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Eduard Storm[1]

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Abstract

This paper studies wage effects and job mobility as a result of skill mismatch in workeroccupation pairs. I develop a Roy model in which learning on the job induces workers to shift more time towards job-specific activities. Using a short task panel containing data on worker's time allocation of job tasks, I test the model's implications and present three main findings. First, workers who are overqualified in their initial occupation in regards to abstract tasks are more likely to switch to another job by up to 19 pp. Second, task-based learning only pays off with respect to acquisition of abstract skills and is associated with a return of up to 2-3% with each year of experience. Third, gains from task-based learning are heterogenous and benefit primarily workers in abstract-intensive occupations. My findings highlight the effects of investments in job-specific skills on wage growth and job mobility.

JEL-Codes: J24, J31, J62

Keywords: : Learning-by-Doing, occupational mobility, skill mismatch, task panel, task tenure, wage determination

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1 Introduction

A growing literature has highlighted the crucial role of skill matching in worker-job pairs in shaping occupational mobility and wage growth.[1] This research highlights an important distinction between skills workers possess and skills that are required in an occupation. Discrepancies between these skill measures affect worker's initial match quality with their employer and thus productivity and subsequent career trajectory. The key feature underlying these models is that employers and/ or employees learn about underlying job-specific skills and utilize this information to optimize decisions on task assignments.

A key limitation in this literature is that studies typically approximate job requirements with occupation-level data, implicitly assuming workers within an occupation perform the same tasks. Even when individual-level data is available, researchers make use of task intensity measures that are based on the relative frequency of job tasks.[2] Instead, I complement these conventional measures with information on the time allocation of job tasks among German workers that captures the efficiency at which tasks are being performed more directly. Using this task measure, I apply the idea of learning-by-doing (LBD) to learning of tasks and study whether benefits of task-based learning depend on the skill mismatch (SMM) in the (i) initial occupation and (ii) current occupation.

To conceptualize the link between task-based learning and SMM, I develop a Roy model that incorporates differential incentives to acquire job-specific skills. I define SMM as the difference between worker's general skills, comprising a high degree of portability between occupations, and specific skills, comprising occupational specificity and limited portability. The SMM shapes benefits and costs of acquisition of job-specific skills, thereby inducing differential time allocation on tasks. In this framework, LBD results from the time workers spend on different job tasks. Differences in the time allocation of tasks, in turn, affect career trajectories as workers develop different levels of task-specific human capital (Gathmann & Schönberg 2010). I refer to this type of job experience as

[1] See, e.g., Antonovics & Golan (2012), Fredriksson, Hensvik & Skans (2018), Guvenen, Kuruscu, Tanaka & Wiczer (2020), Lise & Postel-Vinay (2020) for recent evidence.

[2] See Spitz-Oener (2006), Antonczyk, Fitzenberger & Leuschner (2009), Cassidy (2017), Rohrbach-Schmidt (2019).

task tenure, a more nuanced representation of occupational tenure. Using this framework, I study implications on worker's career trajectory by answering the following two research questions.

First, how does the initial SMM affect worker's job mobility?[3] Probit estimates suggest workers that are overqualified in their first job in terms of abstract skill requirements are more likely to switch their occupation by up to 19 pp. Overqualification in this context means, based on observable skills prior to job entry, workers are presumed to have greater ability to perform more abstract tasks than required at their first job. Following similar logic, workers that are initially overqualified in terms of routine skill requirements are less likely to switch their occupation by up to 11 pp. The initial SMM has therefore persistent effects on worker's career trajectory.

Second, how large are returns to task-based learning? On average, with each year of abstract task tenure workers receive a return of 2-3% in their hourly wage. Individual wage growth is more pronounced among underqualified workers, however. Underqualification in this context means workers begin their careers in abstract-intensive occupations with many complex tasks, thus requiring substantial investments in the acquisition of job-specific skills.

Heterogeneity analysis reveals the only beneficiaries are workers who acquire abstract skills as those acquiring routine and manual skills receive no wage gains. The positive wage effects of investments in abstract human capital are driven by workers who (i) acquired skills in training that are useful in the current occupation and (ii) switched jobs during their career. Interestingly, the motives for a new career likely differ among job-switchers. The evidence suggests workers initially overqualified in terms of abstract skills move into more abstract-intensive occupations to make up for a suboptimal skill match at the beginning of their career, implying upward mobility. In contrast, underqualified workers leave their first occupation to alleviate diminishing returns to LBD. These findings are consistent with a skill obsolescence mechanism in which task-based learning becomes devalued over time (Deming & Noray 2020). Back-of-the-envelope calculations suggest

[3] I define a job as an occupation. Job mobility therefore implies an occupational change.

these job moves extend the period of wage growth by 16 years and imply a wage peak after 39 years of employment.

This study contributes primarily to the broad literature on LBD by highlighting differential consequences of initial and current SMM through the lens of a Roy model. The basic structure of the model follows Antonovics & Golan (2012) who study job experimentation in the US labor market in form of different job tasks using (occupation-level) O*NET data. Subsequent research has adopted this framework to explore the link between skill uncertainty and occupational matching (Sanders 2016, Golan & Sanders 2019). Compared to these papers, I employ worker-level data to account for individual task specialization. Moreover, recent research has highlighted the importance of multidimensional skill matching (Guvenen, Kuruscu, Tanaka & Wiczer 2020, Lise & Postel-Vinay 2020) and differential timing of skill acquisition (Fredriksson, Hensvik & Skans 2018). I incorporate these features in my model and find asymmetric effects on career trajectories, depending on whether workers were initially under- or overqualified at labor market entry, mirroring evidence from Lise & Postel-Vinay (2020).

Importantly, I introduce the concept of task tenure. This idea highlights the importance of time allocation on job tasks for subsequent career trajectories, providing new insights to the development of task-specific human capital (Gathmann & Schönberg 2010) and learning by doing at different career stages (Fredriksson, Hensvik & Skans 2018).

Moreover, I contribute to the literature by highlighting individual heterogeneity in tasks using panel data.[4] In contrast, most of the literature is limited to cross-sectional data. A notable exception is Stinebrickner, Stinebrickner & Sullivan (2019) who use survey information from two cohorts of college students. Instead, my sample includes workers with various educational backgrounds and is thus more representative. However, Stinebrickner, Stinebrickner & Sullivan (2019) have better data on the time dimension of tasks, comprising information on time allocation on tasks over up to ten years. In

[4]In recent years, several studies have documented the importance of individual-level information on tasks, especially to study the predictive power of variation in tasks on wage differences. See, e.g., Autor & Handel (2013) using the PDII data from the US; Cassidy (2017), Rohrbach-Schmidt (2019), and, respectively, Storm (2022, 2023) using the German BIBB/IAB surveys; and de La Rica, Gortazar & Lewandowski (2020) for cross-country evidence based on PIAAC data.

contrast, my data provides information on worker's time allocation of tasks for one out of two years. I provide remedy by using broader assessment on time allocation based on a Likert scale to impute missing information.

2 Model

2.1 Basic Structure

In this section, I present a 2-period model to study task specialization *within* occupations. The economic environment is characterized by competitive markets, thus workers are being paid their marginal product. There is free entry into the labor market and all agents are assumed to be risk-neutral, so there will be no discrepancies resulting from risk-loving or risk-averse behavior. Workers are heterogeneous with respect to (time-*invariant*) general skills acquired via formal schooling and (time-*varying*) job-specific skills. Likewise, firms are heterogenous in their skill requirements, i.e. the (time-invariant) tasks that are required on the job.[5]

Timing is as follows: In the first period, workers choose an occupation in accordance with their skills. Subsequently, they receive jobs which they accept or reject. Should workers realize their skills do not align with the occupation, they may switch occupations in the second period or stay put.

2.2 Job Search and Production

Before entering the labor market in the first period, individuals i acquire general skills via schooling. Afterwards, they search for an occupation o that matches their formal schooling requirements and projected ability to perform job-specific tasks j. Potential employers do not know to what extent candidates are equipped to perform tasks j, hence there is uncertainty about matching as in the seminal study by Jovanovic (1979) and most of the literature thereafter. Yet, schooling outcomes serve as a perfect signal for formal

[5]While the time-invariant aspect of firm heterogeneity is unrealistic in light of rapid occupational changes in the last few decades, it is a plausible assumption in a setup with only two years.

qualifications and these are in turn correlated with occupation-specific skill requirements.

In the following, I assume workers and firms alike know the applicant's relative position in the general skill distribution. Formally, skill mismatch m_{io} can be defined as follows:

$$m_{io} = (P_i - T_o) \tag{1}$$

where P_i is the general skill level of i, acquired prior to job entry, and T_o reflects job-specific skills that are required to perform tasks and vary across occupations o. P can be thought of as general skills in the spirit of Becker (1964), representing human capital that is general in nature and thus portable across occupations —e.g. communication skills and basic IT skills. In contrast, I view T as specific skills in the sense that they require a specific combination of tasks that substantially varies by occupation —e.g. legal skills, medical skills, or technical skills. The key difference between these two skill measures is that skills T are less portable than those included in P. Moving forward, I will refer to workers for whom $m_{io} > 0$ as *overqualified* in the sense that they bring more general skills into their job as needed. Conversely, workers characterized by $m_{io} < 0$ are considered *underqualified* following the same logic. This assumption allows for asymmetric labor market effects of a SMM depending on the relative endowment of skills P and T, respectively, similar to Lise & Postel-Vinay (2020).[6]

Once hired into occupation o, worker i combines j tasks to produce output Y according to:[7]

$$Y_{iot} = \underbrace{(\theta_{it}) \left[\sum_J (\tau_{ijt} T_{ijt}) \lambda_{jo}\right]}_{\text{Job-Specific Skills}} + \underbrace{(1 - \theta_{it}) P_i}_{\text{General Skills}} + \epsilon_{iot} \equiv H_{it}(T_{it}, P_i, \epsilon_{it}) \tag{2}$$

Production is simply represented by the underlying human capital H of workers who combine their multidimensional skills, similar to the skill-weight approaches in Lazear (2009) and Gathmann & Schönberg (2010). By entering the labor market and spending

[6]Guvenen, Kuruscu, Tanaka & Wiczer (2020) use a similar measure for skill mismatch, defined as the difference between ability and occupational skill requirements. They do not allow for over- or underqualification, however, indicated by the sign of m_{io}.

[7]I follow Autor & Handel (2013) and normalize the output price in each occupation to unity for the sake of simplification.

some number of hours τ on tasks j, workers accumulate task-specific human capital necessary to produce output in their job.

The relative importance of skills P and T is governed by the parameter θ. Hence, jobs with very specific skill requirements induce workers to place a greater weight on T and vice versa for P. To account for the uncertain nature of human capital at time t, ϵ is an independent and identically distributed (i.i.d.) shock that reflects uncertainty about workers skills. This production function has two noteworthy features.

First, it incorporates time allocation of job tasks. Conceptually, weighing the task endowment by τ permits an interpretation in terms of efficiency units of task j: The more units of j individual i performs, the more efficient she is at performing those tasks. This interpretation facilitates LBD as a result of differential time allocation on tasks. Second, job activities are compensated by occupation-specific task returns $\lambda_{jo} \geq 0$. As occupations may value tasks differentially, λ not only varies across tasks, but also across different jobs.

My model structure closely follows Antonovics & Golan (2012), however, differs from their framework in three important ways. First, they assume all types of skills are time-invariant. By fixing P, however, I focus on investments into job-specific skills that facilitate LBD. Second, Antonovics & Golan (2012) do not address the origin nor the timing of skill acquisition. In contrast, I distinguish between skills acquired prior to job entry and those acquired on the job. This differentiation is important in the present setup as it emphasizes variation in job-specific skills as a driver in wage differentials. Third, I incorporate time allocation on tasks to study task specialization within occupations.

2.3 Learning

Learning in this model assumes two-sided information frictions, i.e. workers and firms alike do not know the former's ability to perform tasks on the job. Yet, both know the prior distribution of T. As workers spend τ hours per day on performing tasks, they accumulate task-specific human capital via LBD and provide new information on the match quality. Following Antonovics & Golan (2012), this progress sends signals ζ_t to their employer:

$$\zeta_t = \frac{Y_{iot} - (1-\theta)P_e}{\theta} = \sum_J (\tau_{ijt} T_{ijt}) \lambda_{jo} + \frac{\epsilon_{iot}}{\theta} \tag{3}$$

By adding more output than would be expected based on known P, workers indicate greater productivity than initially assumed. Tracking output over time is not only beneficial to employers who receive new information about their employee's productivity, but also for workers whose compensation is tied to their marginal product. For simplicity, I assume the surplus generated by excess production is shared between firms and workers. This assumption reinforces their incentive to learn more about their job-specific skills with the objective of choosing the optimal $\theta^\star$ and thus maximize intertemporal earnings.[8] The Online Appendix provides more details on worker's beliefs about their productivity and how these shape their decision-making process.

2.4 Solving the model

This section sketches the solution to the model. The interested reader is referred to the Online Appendix for proofs and more details. Each worker works for T=2 periods in which she supplies one unit of labor inelastically.[9] For simplicity, she maximizes utility by maximizing the expected present value of lifetime wages, i.e. $U = E\left[\sum_{t=1}^{T=2} \beta^{t-1} w_t\right]$.

Proposition 1: Solution to Second-Period Problem for all workers

Productivity is highest when task assignments are optimal. Workers will thus specialize in tasks in which they exert the greatest productivity, implying a corner solution:

[8] In reality, firms may instead choose the time allocation of their workers. Given the assumptions on the market environment and symmetric information, however, Antonovics & Golan (2012) have shown it is trivial who ultimately chooses θ. The equilibrium outcome remains unaffected by the nature of the decision-maker.

[9] This assumption implies that if worker i spends one less hour on routine tasks, she instead devotes an one additional on a combination of abstract and manual tasks, thereby leaving her total working time unaffected.

$$\theta_2(\mu_2) = \begin{cases} 1 & \text{if } \mu_{i2} = E(T_{ij2}|\mu_{i2}, \sigma_2) \ \geq P_i \\ 0 & \text{otherwise} \end{cases} \tag{4}$$

where μ denotes beliefs about worker's productivity.

Proof: See Online Appendix.

Put simply: If job-specific skills T are expected to exceed general skills P, underqualified workers will find it optimal to only utilize specific skills in the production of output and vice versa for overqualified workers.

Proposition 2: Solution to First-Period Problem for underqualified workers

If $\mu_1 > P$, workers believe they can exert their greatest productivity by specializing in job-specific skills. Consequently, they will choose a corner solution:

$$\theta_1(\mu_1) = \begin{cases} 1 & \text{if } \mu_{i1} = E(T_{ij1}|\mu_{i1}, \sigma_1) \ \geq P_i \\ 0 & \text{otherwise} \end{cases} \tag{5}$$

Proof: See Online Appendix.

Intuitively, if a worker is more productive utilizing job-specific skills, she will expect to produce more output in the second period, inducing her to attach greater weight to θ. As a consequence, with $U_1 = w_1$, wage maximization implies that the corner solution for $t = 2$ likewise applies in $t = 1$.

Proposition 3: Solution to First-Period Problem for overqualified workers

If $\mu_1 < P$, investing in job-specific skills comes at a cost of foregone output if workers select a positive weight on job-specific skills. By gauging the potential benefits in terms of additional output in period 2 versus the costs of reduced output in period 1, this scenario implies an interior solution:

$$\frac{m_{io}}{\beta} = \frac{\partial s_2}{\partial \theta_1}\phi(\xi) \tag{6}$$

where $m_{io} = (P - \left[\sum_J (\tau_{ij,1}\mu_{ij,1})\lambda_{jo}\right])$ *is the SMM for* i *employed in* o *and* $\phi(\xi)$ *is a standard normal pdf with* $\xi = \frac{m_{io}}{s_2}$ *and* s_2 *reflecting the variance in beliefs.*

Proof: See Online Appendix.

This condition states that the marginal cost of time devoted to acquiring job-specific skills in period 1 (LHS) equals its marginal benefit that will be accrued in period 2 (RHS).

2.5 Empirical Predictions

As is common in learning models, suboptimal realizations in the past have an impact on current productivity. In the present context, negative effects on productivity are the result of suboptimal assignment of tasks in the present *and* the past. I view these outcomes related to the concept of task-specific human capital introduced in Gathmann & Schönberg (2010). Because of imperfect transferability of skills across occupations, differential task specialization at the beginning of a career can have persistent effects throughout one's career with important implications on individual wage growth and job mobility. A key implication of the model is asymmetry in matching. Skills of overqualified are underutilized at job entry, reducing their incentives to invest in job-specific skills. Conversely, underqualified workers devote a disproportionate amount of time on job-specific skills, allowing them to develop those at a rapid pace in spirit of a Ben-Porath (1967) framework.

To summarize, the model has the following testable predictions:

1. Underqualified workers ($\tau_{ijt} \times T_{ijt} > P$) experience positive wage growth.
2. Overqualified workers ($P > \tau_{ijt} \times T_{ijt}$) exhibit ambiguous wage growth, but, if positive, at a slower pace than underqualified workers.
3. Overqualified workers are more likely to rely on general skills and switch occupations to improve their skill match. In contrast, underqualified workers invest more time on job-

specific skills. Consequently, they accumulate task-specific human capital that is specific to their initial occupation, making a switch to another occupation less likely.

3 Data

3.1 Description

A. BIBB/BAuA

The primary data is taken from German employment surveys on qualification and working conditions of workers in Germany. A total of 20,000 individuals have been surveyed in 2012, notably comprising self-reported information on job tasks (Hall, Siefer, Tiemann & BIBB/BAuA 2018). However, in this survey, workers were not required to elaborate on the actual time allocation of job-related activities. Instead, frequency of task assignments has been approximated by a three-point Likert scale.

Essential for the purpose of this study is a supplementary survey that was conducted in 2013 and followed up on some 4,300 workers from the 2012 main survey (Tiemann, Alda, Rohrbach-Schmidt & BIBB 2015). This survey consists of two parts. In the first questionnaire, workers report notable changes at the workplace with respect to (i) type of tasks performed, (ii) occupational affiliation, and (iii) weekly working hours. Subsequently, they were asked to participate (voluntarily) in the second part of the survey on a day of their choice. In these interviews workers were asked about the work time (in hours) devoted to job tasks. Around 2,300 individuals have participated in the second round and provided task information in time units.

Three key features make the data suitable for the present study. First, workers self-report their activities, thereby allowing me to account for individual heterogeneity. Second, the longitudinal nature of this data allows me to observe variation in tasks over time. Third, data on the time allocation of tasks facilitates an analysis on task returns in time units, as opposed to conventional binary information on tasks (Yes/No). It therefore provides a more direct way to analyze wage outcomes resulting from LBD.[10]

[10]To my knowledge, the only data with comparable information is the *Berea Panel Study*, which

Despite these compelling features, the data has a few notable disadvantages. First, wages are not consistently observed in both years. While data on monthly labor income is available in the 2012 main survey, the 2013 supplementary survey merely asks for income changes.[11] Second, information on tasks in detailed time units is only available for one year (= 2013). Based on related survey responses, I impute the detailed time units for the main survey in 2012. Section 3.2.2 provides more details on my imputation strategy. Third, the data only includes two consecutive years, implying relatively little variation in tasks within individuals.

B. BERUFENET

The secondary data is taken from BERUFENET, an online job portal provided by the German Federal Employment Agency (BA). This database is a popular research tool for German job entrants seeking career guidance and exploring job placements, thus conceptually related to the widely known O*NET, collected by the US department of labor. Motivated by the model outlined in section 2, I use this data to capture the information set of workers prior to job entry. Using data compiled by Dengler, Matthes & Paulus (2014), I gather information on the relative importance of occupation-level tasks (3-digit level) for the years 2011-13.[12] I average task measures across all years to enhance statistical precision.

follows two cohorts of students at Berea College over ten years, and includes the percentage of time spent on tasks (Stinebrickner, Stinebrickner & Sullivan 2018, 2019). One drawback of this data, however, is that it does represent the broad workforce. Instead, the cohorts consist only of college graduates. In comparison, the BIBB/BAuA data used in the present study covers all education levels and occupational groups, including those typically not represented by high-skilled workers. Other well-known data such as Time Use Surveys for Europe (HETUS), UK (UKTUS), and US (ATUS) do offer accounts on how much time people spend at work, but not on the time allocation of job-specific activities.

[11] Out of all workers providing information on the time allocation of tasks, 591 individuals (29%) report changes in their monthly labor income. In the first stage, workers reported whether their monthly labor income (1) improved, (2) deteriorated, or (3) stayed roughly the same. Subsequently, they were asked to quantify these income changes in EUR. Out of the 591 workers with information on time allocation of tasks, 576 individuals report numerical changes. An additional 15 workers provide information in binned form, indicating changes between (1) 3-10% or (2) 11-100%. In the baseline specification, I use the lower bound of the binned information to impute income changes, thus assuming a conservative approximation.

[12] The data by Dengler, Matthes & Paulus (2014) is especially useful for research on occupational skill requirements and has been widely used ever since its release, for instance in the context of substitution potentials of the digital transformation (Dengler & Matthes 2018), the “greening of jobs” (Janser 2018), labour market entry (Reinhold & Thomsen 2017), and labour market mismatch (Kracke, Reichelt & Vicari 2018, Kracke & Rodrigues 2020).

3.2 Construction of Task Measures

The key variables are individual skills, approximated by tasks performed on the job. In terms of the classification of job-related activities, I follow Acemoglu & Autor (2011) by pooling narrow activities into $J = 3$ task categories: (i) Abstract, (ii) Routine, and (iii) Manual. Abstract tasks involve strong problem-solving skills. In contrast, routine tasks are characterized by following explicit and easily codifiable rules. Lastly, manual tasks require physical labor pronounced in basic services, among others. Figure (1) illustrates the process of collecting related individual activities, followed by aggregation into broader task groups.

[Figure (1) here]

3.2.1 Traditional Task Measure: Task Intensity T_{ijt}

I follow Antonczyk, Fitzenberger & Leuschner (2009) (henceforth AFL) by defining T_{ijt} for worker i at time $t \in (2012, 2013)$ as

$$T_{ijt} = \frac{\text{No. of activities performed by i in task category j at time t}}{\text{Total no. of activitites by i across } \textit{all} \text{ j's at time t}} \tag{7}$$

where $j = 1$ (Abstract), $j = 2$ (Routine), and $j = 3$ (Manual), with properties (i) $T_{ijt} \in [0, 1]\ \forall j$ and (ii) $\sum_J T_{ijt} = 1$. This measure has been widely adopted in the literature and describes the relative importance of each task group j.[13] For example, if worker i performs two abstract, two routine, and one manual task, then her abstract, routine, and manual task content, respectively, is 0.4, 0.4, and 0.2. Therefore, 40% of her overall activities comprise abstract and routine tasks each. The remaining 20% involve manual activities.

3.2.2 New Task Measure: Time allocation τT_{ijt}

Antonczyk, Fitzenberger & Leuschner (2009, p.8) view the task measure illustrated in eq. (7) “as an approximation of the share of working time”. Therefore, they implicitly

[13]See, for instance, Senftleben & Wielandt (2014), Bachmann, Cim & Green (2019) and Bachmann, Demir & Frings (2021).

assume each activity belonging to task group j is equally important in terms of a worker's time allocation. This assumption, however, is strong in light of existing evidence on the heterogeneity of time allocation on tasks (Stinebrickner, Stinebrickner & Sullivan 2019). I thus propose a modified task measure that accounts for differential time allocation on tasks:

$$\tau_{ijt} = \frac{\text{Hours spend by i on task j at time t}}{\text{Total no. of of hours spend by i across } \textit{all} \text{ j's at time t}} \tag{8}$$

where τ_{ijt} captures the share of working time devoted to task j. Unfortunately, the data used in the present study only offers information on the time allocation on tasks for the year 2013. To provide remedy, I impute the 2012 value using broader information on the time dimension of tasks available in both years. Specifically, both surveys ask workers whether they perform an activity (i) often, (ii) sometimes, or (iii) never.

Based on their responses, I create a dummy variable equal to 1 if individual i performs activity a belonging to task group j "often" —i.e. $d^{oft}_{iajt} = 1$ if $a =$ "often"—and $d^{oft}_{iajt} = 0$ otherwise. Similarly, I create a dummy $d^{some}_{iajt} = 1$ if $a =$ "often" <u>or</u> $a =$ "sometimes" and $d^{some}_{iajt} = 0$ if $a =$ "never". Using these definitions, I construct corresponding task measures T^{oft}_{ijt} and T^{some}_{ijt}, respectively, per eq. (7), as follows:

$$\begin{aligned} T^{oft}_{ij} &= \frac{\sum_{a=1}^{A_j} d^{oft}_{iaj}}{A} \\ T^{some}_{ij} &= \frac{\sum_{a=1}^{A_j} d^{some}_{iaj}}{A} \end{aligned} \tag{7'}$$

where a is the number of activities belonging to j relative to all activities A.

[Figure (2) here]

Figure 2 illustrates this distinction by plotting densities of the three task groups with different assumptions on the underlying frequency. Using the broader definition of tasks (i.e. T^{some}_{ijt}) produces a distribution with greater kurtosis as workers are now assumed to perform a broader set of activities. This difference is attributed to the fact that more workers perform, e.g.,, abstract tasks "often" or "sometimes" as opposed to highly specialized workers performing abstract tasks "often". I use variation between T^{oft}_{ijt} and

T_{ijt}^{some} that occurred between 2012 and 2013 as a proxy for differential skill accumulation. In the context of the model in section 2, I interpret a shift away from T_{ijt}^{some} towards T_{ijt}^{oft} as a learning shock. This shift reflects greater specialization in task j as workers spend more time on j. Formally, the learning shock is embodied in ϵ (see eq. 3) and inferred from the data as follows:

$$\epsilon_{ijt} = \frac{T_{ijt}^{oft}}{T_{ijt}^{some}} = \frac{\sum_{a=1}^{A_j} d_{iaj}^{oft}}{\sum_{a=1}^{A_j} d_{iaj}^{some}} \tag{9}$$

Figure (3) plots learning shocks for each of the three task measures. If $\epsilon_{ijt} > 1$, worker i experiences a positive learning shock as a result of performing task j more efficiently than expected and vice versa for $\epsilon_{ijt} < 1$. While learning shocks associated with routine and manual tasks are fairly symmetric, the density with respect to abstract tasks is slightly positively skewed. This observation implies relatively more workers are sending a negative signal about their productivity pertaining to abstract tasks. Lastly, I use the ϵ_{ijt} values to impute time allocation on tasks in $t = 2012$ as follows:

$$\tau_{ijt} = \begin{cases} \tau_{ij,t+1} \times \frac{\epsilon_{ij,t}}{\epsilon_{ij,t+1}}, & \text{if } t = \ 2012 \\ \tau_{ij,t}, & \text{if } t = \ 2013 \end{cases} \tag{10}$$

Intuitively, I impute time allocation in $t = 2012$ by multiplying (known) time allocation in $t = 2013$ by the (known) inverse learning shocks $\frac{\epsilon_{ij,t}}{\epsilon_{ij,t+1}}$. This formulation implies time allocation on tasks in $t = 2012$ is proportional to learning shocks, i.e. i.e. $\frac{\tau_{13}}{\tau_{12}} = \frac{\epsilon_{13}}{\epsilon_{12}}$. Since τ_{12} is the only unknown, I can impute it with information on τ_{13}, ϵ_{13}, and ϵ_{12}.[14]

[Figure (3) here]

The Online Appendix provides more details on the imputation procedure along with

[14] Consider a brief numerical example to illustrate the logic of the imputation method: Assume an Econ postdoc named Jane who spends six hours on research in 2013. Using definitions d_{iaj}^{oft} and d_{iaj}^{some}, I deduce from the data that $T_{13}^{oft} = 1$ & $T_{13}^{some} = 1$. By eq. (9) this implies $\epsilon_{13} = 1$. In 2012 I do not observe her hours spend on task j, but I do observe the same information that allows me to calculate the T's. Specifically, assume I find $T_{12}^{oft} = 0.5$ & $T_{12}^{some} = 1$. Using eq. (9) once more, implies $\epsilon_{12} = 0.5$. Assuming time allocation on tasks is proportional to learning shocks (i.e. $\frac{\tau_{13}}{\tau_{12}} = \frac{\epsilon_{13}}{\epsilon_{12}} = \frac{1}{0.5} = 2$), I observe Jane experienced a positive learning shock and impute the number of hours spend on task j according to eq. (10). Completing our example from above, the imputation procedure suggests that Jane spent $\tau_{12} = 3$ hours on research in 2012 ($= 6 \times \frac{0.5}{1}$).

validity tests, including (i) comparisons of occupations intensive in task j using imputed and conventional AFL task measures (i.e., eq. 7), and (ii) wage regressions using either task measure. In summary, these exercises suggest both task definitions imply qualitatively similar conclusions. Yet, my imputed task measure captures richer variation in task specialization that is not embedded in AFL measures. Moreover, I perform robustness checks based on a regression-based imputation method in section 7, implying similar conclusions as well.

4 Sample Selection and Descriptive Statistics

Given a small sample, my baseline analysis is based on parsimonious restrictions to preserve statistical power. Specifically, workers need to be (i) aged 18-65 and (ii) employed in an occupation with at least three observations. With those restrictions in place, it leaves a panel consisting of 1,224 workers (male and female), thus a sample size of 2,448 observations.

[Table (1) here]

Table (1) displays a set of socio-economic characteristics, showing that more than three quarters of the sample earned a vocational degree. This observation points to the prominence of the vocational track in the German labor market. Among the remaining workers, most have a college degree with almost no dropouts.

[Table (2) here]

Table 2 displays the relative importance of tasks, both using conventional AFL definitions and my definition in terms of time units. The AFL value for abstract tasks of 0.53 in the top line implies that 53% of all job activities are abstract in nature. In comparison, the hours-based definition (line 7) suggests workers spend on average 52% of their working time on abstract tasks. On average, both definitions yield similar summary statistics, lending credence to the AFL interpretation as a proxy for the share of working time. Similar conclusions carry over to routine and manual tasks. However, the AFL definition masks heterogeneity as suggested by their smaller standard deviation.

This point becomes evident in Figure (4), plotting the distribution of time allocation of tasks across abstract, routine, and manual tasks. While the average worker devotes around three hours on abstract tasks, the graph likewise illustrates a wide range of outcomes. Many workers spend only up to an hour a day on abstract tasks while others perform almost exclusively abstract tasks, illustrating substantial heterogeneity masked by conventional AFL definitions. Task time units with respect to routine and manual tasks likewise display heterogeneities, though both also display an exponential decrease along the distribution.

Similarly, for task measures à la AFL to serve as a valid proxy for time units, workers must also be assumed to spend an equal amount of time on each task-specific activity. I test this assumption in Figures (5) - (7), plotting the distribution of time allocation for each individual activity belonging to abstract, routine, and manual tasks, respectively. Note these figures are illustrated conditional on workers performing said task, as most activities are heavily centered around zero.

Some activities display an unimodal distribution with the mode between 0-1 hours. Others, show a bimodel distibution with an additional mode at 1 hour or above. Figure (5) highlights that abstract activities least common among workers, especially if marketing-oriented, tend to be more skewed to the right with only a few minutes a day. More common activities such as organizing, consulting, and investigating, however, are more evenly distributed. This observation implies that many workers spend at least an hour a day on those customary activities. These discrepancies are even more pronounced for routine (Figure 6) and manual activities (Figure 7). Overall, the descriptive statistics are at odds with the implicit assumptions underlying AFL-like task definitions. Moving forward, I exploit this rich variation in task time units in order to study its implications on task-based learning and, ultimately, job mobility and wages.

[Figure (4) here]

[Figure (5) - (7) here]

5 Estimation Strategy

In this section, I first explain how I construct general skills from self-reported information of workers. Subsequently, I describe the creation of job-specific skills and SMM measures.

A. Construction of General Skills

I use two pieces of information from the BIBB/BAuA surveys to approximate general skills. First, the main survey from 2012 asks workers about their final grades in school. Second, I account for quality differences in schooling. For instance, a "good" grade associated with a high school diploma ("Abitur") is valued higher than a "good" grade associated with a middle school diploma ("Realschule"). I combine these pieces of information to compute quality-adjusted proxies for general skills, acquired prior to job entry, to conduct a Principal Component Analysis (PCA). Using the first component, I condense information about general skills into one variable. This variable has no intrinsic meaning, hence I standardize it to take values between 0 and 1. The Online Appendix provides more details on the construction of general skills.

Regarding interpretation, this measure proxies individuals' position in the distribution of general skills P. Conceptually, this idea implies students' rankings throughout school is what matters most prior to job entry. This link is informative as it signals capacity to perform abstract job tasks (Acemoglu & Autor 2011) and is supported by prior research finding, e.g., higher placement in STEM fields among students near the top of their classes (Murphy & Weinhardt 2020).

B. Construction of Job-Specific Skills

The BERUFENET data compiled by Dengler, Matthes & Paulus (2014) captures the idea that labor market entrants gather information about occupations by exploring platforms that summarize job-specific skills. The data therefore approximates individual's information set on job-specific skill requirements and affects the initial occupational choice. The BIBB/BAuA data, on the other hand, approximates worker's information set *after* job entry. Specifically, I add up the total amount of time spent on the activities summarized in Figure (1) and illustrated at the bottom three rows in Table (2). Like all previous skill measures, these variables are bound between 0 and 1.

C. Construction of SMM Measures

The BIBB/BAuA survey provides information on the (i) current and (ii) first occupation. Using this information, I construct an initial SMM by assigning the occupational skill requirements per Dengler, Matthes & Paulus (2014) to a worker's initial occupation.[15] I use the skill requirements from BERUFENET for initial SMM to approximate individual's information set prior to job entry. This proceeding assumes occupations are time-invariant in terms of their distribution of skill requirements. For instance, an occupation ranking at the 75th percentile in the abstract distribution in 2012 is assumed to have also been ranked at the 75th percentile when worker i entered the labor market. Combining information on occupational biography from the BIBB/BAuA surveys with BERUFENET data, I construct the initial SMM measure m_{ijo}^{init} as follows:

$$m_{ijo}^{init} = (P_{i,\rho} - T_{o,\rho(j)}^{init}) \tag{11}$$

where ρ denotes the percentile rank of worker i in P, the general skill distribution of all workers, and $\rho(j)$ denotes the percentile rank in $T_{o,\rho}^{init}$, i.e. the rank of the initial occupation o in the the job-specific skill distribution with respect to task j.

This SMM measure is closely related to variables used in previous research. For instance, Lise & Postel-Vinay (2020) propose a search model in which SMM is determined at job entry. Subsequently, workers accumulate more skills as they gain experience and lose others that are not needed at their job. Similarly, Guvenen, Kuruscu, Tanaka & Wiczer (2020) construct a measure for cumulative mismatch to account for responses to initial mismatches and subsequent job mobility. In this paper, I combine the approach from both of these studies by complementing the initial SMM with current SMM m_{ijo}^{now}:

[15] Ideally, I would observe all occupations worker i ever exercised to characterize her entire job history. Unfortunately, the data does not provide such detailed information, making it impossible to construct a detailed cumulative mismatch in spirit of Guvenen, Kuruscu, Tanaka & Wiczer (2020), weighing each mismatch episode by the duration of employment. Nonetheless, the initial occupation appears the next-best strategy as prior research has identified initial conditions at labor market entry, including initial occupation choice, as a main source of wage variation among workers (Speer 2017, Taber & Vejlin 2020).

$$m_{ijo}^{now} = P_{i,\rho} - (\tau_{ij} T_{o,\rho(j)}^{now}) \tag{12}$$

where τ_{ij} denotes the percentage of time i devotes task j. Since $\sum_J \tau_{ij} T_{o,\rho(j)}^{now} = 1$, one task must be omitted to avoid multicollinearity. In light of the "Routinization Hypothesis", I choose routine tasks as reference group to reflect the ongoing shift away from routine towards abstract and manual tasks (Autor & Dorn 2013, Bachmann, Cim & Green 2019).

D. Empirical Specifications

To estimate the impact of SMM on job mobility, I run standard Probit regressions, separately by (mismatch) groups $g = overqualified, underqualified$:

$$P(Y = 1|X)_{io} = \beta m_{io}^{init,g} + \gamma \mathbf{X}_i + \epsilon_{io} \tag{13}$$

where Y is a dummy, indicating whether a worker switched occupations during their career ($Y = 1$) or have remained in their initial occupation ($Y = 0$). The coefficient β captures the propensity to switch jobs subject to the initial $SMM m_{io}^{init,g}$. The matrix $\mathbf{X}$ controls for socio-economic characteristics, sectoral dummies, and year dummies while ϵ_{io} is a standard i.i.d. error term.[16]

Regarding wage effects, I use initial and current SMM measures to run the following regressions, again separately by $g = overqualified, underqualified$:

$$\begin{aligned} ln\ w_{io} = & \underbrace{\lambda^{init,g} m_{io}^{init,g}}_{\text{Returns to SMM in initial occ.}} + \underbrace{\Psi^{init,g} TEN_{jo}^{init,g} + \Lambda^{init,g}(m_{io}^{init,g} \times TEN_{jo}^{init,g})}_{\text{Cum. Returns to SMM in initial occ.}} \\ & + \underbrace{\lambda^{now,g} m_{io}^{now,g}}_{\text{Returns to SMM in current occ.}} + \underbrace{\Psi^{now,g} TEN_{jo}^{now,g} + \Lambda^{now,g}(m_{io}^{now,g} \times TEN_{jo}^{now,g})}_{\text{Cum. Returns to SMM in current occ.}} \\ & + \gamma \mathbf{X}_i + \epsilon_{io} \end{aligned} \tag{14}$$

[16]The matrix of controls comprises sex, education, age, dummies for citizenship (German/Foreign), dummies for a German-speaking household during childhood (Yes/No), labor market tenure, firm tenure, squared terms for age and tenure measures, year dummies, and industry dummies.

where $TEN_{jo}^{init,g}$ and, respectively, $TEN_{jo}^{now,g}$ represent *task tenure* in the first and current job. I calculate task tenure by weighing worker's occupational tenure by the proportion of time associated with each task (hence the subscript j). Task tenure is a more nuanced representation of task-specific human capital (Gathmann & Schönberg 2010) by incorporating individual time allocation on tasks. It therefore provides richer information on the skill acquisition during a career than conventional measures such as occupational tenure or labor market experience.[17] Interacting $TEN_{jo}^{init,g}$ with $m_{ijo}^{init,g}$ captures the idea that tasks performed at the beginning of a career have persistent effects on productivity. The terms in the second line of eq. (14) capture similar intuition for the current occupation.

Of primary interest are the coefficients $\lambda^{init,g}$, $\lambda^{now,g}$, $\Psi^{init,g}$, $\Psi^{now,g}$, $\Lambda^{init,g}$, and $\Lambda^{now,g}$. While the former two capture base wage effects associated with a given mismatch g, the latter four coefficients pick up cumulative returns that can be attributed to LBD. For instance, positive estimates for the Ψ terms are indicative of returns resulting from task-based learning in task j. If Λ is negative, however, these returns are diminishing with rising tenure.

In the baseline analysis, I estimate variations of eq. (14) using a Random-Effects (RE) estimator. While fixed effects (FE) estimates are generally preferable in longitudional settings (Wooldridge 2010, Ch. 10), this approach is not practical in the present setting. First, a FE estimator naturally differences out all time-invariant regressors. One of the key regressors, initial SMM, would thus be excluded from the analysis. Second, given small sample limitations, there is not sufficient within-individual variation in task measures, causing imprecise estimates. Compared to pooled OLS (POLS), however, the RE estimator is more efficient by accounting for serial correlation in the error term, making it my preferred choice. I validate this choice in section 7 where I perform robustness checks using POLS instead.

[17]For instance, consider our postdoc Jane, whom I introduced in section 3.2.2 to illustrate my imputation procedure (footnote 14). If she has five years of experience in her job and devotes 80% of her time on abstract activities, she earned the equivalent of four years of experience with respect to abstract tasks (= 5 × 0.8) - and one year of experience with respect to routine and manual tasks (combined).

6 Results

In this section I test the theoretical model's implications of (i) differential job mobility and (ii) heterogeneous wage growth, contingent on initial type of SMM.

6.1 Skill Mismatch & Job Mobility

Table (3) summarizes the results of my Probit specification from eq. (13). Regardless of specifications, the coefficients are always positive and highly significant if job-specific skills are defined in terms of abstract tasks and negative if job-specific skills are defined in terms of routine tasks. Hence, job mobility depends on the type of SMM at job entry. How meaningful are these differences? To answer this question I plot average marginal effects at different points of the distribution of initial SMM against the probability of moving to a new job sometime in their career. Underqualified workers are located towards the left of this distribution, while overqualified workers are located towards the right.

[Table (3) here]

Figure (8) summarizes these results, spanning the probability of a job switch for workers at the 10th percentile of the initial SMM distribution all the way to the 90th percentile. Job-specific skills are defined for each of the three task groups. Panel (a) shows that the probability of a job switch is 51% for workers at the 10th percentile compared to 70% at the 90th percentile if job-specific skills are defined in terms of abstract tasks. Therefore, the likelihood of switching an occupation is higher by up to 19 pp. for overqualified workers relying more on general skills.

Defining job-specific skills in terms of routine (b) and manual (c) skills implies the opposite. Following these definitions, underqualified workers are more likely to switch occupations by up to 11 pp. (routine) and 6 pp. (manual), respectively. The findings are thus consistent with the empirical predictions of the model in section (2), though only if occupations are defined in terms of abstract skills, and related literature documenting higher job separation rates for overqualified workers (Roller, Rulff & Tamminga 2020, Le Wen, Maani & Dong 2023).

[Figure (8) here]

6.2 Skill Mismatch & Learning

6.2.1 Learning of Abstract Tasks

The wage effects of a SMM are displayed in Table (4), defining job-specific skills in terms of abstract tasks. Results are reported such that wage effects are associated with an incremental increase in job-specific skills T over general skills P, hence permitting an interpretation of returns to task-based learning. Columns (1) - (5) display results for overqualified workers, successively adding SMM measures at different stages of their career. Positive estimates on both tenure measures (first and current occupation) suggest average wage gains from task-based learning. On average, with each year of abstract task tenure, wages increase by 2% (column 5).

In comparison, the corresponding wage gains for underqualified workers amount to 2-3% (column 10). Over the course of five years, the wage increase associated with abstract task tenure thus amounts to 10% for overqualified workers and 16% for underqualified workers. These findings are well in line with Kambourov & Manovskii (2009) who document returns to occupational tenure over a 5-year span of 12-20% among US workers. Larger individual wage growth for underqualified workers is consistent with my theoretical model from section 2, as these workers are incentivized to invest more time in job-specific skills. Interestingly, the negative estimate on the interaction term with respect to the first occupation implies their wage growth diminishes over time.

[Table (4) here]

How can these findings be reconciled with the model? While some underqualified workers may be stuck in an occupation with stagnant, or even negative, wage growth, others will take this opportunity to change occupations. On the one hand, a job switch implies depreciation of human capital (Kambourov & Manovskii 2009). On the other hand, similarity in skill requirements between new and source occupation is rising with experience (Gathmann & Schönberg 2010). Senior workers may thus accumulate sufficient abstract skills, which are transferable across occupations and are mitigating the loss of human capital.

The positive estimates associated with a current SMM lend credence to this hypothesis. Each additional 1 pp. of working time devoted to abstract tasks subsequently implies a baseline wage premium of 21%.[18] With each additional year of abstract tenure in the new job, workers receive another 2% return on their investments in task-specific human capital.

This discussion on task-specific human capital does not explain, however, *why* returns to LBD are diminishing. To shed more light on underlying mechanisms, I plot marginal effects of SMM measures for each group at different levels of tenure (Figure 9, Panel a). For underqualified workers, diminishing returns on job-specific skills imply negative wage growth after 14 years of abstract task tenure. Note that this group of workers devotes around 60% of their time on abstract activities. Extrapolating this value throughout their career provides a rough estimate on the timing of their wage peak, in this case a total of 23 years on the (first) job (Panel: Initial SMM, underqualified). Workers who switch jobs sometime, experience positive wage growth for another 10 years of abstract task tenure (Panel: Current SMM, underqualified). The same extrapolation implies their period of positive wage growth is extended by another 16 years, implying a wage peak after 39 years.

Depending on underlying job mobility, underqualified workers thus reach their wage peak after 23-39 years. In comparison, Lagakos, Moll, Porzio, Qian & Schoellman (2018) use data from a representative German household panel for the years 1991-2009 and show life cycle wage growth peaks after potential labor market experience of 35-39 years. My back-of-the-envelope calculation therefore seems a reasonable upper bound of the maximum height of experience-earnings profiles.

These wage implications are unique to the group of underqualified workers and are consistent with skill obsolescence as described in Deming & Noray (2020). In their model, learning on the job is devalued in occupations in which technological change erodes specific

[18]Keep in mind this premium reflects relative returns. In order to spend 1 pp. more time on abstract tasks, a worker must spend less time on routine and manual tasks.

skills. Hence, gains resulting from LBD do not accumulate enough to offset depreciation of human capital resulting from rapidly changing skill requirements.[19] Focusing on STEM occupations, Deming & Noray (2020) document transitions to more slow-changing occupations among experienced workers. These senior workers are selected on ability, thus enabling quick reemployment. Better match quality among experienced workers likewise mirrors evidence on mismatch and wage growth in Sweden (Fredriksson, Hensvik & Skans 2018). These authors show (occupation-level) sorting on comparative advantages across jobs is important for wage growth among senior workers, while learning is more relevant among junior workers.

[Figure (9) here]

Lastly, a few words of caution: While the results are consistent with theory and prior research, they are likely contaminated by several factors. First, I only observe two years and impute some of the information on time allocation on tasks. This proceeding naturally introduces measurement error. Second, I do not observe a full history of stratified occupation choices, making it challenging to depict the evolution of skill accumulation.[20] Given the rapid increase in abstract skill requirement within occupations over time (Spitz-Oener 2006), especially underqualified workers, who tend to be employed in abstract-intensive occupations, may have therefore benefitted disproportionately from technological change. Third, by assigning contemporanous task measures on the initial occupation and comparing these outcomes to the contemporaneous task content of a worker's current occupation, I implicitly assume that task prices have not changed since job entry - an assumption at odds with existing research (Boehm, von Gaudecker & Schran 2020). Once more, workers in abstract-intensive occupations may have benefitted from this development to a greater extent. For these reasons, my findings on wage effects

[19] Hanushek, Schwerdt, Woessmann & Zhang (2017) offer similar evidence in a cross-country setting, including Germany. Using IALS data, they classify workers as those receiving general vs vocational education, where the latter is broadly comparable to job-specific skills explored in the present study. The authors document a trade-off in the acquisition of job-specific skills as they facilitate quick transition into the laber markets. Yet, this advantages disappears over time as their skills depreciate at a faster clip. In comparison, labor market outcomes for workers receiving general education improve over time.

[20] Keep in mind that I extrapolate the initial SMM to all jobs a worker may have had up until the current one since I only observe the first and current occupation.

may only be interpreted as suggestive evidence that is supported by theory.

6.2.2 Learning of Routine & Manual Tasks

Table (5) summarizes results on wage effects and task-based learning, if job-specific skills are defined in terms of routine tasks. Overall, I do not find evidence in favor of LBD-induced wage returns (columns 5 & 10). Similar conclusions carry over if job-specific skills are defined in terms of manual tasks (Table 6). If anything, workers specializing in either of those tasks experience negative wage growth. Especially underqualified workers may be affected by wage losses as they tend to be employed in comparably routine- and manual-intensive occupations, respectively.

[Table (5) here]

[Table (6) here]

6.2.3 Heterogeneity

A. Skill similarity between training and current job

One caveat in the baseline analysis is that general skills embodied in P are derived from knowledge acquired in school. Especially in Germany, however, vocational schooling is very important as it prepares future labor market entrants with the prerequisite skills to succeed in their chosen profession. In this section I explore this link by making use of a survey question on the similarity of skills (i) acquired in training and (ii) required in the current job.[21] To this end, I repeat the baseline analysis applied to two sub-samples. Odd columns in Table (7) show results for workers whose skills in the current job are sufficiently similar to those acquired in training. In contrast, even columns show results for workers whose skills in the current job differ from those acquired in training. For brevity, I only report results of my preferred specification comprising all SMM measures.

[21]Respondents were asked: "If you now compare your current occupational activity as [current job] with your training as [last training completed], what would you say?" Possible answers were: (1) "the occupational activity corresponds to the activity this course of training usually prepares for", (2) "the occupational activity is related to the course of training", and (3) "the current activity has nothing to do with this training". If workers responded with either option (1) or (2), I define their skills acquired in training and the current job to be similar. Otherwise, I define skills to be different.

The key takeaway from this exercise follows from defining job-specific skills in terms of abstract tasks. Using this definition, baseline results on underqualified workers are driven by workers who acquired skills in training that are useful in their current job (column 3). This observation makes sense as (i) their jobs tend to be more abstract-intensive, and (ii) skill similarity between training and job facilitates the acquisition of further job-specific skills.

[Table (7) here]

B. Job-Switchers vs Non-Switchers

This section takes a closer look at the relationship between SMM, job mobility, and wage effects. Motivated by the differential impact of initial SMM on job mobility and individual wage growth, I split the sample into (i) job-switchers and (ii) non-switchers. For brevity, Table (8) summarizes results only from the preferred specification comprising all SMM measures. In this exercise, two observations stand out, in both cases defining job-specific skills in terms of abstract tasks.

First, baseline evidence on underqualified workers is driven by job-switchers (column 3). Consistent with the idea of skill obsolescence, this group of workers faces diminishing returns to LBD in their first occupation, inducing an occupational change. Compared to baseline results, the coefficient associated with the interaction term for the first occupation (= -0.06) is twice as large, pointing to a substantially shorter half life of job-specific skills. In response, a new career alleviates skill depreciation and allows these workers to extend the period of positive wage growth.

Second, motives for a career change seem different for overqualified workers. Job-switchers experience much faster wage growth in their first job compared to non-switchers. And yet, despite absence of evidence on diminishing returns, they decide to change occupations (column 1). How come? A glance at descriptive statistics provides suggestive evidence for upward mobility. I use BERUFENET data to compare the task content of their first and current occupation. This comparison reveals 20% of activities in their first occupation involve abstract activities. In their current occupation, however, 44% of all activities are of abstract nature. In contrast, the share of abstract activities among underqualified workers who switch jobs remains stable.

Taken together, the key takeaways from this exercise suggest (i) underqualified job-switchers tend to make lateral moves in their career while (ii) overqualified workers tend to make upward moves.

[Table (8) here]

7 Robustness

To test the validity of my baseline results, I conclude the empirical analysis with three types of robustness checks. For brevity, I provide the key takeaways from these exercises and refer the interested reader to the Online Appendix for details.

First, I contrast findings resulting from an RE estimation with POLS estimates. Regarding underqualified workers, POLS estimates suggest (i) diminishing returns to LBD in the current occupation rather than the first and (ii) higher wage premia. Regarding overqualified workers, POLS estimates suggest increasing returns in the current occupation for overqualified workers, as opposed to constant returns. While these discrepancies may weaken my baseline results, I consider the RE estimates more reliable. Breusch-Pagan LM tests suggest strong serial correlation in most specifications, thereby supporting RE estimates. Moreover, I report values of "theta", which summarize the relative share of between- versus within-variation captured in RE estimates (Wooldridge 2010, Ch. 10). These values suggest RE estimates are closer to FE than POLS on time-varying variables, reinforcing the case of using RE over POLS.

Second, I impute information on time allocation on tasks in 2012 with a regression-based approach and repeat the baseline analysis using this newly imputed data. The findings of this exercise are very similar to baseline specifications. Consequently, key conclusions with respect to task-based learning remain unaffected.

Third, I test the robustness in response to varying assumptions on the sample as well as task and occupational definitions. Specifically, I (i) enforce stricter sample requirements, among others a restriction on younger workers, (ii) define occupations at the 2-digit level, rather than 3-digit, (iii) vary the approximation procedure for the binned income data, and (iv) use conventional task definitions in spirit of AFL instead. Robustness tests (i) - (iii) leave the main results unaffected.

Regarding (iv), a couple of notable differences emerge compared to my task definition in terms of time units. First, the AFL task definition is not consistent with the theoretical prediction of faster wage growth among underqualified workers. In fact, this pattern reverses in favor of overqualified workers. Second, the base wage premium associated with the current SMM among underqualified workers is inflated by almost 40% (0.29 vs. 0.21) compared to a model with time units. This comparison highlights conceptual differences between both task definitions and reinforces prior research, suggesting assumptions on the construction of task measure are among the most crucial ones in research using task data (Storm 2023).

8 Conclusions

This paper explores the role of task-based learning on the job and its impact on wages and job mobility. To this end, I develop a Roy model in which workers acquire job-specific skills via learning-by-doing. The key feature of the model are different incentives to acquire job-specific skills depending on the quality of the initial skill mismatch at labor market entry. The quality of a worker-occupation match depends on general skills acquired via schooling and job-specific skills unique to each occupation. Consequently, workers spend different amounts of time on job tasks, which affects their current and future productivity. This mechanism represents a more nuanced representation of task-specific human capital (Gathmann & Schönberg 2010) and shapes their career trajectories, which I demonstrate with implications on job mobility and wage growth. Using a short task panel from Germany with novel information on the number of working hours devoted to job-specific activities, I contribute three main findings to the literature.

First, the type of tasks performed on the first job have effects on the propensity to switch occupations during a career. Workers that are overqualified in their first job in terms of the occupation's abstract skill requirements are more likely to move to a different occupation by up to 19 pp.

Second, investments in job-specific skills only pay off if skill accumulation involves abstract activities. On average, with each year of experience in abstract tasks, workers receive a return of 2-3% in their hourly wage. However, some workers in abstract-intensive occupations experience diminishing returns to task-based learning.

Third, the wage effects of job-specific skills are heterogeneous and favor especially workers who (i) acquired skills in training that are useful in the current occupation and (ii) switched jobs during their career. Back-of-the-envelope calculations suggest these workers can extend their wage peak by up to 16 years due to the accumulation of abstract task tenure.

These findings are robust to various specification checks, sample and task definitions, and an alternative imputation procedure for missing data. On that note, however, the results must be treated with caution. Next to incomplete information on a key variable, time allocation on tasks, the data has limitations with respect to sample size and occupational biography.

Overall, this study echoes previous calls in the literature to enhance our understanding about the role of task-specific human capital in the process of wage determination and labor market transitions (e.g., Taber & Vejlin (2020)). Due to data limitations, however, we still know very little about the time aspect of work and how it shapes productivity of workers. This point is especially relevant in the age of digitization and greater prevalence of Work from Home (Barrero, Bloom & Davis 2021) and substantial worker reallocation across economic sectors (Acemoglu & Restrepo 2019, Dauth, Findeisen, Suedekum & Woessner 2021). Against this background, I advocate for consistent integration of time allocation of job tasks in well-known surveys to promote data quality. In the German context, for instance, this information could be included in future iterations of the BIBB/BAuA employment surveys or the SOEP-CMI-ADIAB, a new database linking household surveys with rich socio-demographic information to administrative data sources with extensive job biographies (Antoni, Beckmannshagen, Grabka, Keita & Trübswetter 2023).

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Figures

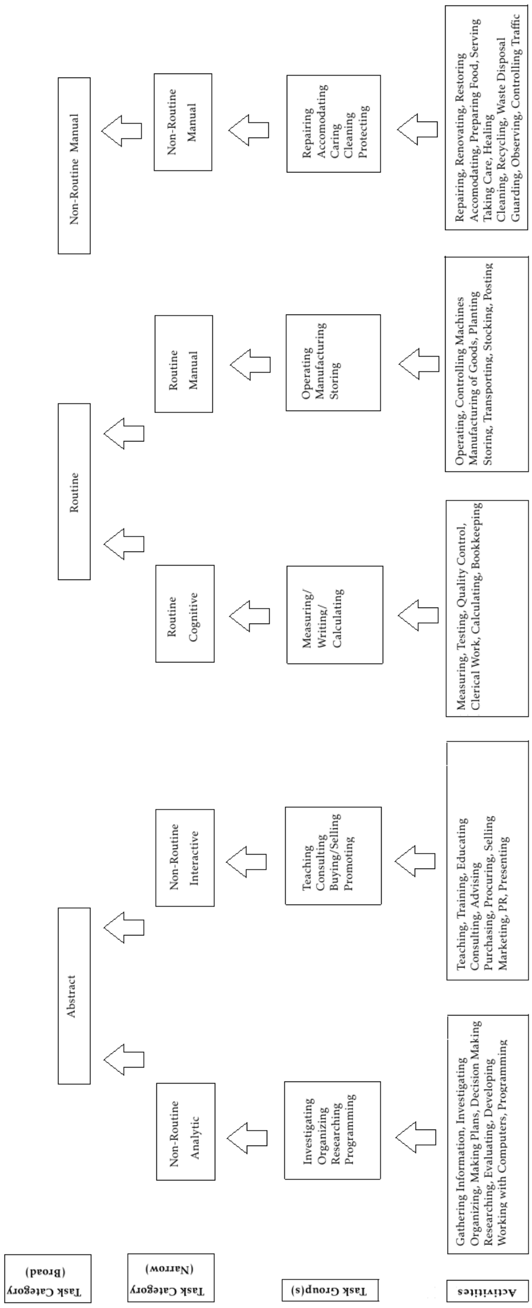
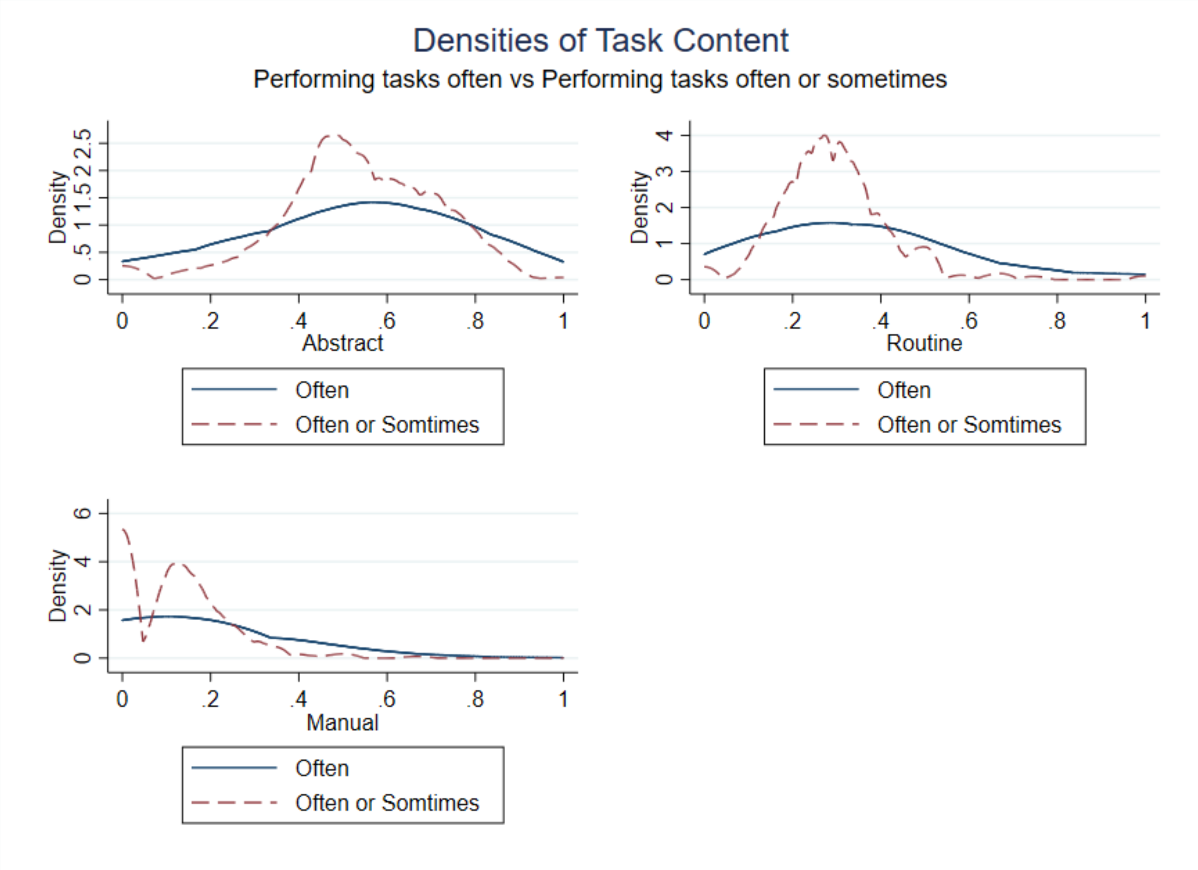
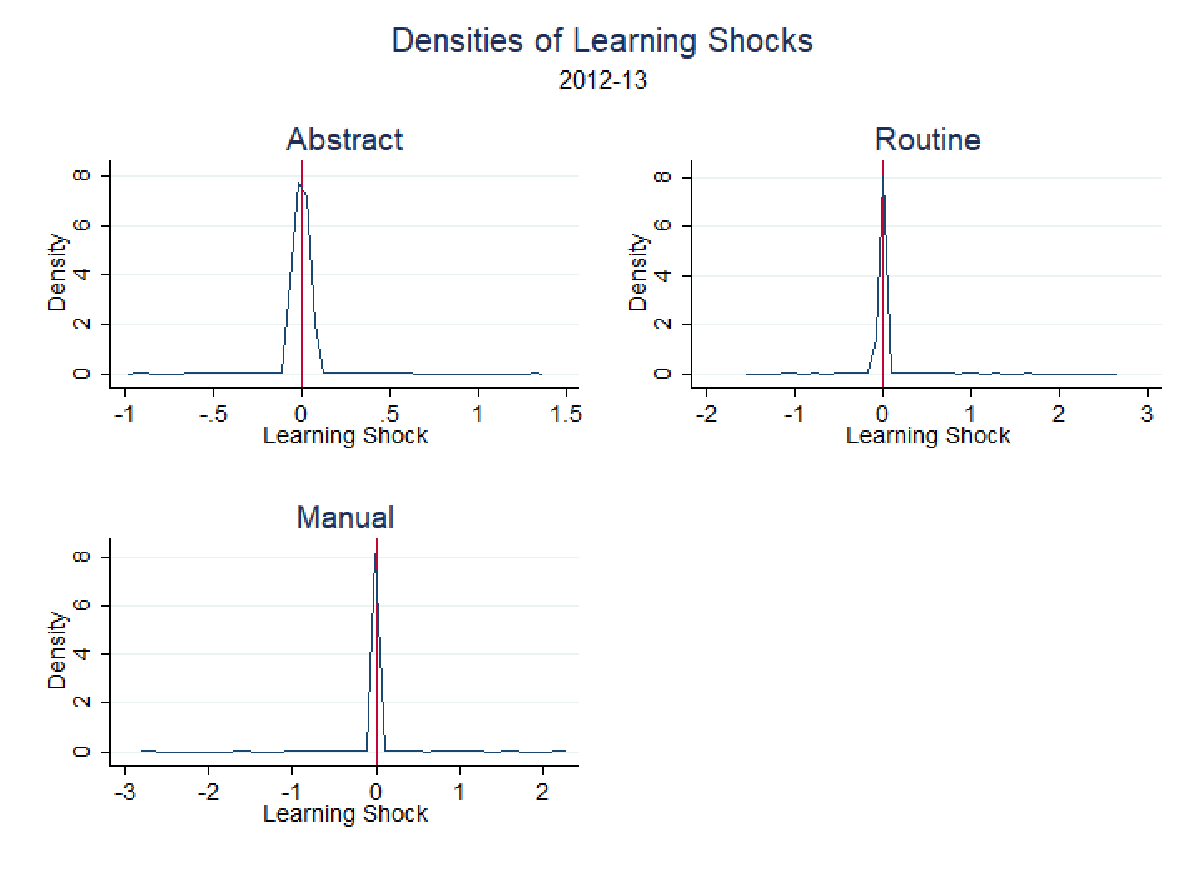


Figure 1: From Activities to Task: Construction of the Task Content



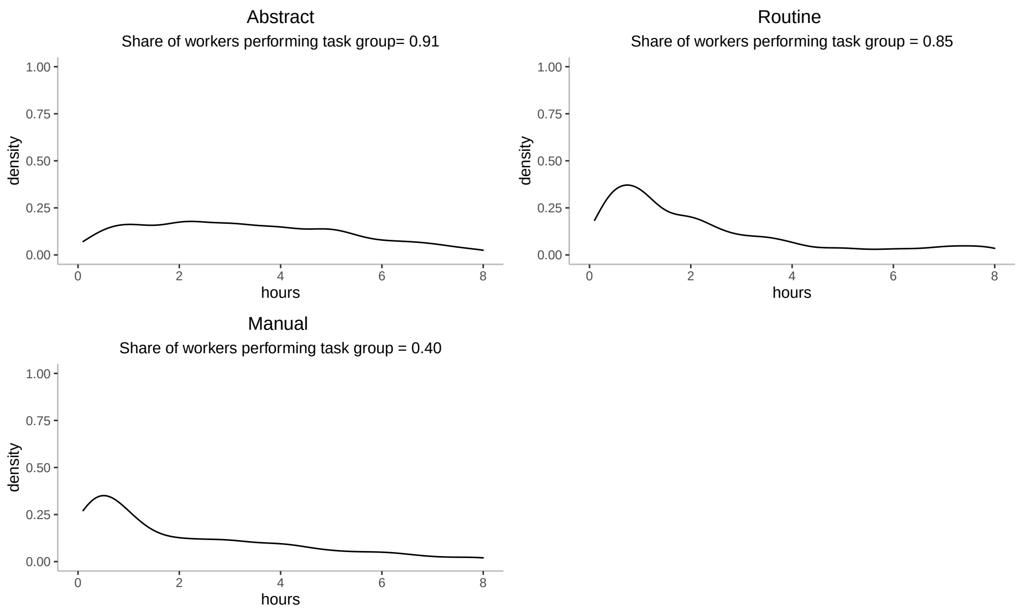
NOTE. —The graphs plot the density associated with the relative importance of abstract, routine, and manual tasks, respectively, based on eq. (7), and following Antonczyk, Fitzenberger & Leuschner (2009). The blue solid line assumes workers perform a task only if they report to engage in those activities "often". In contrast, the red dashed line assumes workers perform a task if they report to engage in those activities "often" or "sometimes".

Figure 2: Number of hours devoted to job tasks (conditional on performing tasks)

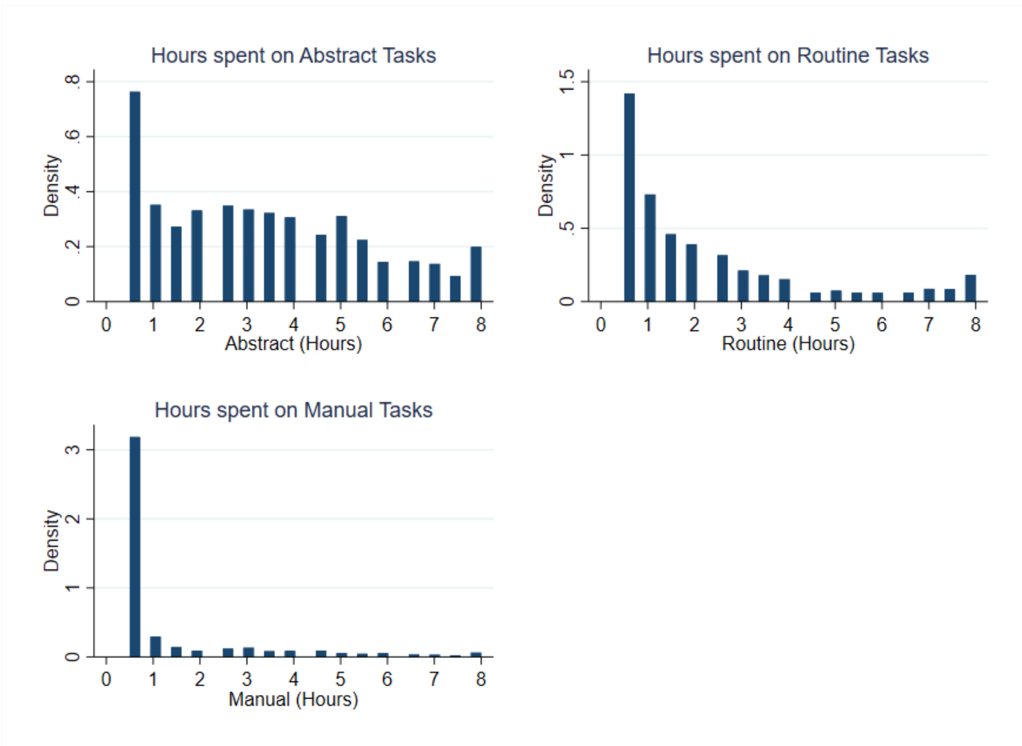


NOTE. —The graphs plot the density of a learning shock, formalized in eq. (9). In terminology of the theoretical model developed in section (2), workers to the right of zero experience a positive learning shock as a result of performing task j more efficiently than expected and vice versa for workers to the left of zero.

Figure 3: Learning shock



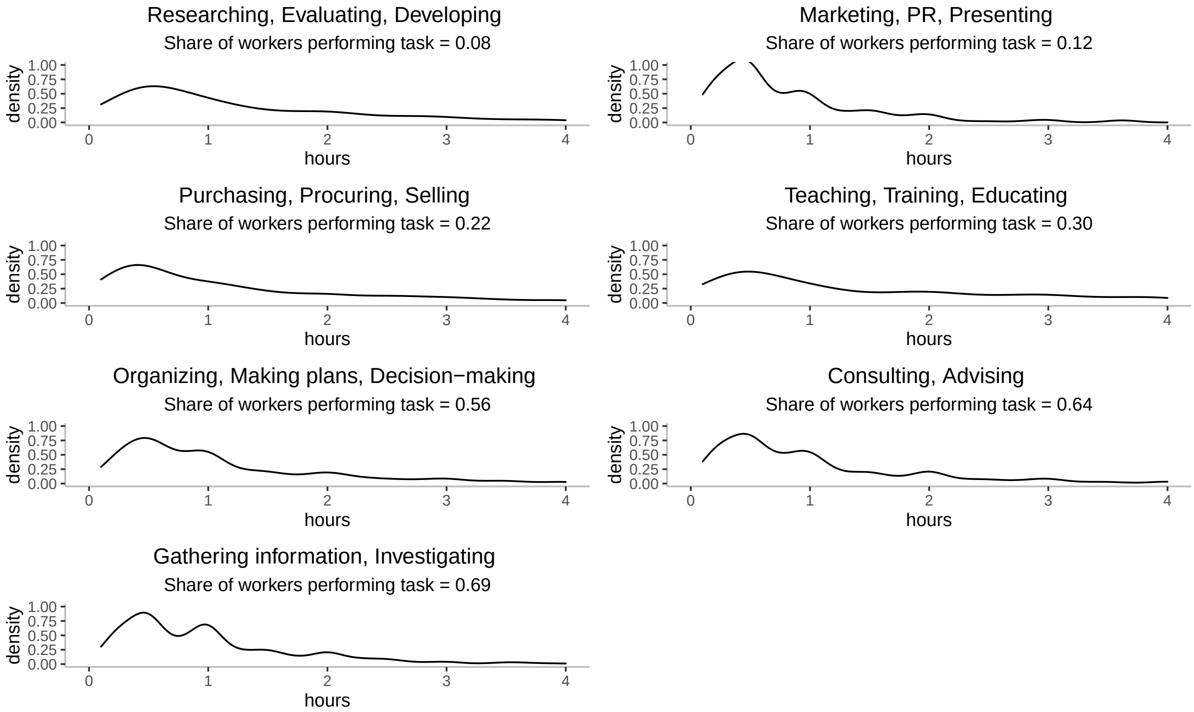
(a) Density



(b) Binned Distribution

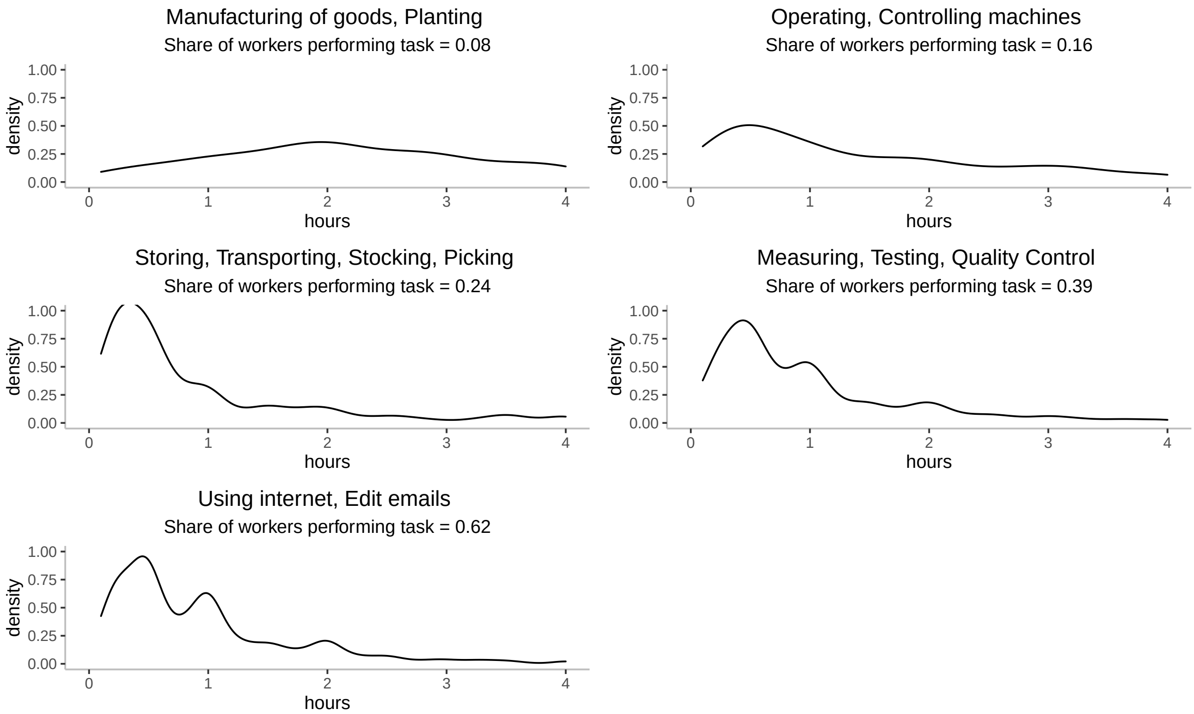
NOTE. —Panel (a) plots the density associated with the number of hours spend on either abstract, routine, or manual tasks. Only workers who perform at least one activity belonging to teach task group are considered. Each panel displays the share of workers performing those tasks to give a sense about how common they are. Panel (c) displays the full range of time allocation on tasks in binned form.

Figure 4: Distribution of Number of hours spend on Tasks



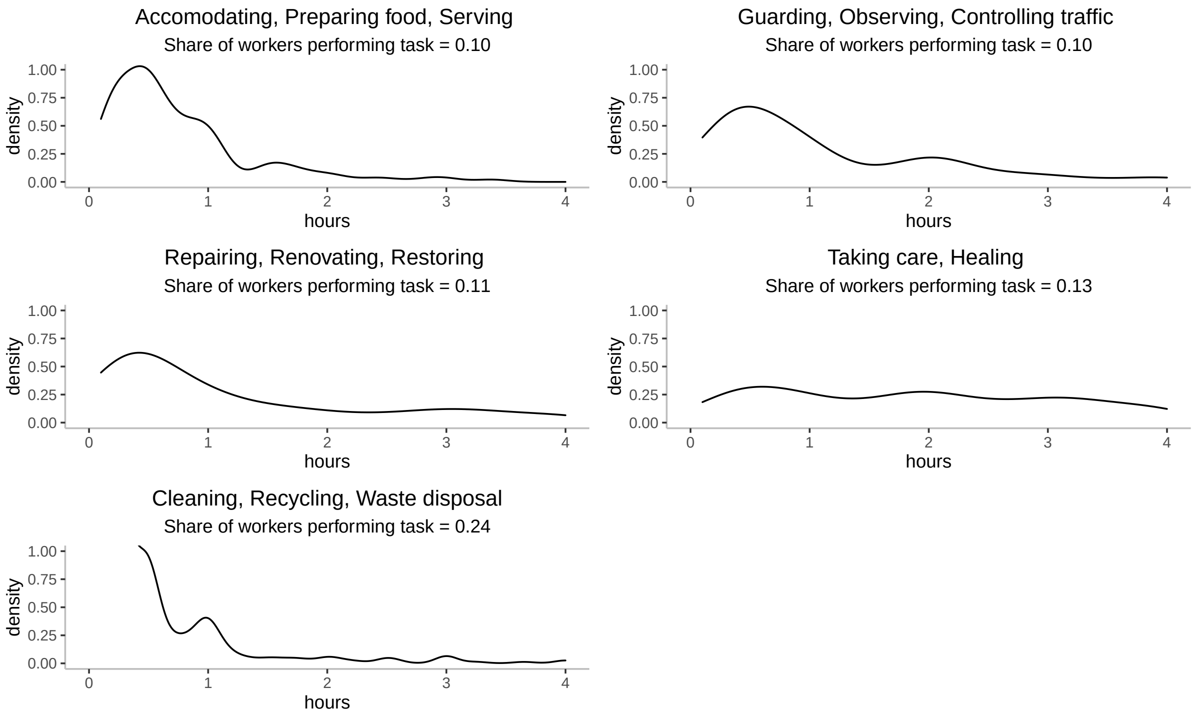
NOTE. —The graph plots the density associated with the number of hours spend on either abstract, routine, or manual tasks. Only workers who perform at least one activity belonging to teach task group are considered. Each panel displays the share of workers performing those tasks to give a sense about how common they are.

Figure 5: Number of hours spend on Abstract Tasks (conditional on performing tasks)



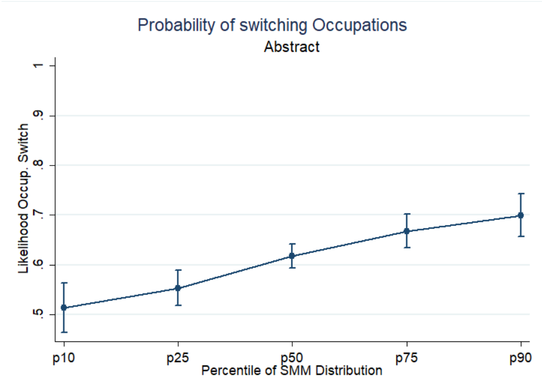
NOTE. —The graph plots the density associated with the number of hours spend routine tasks. Only workers who perform at least one activity belonging to teach task group are considered. Each panel displays the share of workers performing those tasks to give a sense about how common they are.

Figure 6: Number of hours spend on Routine Tasks (conditional on performing tasks)

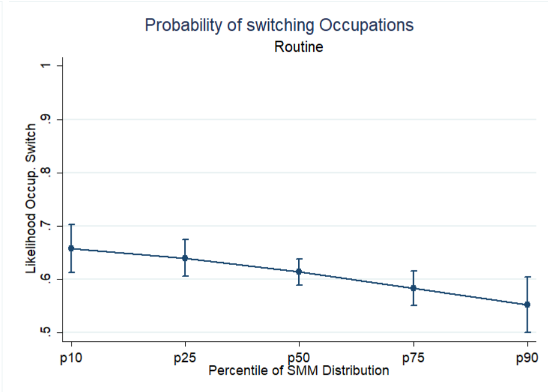


NOTE. —The graph plots the density associated with the number of hours spend on manual tasks. Only workers who perform at least one activity belonging to teach task group are considered. Each panel displays the share of workers performing those tasks to give a sense about how common they are.

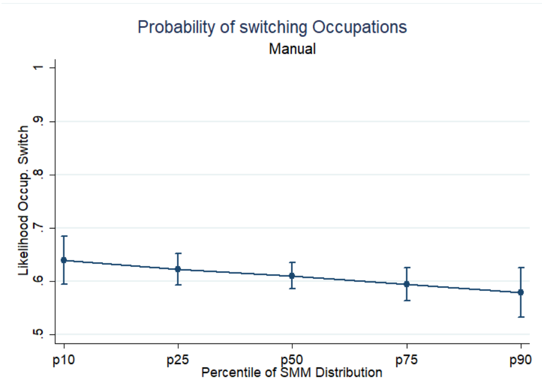
Figure 7: Number of hours spend on Manual Tasks (conditional on performing tasks)



(a) Abstract



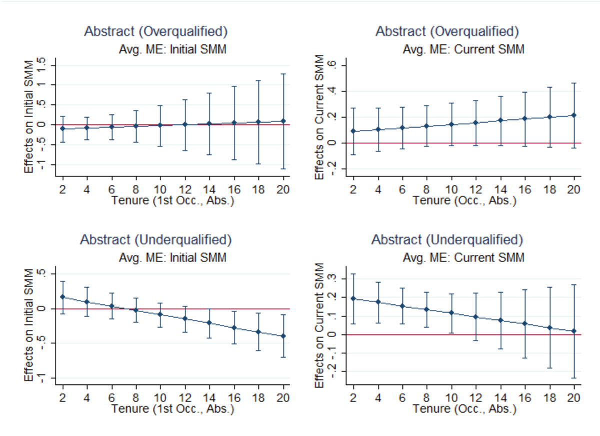
(b) Routine



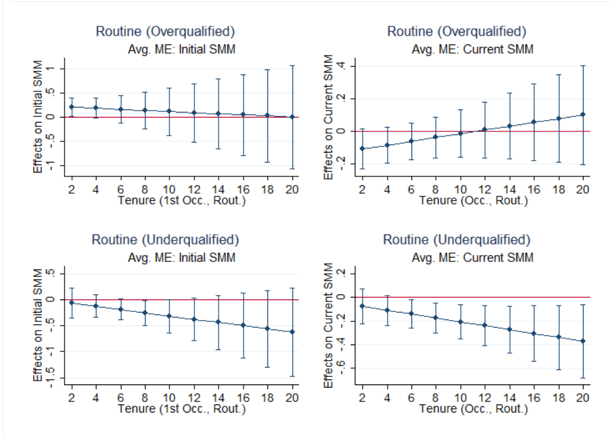
(c) Manual

NOTE. —The graphs depict the average marginal effects of a job switch subject to a worker's position in the distribution of initial SMM. Workers towards the left of the distribution are underqualified in terms of general skills. As we move to the right to higher percentile, workers are increasingly overqualified (general skills > job-specific skills). Job-specific skills are defined for each of the three task groups. An increase in the probability over the distribution suggests overqualified workers are more likely to switch occupations and vice versa for underqualified workers. All probabilities are depicted with a 95% confidence interval.

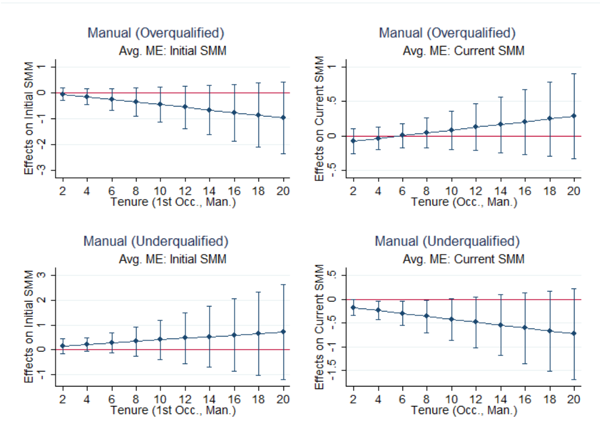
Figure 8: Likelihood of Occupational Change conditional on Initial Skill Mismatch



(a) Abstract



(b) Routine



(c) Manual

NOTE. —The graphs depict the average marginal effect of a SMM for different levels of occupational tenure and subject to the type of SMM (initial job vs current job). Illustrations are based on estimation of eq. (14). Note, tenure reflects the the proportion of time associated with each task, in spirit of the idea of task-specific human capital Gathmann & Schönberg (2010). For instance, tenure equal to ten years amounts to equivalent of ten (working) years spent on abstract tasks. Positive estimates suggest wage gains associated with task-based learning while negative estimates suggest wage losses. All probabilities are depicted with a 95% confidence interval.

Figure 9: Marginal Effects of Occupational Change conditional on Initial Skill Mismatch

Tables

	Mean	SD
Hourly Wage	17.54	8.62
Female	0.55	0.50
Age	48.54	8.88
College degree	0.19	0.39
Vocational degree	0.80	0.40
No Vocational Degree	0.01	0.11
Working Hours	38.02	11.51
Tenure (LM)	28.33	10.19
Tenure (Occ.)	13.31	10.43
Tenure (Firm)	15.10	11.12
Changed Occ. Sometime	0.62	0.48
Observations	2448	

* NOTE. —Tenure (LM) refers to total tenure in the labor market after completion of schooling. Tenure (Occ.) and Tenure (Firm), respecively, denote tenure measures with respect to the current occupation and employer.

Table 1: Summary Statistics

	Mean	SD
Abstract (AFL)	0.53	0.18
Routine (AFL)	0.29	0.13
Manual (AFL)	0.17	0.15
Abstract (Hours)	3.06	2.45
Routine (Hours)	2.04	2.26
Manual (Hours)	0.95	1.82
Abstract (Hours %)	0.52	0.33
Routine (Hours %)	0.33	0.31
Manual (Hours %)	0.14	0.26
Observations	2448	

Table 2: Descriptive Statistics on Task Measures

Dep. Var.: Changed Occupation Sometime	(1)	(2)	(3)
Initial SMM (Abstract)	0.65***	0.62***	0.80***
	(0.12)	(0.14)	(0.18)
Initial SMM (Routine)	-0.53***	-0.31**	-0.37**
	(0.11)	(0.13)	(0.15)
Initial SMM (Manual)	-0.29**	-0.17	-0.26
	(0.12)	(0.14)	(0.17)
Controls		✓	✓
Occup. Dummies			✓
Observations	2448	2448	2262
Pseudo R2 (Abstract)	0.02	0.11	0.22
Pseudo R2 (Routine)	0.02	0.10	0.21
Pseudo R2 (Manual)	0.00	0.10	0.21

Robust standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

* NOTE. —All specifications are based on a standard Probit model and control for sex, education, age, dummies for citizenship (German/Foreign), dummies for a German-speaking household during childhood (Yes/No), labor market tenure, firm tenure, squared terms for age and tenure measures, year dummies, and industry dummies. A positive estimate suggest workers with more general than job-specific skills (abstract, routine, manual) are more likely to switch an occupation.

Table 3: Probit estimation: Likelihood of switching occupation conditional on initial skill mismatch

Initial Skill Mismatch (SMM)	(1) - (5): Overqualified ($P > T$)					(6) - (10): Underqualified ($P < T$)				
(θ = abstract skill requirements)	*(Avg.: 44% of working h on abstract tasks)*					*(Avg.: 59% of working h on abstract tasks)*				
Dep. Var.: Log Wage	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Initial Skill Mismatch	0.06	0.00			-0.13	0.08	0.30**			0.22
	(0.14)	(0.22)			(0.22)	(0.08)	(0.13)			(0.14)
Tenure (1st Occ., Abs.)		0.00			0.02**		0.01**			0.03***
		(0.01)			(0.01)		(0.01)			(0.01)
Initial Skill Mismatch × Tenure (1st Occ., Abs.)		0.01			0.01		-0.03**			-0.03***
		(0.04)			(0.04)		(0.01)			(0.01)
Current Skill Mismatch			0.15**	0.07	0.07			0.17***	0.21**	0.21**
			(0.07)	(0.09)	(0.10)			(0.05)	(0.08)	(0.08)
Tenure (Occ., Abs.)				0.00	0.02***				0.00	0.02***
				(0.00)	(0.01)				(0.01)	(0.01)
Current Skill Mismatch × Tenure (Occ., Abs.)				0.01	0.01				-0.01	-0.01
				(0.01)	(0.01)				(0.01)	(0.01)
Observations	1082	1082	1082	1082	1082	1366	1366	1366	1366	1366
R^2	0.25	0.26	0.27	0.28	0.30	0.37	0.37	0.38	0.39	0.39

Clustered standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

[*] NOTE. —Results are based on estimation of eq. (14). All specifications include controls, including sex, education, age, dummies for citizenship (German/Foreign), dummies for a German-speaking household during childhood (Yes/No), labor market tenure, firm tenure, squared terms for age and tenure measures, year dummies, and industry dummies. Columns (1)-(5) display results for overqualified workers. Columns (6)-(10) display results for underqualified workers.

Table 4: Skill Mismatch & Wage Effects: Job-specific skills defined in terms of abstract tasks

Initial Skill Mismatch	(1) - (5): Overqualified ($P > T$)					(6) - (10): Underqualified ($P < T$)				
(θ = routine skill requirements)	*(Avg.: 27% of working h on routine tasks)*					*(Avg.: 37% of working h on routine tasks)*				
Dep. Var.: Log Wage	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Initial Skill Mismatch	0.13	0.21*			0.23**	-0.23**	-0.05			0.00
	(0.09)	(0.12)			(0.12)	(0.10)	(0.19)			(0.19)
Tenure (1st Occ., Rout.)		-0.01			-0.01		0.01			0.02
		(0.01)			(0.01)		(0.01)			(0.01)
Initial Skill Mismatch × Tenure (1st Occ., Rout.)		-0.03			-0.01		-0.03			-0.03
		(0.03)			(0.03)		(0.03)			(0.03)
Current Skill Mismatch			-0.05	-0.08	-0.13*			-0.15***	-0.07	-0.04
			(0.05)	(0.07)	(0.07)			(0.06)	(0.09)	(0.09)
Tenure (Occ., Rout.)				-0.01	-0.01				0.00	0.01
				(0.01)	(0.01)				(0.01)	(0.01)
Current Skill Mismatch × Tenure (Occ., Rout.)				0.01	0.01				-0.01	-0.02
				(0.01)	(0.01)				(0.01)	(0.01)
Observations	946	946	946	946	946	1502	1502	1502	1502	1502
R^2	0.38	0.38	0.38	0.38	0.39	0.26	0.26	0.26	0.27	0.27

Clustered standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

[*] NOTE. —Results are based on estimation of eq. (14). All specifications include controls, including sex, education, age, dummies for citizenship (German/Foreign), dummies for a German-speaking household during childhood (Yes/No), labor market tenure, firm tenure, squared terms for age and tenure measures, year dummies, and industry dummies. Columns (1)-(5) display results for overqualified workers. Columns (6)-(10) display results for underqualified workers.

Table 5: Skill Mismatch & Wage Effects: Job-specific skills defined in terms of routine tasks

Initial Skill Mismatch	(1) - (5): Overqualified ($P > T$)					(6) - (10): Underqualified ($P < T$)				
(θ = manual skill requirements)	*(Avg.: 11% of working h on manual tasks)*					*(Avg.: 23% of working h on manual tasks)*				
Dep. Var.: Log Wage	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Initial Skill Mismatch	-0.19**	-0.12			0.03	0.10	-0.14			0.09
	(0.07)	(0.09)			(0.12)	(0.13)	(0.23)			(0.23)
Tenure (1st Occ., Man.)		-0.01			-0.02		-0.01			-0.03
		(0.01)			(0.02)		(0.03)			(0.03)
Initial Skill Mismatch × Tenure (1st Occ., Man.)		-0.04			-0.05		0.07			0.03
		(0.03)			(0.04)		(0.06)			(0.06)
Current Skill Mismatch			-0.14**	-0.15*	-0.12			-0.29***	-0.12	-0.11
			(0.06)	(0.08)	(0.11)			(0.10)	(0.11)	(0.10)
Tenure (Occ., Man.)				-0.02**	-0.02**				-0.02	-0.03
				(0.01)	(0.01)				(0.02)	(0.02)
Current Skill Mismatch × Tenure (Occ., Man.)				0.02	0.02				-0.03	-0.03
				(0.02)	(0.02)				(0.03)	(0.03)
Observations	1850	1850	1850	1850	1850	598	598	598	598	598
R^2	0.29	0.29	0.29	0.30	0.30	0.27	0.27	0.30	0.32	0.32

Clustered standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

* NOTE. —Results are based on estimation of eq. (14). All specifications include controls, including sex, education, age, dummies for citizenship (German/Foreign), dummies for a German-speaking household during childhood (Yes/No), labor market tenure, firm tenure, squared terms for age and tenure measures, year dummies, and industry dummies. Columns (1)-(5) display results for overqualified workers. Columns (6)-(10) display results for underqualified workers.

Table 6: Skill Mismatch & Wage Effects: Job-specific skills defined in terms of manual tasks

Initial Skill Mismatch (SMM)	(1) - (4): Abstract				(5) - (8): Routine				(9) - (12): Manual			
	Overqualified		Underqualified		Overqualified		Underqualified		Overqualified		Underqualified	
Dep. Var.: Log Wage	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Initial Skill Mismatch	-0.23	0.05	0.22	-0.18	0.18	-0.25	-0.29*	-0.71	-0.03	0.02	0.03	-0.05
	(0.24)	(0.39)	(0.15)	(0.38)	(0.14)	(0.32)	(0.15)	(0.59)	(0.13)	(0.26)	(0.27)	(0.40)
Tenure (1st Occ., Task j)	0.02**	0.03*	0.03***	0.03	-0.01	-0.01	0.01	06	-0.01	-0.03	-0.02	-0.06
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.04)	(0.02)	(0.04)	(0.04)	(0.04)
Initial Skill Mismatch × Tenure (1st Occ., Task j)	0.01	-0.02	-0.03**	0.04	-0.06	-0.01	0.01	0.13	0.05*	-0.02	0.03	-0.06
	(0.03)	(0.07)	(0.01)	(0.04)	(0.04)	(0.06)	(0.02)	(0.09)	(0.03)	(0.11)	(0.07)	(0.09)
Current Skill Mismatch	0.13*	-0.14	0.14	-0.14	-0.04	0.20	-0.14	-0.08	-0.15	0.08	-0.21	-0.03
	(0.07)	(0.25)	(0.10)	(0.12)	(0.09)	(0.16)	(0.09)	(0.15)	(0.09)	(0.22)	(0.15)	(0.12)
Tenure (Occ., Task j)	0.01*	0.02**	0.02**	0.01	-0.00	-0.01	0.00	0.02	-0.01	-0.08***	-0.04*	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)
Current Skill Mismatch × Tenure (Occ., Task j)	-0.00	0.01	-0.01	-0.02	-0.00	0.01	-0.01	0.03	0.02	0.04	0.00	0.06
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.03)	(0.03)	(0.05)
Skills in training and job similar	✓		✓		✓		✓		✓		✓	
Observations	666	416	950	416	690	256	926	576	1248	598	364	238
R^2	0.29	0.36	0.37	0.46	0.37	0.47	0.28	0.31	0.30	0.35	0.37	0.41

Clustered standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

* NOTE. —Results are based on estimation of eq. (14), separately for workers who assess their current job requirements are similar to those acquired in training and workers for whom these skills differ. All specifications include controls, including sex, education, age, dummies for citizenship (German/Foreign), dummies for a German-speaking household during childhood (Yes/No), labor market tenure, firm tenure, squared terms for age and tenure measures, year dummies, and industry dummies. Columns (1) - (4) define job-specific skills in terms of abstrac tasks. Similarly, columns (6) - (8) define job-specific skills in terms of routine tasks and columns (9) - (12) in terms of manual tasks.

Table 7: Skill Mismatch & Wage Effects: Similarity between skills acquired in training and requirements in current job

Initial Skill Mismatch (SMM)	(1) - (4): Abstract				(5) - (8): Routine				(9) - (12): Manual			
	Overqualified		Underqualified		Overqualified		Underqualified		Overqualified		Underqualified	
Dep. Var.: Log Wage	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Initial Skill Mismatch	-0.28	-0.30	0.49**	0.23	0.47***	0.05	-0.11	0.04	0.07	-0.14	0.50	0.12
	(0.37)	(0.22)	(0.21)	(0.20)	(0.16)	(0.21)	(0.30)	(0.22)	(0.18)	(0.19)	(0.35)	(0.39)
Tenure (1st Occ., Task j)	0.03***	0.01	0.03***	0.03**	-0.03***	0.00	0.02	-0.00	-0.03	-0.02	-0.04	0.02
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)	(0.03)	(0.05)
Initial Skill Mismatch × Tenure (1st Occ., Task j)	0.04	0.02	-0.05***	-0.02	0.07**	0.04	-0.05	0.03	0.07*	-0.05	-0.03	-0.07
	(0.06)	(0.04)	(0.02)	(0.02)	(0.03)	(0.06)	(0.04)	(0.03)	(0.04)	(0.08)	(0.08)	(0.09)
Current Skill Mismatch	0.05	0.03	0.21*	0.05	-0.06	-0.13	-0.05	-0.11	-0.13	-0.02	-0.03	0.22
	(0.13)	(0.14)	(0.12)	(0.13)	(0.07)	(0.13)	(0.13)	(0.11)	(0.17)	(0.14)	(0.11)	(0.20)
Tenure (Occ., Task j)	0.02**	0.03**	0.02*	0.01	-0.00	0.00	0.01	0.01	-0.04**	-0.01	-0.01	-0.05
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.02)	(0.04)
Current Skill Mismatch × Tenure (Occ., Task j)	0.01	0.02	-0.00	-0.00	-0.00	0.02*	-0.03*	-0.01	0.03	0.00	-0.08**	-0.01
	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.02)	(0.03)	(0.04)	(0.04)
Changed Occupation	✓		✓		✓		✓		✓		✓	
Observations	732	350	788	578	502	446	1018	482	1114	734	406	194
R^2	0.30	0.45	0.44	0.34	0.39	0.47	0.29	0.33	0.31	0.34	0.38	0.39

Clustered standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

* NOTE. —Results are based on estimation of eq. (14), separately for workers who changed occupations at some point during their career and those who did not. All specifications include controls, including sex, education, age, dummies for citizenship (German/Foreign), dummies for a German-speaking household during childhood (Yes/No), labor market tenure, firm tenure, squared terms for age and tenure measures, year dummies, and industry dummies. Columns (1) - (4) define job-specific skills in terms of abstract tasks. Similarly, columns (6) - (8) define job-specific skills in terms of routine tasks and columns (9) - (12) in terms of manual tasks.

Table 8: Skill Mismatch & Wage Effects: Job-Switchers vs Non-Switchers