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Changes in Occupational Tasks and Their Association with Individual Wages and Occupational Mobility

by

Alexandra Fedorets[†]

Abstract

This study provides novel evidence on the relevance of task content changes between and within occupations to wage dynamics of occupational changers and stayers. I use individual-level, cross-sectional data featuring tasks performed on the job to compute a measure of proximity of job contents. Then, I merge this measure to a large-scale panel survey to show that occupational changers experience a wage growth that is declining when the accompanying alterations in task contents are big. For occupational stayers, alterations in task contents generate a positive wage component, beyond tenure effect. However, the results are not robust with respect to the choice of proximity measure and over time.

JEL-Classification: J24, J62.

Keywords: Human capital, wage premium, occupational change, task-based approach.

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1 Introduction

The notion of occupations being bundles of heterogeneous tasks enjoys much attention in the literature. Following Autor et al. (2003), the view that occupational tasks are a key determinant of labor market outcomes is well established and supported by international evidence (e.g. Card and DiNardo (2002), Autor and Handel (2013) for the US; Spitz-Oener (2006) and Black and Spitz-Oener (2010) for Germany; and Goos et al. (2009) for Europe). The task-related literature also documents that task portfolios are of higher importance to wages than industry or occupational affiliation alone (Poletaev and Robinson, 2008; Kambourov and Manovskii, 2009). Moreover, the patterns of occupational mobility are confirmed to depend on the content similarity *between* occupations (Gathmann and Schönberg, 2010). However, the literature almost completely neglects the impact of over-time changes in task contents occurring *within* occupations, other than documenting that occupations experience substantial alterations in job tasks over time (Autor and Handel, 2013; Cassidy, 2017).

In the present paper, I argue that task content changes within occupations are an important factor for individual wage dynamics, playing a role for employees, whether they experience occupational mobility or they stay in their occupations. In particular, the analysis relates individual wage growth to occupational mobility, the magnitude of the resulting job tasks alteration, and the magnitude to which job tasks change for employees who do not change occupations. Empirically, such a detailed analysis is a challenge for the existing data and requires a combination of data sets. To measure occupational task contents, I use the German Employment Survey, which is a series of cross-sections with detailed self-reported information on the tasks performed by respondents in their jobs. This task information is merged with the German Socio-Economic Panel data set, which allows for observing occupational mobility and wage

dynamics over time, as well as to control for individual-specific fixed effects in regression analysis. The analysis includes prime-age German male employees and embraces the longest time span that is allowed when linking the two data sets – between 1985 and 2012. The empirical estimation shows that a change of an occupation is associated with a wage premium, which is lower for those occupational changers who experience bigger alterations in occupational contents. In contrast to that, changes in job tasks experienced by occupational stayers create a positive wage component, beyond the tenure effect. These results imply that neglecting the positive relationship of tasks and wages for occupational stayers results in underestimating the task-related wage loss for occupational changers. However, the result is not robust to the choice of the measure of proximity between occupational contents and over time.

The analysis contributes to two strands of literature. First, it contributes novel insights on the relationship between task dynamics within occupations and individual wages. Becker (1975) postulates that there should be an “effect of the productive process itself on worker productivity.” However, channels through which tenure affects productivity remain largely inconclusive (Altonji and Shakotko, 1987; Altonji and Williams, 2005). Given that tasks themselves are predictive of wages (Autor and Handel, 2013; Cassidy, 2017), proficiency in tasks can be one of the channels of wage growth (Gathmann and Schönberg, 2010). My results show that experiencing job content changes is also associated with wage growth. This finding implies that contact with different kinds of related tasks helps to build a more comprehensive stock of human capital to gain additional remuneration. Snower and Görlich (2013) yield supporting evidence to this argument by studying the association of wage levels with multitasking, i.e. the number of tasks the respondent currently performs on the job. In contrast to this, my analysis does not account for the number of tasks performed, but focuses on the impact dynamics of job task changes.

Secondly, the study contributes to the understanding of how human capital can be transferred between occupations. In theory, similarity between job contents were stated to be crucial for the patterns of occupational mobility (McCall, 1990; Neal, 1999). However, earlier empirical studies do not account for content similarities between jobs due to a lack of appropriate data (see e.g. Addison and Portugal, 1989; Carrington, 1993; Acemoglu and Pischke, 1998; Burda and Mertens, 2001; Couch, 2001; Fitzenberger and Spitz, 2004). Emergence of the data describing job tasks allows to represent occupations by multidimensional vectors of their task contents and to measure dissimilarities between occupations (Yamaguchi, 2012; Gathmann and Schönberg, 2010; Poletaev and Robinson, 2008). Measures of distances between these task vectors allow not only examining wage dynamics due to the observed occupational mobility, but also to additionally control for the magnitude of the related job task change. For instance, Gathmann and Schönberg (2010) show that occupational moves between less similar occupations imply higher wage penalties. My analysis links the wage dynamics of occupational changers to the wage dynamics of occupational stayers and accounts for the fact that both changers and stayers experience alterations in their job tasks over time. These findings relate to the human capital and job matching theory. In particular, the positive association of occupational change with wage growth can be interpreted as an increase of individual's productivity in the new occupation (better occupation-employee match), whereas wage penalties associated with changes between more distant occupations depict the skills that can be used in the new occupation (human capital transferability). For occupational stayers, the positive association of job task alterations with wage growth can be interpreted as a channel of human capital accumulation.

This paper proceeds as follows: the next section sketches the mechanism of human capital accumulation and transfer, section 3 describes the data sets and their merge. Section 4 provides

descriptive statistics of the data. Regression specification and the main estimation results are described in section 5, followed by a discussion of the potential estimation bias in section 6. Section 7 concludes.

2 Conceptual framework

In this section, I illustrate how alterations in job contents can be introduced into a standard framework of human capital accumulation. Firstly, I rely on the ideas of Gathmann and Schönberg (2010) to show how occupations can be defined by task bundles and what parameters explain differences in productivity between occupations. Second, I derive implications for individual productivity stemming from over-time changes in task content within occupations to motivate the regression specification for the subsequent empirical analysis.

2.1 Occupations as task bundles

Assume that an occupation requires productive usage of a bundle of tasks, which are general in nature and productive in different occupations. Occupational contents, in turn, differ only by the way they combine these tasks. Though the subsequent empirical exploration involves 13 tasks, for understanding of the underlying motivation it is sufficient to assume that an occupation, denoted by o , requires only two tasks – $j = A, M$ (e.g. analytical and manual). Workers, denoted by i , differ by their productivity in these tasks. Given that the way in which an occupation combines tasks can differ with time t , workers' productivity in this occupation depends on the worker's characteristics, the characteristics of the occupation, and time: S_{iot} . In particular, if an occupation o at time t is defined as a linear combination of tasks A, M with respective weights β_{ot} and $(1 - \beta_{ot})$, then the log productivity of the worker in this occupation

$\ln S_{iot}$ can be written down as a linear combination of her productivity in each of the tasks, τ_{iot}^A and τ_{iot}^M :

$$\ln S_{iot} = \beta_{ot} \tau_{iot}^A + (1 - \beta_{ot}) \tau_{iot}^M. \quad (1)$$

A worker's productivity in each task depends on her initial ability in this task, τ_i^j , and the human capital accumulated in this task until the time point t , H_{it}^j : $\tau_{iot}^j = \tau_i^j + \gamma_o H_{it}^j$ with $j = \{A, M\}$. Using this definition, equation 1 can be re-written as:

$$\ln S_{iot} = \underbrace{\beta_{ot} \tau_i^A + (1 - \beta_{ot}) \tau_i^M}_{m_{iot}} + \underbrace{\gamma_o [\beta_{ot} H_{it}^A + (1 - \beta_{ot}) H_{it}^M]}_{T_{iot}}, \quad (2)$$

where m_{iot} can be interpreted as the occupation match (productivity of the individual in the tasks as they are combined in this occupation, irrespective of human capital) and T_{iot} is the occupation-specific human capital.¹ Note that both elements depend on the task composition of the occupation and vary by individual, occupation and time.

Equation 2 allows us to compare productivity of the same worker in occupations – o and o' .

Note that two occupations are similar, if they assign similar weights to tasks: $\beta_{iot} \approx \beta_{io't}$, with $|\beta_{iot} - \beta_{io't}|$ being a distance measure between these occupations. Then, the contemporaneous

¹In the present paper, I focus solely on occupational mobility. However, job mobility takes place across different levels - between firms, sectors, and occupations. The main distinction between the different levels of labor mobility lies in the magnitude of the required change of job tasks. Thus, mobility between firms (without changing occupation) involves less content change than mobility between occupations, which is often only possible by switching employers. This has implications on individual productivity both through the match quality and transferability of human capital (McCall, 1990; Neal, 1999; Gathmann and Schönberg, 2010). Thus, a mere change of an employer implies less human capital losses and, therefore, is a more feasible instrument to improve the match quality between the firm and the worker. A change of an occupation implies higher human capital losses and, therefore, is beneficial only when a substantial gain in the match quality between the worker and the occupation is expected. Moreover, an occupation change may require additional training or certificates that constitute another hurdle to this type of mobility.

difference in productivity of worker i in occupations o to o' at time t is:

$$\begin{aligned}
\ln S_{iot} - \ln S_{io't} &= \underbrace{\beta_{ot} \tau_i^A + (1 - \beta_{ot}) \tau_i^M - (\beta_{o't} \tau_i^A + (1 - \beta_{o't}) \tau_i^M)}_{m_{iot} - m_{io't}} \\
&+ \underbrace{\gamma_{ot} [\beta_{ot} H_{it}^A + (1 - \beta_{ot}) H_{it}^M] - \gamma_{o't} [\beta_{o't} H_{it}^A + (1 - \beta_{o't}) H_{it}^M]}_{T_{iot} - T_{io't}} \\
&= (\beta_{ot} - \beta_{o't}) \tau_i^A + (\beta_{o't} - \beta_{ot}) \tau_i^M \\
&+ ((\gamma_{ot} \beta_{ot} - \gamma_{o't} \beta_{o't}) H_{it}^A + (\gamma_{o't} \beta_{o't} - \gamma_{ot} \beta_{ot}) H_{it}^M). \tag{3}
\end{aligned}$$

Thus, the difference in productivity of a worker employed in different occupations depends on the difference in occupational matches and on the difference in occupation-specific human capital. The former depends on the worker's productivity in different tasks and the distance in occupational contents. The latter depends on the distance in occupational contents (represented by β_{ot} and $\beta_{o't}$), returns to human capital in the occupation (γ_{ot} and $\gamma_{o't}$), and occupation-specific human capital (H_{it}^A and H_{it}^M). Based on the interplay of these components, the difference in productivity can be either positive or negative.

2.2 Over-time content changes within occupations

The presented framework also allows to define, over time ($t \rightarrow t + 1$), changes in individual productivity if an individual remains in the occupation o :

$$\begin{aligned}
\ln S_{iot} - \ln S_{io,t+1} &= \underbrace{\beta_{ot} \tau_i^A + (1 - \beta_{ot}) \tau_i^M - (\beta_{o,t+1} \tau_i^A + (1 - \beta_{o,t+1}) \tau_i^M)}_{m_{iot} - m_{io,t+1}} \\
&+ \underbrace{\gamma_{ot} [\beta_{ot} H_{it}^A + (1 - \beta_{ot}) H_{it}^M] - \gamma_{o,t+1} [\beta_{o,t+1} H_{i,t+1}^A + (1 - \beta_{o,t+1}) H_{i,t+1}^M]}_{T_{iot} - T_{io,t+1}} \\
&= (\beta_{ot} - \beta_{o,t+1}) \tau_i^A + (\beta_{o,t+1} - \beta_{ot}) \tau_i^M \\
&+ ((\gamma_{ot} \beta_{ot} - \gamma_{o,t+1} \beta_{o,t+1}) H_{it}^A + (\gamma_{o,t+1} \beta_{o,t+1} - \gamma_{ot} \beta_{ot}) H_{it}^M). \tag{4}
\end{aligned}$$

with $\delta^j = H_{i(t+1)}^j / H_{it}^j > 0$ being the time-invariant accumulation rate of human capital in task $j = \{A, M\}$. Thus, the change over time in productivity depends on the alteration of the match with the task composition of the occupation and the accumulation of the human capital, which, in turn, depend on the dissimilarity in occupational contents (represented by β_{ot} and $\beta_{o,t+1}$), returns to human capital in the occupation (γ_{ot} and $\gamma_{o,t+1}$), human-capital accumulation rate (δ^A and δ^M), and occupation-specific human capital (H_{it}^A and H_{it}^M). Even under the assumption of time-constant returns to occupation-specific human capital $\gamma_{ot} = \gamma_{o,t+1}$, individual productivity in an occupation can diminish over time if the individual match with the occupation gets worse over time and is not balanced out by the improvement of human capital in the occupation.

2.3 Occupational change

In their paper, Gathmann and Schönberg (2010) define the change in individual productivity after an occupational change from o to o' by equation 3: $\ln S_{io't} - \ln S_{io't}$. However, when comparing the alterations in individual productivity of occupational changers and stayers, the following definition is more accurate:

$$\ln S_{io',t+1} - \ln S_{io't} = \underbrace{\ln S_{io',t+1} - \ln S_{io't}}_{\Delta \ln S_{io't \rightarrow t+1}} + \underbrace{\ln S_{io't} - \ln S_{io't}}_{\Delta \ln S_{io \rightarrow o't}}, \quad (5)$$

where $\Delta \ln S_{io't \rightarrow t+1}$ is the over-time change in productivity in the occupation o' , and $\Delta \ln S_{io \rightarrow o't}$ is the contemporaneous difference in individual productivities in two occupations o and o' . Equations 4 and 3 describe these components, respectively. Thus, the overall change in pro-

ductivity equals to:

$$\ln S_{io'(t+1)} - \ln S_{iot} = (\text{Occ.change}=0)\Delta \ln S_{io't \rightarrow (t+1)} + (\text{Occ.change}=1)\Delta \ln S_{io \rightarrow o't}. \quad (6)$$

Note that equation 6 does not describe the productivity change of one individual, as the states of having changed an occupation and remaining in an occupation are mutually exclusive. Therefore, this relation rather describes the alteration of individual productivity of occupational changers relative to the contemporaneous evolution of individual productivity of occupational stayers.

Based on equation 6, a specification for an empirical estimation can be derived under additional assumptions. In particular, I assume that the returns to human capital are time invariant ($\gamma_{ot} = \gamma_{o,t+1}$). Moreover, as task weights (β_{ot} and $1 - \beta_{ot}$) enter productivity components related to match quality and human capital returns, the respective returns cannot be estimated separately. Therefore, I assume that returns to occupational match are stable over time (m_{io}) and the change in occupational task mix is attributed only to the change in task-specific human capital (T_{iot}). For occupational stayers this assumption implies that there is no penalty associated with the reduction in match quality with occupational tasks over time. For them, returns to productivity still can decrease if the job content is moving from better-paid to less-well paid tasks.

Thus, assuming that individual wages are a good approximation of individual productivity ($\ln w_{iot} = \ln S_{iot}$), the one-year wage differential $\ln w_{io',t+1} - \ln w_{iot}$ would depend on:

- the binary indicator of observing an occupational change between the years t and $t + 1$;
- the magnitude of dissimilarity of occupations between which the change occurs, o and o' ;
- the adjustment of task composition of occupational stayers over time;

- the human capital accumulated in the source occupation o ; and
- the common socio-demographic characteristics that affect wage dynamics, including time and individual heterogeneity.

3 Data

For the empirical analysis, I combine two data sources – the German Employment Survey (GES) and the German Socio-Economic Panel (SOEP). In the following, I describe each data set and the components influencing changes in individual wages as described above.

3.1 German Employment Survey (GES)

The German Employment Survey (in literature also referred to as Qualification and Career Survey, QCS) contains detailed information on job tasks performed by respondents and, for this reason, it is widely used in the task-related literature. Due to the self-reported nature of the data, an underestimation of true changes in job content is unlikely (Black and Spitz-Oener, 2010). The survey is carried out by the Federal Institute for Vocational Education and Training (BiBB) together with the Institute for Employment Research (IAB) and the Federal Institute for Occupational Safety and Health (BAuA). The survey consists of several cross-sections (carried out in 1979, 1985, 1991, 1998, 2006, and 2012) and includes a time-consistent set of occupational classifications. Due to comparability reasons in task variables, I am not able to use the 1979 wave and, thus, perform my analysis for the 1985-2012 period.

For the subsequent analysis, I restrict my sample to West-German male employees aged between 20 and 55, who are not self-employed, in civil service, or in the public sector. Based on this sample, I use information on job tasks from the GES to describe task contents of occupations

defined at a 2-digit level. A more detailed description of occupational codes and job tasks are in Appendix A.1.

3.2 German Socio-Economic Panel (SOEP)

The German Socio-Economic Panel (SOEP) is an ongoing longitudinal panel survey with about 20,000 survey participants in 11,000 households per year, conducted annually since 1984 (see Wagner et al., 2007). Most importantly for my purposes, SOEP provides detailed annual information on the employment status, monthly earnings, weekly hours worked, and work experience. The data also contain information on the occupation of employment for each employment spell and allows to explicitly identify job-to-job changes accompanied by an occupational change. More detailed information on the variables can be found in Appendix A.2. As a longitudinal study, SOEP allows to control for time-invariant individual effects in a fixed-effects estimation. Moreover, based on the occupation of employment, I am able to merge occupation-level information on tasks from the German Employment Survey. In order to match the five waves of the German Employment Survey, I employ data from 1985 to 2012 from the data release SOEP v32 (2016).

For the SOEP data, I impose the same sample restrictions as for the GES. Namely, I restrict my working sample to contain West-German men aged between 20 and 55 whose current self-reported employment status is full-time, part-time, or marginal employment. Moreover, I exclude all respondents with item non-response on the core variables.

3.3 Merge of task information

The GES data provides me with 13-dimensional task vectors describing occupational contents for the survey years 1985, 1991, 1998, 2006 and 2012. Between consecutive survey years (for instance, between $t_0 = 1985$ and $t_1 = 1991$), I linearly interpolate the task content, so that the input $\tau_t^o(j)$ of each task $j \in \{1, \dots, 13\}$ is equal to:

$$\tau_t^o(j) = \tau_{t_0}^o(j) \frac{t_1 - t}{t_1 - t_0} + \tau_{t_1}^o(j) \frac{t - t_0}{t_1 - t_0}, \quad t \in (t_0, t_1). \quad (7)$$

By doing this, I obtain 13-dimensional vectors of task contents for each of the years between 1985 and 2012. The resulting task contents are then merged to the respective 2-digit occupation and survey year in the SOEP.

3.4 Dissimilarity of task contents

For validation purposes, my empirical calculations rely on two dissimilarity measures used in literature – the angular separation and the Euclidean distance.

Angular separation measure stems from the literature on proximity of production technologies and is used to quantify task-based job similarities, for instance by Gathmann and Schönberg (2010). In particular, similarity between occupations o and o' is measured as:

$$AngSep_{o \leftrightarrow o'} = \frac{\sum_{j=1}^J \tau_t^o(j) \cdot \tau_t^{o'}(j)}{\left[\left(\sum_{j=1}^J (\tau_t^o(j))^2 \right) \left(\sum_{k=1}^J (\tau_t^{o'}(k))^2 \right) \right]^{1/2}}. \quad (8)$$

The distance measure is then defined by $Dis_{o \leftrightarrow o'}^A = 1 - AngSep_{o \leftrightarrow o'}$ and varies between zero and one, taking higher values for less similar occupations.

Euclidean distance is another measure that is used the literature on the proximity of task

portfolios (Poletaev and Robinson, 2008). This measure is calculated as follows:

$$Dis_{o \leftrightarrow o'}^E = \sqrt{\sum_{j=1}^J (\tau_{o,j}^q - \tau_{o',j}^q)^2} \quad (9)$$

For comparability with the range of the measure based on angular separation, I re-scale the Euclidean distance so that it also varies between zero and one, with higher values corresponding to less similar occupations.

In the subsequent analysis, I use both measures to check the robustness of my findings. Euclidean distance is sensitive to the intensity of task usage, whereas angular separation is sensitive to the composition of tasks. Thus, for two occupations that employ all tasks moderately, but with different intensity, the Euclidean measure will be high, whereas the distance based on angular separation will be low.

Computation of both content similarity measures relies on several assumptions. First, it assumes that the tasks themselves are general in nature and transferable between occupations. Second, it also assumes that different occupations combine tasks in different ways. Third, the suggested measures assume that task transferability is symmetrical, i.e. it is same when changing from occupation o to o' , or from o' to o . Last, but not least, both measures assume same transferability of each task describing the task content. Alternatively, one could assign weights that mirror their transferability potential to each task dimension, which would require imposition of additional assumptions.

4 Descriptive statistics

4.1 Working sample

Across all survey years, 39,848 observations are available for the relevant working sample (Table B.2 in Appendix B presents descriptive statistics). Among these observations, the annual share of occupational changes at the 2-digit level that will be used in the analysis, is equal to 3.6 percent.² At a lower levels of aggregation the annual share of changes is 4.4 percent at the 3-digit level and 5.0 percent at the 4-digit level. Occupational stayers are defined as respondents without an occupational change at the 2-digit level since last year. Occupational changers are respondents who experienced an occupational change at the 2-digit level since last year.

Summary statistics reveal some systematic differences between stayers and changers. On average and in all survey years, occupational stayers have higher log real hourly wages than occupational changers. At the same time, annual wage growth for occupational stayers is lower than the unconditional growth related to an occupational change. Occupational stayers are, on average, 6 years older than changers, which is in line with the theory of “job shopping” that is likely to occur in younger ages (Johnson, 1978). Concerning the educational levels, differences between stayers and changers are minuscule. At the same time, changers have about seven years less of experience in full-time jobs and have spent slightly more time in part-time and unemployment. In total, the summary statistics suggest that changers have poorer observable characteristics than stayers. Table B.3 in Appendix B presents statistics for the time brackets 1985-1991, 1991-1998, 1998-2006, and 2006-2012, with the cutoff years corresponding to the available waves of the German Employment Survey. The over-time comparison reveals

²Appendix A.2 describes the removal of spurious correlation in occupational codes. Without this correction, the share of occupational changes at the 2-digit level varies from 3 percent (in years when questions on current occupations are asked only in the case of a reported change) to 25 percent (in years when the question on the current occupation addresses every respondent without filtering).

that the presented characteristics are stable over the analyzed time frame, with the exception of the educational levels that substantially improve for both stayers and changers.

4.2 Task content of occupations

Table B.4 in Appendix B reports task intensities measured by the proportion of workers performing the task by survey waves. The upper panel of the table reports the observed task intensities in GES for survey years 1985, 1991, 1998, 2006, and 2012, while the lower panel presents the merged task intensities for the same years in SOEP. In both data sets, distinct task categories exhibit non-trivial changes over time (also documented by Cassidy, 2017). Some tasks, like *Task 1: Research, evaluate*, increase over time almost monotonically, whereas other tasks, like *Task 10: Repair, renovate* almost steadily decrease. In some other cases (e.g. *Task 4: Execute, interpret rules*), the task evolutions do not show a clear pattern. The original task shares in GES and the merged shares in SOEP differ only marginally, implying that the occupational structures in the two data sets do not differ much.

To better understand content changes within occupations, it might be informative to take a closer look at one particular occupation. Table B.5 in Appendix B gives an overview of the changes in job contents of clerks, who constitute one of the most sizable groups according to the occupational classification KldB92 (group code 78).³ In 1985, the two most common tasks for this occupational group were *Task 5: Sell, buy, advertise* (engaging 28.6 percent of clerks) and *Task 7: Employ, organize* (engaging 19.3 percent of clerks). By 2012, the most common tasks for clerks became *Task 1: Research, evaluate* (involving 19 percent of clerks) and *Task 6: Teach, train others* (involving 21.4 percent of clerks).

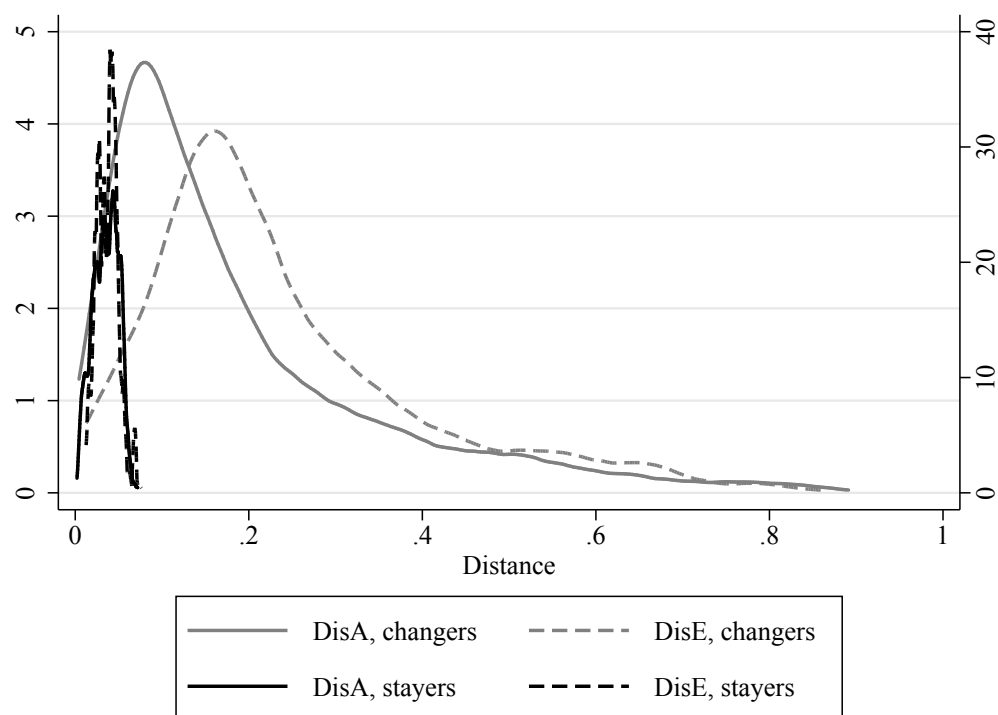
³Note, that by construction, the original task intensities in GES and the merged task intensities in SOEP are same within one occupation group by construction. Therefore, the table reports only the original shares from GES.

4.3 Content similarities

In order to compare the extent to which occupations alter over time, Table B.6 in Appendix B provides average annual dissimilarity based on both angular separation (Dis^A) and on Euclidean distance (Dis^E) for occupational changers and stayers. Among occupational changers, the average annual dissimilarity is 0.190 based on angular separation and 0.239 based on Euclidean distances. Among occupational stayers, one-year changes evolve at a much lower level: on average, the distance measure based on angular separation is 0.035, whereas the average Euclidean measure is 0.037. Table B.7 in Appendix B features the summary statistics for the two distance measures for sub-periods 1985-1991, 1991-1998, 1998-2006, and 2006-2012. Over time, both distance measures for occupational changers exhibit a decrease, whereas both measures for stayers increase over time. When dividing distance of stayers by the distance of changers, we see that the resulting ratio increases from less than 10 percent in 1985-1991 to more than 20 percent in 2006-2012, pointing toward the increasing importance of job content alterations among stayers comparing to changers.

Figure 1 provides more details on the distribution of the distance measures of occupational changers and stayers. Both distance measures for stayers are compactly located in the range of low distances. In contrast to this, the distribution of both distance measures for changers is broad, having a fat right tail and an overlap with the distances of the stayers at the low tail. For occupational changers, the distribution of the distance based on angular separation has lower variation and lower mean. Despite these differences in the distributional moments, the distributions of the two measures have a very similar shape. Contrary to this unimodal distributional shape, distributional shapes presented in Figure 2 from Gathmann and Schönberg (2010) are bimodal. This discrepancy stems from the differences in time frames: calculations

of Gathmann and Schönberg (2010) refer to an earlier time period. Figures B.1 and B.2 in Appendix feature distributions of distances for occupational changers and shows that, for both distance measures, the distribution changes its shape from a wide and almost bimodal form in 1985-1998 to a compact unimodal form in 1998-2012. Further, Figures B.3 and B.4 show that the distributions of the distance measures for the stayers also experienced alterations, in particular, they shifted to the right with time.



Notes: SOEP v32, working sample, own calculations. N=39,848.
Left axis: occupational changers, right axis: occupational stayers.

Figure 1: Distribution of distance measures for occupational changers and stayers

Table B.8 in Appendix B provides examples on the longest and shortest distances that accompanied an occupational change or an annual evolution within an occupation for occupational stayers, according to both distance measures. Tables B.9 and B.10 of the Appendix B provide a more details overview of this issue for each of the time periods 1985-1991, 1991-1998, 1998-2006, and 2006-2012.

5 Wage dynamics

5.1 Regression specification

Based on the theoretical considerations described in Section 2, the subsequent estimation of returns to occupational changes will rely on the standard Mincer-type wage regression. In particular, I aim at estimating a specification that includes both the indicator for an occupational change, a distance measure, and their interaction (equation 10). This specification relates the annual wage change of occupational changers to the annual wage change of occupational stayers, additionally controlling for the fact that both groups experience content changes:

$$\Delta \ln w_{iot} = \alpha + \beta_1 \text{Occ. change}_{iot} + \beta_2 \text{Dis}^m_{ot} + \beta_3 \text{Dis}^m_{ot} \cdot \text{Occ.change}_{iot} + \gamma X_{iot} + \epsilon_{iot}, \quad m = A, E. \quad (10)$$

For the sake of comparison with the literature on human capital accumulation and transfer, I estimate wage regression as specified by equation 10 by stepwise introduction of the variables characterizing occupational change. First, I estimate a wage regression including only a dummy variable for an occupational change and without accounting for alterations of occupational task contents (separate estimation of β_1). This specification corresponds to the customary estimation of the return to occupational mobility in literature (see, e.g. McCall, 1990). Second, I estimate a regression containing only a measure of the distance of annual change in the task content (separate estimation of β_2). Third, I estimate a specification including both the indicator for the occupational change and the distance measure (estimation of β_1 and β_2). The fourth specification includes the indicator for the occupational change and a task measure for occupational movers (estimation of β_1 and β_3). By doing this, I isolate the value of the change in the match between the employee and his occupation from the transferability of task

contents between occupations. This specification relates to the estimation presented in Gathmann and Schönberg (2010) for occupational changers and assumes that the content changes within occupations do not impact wage differentials. Last, but not least, I jointly estimate the parameters β_1 , β_2 and β_3 , as specified in equation 10.

In all specifications, vector X_t contains controls for the highest educational level (3 groups); years spent in full-time employment, part-time employment, and unemployment; age and age squared; the set of 2-digit occupational controls; 1-digit NACE dummies (21 groups); sets of dummies for the NUTS-1 regions; firm size; and the survey year. In order to account for potential sampling differences, the specification additionally includes sample dummies and type of household. The standard errors are calculated using two-way clustering – at the level of occupations (2-digit KldB92) and individuals.

5.2 Estimation results

In the following, I report the estimation results based on the regression equation 10 from the preferred specification including individual fixed effects.⁴ Table 1 presents the respective results for the distance measures based on angular separation (Dis^A , upper panel) and the Euclidean distance (Dis^E , lower panel).⁵

The first column of Table 1 shows that, after controlling for individual fixed effects, wage growth for occupational changers exceeds the annual wage growth of occupational stayers by 3.6 percentage points. This estimation is in line with the finding of Burda and Mertens (2001) that voluntary job switchers experience wage growth. The second column shows that both distance measures are positively associated with wages. However, given that occupational

⁴Section 6 compares the pooled and fixed-effects estimation as a part of a discussion on the estimation bias.

⁵To simplify the display, here I present only the results on the relevant regression coefficients. Tables D.15 and D.16 in Appendix D feature the results of the full specification.

Table 1: Returns to occupational change and distance measures, 1986-2012

	(1)	(2)	(3)	(4)	(5)
Occ. change	0.036*** (0.013)		0.041** (0.018)	0.047** (0.020)	0.067*** (0.021)
Dis ^A		0.077 (0.057)	-0.038 (0.078)		0.506* (0.255)
Occ. change × Dis ^A				-0.062 (0.080)	-0.579** (0.255)
r ²	0.145	0.145	0.145	0.145	0.145
	(1)	(2)	(3)	(4)	(5)
Occ. change	0.036*** (0.013)		0.041* (0.021)	0.045* (0.024)	0.049** (0.024)
Dis ^E		0.093* (0.050)	-0.029 (0.078)		0.132 (0.238)
Occ. change × Dis ^E				-0.038 (0.082)	-0.171 (0.249)
r ²	0.145	0.145	0.145	0.145	0.145

Source: SOEP v32, working sample, own calculations. N = 39,848.

Significance levels: * 10 percent, ** 5 percent, *** 1 percent.

Fixed effects with standard errors, clustered at the level of occupations and individuals.

All specifications control for the highest educational level (3 groups); years spent in full-time employment, part-time employment, and unemployment; age and age squared; 2-digit occupational controls; 1-digit NACE dummies (21 groups); sets of dummies for the NUTS-1 regions; firm size; and the survey year. In order to account for potential sampling differences, the specification additionally includes sample dummies and type of household.

changers are those who experience bigger alterations of task contents, this positive association can be driven by the wage growth associated with an occupational change. Therefore, in the third column I include both these variables to show that the indicator for an occupational change is positively associated with wages, whereas the coefficient of distance is negative, though insignificant. However, the descriptive statistics show that the mean distance experienced by changers and stayers differs substantially, suggesting that the empirical specification should incorporate a differentiation for the distance measure for changers and stayers. The fourth column contains the indicator for an occupational change and its interaction with the distance measures. This specification assumes that the occupational stayers do not experience any changes in their job contents. In line with the conclusions of Gathmann and Schönberg

(2010), the estimation reveals that the positive association of occupational changes with wages decreases with the similarity of content between the source and the target occupation. This negative component can be interpreted as human capital loss after an occupational change, whereas the dummy for an occupational change can be interpreted as the improvement of the match between the employee and the occupation. The coefficients from column four help to compute the threshold for the distance of change, under which the short-term returns to an occupational change remain positive. For the upper panel, it is $Dis^A = 0.047/0.062 = 0.76$, meaning that those respondents whose task distance related to the occupational change lies below this threshold (99 percent of all changers) experience an increase in wages. For the lower panel, this threshold implies that all changers experience wage increase. The fifth column additionally controls for the content changes for occupational stayers. This estimation featuring the distance measure based on angular separation shows that, as such, an occupational change is associated with 6.7 percentage points higher wage growth. At the same time, content changes of occupational stayers generate a positive wage component, which leads to a decrease in the association of content change for occupational changers with wages (interaction term). Based on this specification, an occupational change generates positive wage returns for changers with the distance of change below $Dis^A = 0.067/0.579 = 0.12$, i.e. for 46 percent of the changers. For the Euclidean distance, we observe the same pattern, though the respective coefficients are insignificant. Thus, we see that neglecting alteration of tasks for occupational stayers leads to an overestimation of the wage benefits associated with an occupational change.

Thus, the coefficients in column five help us to detect divergent channels driving wage formation.⁶ The first channel is the positive association of the indicator variable for the occupa-

⁶The correlation between three main variables in this specification is high. The correlation between occupational change (2-digit KldB92) and the distance measure based on angular separation measure is 0.68. The correlation between occupational change (2-digit KldB92) and the interaction term is 0.75. The correlation between the measure based on angular separation and its interaction with the occupational change is 0.94.

tional change with wages, which mirrors the improvement of the quality of the match between the employee and the occupation. The second channel is represented by the interaction of this indicator with the distance variable. It reflects the loss of task-specific human capital through the occupational change. The third channel describes wage dynamics of occupational stayers who serve as the comparison group for the analysis. The positive coefficient of the distance measure for stayers implies that their experience of bigger changes within occupations helps to accumulate more profound task capital that generates positive wage returns. This component exists in addition to the positive returns to labor market experience or occupation-specific human capital that are explicitly controlled for. However, the results is not robust to the choice of the distance measure.

Table B.11 in Appendix B replicates the estimation results for equation 10 for the time periods of 1985-1991, 1991-1998, 1998-2006, and 2006-2012. Generally, the results based on subsamples confirm the findings based on the total samples. Deviating results are observed in 1991-1998 (post-unification period in Germany) and in 2006-2012 (includes the economic crisis), which points to the sensitivity of the results to institutional settings or economic conditions.

6 Estimation bias

The problem of endogeneity is inevitable and hard to overcome when analyzing the association of career choices and wages (Sullivan, 2010). In my analysis, one would expect that both main variables (the decision to change an occupation and the distance of the change) are endogenous with respect to unobservable characteristics of the respondents, such as motivation and talents, in particular tasks or occupations. Moreover, if these unobservable characteristics vary over

time, they do not vanish after an inclusion of individual fixed effects in the estimation. In order to tackle endogeneity issues when estimating equation 10, at least three instrumental variables are needed – for the indicator of the occupational change, for the distance of change, and for the content changes experienced by stayers – which is a challenge for the existing sources of identifying variation. Although the endogeneity issue cannot be addressed using an appropriate identification strategy, in the following I discuss the likely direction of the bias for the estimated association of the three relevant variables with wages.

6.1 Bias in wage returns to occupational change

With respect to the endogeneity of the occupational change itself, literature is inconclusive. The literature on voluntary job and occupational mobility shows that the group of movers is positively selected with respect to their average characteristics (Booth and Satchell, 1996; Fitzenberger and Spitz, 2004; Winkelmann, 1996). The main argument underlying this finding is that workers decide to change their job if they (at least in the long-run) expect better pecuniary or non-pecuniary career perspectives, even after accounting for possible job losses. At the same time, Addison and Portugal (1989), Neal (1999), Burda and Mertens (2001) show that involuntary job mobility primarily concerns workers with weaker labor market characteristics. Moreover, there is evidence that occupational mobility after an apprenticeship is affected by negative selectivity of movers (Von Wachter and Bender, 2006; Fitzenberger et al., 2015).

Table 2 compares wage returns to an occupational change (measured by an indicator variable) for different econometric models. The first column (OLS) contains results of an OLS regression of wage growth on an indicator of an occupational change conditional on highest educational level (3 groups); years spent in full-time employment, part-time employment, and unemployment; age and age squared; 2-digit occupational controls; 1-digit NACE dummies

(21 groups); and sets of dummies for the NUTS-1 regions, firm size, and survey year. In order to account for potential sampling differences, the specification additionally includes sample dummies and type of household. The OLS estimation shows that occupational changers experience wage growth that is by 4.5 percentage points higher than the annual wage growth of occupational stayers. The second column (FE) additionally controls for individual-specific fixed effects and replicates the main result presented in the first column of Table 1. Since the FE estimation yields a lower coefficient than the OLS, it implies that time-invariant individual heterogeneity is positive correlation with wage growth. The third column presents the results of a 2SLS-estimation of the relationship between individual wage growth and occupational change, where the occupational change from occupation o is instrumented by the share of changes from this occupation in the given year, as suggested by Von Wachter and Bender (2006). The inclusion of the instrument makes the respective coefficient negligibly small and insignificant. The fourth column (IVFE) additionally includes individual-specific fixed effects, which yields negative and insignificant estimates of the coefficient of interest. Note that the F-Statistics indicates that the first stage estimation is valid in both IV and IVFE specifications. Thus, the evidence presented in Table 2 points to positive selection of occupational movers with respect to wage growth and implies that the coefficient estimates involving the dummy for an occupational change in Table 1 are upward-biased.

6.2 Bias in wage returns to distance measures

The sign of the correlation between the distance of change and the error term is not straightforward and, moreover, can be different for occupational stayers and changers. As for the occupational changers, the most motivated and talented workers might tend to seek for jobs with substantially different task profiles, as they are flexible, learn quickly, and are ready for

Table 2: Returns to occupational change for various regression models, 1986-2012

	(1)	(2)	(3)	(4)
	OLS	FE	IV	IVFE
Occ. change	0.045*** (0.016)	0.036*** (0.013)	-0.013 (0.084)	-0.055 (0.113)
F-stat			59.255	124.573

Source: SOEP v32, working sample, own calculations. N = 39,848.

Significance levels: * 10 percent, ** 5 percent, *** 1 percent.

OLS: Robust standard errors, clustered at the level of the 2-digit KldB92. FE: Standard errors clustered at the individual and occupational levels. IV: Robust standard errors, clustered at the level of the 2-digit KldB92. IVFE: Robust standard errors.

All specifications control for the highest educational level (3 groups); years spent in full-time employment, part-time employment and unemployment; age and age squared; 2-digit occupational controls; 1-digit NACE dummies (21 groups); and sets of dummies for the NUTS-1 regions, firm size, and the survey year. In order to account for potential sampling differences, the specification additionally includes sample dummies and type of household.

challenges in new professional areas. Alternatively, most capable workers might be strategic in the use of their accumulated human capital, choosing their new occupation because it requires a similar skill profile to the one they acquired in the previous occupation. As for the occupational stayers, they can be employed in an occupation that is changing its task profile in order to better satisfy demands of the technological progress, but it also may be shifting toward tasks that are relatively less valued by the economy.

Tables B.12 and B.13 in Appendix present the results of a regression estimation of the distance measures on the available observables based on the OLS and fixed-effects estimation. For occupational changers (Table B.12), the OLS shows that both distance measures are uncorrelated with age, labor market experience and firm size. However, they are positively correlated with higher educational levels. In the fixed-effects estimation, this correlation vanishes. At the same time, in the FE estimations the correlation of the distance measures with part-time employment is negative and significant. These results point at the positive selection of respondents into distance of occupational change. Concerning occupational stayers (Table B.13), the OLS results reveal almost no correlation with age, labor market experience or firm size and a

positive correlation with higher educational levels. The latter decreases after controlling for individual fixed effects, pointing at the potential positive selection of respondents into occupations experiencing larger content changes. In sum, the results for occupational changers and stayers imply that the coefficients of the variables involving distance measures are upward-biased.

7 Conclusion

The main goal of this study is to explore the extent to which occupational tasks alter over time and how these alterations affect wage formation. My results show that annual changes in task contents are lower than task changes experienced by occupational changers, but they are greater than zero and they positively correlate with individual wage growth, revealing an additional channel (beyond tenure) of human capital accumulation. This is a new result for the literature. Concerning occupational changers, I find that bigger alterations of job contents after an occupational change are negatively related to wage growth, which may be explained by human capital losses. At the same time, the results show that these losses are even bigger when related to occupational stayers who keep accumulating human capital within their occupations. Apart from the human capital component, the results show that, as such, occupational change is positively correlated with wage growth, implying that the match between the employee and the occupation improves. Thus, the task-based evidence presented above confirms, on the one hand, the main predictions of the human capital and match theories. On the other hand, it demonstrates the importance of accounting for content similarities both between occupations and within one occupation over time when analyzing job or occupational mobility. However, the obtained results are sensitive to the choice of the distance measure and the chosen time

frame.

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A Variable description

A.1 German Employment Survey (GES)

Occupational codes and occupational change The data contain occupational codes KldB 92 at the 3- and 2-digit levels. Due to the limited number of observations that remains in each occupational group after sample restrictions, I use 2-digit occupational codes and, moreover, exclude groups with sizes below 10 in one of the survey years. This leaves me with 75 occupational groups with, on average, 90 observations per group. Given that the survey consists of cross-sections, the occupational history of the respondents can be reconstructed only based on the available retrospective information, which is scarce. The only element of the occupational history that is known is the occupation of the first vocational training (or, in some survey waves first five trainings). Therefore, using GES data alone, I am unable to accurately identify the time when an occupational change occurs and have to employ additional data that have panel structure and allow precise tracking of occupational histories.⁷

Job tasks The available information on job tasks can be used to quantify job contents and a measure of their proximity. To do this, I arrange job tasks into $J = 13$ categories that constitute dimensions of a task space and rely on questionnaire items that are comparable over the five survey waves chosen for the analysis. Table A.1 describes the dimensions of the resulting task space. The task information is then used to construct task vectors characterizing content of each occupation for each survey wave. The entries of the vector represent the fraction of

⁷Fitzenberger and Spitz (2004) study occupational mobility defined by the mismatch of the current occupation and the occupation of training. In a previous version of this paper (<http://sfb649.wiwi.hu-berlin.de/papers/pdf/SFB649DP2011-074.pdf>), I also employ the same definition on an occupational change and obtain results for the survey waves 1991 and 1998 that are comparable to those in the main part of the present paper.

respondents in an occupational group who report performing a particular task.⁸ Thus, for each occupation o and for each survey year t I obtain a 13-dimensional task vector τ_{ot} . These vectors can be used to compare task contents between occupations, as well as changes in the contents of one occupation over time. At the level of occupations, I merge these vectors to the German Socio-Economic Panel (SOEP).

Table A.1: Description of the 13 dimensions of the task space

Task (space dimensions)	Description based on the QCS questionnaires
<i>Non-routine cognitive tasks</i>	
Task 1: Research, evaluate	Analyze, research, test, evaluate information, develop
Task 2: Design, plan	Design, plan, layout
Task 3: Program	Programming, system analysis
Task 4: Execute, interpret rules	Execute, interpret rules
Task 5: Sell, buy, advertise	Sell, buy, advertise, acquire
Task 6: Teach, train	Educate/teach/train others, mentoring help
Task 7: Employ, organize	Guide/instruct employees, employ, administrate, organize, coordinate, manage personnel
<i>Routine tasks</i>	
Task 8: Operate machines	Monitor and operate machines
Task 9: Manufacture	Manufacture, production of goods and services
<i>Non-routine manual tasks</i>	
Task 10: Repair, renovate	Repair, service machines
Task 11: Serve, accommodate	Serve, accommodate, take care of others
Task 12: Pack, ship	Pack, ship, transport
Task 13: Secure	Secure, guard

Source: German Employment Survey, 1985, 1992, 1998, 2006, 2012.

A.2 Socio-Economic Panel (SOEP)

Occupational codes and occupational change The SOEP data contain detailed information on occupational codes. The empirical analysis relies on the 2-digit occupational codes given by KldB-92 (Klassifikation der Berufe 1992) and excludes occupations with fewer than 20 observations, which yields 63 groups with, on average, 72 observations per survey year. As

⁸Appendix C provides details on the coding procedure and a robustness check of the task measure.

mentioned in Longhi and Brynin (2010); Rhein et al. (2013), occupational coding in survey data is prone to errors that result in spurious indication of occupational changes and, therefore, requires additional (self-reported) information on having conducted an occupational change. Given that I use occupational codes to merge additional information and, therefore, need to rule out coding-induced occupational changes, I undertake a correction of occupational coding using the self-reported job change status since last year's interview. If the respondent reports that no job change has occurred, I replace the occupational code by the occupational code from the previous year. In this case, no occupational change is recorded. If the respondent reports a job change and there is a change in occupational codes, I record an occupational change and do not correct subsequent occupational codes.

Human capital characteristics The SOEP data provides detailed information on the highest educational level (9 groups, according to the CASMIN classification), which I aggregate to three broad groups (primary, secondary, tertiary education) for the simplicity of display. Moreover, the SOEP data provide generated indicators of aggregated experience in full-time employment, part-time employment and unemployment (measured in years).

Wages Real hourly wages result from dividing monthly earnings by monthly hours worked. I correct monthly earnings by the consumer price index (CPI) for the base year 2011, which is provided with the data. Monthly hours worked are calculated by multiplying weekly contractual working hours by the factor 4.33. The subsequent analysis features the resulting (logarithmic) real hourly wage.

B Additional tables and figures

Table B.2: Summary statistics

	Stayers	Changers	Total
Share occ. changes 2-digit	0.964	0.036	
Share occ. changes 3-digit	0.956	0.044	
Share occ. changes 4-digit	0.950	0.050	
Observations	38,396	1,452	39,848
Log real hourly wages	2.92	2.71	2.91
Δ Log real hourly wages	0.03	0.10	0.03
Age	39.92	33.75	39.70
Primary education	0.47	0.51	0.47
Secondary education	0.33	0.33	0.33
Tertiary education	0.20	0.17	0.20
Years in full time	18.23	11.75	18.00
Years in part time	0.46	0.64	0.46
Years in unemployment	0.34	0.65	0.35

Source: SOEP v32, working sample, own calculations.

Summary statistics for number of observations differentiates among occupational stayers and changers at a 2-digit level.

Stayers: respondent without an occupational change at the 2-digit level since last year, Changers: respondents with an occupational change at a 2-digit level since last year.

Table B.3: Summary statistics by time brackets

		1985-1991	1991-1998	1998-2006	2006-2012	All years
Observations	N	5,286	5,538	19,117	15,255	39,848
Share occ. changes 2-digit		0.047	0.043	0.033	0.034	0.036
Share occ. changes 3-digit		0.054	0.052	0.040	0.041	0.044
Share occ. changes 4-digit		0.061	0.059	0.046	0.047	0.050
Log real hourly wages	ST	2.78	2.84	2.95	2.95	2.92
Log real hourly wages	CH	2.65	2.73	2.74	2.71	2.71
Δ Log real hourly wages	ST	0.05	0.04	0.02	0.02	0.03
Δ Log real hourly wages	CH	0.15	0.15	0.07	0.10	0.10
Age	ST	38.71	38.28	39.50	41.20	39.92
Age	CH	29.62	31.71	33.94	36.05	33.75
Primary education	ST	0.70	0.66	0.45	0.37	0.47
Primary education	CH	0.75	0.69	0.49	0.36	0.51
Secondary education	ST	0.19	0.23	0.35	0.38	0.33
Secondary education	CH	0.19	0.18	0.33	0.43	0.33
Tertiary education	ST	0.11	0.12	0.20	0.25	0.20
Tertiary education	CH	0.06	0.13	0.18	0.21	0.17
Years in full time	ST	18.35	17.67	17.85	18.77	18.23
Years in full time	CH	9.64	10.82	11.71	13.10	11.75
Years in part time	ST	0.22	0.25	0.39	0.66	0.46
Years in part time	CH	0.17	0.43	0.58	0.95	0.64
Years in unemployment	ST	0.27	0.33	0.34	0.36	0.34
Years in unemployment	CH	0.48	0.59	0.63	0.74	0.65

Source: SOEP v32, working sample, own calculations.

Stayers (ST): respondent without an occupational change at the 2-digit level since last year, Changers (CH): respondents with an occupational change at a 2-digit level since last year.

Table B.4: Average task intensity

	1985	1991	1998	2006	2012	All years
GES						
Task 1: Research, evaluate	0.112	0.109	0.139	0.135	0.186	0.134
Task 2: Design, plan	0.046	0.034	0.040	0.093	0.034	0.051
Task 3: Program	0.021	0.039	0.011	0.021	0.107	0.033
Task 4: Execute, interpret rules	0.021	0.056	0.020	0.073	0.040	0.043
Task 5: Sell, buy, advertise	0.072	0.076	0.049	0.037	0.044	0.056
Task 6: Teach, train	0.043	0.040	0.105	0.091	0.118	0.079
Task 7: Employ, organize	0.089	0.094	0.060	0.127	0.096	0.093
Task 8: Operate machines	0.197	0.233	0.164	0.060	0.079	0.149
Task 9: Manufacture	0.107	0.093	0.099	0.080	0.106	0.095
Task 10: Repair, renovate	0.121	0.077	0.054	0.041	0.052	0.066
Task 11: Serve, accommodate	0.034	0.025	0.065	0.147	0.025	0.064
Task 12: Pack, ship	0.120	0.113	0.140	0.064	0.077	0.106
Task 13: Secure	0.018	0.012	0.055	0.032	0.035	0.032
SOEP						
Task 1: Research, evaluate	0.117	0.115	0.145	0.145	0.194	0.144
Task 2: Design, plan	0.043	0.030	0.039	0.086	0.037	0.051
Task 3: Program	0.029	0.053	0.017	0.027	0.105	0.044
Task 4: Execute, interpret rules	0.027	0.058	0.024	0.065	0.038	0.045
Task 5: Sell, buy, advertise	0.075	0.079	0.056	0.043	0.050	0.059
Task 6: Teach, train	0.045	0.039	0.111	0.109	0.141	0.095
Task 7: Employ, organize	0.092	0.097	0.068	0.122	0.105	0.098
Task 8: Operate machines	0.172	0.211	0.145	0.049	0.062	0.118
Task 9: Manufacture	0.103	0.074	0.084	0.064	0.084	0.077
Task 10: Repair, renovate	0.133	0.096	0.060	0.040	0.052	0.068
Task 11: Serve, accommodate	0.012	0.011	0.056	0.159	0.023	0.065
Task 12: Pack, ship	0.132	0.123	0.142	0.061	0.076	0.104
Task 13: Secure	0.020	0.012	0.053	0.029	0.033	0.032

Source: SOEP v32 and German Employment Survey, working sample, own calculations.

Table B.5: Average task intensity of clerks

	1985	1991	1998	2006	2012	All years
GES						
Task 1: Research, evaluate	0.055	0.046	0.145	0.154	0.190	0.119
Task 2: Design, plan	0.050	0.020	0.077	0.093	0.088	0.066
Task 3: Program	0.111	0.199	0.019	0.018	0.109	0.083
Task 4: Execute, interpret rules	0.105	0.082	0.054	0.056	0.046	0.066
Task 5: Sell, buy, advertise	0.286	0.267	0.170	0.086	0.102	0.178
Task 6: Teach, train	0.040	0.038	0.188	0.135	0.214	0.125
Task 7: Employ, organize	0.193	0.185	0.140	0.127	0.115	0.151
Task 8: Operate machines	0.042	0.027	0.032	0.020	0.025	0.028
Task 9: Manufacture	0.007	0.006	0.008	0.030	0.029	0.015
Task 10: Repair, renovate	0.013	0.007	0.008	0.006	0.005	0.007
Task 11: Serve, accommodate	0.002	0.003	0.078	0.198	0.005	0.072
Task 12: Pack, ship	0.082	0.117	0.060	0.062	0.056	0.076
Task 13: Secure	0.015	0.002	0.021	0.016	0.017	0.014

Source: German Employment Survey, working sample, own calculations. Shares based on SOEP v32 are, by construction, identical.

Table B.6: Distance measures for occupational stayers and changers

		Stayers	Changers	Total
Dis ^A	mean	0.035	0.190	0.041
	sd	0.014	0.166	0.045
Dis ^E	mean	0.037	0.239	0.045
	sd	0.012	0.159	0.050

Source: SOEP v32, working sample, own calculations. N = 39,848.

Table B.7: Distance measures for occupational stayers and changers by time brackets

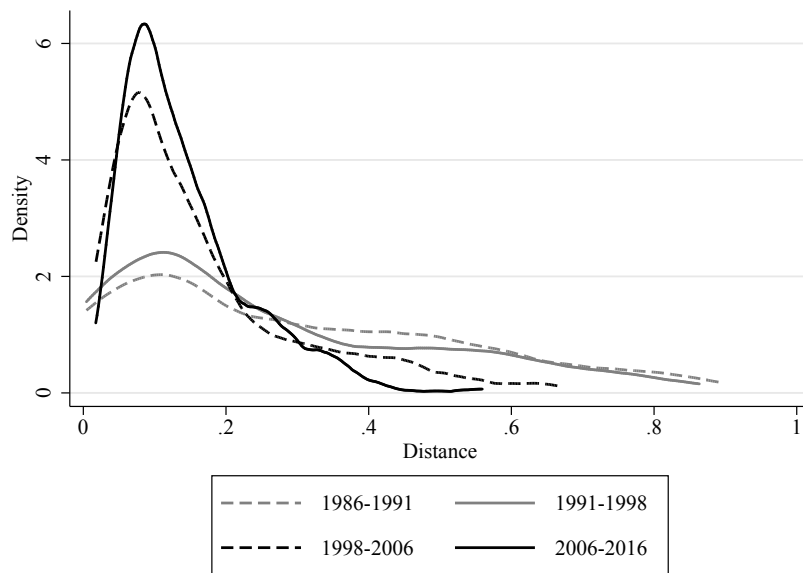
	1985-1991	1991-1998	1998-2006	2006-2012	All years
Changers					
Dis ^A	0.292	0.260	0.168	0.142	0.190
sd	0.234	0.220	0.136	0.089	0.166
Dis ^E	0.385	0.343	0.205	0.178	0.239
sd	0.203	0.195	0.126	0.078	0.159
Stayers					
Dis ^A	0.016	0.021	0.038	0.041	0.035
sd	0.009	0.011	0.011	0.012	0.014
Dis ^E	0.029	0.036	0.036	0.042	0.037
sd	0.012	0.013	0.012	0.009	0.012

Source: SOEP v32, working sample, own calculations. N = 39,848.

Table B.8: The shortest and longest distances among changers and stayers 1985-2012

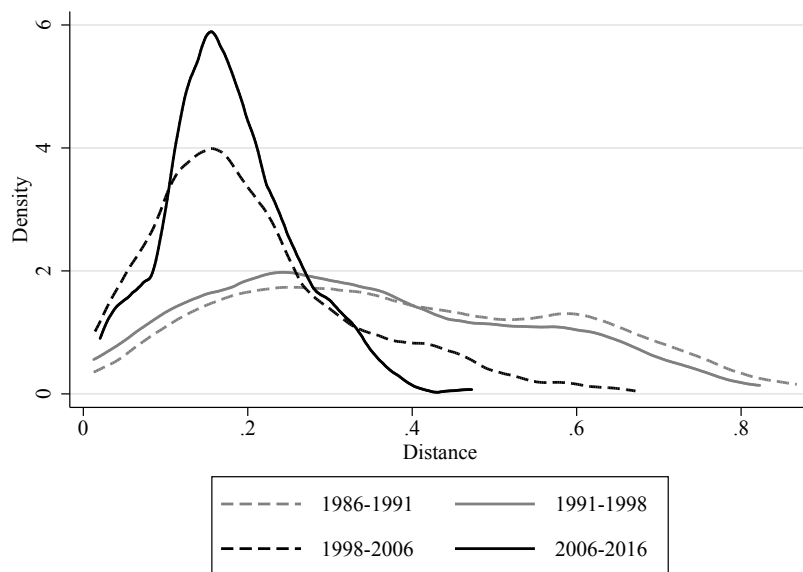
Longest distance			
	Measure	From:	To:
Changers	Dis^A	91 Hotels and restaurants	22 Machining metal forming
	Dis^E	91 Hotels and restaurants	22 Machining metal forming
Stayers	Dis^A	79 Security guard	
	Dis^E	7 Mineworkers	
Shortest distance			
	Measure	From:	To:
Changers	Dis^A	32 Assembler	14 Chemical professions
	Dis^E	29 Tool/mould construction	27 Machine construction/maintenance
Stayers	Dis^A	64 Technical draftsmen	
	Dis^E	74 Warehouse and transport workers	

Source: SOEP v32, working sample, own calculations. N = 39,848.



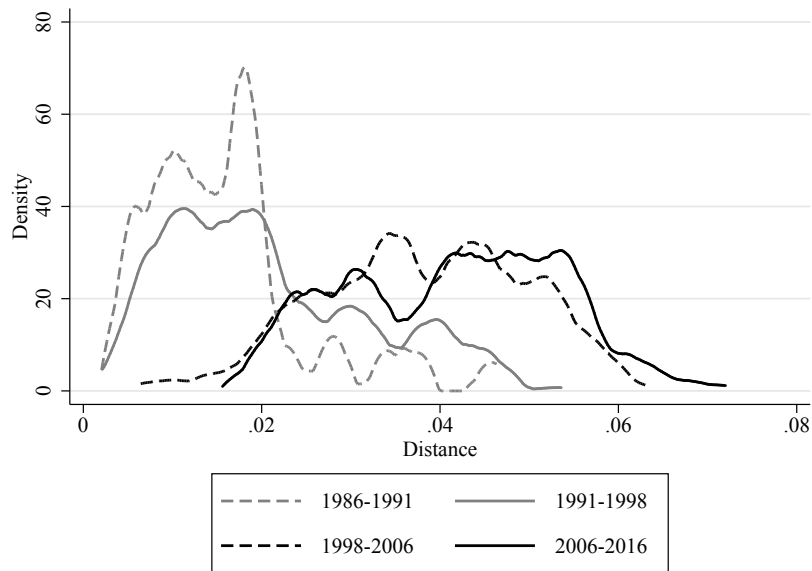
Notes: SOEP v32, working sample, own calculations.

Figure B.1: Distribution of the distance measure based on angular separation for occupational changers over time



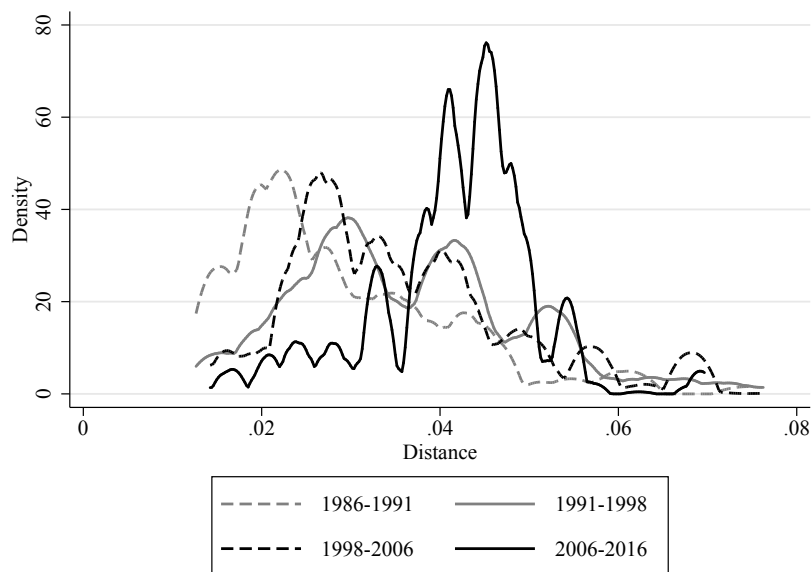
Notes: SOEP v32, working sample, own calculations.

Figure B.2: Distribution of the Euclidean distance measure for occupational changers over time



Notes: SOEP v32, working sample, own calculations.

Figure B.3: Distribution of the distance measure based on angular separation for occupational stayers over time



Notes: SOEP v32, working sample, own calculations.

Figure B.4: Distribution of the Euclidean distance measure for occupational stayers over time

Table B.9: The longest distances among occupational changers and stayers

Longest distance				
	Measure	Years	From:	To:
Changers	<i>Dis^A</i>	1985-1991	91 Hotels and restaurants	22 Machining metal forming
	<i>Dis^A</i>	1991-1998	22 Machining metal forming	67 Wholesale and retail sales
	<i>Dis^A</i>	1998-2006	71 Surface transport	78 Office and commercial clerks
	<i>Dis^A</i>	2006-2012	69 Banking, home loans, insurance specialists	71 Surface transport
	<i>Dis^E</i>	1985-1991	91 Hotels and restaurants	22 Machining metal forming
	<i>Dis^E</i>	1991-1998	85 Other health service professions	74 Warehouse and transport workers
	<i>Dis^E</i>	1998-2006	71 Surface transport	78 Office and commercial clerks
	<i>Dis^E</i>	2006-2012	69 Banking, home loans, insurance specialists	71 Surface transport
Stayers	<i>Dis^A</i>	1985-1991	80 Security occupations	
	<i>Dis^A</i>	1991-1998	65 Training supervisors, industry masters, foremen	
	<i>Dis^A</i>	1998-2006	46 Underground construction	
	<i>Dis^A</i>	2006-2012	79 Security guard	
	<i>Dis^E</i>	1985-1991	7 Mineworkers	
	<i>Dis^E</i>	1991-1998	7 Mineworkers	
	<i>Dis^E</i>	1998-2006	7 Mineworkers	
	<i>Dis^E</i>	2006-2012	81 Occupations in enforcement and legal system	

Source: SOEP v32, working sample, own calculations. N = 39,848.

Table B.10: The shortest distances among occupational changers and stayers

Shortest distance				
	Measure	Years	From:	To:
Changers	Dis ^A	1985-1991	32 Assembly workers and metal professions	14 Chemical professions
	Dis ^A	1991-1998	32 Assembly workers and metal professions	54 Machine/systems operators
	Dis ^A	1998-2006	74 Warehouse and transport workers	71 Surface transport
	Dis ^A	2006-2012	60 Engineers	64 Technical draftsmen
	Dis ^E	1985-1991	32 Assembly workers and metal professions	14 Chemical professions
	Dis ^E	1991-1998	60 Engineers	61 Chemists, physicists, mathematicians
	Dis ^E	1998-2006	50 Wood and plastic processing	27 Machine construction/maintenance
	Dis ^E	2006-2012	29 Tool and mold making	27 Machine construction/maintenance
Stayers	Dis ^A	1985-1991	64 Technical draftsmen	
	Dis ^A	1991-1998	73 Communication	
	Dis ^A	1998-2006	71 Surface transport	
	Dis ^A	2006-2012	81 Occupations in enforcement and legal system	
	Dis ^E	1985-1991	74 Warehouse and transport workers	
	Dis ^E	1991-1998	74 Warehouse and transport workers	
	Dis ^E	1998-2006	87 Teachers	
	Dis ^E	2006-2012	87 Teachers	

Source: SOEP v32, working sample, own calculations. N = 39,848.

Table B.11: Returns to occupational change and distance measures by time brackets

	(1) 1985-1991	(2) 1991-1998	(3) 1998-2006	(4) 2006-2012
Occ. change	0.122* (0.063)	0.103** (0.051)	0.041 (0.026)	0.076** (0.038)
Occ. change \times Dis ^A	-1.257 (1.548)	0.529 (1.104)	-0.707** (0.302)	-0.295 (0.747)
Dis ^A	1.256 (1.523)	-0.656 (1.077)	0.686** (0.273)	0.130 (0.839)
r2	0.371	0.405	0.139	0.203
Occ. change	0.228** (0.099)	0.156** (0.060)	0.006 (0.032)	0.052 (0.052)
Occ. change \times Dis ^E	-3.748* (2.161)	-0.319 (0.659)	-0.140 (0.414)	0.031 (0.452)
Dis ^E	3.687* (2.134)	0.113 (0.610)	0.199 (0.430)	-0.073 (0.483)
r2	0.372	0.405	0.139	0.203

Source: SOEP v32, working sample, own calculations.

Significance levels: * 10 percent, ** 5 percent, *** 1 percent.

Fixed effects with standard errors clustered at individual and occupational levels.

All specifications control for the highest educational level (3 groups); years spent in full-time employment, part-time employment and unemployment; age and age squared; 2-digit occupational controls; 1-digit NACE dummies (21 groups); sets of dummies for the NUTS-1 regions; firm size; and the survey year. In order to account for potential sampling differences, the specification additionally includes sample dummies and type of household.

Table B.12: Factors explaining the distance measure for occupational changers, 1986-2012

	(1) Dis ^A , OLS	(2) Dis ^E , OLS	(3) Dis ^A , FE	(4) Dis ^E , FE
Age	0.000 (0.001)	0.000 (0.001)	0.020 (0.030)	0.024 (0.028)
Years in full time	0.001 (0.001)	0.000 (0.001)	0.021 (0.039)	-0.001 (0.034)
Years in part time	0.002 (0.003)	0.002 (0.002)	-0.063 (0.054)	-0.078* (0.046)
Years in unemployment	0.002 (0.002)	0.001 (0.002)	0.018 (0.056)	-0.028 (0.049)
Secondary education	0.046*** (0.017)	0.039*** (0.014)	0.000 (0.128)	0.019 (0.122)
Tertiary education	0.034** (0.013)	0.028** (0.012)	0.073 (0.107)	0.061 (0.109)
Firm with 20 to \leq 200 workers	-0.005 (0.011)	-0.007 (0.010)	0.006 (0.026)	0.020 (0.022)
Firm with 200 to \leq 2000 workers	-0.020 (0.014)	-0.020 (0.012)	-0.011 (0.027)	-0.011 (0.023)
Firm with more than 2000 workers	-0.009 (0.012)	-0.007 (0.011)	-0.040 (0.033)	-0.035 (0.030)
Constant	-0.086 (0.067)	0.016 (0.065)		

Source: SOEP v32, working sample, subsample of occupational changers, own calculations. N = 1,452.

Significance levels: * 10 percent, ** 5 percent, *** 1 percent.

OLS: Standard errors are clustered at the occupational level of the 2-digit KldB92. FE: Standard errors are clustered at the individual and occupational levels.

All specifications additionally include 2-digit occupational controls; 1-digit NACE dummies (21 groups); and sets of dummies for the NUTS-1 regions, and the survey year. In order to account for potential sampling differences, the specification additionally includes sample dummies and type of household.

Table B.13: Factors explaining the distance measure for occupational stayers, 1986-2012

	(1) Dis ^A , OLS	(2) Dis ^E , OLS	(3) Dis ^A , FE	(4) Dis ^E , FE
Age	0.000 (0.000)	0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)
Years in full time	-0.000 (0.000)	-0.000 (0.000)	0.001** (0.000)	-0.000 (0.000)
Years in part time	-0.000* (0.000)	-0.000** (0.000)	0.001** (0.000)	-0.001** (0.000)
Years in unemployment	0.000* (0.000)	-0.000 (0.000)	0.002*** (0.000)	-0.000 (0.000)
Secondary education	0.001** (0.000)	0.000 (0.000)	0.003 (0.002)	0.002 (0.002)
Tertiary education	0.001*** (0.000)	0.000 (0.000)	0.003* (0.001)	0.002 (0.001)
Firm with 20 to \leq 200 workers	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Firm with 200 to \leq 2000 workers	-0.000 (0.000)	-0.000 (0.000)	0.001 (0.000)	0.000 (0.000)
Firm with more than 2000 workers	-0.000 (0.000)	0.000 (0.000)	0.001 (0.000)	0.000 (0.000)
Constant	0.021*** (0.002)	0.050*** (0.003)		

Source: SOEP v32, working sample, subsample of occupational stayers, own calculations. N = 38,396.

Significance levels: * 10 percent, ** 5 percent, *** 1 percent.

OLS: Standard errors are clustered at the occupational level of the 2-digit KldB92. FE: Standard errors are clustered at the individual and occupational levels.

All specifications additionally include 2-digit occupational controls and sets of dummies for the NUTS-1 regions, survey year, sample dummies and type of household.

C Robustness of the task measure

One of the challenges in working with the task data in GES lies in the changes in the questionnaires over time. In the following, I explain main differences in the waves of questionnaires, thus allowing for different coding possibilities. I also present estimation results that are based on an alternative coding.

For the construction of the distance measures, I relied on both questions relating to task, as well as to tools and knowledge required in the occupations. Some of these questions have only two answer categories (such as “task belongs to the respondent’s job” or “does not belong to respondent’s the job”) and can unambiguously be coded as binary variables. Other questions foresee three answer categories, which also differ over time. In 1985, answer categories for task questions entail categories “task not mentioned,” “task belongs to the respondent’s job,” and “respondent’s main task.” In 1992, task questions are binary. In 1998, task questions foresee three answer categories – “usual task,” “rare task,” or “task does not belong to the respondent’s job.” In 2006 and 2012, the wording slightly changes to “task performed frequently,” “task performed sometimes,” and “task not performed.” These differences in wording require decisions on when to count a task as being a part of the respondent’s job. In the main part of the paper, I assumed that the respondent performs a particular task if it belongs to the job or is the main task in 1985, if it mentioned in 1992, if it is a usual task in 1998, and if it is a frequently performed task in 2006 and 2012. Such classification allows for the plausible distribution of respondents among tasks. However, in order to explicitly check the sensitivity of the results to the decisions made by the task classification, I construct a task measure that relies on an alternative classification of tasks. For this measure, I assume that the respondent performs a particular task, if it is his main task in 1985, if it is mentioned in 1992, if it is a

usual or rare task in 1998, and if it is frequently or sometimes performed in 2006 and 2012. Note that these differences are alleviated by the construction of the task measure, first, because other binary questions also enter the calculation of the task measure and, second, because the information on the individual tasks is then related to the total number of tasks performed by the respondents (see equation 8).

Table C.14 provides the replication of the main results from Table 1 featuring distance measures that stem from an alternative task classification, as described above. The result based on the angular separation remain qualitatively unchanged. The results based on the Euclidean measure remain unchanged up to the specification 5, where the coefficients flip the signs while remaining insignificant. The estimation with the alternative task classification suggests that the angular separation measure is more resistant to alterations in the task information than the Euclidean distance measure.

Table C.14: Returns to occupational change and distance measures, alternative task classification

	(1)	(2)	(3)	(4)	(5)
Occ. change	0.036*** (0.013)		0.038** (0.016)	0.042** (0.018)	0.074*** (0.026)
Dis ^A		0.076 (0.062)	-0.023 (0.075)		0.589* (0.350)
Occ. change × Dis ^A				-0.043 (0.080)	-0.664* (0.374)
r2	0.145	0.145	0.145	0.145	0.145
	(1)	(2)	(3)	(4)	(5)
Occ. change	0.036*** (0.013)		0.041** (0.017)	0.041** (0.019)	0.036* (0.019)
Dis ^E		0.104 (0.073)	-0.049 (0.097)		-0.259 (0.298)
Occ. change × Dis ^E				-0.037 (0.098)	0.212 (0.307)
r2	0.145	0.145	0.145	0.145	0.145

Source: SOEP v32, working sample, own calculations. N = 39,8448.

Significance levels: * 10 percent, ** 5 percent, *** 1 percent.

Fixed effects with standard errors clustered at individual and occupational levels.

All specifications control for the highest educational level (3 groups); years spent in full-time employment, part-time employment and unemployment; age and age squared; 2-digit occupational controls; 1-digit NACE dummies (21 groups); sets of dummies for the NUTS-1 regions; firm size; and the survey year. In order to account for potential sampling differences, the specification additionally includes sample dummies and type of household.

D Online Appendix

Table D.15: Returns to occupational change and distance
measure based on angular separation (full results), 1986-
2012

	(1)	(2)	(3)	(4)	(5)
Occ. change	0.036*** (0.013)		0.041** (0.018)	0.047** (0.020)	0.067*** (0.021)
Dis ^A		0.077 (0.057)	-0.038 (0.078)		0.506* (0.255)
Occ. change × Dis ^A				-0.062 (0.080)	-0.579** (0.255)
Primary education	-0.010 (0.072)	-0.010 (0.071)	-0.010 (0.072)	-0.010 (0.072)	-0.009 (0.071)
Secondary education	-0.047 (0.073)	-0.047 (0.073)	-0.047 (0.073)	-0.047 (0.073)	-0.046 (0.072)
Working Experience Full-Time Employment	0.011* (0.006)	0.011* (0.006)	0.011* (0.006)	0.011* (0.006)	0.011* (0.006)
Working Experience Part-Time Employment	0.010** (0.004)	0.010** (0.004)	0.010** (0.004)	0.010** (0.004)	0.010** (0.004)
Unemployment Experience	0.021 (0.013)	0.021 (0.013)	0.021 (0.013)	0.021 (0.013)	0.020 (0.013)
Age	-0.017**	-0.017**	-0.017**	-0.017**	-0.017**

	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Age squared	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Firm size GE 20, LT 200	0.011	0.011	0.011	0.011	0.011
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Firm size GE 200, LT 2000	0.011	0.012	0.011	0.011	0.011
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Firm size more than 2000	0.014	0.015	0.014	0.014	0.014
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
NUTS1: Hamburg	0.022	0.020	0.022	0.023	0.022
	(0.036)	(0.036)	(0.036)	(0.036)	(0.036)
NUTS1: Lower Saxony	-0.013	-0.014	-0.012	-0.012	-0.014
	(0.041)	(0.041)	(0.041)	(0.041)	(0.041)
NUTS1: Bremen	-0.096**	-0.099**	-0.095**	-0.095**	-0.095**
	(0.046)	(0.047)	(0.046)	(0.046)	(0.047)
NUTS1: North Rhine-Westphalia	0.026	0.026	0.027	0.027	0.025
	(0.055)	(0.054)	(0.055)	(0.055)	(0.055)
NUTS1: Hesse	-0.057	-0.058	-0.056	-0.056	-0.058
	(0.066)	(0.066)	(0.066)	(0.065)	(0.065)
NUTS1: Rhineland-Palatinate	-0.053	-0.053	-0.052	-0.052	-0.053
	(0.054)	(0.054)	(0.054)	(0.054)	(0.054)
NUTS1: Baden-Wuerttemberg	-0.007	-0.007	-0.007	-0.006	-0.008
	(0.049)	(0.049)	(0.049)	(0.049)	(0.049)

NUTS1: Bavaria	-0.021	-0.021	-0.020	-0.020	-0.022
	(0.053)	(0.052)	(0.053)	(0.053)	(0.053)
NUTS1: Saarland	-0.014	-0.015	-0.013	-0.013	-0.015
	(0.054)	(0.053)	(0.053)	(0.053)	(0.054)
<hr/>					
r ²	0.145	0.145	0.145	0.145	0.145
<hr/>					

Source: SOEP v32, working sample, own calculations. N = 39,848.

Significance levels: * 10 percent, ** 5 percent, *** 1 percent.

Fixed effects with standard errors, clustered at the level of occupations and individuals.

All specifications control for the highest educational level (3 groups); years spent in full-time employment, part-time employment, and unemployment; age and age squared; 2-digit occupational controls; 1-digit NACE dummies (21 groups); sets of dummies for the NUTS-1 regions; firm size; and the survey year. In order to account for potential sampling differences, the specification additionally includes sample dummies and type of household.

Table D.16: Returns to occupational change and Euclidean
distance measure (full results), 1986-2012

	(1)	(2)	(3)	(4)	(5)
Occ. change	0.036***		0.041*	0.045*	0.049**
	(0.013)		(0.021)	(0.024)	(0.024)
Dis ^E		0.093*	-0.029		0.132
		(0.050)	(0.078)		(0.238)
Occ. change × Dis ^E				-0.038	-0.171
				(0.082)	(0.249)
Primary education	-0.010	-0.009	-0.010	-0.010	-0.009
	(0.072)	(0.071)	(0.072)	(0.072)	(0.071)
Secondary education	-0.047	-0.046	-0.047	-0.047	-0.046
	(0.073)	(0.072)	(0.073)	(0.073)	(0.072)
Working Experience Full-Time Employment	0.011*	0.011*	0.011*	0.011*	0.011*
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Working Experience Part-Time Employment	0.010**	0.010**	0.010**	0.010**	0.010**
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Unemployment Experience	0.021	0.021	0.021	0.021	0.021
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Age	-0.017**	-0.017**	-0.017**	-0.017**	-0.017**
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Age squared	0.000***	0.000***	0.000***	0.000***	0.000***

	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Firm size GE 20, LT 200	0.011	0.011	0.011	0.011	0.011
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Firm size GE 200, LT 2000	0.011	0.012	0.011	0.011	0.011
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Firm size more than 2000	0.014	0.015	0.014	0.014	0.014
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
NUTS1: Hamburg	0.022	0.020	0.022	0.022	0.022
	(0.036)	(0.036)	(0.036)	(0.036)	(0.036)
NUTS1: Lower Saxony	-0.013	-0.014	-0.013	-0.012	-0.012
	(0.041)	(0.041)	(0.041)	(0.041)	(0.041)
NUTS1: Bremen	-0.096**	-0.099**	-0.095**	-0.095**	-0.095**
	(0.046)	(0.046)	(0.046)	(0.046)	(0.046)
NUTS1: North Rhine-Westphalia	0.026	0.026	0.026	0.027	0.027
	(0.055)	(0.055)	(0.055)	(0.055)	(0.055)
NUTS1: Hesse	-0.057	-0.058	-0.057	-0.056	-0.056
	(0.066)	(0.066)	(0.066)	(0.065)	(0.065)
NUTS1: Rhineland-Palatinate	-0.053	-0.054	-0.053	-0.053	-0.053
	(0.054)	(0.054)	(0.054)	(0.054)	(0.054)
NUTS1: Baden-Wuerttemberg	-0.007	-0.008	-0.007	-0.006	-0.006
	(0.049)	(0.049)	(0.049)	(0.049)	(0.049)
NUTS1: Bavaria	-0.021	-0.022	-0.020	-0.020	-0.020
	(0.053)	(0.053)	(0.053)	(0.053)	(0.053)

NUTS1: Saarland	-0.014	-0.015	-0.014	-0.013	-0.013
	(0.054)	(0.054)	(0.054)	(0.053)	(0.053)
r2	0.145	0.145	0.145	0.145	0.145

Source: SOEP v32, working sample, own calculations. N = 39,848.

Significance levels: * 10 percent, ** 5 percent, *** 1 percent.

Fixed effects with standard errors, clustered at the level of occupations and individuals.

All specifications control for the highest educational level (3 groups); years spent in full-time employment, part-time employment, and unemployment; age and age squared; 2-digit occupational controls; 1-digit NACE dummies (21 groups); sets of dummies for the NUTS-1 regions; firm size; and the survey year. In order to account for potential sampling differences, the specification additionally includes sample dummies and type of household.

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