On the Measurement of Tasks: Conceptual Benefits of Using Survey over Expert-based Data

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Abstract

Using task data from Germany with self-reported information on job-related activities by individuals, I measure tasks at the worker level and compare its wage implications with Expert-based data provided by the German Federal Employment Agency. The findings show substantial heterogeneity in tasks at the individual level, which are predictive of wage differences between and within occupations and robust to a series of alternative model specifications. Importantly, various statistical tests favor worker-level information on tasks over occupational measures due to greater explanatory power on wages. The superior statistical performance of Survey data can be motivated by intra-occupational efficiency gains workers earn as a result of task specialization within occupations. Suggestive evidence indicates this enhanced degree of task specialization may become even more important if greater weight is given to the time allocation of job-related activities. Overall, the results suggest incomplete information on the part of Expert data and recommend worker-level information in studies on job tasks.

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1 Introduction

A growing body of research has gone beyond the canonical model which describes a production function as the collection of inputs. Instead, over the past decade, a rising number of studies have explored which services these factors provide (Acemoglu & Autor 2011). The idea behind this research is to observe the different *tasks* production inputs have to offer. A key emphasis is to better understand quality differences in the labor aggregate of the production function and why technology helped some types of labor, while hurting others. Traditionally, Economists have used formal qualifications such as completed schooling or potential years of work experience to measure differences in *skill*. However, skills are merely a representation of the human capital endowment workers can draw on to perform tasks. It is these tasks that produce output and that workers are being compensated for. Traditional models implicitly assume skills and task to be equivalent. Yet, workers differ in their human capital endowment and different skills make them differently equipped to perform one task over another.[1] The "task-approach" to labor markets (Autor 2013) thus allows a more nuanced evaluation on the role of skills in the production process.

Most studies employing task data use information at the occupation-level, externally assessed by labor market experts. However, this approach is based on strong assumptions, namely that i) there is a common set of tasks within occupations and ii) labor market experts have a complete understanding of occupation-specific task requirements. In a recent study, Autor & Handel (2013) use the Princeton Data Improvement Initiative (PDII), a survey collecting information on cognitive, interpersonal, and manual job activities of US workers at the workplace. This allows them to compare the implications of individual-level information on tasks with the most commonly used data source on tasks, the Occupational Information Network (O*Net). If the assumptions underlying occupation-level data were valid, we would expect little explanatory power added by individual-level information. Their findings suggest, however, that worker-level information on tasks is predictive of wage differences not only between occupations, but also within.[2] Their analysis therefore

[1] This idea reflects the classic unbundling problem: Workers choose to perform tasks that offer the highest return on their overall skills, yet, this does not imply that each element of their skill set will be equally valuable. As a consequence, workers with similar education-experience profile may perform a different combination of tasks, reflecting differences in the valuation of single skill elements.

[2] Related evidence on dispersion of tasks within occupations can be found in Atalay, Phongthiengtham, Sotelo & Tannenbaum (2018), Deming & Noray (2019), Modestino, Shoag & Ballance (2019), Atalay, Phongthiengtham, Sotelo & Tannenbaum (2020), and Ziegler (2020). Similarly, Ma (2020) models the STEM market, highlighting how native and immigrant worker may specialize in a different set of activities. Her results are interesting inasmuch they illustrate that task specialization within occupations can induce skilled workers to be gross complements in the production function, thus possibly generating welfare benefits.

casts doubt on the strong assumptions embedded in occupation-level data derived from external assessment.

The PDII data, however, is limited in its scope. On the one hand, its information on tasks is sparse and generic in nature, such as the frequency of problem-solving tasks requiring at least 30 minutes for Abstract tasks or the absence of face-to-face interactions with several entities as a proxy for routine tasks. On the other hand, it has a limited sample size of around 2,500 observations.[3]

Two recent studies extend their analysis. Cassidy (2017) uses the same employment surveys used in this study, showing that individual-level variation in tasks is predictive of income differences. However, his paper uses old data from 1986 and 1992, thus missing out on the implications on the task content resulting from technological change (Autor, Levy & Murnane 2003) or the growing importance of social skills (Deming 2017). A more contemporary horizon can be found in Rohrbach-Schmidt (2019). She likewise uses German employment survey data, yet for 2011-12, and confirms most of the findings found in Autor & Dorn (2013) and Cassidy (2017). While more recent, her study uses a smaller sample and focuses on the occupational specificity of tasks instead.

In the present paper, in comparison, I evaluate the statistical performance of different types of task data, emphasizing the conceptual benefits of survey data.[4] This paper is most closely related to the three studies cited above, which use survey data to assess workplace heterogeneity in tasks. The main contributions can be summarized as follows.

First, employing a sizable cross-section of more than 31,000 workers in Germany for 2012 and 2018, I utilize information on job-related activities to conduct a more formal testing of the underlying assumptions of Expert-based data. To facilitate this analysis, I compare task data derived from employment surveys with recently made available Expert-based data in Germany (Dengler, Matthes & Paulus 2014).[5] In line with prior research my findings reject the assumption of common tasks within occupations, thus suggesting a prominent role for workplace heterogeneity.[6] In fact, a comparison of various goodness-of-fitness measures across a set of specifications strongly suggests variation in individual-level tasks to be more important in the process of wage determination compared to occupational

[3] For a consistent sample, comprising at least two observations per occupation, Autor & Handel (2013) only have 1,333 observations at their disposal.

[4] Notably, Rohrbach-Schmidt (2019) documents how manual tasks are more occupational specific whereas abstract and routine tasks display greater workplace heterogeneity. Similar results are found in the present study, suggesting larger loss of statistical precision of more aggregated measures of these tasks.

[5] This data is derived from the Berufenet Database, a free online portal for occupations provided by the German Federal Employment Agency, thus comparable to the O*Net database in the US.

[6] See Card, Heining & Kline (2013), Barth, Bryson, Davis & Freeman (2016), Rohrbach-Schmidt (2019), Song, Price, Guvenen, Bloom & von Wachter (2019), and Dostie, Li, Card & Parent (2020) for related evidence.

task measures. The baseline specification reveals an incremental R-squared of 8.8% of tasks at the worker-level in specifications in which both task dimensions are included. In contrast, the incremental R-squared of tasks derived from Expert-based data amounts to 6.6%.

Second, I conceptualize the benefits of using worker-level information on tasks based on a framework accounting for intra-occupational efficiency gains. This wage premium reflects an enhanced degree of specialization within occupations if workers are more efficient at performing occupation-specific core tasks. The empirical analysis supports the notion that this premium is an important component of wage differences and is especially pronounced for occupations intensive in abstract tasks, which require problem-solving skills. Specifically, baseline results imply additional incremental wage gains of at least 70% compared to workers performing predominantly manual tasks. Notably, those gains experience diminishing returns, indicating a closed-form solution for the optimal degree of specialization.

Third, returns to tasks performed at work are a function of some underlying level of skill and time devoted to performing said task. Suggestive evidence indicates that task specialization within occupations is reinforced by greater variation in time spent on job-related activities. In models in which workers are allowed to spend a differential amount of time on activities (measured by a 3 point Likert scale) incremental wage gains are at least 90%. Hence, the explanatory power of tasks on wages may not only be driven by variation in skill, but also by variation in time spent on a task. The findings of this study thus have important implications on modeling human capital, specifically pertaining to the acquisition of on-the-job skills.

2 Conceptual Background on Tasks and Wages

Let me first sketch a brief conceptual framework to develop some thoughts on the role of tasks in the process of wage determination and to motivate the subsequent empirical analysis. The task approach allows the researcher to shed light on how workers use skills embodied in their human capital to carry out tasks that are demanded by their employer to produce output. As workers differ in their human capital endowment, they will be differentially compensated depending on their ability to perform tasks specific to a particular job.

Following Autor & Handel (2013), let worker i be employed in occupation o in which she receives a wage w in return for performing J tasks. Abstracting from inherent ability and idiosyncratic shocks to output, a worker combines these tasks to produce output according to

$$Y_{io} = exp\left(\sum_{J} \lambda_{jo} T_{ij}\right) \tag{1}$$

where the output price in each occupation is normalized to unity.[7] Assuming she is being paid her marginal product we can write her log wage as

$$ln\ w_i = \sum_{J} \lambda_{jo} T_{ij} \tag{2}$$

where T_{ij} denotes task j performed by i and $\lambda_{jo} \geq 0$ represents returns earned for performing task j in o, i.e. tasks returns are occupation-specific. To conceptualize quality differences in labor, let's expedite on the idea that employers seek to hire workers with similar skills. Workers need to be able to perform tasks necessary to produce occupation-specific output, but may have different levels of expertise in carrying out those activities. Let $\boldsymbol{T_i} = \left(T_{i1}, T_{i2}, ..., T_{iJ}\right)$ summarize her task endowment across J tasks and $\boldsymbol{\Lambda_o} = \left(\lambda_{1o}, \lambda_{2o}, ..., \lambda_{Jo}\right)$ summarize the occupation-specific task returns. By adding and subtracting the average task endowment of the N_o workers already employed in occupation o, i.e. $\pm\frac{1}{N_o}\sum_{i=i'} \boldsymbol{T_{i'}}\boldsymbol{\Lambda_o}$, we can allow workers to be differentially specialized within an occupation:

$$ln\ w_{io} = \frac{1}{N_o}\sum_{i=i'} \boldsymbol{T_{i'}}\boldsymbol{\Lambda_o} + \left(\boldsymbol{T_i} - \frac{1}{N_o}\sum_{i=i'} \boldsymbol{T_{i'}}\right)\boldsymbol{\Lambda_o} \tag{3}$$

Following this representation, worker i's wage is not only a function of her own task endowment $\boldsymbol{T_i}$, but also its relative comparison to her peers. The first term can be interpreted as an occupational entry barrier explicitly derived from the stock of task endowment of workers i' already employed in occupation o. The second term is a representation for the distribution of the *relative* task endowment of workers with common occupational affiliation. The further up the distribution, the higher i's degree of specialization in tasks demanded in o. Conceptually, elements collected in $\boldsymbol{T_i}$ can therefore be interpreted in terms of efficiency units, i.e. the more units T_{ij} of task j individual i performs, the more efficient she is (e.g. think of output produced per hour).

Note that task endowments are valued by occupation-specific returns embodied in $\boldsymbol{\Lambda_o}$,

[7] As pointed out in Autor & Handel (2013) this assumption is not restrictive as a logarithmic change in the price of output can be re-expressed in form of multiplicative change in the exponential in the exponential term of eq. (1). For instance, we can think of productivity shifters embodied in the tasks workers perform, possibly reflecting market demand factors and affecting the output price that way.

implying a particular skill will not be equally valuable across occupations. Of course, this does not solve the classic unbundling problem: Workers choose an occupation that offers the highest return on their overall skills, yet, this does not imply that each element of their skill set will be equally valuable across occupations (Heckman & Scheinkman 1987, Lazear 2009, Eggenberger et al. 2018). Nonetheless, this simple conceptual framework has testable implications related to task specialization. If worker i is more efficient in performing task j relative to the overall population and if j is of great importance for o, then (i) she is more likely to pass the occupational entry barrier implied by the current skill structure and (ii) she will be relatively specialized in task j, even compared to her colleagues. According to eq. (3), these intra-occupational efficiency gains subsequently translate into wage gains.

In a nutshell, not only do we expect individual-level tasks to be predictive because of the unique skills they embody, but also because workers with a skill endowment suited to perform occupation-specific core tasks are able to specialize to a degree beyond their peers. This enhanced task specialization *within* occupation is the unique contribution of worker-level data on the measurement of tasks. The more meaningful this channel, the greater the benefit of using Survey-based data on individual task assignments over occupation-level data derived from external assessment.

3 Data

3.1 Data Sources

The primary data source is a series of German employment surveys, assembled by the Federal Institute for Vocational Education (BIBB) and the Federal Institute of Occupational Safety and Health (BAuA), respectively, in 2012 and 2018.[8] This data set establishes a repeated labor force cross-section on qualification and working conditions of workers in Germany, covering 20,000 in each wave. The secondary data source is derived from the Berufenet Database, a free online portal for occupations provided by the German Federal Employment Agency (BA). This database is a popular research tool for people seeking career guidance and exploring job placements. Occupations must offer legally regulated vocational training to be included in the database and provide a rich set of occupation-specific information, including task requirements. Using data compiled by previous research (Dengler, Matthes & Paulus 2014) (henceforth DMP), I gather information on

[8] See Hall, Siefer & Tiemann (2014) and Hall, Hünefeld & Rohrbach-Schmidt (2020) for data manuals for each of the surveys used in this study.

the relative importance of occupation-level tasks. This database is conceptually similar to the frequently used O*Net data in the US, thus allowing comparisons with the bulk of the literature employing task data. Key downsides of this type of data are (i) limited scope as any analysis is restricted to the occupation-level and (ii) reliance on the external assessment about the importance of occupation-specific tasks.

In contrast, three key features make the BIBB/BAuA employment surveys suitable for the present study. First, workers self-report job-related activities. While the primary interest of Expert-based data is on the occupational dimension, the unit of interest in Survey data is the workplace. Hence, Survey data naturally introduces more variation in task measures (Rohrbach-Schmidt 2019). This detailed information permits an analysis on individual variation in task assignments and therefore relaxes the implicit assumption of a common set of tasks performed within occupations in studies utilizing occupation-level data. Second, compared to other surveys providing task information at the individual level, the BIBB/BAuA surveys offer a sizable sample.[9] Third, each of the employment surveys provides information on monthly labor income. This allows a study on the effects of individual variation in task assignments on wages. Expert-based data, on the other hand, has to be combined with other data sources to infer wage implications. I convert nominal income levels into real terms using CPI=100 as of 2015 and calculate the hourly wage rate using information on weekly hours worked and assuming that each individual works 8 hours per day.[10]

3.2 Measuring Task Content

3.2.1 Survey Selection

The key variables are individual skills, approximated by tasks performed on the job. Prior to 2012 and 2018, there had been five more employment surveys released, offering information on job activities. BIBB/ BAuA collaboratley released another survey in 2006. Prior to that, from 1979 - 1999, the BIBB released four more surveys in cooperation with the Institute of Employment Research (IAB). Despite the possibility to include more data, I restrict the analysis to the most recent surveys from 2012 and 2018 for two reasons. First, DMP use information on occupational requirements from years 2011-2013 for their classification. Hence, using the most recent surveys aligns well with the time horizon in the Expert-based data they made available. Second, unlike earlier versions of the

[9] See Rohrbach-Schmidt & Tiemann (2013) for a comprehensive comparison among task data sets.

[10] The CPI data is taken from the Federal Reserve Bank of St. Louis (FRED) and can be downloaded under the following link: `https://fred.stlouisfed.org/series/DEUCPIALLAINMEI` (Date accessed: 01/18/2020).

questionnaire, the surveys released in 2012 and 2018 are conceptually alike, i.e. tasks questioned in 2012 have likewise been included in 2018. The definition and framing of tasks is therefore consistent in this data set and avoids measurement error resulting from pooling activities over time, an approach that has been criticized in prior research (Rohrbach-Schmidt & Tiemann 2013).

3.2.2 Occupational Dimension

To increase statistical precision, I use average values of worker-level information from 2012 and 2018. The 3-digit occupations are subsequently aggregated into 2-digit occupational groups based on the official BA Classification of Occupations, issue 2010 (KldB 2010). This classification scheme has a high degree of compatibility with the International Standard Classification of Occupations 2008 (ISCO-08), thus making it comparable with international classifications. Analyzing occupational groups at these two dimensions provides a reference about the degree of similarity in task requirements across related occupations of distinct dimension. Baseline specifications, however, are based on a 2-digit definition to enhance statistical precision for occupational averages.

3.2.3 Task Classification & Characteristics of underlying Activities

In terms of the classficiation of job-related activites, I follow Autor, Levy & Murnane (2003) and Spitz-Oener (2006) by pooling activities into J = 5 task categories: (i) non-routine (NR) analytic tasks (NRA), (ii) NR interactive tasks (NRI), (iii) routine cognitive tasks (RC), (iv) routine manual tasks (RM), and (v) NR manual tasks (NRM). Table (1) provides an overview of activities included in the task categories. Following DMP, it moreover offers a comparison of task requirements based on the Berufenet Database (column 3) and comparable requirements based on the BIBB/BAuA surveys (4), along with descriptions about underlying activities (5).

Previous studies have criticized this narrow classification and its underlying activities, displayed in Table (1). Key objections are with regard to the sensitivity of the task measures subject to the number of tasks performed (Rohrbach-Schmidt & Tiemann 2013) and the unclear distinction between RC and NRA. Some activities, for instance in regards to clerical work, require cognitive skills involving routine and NR tasks. This overlap in narrow task groups makes any task classification somewhat inconsistent. To account for this ambiguity, I follow Acemoglu & Autor (2011) in subsuming NRA and NRI under "Abstract". Similarly, RC and RM are subsumed under "Routine". NR manual tasks, on the other hand, are not categorized further.

Abstract tasks involve strong problem-solving skills, yet, communication-heavy activities are more relevant for the interactive category. In contrast, routine tasks are characterized by following explicit rules which can be codified and thus easily automated compared to NR tasks.[11] Lastly, NR tasks require hand-eye coordination which is difficult to automate. These activities are pronounced in basic services and are disproportionately found in lower parts of the income distribution. For the sake of brevity I will refer to this task group simply as "Manual", as opposed to RM tasks which are easier to automate.

3.2.4 Classification of Survey Responses

Unfortunately, the BIBB/BAuA surveys do not provide detailed information on time devoted to each activity, thus not making it possible to distinguish whether a task is important because of a worker's underlying skill level or because of the time devoted to a task.[12] Similar to the PDII, the Survey data used in the present study nonetheless offers some insight on the time dimension of tasks. Specifically, workers are asked whether they perform an activity "never", "sometimes", or "often". Based on their responses, I create a dummy variable equal to 1 if individual i performs activity a belonging to task group j "often":

$$d_{iaj} = \begin{cases} 1, & \text{if } a = \text{"often"} \\ 0, & \text{if } a = \text{"sometimes"} \vee a = \text{"never"} \end{cases} \tag{4}$$

Subsequently, I will thus focus on workers who spend a considerable amount of time on a particular task. Of course, however, performing a task "often" may be perceived differentially from one worker to another. Table (6) in Appendix A.3 illustrates the answers of workers, providing a sense for the time allocation devoted to each task. Unsurprisingly, college graduates are over-represented in performing abstract tasks "often" and under-represented in performing manual tasks "often". The opposite is true for workers with no vocational degree, while those who have earned some vocational degree lie in between

[11]Because of these characteristics, a series of papers has identified routine tasks as a primary reason for increasing employment polarization over the last decades (Autor, Levy & Murnane 2003, Spitz-Oener 2006, Goos & Manning 2007, Autor & Dorn 2013, Goos, Manning & Salomons 2014, Senftleben & Wielandt 2014). In particular, people with medium education (e.g. high school degree, some college) have been detrimentally affected by this trend as they perform clerical work, quality control, bookkeeping (routine cognitive) or manual tasks that follow a set of strict rules and, in the latter case, demand more physical activities.

[12]There is, however, a supplementary survey for the 2012 version which is based on follow-up questionnaires with a subset of workers. This supplementary data does offer information on time devoted on tasks, yet, comes at the cost of substantial loss of data (Rohrbach-Schmidt 2019). Moreover, Stinebrickner, Stinebrickner & Sullivan (2018, 2019) use a novel longitudinal data set in which two cohorts of students of the Berea College reported the percentage of time spent on tasks. To my knowledge, this Berea Panel Study is the only panel data available offering information on worker-level tasks.

those specialization patterns. In a few instances, workers answer whether they require no knowledge, basic knowledge, or advanced knowledge of a particular activity. In these cases, the dummy variable equals 1 if they require advanced knowledge. For two activities, managing personnel and programming, there is no additional information on time allocation or required skill level.[13]

3.2.5 Task Construction

In the construction of the individual task content T_{ij}, the key variable of this study, I follow DMP, who themselves apply a common measure introduced by Antonczyk, Fitzenberger & Leuschner (2009). Let A_j denote the number of activities included in task group j and let A denote the total number of activities across all j. The individual task content T_{ij} is then defined as:

$$T_{ij} = \frac{\text{No. of activities a performed by i in task category j}}{\text{Total no. of activitites a by i across } \textit{all} \text{ j's}} = \frac{\sum_{a=1}^{A_j} d_{iaj}}{A} \tag{5}$$

where $j = 1$ (NRA), $j = 2$ (NRI), $j = 3$ (RC), $j = 4$ (RM), and $j = 5$ (NRM) reflect the narrow task categories defined above. Hence, for each i we compare the number of activities a belonging to j relative to all activities A. This definition implies that the number of task-specific activities is proportional to all activities and adds up to 1 over all tasks, i.e. $\sum_J T_{ij} = 1$. Intuitively, it thus describes the relative importance of each task category. Pertaining to the empirical implementation, the task endowment $\boldsymbol{T_i}$ is based on a series of dummy variables which, using eq. (5), are subsequently converted into a continuous measure $T_{ij} \in [0,1]\ \forall j$. For example, if employee i, Jane, indicates that she performs three analytic, three interactive, and two RC activities, then her NRA, NRI, and RC task content, respectively, is 0.375, 0.375, and 0.25. Therefore, 75% of Jane's overall activities comprise abstract tasks with equal contributions from NRA and NRI. The remaining 25% involve RC activities.[14] Note that two workers employed in the same

[13] The selection of activities slightly differs from previous studies. Typically, only activities which workers perform "never", "sometimes", or "often" are considered. I extend the range of activities to include relevant levels of skill, primarily to make the relative importance of tasks between the Expert-based and Survey data more comparable. From Table (1) it can be inferred that RC and NRA would be under-represented without this extension. Moreover, information aimed at the required skill level of an activity has changed substantially across surveys and generally been asked infrequently. Therefore, inconsistent appearance of questions is another reason these activities have not been included in prior research. Restricting the analysis to surveys conducted in 2012 and 2018 avoids this measurement error, though, maintaining consistency in the type of activities asked over time.

[14] Intuitively, this task definition is related to the skill-weight approach in Lazear (2009). In this study, returns to skills are determined by weights firms attach to core skills. Constructing these weights implies that

occupation may have a different task content if they perform a different combination of activities.

By collecting individual responses for each of the N_o workers employed in o, we can compute occupational averages $\forall j$, the common task dimension used in the literature:

$$T_{jo}^{S} = \frac{1}{N_o} \sum_i T_{ij} \tag{6a}$$

$$T_{jo}^{Exp} = T_{jo} \text{ if data source = BERUFENET} \tag{6b}$$

where T_{jo}^{S} merely represents occupation-specific averages across individual responses and T_{jo}^{Exp} is taken from the data set made available by DMP, comprising occupation-level task measures assessed by labor market experts. Both measures proxy the stock of task endowment of workers employed in occupation o (first term in eq. (3)) and have an interpretation analogous to T_{ij}, defining the importance of each task category at the occupation-level instead.

The intuition behind these task measures will turn out to be useful when testing the implications of the conceptual framework in section 2 in regards to intra-occupational efficiency gains resulting from task specialization within occuaptions. Let $\boldsymbol{T_o^S} = \left(T_{1o}^S, T_{2o}^S, ..., T_{Jo}^S\right)$ summarize the occupation-specific averages of tasks $\forall j$ based on Survey data. Analogously, let $\boldsymbol{T_o^{Exp}} = \left(T_{1o}^{Exp}, T_{2o}^{Exp}, ..., T_{Jo}^{Exp}\right)$ summarize the occupation-specific averages of tasks based on Expert data. We can then define the within-occupation degree of task specialization by computing the deviation between individual task content from the occupational average:

$$\boldsymbol{\widetilde{T}_{io}^{S}} = \boldsymbol{T_i} - \boldsymbol{T^{S}_{o,i\neq i}}', \tag{7a}$$

$$\boldsymbol{\widetilde{T}_{io}^{Exp}} = \boldsymbol{T_i} - \boldsymbol{T^{Exp}_{o,i\neq i}}', \tag{7b}$$

where $\boldsymbol{\widetilde{T}_{io}^{S}} = \left(\widetilde{T}_{i1o}^{S}, \widetilde{T}_{i2o}^{S}, ..., \widetilde{T}_{iJo}^{S}\right)$ summarizes worker i's degree of specialization across J tasks based on occupation-level tasks derived from Survey data. Note that $\boldsymbol{T^{S}_{o,i\neq i}}'$, reflects occupation-level averages in spirit of (6a), yet, is calculated as a leave-out mean. It therefore excludes worker i's own individual task content and proxies the average task

a high weight attached to a particular skill means a low weight on the other skills. This trade-off is motivated by constraining all workers to enter the same occupations, i.e. making worker's skills distinguishable. Hence, workers will choose a firm which places a high weight on skills they are well-endowed with. This idea likewise applies to the construction of the task content in the present study with a focus on the occupational dimension instead.

endowment of peers. Similarly, $\widetilde{\boldsymbol{T}}_{\boldsymbol{io}}^{\boldsymbol{Exp}} = \left(\widetilde{T}_{i1o}^{Exp}, \widetilde{T}_{i2o}^{Exp}, ..., \widetilde{T}_{iJo}^{Exp}\right)$ summarizes worker i's degree of specialization across J activities based on occupation-level tasks derived from Expert data. Continuing on above example, recall that Jane's individual task content in abstract activities is equal to 0.75. If the occuapation-level average is equal to 0.50, her degree of specialization amounts to 0.25. Therefore, she is more specialized in abstract tasks than her peers by 25 pp. According to wage equation (3), we would expect her to earn intra-occupational efficiency gains due to an enhanced degree of task specialization *within* her occupation.

3.3 Sample Selection & Descriptive Statistics

To be included in the baseline sample, workers need to meet two criteria. First, their individual tasks must be observed. Second, their occupation can be matched with the Berufenet Database. Applying these restrictions leaves a baseline sample comprising 31,647 workers. Table (2) provides descriptive statistics. In particular, it compares the relative importance of tasks based on the BIBB/BAuA surveys (column 2) and the Berufenet Database (3). Note that values based on the employment surveys reflect averages across all workers. Abstract task measures represent around half of activities of workers while two fifths of tasks are of routine nature. In terms of broad task groups, the average distribution between job-related activities is almost identical among both data sources. While similar patterns do carry over to a more narrow task classification, one key discrepancy stands out. Interactive tasks are somewhat over-represented in the employment surveys at the detriment of NRA. Overall, though, both data sources tell a similar story and avoid substantial over- or under-representation of any task group when tasks are defined broadly.

For the empirical analysis below, the baseline sample comprises broad task groups (Abstract, Routine, Manual) based on 36 2-digit occupations. The broad task classification alleviates measurement error in the task content outlined in section 3.2.3. Meanwhile, adopting a broader occupational classification enhances statistical precision when computing occupational averages. Of course, these broad definitions come at the cost of potentially generalizing job-related activities and thus alleviating the importance of occupational specificity in skills.[15] To test for the robustness of baseline classifications, I adopt more narrow definitions of tasks and occupations in section 5.2, using 139 3-digit occupations instead.

Tables (3)-(5) compare the occupation-specific task content (2-digit) and average wages

[15]See See Poletaev & Robinson (2008), Kambourov & Manovskii (2009), Gathmann & Schönberg (2010), Yamaguchi (2012), Cortes & Gallipoli (2018), Eggenberger, Rinawi & Backes-Gellner (2018), Robinson (2018), and Goos, Rademakers, Salomons & Willekens (2019).

of Survey and Expert data, respectively. Overall, both data sources identify the same set of occupations which have a clear core task. According to Table (3), both data sources agree on four out of the five occupations with the highest and lowest abstract task-intensity, respectively. Notably, specialization in abstract tasks among the Top 5 is smaller based on Survey data (0.57-0.63) compared to Expert data (0.73-0.96), while abstract activities are around four times as important for the Bottom 5.[16] Further, note that a higher abstract task content does not automatically translate into higher average wages. For instance, the average worker in “Education, Social Work, Housekeeping, Theology” earns as much as a worker in “Metal-making/ - working, Metal construction”.

The overlap between Survey and Expert data is somewhat less pronounced for routine tasks (Table 4). In this instance, they agree on three out of the Top 5 occupations, but only two out of the Bottom 5. There are likewise substantial differences in the degree of specialization between both data sources. Yet, by and large, average wages are roughly comparable across routine-heavy and routine-light occupations.[17] Similarly, Survey and Expert data agree on only two out of the Top 5 manual-intensive occupations, but three out of the Bottom 5 (Table 5). Notably, aside from “Cleaning services”, there are extreme gaps in manual-intensity. For instance, the occupation with the fifth-highest task content according to Expert data (“Interior construction”) is about 2.5 times as manual-intensive as the fifth-highest task content according to Survey data (“Tourism, Hotels and Restaurant occupations”). This observation is consistent with above finding according to which Survey data suggests greater importance of abstract activities in manual-heavy occupations. Hence, Expert data appears to underestimate the importance of abstract activities at the workplace. Unsurprisingly, though, average wages are substantially smaller in the Top 5 manual-intensive occupations as opposed to Bottom 5 - on the order of 40-60 log points.

4 Empirical Methodology

The conceptual framework laid out in section 2 suggests an important role for individual-level variation of tasks in the process of wage determination. To explore task elements embodied in different data sources more formally, the empirical analysis emphasizes two key questions: First, are worker-level tasks predictive of wage differences in ways that

[16]The comparably large standard deviations for the Bottom 5 does suggest, however, that there is substantial heterogeneity in occupations in which abstract tasks only have a subordinate role. Hence, there are a few workers with a notable amount of abstract activities, explaining the greater overall importance of abstract tasks in manual-heavy occupations using Survey data (compared to Expert data).

[17]A notable exception is “Mathematics, Biology, Chemistry, Physics”, an occupation group characterized by plenty of routine cognitive tasks, which are not always easiliy differentiable from analytic activities.

occupation-level data is not? In particular, if they are not correlated with unobserved features of occupation beyond occupation-level tasks, this would be consistent with the task content being a key component of occupations, reinforcing the need to measure tasks precisely. Second, which task dimension is economically more meaningful? Greater emphasis on occupation-level measures of tasks may place greater entry barriers to occupations. On the other hand, greater importance of individual characteristics gives workers more opportunities to exert comparative advantages beyond occupational borders. Hence, workers may likewise specialize within occupations according to their task endowment, allowing them to earn higher wages per eq. (3).

4.1 Baseline Wage Regressions

To assess the predictive elements embodied in the task content, I run a series of wage regressions comprising task measures of distinct dimension. The key regression takes the following form:

$$ln\ w_i = \alpha + \boldsymbol{\beta T_i} + \boldsymbol{\gamma X_i} + \delta_r + \eta_s + \epsilon_i \tag{8}$$

where w_i is the hourly real wage for individual i. Note that the mix of tasks is not occupation-specific, workers can thus differentially specialize according to their skill endowment $\boldsymbol{T_i} = \left(T_{i1}, T_{i2}, ..., T_{iJ}\right)$. The vector $\boldsymbol{X_i}$ comprises control variables, including demographic characteristics (sex, age, age squared, metropolitan area), education dummies (college degree, vocational schooling, no vocational degree), and firm- and occupation-specific variables (firm tenure, firm tenure squared, occupational tenure, occupational tenure squared, firm size indicator). Moreover, δ_r and η_s, respectively, denote region and sectoral dummies.[18] Each regression is weighted by (survey weight × occupation-specific workforce) to account for size effects.

Importantly, the vector of coefficients $\boldsymbol{\beta}$ should not be interpreted as average task returns in a causal sense. This is because workers choose an occupation in which they can carry out activities they are particularly efficient at. Since workers are non-randomly assigned into occupations, perhaps due to comparative advantage, this self-selection introduces a bias. One would ideally use longitudinal data to conduct FE regressions, yet, the cross-sectional nature of most data sets prevents this approach from being used widely. The regressions conducted in this study should thus be considered exploratory

[18] To be specific, the dummies encompass 16 states (Western & Eastern Germany) and 34 sectoral groups (industrial, craft, commerce, services, others). Note that there are no time dummies as the data from the 2012 and 2018 surveys has been pooled for the purpose of greater statistical precision.

as they merely reflect correlations between tasks and wages. Despite these identification issues, Stinebrickner, Stinebrickner & Sullivan (2019) find task returns from OLS and FE regressions to be remarkably similar based on US panel data. Hence, OLS regressions may serve as credible suggestive evidence.

A comparison of eq. (8) with models comprising occupation-level tasks based on Survey data, $\boldsymbol{T_o^S}$, and Expert-based data, $\boldsymbol{T_o^{Exp}}$, is informative on the validity of the latter to capture task-related occupational characteristics as self-selection into occupations should be embodied in both measures. Augmenting eq. (8) by occupational dummies θ_o stresses the importance of idiosyncratic factors embodied in the task content by exploring task specialization *within* occupations.[19] Estimating models containing both task dimensions, on the other hand, will shed light on the unique variation in wages that can be attributed to worker-level differences in tasks. Other than task measures, all regressions are identical and are weighted by survey weights. In order to asses the relative importance of task measures across specifications formally, I report (i) R-squared, (ii) Adjusted R-squared, (iii) F-test for joint significance of task measures, (iv) Incremental R-squared for task measures, and (v) Akaike (AIC) and Bayesian (BIC) Information Criterion. While the first four measures offer insight on the goodness of fit across specifications, the AIC and BIC shed light on model selection by virtue of out-of-sample prediction errors.

Lastly, two more aspects worth mentioning. First, manual tasks are omitted as, by construction, the task measures add up to 100. Second, for similar reasons, one education group has to be omitted, in this case workers who have not completed any vocational schooling. Therefore, the reference group consists of workers with no vocational degree who perform predominantly manual tasks. Since these workers are typically found in lower parts of the wage distribution, we should expect positive and sizable task returns.

4.2 Degree of Specialization within Occupations

A key implication of the conceptual framework linking tasks to wages is that enhanced task specialization within occupations should translate into wage premia. The underlying idea is that these workers are more efficient at performing occupation-specific core tasks relative to their peers. To expedite on this hypothesis, we can empirically test eq. (3) by running the following wage regression:

$$ln\ w_{io} = \alpha + \boldsymbol{\lambda} \boldsymbol{T}^S_{\boldsymbol{o,i \neq i'}} + \boldsymbol{\Omega} \widetilde{\boldsymbol{T}}^S_{\boldsymbol{io}} \times \boldsymbol{T}^S_{\boldsymbol{o,i \neq i'}} + \boldsymbol{\gamma} \boldsymbol{X_i} + \delta_r + \eta_s + \epsilon_{io} \tag{9}$$

[19]Depending on the definition of occupations, the model comprises 36 (139) 2-digit (3-digit) occupational groups.

where $\widetilde{\boldsymbol{T}}^S_{io}$ represents worker i's degree of specialization across J tasks in occupation o as defined in eq. (7a). Of key interest are the interaction terms, which offer insight on worker's degree of task specialization. Positive coefficients in the vector $\boldsymbol{\Omega}$ would be consistent with intra-occupational efficiency gains. The larger these gains, the more lucrative is task specialization within occupations. Replacing Survey-based tasks at the occupation-level, $\boldsymbol{T}^S_{o,i\neq i'}$, with Expert data, $\boldsymbol{T}^{Exp}_{o,i\neq i'}$, offers a robustness exercise to check whether the latter points to the same direction. Of course, such an analysis would not be feasible relying only on Expert data, however.

5 Results

5.1 Baseline: Individual vs Occupation-level Task Measures

The baseline estimates can be found in Table (7). Columns (1) - (3) correspond to eq. (8), displaying specifications including occupation-level tasks from Survey data, individual-level tasks, and occupation-level tasks from Expert data, respectively. All three models show significant and positive estimates as expected, illustrating the returns to performing abstract and routine tasks compared to manual. For instance, relative to manual tasks, column (2) indicates that performing 1 pp. more abstract tasks individually raises the log wage by 0.56 points.[20]

To assess whether individual-level tasks have statistically significant explanatory power beyond the occupational level, columns (4) and (5) combine task measures of both dimensions. Notably, not only does worker-level variation remain robust to inclusion of either occupational measures, it also absorbs substantial variation from both occupation-level tasks. Specifically, both shrink by up to 50% compared to specifications excluding individual-level measures. These findings suggest idiosyncratic factors embodied in the task content are an important component in the process of wage determination. Accounting for occupational affiliation via FE supports this narrative, consistent with task specialization within occupations. The robustness of the point estimates suggests that worker-level information on tasks is not correlated with unobserved features of occupations beyond the task content (6), making it an informative measure of occupational characteristics.

The general deduction that tasks are predictive of wage differences is in line with

[20] The mean abstract task content is 0.48, compared to 0.13 in the manual task content. The average worker thus performs more abstract tasks to begin with. In fact, a quarter of workers performs no manual tasks at all. Tilting the task content even more in favor of abstract tasks therefore leads to the sizable wage gains presented above.

results reported in prior research.[21] F-tests on joint significance of task measures reinforce this finding and indicate that each measure, regardless of specification and task dimension, makes independent and statistically significant contributions in explaining variation in wages. At the same time, the evidence points to a prominent role for the worker-level dimension, especially pertaining to abstract tasks. Not only are estimates on individual-level tasks significant, but both measures of R-squared also suggest they consistently have a greater explanatory power than either occupation-level variables (columns 1-3). The information criteria displayed at the bottom reaffirm this view. Both, AIC and BIC, suggest a model comprising individual-level task measures has a superior relative likelihood than including either occupation-level measure, thus implying the smallest out-of-sample prediction error.

To quantify the relative importance of worker-level task measures more directly, Table (8) displays the incremental R-squared of task measures. The results are based on computing the squared semipartial correlation between log wages and the task measure of interest and are relative to the R-squared of a specification with a full set of variables for each of the models (1) - (6). For instance, column (2) implies a reduction in R-squared by 13.5% once individual abstract tasks are removed from the model. Similarly, 10.3% and 11.9%, respectively, of R-squared are lost once occupation-level measures from Survey or Expert data are removed (columns 1 & 3). Columns (4) and (5) combine individual and occupation-level measures, reaffirming that individual-level tasks are more informative. The bottom two rows summarize these findings, highlighting that worker-level tasks have a larger incremental R-squared compared to occupation-level measures by about 50%.

Table (9) tells a similar story, displaying the unique variation in wages associated with task measures, once more in relative terms. These values are based on computing the squared partial correlation between log wages and the task measure of interest. Individual task measures consistently explain a substantial share of the residual variance in log wages that other covariates are not able to explain. For instance, the common approach in the literature is based on model (3), comprising occupation-level information derived from Expert data. This model explains 15.6% of variation that traditional wage regressions are not able to explain. But how much of the variance in wages does this standard task-approach disregard by not accounting for worker-level variation? According to column (5), idiosyncratic factors account for 7.4% of the variation not explained by occupation-level measures nor any other covariates. Two thirds of these contributions are due to variation in abstract activities. Model (6), conditioning individual task measures on occupational

[21] See Autor & Handel (2013), Cassidy (2017), Rohrbach-Schmidt (2019), and de La Rica, Gortazar & Lewandowski (2020).

FE, supports this conjecture. Within occupations, almost 17% of the unexplained variance in a traditional wage regression can be attributed to variation in tasks.

5.2 Robustness: Individual vs Occupation-level Task Measures

5.2.1 Narrow Task Classification

The descriptive statistics displayed in Table (2) show minor discrepancies in the relative importance of analytic and interactive tasks. While these differences do not matter in a broad classification scheme, they are relevant in empirical settings in which a narrow task classification is imperative. The migration literature, for instance, has emphasized the importance of interactive tasks to explain wage differences between native and foreign workers.[22] Similarly, other studies have highlighted rising returns of social skills in recent decades (Deming 2017, Michaels, Rauch & Redding 2019) and how those have especially helped females in reducing the gender pay gap.[23] To test this hypothesis, I revisit the wage implications of task variation by disaggregating abstract task measures into NR Analytic and NR Interactive and routine task measures into Routine Cognitive and Routine Manual. Hence, NR Manual remains the relevant base group. The results of this exercise are summarized in Table (10).

Qualitatively, the main conclusions carry over in the sense that most coefficients are positive and statistically significant. Regardless of which task measure is being used, all tasks continue to be jointly significant in their own right (columns 1-3). Nonetheless, a few interesting observations stand out. First, the positive coefficients for routine tasks are unsurprisingly driven by Routine Cognitive with wage gains of up to 40%.[24] Hence, performing more routine manual tasks instead of NR Manual has no positive wage effects. Second, the positive impact of abstract tasks is primarily driven by NR Analytic with wage gains of up to 111% relative to manual tasks (1 & 3).[25] Once occupation-level measures are

[22]See, e.g., Peri & Sparber (2009, 2011), Amuedo-Dorantes & de La Rica (2011) and Haas, Lucht & Schanne (2013). For an application of distinct specialization patterns between natives and foreigners in the STEM market see Ma (2020).

[23]See Black & Spitz-Oener (2010), Cortes, Jaimovich & Siu (2018), and Yamaguchi (2018).

[24]It could be argued this result is driven by the broader selection of activities outlined in section 3.2. Including activities in the definition of the task content for which workers reported required skill levels does indeed bolster the importance of Routine Cognitive. Restricting the analysis only to activities which workers perform “often”, “sometimes”, or “‘never” does not change these results substantially, however. Applying this definition of the task content alleviates the importance of routine cognitive tasks to some extent, but they remain statistically and economically significant throughout specifications. These results are not reported but are available from the author upon request.

[25]These findings are consistent with Stinebrickner, Stinebrickner & Sullivan (2019) who find information tasks to be relatively more important in the determination of wages compared to people tasks. Conceptually, this distinction is similar to NR Analytic vs NR Interactive. Possibly, an increasing amount of time devoted to

combined with worker-level information (4 & 5), much of the predictive elements in tasks is absorbed by individual variation. For instance, compare the benchmark case of utilizing only Expert data (column 3) with model (5). Inclusion of individual task information substantially attenuates coefficients of Expert-based data, at least cutting them by half or turning them insignificant altogether. Conditioning on occupational FE (column 6) even raises point coefficients, indicating that task specialization within occupations also takes place in narrowly defined task groups.

5.2.2 Finer Occupational Classification: 3-digit Codes

An additional caveat in the baseline specification is the dimension of occupations. This aspect matters especially with respect to the transferability of skills as employment in an occupation allows workers to accumulate task-specific human capital. Hence, if occupational groups are defined too broadly, occupations lumped together may be too different in regards to their skill requirements. As a consequence, tasks become less portable, leading to a greater depreciation of task-specific human capital in the aftermath of an occupational transition.[26] Vice versa, sufficiently narrow definitions make it easier to transfer skills. Following this logic, occupation-level measures should be more important for 3-digit occupations as they capture occupation-specific task requirements more accurately. Indeed, estimates displayed in Table (11) suggest that occupation-level measures contain at least as much explanatory power as individual task measures and provide a superior goodness of fit. In particular, variation at the occupational level pertaining to abstract tasks adds at least an additional 20 pp. in wage gains (column 1 & 4).

These results are partially driven by specific occupational groups, however. To show this I re-run the regressions using a sample of workers subject to social security payments instead, i.e excluding civil servants and the self-employed. Especially the former group ("*Beamte*") has a unique role in Germany, comprising administrative officials, but also other public servants such as policemen or teachers. Importantly, their salary and working hours are legally set as opposed to the more common wages determined by collective agreement. In order to become a civil servant one (i) must be Germany citizen and (ii) undergo specific training periods to acquire formal qualifications. These restrictions thus represent occupational barriers in spirit of eq. (3) and diminish the transferability of skills.

In Table 12 it can be seen that results based on this set of workers are in between

information tasks is an important reason for these findings, as suggested by their longitudinal data. Hence, next to variation in skill levels, the time dimension may contribute to the dominance of NR Analytic among narrow task categories.

[26] See Poletaev & Robinson (2008), Gathmann & Schönberg (2010), Yamaguchi (2012), Cortes & Gallipoli (2018), and Goos, Rademakers, Salomons & Willekens (2019).

those from the baseline sample using 2- and 3-digit occupations, respectively. Notably, the goodness of fit measures and both information criteria once more favor a model comprising individual-level tasks (albeit barely). The key takeaway of this exercise is thus that practitioners employing occupation-level task data should strive to use fine occupational codes to reduce measurement error resulting from aggregation and pay attention to the composition of the workforce.

5.2.3 Different Task Definition: Principal Component Analysis

The main downside of the task content as defined in (5) is multicollinearity, forcing the researcher to drop one of the task variables. To test whether results are robust to the construction of the task content, one can alternatively assume a different base in the denominator, e.g. total no. of activities within a task group[27], or conduct a Principal Component Analysis (PCA).

This technique aims at reducing the dimension of the data, thereby mitigating problems related to overfitting a model. In essence, a PCA is based on linearly transforming the data by subtracting the mean of each variable and performing an Eigendecomposition of the Covariance matrix of covariates. Normalizing each of the (orthogonalized) eigenvectors then yields principal components (PCs), which can be included as covariates in a simple OLS regression. The premise of a PCA is that a small number of PCs suffices to explain most of the variability in the data. In principle, one could use as many PCs as covariates. Yet, the first PC contains the most information as it minimizes the initial sum of the squared residuals, thus capturing the direction of the data along which the observations vary the most. All subsequent PCs must be orthogonal to the direction of the first one, thus only capturing variance subject to this constraint, containing less information.

For these reasons, I follow Autor & Handel (2013) and use the first component of a PCA to condense the task content into a single measure for abstract, routine, and manual tasks. Specifically, I extract information embodied in task groups based on the single activities displayed in Table (1). A PCA is then conducted for each of the three task categories where

[27] See Spitz-Oener (2006), Black & Spitz-Oener (2010), Cassidy (2017) and Rinawi & Backes-Gellner (2019) for studies using this definition instead. While appealing due to the possibility of including all tasks, this measure confounds the time dimension of activities within a task group with the overall number of tasks performed. Since the latter characteristic sheds light on overall job complexity (e.g. if all or most activities are of abstract nature), conflicting both dimensions reduces the interpretative value compared to the baseline definition in the present study. Using this alternative task measurement does not change the main results, however. Performing more routine and especially abstract tasks is correlated with wage gains while performing more manual tasks implies wage losses (not reported). Importantly, individual-level variation remains the dominant predictor among the task measures considered. Results of this exercise are available from the author upon request.

the first PC is a linear combination of underlying activities. To make the interpretation more intuitive, I standardize all resulting components (individual and occupational) with mean zero and a variance equal to one.

Table (13) summarizes the results of this exercise. Qualitatively, the estimates are in line with previous specifications, highlighting the explanatory power of worker-level task data and its benefits over occupation-level measures.[28] For instance, a one standard deviation increase in individual-level variation in abstract (routine) tasks raises wages by 8% (5%) per column 2. Performing more manual tasks, on the other hand, implies wage losses on the order of 3% as these activities are predominant in low-wage occupations. Accounting for occupation-level measures does not change these results much (4 & 5). Similarly, wages rise by 7% in response to a one standard deviation increase in abstract tasks even if conditioned on occupational FE.

The key difference to prior research is the positive coefficient on Routine, which is usually estimated to be negative. The discrepancy can be attributed to two factors. One is related to the selection of activities. In the present study activities are tailored to the information embedded in the Expert data. This implies inclusion of a disproportionate amount of routine cognitive activities which tend to be better paid. Moreover, previous studies use generic task measures such as "performing short, repetitive tasks" Rohrbach-Schmidt (2019, p. 126), whereas I conduct a PCA based on practical activities (see Table 1).[29] In sum, individual-level variation remains not only robust to inclusion of different occupational measures, but also economically meaningful.

5.2.4 Time Dimension of Tasks

Most task measures provide imperfect identification on the importance of job-related activities as they confound the skill and time dimension. It is generally not clear whether explanatory power of variation in tasks can be attributed to greater level of skill, more time devoted to a task, or a combination of both. A key interest lies in abstract tasks which have been shown to be of particular importance.[30] This limitation also applies to

[28] Note that the estimates from Expert-based Survey data are scaled. Occupation-level tasks are more dispersed in this data compared to information derived from the surveys. This implies larger jumps along the wage distribution resulting from an increase by one standard deviation.

[29] In terms of abstract tasks, however, the reported results are comparable to prior research. Autor & Handel (2013) estimate returns to abstracts tasks on the order of 8-20% depending on specification. Rohrbach-Schmidt (2019) estimates coefficients between 2-17%, hence a somewhat broader range. Lastly, de La Rica, Gortazar & Lewandowski (2020) find a one standard deviation increase in individual-level variation in abstract (routine & manual) tasks raises (reduces) wages within occupations by 3.3% (2.6-2.9%) for a European sample (excluding Germany).

[30] For instance, Stinebrickner, Stinebrickner & Sullivan (2019) show that, despite most workers spending some time on almost all tasks throughout the year, time devoted to information tasks, similar to NR Analytic,

the present study. Baseline specifications are based on eq. (4), imposing that workers only carry out an abstract task if they perform underlying activities "often".

Thinking of the skill dimension by education, the breakdown of time allocation devoted to tasks displayed in Table (6) shows the implications of this alternative assumption in the construction of tasks measures. With respect to abstract (and routine cognitive) tasks, college graduates are over-represented among workers who perform them "often" whereas workers with some or no vocational degree are under-represented in most instances. Hence, including "sometimes" in the definition of the task content adds a disproportionate amount of Non-college graduates to the group of workers performing abstract tasks, making the skill-specific distinction between who's performing a task and who isn't less sharp. The baseline task definition thus implies that a disproportionate amount of the variation in wages is driven by differences in skill.

In Table (14) I relax this assumption, creating dummies based on the following classification instead:

$$d_{iaj} = \begin{cases} 1, & \text{if } a = \text{"often"} \ \vee a = \text{"sometimes"} \\ 0, & \text{if } a = \text{"never"} \end{cases} \tag{10}$$

While the most skilled workers are still assumed to perform tasks, workers who are less skilled, but spend *some* time on tasks, are now likewise accounted for.[31] The average skill level for the group performing tasks thus becomes more diluted, reducing the impact of variation in skill as a driver of wage differences altogether.[32] Larger coefficients on task measures compared to the baseline analysis in section 5.1 would thus provide exploratory evidence that the time dimension in tasks is meaningful, e.g. by facilitating learning-by-doing (Yamaguchi 2012, Stinebrickner, Stinebrickner & Sullivan 2019). For reference, a 1 pp. increase in the individual abstract content in the baseline regression implies wage gains on the order of 58%, relative to manual tasks. Indeed, adding more importance to the time dimension raises the coefficient to 91% (column 2). Similar results are found for other specifications including individual- and occupational-level tasks. These findings are

has increased substantially over time at the detriment of people tasks. Hence, one might suspect that the time dimension has become disproportionately more important for information tasks relative to other activities.

[31] For instance, Yamaguchi (2012) shows that returns to skills increase with task complexity (e.g. abstract tasks). Moreover, skills grow faster when the worker is employed in an occupation intensive in complex tasks. These findings can be interpreted in the sense that occupations provide different learning opportunities. Performing more complex tasks therefore helps workers develop their skills faster, e.g. via learning-by-doing.

[32] Another way to see this is to keep in mind that the three time categories "often", "sometimes", and "never" still consist of workers of all three education groups. Yet, we now have a sharp distinction between workers who are never performing a task and those who are performing it at least once in a while.

thus consistent with the hypothesis that the predictive power of task variation does not merely reflect variation in skill, but also time workers differentially devote to a task.

5.3 Degree of Specialization within Occupations

5.3.1 Time Dimension of Tasks: "Often"

In this section I empirically test the implications of the conceptual framework outlined in section 2. In particular, the model implies that workers can earn intra-occupational wage gains by specializing in occupation-specific core tasks beyond the level of their peers. While it is straightforward to calculate the main task by occupations in case of dominant tasks, it is less clear how to proceed when several categories are equally important. To decide on tiebreakers, I follow DMP, implementing the following rules: If NR Analytic and Interactive tasks (at the occupation-level) are equally important, NR Interactive tasks are considered the main task. If Cognitive Routine and Routine Manual or NR Manual, respectively, are equally important, either Manual task category is considered the main task. Lastly, should all three task categories happen to have the same task content, NR Manual is considered the main task. All remaining ties are considered inconclusive, therefore omitted from the sample. It turns out that this algorithm is not restrictive. Deviations, such as flipping all inequalities in favor of another task category, affect only a few instances and thus leave the findings below virtually unchanged.

The reported results are based on eq. (9), illustrating this wage premium stemming from task specialization within occupations. Table (15) displays task measures, respectively, from Survey and Expert data and accounts for the importance of time workers devote to tasks as discussed in the in the robustness analysis above. Columns (1)-(4) assume workers perform a task only if they engage in underlying activities "often".

Regardless of data source, abstract interaction terms show statistically significant positive estimates, consistent with the idea of efficiency gains from an enhanced degree of specialization relative to peers. For reference, consider model (1) based on Survey data. Relative to the omitted task category Manual, the average task endowment of abstract activities implies wage gains of 47%. An incremental specialization by 1 pp. beyond that average adds another 70% in relative wage gains compared to performing manual tasks. Hence, efficiency gains are incrementally almost 50% larger than the base wage gains resulting from matching the average task endowment of workers employed in an occupation.

The summary statistics at the bottom of Table (15) for the distribution of the *relative* abstract task endowment suggest these efficiency gains are unevenly distributed. Specifically, they correspond to the second term in eq. (3), capturing the relative task specialization within an occupation. The median worker is, unsurprisingly, not specialized beyond the average level of peers. A more specialized worker, though, can earn a substantial wage premium. For instance, if Jane is the worker at the 75th percentile of the distribution of the relative task endowment of workers in occupations with main task "Abstract", she performs 10 pp. more abstract tasks than the average worker. Her cumulative wage gains from task specialization are thus seven times as large as those at the (occupational) base level (10×0.7). Likewise, workers at the bottom quartile face relative wage losses compared to more efficient peers such as Jane. Note the negative coefficient on the squared interaction term, suggesting diminishing returns to specialization. Performing only one core task may thus be suboptimal for workers, providing incentives to diversify the set of activities.

Figure 1 lends further credence to this finding, plotting specialization gains for each occupation. Occupations characterized by a higher abstract task content reward specialization comparably less than those with a modest intensity in abstract tasks, regardless whether occupations are defined at the 2- or 3-digit level. Part of these results are mechanical as there is less room to specialize in occupations with already high requirements on abstract skills. Yet, findings pertaining to the diminishing returns of specialization are less conclusive for routine tasks, suggesting a mechanism that rewards worker's specialization differentially subject to occupational requirements and composition of workforce. I leave this question for future research.

Getting back to Table (15), the incremental efficiency gains are somewhat counterintuitive based on Expert data (column 2). While the interaction term is positive, it is based on consistently negative deviations from the occupational average. However, keep in mind, that Expert data suggests a much greater degree of task specialization at the occupation-level among abstract-intensive professions (0.73-0.96, see Panel B in 3) . By default, there is thus little room to specialize. This finding is also reflected in the large coefficient for returns to abstract tasks at the occupation-level of 223% relative to manual tasks, or five times as large compared to using Survey data measures. In regards to routine-intensive occupations, results look similar using Survey data (column 3). Specialization gains are somewhat less pronounced even though effects at the margin are comparable to abstract tasks.

5.3.2 Time Dimension of Tasks: "Often" & "Sometimes"

To address the time dimension of tasks, columns (5)-(8) in Table (15) display results assuming workers need to perform a task at least "sometimes". Notably, adding more weight to the time dimension raises the coefficient associated with wage gains from selection into abstract-heavy occupations substantially to 333% - relative to workers performing primarily manual tasks. This finding points to substantial entry barriers, requiring workers to signal they can devote *some* time to abstract activities to be even considered working in an abstract-intensive occupation.

The cumulative wage gains from within-occupations specialization are somewhat smaller as Jane's specialization gains are now 5.4 times as large as those at the base level (6×0.9). Notably, incremental efficiency gains are 20 pp. larger, however, compared to baseline estimates requiring workers to perform tasks "often". Figure 2 illustrates these findings are attributed to differences in the distribution of the abstract relative task endowment for both task dimensions. In the baseline sample, workers are required to perform tasks "often". The mean abstract task content in this case amounts to 0.56 with a standard deviation of 0.19. Thus, many workers are heavily specialized in abstract activities, yet, still lie within one standard deviation of the mean (0.37-0.75).

In comparison, when workers are only required to perform tasks "sometimes", the distribution is more compressed with a mean abstract task content of 0.50 and corresponding standard deviation of 0.11. Consequently, one standard deviation around the mean constitutes a much tighter range of the abstract task content (0.39-0.61), allowing those who stand out to earn even higher efficiency gains by specializing substantially beyond the level of their peers. This finding is consistent with greater dispersion of individual wage components and rising assortativeness between high-wage workers and high-wage firms, implying that large parts of wage gaps between high- and less-educated workers are due to greater dispersion of workplace premia.[33]

Based on these findings it can be speculated that the skill dimension is more relevant at the occupation-level, e.g. via self-selection embedded in a Roy model.[34] Within occupations, however, workers have similar skill endowments and may thus increasingly specialize along the time margin. Ideally, one would use longitudinal data to test whether workers attach more weight to the time dimension as their career in an occupation progresses. This question is beyond the scope of this paper, however, and is left for future research.

[33] See Card, Heining & Kline (2013), Barth, Bryson, Davis & Freeman (2016) and Song, Price, Guvenen, Bloom & von Wachter (2019).

[34] See, e.g., Heckman & Sedlacek (1985), Heckman & Scheinkman (1987), Keane & Wolpin (1997), Lee (2005), Sullivan (2010), Yamaguchi (2012), and Autor & Handel (2013).

6 Conclusions

This paper adds new theoretical and empirical insights to the growing literature on task-based models. Employing a sizable cross-section of more than 31,000 workers in Germany since 2012, I compare task measures derived from Survey data with recently made available German Expert-based task data and conduct formal tests of the underlying assumptions of more commonly used Expert data, especially pertaining to the assumption of a common set of tasks within occupations. The evidence reveals that worker-level information on tasks is uniquely predictive of wage differences between *and* within occupations. Several goodness-of-fit measures and information criteria suggest that models comprising worker-level information are statistically superior to models relying on occupation-level measures only. Notably, individual-level tasks explain 7.5% of unique variation in wages that other covariates cannot address, including occupation-level measures. Combined, these findings reject the implicit assumption of common tasks within occupations.

To conceptualize the benefits of using worker-level information on tasks, I empirically test a wage equation accounting for task specialization within occupations. This framework is based on the idea that more efficient workers have an incentive to specialize in occupation-specific core tasks. The results strongly support the notion that these intra-occupational efficiency gains are an important component of wage differences. Relative to performing manual tasks, occupational averages imply base wage gains on the order of at least 47% in activities which require various problem-solving skills, thus serving as an entry barrier for less-skilled workers. Incremental individual deviations from this average imply additional wage gains of up to 90%, yet, tend to experience diminishing return with increasing specialization.

The evidence presented in this study recommends using worker-level information on tasks, whenever feasible. On the one hand, sufficiently detailed information on occupational affiliation may not always be available, thus distorting measurement of the task content. On the other hand, a growing body of research has pointed to rising heterogeneity within important dimensions of interest, such as occupations[35], industries[36], or firms[37]. Using detailed information on what workers do at their job can help shed light on these phenomena.

Moreover, it is recommended exploring time-related aspects of tasks in more detail.

[35]See Hershbein & Kahn (2018), Atalay, Phongthiengtham, Sotelo & Tannenbaum (2018, 2020), Deming & Noray (2019), Modestino, Shoag & Ballance (2019), and Ma (2020).

[36]See Acemoglu & Restrepo (2019, 2020), Bajgar, Berlingieri, Calligaris, Criscuolo & Timmis (2020), and Autor, Dorn, Katz, Patterson & van Reenen (2020).

[37]See Card, Heining & Kline (2013), Barth, Bryson, Davis & Freeman (2016), Song, Price, Guvenen, Bloom & von Wachter (2019), and Dostie, Li, Card & Parent (2020).

Typically, the time dimension relating a worker's skills to time spent on job-related activities is not observed by the practitioner. Exploratory findings in this paper indicate, however, that they are a meaningful component of the skill endowment as wage premia resulting from task specialization within occupations are more pronounced in specifications attaching greater weight to the time dimension of tasks. These findings are in line with novel research explicitly investigating the time dimension using longitudinal data (Stinebrickner, Stinebrickner & Sullivan 2018, 2019). Future research should continue to shed light on these questions.

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A Details on Data

A.1 Description of Task Contents

(1)	(2)	(3)	(4)	(5)
Task Category (Broad)	**Task Category (Narrow)**	**Requirements (Berufenet)**	**Requirements (BIBB/BAuA)**	**Task Content**
Abstract	Non-Routine Analytic	Management, Planning & Supervision, Fields of Competencies, Economy, Leadership, Network Certifications, Monitoring, Music, Singing, Ballet, Musical Instruments, Optics, Applying Laws Design, Design (Art), Analysis, Control, Therapy, Programming	Research, Analyse Plan, Construct Design, Create, Evaluate Apply & Interpret Rules Work out Rules/ Regulations, Employ or Manage Staff	Gathering Information, Investigating, Researching Organizing, Making Plans, Decision Making Constructing, Devloping, Evaluating Applying Law, Notirizing Working with Computers, Programming Managing Personnel, Leading, Employing
	Non-Routine Interactive	Commerce, Counselling, Service, Support, Training, Marketing, Advertisting	Consult, Inform Negotiate, Represent Interests Teach, Train Sell, Purchase, Acquire Customers, Advertise, Entertain, Present	Consulting, Advising, Negotiating , Lobbying Teaching, Training, Educating Purchasing, Procuring, Selling Marketing, PR, Presenting
Routine	Routine Cognitive	Technology, Metrics, Administration, Graphics, Network Technology, Network Protocols Operating Systems, Certificates, Languages, Knowledge of Goods & Products, Competencies, Sensor Technology, Electronics, Mechanics, Mechanotrics, Hydraulics, Processing, Revision, Test, Inspection, Measurement, Monitoring, Procedures, Diagnostics	Correct Texts/ Data Measure Length/ Height/ Temperature Apply Languages Calculate, Accounting Application User Programs Administration (IT)	Use of Email, Internet Measuring, Evaluating Frequent Use of Foreign Languages Frequent Calculating/ Applying Math and Statistics Frequent Use of Software database, Computer Programs Administration of database, Networks, IT-Systems
	Routine Manual	Cultivation, Farming, Construction, Manufacture, Production, Harvesting	Pack, Ship Operate Machines Process	Planting, Storing, Transporting, Stocking, Posting Operating, Controling, Equipping Producing, Manufacturing Goods
Non-Routine	Non-Routine Manual	Dancing, Refurbishing, Service, Therapy (Manual Focus), Special/ Custom/ Bespoke Productions, Handicraft Businesses (Bakery, Carpentry, etc.)	Clean Guard Caretake Repair, Renovate Host	Cleaning, Recycling Guarding Caretaking, Healing Repairing, Renovating, Restoring, Refurbishing Preparing Food, Serving

Table 1: Task Categories and their Contents

A.2 Descriptive Statistics

(1)		(2)		(3)	
Socio-Economic		**Tasks (BIBB/BAuA)**		**Tasks (Berufenet)**	
Log Wage	3.12	NR Analytic	0.23	NR Analytic	0.34
Female (% of total workforce)	0.61	NR Interactive	0.26	NR Interactive	0.18
Age	45.46	Routine Cognitive	0.31	Routine Cognitive	0.31
College Degree	0.29	Routine Manual	0.08	Routine Manual	0.05
Vocational Degree	0.66	NR Manual	0.12	NR Manual	0.12
Dropouts	0.05				
Hours worked (Weekly)	34.71	Abstract	0.49	Abstract	0.52
Tenure (Firm, in Years)	14.16	Routine	0.39	Routine	0.36
Tenure (Occup., in Years)	24.68	Manual	0.12	Manual	0.12
N = 31,647					

NOTE. —The descriptive statistics displayed are weighted by the product of survey weights and occupation-specific workforce, thus accounting for differential employment sizes. For instance, the three largest occupational groups - clerical/mercantile, medical employees, teachers - employ a quarter of the workers in the sample. These professions moreover employ a disproportionate number of females, explaining their large share in the weighted sample.

Table 2: Descriptive Statistics

A. BIBB/AuA (Survey Data)

Top 5 Abstract	T	log w	**Bottom 5 Abstract**	T	log w
Philology, Literature,	0.63	3.08	Production/Processing of raw materials,	0.26	2.88
Humanities, Social Sciences	(0.17)	(0.74)	Glass-/ Ceramic-making	(0.24)	(0.56)
Teaching, Training	0.62	3.41	Plastic-making/ -processing,	0.24	2.90
	(0.14)	(0.61)	Wood-working/ -processing	(0.21)	(0.70)
Advertising, Marketing,	0.60	3.13	Metal-making/ -working,	0.24	2.99
Media design	(0.17)	(0.65)	Metal construction	(0.21)	(0.55)
Education, Social Work,	0.58	2.99	Drivers, Operators of vehicles,	0.22	2.74
Housekeeping, Theology	(0.19)	(0.68)	Transport equipment	(0.22)	(0.73)
Purchasing, Sales, Trading	0.57	3.25	Cleaning services	0.19	2.61
	(0.18)	(0.60)		(0.26)	(1.04)

B. Berufenet (Expert Data)

Top 5 Abstract			**Bottom 5 Abstract**		
Philology, Literature,	0.96	3.08	Plastic-making/ -processing,	0.07	2.90
Humanities, Social Sciences		(0.74)	Wood-working/ -processing		(0.70)
Teaching, Training	0.95	3.41	Metal-making/ -working,	0.06	2.99
		(0.61)	Metal construction		(0.55)
Advertising, Marketing,	0.85	3.13	Building, Construction	0.05	2.90
Media design		(0.65)			(0.51)
Education, Social Work,	0.78	2.99	Cleaning Services	0.05	2.61
Housekeeping, Theology		(0.68)			(1.04)
Geology, Geography,	0.73	3.34	Production/ Processing of raw materials,	0.04	2.88
Environmental protection		(0.68)	Glass-/ Ceramic-making		(0.56)

NOTE. —The occupation-specific task contents and average wages are weighted by the product of survey weights and occupation-specific workforce to account for differential employment sizes. Standard deviations are displayed in parenthesis. Note there are no standard deviations for the task contents based on Expert data. This is because, by construction, this data is only available at the occupational level, thus does not account for workplace heterogeneity.

Table 3: Comparison of Occupation-specific **Abstract** Task Content and Wages of Survey and Expert Data for selected occupations

A. BIBB/AuA (Survey Data)

Top 5 Routine	T	log w	**Bottom 5 Routine**	T	log w
Metal-making/ -working,	0.60	2.99	Medical and	0.28	3.05
Metal construction	(0.22)	(0.55)	health care occupations	(0.17)	(0.64)
Textile- and	0.58	2.92	Tourism, Hotels and	0.26	2.57
Leather-making /-processing	(0.23)	(0.58)	Restaurant occupations	(0.18)	(0.87)
Paper-making/-processing,	0.58	2.79	Non-medical healthcare,	0.23	2.83
Printing, Technical media design	(0.27)	(0.68)	Body care, Wellness	(0.19)	(0.75)
Production/Processing of raw materials,	0.56	2.88	Education, Social Work,	0.16	2.99
Glass-/Ceramic-making	(0.25)	(0.56)	Housekeeping, Theology	(0.15)	(0.68)
Mathematics, Biology,	0.56	3.23	Cleaning services	0.13	2.61
Chemistry, Physics	(0.18)	(0.58)		(0.22)	(1.04)

B. Berufenet (Expert Data)

Top 5 Routine			**Bottom 5 Routine**		
Metal-making/ -working,	0.77	2.99	Non-medical healthcare,	0.09	2.83
Metal construction		(0.55)	Body care, Wellness,		(0.75)
Production/Processing of raw materials,	0.77	2.88	Education, Social Work,	0.09	2.99
Glass-/Ceramic-making		(0.56)	Housekeeping, Theology		(0.68)
Mechatronics, Energy electronics,	0.75	3.12	Building, Construction	0.08	2.90
Electrical engineering		(0.58)			(0.51)
Textile- and	0.73	2.79	Philology, Literature,	0.04	3.08
Leather-making /-processing		(0.68)	Humanities, Social Sciences		(0.74)
Plastic-making/ -processing,	0.72	2.90	Teaching, Training	0.02	3.41
Wood-working/ -processing		(0.70)			(0.61)

NOTE. —The occupation-specific task contents and average wages are weighted by the product of survey weights and occupation-specific workforce to account for differential employment sizes. Standard deviations are displayed in parenthesis. Note there are no standard deviations for the task contents based on Expert data. This is because, by construction, this data is only available at the occupational level, thus does not account for workplace heterogeneity.

Table 4: Comparison of Occupation-specific **Routine** Task Content and Wages of Survey and Expert Data for selected occupations

A. BIBB/AuA (Survey Data)

Top 5 Manual	T	log w	**Bottom 5 Manual**	T	log w
Cleaning services	0.68	2.61	Business management,	0.03	3.17
	(0.35)	(1.04)	Organisation	(0.08)	(0.67)
Building services, Engineering,	0.31	2.92	Purchasing, Sales, Trading	0.03	3.25
Technical building services	(0.27)	(0.66)		(0.09)	(0.60)
Non-medical healthcare,	0.31	2.83	Law, Public administration	0.03	3.18
Body care, Wellness	(0.20)	(0.75)		(0.08)	(0.53)
Food-production/ -processing	0.28	2.75	Financial services, Accounting,	0.03	3.24
	(0.20)	(0.71)	Tax consultancy	(0.08)	(0.60)
Tourism, Hotels and	0.27	2.57	Advertising, Marketing,	0.02	3.13
Restaurant occupations	(0.24)	(0.87)	Media design	(0.05)	(0.65)

B. Berufenet (Expert Data)

Top 5 Manual			**Bottom 5 Manual**		
Building, Construction	0.87	2.90	Purchasing, Sales, Trading	0.00	3.25
		(0.51)			(0.60)
Cleaning services	0.74	2.61	Advertising, Marketing,	0.00	3.13
		(1.04)	Media design		(0.65)
Drivers, Operators of vehicles,	0.67	2.74	Computer science, IT	0.00	3.38
Transport equipment		(0.73)			(0.48)
Non-medical healthcare,	0.65	2.83	Philology, Literature,	0.00	3.08
Body care, Wellness		(0.75)	Humanities, Social Sciences		(0.74)
Interior construction	0.65	2.77	Financial services, Accounting,	0.00	3.24
		(0.48)	Tax consultancy		(0.60)

NOTE. —The occupation-specific task contents and average wages are weighted by the product of survey weights and occupation-specific workforce to account for differential employment sizes. Standard deviations are displayed in parenthesis. Note there are no standard deviations for the task contents based on Expert data. This is because, by construction, this data is only available at the occupational level, thus does not account for workplace heterogeneity.

Table 5: Comparison of Occupation-specific **Manual** Task Content and Wages of Survey and Expert Data for selected occupations

A.3 Time Dimension of Task Contents

Task Category (Broad)	Task Category (Narrow)	Requirements (BIBB/BAuA)	Task Time Allocation	All	College	Voca.	No Voca.	Requirements (BIBB/BAuA)	Skill Level Required	Percent	College	Voca.	No Voca.
Abstract	NR Analytic	Research, Analyse	Often	0.60	0.80	0.54	0.35	Apply, Interpret Rules	No Knowledge	0.32	0.17	0.36	0.55
			Sometimes	0.25	0.18	0.28	0.27		Basic Knowledge	0.44	0.50	0.42	0.34
			Never	0.15	0.03	0.17	0.38		Advanced Knowledge	0.25	0.33	0.22	0.12
								Requirements (BIBB/BAuA)	**Occurrence**	**Percent**	**College**	**Voca.**	**No Voca.**
		Plan, Construct	Often	0.44	0.55	0.41	0.29	Work out Rules, Regulations	Yes	0.07	0.14	0.05	0.05
			Sometimes	0.29	0.29	0.29	0.27		No	0.93	0.86	0.95	0.95
			Never	0.27	0.16	0.30	0.44						
		Design, Create, Evaluate	Often	0.13	0.25	0.09	0.07	Employ, Manage Staff	Yes	0.30	0.35	0.28	0.19
			Sometimes	0.23	0.30	0.21	0.15		No	0.70	0.65	0.72	0.81
			Never	0.64	0.45	0.70	0.78						
	NR Interactive	Consult, Inform	Often	0.64	0.78	0.59	0.43						
			Sometimes	0.25	0.19	0.27	0.30						
			Never	0.11	0.03	0.13	0.27						
		Negotiate, Represent Interests	Often	0.48	0.64	0.40	0.30						
			Sometimes	0.40	0.33	0.45	0.44						
			Never	0.11	0.04	0.15	0.27	‘					
		Teach, Train	Often	0.24	0.36	0.20	0.11						
			Sometimes	0.35	0.36	0.36	0.24						
			Never	0.40	0.28	0.44	0.65						
		Sell, Purchase, Acquire Customers	Often	0.20	0.14	0.23	0.21						
			Sometimes	0.26	0.31	0.24	0.17						
			Never	0.54	0.55	0.53	0.62						
		Advertise, Entertain, Present	Often	0.11	0.15	0.10	0.08						
			Sometimes	0.30	0.42	0.27	0.20						
			Never	0.58	0.43	0.63	0.72						
Routine	Routine Cognitive	Correct Texts/ Data	Often	0.70	0.88	0.63	0.51	Apply Languages	No Knowledge	0.41	0.19	0.45	0.56
			Sometimes	0.18	0.10	0.22	0.21		Basic Knowledge	0.40	0.42	0.41	0.32
			Never	0.12	0.02	0.16	0.28		Advanced Knowledge	0.19	0.40	0.14	0.12
		Measure Length, Height, Temperature	Often	0.43	0.39	0.45	0.39	Calculate, Accounting	No Knowledge	0.25	0.18	0.25	0.46
			Sometimes	0.26	0.32	0.24	0.23		Basic Knowledge	0.49	0.47	0.50	0.42
			Never	0.31	0.29	0.31	0.38		Advanced Knowledge	0.27	0.35	0.25	0.12
								Application User Programs	No Knowledge	0.05	0.01	0.06	0.12
									Basic Knowledge	0.49	0.42	0.51	0.56
									Advanced Knowledge	0.47	0.56	0.43	0.32
								Requirements (BIBB/BAuA)	**Occurrence**	**Percent**	**College**	**Voca.**	**No Voca.**
								Administration (IT)	Yes	0.02	0.05	0.01	0.01
									No	0.98	0.95	0.99	0.99
	Routine Manual	Pack, Ship	Often	0.22	0.08	0.27	0.33						
			Sometimes	0.27	0.24	0.28	0.23						
			Never	0.51	0.68	0.44	0.45						
		Operate Machines	Often	0.22	0.11	0.26	0.22						
			Sometimes	0.17	0.15	0.17	0.19						
			Never	0.62	0.74	0.57	0.59						
		Process	Often	0.13	0.06	0.16	0.18						
			Sometimes	0.07	0.06	0.07	0.07						
			Never	0.80	0.87	0.77	0.75						
Manual	NR Manual	Clean	Often	0.23	0.06	0.28	0.38						
			Sometimes	0.24	0.20	0.26	0.25						
			Never	0.53	0.74	0.46	0.37						
		Guard	Often	0.20	0.15	0.22	0.19						
			Sometimes	0.15	0.15	0.16	0.14						
			Never	0.65	0.70	0.62	0.66						
		Caretake	Often	0.18	0.15	0.18	0.13						
			Sometimes	0.08	0.10	0.07	0.07						
			Never	0.75	0.75	0.75	0.80						
		Repair, Renovate	Often	0.14	0.05	0.17	0.14						
			Sometimes	0.25	0.21	0.26	0.26						
			Never	0.62	0.74	0.57	0.61						
		Host	Often	0.09	0.04	0.11	0.14						
			Sometimes	0.11	0.12	0.11	0.09						
			Never	0.80	0.84	0.79	0.77						
			N	32,002	8,922	21,635	1,445						

Table 6: Task and Time Allocation by Education Groups (College, Vocational Degree, No Vocational Degree)

B Regression Tables

B.1 Baseline: Individual vs Occupation-level Task Measures

Dependent Variable: Log Hourly Real Wage	(1)	(2)	(3)	(4)	(5)	(6)
Abstract (Occ.)	0.97***			0.57***		
	(0.07)			(0.08)		
Routine (Occ.)	0.50***			0.31***		
	(0.07)			(0.08)		
Abstract (Ind.)		0.56***		0.44***	0.48***	0.45***
		(0.04)		(0.04)	(0.04)	(0.04)
Routine (Ind.)		0.35***		0.25***	0.29***	0.25***
		(0.04)		(0.04)	(0.04)	(0.04)
Abstract (Exp.)			0.43***		0.24***	
			(0.03)		(0.03)	
Routine (Exp.)			0.30***		0.18***	
			(0.04)		(0.04)	
Survey tasks (Occupational)	✓			✓		
Survey tasks (Individual)		✓		✓	✓	✓
Expert tasks (Occupational)			✓		✓	
Occupation Dummies						✓
F (Task Measures, Occ.)	109.42		94.11	28.33	24.86	
F-pval (Task Measures, Occ.)	(0.00)		(0.00)	(0.00)	(0.00)	
F (Task Measures, Ind.)		125.79		64.57	76.12	69.19
F-pval (Task Measures, Ind.)		(0.00)		(0.00)	(0.00)	(0.00)
R-squared	0.174	0.179	0.172	0.182	0.181	0.189
Adj. R-squared	0.172	0.178	0.171	0.180	0.179	0.186
AIC	58785.06	58587.84	58854.52	58496.90	58515.89	58275.17
BIC	59286.81	59089.58	59356.27	59015.36	59034.36	59061.23
Observations	31647	31647	31647	31647	31647	31647

Robust standard errors in parentheses

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

NOTE. —The first two rows display coefficients based on occupational averages derived from individual responses in the employment surveys ("(Occ.)"). Point estimates corresponding to those individual responses are displayed in the third and fourth row ("(Ind.)"). Lastly, the last two rows display coefficients based on occupational averages derived from the Expert database ("(Exp.)"). All specifications include controls for gender, age, age squared, a dummy for living in an urban area, education dummies, occupational tenure, firm tenure, squared tenure for each dimension of experience, and a categorical variable reflecting firm size. Each regression is weighted by the product of sample weight and occupation-specific workforce to account for size effects. The omitted task category is "Manual".

Table 7: Task Measures as Wage Predictors: Survey vs Expert Data (Baseline: Broad Task Categories, 2-digit Occupations)

Model:	(1)	(2)	(3)	(4)	(5)	(6)
Abstract (Occ.)	10.3%			2.5%		
Routine (Occ.)	5.7%			1.3%		
Abstract (Ind.)		13.5%		5.2%	5.9%	12.7%
Routine (Ind.)		7.4%		2.1%	2.9%	7.0%
Abstract (Exp.)			11.9%		4.0%	
Routine (Exp.)			6.2%		2.6%	
Total (Occ.)	16.0%		18.2%	3.8%	6.6%	
Total (Ind.)		20.9%		7.3%	8.8%	19.7%

NOTE. —The displayed values represent the percentage drop-off in R-squared after removing task measures and are relative to the R-squared of the full model. Results are based on computing the squared semipartial correlation between log wages and the task measure of interest. Models (1)-(3) correspond to specifications including occupation-level tasks from Survey data ("(Occ.)"), individual-level tasks ("(Ind.)"), and occupation-level tasks from Expert data ("(Exp.)"), respectively. Models (4) and (5) combine individual-level tasks with occupation-level tasks from Survey and Expert data, respectively. Lastly, model (6) includes individual-level tasks and occupational FE. The two bottom rows summarize the importance of different dimensions of task measures by adding up the decrease in R-squared after removing individual- and occupation-level tasks, respectively, from the model. All specifications include controls for gender, age, age squared, a dummy for living in an urban area, education dummies, occupational tenure, firm tenure, squared tenure for each dimension of experience, and indicator for firm size.

Table 8: Incremental R-squared
(Baseline: Broad Task Categories, 2-digit Occupations)

Model:	(1)	(2)	(3)	(4)	(5)	(6)
Abstract (Occ.)	8.8%			2.1%		
Routine (Occ.)	4.8%			1.1%		
Abstract (Ind.)		11.6%		4.4%	5.0%	10.9%
Routine (Ind.)		6.3%		1.8%	2.4%	5.9%
Abstract (Exp.)			10.3%		3.3%	
Routine (Exp.)			5.3%		2.2%	
Total (Occ.)	13.6%		15.6%	3.2%	5.5%	
Total (Ind.)		17.8%		6.2%	7.4%	16.8%

NOTE. —The displayed values represent the unique variation in log wages associated with the task measure of interest, expressed relative to the R-squared of the full model. Results are based on computing the squared partial correlation between log wages and the task measure of interest. The model description for specifications (1)-(6) along with controls included is the same as in Table (8) described above. The two bottom rows summarize the variance in low wages associated with task measures of interest, which has not been explained by all other covariates (including other task dimensions).

Table 9: Unique Variation Explained by Task Measures
(Baseline: Broad Task Categories, 2-digit Occupations)

B.2 Robustness: Individual vs Occupation-level Task Measures

B.2.1 Narrow Task Groups

Dependent Variable: Log Hourly Real Wage	(1)	(2)	(3)	(4)	(5)	(6)
NR Analytic (Occ.)	1.11***			0.73***		
	(0.22)			(0.22)		
NR Interactive (Occ.)	0.22*			-0.11		
	(0.11)			(0.12)		
Routine Cognitive (Occ.)	0.34***			0.07		
	(0.08)			(0.09)		
Routine Manual (Occ.)	-0.29**			-0.25*		
	(0.13)			(0.13)		
NR Analytic (Ind.)		0.56***		0.49***	0.49***	0.50***
		(0.04)		(0.05)	(0.05)	(0.05)
NR Interactive (Ind.)		0.42***		0.37***	0.35***	0.37***
		(0.04)		(0.05)	(0.05)	(0.05)
Routine Cognitive (Ind.)		0.40***		0.31***	0.31***	0.31***
		(0.04)		(0.04)	(0.04)	(0.04)
Routine Manual (Ind.)		-0.00		0.02	-0.03	0.01
		(0.05)		(0.05)	(0.05)	(0.05)
NR Analytic (Exp.)			0.44***		0.22***	
			(0.04)		(0.04)	
NR Interactive (Exp.)			0.08		-0.08	
			(0.06)		(0.06)	
Routine Cognitive (Exp.)			0.25***		0.05	
			(0.04)		(0.04)	
Routine Manual (Exp.)			-0.12**		-0.09	
			(0.06)		(0.06)	
Survey tasks (Occupational)	✓			✓		
Survey tasks (Individual)		✓		✓	✓	✓
Expert tasks (Occupational)			✓		✓	
Occupation Dummies						✓
F (Task Measures, Occ.)	72.50		66.46	14.34	12.00	
F-pval (Task Measures, Occ.)	(0.00)		(0.00)	(0.00)	(0.00)	
F (Task Measures, Ind.)		101.41		51.08	59.43	53.36
F-pval (Task Measures, Ind.)		(0.00)		(0.00)	(0.00)	(0.00)
R-squared	0.177	0.185	0.175	0.188	0.187	0.192
Adj. R-squared	0.176	0.184	0.173	0.186	0.185	0.190
AIC	58666.66	58347.23	58744.66	58259.46	58287.20	58161.29
BIC	59185.13	58857.33	59254.77	58811.38	58839.12	58972.44
Observations	31647	31647	31647	31647	31647	31647

Robust standard errors in parentheses

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

* Note: The first four rows display coefficients based on occupational averages derived from individual responses in the employment surveys ("(Occ.)"). Point estimates corresponding to those individual responses are displayed in rows five to eight ("(Ind.)"). Lastly, the last four rows display coefficients based on occupational averages derived from the Expert database ("(Exp.)"). All specifications include controls for gender, age, age squared, a dummy for living in an urban area, education dummies, occupational tenure, firm tenure, squared tenure for each dimension of experience, and a categorical variable reflecting firm size. Each regression is weighted by the product of sample weight and occupation-specific workforce to account for size effects. The omitted task category is "NR Manual".

Table 10: Task Measures as Wage Predictors: Survey vs Expert Data (Narrow Task Categories, 2-digit Occupations)

B.2.2 Finer Occupational Classification (3-digit)

Dependent Variable: Log Hourly Real Wage	(1)	(2)	(3)	(4)	(5)	(6)
Abstract (Occ.)	1.17***			0.90***		
	(0.08)			(0.10)		
Routine (Occ.)	0.49***			0.36***		
	(0.08)			(0.10)		
Abstract (Ind.)		0.48***		0.30***	0.37***	0.33***
		(0.05)		(0.05)	(0.05)	(0.05)
Routine (Ind.)		0.29***		0.15***	0.23***	0.17***
		(0.05)		(0.05)	(0.05)	(0.05)
Abstract (Exp.)			0.42***		0.29***	
			(0.04)		(0.04)	
Routine (Exp.)			0.16***		0.05	
			(0.05)		(0.06)	
Survey tasks (Occupational)	✓			✓		
Survey tasks (Individual)		✓		✓	✓	✓
Expert tasks (Occupational)			✓		✓	
Occupation Dummies						✓
F (Task Measures, Occ.)	113.07		74.83	48.34	33.42	
F-pval (Task Measures, Occ.)	(0.00)		(0.00)	(0.00)	(0.00)	
F (Task Measures, Ind.)		60.96		19.68	29.11	24.35
F-pval (Task Measures, Ind.)		(0.00)		(0.00)	(0.00)	(0.00)
R-squared	0.161	0.159	0.159	0.165	0.164	0.180
Adj. R-squared	0.160	0.157	0.157	0.163	0.162	0.175
AIC	57186.98	57280.41	57279.84	57060.01	57100.93	56748.34
BIC	57688.72	57782.15	57773.22	57570.12	57611.04	58395.73
Observations	31647	31647	31647	31647	31647	31647

Robust standard errors in parentheses

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

* Note: The first two rows display coefficients based on occupational averages derived from individual responses in the employment surveys ("(Occ.)"). Point estimates corresponding to those individual responses are displayed in the third and fourth row ("(Ind.)"). Lastly, the last two rows display coefficients based on occupational averages derived from the Expert database ("(Exp.)"). All specifications include controls for gender, age, age squared, a dummy for living in an urban area, education dummies, occupational tenure, firm tenure, squared tenure for each dimension of experience, and a categorical variable reflecting firm size. Each regression is weighted by the product of sample weight and occupation-specific workforce to account for size effects. The omitted task category is "Manual".

Table 11: Task Measures as Wage Predictors: Survey vs Expert Data (Broad Task Categories, 3-digit Occupations)

B.2.3 Finer Occupational Classification (3-digit) & Sample of workers subject to social security payments

Dependent Variable: Log Hourly Real Wage	(1)	(2)	(3)	(4)	(5)	(6)
Abstract (Occ.)	1.07***			0.74***		
	(0.08)			(0.09)		
Routine (Occ.)	0.48***			0.34***		
	(0.09)			(0.10)		
Abstract (Ind.)		0.52***		0.36***	0.42***	0.39***
		(0.05)		(0.05)	(0.05)	(0.05)
Routine (Ind.)		0.27***		0.16***	0.22***	0.18***
		(0.05)		(0.06)	(0.05)	(0.06)
Abstract (Exp.)			0.40***		0.25***	
			(0.04)		(0.04)	
Routine (Exp.)			0.21***		0.10*	
			(0.05)		(0.06)	
Survey tasks (Occupational)	✓			✓		
Survey tasks (Individual)		✓		✓	✓	✓
Expert tasks (Occupational)			✓		✓	
Occupation Dummies						✓
F (Task Measures, Occ.)	100.24		61.75	33.22	20.20	
F-pval (Task Measures, Occ.)	(0.00)		(0.00)	(0.00)	(0.00)	
F (Task Measures, Ind.)		67.41		27.41	36.13	30.77
F-pval (Task Measures, Ind.)		(0.00)		(0.00)	(0.00)	(0.00)
R-squared	0.153	0.154	0.150	0.158	0.157	0.173
Adj. R-squared	0.151	0.152	0.148	0.156	0.155	0.167
AIC	53470.12	53427.12	53566.31	53282.40	53321.58	53050.33
BIC	53957.35	53922.60	54061.80	53786.14	53825.33	54668.92
Observations	28513	28513	28513	28513	28513	28513

Robust standard errors in parentheses

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

* Note: The first two rows display coefficients based on occupational averages derived from individual responses in the employment surveys ("(Occ.)"). Point estimates corresponding to those individual responses are displayed in the third and fourth row ("(Ind.)"). Lastly, the last two rows display coefficients based on occupational averages derived from the Expert database ("(Exp.)"). All specifications include controls for gender, age, age squared, a dummy for living in an urban area, education dummies, occupational tenure, firm tenure, squared tenure for each dimension of experience, and a categorical variable reflecting firm size. Each regression is weighted by the product of sample weight and occupation-specific workforce to account for size effects. The omitted task category is "Manual".

Table 12: Task Measures as Wage Predictors: Survey vs Expert Data
(Broad Task Categories, 3-digit Occupations, No Civil Servants, No Self-Employed)

B.2.4 Task Content derived from Principal Component Analysis

Dependent Variable: Log Hourly Real Wage	(1)	(2)	(3)	(4)	(5)	(6)
Abstract (Occ.)	0.12***			0.10***		
	(0.02)			(0.02)		
Routine (Occ.)	0.02			-0.03		
	(0.02)			(0.02)		
Manual (Occ.)	-0.05***			-0.06***		
	(0.02)			(0.02)		
Abstract (Ind.)		0.08***		0.08***	0.08***	0.07***
		(0.01)		(0.01)	(0.01)	(0.01)
Routine (Ind.)		0.05***		0.05***	0.05***	0.05***
		(0.01)		(0.01)	(0.01)	(0.01)
Manual (Ind.)		-0.03***		-0.02***	-0.03***	-0.02***
		(0.01)		(0.01)	(0.01)	(0.01)
Abstract (Exp.)/100			0.083		0.052	
			(0.059)		(0.062)	
Routine (Exp.)/100			0.067		0.042	
			(0.047)		(0.047)	
Manual (Exp.)/100			0.067		0.042	
			(0.047)		(0.047)	
Survey tasks (Occupational)	✓			✓		
Survey tasks (Individual)		✓		✓	✓	✓
Expert tasks (Occupational)			✓		✓	
Occupation Dummies						✓
F (Task Measures, Occ.)	49.91		48.92	17.71	2.86	
F-pval (Task Measures, Occ.)	(0.00)		(0.00)	(0.00)	(0.04)	
F (Task Measures, Ind.)		71.81		47.46	53.55	41.90
F-pval (Task Measures, Ind.)		(0.00)		(0.00)	(0.00)	(0.00)
R-squared	0.154	0.163	0.150	0.167	0.164	0.180
Adj. R-squared	0.152	0.162	0.148	0.165	0.163	0.175
AIC	57069.49	56724.66	57229.76	56577.18	56681.59	56283.53
BIC	57571.23	57234.76	57723.14	57104.01	57208.43	57629.87
Observations	31647	31647	31647	31647	31647	31647

Robust standard errors in parentheses

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

* Note: Above results are based on the first component of a Principal Component Analysis. Hence, the activities displayed in Table (1) have been condensed into a single measure for abstract, routine, and manual tasks. All task measures are standardized with mean zero and a variance equal to one. The first three rows display coefficients based on occupational averages derived from individual responses in the employment surveys ("(Occ.)"). Point estimates corresponding to those individual responses are displayed in the fourth, fifth, and sixth row ("(Ind.)"). Lastly, the last three rows display coefficients based on occupational averages derived from the Expert database ("(Exp.)"). All specifications include controls for gender, age, age squared, a dummy for living in an urban area, education dummies, occupational tenure, firm tenure, squared tenure for each dimension of experience, and a categorical variable reflecting firm size. Each regression is weighted by the product of sample weight and occupation-specific workforce to account for size effects. The omitted task category is "Manual".

Table 13: Task Measures as Wage Predictors: Survey vs Expert Data
(Broad Task Categories, 2-digit Occupations)

B.2.5 Task Content includes activities that are performed "often" or "sometimes"

Dependent Variable: Log Hourly Real Wage	(1)	(2)	(3)	(4)	(5)	(6)
Abstract (Occ.)	1.46***			0.77***		
	(0.10)			(0.11)		
Routine (Occ.)	0.45***			0.14		
	(0.13)			(0.14)		
Abstract (Ind.)		0.91***		0.75***	0.80***	0.76***
		(0.05)		(0.06)	(0.06)	(0.06)
Routine (Ind.)		0.52***		0.41***	0.46***	0.39***
		(0.06)		(0.07)	(0.07)	(0.07)
Abstract (Exp.)			0.42***		0.22***	
			(0.03)		(0.03)	
Routine (Exp.)			0.30***		0.11***	
			(0.04)		(0.04)	
Survey tasks (Occupational)	✓			✓		
Survey tasks (Individual)		✓		✓	✓	✓
Expert tasks (Occupational)			✓		✓	
Occupation Dummies						✓
F (Task Measures, Occ.)	108.40		93.39	23.26	21.74	
F-pval (Task Measures, Occ.)	(0.00)		(0.00)	(0.00)	(0.00)	
F (Task Measures, Ind.)		159.61		84.71	103.16	87.23
F-pval (Task Measures, Ind.)		(0.00)		(0.00)	(0.00)	(0.00)
R-squared	0.174	0.181	0.172	0.183	0.183	0.190
Adj. R-squared	0.172	0.179	0.170	0.181	0.181	0.187
AIC	58812.36	58544.17	58894.61	58473.53	58482.21	58268.90
BIC	59305.78	59037.59	59388.02	58992.03	58992.36	59063.39
Observations	31647	31647	31647	31647	31647	31647

Robust standard errors in parentheses

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

* Note: In contrast to baseline results, above estimates are based on a different assumption in the construction of the task content. In the baseline definition, a dummy indicating whether a worker performs task is equal to one if she carries out the task "often". Instead, above estimates assume she carries out the task "often" or "sometimes". The first two rows display coefficients based on occupational averages derived from individual responses in the employment surveys ("(Occ.)"). Point estimates corresponding to those individual responses are displayed in the third and fourth row ("(Ind.)"). Lastly, the last two rows display coefficients based on occupational averages derived from the Expert database ("(Exp.)"). All specifications include controls for gender, age, age squared, a dummy for living in an urban area, education dummies, occupational tenure, firm tenure, squared tenure for each dimension of experience, and a categorical variable reflecting firm size. Each regression is weighted by the product of sample weight and occupation-specific workforce to account for size effects. The omitted task category is "Manual".

Table 14: Task Measures as Wage Predictors: Survey vs Expert Data (Broad Task Categories, 2-digit Occupations)

B.3 Degree of Specialization within Occupations

Task Time Dimension	"Often"				"Often" or "Sometimes"			
Main Task (Occupation-level)	Abstract		Routine		Abstract		Routine	
Dependent Variable: Log Hourly Real Wage	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Abstract (Occ.)	0.47**				3.33***			
	(0.22)				(0.54)			
Abstract (Occ.) × Abstract Deviation from Occ. Avg.	0.70***				0.90***			
	(0.13)				(0.23)			
(Abstract (Occ.) × Abstract Deviation from Occ. Avg.)^2	-1.22*				-7.31**			
	(0.69)				(3.02)			
Abstract (Exp.)		2.23***				2.25***		
		(0.23)				(0.24)		
Abstract (Exp.) × Abstract Deviation from Occ. Avg. (Exp.)		0.49**				1.13***		
		(0.15)				(0.25)		
Abstract (Exp.) × Abstract Deviation from Occ. Avg. (Exp.))^2		0.33				1.27***		
		(0.26)				(0.40)		
Routine (Occ.)			1.13**				-0.25	
			(0.17)				(0.27)	
Routine (Occ.) × Routine Deviation from Occ. Avg.			0.40***				1.47***	
			(0.11)				(0.20)	
(Routine (Occ.) × Routine Deviation from Occ. Avg.)^2			-2.69***				-4.91***	
			(0.50)				(1.71)	
Routine (Exp.)				0.30*				0.45***
				(0.18)				(0.21)
Routine (Exp.) × Routine Deviation from Occ. Avg. (Exp.)				-0.11				0.64**
				(0.11)				(0.27)
(Routine (Exp.) × Routine Deviation from Occ. Avg. (Exp.))^2				-1.21***				0.68
				(0.30)				(0.76)
Survey tasks (Occupational)	✓		✓		✓		✓	
Survey tasks (Individual)	✓	✓	✓	✓	✓	✓	✓	✓
Expert tasks (Occupational)		✓		✓		✓		✓
Main Task: Deviation from Occ. Avg. (p25)	-0.09		-0.13		-0.06		-0.06	
Main Task: Deviation from Occ. Avg. (p50)	0.00		-0.03		0.00		-0.01	
Main Task: Deviation from Occ. Avg. (p75)	0.10		0.10		0.06		0.05	
Main Task: Deviation from Occ. Avg. (Exp.) (p25)		-0.32		-0.09		-0.37		-0.01
Main Task: Deviation from Occ. Avg. (Exp.) (p50)		-0.20		0.03		-0.21		0.15
Main Task: Deviation from Occ. Avg. (Exp.) (p75)		-0.07		0.16		-0.11		0.23
Observations	10254	12053	18918	11188	9210	12061	20570	11193
R-Squared	0.228	0.199	0.170	0.173	0.228	0.222	0.170	0.162
Adj. R-Squared	0.222	0.195	0.167	0.168	0.222	0.217	0.167	0.160

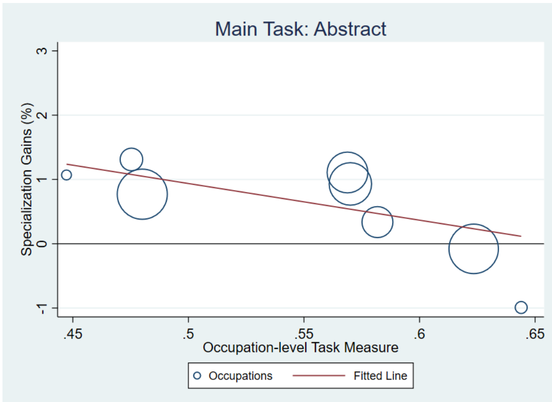
Robust standard errors in parentheses

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

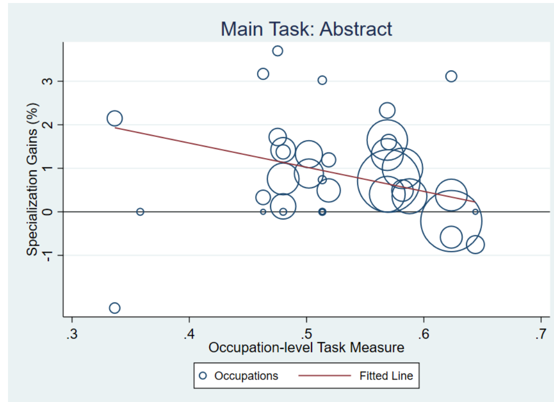
* Note: Above estimates are based on eq. (9) to describe wage gains resulting from task specialization within occupations. The first four rows display occupation-level averages and individual deviations based on task measures for which workers are required to perform underlying activities "'often". The last four rows display occupation-level averages and individual deviations based on task measures for which workers are required to perform underlying activities either "sometimes" or "'often". To check for robustness of data source, tasks derived from Survey data ("(Occ.)") and Expert data ("(Exp.)") are used. All specifications include controls for gender, age, age squared, a dummy for living in an urban area, education dummies, occupational tenure, firm tenure, squared tenure for each dimension of experience, and a categorical variable reflecting firm size. Each regression is weighted by the product of sample weight and occupation-specific workforce to account for size effects. The omitted task category is "Manual".

Table 15: Task Measures as Wage Predictors: Interaction between Occupation-level Averages and Individual Deviations from Mean Task Content by Main Tasks (Broad Task Categories, 2-digit Occupations)

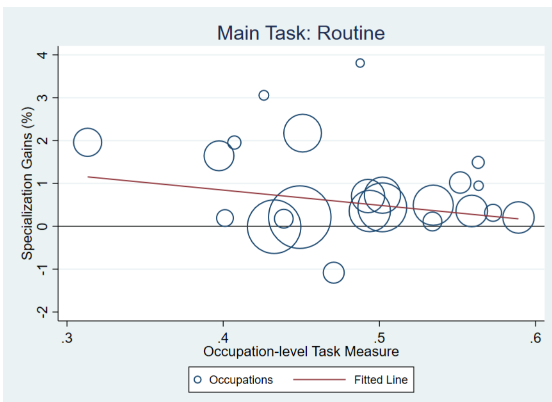
C Figures



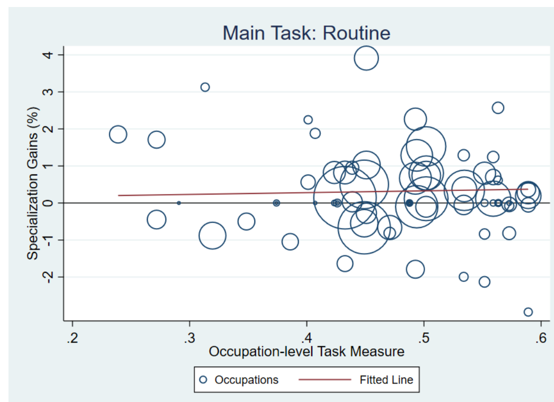
(a) 2-digit Occupations



(b) 3-digit Occupations



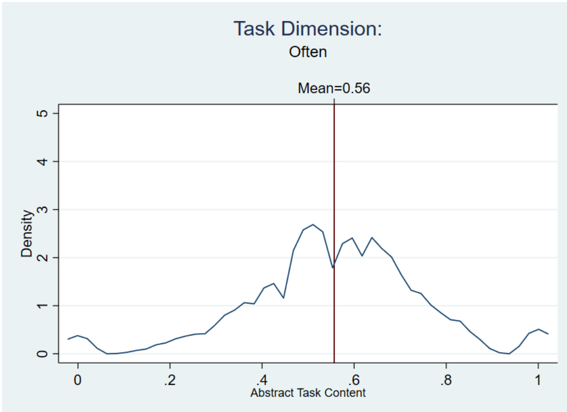
(c) 2-digit Occupations



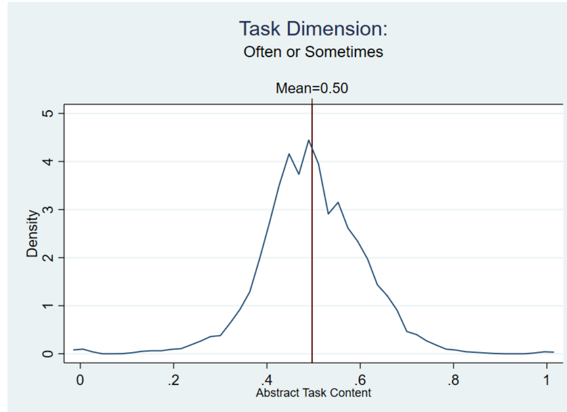
(d) 3-digit Occupations

NOTE. —The scatter plots display the coefficients of wage regressions by occupations with the average degree of task specialization as key covariate. They thus reflect a modified regression of eq. (9) to account for variability in task specialization within occupations. The horizontal axis reflects the average task content by occupation, while the vertical axis represents average specialization gains by occupation. Regression are weighted by the product of sample weight and occupation-specific employment to account for size effects.

Figure 1: Wage premium due to Task Specialization by Occupations



(a) Task Distribution - Baseline Sample



(b) Task Distribution - Alternative Task Dimension

NOTE. —The distributions are based on fitting kernel densities of the abstract task content for workers who are employed in abstract-intensive occupations. Panel (a) assumes workers perform abstract tasks only if they engage in underlying activities "often" while panel (b) assumes workers perform abstract tasks if they engage in underlying activities "often" or "sometimes".

Figure 2: Distribution of the relative abstract task endowment (Occupations with main task "Abstract")