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Occupation-specific matching efficiency

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Abstract

Based on rich administrative data from Germany, we address the differences in occupation specific job-matching processes where an occupation consists of jobs that share extensive commonalities in their required skills and tasks. These differences can be explained by the degree of standardization (determined by the existence of certifications or legal regulations) in an occupation and the diversity of tasks in an occupation. We find that the matching efficiency improves with higher degrees of standardization and lower task diversity. We discuss the possible mechanisms of these empirical findings in a search theoretic model: as the standardization of an occupation increases or the diversity of tasks decreases, search costs decrease and the optimal search intensity increases. However, the model reveals that higher search intensities can have positive or negative effects on the matching efficiency. We discuss the conditions under which the empirical results can be predicted.

Zusammenfassung

Auf der Grundlage eines umfangreichen administrativen Datensatzes für den deutschen Arbeitsmarkt untersuchen wir die Unterschiede in berufsspezifischen Matchingprozessen. Ein Beruf besteht hierbei aus Jobs, die sich durch Gemeinsamkeiten in den erforderlichen Kenntnissen und Tätigkeiten auszeichnen. Wir zeigen, dass diese Unterschiede durch berufsspezifische Eigenschaften erklärt werden können. Zum einen spielt der Grad der Standardisierung eines Berufes eine Rolle, der durch das Vorhandensein von Ausbildungsvorschriften oder einer gesetzlichen Reglementierung bestimmt wird. Zum anderen kann ein Einfluss der Diversität der Tätigkeiten, sog. Tasks, in einem Beruf nachgewiesen werden. Unsere Ergebnisse zeigen, dass die Matchingeffizienz mit einem höheren Grad der Standardisierung und einer niedrigeren Diversität der Tasks steigt. Die möglichen Mechanismen, die unseren Befunden zugrundeliegen, diskutieren wir in einem suchtheoretischen Modell: mit zunehmenden Grad der Standardisierung und abnehmender Diversität der Tasks nehmen die Suchkosten ab und die optimale Suchintensität zu. Allerdings ergibt sich aus dem Modell, dass eine höhere Suchintensität sowohl positive als auch negative Auswirkungen auf die Matching-Effizienz haben kann. Daher diskutieren wir die Bedingungen, unter denen die empirischen Ergebnisse vorhergesagt werden.

JEL classification: C23, J44, J64

Keywords: search costs, unemployment, vacancies, job matching model, occupational licensing and certifications, occupational tasks

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1 Introduction

The efficiency of job matching processes determines crucially the extent of unemployment. Thus, information about the efficiency and its determinants are important for labour market policy decisions. At the beginning of search and matching processes, firms and workers fix further aspects of their search behaviour along their expectations to be successful; one of these aspects is the choice of occupation[1] they plan to search in.
Studies showed already that the efficiency of matching processes in occupational labour markets are quite different due to specific tightening on these markets and due to the different necessary efforts to find a job or a worker, respectively (compare, e.g., Fahr/Sunde, 2004; Stops/Mazzoni, 2010). However, not much is known about the determinants of the latter differences. We argue that, beside other factors, the extent of labour market transparency is one of these determinants and that occupation-specific properties might influence it. We consider two occupational properties: firstly, the degree of standardization of an occupation, which depends on the existence or non-existence of legal regulations or formal skill requirements to perform a job, and, secondly, the diversity of tasks in an occupation, which is based on the shares of different types of tasks that individuals have to perform in these occupations.
We explain why an increase of the degree of an occupation's standardization reduces the information asymmetries between a firm and a worker. We define occupations as standardized when there is a particular corresponding professional qualification with curricula and/or final examinations that are uniform under federal or state law or bound to legal and administrative regulations. Such occupations serve as an orientation for actors in the labor market by providing information about the skills of a potential applicant that would meet the requirements of a job (Beck/Brater/Daheim, 1980). Thus, as standardized occupations potentially reduce information asymmetries, the efforts that must be undertaken to obtain further information about – and to find – these jobs that are worth applying for decrease. Next, we map a second assumption on the task diversity of an occupation: as the diversity of tasks increases, the information asymmetries between a firm and a worker increase. If a job requires high task diversity, a firm must investigate more extensively whether an applicant is the correct hire. Furthermore, applicants also must exert greater efforts to determine whether a job is suitable.
However, it is hardly possible to observe individual search processes, and relevant analyses in this field are based on macroeconomic matching functions that model the dependency of the number of flows into employment on the number of job seekers and vacancies; for an overview of the foregoing, compare the surveys of Petrongolo/Pissarides (2001); Rogerson/Shimer/Wright (2005); Yashiv (2007). We estimate such matching functions, which also consider matching productivities that differ in occupational labor markets and are partly explained by occupation-specific properties. Accordingly, we derive the indicators for both occupation-specific properties from the German BERUFENET, an administrative expert database that contains information that is quite similar to the US O*NET. The estimations are based on a recent, detailed and high-frequency administrative panel

[1] A part of the literature refers to "job titles" instead of the term "occupations". Both terms can be handled as synonyms and should be understood as jobs that share extensive commonalities in their required skills and tasks.

dataset for small regional areas and occupations. We find that matching efficiency increases with the degree of standardization and decreases with the diversity of tasks.

To explain our results, we develop a search theoretic model that is based on the "bulletin board" matching process model conceived by Hall (1979) and Pissarides (1979). To our knowledge, we are the first to establish the assumption that the search costs are specific to the occupation where the search takes place. We enhance that model with two components involving search costs that are driven by the degree of standardization of an occupation (which leads to a positive impact on optimal search intensity in terms of the optimal number of applications) and the degree of diversity of tasks (which leads to a negative impact on the optimal search intensity). Moreover, we show that both components influence the matching efficiency; the plausible reason for this result is that, ceteris paribus, the matching efficiency is influenced by the optimal search intensity. The model reveals that a higher search intensity can lead to either positive or negative effects on matching efficiency: from the employer's perspective, a higher search intensity leads to a higher probability of recruiting the right worker(s), whereas from the employee's perspective, the job-finding rate decreases as the number of applications on the market increases. Thus, the theoretically derived effects do not reveal a clear direction, and we instead focus on the conditions under which the empirical results would be predicted.

The remainder of this paper is organized as follows. In section 2, we give an overview of the literature on both occupational indicators. In section 3, we describe the data and the construction of the indicators and provide descriptive statistics. Section 4 includes the empirical strategy, estimation results and some robustness checks based on alternative operationalizations of the indicators. In section 5 we discuss our theoretical framework and the conditions that explain the empirical results. Finally, we summarize our findings in section 6.

2 Literature on occupational standardization and task diversity

Regarding the indicators for the standardization of an occupation, our analysis refers to the stream of literature related to occupational licensing. As Kleiner (2006: p.3) notes, this is a topic that is already quite important as part of the European Economic Policy in the 18th century and is discussed by Adam Smith's "Wealth of Nations" (compare, e.g., with Smith, 1990: Book I, Chapter 10, Part II). Smith refers to the effects of occupational licensing on competition in labor and goods markets, with the result that there are positive wage effects for employers who offer apprenticeships and grant licenses and somewhat negative effects for the apprentices on prices, which tend to be higher, and on occupational and regional mobility, which will become more difficult. The persistence of the positive wage effects in licensed occupations is demonstrated by Weeden (2002), among others, for the US labor market and Bol/Weeden (2014) for the European market, while Damelang/Schulz/Vicari (2015), among others, display empirical evidence of mobility hurdles for standardized or licensed occupations. Kleiner (2006) also indicates that some of these issues that arise due to licensing might be avoided by occupational certification.[2] Our standardization in-

[2] According to Kleiner (2006: p.7), "[...] Licensing is contrasted with certification because, with certification, any person can perform the relevant tasks, but the government or generally another nonprofit agency ad-

dicator is equivalent to either occupational licensing or certification, and we point to another important effect: the contribution of licensing and certification to reducing information asymmetries between labor supply and labor demand. We suggest that this is part of the explanation for why people with a license are more likely to be employed, as has recently been found by Gittleman/Klee/Kleiner (2015).

Regarding the indicator on task diversity, our analysis refers to the tasks within the task-based approach (TBA) as developed and defined by Autor/Levy/Murnane (2003). Thus far, tasks have been applied mainly to explain the rising wage inequality in many industrialized countries by a change of tasks: machines substitute for routine tasks and complement non-routine tasks. Therefore, the wages of high-skilled and low-skilled individuals increase relative to the wages of medium-skilled individuals, who are more likely to perform routine tasks (Autor/Katz/Kearney, 2008; Autor, 2013; Autor/Dorn, 2013). To measure task diversity, we consider the composition of task types for each single occupation and use the variance of this composition as an indicator of task diversity. Therefore, our paper is also the first to measure task diversity and to test the effects of task diversity on the matching efficiency in occupational labor markets.

3 Data

We employ a unique administrative panel dataset for 309 occupational groups in 402 NUTS3 regions with 138 observation periods measured from January 2000 to June 2011. The occupational groups (3-digit level) are coded based on the German Classification of Occupations 1988 (KldB 1988). All the data stem from the German Federal Employment Agency.

We use monthly data regarding stocks, inflows, and outflows of unemployment and registered vacancies. To obtain unbiased matching parameter estimations, we adjust the dataset by observations for occupations and NUTS3 regions, respectively, where vacancies, unemployment or flows into employment are zero. This process leads to an unbalanced panel data structure with 2,365,080 observations. Table 1 shows some descriptive statistics for the aggregated stocks and flows from the dataset.

Table 1: Descriptive statistics

Measure	Monthly averages 1/2000-6/2011 (in 1,000)
Unemployment outflows M	259
Unemployment stock U	3,750
Registered vacancies stock V	332

Source: Administrative data from the Statistics Department of the Federal Employment Agency 2000-2011.
Note: Own calculations of average stocks and flows.

ministers an examination and certifies those who have passed, as well as identifies the level of skill and knowledge for certification.[...]"

To derive occupation-specific properties, we use data from BERUFENET, which is a free online information portal provided by the German Federal Employment Agency for all occupations known in Germany that is used mainly for career guidance and job placement.[3] Occupational titles are included in BERUFENET if there is a corresponding initial or further vocational training or degree that is regulated legally or quasi-legally or if an occupational activity is relevant for the labor market. This holds if the occupational title is used in collective agreements, if a certain number of employees are working in equivalent jobs or if generally binding further trainings are available for this occupation. In summary, BERUFENET includes nearly all occupational titles used in Germany (Matthes/Burkert/Biersack, 2008).

Currently, BERUFENET describes approximately 3,900 single occupations,[4] providing a rich set of occupational information (such as information on the required qualifications and requirements in an occupational activity, the equipment used, working conditions, potential specializations or further training, and legal regulations). We use occupations at the 3-digit level of KldB 1988 to provide both occupation-specific indicators for both standardization and diversity of tasks.

For the first indicator, we use the operationalization of Vicari (2014): The information on the standardization of the corresponding professional qualification is available from BERUFENET under the attribute "Career Group" describing the "entry requirements [of the occupation] in terms of a required qualification" (Bundesagentur für Arbeit, 2011). In accordance with the Career Group, the professional qualification of each single occupation is classified as either requiring a standardized certification or an unstandardized certification. Additionally, the attribute "legal regulation", which is also available in BERUFENET, is used to adjust the standardization of occupations. Legal regulations, such as occupational licensing, control entry into an occupation by imposing minimum qualification requirements (Kleiner, 2000; Weeden, 2002). To be able to practice the professional activity of a regulated occupation and to use the specific job title associated with such occupation, proof is required of a certified professional qualification that is governed by legal and administrative regulations (Bundesagentur für Arbeit, 2015). This requirement applies to occupations in which the professional activity must meet specific quality standards to protect the general public interest, such as medical doctors, lawyers, teachers, etc. To compute the indicator, Vicari (2014) combines information from the Career Group and legal regulation for the year 2012. We assume that the information from this year is also valid for the observation period of our data. For our analysis, we employ the indicator aggregated to occupational orders at the 3-digit level. For the aggregation, each single occupation at the 7-digit level is weighted with the number of all employees at the 7-digit level divided by the number of employees at the 3-digit level. This weighting is necessary to ensure that the indicators are driven by more frequent single occupations within the occupational orders[5]. This standardization indicator at the 3-digit level of the KldB 1988 displays an average degree of standardization of 0.69 (see Table 2).

[3] For more information, please visit the BERUFENET homepage: `http://berufenet.arbeitsagentur.de/berufe/index.jsp`.

[4] The single occupations in BERUFENET are classified according to the new German Classification of Occupations 2010 (KldB 2010) and are listed at the lowest possible differentiation level, i.e., the 8-digit level. For the single occupations of KldB 2010, there is an unambiguous conversion table for single occupations of KldB 1988 at the 7-digit level.

[5] See Vicari (2014) for more details on the assignment and calculation.

Table 2: Summarizing statistics of the standardization indicator for each occupation i

Indicator	*Mean*	*Std. Dev.*	*Min*	*Max*
Degree of standardization D_i	0.69	0.30	0	1

Source: Data from Vicari (2014) on the basis of BERUFENET.
Note: Own calculations.

For the second indicator, we use the operationalization of Dengler/Matthes/Paulus (2014). They follow the extension of the TBA made by Spitz-Oener (2006) for Germany by considering five task categories: analytical non-routine tasks, interactive non-routine tasks, cognitive routine tasks, manual routine tasks and manual non-routine tasks. Based on these five task categories, we can determine the task diversity of an occupation, which is high if all five task types are required with similar shares and low if, for example, only one task type is required.

The information on the five task types in each single occupation is available in the so-called requirement matrix of the expert database BERUFENET, which assigns approximately 8,000 requirements to single occupations. Dengler/Matthes/Paulus (2014) assign one of the five task types in an "independent three-coder approach" to each core requirement[6] and calculate the composition of the five tasks types by dividing the requirements in each single occupation at the 7-digit level in the respective task type by the total number of requirements in the single occupation.[7] We use this task composition, i.e., the share of the five task types in each single occupation at the 7-digit level, for the year 2012. We determine the indicator for the diversity of tasks by calculating the variance of the composition of the five task types in each single occupation at the 7-digit level and taking 1 minus this variance. For aggregation of this measure on the 3-digit level, the same weighting procedure is applied as used for the occupational standardization indicator: each single occupation at the 7-digit level is weighted with the number of all employees at the 7-digit level divided by the number of employees at the 3-digit level. This diversity of tasks indicator ranges between 0.84 (low task diversity) and 0.99 (high task diversity). The indicator tends to increase with the required number of task types. However, the indicator does not always increase with the required number of task types, as we calculate the variance by considering the composition of task types in each single occupation. For example, a single occupation with positive shares in four task types may reveal lower task diversity if some task types have very low shares compared with a single occupation with positive shares in three task types.

Table 3 provides descriptive statistics for the average share of task types, as well as for the indicator diversity of tasks in each occupation at the 3-digit level of the KldB 1988. The most common task type involves manual non-routine tasks at 27 percent, whereas interactive non-routine tasks show the lowest average share with 8 percent. The resulting average diversity of tasks is 0.93.

[6] In general, the requirement matrix contains requirement groups, additional requirements and core requirements. The requirement groups specify tools that may be necessary to perform an activity (such as IT programming languages). Additional requirements include those that might be important to perform an occupational activity but that are not mandatory. The authors only consider core requirements that are mandatory requirements to work in the various single occupations.

[7] See Dengler/Matthes/Paulus (2014) for more details on the assignment and calculation.

Table 3: Summarizing statistics of the share and the diversity of tasks in each occupation i

Shares	*Mean*	*Std. Dev.*	*Min*	*Max*
Analytical non-routine tasks	0.19	0.22	0	1
Interactive non-routine tasks	0.08	0.15	0	1
Cognitive routine tasks	0.24	0.22	0	1
Manual non-routine tasks	0.27	0.30	0	1
Manual routine tasks	0.22	0.27	0	1
Resulting indicator	*Mean*	*Std. Dev.*	*Min*	*Max*
Diversity of tasks E_i	0.93	0.033	0.84	0.99

Source: Data from Dengler/Matthes/Paulus (2014) on the basis of BERUFENET.
Note: Own calculations, the diversity of tasks is based on the variance of shares of task types in each single occupation.

4 Empirical strategy and results

We modify the random matching function $M = f(U, V)$, conceived by Pissarides (1979, 1985); Diamond (1982b,a); Mortensen (1982), as specified by a Cobb-Douglas form:

$$M = AU^{\beta_U} V^{\beta_V}, \tag{1}$$

where A is the augmented matching productivity. The random matching approach generally assumes that workers and firms are randomly matched and stem from the pool of existing unemployed workers and job vacancies.
Following the theoretical model, our analysis refers to an estimation of the parameter A of the matching function, based on the grade of standardization D_i and task complexity E_i in an occupation i. Thus, the model is modified to

$$M_i = A(D_i, E_i)U_i^{\beta_U} V_i^{\beta_V}. \tag{2}$$

We write $A(D_i, E_i)$ as

$$A(D_i, E_i) = \exp(\delta D_i)\exp(\omega E_i)C = \exp(\delta D_i + \omega E_i)C. \tag{3}$$

This implies that if the standardization and the diversity of tasks are zero, augmented productivity amounts to C because $A(0, 0) = C$. This constant is adjusted by the two exponential functions that are driven by the standardization and the diversity of tasks.[8] To summarize, the parameters of interest are δ and ω. We use a logarithmic and augmented version of equation (2) for the empirical analysis:

$$\log M_{ijt} = c + \delta D_i + \omega E_i + \beta_U \log U_{ijt} + \beta_V \log V_{ijt} + \gamma GDP_{cyc,FS(i),year(t)} + \mu_j + d_t + \epsilon_{ijt}. \tag{4}$$

Hereby, $\log M_{ijt}$ denotes the logarithm of the flows from unemployment to employment for occupation i, region j and observation period t. The variable c is the economy-wide fixed portion of the augmented matching productivity. The variables $\log U$ and $\log V$ are the log-

[8] Hereby, we assume that high values of standardization or diversity of tasks have a greater influence on the augmented matching productivity than small values.

arithms of the unemployment and vacancy stocks, whereas β_U and β_V denote the matching elasticities of unemployed and vacancies, respectively. The term $GDP_{cyc,FS(j),year(t)}$ is the cyclical component of the real gross domestic product for federal state FS in region j and year t (computed with the Hodrick-Prescott filter Hodrick/Prescott, 1997). This variable is used as a control for the economic situation. Furthermore, the regression equation contains a regional fixed effects term μ_j for each region j that can be interpreted as the local area's specific augmented productivity, as well as time fixed effects d_t, and an error term ϵ for each occupation i, region j and observation period t.

Estimation results can be found in Table 4. This table presents model versions OLS 1a – OLS 4. OLS 1a – OLS 1c correspond to baseline regression equations for a "pure" matching function without the occupation-specific parameters. Model equation OLS 1a contains only the constant and the logarithms of unemployment and vacancy stocks as explaining variables. In addition, the equation for OLS 1b includes time and regional fixed effects, and the equation for OLS 1c contains the cyclical component of the GDP. All further model versions contain also control variables for the cyclical component of the GDP, the local area effects and the time fixed effects. We computed Driscoll-Kraay standard errors that account for general forms of spatial (and temporal dependence) in case of a relative large time dimension and a quite larger number of cross-sectional units (Driscoll/Kraay, 1998).[9]

Table 4: Estimation results with $\log M_{ijt}$ as the dependent variable

	(1) OLS 1a	(2) OLS 1b	(3) OLS 1c	(4) OLS 2	(5) OLS 3	(6) OLS 4
β_U	0.570***	0.598***	0.598***	0.620***	0.601***	0.624***
	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
β_V	0.117***	0.129***	0.128***	0.114***	0.132***	0.118***
	(0.006)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
δ (Standardization)				0.336***		0.345***
				(0.020)		(0.020)
ω (Task diversity)					-1.098***	-1.319***
					(0.161)	(0.157)
$\gamma(GDP_{cyc,FS(i),year(t)})$			1.173***	1.294***	1.169***	1.292***
			(0.270)	(0.277)	(0.270)	(0.277)
Constant	-0.775***	-1.012***	-1.025***	-1.337***	-0.019	-0.137
	(0.028)	(0.017)	(0.018)	(0.029)	(0.142)	(0.127)
Time/area fixed effects		x	x	x	x	x
Observations	2,365,217	2,365,217	2,365,217	2,365,217	2,365,080	2,365,080
Adj. R-squared	0.654	0.707	0.707	0.716	0.708	0.718

Source: Administrative data from the Statistics Department of the Federal Employment Agency 2000-2011.
Note: Own calculations, Driscoll-Kraay standard errors are in parentheses.
Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

9 We use the procedure conceived by Hoechle (2007) with a default lag length of 4. We do this because, generally, one has to consider cross-sectional dependence in panel data sets like we utilized here. The consequence is that (ordinary or even cluster) robust standard errors would be underestimated. However, to get further indications whether cross-sectional dependence has to be considered, we calculated Pesaran's CD statistic that can be used as a test for cross-sectional dependence in the residuals (Pesaran, 2004). The results reveal that the Null of strong cross-sectional dependence in the residuals cannot be rejected. Details about the computation, the specifications and results are provided on request.

The estimates for the matching elasticities of unemployed and vacancies are comparable with the estimates from previous studies (compare with Burda/Wyplosz, 1994; Entorf, 1998; Fahr/Sunde, 2004; Stops/Mazzoni, 2010; Klinger/Rothe, 2012; Stops, 2014). Thus, both elasticities are significantly positive. The matching elasticities of unemployed are larger than the matching elasticities of vacancies. Furthermore, the magnitude of the elasticities does not differ much among all model versions. OLS 2 includes the indicator for standardization, revealing a significantly positive effect on the number of matches. OLS 3 contains the indicator for the diversity of tasks: the coefficient shows a significant and negative impact on the number of matches. OLS 4 presents the results based on equations including both indicators, and the results remain robust. Thus, we can conclude that the standardization of an occupation i has a positive effect and the diversity of tasks in an occupation i has a negative effect on the number of matches for the occupation i.
To check the robustness of our results, we use alternative operationalizations of both occupation-specific indicators. The indicator for standardization combines two components of previous analyses, standardization of corresponding certifications and legal regulations for entering into an occupation. Both components decrease information asymmetry by providing information on the knowledge and skills traded between job seekers and employers and thus decrease search costs. However, the underlying mechanisms differ slightly. On the one hand, standardized certifications are only implicitly required to practice an occupation, as they allow the assessment and the comparison of skill bundles among workers. Therefore, a job seeker with the requested certification will be preferred over one without this certification. On the other hand, certifications are explicitly required in the case of occupations that are legally regulated and represent a closing mechanism, as a job seeker without the requested certification is not allowed to perform the job. Therefore, it is reasonable to check the robustness of the initial indicator by separately considering both components in our regression equation. For the considered occupations, the average degree of standardized certifications is 0.64, and the average degree of legal regulation is 0.1 (see upper rows of Table 5).

Table 5: Summarizing statistics for the alternative indicators

Indicator	*Mean*	*Std. Dev.*	*Min*	*Max*
Degree of standardized certifications D_i	0.636	0.32	0	1
Degree of legal regulation D_i	0.097	0.238	0	1
Number of requirements E_i	7.37	3.256	2	20

Source: Data from Vicari (2014) and Dengler/Matthes/Paulus (2014) on the basis of BERUFENET.
Note: Own calculations.

Furthermore, we consider the number of requirements that must be performed in an occupation as an alternative for the diversity of tasks indicator by adding the number of requirements for each single occupation. Again, for aggregation at the 3-digit level, each single occupation at the 7-digit level is weighted with the number of all employees at the 7-digit level divided by the number of employees at the 3-digit level. On average, an occupation consists of seven requirements that must be performed (see the bottom row of Table 5).

The additional estimation results are presented in Table 6. All regression equations include control variables for the cyclical component of GDP, the local area effects and the time fixed effects. Again, we find significant positive coefficients for the standardization indicators and significant negative coefficients for the diversity of tasks indicators. The results are robust through all model versions (with all conceivable combinations of our 5 indicators, OLS 5 – OLS 20) and thus corroborate our previous findings. We further estimate a matching function in that constant returns to scale are assumed. Constant returns to scale ($\beta_U + \beta_V = 1$ with $\beta_U, \beta_V > 0$)[10] are widely discussed in the literature (compare, e.g., with Petrongolo/Pissarides, 2001). Dividing equation (1) by the unemployment stock, modifying it for an occupational property specific matching productivity and taking the logarithm leads to the estimation equation:

$$\log MR_{ijt} = c + \delta D_i + \omega E_i + \beta \log \theta_{ijt} + \gamma GDP_{cyc,FS(i),year(t)} + \mu_j + d_t + \epsilon_{ijt}. \quad (5)$$

Therefore, the matching function in its reduced form consists of the matching rate (number of matches as the share of unemployment stocks) on the left side. This matching rate is explained by the ratio of vacancies and unemployment and – as a result – the tightness of the labor market θ on the right side (with coefficient $\beta = \beta_V$). The main results can be found in Table 7; further results based on the modified occupation-specific indicators can be found in Table 9 in the Appendix A. Again, we find a positive influence of the degree of standardization and a negative influence of the diversity of tasks measures on matching productivity.[11]

Though we computed standard errors that are robust to cross-sectional and temporal dependence, our estimates remain highly significant. One reason for this is the enormous variation in our data set. As a further robustness check, we now conduct the same analyses at a higher aggregation level. We do this because one potential shortcoming of our detailed data is that there could be measurement errors at the small local area level or occupational level. In more aggregated data sets, these measurement errors could be "compensated" for, notwithstanding that the prize are higher standard errors. Thus, we aggregated the data sets by the occupations over the NUTS3 regions. In the following, we present specifications without a control for the Gross Domestic Product because we could only use a variable without regional variation and, therefore, this variable would be redundant considering that we included time fixed effects.[12] As expected, the estimates come with higher standard errors but also higher coefficients of determination (see Table 8, all further results can be found in the Appendix, Tables 10–12).[13] Our results corroborate the

[10] Although our results clearly reveal decreasing returns to scale, we perform this exercise as a further opportunity to check the robustness of our results. Technically, we will examine whether the restriction of constant returns to scale would affect the estimates for the coefficients of the occupation-specific properties.

[11] We are aware that in this reduced specification, the magnitude of the coefficients for the diversity of tasks measure is approximately two times larger than in the unrestricted specification. Furthermore, the coefficient of determination is much smaller. Our explanation for these results is as follows: decreasing returns to scale, as we found in our unrestricted specification, are expected to reveal a biased estimation of one or more coefficients in our reduced specification because the estimation equation must be complemented by $\log U_{ijt}$ and its coefficient that is equal to $\beta_U + \beta_V - 1$. Due to decreasing returns to scale imply $\beta_U + \beta_V - 1 < 0$, omission of $\log U_{ijt}$ leads to a downward-biased estimation of one or more coefficients. This is what we see in the different versions of the reduced specifications.

[12] We tested, however, specifications with the GDP variable. It's coefficients are insignificant in all specifications and the further results hardly changed. The authors provide this results upon request.

[13] The results imply that the returns to scale of the matching efficiencies of unemployed and vacancies

Table 6: Further estimation results with $\log M_{ijt}$ as the dependent variable

	(1) OLS 5	(2) OLS 6	(3) OLS 7	(4) OLS 8	(5) OLS 9	(6) OLS 10	(7) OLS 11	(8) OLS 12	(9) OLS 13	(10) OLS 14	(11) OLS 15	(12) OLS 16	(13) OLS 17	(14) OLS 18	(15) OLS 19	(16) OLS 20
β_U	0.629***	0.630***	0.603***	0.608***	0.619***	0.614***	0.615***	0.619***	0.605***	0.620***	0.618***	0.612***	0.620***	0.628***	0.623***	0.630***
	(0.006)	(0.006)	(0.006)	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
β_V	0.113***	0.116***	0.127***	0.118***	0.114***	0.124***	0.127***	0.122***	0.131***	0.125***	0.117***	0.122***	0.120***	0.112***	0.118***	0.116***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
δ (Standardization)	0.301***	0.313***														
	(0.019)	(0.020)														
δ (Standard. certificates)				0.250***	0.294***						0.213***	0.262***	0.228***	0.257***	0.308***	0.275***
				(0.018)	(0.019)						(0.017)	(0.019)	(0.019)	(0.018)	(0.019)	(0.019)
δ (Leg. regulation)			0.096***		0.210***			0.110***	0.098***	0.111***				0.206***	0.219***	0.214***
			(0.021)		(0.020)			(0.022)	(0.021)	(0.022)				(0.020)	(0.020)	(0.020)
ω (Task diversity)		-1.090***					-0.757***		-1.110***	-0.764***		-1.366***	-1.109***		-1.442***	-1.194***
		(0.159)					(0.156)		(0.158)	(0.154)		(0.167)	(0.172)		(0.160)	(0.165)
ω (Number of requirements)	-0.012***	-0.010***				-0.018***	-0.017***	-0.019***		-0.017***	-0.013***		-0.011***	-0.013***		-0.011***
	(0.000)	(0.000)				(0.001)	(0.001)	(0.001)		(0.001)	(0.000)		(0.001)	(0.000)		(0.001)
$\gamma(GDP_{cyc,FS(i),year(t)})$	1.324***	1.317***	1.192***	1.233***	1.285***	1.235***	1.228***	1.258***	1.188***	1.251***	1.269***	1.231***	1.262***	1.319***	1.285***	1.313***
	(0.277)	(0.277)	(0.270)	(0.276)	(0.276)	(0.272)	(0.272)	(0.271)	(0.270)	(0.271)	(0.276)	(0.276)	(0.276)	(0.277)	(0.277)	(0.277)
Constant	-1.239***	-0.261**	-1.049***	-1.221***	-1.309***	-0.928***	-0.240*	-0.954***	-0.032	-0.260*	-1.122***	0.021	-0.128	-1.210***	-0.001	-0.143
	(0.027)	(0.128)	(0.018)	(0.025)	(0.026)	(0.016)	(0.137)	(0.016)	(0.144)	(0.139)	(0.024)	(0.136)	(0.139)	(0.024)	(0.134)	(0.137)
Time/area fixed effects	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Observations	2,365,002	2,365,002	2,365,217	2,365,217	2,365,217	2,365,002	2,365,002	2,365,002	2,365,080	2,365,002	2,365,002	2,365,080	2,365,002	2,365,002	2,365,080	2,365,002
Adj. R-squared	0.718	0.719	0.708	0.713	0.716	0.711	0.712	0.712	0.709	0.712	0.715	0.715	0.716	0.717	0.717	0.718

Source: Administrative data from the Statistics Department of the Federal Employment Agency 2000-2011.
Note: Own calculations, Driscoll-Kraay standard errors are in parentheses.
Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table 7: Estimation results with $\log MR_{ijt}$ as the dependent variable

	(1) OLS 1a	(2) OLS 1b	(3) OLS 1c	(4) OLS 2	(5) OLS 3	(6) OLS 4
θ	0.321***	0.302***	0.301***	0.279***	0.300***	0.277***
	(0.007)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
δ (Standardization)				0.396***		0.411***
				(0.025)		(0.024)
ω (Task diversity)					-2.581***	-2.785***
					(0.146)	(0.137)
$\gamma(GDP_{cyc,FS(i),year(t)})$			1.026***	1.173***	1.024***	1.177***
			(0.299)	(0.304)	(0.299)	(0.304)
Constant	-1.639***	-1.746***	-1.757***	-2.102***	0.648***	0.481***
	(0.033)	(0.010)	(0.010)	(0.026)	(0.136)	(0.120)
Time/area fixed effects		x	x	x	x	x
Observations	2,365,217	2,365,217	2,365,217	2,365,217	2,365,080	2,365,080
Adj. R-squared	0.291	0.431	0.431	0.452	0.440	0.462

Source: Administrative data from the Statistics Department of the Federal Employment Agency 2000-2011.
Note: Own calculations, Driscoll-Kraay standard errors are in parentheses.
Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

previous findings regarding the direction and significance of the effects of the indicators. Thus, we can finally conclude from our empirical analysis, throughout all model specifications and the two different aggregation levels, that the degree of standardization of an occupation has a positive and the task diversity of an occupation has a negative impact on the efficiency of job matching.

are nearly constant; therefore, as already discussed, there are smaller differences in the effect estimates between the unrestricted (Table 8 and Table 10 in the Appendix) and the reduced specifications (Tables 11 and 12 in the Appendix) for the aggregated data set.

Table 8: Estimation results with $\log M_{it}$ as the dependent variable, based on the higher aggregated data set

	(1) OLS 1a	(2) OLS 1b	(3) OLS 2	(4) OLS 3	(5) OLS 4
β_U	0.779***	0.779***	0.785***	0.778***	0.785***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
β_V	0.231***	0.231***	0.225***	0.232***	0.224***
	(0.010)	(0.010)	(0.011)	(0.010)	(0.010)
δ (Standardization)			0.191***		0.194***
			(0.020)		(0.020)
ω (Task diversity)				-0.372***	-0.506***
				(0.108)	(0.109)
Constant	-2.175***	-2.175***	-2.325***	-1.824***	-1.850***
	(0.060)	(0.060)	(0.074)	(0.136)	(0.135)
Time fixed effects		x	x	x	x
Observations	42,053	42,053	41,761	41,102	41,102
Adj. R-squared	0.927	0.927	0.927	0.927	0.928

Source: Administrative data from the Statistics Department of the Federal Employment Agency 2000-2011.
Note: Own calculations, Driscoll-Kraay standard errors are in parentheses.
Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

5 Search costs and matching efficiency

In this section, we discuss the possible micro-level mechanism that might explain our empirical findings. We base our reflections on the "bulletin board" matching process model conceived by Hall (1979) and Pissarides (1979). The same model basis was used to explain job search with regional mobility (Burda/Profit, 1996) and, based on this reference, occupational mobility (Stops, 2014). Generally, this model assumes that workers can find all open vacancies on a bulletin board, provided by a central employment service, and derive their optimal search intensity in terms of the number of applications from this information.

Here, we will motivate the following modification of this model: Assume an economy with I occupational labor markets, which are denoted by $i = 1, ..., I$. There are U_i identical unemployed job searchers in each occupational labor market and V_i identical firms, each of which is searching for one worker in occupation i. All the potential workers reach decisions about their search intensity. Assuming that these workers choose to engage in a search for employment in "their" occupation i, they fix the number of jobs that they apply for. Further we assume that the return of an effective search in terms of the wage w is equal for each potential occupation. An application or a job interview can be regarded as a random draw and costs $c + a(1 - D_i) + bE_i$. Thus, we implement the assumption that the amount of the search costs are specific to the occupation where the search takes place. The terms c, a, and b are constants, D_i is an indicator for the standardization of the occupation i, and E_i is an indicator for the diversity of tasks in occupation i.

Thus, the term $a(1 - D_i)$ denotes the portion of the costs that are induced by information asymmetries due to the fact that some occupations i are more standardized than other occupations. Standardized occupations potentially reduce information asymmetries in the job search by providing reliable signals about the applicant's knowledge and skills to meet the requirements of a job that reduce both individual and firm search costs: The firm knows whether the applicant is sufficiently qualified for the vacant position, and the applicant has a clear picture of the requirements and other determinants of the job (Damelang/Schulz/Vicari, 2015), which implies that as occupations become more standardized, the amount of effort decreases, that must be made to obtain information about each vacancy and to find out whether they are worth applying for.

The term bE_i denotes the portion of the costs that are induced by information asymmetries due to the diversity of tasks. If a job offer in occupation i requires a high diversity of tasks, it is more laborious for a job searcher to explore whether he or she is the right person to apply for the job. The same is true for a firm that must find out whether the applicant can perform a lower or higher range of diverse tasks. Thus, we argue that a higher diversity of tasks leads to higher search costs because of stronger information asymmetries.

The job searchers decide on their search intensities, which can be denoted by their optimal number of job interviews N_i^* in occupation i. The probability of obtaining a job after an interview within occupation i is provided by p_i for each occupation $i = 1, ..., I$. The job searcher is assumed to maximize the utility of the job search, which is equal to the difference between the revenue from the job search and the costs of this search:

$$\max_{N_i}\{[1-(1-p_i)^{N_i}]\frac{w}{r} - N_i[c + a(1-D_i) + bE_i]\}. \tag{6}$$

In the above equation, $[1-(1-p_i)^{N_i}]w/r$ denotes the expected revenue to a job searcher who is currently in occupation i from realizing N_i interviews in occupation i, given p_i, the probability of obtaining a job, and the assumption that a worker cannot hold more than one job at a given time. We also assume that the expected income from unemployment is zero. The first-order condition of the optimization problem in (6) is:

$$-(1-p_i)^{N_i}\ln(1-p_i)\frac{w}{r} - [c + a(1-D_i) + bE_i] = 0 \tag{7}$$

with the solution:

$$N_i^* = \frac{1}{\ln(1-p_i)}\ln\left[-\frac{c + a(1-D_i) + bE_i}{\frac{w}{r}\ln(1-p_i)}\right]. \tag{8}$$

For small p_i, we obtain the approximation:

$$N_i^* = \begin{cases} \frac{1}{p_i}\ln[\frac{(w/r)p_i}{c+a(1-D_i)+bE_i}] & \text{for } \frac{w}{r}p_i \geq [c + a(1-D_i) + bE_i], \\ 0 & \text{for } \frac{w}{r}p_i < [c + a(1-D_i) + bE_i]. \end{cases} \tag{9}$$

Therefore, optimal job search intensity depends positively on the ratio of the gains to the costs of a particular job search. A higher wage w has positive effects on job search intensity, whereas higher search costs and higher interest rates have negative effects on this intensity. The differentiation of the upper case on the right-hand side of equation (9) with respect to each cost component, the standardization and the diversity of tasks in an occupation, leads to the equivalent expressions:

$$\frac{\partial N_i^*}{\partial D_i} = \begin{cases} \frac{1}{p_i}\frac{a}{c+a(1-D_i)+bE_i} > 0 & \text{for } \frac{w}{r}p_i \geq [c + a(1-D_i) + bE_i], \\ 0 & \text{for } \frac{w}{r}p_i < [c + a(1-D_i) + bE_i]. \end{cases} \tag{10}$$

$$\frac{\partial N_i^*}{\partial E_i} = \begin{cases} (-\frac{1}{p_i})\frac{b}{c+a(1-D_i)+bE_i} < 0 & \text{for } \frac{w}{r}p_i \geq [c + a(1-D_i) + bE_i], \\ 0 & \text{for } \frac{w}{r}p_i < [c + a(1-D_i) + bE_i]. \end{cases} \tag{11}$$

Equations (10) and (11) imply that a higher standardization, D_i, has positive effects on the optimal search intensity, whereas a higher diversity of tasks, E_i, has negative effects on the optimal search intensity, as long as the expected gain from a job search is larger than or equal to the search costs. Thus, $(w/r)p_i \geq [c + a(1-D_i) + bE_i]$.

In the next step of the analysis, the unconditional job-finding probabilities in any occupation i will be derived from the optimal number of interviews, N_i^*. We assume that there is no information exchange between job searchers. Therefore, it is reasonable that certain vacancies might attract many applicants whereas other vacancies do not. Furthermore, we assume that the vacancies in a certain occupation i are all known by at least the job searchers belonging to that occupation, which compares with the existence of a "bulletin board" of potential jobs. By defining $U_i \equiv N_i{}^* u_i$ as the sum of applications by unemployed job searchers in occupation i, we approximately derive the probability that a vacancy in occupation i will not be considered by the job searchers:

$$\prod_{k=1}^{N_i^*}(1 - \frac{1}{V_i - k + 1})]^{u_i} \approx \prod_{k=1}^{N_i^*} \exp(-\frac{u_i}{V_i}) = \exp(-\frac{U_i}{V_i}). \tag{12}$$

The job-finding probability, p_i, will be equal to the ratio of the number of vacancies considered $V_i[1 - \exp(-\frac{U_i}{V_i})]$ to U_i, the number of applications that were submitted by unemployed workers:

$$p_i = \frac{V_i}{U_i}[1 - \exp(-\frac{U_i}{V_i})]. \tag{13}$$

Finally, a matching function that returns the number of flows from unemployment to employment in an occupation i can be formulated as follows:

$$M_i(u_i, v_i) = u_i P_i = u_i[1 - (1 - p_i)^{N_i^*}]. \tag{14}$$

In the equation above, P_i represents the probability that a job searcher in occupation i will receive at least one job offer. This probability is equal to 1 minus the probability of receiving no job offer from all the vacancies in occupation i.

The matching function above relates exits from unemployment to employment in a certain occupation to the labor market situation in every occupation. From an empirical perspective, a problem arises, namely, the optimal search intensity and the search costs cannot be directly observed. To address this issue, this matching function could be formulated as a quasi-reduced form that regards vacancies (as well as wages and interest rates, resp.) as given quantities. This approach renders it possible to study the effects of variations in portions of the search costs on the number of matches:

$$\begin{aligned} \frac{\partial M_i}{\partial D_i} &= \frac{\partial M_i}{\partial N_i^*}\frac{\partial N_i^*}{\partial D_i} \\ &= \underbrace{N_i^*(1-p_i)^{-1}u_i(1-p_i)^{N_i^*}\frac{\partial p_i}{\partial N_i^*}\frac{\partial N_i^*}{\partial D_i}}_{<0} \underbrace{- \ln(1-p_i)u_i(1-p_i)^{N_i^*}\frac{\partial N_i^*}{\partial D_i}}_{>0}, \end{aligned} \tag{15}$$

$$
\begin{aligned}
\frac{\partial M_i}{\partial E_i} =& \frac{\partial M_i}{\partial N_i^*}\frac{\partial N_i^*}{\partial E_i} \qquad (16)\\
=& \underbrace{N_i^*(1-p_i)^{-1}u_i(1-p_i)^{N_i^*}\frac{\partial p_i}{\partial N_i^*}\frac{\partial N_i^*}{\partial E_i}}_{>0}\underbrace{-\ln(1-p_i)u_i(1-p_i)^{N_i^*}\frac{\partial N_i^*}{\partial E_i}}_{<0}.
\end{aligned}
$$

Each of the terms in the equations (15) and (16) reveal contrary effects. There is a positive (or negative) effect of search intensity on the number of matches given that the job finding probability would not change, see the last term in equation (15) (or equation (16), resp.) but there is also an indirect effect because the search intensity influences also the job finding probability, $\frac{\partial p_i}{\partial N_i^*}$, in the first term:

$$
\frac{\partial p_i}{\partial N_i^*} = \frac{1}{N_i^*}[\exp^{-\frac{U_i}{V_i}}(1+\frac{V_i}{U_i}) - \frac{V_i}{U_i}]. \qquad (17)
$$

It can be shown that $\frac{\partial p_i}{\partial N_i^*} < 0$ for all N_i^* and $\frac{U_i}{V_i}$ (with $0 \leq \frac{U_i}{V_i} \leq u_i$).
Because we found that $\frac{\partial N_i^*}{\partial D_i} > 0$, the sign of the last term in equation (15) is positive and due to $\frac{\partial N_i^*}{\partial E_i} < 0$, the sign of the last term in equation (16) is negative. Considering the conditions above, the first term would be smaller than zero in equation (15) and larger than zero in (16). This would imply that the signs of $\frac{\partial M_i}{\partial D_i}$ and $\frac{\partial M_i}{\partial E_i}$, respectively, depend on the relation of the first and the last terms.
We can conclude from our model that occupation-specific properties, including the degree of standardization and the degree of task diversity, might have an important impact on the intensity with which a worker searches for jobs. However, the direction of the effects for matching elasticity can be positive or negative. On the one hand, a higher search intensity tends to lead directly to more matches because workers contact more firms; on the other hand, a worker's probability of finding a job decreases due to the intensified competition among workers. However, our model delivers an explanation regarding the mechanisms behind our empirical observations. In case the direct positive influence of the search intensity on the number of matches overcompensates the eventual negative effect on the job finding probability, our empirical results, $\frac{\partial M_i}{\partial D_i} > 0$ and $\frac{\partial M_i}{\partial E_i} < 0$, are predicted by the model.

6 Conclusions

We discuss implications of two well identifiable occupation-specific properties: the degree of standardization and the diversity of tasks in an occupation. In particular, these indicators might have an influence on job or workers search, respectively, and job matching. During search, firms and workers spend resources such as money and time to provide information about themselves and to collect information about one another. In economic terms, they make efforts to reduce information asymmetries. Information asymmetries determine, among other factors, the search costs and, given the returns of the search, the optimal search intensity. Standard job and matching models assume constant search costs for the entire economy. This assumption is affected by several empirical results that show that the efficiency of matching firms and workers is quite different in different occupational labor markets, which are defined as having jobs that share extensive commonalities in their required skills and tasks. To date, there is not much known about the determinants of these differences. It is reasonable to assume that both occupation-specific properties might determine information asymmetries and, therefore, the costs of search, as well as – finally – the observed matching efficiency. We empirically validate the relationship between these indicators and matching efficiency based on rich administrative data for the period from 2000 to 2011. We find that the degree of standardization exerts a positive influence on the matching efficiency and that the diversity of tasks exerts a negative influence. The results are robust to variations in the indicators. We discuss the search mechanisms behind these findings in a search theoretic model: as the degree of standardization increases and the task diversity of an occupation decreases, ceteris paribus, the search costs in these occupations decrease and the search intensity per observation period increases. Firstly, this can lead to more matches per observation period because a higher number of applications would lead to a higher probability that each firm is reached by applications and can recruit a worker. Secondly, the probability that workers will find a job decreases, which would produce a negative effect on the number of matches. However, we can show that our empirical observations are predicted by the model under the condition that the first effect overcompensates the second effect.

Finally, our results suggest that both occupational specific indicators contribute to the extent of labour market transparency. However, regarding policy decisions for regulations for vocational training standards or market accesses, the positive implications on job matching should obviously be weighed up against bureaucratic costs or potentially less flexibility.

A Appendix

Table 9: Further estimation results with $\log MR_{ijt}$ as the dependent variable

	(1) OLS 5	(2) OLS 6	(3) OLS 7	(4) OLS 8	(5) OLS 9	(6) OLS 10	(7) OLS 11	(8) OLS 12	(9) OLS 13	(10) OLS 14	(11) OLS 15	(12) OLS 16	(13) OLS 17	(14) OLS 18	(15) OLS 19	(16) OLS 20
θ	0.268***	0.269***	0.294***	0.291***	0.278***	0.283***	0.284***	0.275***	0.294***	0.276***	0.278***	0.289***	0.279***	0.266***	0.276***	0.266***
	(0.005)	(0.004)	(0.004)	(0.005)	(0.004)	(0.005)	(0.005)	(0.005)	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)
δ (Standardization)	0.329***	0.354***														
	(0.022)	(0.022)														
δ (Standard. certificates)				0.248***	0.319***						0.177***	0.273***	0.210***	0.247***	0.347***	0.284***
				(0.022)	(0.023)						(0.020)	(0.022)	(0.021)	(0.021)	(0.023)	(0.022)
δ (Leg. regulation)			0.220***		0.343***			0.234***	0.218***	0.231***				0.327***	0.351***	0.337***
			(0.024)		(0.023)			(0.024)	(0.024)	(0.024)				(0.022)	(0.022)	(0.022)
ω (Task diversity)		-2.342***					-1.991***		-2.572***	-1.970***		-2.853***	-2.323***		-2.912***	-2.409***
		(0.135)					(0.136)		(0.146)	(0.137)		(0.152)	(0.152)		(0.144)	(0.144)
ω (Number of requirements)	-0.023***	-0.018***				-0.029***	-0.026***	-0.030***		-0.026***	-0.025***		-0.021***	-0.024***		-0.019***
	(0.001)	(0.000)				(0.001)	(0.001)	(0.001)		(0.001)	(0.001)		(0.001)	(0.001)		(0.000)
$\gamma(GDP_{cyc,FS(i),year(t)})$	1.233***	1.224***	1.073***	1.086***	1.176***	1.135***	1.121***	1.187***	1.070***	1.172***	1.162***	1.089***	1.151***	1.245***	1.181***	1.236***
	(0.305)	(0.304)	(0.298)	(0.304)	(0.303)	(0.300)	(0.299)	(0.298)	(0.297)	(0.298)	(0.303)	(0.304)	(0.303)	(0.303)	(0.303)	(0.303)
Constant	-1.885***	0.246**	-1.795***	-1.953***	-2.067***	-1.553***	0.280**	-1.589***	0.602***	0.224*	-1.721***	0.686***	0.386***	-1.839***	0.623***	0.343***
	(0.023)	(0.118)	(0.011)	(0.023)	(0.024)	(0.010)	(0.127)	(0.011)	(0.139)	(0.131)	(0.020)	(0.130)	(0.128)	(0.021)	(0.128)	(0.127)
Time/area fixed effects	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Observations	2,365,002	2,365,002	2,365,217	2,365,217	2,365,217	2,365,002	2,365,002	2,365,002	2,365,080	2,365,002	2,365,002	2,365,080	2,365,002	2,365,002	2,365,080	2,365,002
Adj. R-squared	0.461	0.468	0.435	0.441	0.450	0.448	0.453	0.452	0.444	0.458	0.452	0.452	0.459	0.461	0.462	0.468

Source: Administrative data from the Statistics Department of the Federal Employment Agency 2000-2011.
Note: Own calculations, Driscoll-Kraay standard errors are in parentheses.
Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table 10: Further estimation results with $\log M_{it}$ as the dependent variable, based on the higher aggregated data set

	(1) OLS 5	(2) OLS 6	(3) OLS 7	(4) OLS 8	(5) OLS 9	(6) OLS 10	(7) OLS 11	(8) OLS 12	(9) OLS 13	(10) OLS 14	(11) OLS 15	(12) OLS 16	(13) OLS 17	(14) OLS 18	(15) OLS 19	(16) OLS 20
β_{Us}	0.787***	0.786***	0.790***	0.779***	0.796***	0.779***	0.778***	0.792***	0.790***	0.792***	0.780***	0.779***	0.779***	0.799***	0.796***	0.797***
	(0.013)	(0.013)	(0.012)	(0.012)	(0.013)	(0.012)	(0.012)	(0.012)	(0.012)	(0.013)	(0.012)	(0.012)	(0.012)	(0.013)	(0.013)	(0.013)
β_{Vs}	0.223***	0.224***	0.222***	0.232***	0.215***	0.232***	0.233***	0.220***	0.221***	0.221***	0.230***	0.231***	0.231***	0.213***	0.214***	0.214***
	(0.011)	(0.011)	(0.010)	(0.010)	(0.011)	(0.010)	(0.010)	(0.010)	(0.010)	(0.011)	(0.010)	(0.010)	(0.011)	(0.011)	(0.011)	(0.011)
δ (Standardization)	0.194***	0.197***														
	(0.020)	(0.020)														
δ (Standard. certificates)				0.065***	0.164***						0.066***	0.069***	0.069***	0.171***	0.169***	0.175***
				(0.021)	(0.021)						(0.021)	(0.021)	(0.022)	(0.021)	(0.021)	(0.021)
δ (Leg. regulation)			0.320***		0.394***			0.334***	0.317***	0.334***				0.413***	0.393***	0.414***
			(0.024)		(0.024)			(0.024)	(0.024)	(0.024)				(0.024)	(0.023)	(0.024)
ω (Task diversity)		-0.345***					-0.207*		-0.366***	-0.157		-0.441***	-0.286**		-0.534***	-0.344***
		(0.114)					(0.113)		(0.106)	(0.112)		(0.117)	(0.124)		(0.110)	(0.117)
ω (Number of requirements)	-0.007***	-0.006***				-0.007***	-0.006***	-0.009***		-0.008***	-0.007***		-0.006***	-0.008***		-0.008***
	(0.001)	(0.001)				(0.001)	(0.001)	(0.001)		(0.001)	(0.001)		(0.001)	(0.001)		(0.001)
Constant	-2.275***	-1.959***	-2.243***	-2.221***	-2.368***	-2.127***	-1.935***	-2.187***	-1.897***	-2.042***	-2.171***	-1.806***	-1.909***	-2.317***	-1.869***	-2.002***
	(0.075)	(0.138)	(0.064)	(0.072)	(0.077)	(0.063)	(0.139)	(0.066)	(0.139)	(0.143)	(0.073)	(0.135)	(0.139)	(0.078)	(0.137)	(0.141)
Time/area fixed effects	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Observations	40,964	40,964	41,761	41,761	41,761	40,964	40,964	40,964	41,102	40,964	40,964	41,102	40,964	40,964	41,102	40,964
Adj. R-squared	0.928	0.928	0.928	0.927	0.929	0.927	0.927	0.929	0.928	0.929	0.927	0.927	0.927	0.929	0.929	0.929

Source: Administrative data from the Statistics Department of the Federal Employment Agency 2000-2011.
Note: Own calculations, Driscoll-Kraay standard errors are in parentheses.
Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table 11: Estimation results with $\log MR_{it}$ as the dependent variable, based on the higher aggregated data set

	(1) OLS 1a	(2) OLS 1b	(3) OLS 2	(4) OLS 3	(5) OLS 4
θ	0.230***	0.230***	0.224***	0.231***	0.223***
	(0.010)	(0.010)	(0.011)	(0.010)	(0.011)
δ (Standardization)			0.194***		0.196***
			(0.021)		(0.021)
ω (Task diversity)				-0.382***	-0.516***
				(0.108)	(0.109)
Constant	-2.103***	-2.103***	-2.251***	-1.740***	-1.774***
	(0.043)	(0.043)	(0.057)	(0.123)	(0.123)
Time fixed effects		x	x	x	x
Observations	42,053	42,053	41,761	41,102	41,102
Adj. R-squared	0.201	0.201	0.212	0.202	0.212

Source: Administrative data from the Statistics Department of the Federal Employment Agency 2000-2011.
Note: Own calculations, Driscoll-Kraay standard errors are in parentheses.
Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table 12: Further estimation results with $\log MR_{it}$ as the dependent variable, based on the higher aggregated data set

	(1) OLS 5	(2) OLS 6	(3) OLS 7	(4) OLS 8	(5) OLS 9	(6) OLS 10	(7) OLS 11	(8) OLS 12	(9) OLS 13	(10) OLS 14	(11) OLS 15	(12) OLS 16	(13) OLS 17	(14) OLS 18	(15) OLS 19	(16) OLS 20
θ	0.222***	0.223***	0.221***	0.230***	0.213***	0.231***	0.232***	0.219***	0.220***	0.220***	0.229***	0.229***	0.230***	0.212***	0.213***	0.213***
	(0.011)	(0.011)	(0.010)	(0.010)	(0.011)	(0.010)	(0.010)	(0.010)	(0.010)	(0.011)	(0.011)	(0.010)	(0.011)	(0.011)	(0.011)	(0.011)
δ (Standardization)	0.196***	0.199***														
	(0.020)	(0.021)														
δ (Standard. certificates)				0.068***	0.166***						0.068***	0.071***	0.072***	0.173***	0.170***	0.177***
				(0.022)	(0.021)						(0.021)	(0.022)	(0.022)	(0.021)	(0.022)	(0.022)
δ (Leg. regulation)			0.319***		0.393***			0.332***	0.315***	0.331***				0.412***	0.392***	0.413***
			(0.024)		(0.024)			(0.024)	(0.024)	(0.024)				(0.024)	(0.023)	(0.023)
ω (Task diversity)		-0.376***					-0.240**		-0.378***	-0.193*		-0.453***	-0.320**		-0.547***	-0.380***
		(0.114)					(0.111)		(0.106)	(0.110)		(0.118)	(0.124)		(0.110)	(0.117)
ω (Number of requirements)	-0.006***	-0.006***				-0.006***	-0.006***	-0.008***		-0.007***	-0.006***		-0.005***	-0.008***		-0.007***
	(0.001)	(0.001)				(0.001)	(0.001)	(0.001)		(0.001)	(0.001)		(0.001)	(0.001)		(0.001)
Constant	-2.204***	-1.862***	-2.155***	-2.142***	-2.288***	-2.047***	-1.828***	-2.099***	-1.804***	-1.922***	-2.097***	-1.724***	-1.806***	-2.237***	-1.783***	-1.892***
	(0.059)	(0.123)	(0.045)	(0.054)	(0.059)	(0.045)	(0.123)	(0.047)	(0.125)	(0.126)	(0.056)	(0.123)	(0.124)	(0.060)	(0.123)	(0.125)
Time fixed effects	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Observations	40,964	40,964	41,761	41,761	41,761	40,964	40,964	40,964	41,102	40,964	40,964	41,102	40,964	40,964	41,102	40,964
Adj. R-squared	0.215	0.215	0.220	0.204	0.227	0.205	0.205	0.223	0.219	0.224	0.206	0.203	0.206	0.232	0.227	0.232

Source: Administrative data from the Statistics Department of the Federal Employment Agency 2000-2011.
Note: Own calculations, Driscoll-Kraay standard errors are in parentheses.
Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

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