzenberger/Licklederer/Zwiener (2015); Burda/Mertens (2001) resemble one another is probably due to the fact that the gross of people who switch occupations also switch employers and that voluntary quits into unemployment are a rare event in the German labor market. Although I cannot prove the latter with my data, I can shed some light on the first argument. The findings are reported in Appendix D.

to the question of changing behavior in reallocation over time. While moving from job to job is often procyclical, moving through unemployment is not (Loungani/Rogerson, 1989). However in good times, it might be easier to recoup the costs of reallocation than in bad times.

From a theoretical perspective, extensions that distinguish between moving with and and without an intervening spell of unemployment (e.g., introducing job-to-job switching) could shed some light on these issues. Moreover, introducing shocks that affect the suitability of workers or their preference with respect to the geographical region could be helpful in explaining the observed empirical patterns.

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A Derivation of steady state values for unemployment

Plugging equation 6 in equation 5 yields:

$$U_i = \frac{\left(b + \frac{\beta f_i (w_i + \beta s_i U_i)}{1-\beta(1-s_i)}\right)}{(1 - \beta\,(1 - f_i))} \tag{14}$$

Solving for U_i:

$$(1 - \beta(1 - f_i))U_i = b + \frac{\beta f_i (w_i + \beta s_i U_i)}{1 - \beta(1 - s_i)} \tag{15}$$

$$U_i = \frac{-b + b\beta - b\beta s_i - \beta f_i w_i}{-1 + 2\beta - \beta f_i - \beta^2 + \beta^2 f_i - \beta s_i + \beta^2 s_i} \tag{16}$$

and rearranging:

$$U_i = \frac{-b\,(1 + (-1 + s_i)\,\beta) - \beta f_i w_i}{-1 + 2\beta - \beta f_i - \beta^2 + \beta^2 f_i - \beta s_i + \beta^2 s_i} \tag{17}$$

$$U_i = \frac{-b\,(1 + (-1 + s_i)\,\beta) - \beta f_i w_i}{(1 - \beta)\,(1 - \beta + \beta\,(s_i + f_i))} \tag{18}$$

$$U_i = \frac{b\,(1 - (1 - s_i)\,\beta) + \beta f_i w_i}{(1 - \beta)\,((1 - \beta) + \beta\,(s_i + f_i))} \tag{19}$$

B Data description

I use a 2 percent sample of German register data provided by the Institute for Employment Research (IAB), the so-called Integrated Employment Biographies (IEB). This data set covers 80 percent of the German workforce since 1980 and provides information with daily precision on employment subject to social security, job search, receipt of unemployment compensation and participation in active labor market measures. Not embodied are civil servants, self-employed and students. As the data set is a merger of different sources, spells are partly overlapping (e.g. receiving unemployment insurance while on job search or in a training measure). Thus I refine the sample to include only employment and job search spells, such that people can be identified as either employed or unemployed. Workers are considered to be employed if they have a regular full-time job and unemployed if they are registered as "unemployed and searching for a job". In detail that means, that I exclude workers in part-time jobs, marginal jobs and apprenticeship to receive homogeneity with respect to the working hours of employed individuals as I only know the daily wage, but not the hours worked.Wages and working hours (for full-time employees) are subject to collective bargaining agreements in Germany. For information on the bargaining system and coverage see Schnabel/Zagelmeyer/Kohaut (2006). Furthermore I exclude people that are only seeking advise at the Federal Employment Agency, search on-the-job or are sick up to 6 weeks to get a homogeneous set of unemployed workers. The remaining unemployed workers are searching for a job, and most of them receive unemployment insurance or unemployment benefits. Unemployment insurance in Germany is paid up to 24 months depending on meeting certain eligibility criteria. It replaces 60% of the former income and is granted independently of assets. Unemployment benefits are granted if the workers does not meet the eligibility criteria for unemployment insurance or runs out of unemployment insurance. It is dependent on the family income and assets. It aims at maintaining a certain subsistence level and thus can be granted as well to top up earned income and unemployment insurance, when these are below the subsistence level. When an individual is unemployed, the data set provides information only if the individual registers at the Federal Employment Agency. As unemployment insurance and also unemployment benefits are accessible only via registration, most of the people are registered. The data contains information on the age, gender, education, migration background, and for spells of employment the wage, the occupation, the occupational status (skilled, unskilled, white-collar, master craftsmen/technician) and firm characteristics (e.g. share of females, size of the company, share of high/medium/low skilled workers ect.). As information on employment is reliable throughout the whole observation period, I construct variables that reflect tenure in industry, occupation and the establishment.Afterwards I restrict my analysis to the period spanning from 2000-2010 as information on job search is reliable only after 2000. After all refinements, the data set comprises 640,979 individuals with 7,055,376 spells. The spells in the data set are of undefined length, however, employment spells last for at most one year, while unemployment spell can last for several years. For more details on the data set see vom Berge/König/Seth (2013).

C Reverse causality in estimating unemployment duration

The OLS regression may suffer from endogeneity because of reverse causality. It is unclear whether the worker has a long spell of unemployment because s/he searched for a job in a different occupation or whether the worker was pushed to switch occupation because of the long duration in unemployment. Although the first interpretation is the channel of reallocation in the Lucas-Prescott models, it is not ruled out that in the data, the other channel is more important. Likewise, there might be selection effects for movers and stayers. The bottom line is, that my regression results might be affected through endogeneity bias. To account for this endogeneity I ran several IV-regressions (e.g. endogenous equation models, structural equation models) where I used variables that indicate whether individuals moved before, whether they received unemployment benefits often during their employment biographies, occupational tenure and the degree of standardization of the origin and destination occupations. All these regressions stated higher effects than under the regular OLS and FE estimation. However, the instruments are probably not the best exclusion restrictions as they might have a direct impact not just on the probability to be a mover or a stayer, but also unemployment duration.

D Extensions

Establishment stayers vs. switchers

I classified mover and stayer as people that switch occupations or stay within an occupation, however another relevant dimension in the consideration of switching is whether workers switch occupations within or across firms. As my data set allows to identify wether the individual works in the same or at a different establishment, I use this information to create a dummy that equals 1 when the previous spell of employment was at the same establishment as the current spell of employment.

worker type	establishment switcher	establishment stayer
UE-mover	121,924.0	33,574.0
EE-mover	120,378.0	60,463.0
UE-stayer	98,721.0	62,714.0

Afterwards I rerun my main regressions including this dummy variable (called est. stay). To account for the unequal distribution of the proportion of establishment switchers vs. stayers across UE-movers, EE-movers and UE-stayers (as can be seen from table **??**) I interact the dummy variables of UE-movers, EE-movers and UE-stayers with the establishment stayer dummy variable.

Table 9: Regression results including distinction of establishment stayers vs. switchers

	Duration	Individual wage	Occupation wage
OLS			
UE-mover	77.4152^{***}	-0.0285	-0.0075^{***}
est. stayer	-20.7815^{***}	0.0020	-0.0005^{***}
UE-mover×est.stayer	61.8284^{***}	0.0430^{***}	0.0202^{***}
Fixed-effects			
UE-mover	53.3613^{***}	-0.0249^{***}	-0.0062^{***}
est. stayer	-17.3644^{***}	0.0004^{***}	-0.0005^{***}
UE-mover×est.stayer	18.9100^{***}	0.0395^{***}	0.0184^{***}

Dependent variable: Unemployment duration, difference in individual log(wage) and difference in average occupational (log)wage; Covariates: lagged occupation-year residual wages (squared), difference in year-occupation residual wage percentiles (squared), age (squared), migrant, sex, schooling, (difference in) occupational status, general labor market experience (squared), spell (squared), destination occupation and calendar year dummies, tenure (occupational group, industry) and industry (3-digit); * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$;

Table 9 shows that the effects for UE-movers remain after controlling whether the individual switched establishment or not. Interestingly, workers that are unemployed and return to the same establishment but in a different occupation spent 2 additional months in unemployment (compared to workers that do not return to the same establishment) but are able to offset these costs as they face (small) wage gains at the individual and occupational level. Only around 22 percent of UE-movers return to the same establishment, which suggests that these individuals may return to the establishment because they were unemployed for a long time and have a good bargaining position as they already know they establishment. Another possible explanation would be that these individuals did (further vocational) training during their unemployment spell, which might prolong unemployment duration, but allows to return to the establishment in a different (and probably higher skilled) occupation with a higher wage.

Different occupational classifications

An influential factor driving my results is how detailed the classification maps occupations. Thus I used different occupation schemes which reflect different aggregation mechanisms. One feature of the German occupation classification (KldB88) is that it allows for aggregation, i.e. the 340 3-digit occupations can be aggregated into occupation groups (86), occupation sections (33) and occupation sectors (6). As this classification scheme has the disadvantage that it is relatively detailed in manufacturing compared to services and this disadvantage runs through the all aggregation levels, I additionally use two other aggregation mechanisms. One is developed by Tiemann et al. (2008) and the other one by Matthes/Burkert/Biersack (2008). The first one groups the 3-digit occupations by the mainly exercised action resulting in 54 occupational fields, whereas the latter groups the 3-digit occupations such that the resulting occupational segments are intra-homogenous but inter-heterogenous based on similarity criterions with respect to skills and competencies. In the following I replicate the main results of the paper by using these different classifications.

Occupation sectors (1-digit classification)

Table 10: Average unemployment duration of UE-mover (in comparison to UE-stayers)

	OLS	FE
Baseline		
UE-mover	83.6999^{***}	44.0196^{***}
R^2	0.1224	0.0465
AFT		
UE-mover	0.3315^{***}	0.1941^{***}
R^2	0.1170	0.0428

Note: Standard errors are clustered by person id; dependent variable is un-/nonemployment duration measured in days; reference group is UE-stayer; full table of coefficients on request; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$;

Table 11: Difference in log-wages from 2000-2010 - controlling for unemployment duration

	(1)	(2a)	(2b)
OLS			
UE-mover	-0.0593^{***}	-0.0174^{***}	-0.0209^{***}
EE-mover	0.0379^{***}	0.0379^{***}	0.0379^{***}
UE-stayer	-0.0336^{***}	-0.0065^{***}	-0.0054^{**}
FE			
UE-mover	-0.0518^{***}	-0.0136^{***}	-0.0164^{***}
EE-mover	0.0391^{***}	0.0395^{***}	0.0395^{***}
UE-stayer	-0.0314^{***}	-0.0058^{***}	-0.0048^{**}

Dependent variable: Difference in log-wages; Covariates: lagged occupation-year residual wages (squared), difference in year-occupation residual wage percentiles (squared), age (squared), migrant, sex, schooling, (difference in) occupational status, general labor market experience (squared), spell (squared), destination occupation and calendar year dummies, firm characteristics of current employment (number of employees, share of females, share of part-time worker, share of managers, share of high/medium/low skilled, median daily wage), tenure (occupation, industry) and industry (3-digit); * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; Column (1) without additional controls. Column (2a) includes unemployment duration. Column (2b) includes unemployment duration and an interaction of unemployment duration and dummy UE-mover.

Occupational fields (Tiemann et al. (2008))

Table 12: Average unemployment duration of UE-mover (in comparison to UE-stayers)

	OLS	FE
Baseline		
UE-mover	58.1001^{***}	30.1161^{***}
R^2	0.1178	0.0445
AFT		
UE-mover	0.2539^{***}	0.1462^{***}
R^2	0.1152	0.0411

Note: Standard errors are clustered by person id; dependent variable is un-/nonemployment duration measured in days; reference group is UE-stayer; full table of coefficients on request; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$;

Table 13: Difference in log-wages from 2000-2010 - controlling for unemployment duration

	(1)	(2a)	(2b)
OLS			
UE-mover	-0.0522^{***}	-0.0189^{***}	-0.0159^{***}
EE-mover	0.0551^{***}	0.0548^{***}	0.0548^{***}
UE-stayer	-0.0157^{***}	0.0060^{***}	0.0036^{**}
FE			
UE-mover	-0.0476^{***}	-0.0163^{***}	-0.0131^{***}
EE-mover	0.0549^{***}	0.0549^{***}	0.0550^{***}
UE-stayer	-0.0143^{***}	0.0069^{***}	0.0042^{**}

Dependent variable: Difference in log-wages; Covariates: lagged occupation-year residual wages (squared), difference in year-occupation residual wage percentiles (squared), age (squared), migrant, sex, schooling, (difference in) occupational status, general labor market experience (squared), spell (squared), destination occupation and calendar year dummies, firm characteristics of current employment (number of employees, share of females, share of part-time worker, share of managers, share of high/medium/low skilled, median daily wage), tenure (occupation, industry) and industry (3-digit); * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; Column (1) without additional controls. Column (2a) includes unemployment duration. Column (2b) includes unemployment duration and an interaction of unemployment duration and dummy UE-mover.

Occupational segments (Matthes/Burkert/Biersack (2008))

Table 14: Average unemployment duration of UE-mover (in comparison to UE-stayers)

	OLS	FE
Baseline		
UE-mover	73.2859^{***}	36.9749^{***}
R^2	0.1279	0.0468
AFT		
UE-mover	0.3037^{***}	0.1711^{***}
R^2	0.1239	0.0432

Note: Standard errors are clustered by person id; dependent variable is un-/nonemployment duration measured in days; reference group is UE-stayer; full table of coefficients on request; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$;

Table 15: Difference in log-wages from 2000-2010 - controlling for unemployment duration

	(1)	(2a)	(2b)
OLS			
UE-mover	-0.0560^{***}	-0.0189^{***}	-0.0191^{***}
EE-mover	0.0531^{***}	0.0530^{***}	0.0530^{***}
UE-stayer	-0.0223^{***}	0.0010^{***}	0.0013^{*}
FE			
UE-mover	-0.0503^{***}	-0.0157^{***}	-0.0157^{***}
EE-mover	0.0530^{***}	0.0533^{***}	0.0533^{***}
UE-stayer	-0.0206^{***}	0.0019^{***}	0.0019^{***}

Dependent variable: Difference in log-wages; Covariates: lagged occupation-year residual wages (squared), difference in year-occupation residual wage percentiles (squared), age (squared), migrant, sex, schooling, (difference in) occupational status, general labor market experience (squared), spell (squared), destination occupation and calendar year dummies, firm characteristics of current employment (number of employees, share of females, share of part-time worker, share of managers, share of high/medium/low skilled, median daily wage), tenure (occupation, industry) and industry (3-digit); * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; Column (1) without additional controls. Column (2a) includes unemployment duration. Column (2b) includes unemployment duration and an interaction of unemployment duration and dummy UE-mover.

Movements across occupation (aggregated 1-digit classification)

The following tables depict movements in and out of 1-digit occupations for UE- movers and for EE-movers. Obviously, the bulk of switching happens between manufacturing and service occupations independently of being an UE-mover or an EE-mover.

UE-mover

	origin occupation						
destination occupation	I Agriculture	II Mining	III Manufacturing	IV Technics	V Service	VI Other	Total
I Agriculture	0.0	14.0	2,467.0	83.0	1,307.0	101.0	3,972.0
II Mining	5.0	0.0	122.0	3.0	50.0	2.0	182.0
III Manufacturing	2,185.0	112.0	0.0	1,867.0	20,715.0	933.0	25,812.0
IV Technics	68.0	6.0	2,443.0	0.0	2,441.0	94.0	5,052.0
V Service	1,596.0	52.0	24,786.0	3,010.0	0.0	1,197.0	30,641.0
VI Other	91.0	1.0	955.0	56.0	909.0	0.0	2,012.0
Total	3,945.0	185.0	30,774.0	5,020.0	25,422.0	2,327.0	67,673.0

EE-mover

	origin occupation						
destination occupation	I Agriculture	II Mining	III Manufacturing	IV Technics	V Service	VI Other	Total
I Agriculture	0.0	9.0	1,187.0	74.0	900.0	54.0	2,224.0
II Mining	2.0	0.0	245.0	6.0	101.0	36.0	390.0
III Manufacturing	1,279.0	250.0	1.0	2,384.0	16,522.0	977.0	21,413.0
IV Technics	98.0	49.0	5,552.0	1.0	5,631.0	261.0	11,593.0
V Service	1,101.0	108.0	21,885.0	6,901.0	0.0	1,834.0	31,830.0
VI Other	66.0	265.0	1,280.0	253.0	1,515.0	0.0	3,379.0
Total	2,546.0	681.0	30,150.0	9,619.0	24,671.0	3,162.0	70,831.0

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Imprint

IAB-Discussion Paper 26/2015

Editorial address
Institute for Employment Research
of the Federal Employment Agency
Regensburger Str. 104
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Download of this Discussion Paper
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ISSN 2195-2663

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