Task Heterogeneity, Employee Characteristics, and Within-Firm Wage Inequality

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Abstract

How much of the within-firm wage inequality comes from wage differences among employees with similar characteristics who perform similar tasks? Using matched employer-employee data from Germany, we show that task heterogeneity accounts for half of the overall within-firm wage differences. For employees who perform similar tasks, differences in their characteristics (e.g., ability or education) explain three-quarters of their wage differences. Residual wage inequality (RWI) among employees with similar characteristics who perform similar tasks accounts for 12 percent of the overall wage differences. RWI increases with task complexity, establishment and firm size, profit sharing, and profitability, which points to pay-for-performance schemes as potential drivers of HWI. These results indicate that firms use RWI to incentivize employees and call for the separate disclosure of wage inequality related to task heterogeneity, employee characteristics, and RWI.

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1. Introduction

Wage differences within firms contribute substantially to the inequality of wages in the economy (Song et al., 2019). Because public firms only need to disclose the ratio of CEO to median employee pay (Pan et al., 2022), little is known about the sources of these within-firm wage differences. Understanding the sources of wage inequality is important because they have different policy implications.

This paper analyzes how much of the wage inequality within firms can be explained by task heterogeneity, how much by differences in employee characteristics, and how much comes from employees with similar characteristics who perform similar tasks (which we refer to as residual wage inequality, RWI). We use a matched employer-employee dataset that links administrative employee-level information from the German social security system with firm-level data from Bureau van Dijk's (BvD) Orbis database. This dataset, which contains detailed information on firms and their individual employees (e.g., their wages and occupations), covers 16,630,960 employees, 205,858 establishments, and 87,440 firms between 2010 and 2016. To measure employees' tasks, we rely on 144 occupational groups and up to four different task levels within these groups, which results in 431 occupation-task groups.[1] Examples for occupational groups are "metal-making", "metalworking" and "treatment of metal surfaces", and the task levels are "unskilled/semiskilled", "skilled", "complex", and "highly complex". These occupation-task groups enable us to differentiate between wage inequality among employees who perform similar tasks and those who perform different tasks.

We find that the variance of employees' log wages in the same occupation-task group, which we refer to as horizontal wage inequality (HWI), and the variance of their log wages across different occupation-task groups, which we refer to as vertical wage inequality (VWI), contribute approximately equally to the overall variation of wages within establishments. Specifically, HWI accounts for 49.2 percent of the overall wage variation within establishments, and VWI accounts for 50.8 percent. Please note that we measure wage inequality at the establishment level and not at the firm level. The reason is that different

[1] This classification is based on the German"Klassifikation der Berufe" (KldB) occupations scheme. Appendix A.1 provides a more comprehensive description of the classification scheme, and Appendix A.2 lists all occupation-task groups.

establishments of a firm may have different wage policies, which makes it difficult to separate the effects of task heterogeneity and employee characteristics on wage inequality from general wage differences across establishments.

We assume that individuals in the same occupation-task group perform similar tasks, although it is well possible that there is at least some task heterogeneity within occupation-task groups. To test whether this assumption has a substantial impact on the result of the decomposition, we repeat the analysis using information on occupational subgroups. This more granular classification allows us to distinguish 1,286 unique suboccupation-task groups among which tasks are more homogeneous.[2] Our results reveal that the relevance of HWI decreases only slightly from 49.2 percent for our baseline measure to 46.6 percent. We conclude that unobserved task heterogeneity within occupation-task groups is unlikely to lead to a substantial over-estimation of HWI.

Next, we test how much of the wage inequality among employees who perform similar tasks can be explained by differences in their characteristics. For this purpose, we use a wage model in the spirit of Abowd, Kramarz and Margolis (1999) (henceforth AKM) to decompose HWI into a part that is related to heterogeneous employee characteristics and a residual part. Our implementation of the AKM model that is similar to Card, Heining and Kline (2013) (henceforth CHK) and Lochner and Schulz (2022).[3] In this model, the wage is explained by observable employee characteristics, such as age and education, and unobservable, permanent employee and establishment characteristics, which are measured by fixed effects.[4] We find that heterogeneity in employee characteristics accounts for 87.5 percent of the HWI.

Wage differences among employees with similar characteristics who perform similar tasks, which we refer to as residual wage inequality (RWI), are sizeable as they account for 11.9 percent of the overall within-establishment variance of wages. However, these results apply to the average firm in our sample,

[2]In this more granular classification, the occupation "metalworking" in our baseline classification is divided into "metalworking: non-cutting", "metalworking: grinding", and "metalworking: cutting", each with different task levels. See Appendix A.1 for more details.

[3]The AKM model is widely used in labor economics (e.g., CHK; Card et al., 2018; Song et al., 2019). We are aware of the discussion about the vulnerability of the AKM model to limited mobility bias. We discuss this issue in the context of this paper in Section 3.3.1.

[4]Establishment fixed effects also control for differences across firms related to size, ownership structures, unionization rates, and many other factors that might affect wage levels if these factors are constant during our sample period.

and the explanatory power of task heterogeneity and differences in employee characteristics varies substantially in the cross section. If we sort our dataset by RWI into deciles, we find that RWI accounts for 3.1 percent of the total wage inequality for the lowest decile and 19.9 percent for the highest decile. Thus, in the next step, we want to better understand the heterogeneous relevance of RWI in the cross section.

Conceptually, RWI reflects wage differences of the same hypothetical employee (one with the same characteristics who performs the same tasks) across different employers. These wage differences are employee-employer-specific and may arise due to idiosyncratic match complementarities (see CHK). Such complementarities can lead to performance differences of the same hypothetical employee across different employers. Thus, we expect RWI to be more prevalent in firms with pay-for-performance based compensation that rewards heterogeneous employee performance (Seiler, 1984; Lemieux, MacLeod and Parent, 2009). Examples include bonus payments, piece rates, and base wage adjustments that are related to past or expected productivity (Lazear, 2018).

We use different proxies for pay-for-performance based compensation to explore its role for RWI. We start by exploiting that pay-for-performance based compensation is especially important when monitoring is costly because of uncertainty about employees' optimal actions or because their actions are difficult to observe for the employer (Ross, 1973; Holmstrom, 1979; Prendergast, 2002).[5] We use the task complexity of an occupation as proxy for uncertainty about employees' optimal actions and establishment or firm size as proxy for difficulties in observing their actions (Garen, 1985). Furthermore, we focus on more direct proxies for pay-for-performance based compensation. First, we use measures for the existence of a profit-sharing program in an establishment, which is one particular pay-for-performance scheme that provides payments to employees according to the profitability of the establishment or firm. Second, we exploit cross-sectional variation in firm profitability as indirect way to measure pay-for-performance. The idea is that the positive correlation between wages and profits (Bloom and Van Reenen, 2011) is stronger for more productive employees if firms use profit-related pay-for-performance schemes.

[5]In the context of managerial compensation, it is also often argued that pay-for-performance reduces agency conflicts between owners and managers (Jensen and Murphy, 1990; Aggarwal and Samwick, 2003).

To measure the task complexity of an occupation, we rely on the classification of Autor, Levy and Murnane (2003) and the occupational complexity according to our occupational classification. On the one hand, we find RWI to be highest in occupations with high task complexity and more analytical and interactive tasks that do not follow a routine (e.g., engineering and science). On the other hand, RWI is lowest in occupations with mainly manual tasks (e.g., cleaning and vehicle driving).[6] A one-standard-deviation increase in the fraction of analytical nonroutine tasks is associated with a 19.7 percent higher RWI. The corresponding values for interactive nonroutine tasks and occupational complexity are 10.1 percent and 17.1 percent, respectively.

To measure the size of a firm, we rely on its number of employees. We find that RWI increases monotonically with size and more than doubles when comparing the smallest firm size decile to the largest. Regression models with industry-year and county-year fixed effects further reveal that RWI is about 12.5 percent higher, relative to its mean, for a firm that has twice as many employees. Within multi-establishment firms, we find RWI to be higher in larger establishments and in establishments with a higher share of complex tasks. Using complementary survey data on profit-sharing programs in establishments, we find that RWI increases by 12.3 percent, relative to its mean, for a hypothetical establishment that changes the share of employees participating in a profit-sharing program from zero to one.

Data on firm profitability from BvD's ORBIS database reveals a positive correlation between RWI and EBITDA, EBIT, net income, and cash flow, all scaled by total assets. In terms of economic magnitude, we find that RWI increases by 3.5 percent relative to its mean if firm profitability measured by EBITDA to total assets increases by one standard deviation.

Our paper contributes to the literature that documents within-firm wage inequality. CHK find an increasing trend in wage inequality within firms, Song et al. (2019) show that one-third of the rise in the overall wage inequality in the economy occurred within firms, and Tang, Tang and Wang (2020) show that the majority of the increase in wage inequality in the previous decades occurred within occupations. We complement this literature by showing that

[6]Among the largest 50 occupations, the five with the highest RWI are classified as highly complex with analytical, nonroutine tasks. The bottom five occupations are classified as less complex with manual tasks (four with routine, one with nonroutine tasks).

the residual inequality among employees with similar characteristics who perform similar tasks accounts for only 12 percent of the overall within-firm wage differences, with substantial cross-sectional heterogeneity.

A related strand of the literature focuses on the implications of within-firm wage inequality. Mueller, Ouimet and Simintzi (2017a) and Mueller, Ouimet and Simintzi (2017b) show a positive relationship of pay differences between hierarchy levels with firm growth, valuation, and operating performance, while Martins (2008) find a negative relationship between within-firm pay inequality and firm performance. Rouen (2020) studies CEO-to-mean employee compensation and finds no impact on firm performance. Akerlof and Yellen (1990), Chen and Sandino (2012), and Breza, Kaur and Shamdasani (2018) show that wage inequality can affect employees' efforts and their behavior, and the model of Manso (2011) suggests that wage incentives are crucial for firms' innovation output. We contribute to that literature by showing that the relevance of RWI increases with proxies for pay-for-performance schemes in the cross section. This finding suggests that RWI plays an important role in incentivizing employees and helps firms to overcome agency conflicts.

Lastly, our results add to the discussion on the disclosure of within-firm wage inequality. Exploiting first-time disclosures of CEO pay ratios, Pan et al. (2022) find that higher ratios lead to lower announcement returns. Their finding indicates that investors care about pay ratios because they process this information (Blankespoor, deHaan and Marinovic, 2020). However, Knust and Oesch (2020) find no impact of pay ratio disclosure on investor attention and say-on-pay voting outcomes. Kelly and Seow (2016) show that disclosing a higher-than-industry pay ratio decreases perceived CEO pay fairness and workplace climate. Chang et al. (2022) report the mandated disclosure of CEO pay ratios does not affect total CEO compensation, but the sensitivity of CEO pay to equity price changes is reduced.[7] Our results suggest that the disclosure of simple pay ratios, such as the CEO-to-median employee wage that is mandated by the SEC, provides investors an incomplete picture of the true wage inequality within firms.

[7]Relatedly, Gipper (2021) shows that expanded compensation disclosure leads to higher CEO pay while Mas (2017) finds that pay transparency reduces top managers' pay and increases their quit rates.

2. Data

The core of our dataset is the employee history file (Beschäftigten-Historik, BeH), which is provided by the Institute for Employment Research (Institut für Arbeitsmarkt- und Berufsforschung, IAB). This matched employee-employer data originates from earnings records of the German social security system and includes person-level information on total earnings, occupation, days worked, education, and part-time or full-time status.[8] We identify the main employment period held by each full-time employee in a given year, that is, the employment spell with the highest total wage sum (including bonus payments) in that year. We only include full-time jobs (excluding marginal employment and apprenticeship) held by employees aged 20 to 60 from 2010 to 2017 and then calculate the average daily wage by dividing the total earnings by the total duration of the main employment spell.[9]

The employers allocate occupation codes to each of their employees in each employment spell according to the KldB2010 occupational classification scheme (please refer to Appendix A.1 for a detailed description). We use the first three digits of this classification scheme, which distinguish 144 different occupational groups in our sample, plus the fifth digit, which distinguishes up to four task complexity levels within occupational groups. Because not all complexity levels exist for all occupations, our final dataset includes 431 unique occupation-task groups according to this three-plus-fifth-digit KldB2010 classification (the full list is shown in Appendix A.2).[10]

The BeH provides information on employees and establishments but not on firms. To add information on the firm structure, we use the ORBIS-ADIAB

[8]Since the data originates from the social security system, it does not include information about civil servants or self-employed persons. For further details on the dataset, please refer to the technical report by Antoni, Ganzer and vom Berge (2016).

[9]Wages in the BeH are censored at a time- and region-specific threshold, the so-called contribution assessment ceiling ("Beitragsbemessungsgrenze"), which varies between 4,650 and 6,350 EUR per month. Following the procedure suggested by Dustmann, Ludsteck and Schönberg (2009) and CHK, we impute the upper tail of the wage distribution by running a series of Tobit regressions, allowing for a maximum degree of heterogeneity by fitting the model separately for region, gender, time, education levels, and eight five-year age groups. We also impute missing and inconsistent information in the education variable by using the methodology proposed in Fitzenberger, Osikominu and Völter (2006).

[10]The five-digit KldB2010 classification distinguishes 1,286 occupations in our sample, which reduces the number of employees per occupation substantially. Nevertheless, we repeat our analyses using this classification scheme when we address robustness in Table 3.

dataset, which provides a linking table between the IAB internal (system-free) establishment identifiers and the firm identifiers by BvD. The most important variables for the record linkage are the establishment and the company name, the legal form, the industry code, and the postal code.[11] Comprehensive documentation of the linking process is provided by Antoni et al. (2018). Firm-level financial data comes from the BvD Orbis database, and information on the three-digit WZ2008 industries (German Classification of Economic Activities 2008) of establishments is obtained from the IAB establishment history panel (Betriebs-Historik-Panel, BHP).[12]

We follow Song et al. (2019) and exclude firms with fewer than 20 employees in any sample year to ensure that firm-years with very few observations do not distort the calculation of the wage dispersion measures. We also exclude employee-establishment-years that are not linked to a firm. Unscaled financial variables are adjusted for inflation using the German consumer price index, and all continuous financial variables are winsorized at the 1st and 99th percentiles. Appendix B shows details on the definitions and data sources of variables. The final sample covers 69,268,888 employee-years, 16,630,960 unique employees, 205,858 establishments, and 87,440 firms between 2010 and 2016.

Table 1 provides descriptive statistics. On average, a full-time employee earns a log daily wage of 4.620 EUR in a given year. This corresponds to an average yearly income of 36,538 EUR (monthly: 3,045 EUR) for a full-time employee. The median employee works at an establishment with 170 full-time employees and 19 occupations. Furthermore, about 47 percent of employees work in firms with more than one establishment.

[11] The record linkage is carried out separately for the years 2014 and 2016. For 2010 to 2013 and 2015, we assume that the latest link of an establishment to a firm is still valid. A small share of around 3.8 percent of all establishment-years are mapped to multiple firms, for example because the establishment undergoes an ownership change, which we exclude.

[12] We largely follow the steps followed by Jäger, Schoefer and Heining (2019) to clean the firm-level financial data from Orbis and check its internal consistency. However, we only consider financial data for firm-years that report both total assets and sales.

3. Decomposition of within-firm wage inequality

3.1. Measurement of within-firm wage inequality

We calculate the overall within-establishment wage inequality as the variance of employees' log daily wages,

$$var_t^j(y_t^{i,j}) = \frac{1}{N_t^j}\sum_i (y_t^{i,j} - \bar{y}_t^j)^2, \tag{1}$$

where $y_t^{i,j}$ is the log daily wage of employee i at establishment j in year t. We find that the variance of log wages within establishments is on average 0.118. As the variance of log wages within and between establishments is 0.275 in our sample, this finding implies that the within-establishment wage inequality accounts for 43 percent of the overall wage inequality in the economy.[13]

3.2. The role of task heterogeneity

To distinguish wage differences among employees with similar tasks from those among employees with different tasks, we rely on a fine-grained occupational classification scheme with 144 occupational groups and up to four different task complexity levels within these groups. In total, this scheme differentiates 431 occupation-task groups (see Section 2 for more details). Using this scheme, we decompose within-establishment wage differences into within- and between-occupation components as follows:

$$var_t^j(y_t^{i,j}) = \underbrace{\sum_o w_t^{o,j} \cdot var_t^{o,j}(y_t^{i,j})}_{\text{HWI}} + \underbrace{var_t^j(\bar{y}_t^{o,j})}_{\text{VWI}}, \tag{2}$$

where o denotes an occupation, $w_t^{o,j}$ the fraction of employees in occupation o at establishment j in year t, $var_t^{o,j}(y_t^{i,j})$ the wage dispersion within occupation o and establishment j, and $var_t^j(\bar{y}_t^{o,j})$ the variance of wages between occupations within an establishment. In Table 2, we find that the average HWI and VWI are 0.058 and 0.060, respectively. Thus, both contribute in (nearly) equal parts to the overall wage inequality within establishments (49.2 versus 50.8 percent).

[13] Lochner, Seth and Wolter (2020) report a variance of log daily earnings of 0.291 for the universe of German full-time employees in the same time period. The similarity of their estimate to ours helps to mitigate concerns that our focus on establishments that are linked to a firm in the ORBIS-ADIAB dataset reduces the generalizability of our sample.

A potential concern with our measurement of HWI and VWI is that there could be some task heterogeneity among employees in the same occupation-task group, which would overestimate the role of HWI. To investigate this concern, we refine the occupational scheme. To this end, we use information on occupational subgroups, which allows us to distinguish 1,286 unique suboccupation-task groups.[14] The advantage of this refinement is that employees in the same occupation are even more likely to conduct the same tasks than in our main classification scheme. Intuitively, the more fine-grained the occupational classification scheme is, the less likely it is that wage variation within occupations captures VWI among employees who perform different tasks. The disadvantage, and the reason we do not use this scheme for the main analyses, is that the number of observations is relatively small for many establishment-occupation-years.

Table 3 shows the decomposition into HWI and VWI when using the full five-digit KldB2010 occupational classification scheme. The total wage variation within establishments, which is unaffected by the occupational classification scheme, is 0.118. Using the five-digit scheme, the within-occupation wage variance is 0.055, which implies that HWI accounts for 46.6 percent of the overall wage variance. The corresponding numbers for the three-plus-fifth-digit scheme are 0.058 and 49.2 percent, respectively. Thus, only 2.6 percentage points are additionally attributed to HWI when using the more detailed classification scheme. We conclude that task heterogeneity is unlikely to lead to a substantial over-estimation of HWI.

3.3. The role of employee characteristics

Next, we decompose the overall VWI and HWI into a component that is related to the remuneration of heterogeneous employee characteristics and a residuum. For this purpose, we apply a two-way fixed effects model with employer fixed effects, employee fixed effects, and controls for employees' age, education, and time trends, in the spirit of AKM.

[14] An example for a suboccupation-task group is "24232: Occupations in metalworking: cutting—skilled tasks", which corresponds to "242-2: Occupations in metalworking—skilled tasks" in our baseline classification. See Appendix A.1 for more details.

3.3.1. Implementation of the wage model

Our specification of the AKM model assumes that the log real daily wage $y_t^{i,j}$ of worker i in establishment j is an additively separable function observable and unobservable establishment and worker characteristics. Specifically, α^i is a time-invariant employee fixed effect identified by employees who switch employers over time.[15] ψ^j is an establishment fixed effect.[16] X_t^i is an index of time-varying observable employee characteristics, including an unrestricted set of year dummies and quadratic and cubic terms in age[17] fully interacted with educational attainment. Finally, $r_t^{i,j}$ is an error term which represents the residual wage of employee i at establishment j. Accordingly, we run the following regression model on the largest connected set of establishments from 2010 to 2017 (those that are linked by employee transitions):

$$y_t^{i,j} = \alpha^i + \psi^j + \beta X_t^i + r_t^{i,j}. \tag{3}$$

Subsequently, we follow CHK and use the parameter estimates from Equation 3 to decompose the variance of wages into these components. The variance decomposition of overall wages within establishments can be written as

$$\begin{aligned} var_t^j(y_t^{i,j}) = &\\ &\overbrace{var_t^j(\alpha^i) + var_t^j(\beta X_t^i) + 2cov(\alpha^i, \beta X_t^i) + 2cov(\beta X_t^i, r_t^{i,j}) + 2cov(\alpha^i, r_t^{i,j})}^{\text{variation related to heterogeneous employee characteristics}} \\ &+ \underbrace{var_t^j(r_t^{i,j})}_{\text{variation of residual wages}} . \end{aligned} \tag{4}$$

Note that the wage model estimates the remuneration for an employee's characteristics by means of control variables (βX_t^i) and an employee fixed effect (α^i). This unobserved, permanent wage component is specific to an employee, but not to an employee-employer combination. The residual wage, however,

[15]To obtain estimates for the employee fixed effects of job stayers, we follow CHK. For each worker, we calculate the employee effect as the average difference of the observed individual wage from the estimated establishment effect (on the mover sample) and worker characteristics (using the coefficient estimates from the mover sample) across the number of years we observe an employee. See CHK's Online Appendix for computational details. In the time window 2010 to 2017, 37.4 percent of all employees switch employers at least once.

[16]The dependence of subscript j on employee i and year t is suppressed so that $j = J(i, t)$.

[17]As in CHK, the age variable is normalized to 40 years. See Card et al. (2018) and Song et al. (2019) for a discussion of this normalization.

captures wage adjustments which is specific to an employee-employer match, that is wage premia (or discounts) earned by employee i at establishment j, relative to the the baseline level $\alpha^i + \psi^j$.

3.3.2. Identifying assumptions

Denote N as the number of employees, J as the number of establishments, and T as the numbers of time periods. The wage model assumes strict exogeneity:

$$E(r_t^{i,j} | X_1^1, ..., X_T^N, \alpha^1, ..., \alpha^N, \psi^1, ..., \psi^J) = 0 \tag{5}$$

Equation 5 implies that employees' mobility decisions are independent of $r^{i,j}$, but may be a function of the unobservables α^i and ψ^j. The estimation of the AKM model is vulnerable to limited worker mobility resulting in an incidental parameter problem. To assess the severeness of bias in our estimates, we apply the bias correction as described in Andrews et al. (2008). We find that the variance of the establishment fixed effects is 2.5 percent lower compared to our baseline estimation, and the variance of the employee fixed effects is 4 percent lower. The correlation between the fixed effects when using bias correction is 35 percent, as compared to 33 percent in our baseline AKM regression.[18] The similar results of the bias correction method and the fact that we estimate the model on the entire universe of full-time employees mitigate concerns that our AKM estimation suffers from substantial limited mobility bias. This conclusion is in line with AKM, CHK, Song et al. (2019), and Lochner, Seth and Wolter (2020).[19]

3.3.3. Results

The results are reported in Table 2 and graphically illustrated in Figure 1. 90.5 percent of the overall wage inequality within establishments is explained by the heterogeneity of employee characteristics (=[0.098+0.009]/0.118). Among

[18] Kline, Saggio and Sølvsten (2020) offer an alternative approach of bias correction in AKM models, which, however, is computational very hard to implement for datasets of our size. Furthermore, as Borovičková and Shimer (2017) point out, there is no agreement yet about which (if any) of the approaches is superior.

[19] Bonhomme, Lamadon and Manresa (2019) propose a clustering approach to approximate the underlying, possibly continuous, distribution of unobserved firm heterogeneity. Specifically, these authors classify firms into a small number of k-means clusters. While this approach mitigates the potential incidental parameter problem, it is not practicable in our context as we are interested in wage inequality within establishments or firms, that is single units of production, not clusters of firms.

this heterogeneity, we find that (unobserved) time-invariant worker attributes such ability, measured by the fixed effects, explains the lion's share (82.8 percent), whereas observable time-variant attributes such as age only play a minor role (7.7 percent).[20] This pattern is particularly pronounced for VWI: the person fixed effects amount to 90.4 percent, whereas observable employee characteristics only explain 3 percent.[21] Regarding HWI, we find that remuneration for heterogeneous employee characteristics accounts for 87.5 percent of the wage variation within occupations (=[0.044+0.007]/0.058). Again, most of the explanatory power derives from employee fixed effects.

The variance of the residual component within an establishment and occupation-task group, which we refer to as RWI, can be written as

$$RWI_t^j = \sum_o w_t^{o,j} \cdot var_t^{o,j}(r_t^{i,j}) \tag{6}$$

where $w_t^{o,j}$ is the fraction of employees and $var_t^{o,j}(r_t^{i,j})$ the residual wage dispersion within occupation o at establishment j in year t. Our results show that this RWI among employees with similar characteristics who perform similar tasks accounts for 24.4 percent of HWI which corresponds to 11.9 percent (=0.014/0.118) of the overall wage differences of an establishment.[22]

4. RWI in the cross section

In this section, we analyze how the relevance of RWI differs in the cross section. While RWI accounts for 11.9 percent of the overall wage differences in the average establishment, we find that its share is only 3.1 percent for the lowest decile and 19.9 percent for the highest decile if we sort our dataset by RWI. These numbers show that the explanatory power of task heterogeneity and differences in employee characteristics varies substantially in the cross section. We start by deriving potential factors that affect the relevance of

[20] Song et al. (2019) show that residual wage inequality accounts for approximately 25 percent of the wage dispersion within U.S. firms (from 2007 to 2013). Hence, the role of "residual" wage differences seems to be more pronounced for U.S. firms.

[21] This finding is in line with the conclusion of Mueller, Ouimet and Simintzi (2017b) that the higher wage inequality between different hierarchy levels in larger firms is related to differences in managerial talent.

[22] Note that the three covariance components unambiguously contribute negatively to HWI such that the sum of the variance components exceeds 100 percent.

RWI in the cross-section. After that, we use plots and regressions to explore the correlation between these factors and RWI.

4.1. Conceptual framework

Conceptionally, RWI captures wage differences for the same hypothetical employee who performs the same tasks at a particular firm. These employee-employer-specific wage adjustments can reflect performance differences across different employers due to idiosyncratic match effects.[23] These match effects occur, for example, due to complementarities between employees and employers or drifts in the portable component of employees' earnings power (see CHK). We expect RWI to be more prevalent in firms with pay-for-performance based compensation that rewards heterogeneous employee performance (Barth et al., 2012). The reason is that the adjustment of individual wages to performance creates dispersed wages among employees with similar characteristics who perform similar tasks due to performance differences across employees and over time (Seiler, 1984; Lemieux, MacLeod and Parent, 2009). Examples of those schemes include bonus payments and piece rates, but also base wage adjustments that are related to past or expected performance (Lazear, 2018).

Since detailed information on pay-for-performance schemes is not available in our administrative data, we rely on proxies to explore its relevance for the cross-sectional heterogeneity of RWI.[24] We start by exploiting that pay-for-performance based compensation is most relevant when monitoring is costly. Agency problems between employers and employees may arise because their interests diverge: employers want employees to maximize their efforts, but employees' utility is negatively related to effort (Ross, 1973). Two potential solutions are monitoring and compensation policies that link employees' wages to their performance. The relative attractiveness of monitoring as compared to

[23] An alternative explanation is provided by employer-specific discrimination, which leads to heterogeneous remuneration for the same characteristic across employers (Lang and Lehmann, 2012). Unfortunately, we are not able to separate discrimination from positive wage premiums in the RWI part. The reason is that in the AKM framework, all time-constant characteristics are soaked up by the person and firm effects. While the AKM approach is able to deal with two-sided unobserved heterogeneity, it relies on restrictive assumptions that we partly discuss in Section 3.3.2. The absence of interactions between the worker and firm effects restricts complementarity patterns in wages. All of these interactions end up in the AKM residual. See Bonhomme, Lamadon and Manresa (2019) for a discussion.

[24] In general, direct information on pay-for-performance schemes is scarce. One reason is that they are often not explicitly written down as contracts (Bloom and Van Reenen, 2011).

wage adjustments depends on the monitoring costs of a firm. If a firm can easily monitor its employees, it is likely better off monitoring its employees instead of linking wages to performance, which also come at a cost for firms.[25] However, if monitoring costs are high, linking employees wages to their performance becomes more attractive for firms (Prendergast, 2002).

What determines monitoring costs in the cross section? Two important factors are the uncertainty about employees' optimal actions and the observability of their actions (Holmstrom, 1979; Prendergast, 2002). Uncertainty about optimal actions is closely related to employees' tasks (Holmstrom and Milgrom, 1991), and firms choose compensation policies that fit those characteristics (Holmstrom and Milgrom, 1994; MacLeod and Parent, 2012). Consequently, performance pay is common in occupations that involve complex tasks due to greater uncertainty regarding employees' optimal actions (Prendergast, 2002). The observability of employees' actions depends, among other characteristics, on the size of an establishment because of differences in monitoring costs (Garen, 1985). An important ingredient of his model is that larger firms have higher costs of acquiring information about employees and lower accuracy when screening employees. To explore the role of monitoring costs, we hence use task complexity and the size of a firm or establishment as proxies for monitoring cost.

In addition to proxies related to monitoring costs, we apply two more measures. The first measure focuses on the existence of a profit-sharing program in an establishment. Profit sharing is one particular pay-for-performance scheme that links employees' wages to firm profitability (Bloom and Van Reenen, 2011). As a consequence, wages of employees with similar characteristics who perform similar tasks are more heterogeneous in firms with profit-sharing programs if these programs link the financial rewards to the performance of an employee. A related, but more indirect, measure exploits cross-sectional variation in firm profitability. The idea is that adjustments of employees wages to their performance are more pronounced in firms that are more profitable because these firms share parts of their profits with employees according their individual performance.

[25] For instance, pay-for-performance policies can lead to the manipulation of performance measures or the deceiving of customers (Baker, Gibbons and Murphy, 1994).

4.2. Task complexity and RWI: graphical evidence

To assess the task complexity of an occupation, we rely on two classification schemes. First, we use the classification proposed by Autor, Levy and Murnane (2003). These authors distinguish between the following types of tasks: analytical non/routine, interactive non/routine, cognitive routine (which is a combination of analytical and interactive routine), manual non/routine, and manual routine. Routine and nonroutine tasks differ in whether or not the optimal actions to carry out these tasks follow an explicit procedure. Analytical tasks involve formal analytic skills (e.g., engineering and science), while interactive tasks require managerial or interpersonal skills (e.g., managing a team). Manual tasks, such as cleaning, driving of vehicles, or combining different parts in an assembly line, are relatively straightforward to perform. Task complexity is highest in nonroutine analytical and nonroutine interactive tasks, followed by routine cognitive tasks, and lowest in nonroutine and routine manual tasks.[26] The second classification for task complexity, which we refer to as "occupational complexity," is based on the fifth digit of the KldB2010 occupation code, which indicates the level of task complexity of an occupation-task group (see Appendix A for more details).

We first sort occupations by their median RWI in Figure 2(a).[27] For each occupation, we show the classification of its main task and its occupational complexity. The main tasks of the five occupations with the highest RWI are all classified as nonroutine tasks that require analytical skills, and these occupations are all classified as highly complex. All five occupations with the lowest RWI have mainly manual tasks (four routine, one nonroutine). Figures 2(b) to (f) illustrate the relation between occupations' task composition and RWI. The horizontal axis shows the fraction of tasks of an occupation that are analytical nonroutine (subfigure b), interactive nonroutine (c), cognitive routine (d), manual nonroutine (e), or manual routine (f). Every dot in the figures represents one specific occupation, and we add a linear regression line with a 90

[26] We obtain information on the main task of occupations and their task composition from Dengler, Matthes and Paulus (2014), who follow the approach of Autor, Levy and Murnane (2003). We use the classification from 2013.

[27] The occupation-level RWI is calculated as the employee-weighted average of all establishment-occupation residual wage variances. Please note that we focus on the 50 largest occupations, which account for approximately 70 percent of the employee-years in our dataset, for the analyses in Figure 2.

percent confidence interval. We find that the fraction of analytical nonroutine tasks and interactive nonroutine tasks has a positive relationship with RWI.[28] For all other tasks, we detect a flat or negative relationship. Overall, these results indicate that RWI is higher in occupations with more complex tasks.

4.3. Firm/establishment size and RWI: graphical evidence

Next, we present a graphical analysis of the relationship between RWI and firm size. In Figure 3, we sort firms into deciles based on their number of full-time employees and calculate, for each decile, the average within-establishment variance of residual wages. In Figure 3, we first measure size and wage inequality on the firm level. The corresponding solid line shows that RWI increases with firm size, from about 0.010 in decile one to 0.025 in decile ten. Using establishment size instead of firm size leads to similar results as indicated by the dotted line. These graphical patterns provide first evidence that RWI increases with firm and establishment size in the cross-section.

4.4. Size, task complexity, and RWI: regression results

Next, we conduct regressions to further analyze the relationship between RWI, task complexity, and firm size:

$$RWI_t^f = \alpha + \beta X_t^f + \lambda^f \cdot \tau_t + \kappa^f \cdot \tau_t + \epsilon_t^f, \tag{7}$$

where α is a constant, ϵ the error term, and X_t^f is the independent variable of interest for firm f in year t. These variables are firm size, proxied by the logarithm of number of full-time employees, and various measures for task complexity. The RWI_t^f is calculated over all employees and establishments of firm f in year t. We include county-year fixed effects $\kappa^f \cdot \tau_t$ based on regional districts (so-called "Landkreise," which are comparable to counties in the U.S.) and industry-year fixed effects $\lambda^f \cdot \tau_t$ based on three-digit WZ2008 industries. We estimate this model on the employee-year level and cluster standard errors at the firm level.

The results for firm size are presented in Column 1 of Table 4. The coefficient estimate for $log(emp_t^f)$ is positive and statistically significant at the 1

[28]These patterns cannot be explained by higher task heterogeneity in occupations with analytical or interactive tasks. Appendix D shows that the relationship between RWI and task concentration is flat or even slightly positive.

percent level. The magnitude of β is 0.0020, which indicates that the RWI is about 12.5 percent higher, relative to its mean, for a firm that has twice as many employees. Note that there is a positive relation between the size of the firm and the size of its occupations. To assess the role of occupation size, we add the logarithm of the mean number of employees in an occupation as a control variable in Appendix E. It turns out that about half of the firm-size effect originates from larger occupations in larger firms, whereas the task complexity measures are relatively unaffected by this additional control.

In Columns 2 to 4, we analyze measures for task complexity. We use the average fraction of analytical nonroutine and interactive nonroutine tasks in a firm, which is based on the classification scheme of Autor, Levy and Murnane (2003), and the average occupational complexity of a firm, which is based on the fifth digit of the KldB2010 occupational classification scheme. We find that RWI increases with the average task complexity of a firm. The coefficient estimate for β indicates that a one-standard-deviation increase in the fraction of analytical nonroutine tasks is associated with a 19.7 percent higher RWI, relative to its mean. The corresponding values for interactive nonroutine and occupational complexity are 10.1 percent and 17.1 percent.

Next, we exploit multi-establishment firms to analyze differences in size and task complexity across establishments of the same firm. In this specification, we additionally include firm-year fixed effects, which ensure that the estimation of the parameter of interest, β, is based on differences between establishments within the same firm. This within-firm estimation controls for all time-constant and time-varying firm-specific factors and helps to mitigate concerns that unobservable firm heterogeneity could drive our results. The regression specification for the establishment size analysis can be written as

$$RWI_t^j = \alpha + \beta X_t^j + \lambda^j \cdot \tau_t + \kappa^j \cdot \tau_t + \eta^f \cdot \tau_t + \epsilon_t^j, \tag{8}$$

where X_t^j is the variable of interest for establishment j in year t and $\eta^f \cdot \tau_t$ a firm-year fixed effect. The results, which are reported in Table 5, reveal that RWI is higher in larger establishments and those with more complex tasks. The estimated magnitudes for β are similar to the ones we documented before.

4.5. Profit sharing programs and RWI

The next cross-sectional characteristic that we analyze is the extent of profit sharing in an establishment. Out data on the use of profit-sharing programs in establishments originates from the IAB establishment panel (Betriebspanel, BP)—a representative establishment-level survey for Germany. Among other things, these data include the fraction of employees that participate in a profit sharing program.[29] We observe information on profit sharing for about 3.3 million employee-years, 2.0 million employees, and 16,553 establishments. On average, 37 percent of employees participate in profit-sharing programs.

To test whether RWI is more pronounced if more employees participate in profit-sharing programs, we estimate the following regression:

$$RWI_t^j = \alpha + \beta profit\ sharing_t^j + \gamma log(empl_t^j) + \lambda^j \cdot \tau_t + \kappa^j \cdot \tau_t + \epsilon_t^j, \qquad (9)$$

where $profit\ sharing_t^j$ is the share of employees in establishment j who participate in a profit-sharing program in year t, λ^j denotes establishment-industry dummies (based on three-digit WZ2008 industries), κ^j establishment-county dummies (based on regional districts, so-called "Landkreise," which are comparable to counties in the U.S.), and τ_t year dummies. α is a constant, and ϵ is the error term. We estimate this model on the employee-year level and cluster standard errors at the establishment-level.

The results are shown in Table 6. We start with a simple specification without fixed effects in Column 1. The coefficient estimate for β is 0.0064 (t-value of 4.75) in this specification. The coefficient estimate remains unchanged once we add year fixed effects in Column 2. The magnitude of the coefficient estimate drops to 0.0023 (t-value of 8.21) once we control for county-year- and industry-year fixed effects in Column 3. Additionally controlling for establishment size further reduces the magnitude of the coefficient estimate to 0.0016 (t-value of 5.70), which implies that RWI increases by 12.3 percent, relative to its mean,[30] for a hypothetical establishment that changes the share of employees participating in a profit-sharing program from zero to one.

[29]For legal reasons, we cannot link the survey data with information on firm structures. Hence, we only observe employee-establishment information in this sample.

[30]The mean RWI for the regression sample is 0.013 and the standard deviation is 0.0097.

4.6. Financial performance and RWI

Adjustments of employees wages to their performance are likely more pronounced in firms that are more profitable, for example because firms share part of their profits with employees according their individual or team performance. To test how financial performance is related to RWI, we estimate the following regression for firm f and year t

$$RWI_t^f = \alpha + \beta Financial\ performance_t^f + \vec{\gamma}\vec{C}_t^f + \lambda^f \cdot \tau_t + \epsilon_t^f, \qquad (10)$$

where *financial performance*$_t^f$ is a measure for the financial performance of firm f in year t, $\vec{C}^k$ is a set of firm-level control variables (natural logarithm of total assets, leverage, tangibility, cash holdings, and a public listing dummy), τ_t year dummies, λ^f industry dummies (based on the industry of the firm), and ϵ is an error term. Note that we observe firm outcomes only at the firm level and not at the establishment level. Hence, it is not possible to exploit differences between establishments within firms for these tests.

We use four measures for firms' financial performance: EBITDA, EBIT, net income, and cash flow. All measures are scaled by total assets (please see Appendix B for their construction). Table 7 presents the results. For all measures, we find a positive and statistically significant coefficient estimate of β, indicating a positive relationship between financial performance and RWI. In terms of economic magnitude, the estimates imply that a one-standard-deviation increase in EBITDA per assets increases RWI by about 3.5 percent, relative to its mean.[31] Thus, wages among employees who perform similar tasks and have similar characteristics seem to be more unequal if firms are more profitable.

5. Conclusion

Using a newly available dataset that links employee-, establishment-, and firm-level information from Germany, we find that that task heterogeneity accounts for half of the overall within-firm wage differences. Differences in employees' characteristics, such as ability or education, explain three-quarters of the wage differences among employees who perform similar task. Thus,

[31] The mean RWI for the regression sample is 0.017 and the standard deviation is 0.012.

the part of wage inequality that is not explained by task heterogeneity or differences in employee characteristics only accounts for 12 percent of the overall wage differences within firms (which we call RWI). We document cross-sectional patterns that are consistent with the view that RWI captures, at least partially, pay-for-performance schemes that link employees' wages to their productivity.

What are the implications of this study? First, the finding that task heterogeneity and employee characteristics explain most of the wage differences within firms calls for the separate disclosure of wage inequality related to task heterogeneity, employee characteristics, and RWI since all of them have different policy implications and would require different regulatory interventions. Second, the positive correlation between our proxies for pay-for-performance based compensation and RWI indicates that wage inequality among employees who perform similar task and have similar characteristics fulfills an important incentive role. Regulators may want to consider this incentive role when targeting wage inequality within firms.

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Figures

Figure 1
Decomposition of within-establishment wage differences

This figure visualizes the decomposition of the within-establishment variance of wages, wages after controlling for observable employee characteristics (“wages - Xb”), and wages after controlling for observable and unobservable employee characteristics (“residual wages”) into a vertical (between occupation-task groups) and a horizontal (within occupation-task groups) component. The exact values of the decomposition can be found in Table 2. A detailed description of all variables can be found in Appendix B.

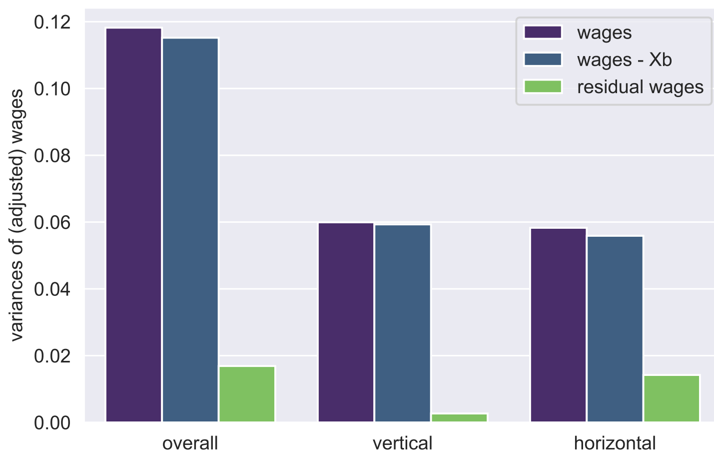
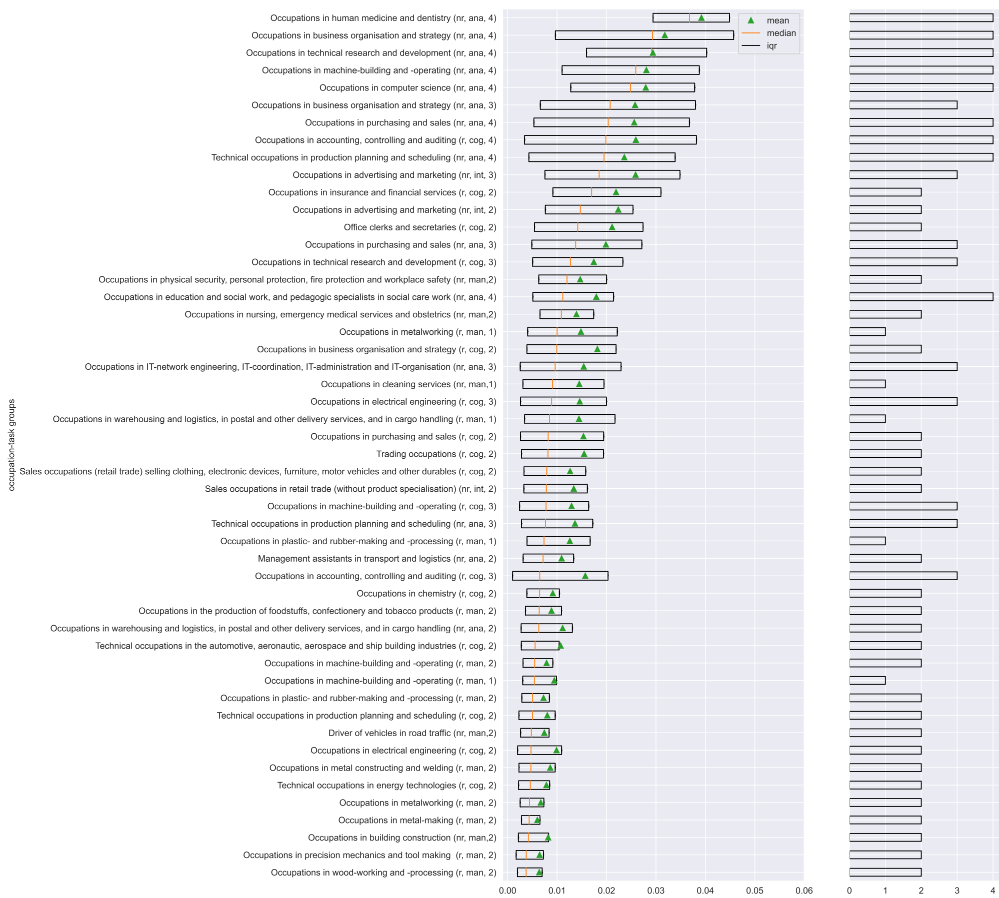


Figure 2

RWI and occupation-task groups

This figure shows the residual wage inequality (RWI) in different occupation-task groups. RWI captures wage differences among employees with similar characteristics in the same occupation-task group. We limit this analysis to the 50 most common occupation-task groups in our sample; they account for approximately 70% of the employee-years. Subfigure (a) presents the occupation-task groups sorted by the median value of the residual HWI measure. In parentheses, we show the task classification according to Autor, Levy and Murnane (2003) and the task complexity level according to the fifth digit of the KldB2010 occupational classification scheme. *nr* denotes a nonroutine task, *r* a routine task, *ana* an analytical task, *int* an interactive task, *cog* a cognitive task, *man* a manual task, *1* unskilled/semi-skilled tasks, *2* skilled tasks, *3* complex tasks, and *4* highly complex tasks. Subfigures (b) to (f) illustrate the relation between the residual HWI and the share of analytic nonroutine, interactive nonroutine, cognitive routine, manual nonroutine, and manual routine tasks using linear regression with 90% confidence interval. A detailed description of all variables can be found in Appendix B.

(a) 50 largest occupations sorted by median RWI



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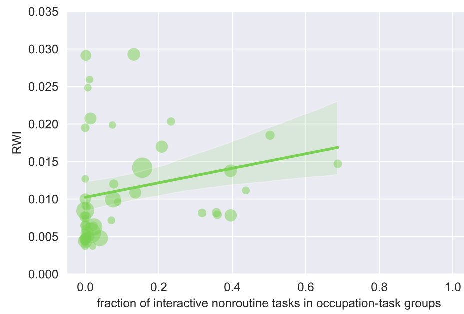
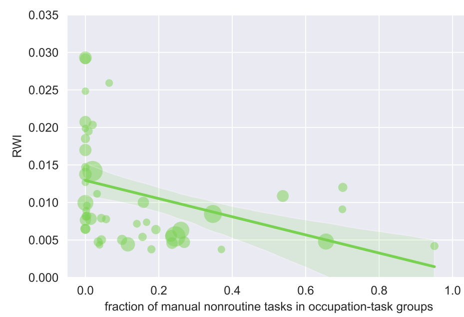
(b) analytical nonroutine tasks

(c) interactive nonroutine tasks



(d) cognitive routine tasks

(e) manual nonroutine tasks



(f) manual routine tasks

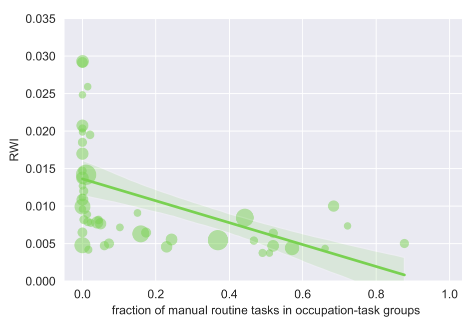


Figure 3
Size and RWI

This figure presents, for each size decile, the mean value of the RWI. RWI captures wage differences among employees with similar characteristics in the same occupation-task group. We measure size and RWI on the firm level and the establishment level. To construct the size deciles, we sort establishments or firms based on their number of full-time employees. A detailed description of all variables can be found in Appendix B.

Tables

Table 1
Descriptive statistics

This table presents descriptive statistics. The sample consists of 69,268,888 employee-years, 16,630,960 individual employees, 205,858 establishments, and 87,440 firms. Reported are the number of observations (Obs), mean value (Mean), standard deviation (SD), 25% percentile (25th), median (50th), and 75% percentile (75th). A detailed description of all variables can be found in Appendix B.

	Obs	Mean	SD	25th	50th	75th
wage	69,268,888	4.620	0.524	4.287	4.612	4.940
HWI_{estab}	69,175,635	0.058	0.047	0.028	0.047	0.075
HWI_{firm}	69,268,888	0.063	0.045	0.033	0.053	0.080
RWI_{estab}	69,175,635	0.014	0.013	0.006	0.011	0.019
RWI_{firm}	69,268,888	0.016	0.012	0.007	0.013	0.022
number of occupation-task groups	69,268,888	26.052	23.012	10.000	19.000	35.000
empl_{estab}	69,268,888	1284	4932	61	166	521
empl_{firm}	69,268,888	5814	19588	93	298	1341
multi-establishment firm	69,268,888	0.470	0.499	0.000	0.000	1.000
number of establishments	69,268,888	44.808	264.195	1.000	1.000	5.000
analytical nonroutine tasks	69,260,523	0.261	0.236	0.053	0.204	0.398
interactive nonroutine tasks	69,260,523	0.095	0.145	0.000	0.015	0.155
occupational complexity	69,268,888	2.322	0.869	2.000	2.000	3.000
listing dummy	31,734,998	0.138	0.344	0.000	0.000	0.000
ebitda to assets_{firm}	27,701,999	0.106	0.120	0.039	0.088	0.159
ebit to assets_{firm}	20,476,558	0.072	0.124	0.015	0.060	0.122
net income to assets_{firm}	22,387,610	0.038	0.092	0.005	0.036	0.070
cash flow to assets_{firm}	27,510,562	0.075	0.086	0.035	0.066	0.108

Table 2

Decomposition of within-establishment wage differences

This table presents the decomposition of the within-establishment variance of wages, the within-establishment variance of wages within occupation-task groups (HWI), and the within-establishment variance of wages between occupation-task groups (VWI). Within-establishment wage inequality, HWI, and VWI are decomposed into the variances and covariances of the parameter estimates from the AKM-type regression as stated in Equation 4. A detailed description of all variables can be found in Appendix B.

	overall within		HWI		VWI	
	mean	share	mean	share	mean	share
var(wage)	0.118	1.000	0.058	1.000	0.060	1.000
var(person FE)	0.098	0.828	0.044	0.750	0.054	0.904
var(Xb)	0.009	0.077	0.007	0.125	0.002	0.030
var(residual)	0.017	0.143	0.014	0.244	0.003	0.045
2cov(person FE, Xb)	-0.006	-0.050	-0.004	-0.076	-0.001	-0.025
2cov(person FE, residual)	0.000	0.004	-0.002	-0.035	0.002	0.041
2cov(Xb, residual)	-0.000	-0.001	-0.000	-0.008	0.000	0.005

Table 3

Decomposition of within-establishment wage differences: five-digit Kldb2010

This table presents the decomposition of the within-establishment variance of wages, the within-establishment variance of wages within suboccupation-task groups (HWI), and the within-establishment variance of wages between suboccupation-task groups (VWI) using the five-digit KldB2010 occupational callssification scheme, which distinguishes 1,286 suboccupation-task groups. Our baseline decomposition in Table 2 uses the first three digits plus the fifth digit of the KldB2010 classification and distinguishes 426 occupation-task groups. A detailed description of all variables can be found in Appendix B.

	overall		HWI		VWI	
	mean	share	mean	share	mean	share
var(wage)	0.118	1.000	0.055	1.000	0.063	1.000
var(person FE)	0.098	0.828	0.041	0.749	0.057	0.897
var(Xb)	0.009	0.077	0.007	0.128	0.002	0.032
var(residual)	0.017	0.143	0.014	0.252	0.003	0.048
2cov(person FE, Xb)	-0.006	-0.050	-0.004	-0.081	-0.001	-0.022
2cov(person FE, residual)	0.000	0.004	-0.002	-0.038	0.003	0.040
2cov(Xb, residual)	-0.000	-0.001	-0.000	-0.009	0.000	0.005

Table 4
Firm size, task complexity, and RWI

The dependent variable is a firm's residual wage inequality (RWI). RWI captures wage differences among employees with similar characteristics in the same occupation-task group. The task-based measures, which follow Autor, Levy and Murnane (2003), capture the average share of analytical nonroutine and interactive nonroutine tasks in a firm. Occupational complexity is based on the fifth digit of the KldB2010 occupational classification scheme and captures the average task complexity level of occupation-task groups in a firm. The regression models are estimated on the employee-year level. T-statistics based on robust standard errors clustered at the firm level are presented in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. A detailed description of all variables can be found in Appendix B.

	(1)	(2)	(3)	(4)
log(empl)$_{firm}$	0.0020***			
	(20.81)			
analytical nonroutine tasks$_{firm}$		0.024***		
		(22.00)		
interactive nonroutine tasks$_{firm}$			0.017***	
			(10.04)	
occupational complexity$_{firm}$				0.0055***
				(19.46)
Year FE	Yes	Yes	Yes	Yes
County x year FE	Yes	Yes	Yes	Yes
Industry x year FE	Yes	Yes	Yes	Yes
Obs	69,250,918	69,250,918	69,250,918	69,250,918
R2	0.44	0.42	0.40	0.42

Table 5

Establishment size, task complexity, and RWI

The dependent variable is an establishment's residual wage inequality (RWI). RWI captures wage differences among employees in the same occupation-task group due to employee-employer-specific wage adjustments. The task-based measures, which follow Autor, Levy and Murnane (2003), capture the average share of analytical nonroutine and interactive nonroutine tasks in an establishment. Occupational complexity is based on the fifth digit of the KldB2010 classification scheme and captures the average task complexity level of occupation-task groups in an establishment. The regression models are estimated on the employee-year level. T-statistics based on robust standard errors clustered at the firm level are presented in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. A detailed description of all variables can be found in Appendix B.

	(1)	(2)	(3)	(4)
log(empl)$_{estab}$	0.0017***			
	(13.11)			
analytical nonroutine tasks$_{estab}$		0.031***		
		(12.71)		
interactive nonroutine tasks$_{estab}$			0.021***	
			(9.49)	
occupational complexity$_{estab}$				0.0075***
				(12.29)
Year FE	Yes	Yes	Yes	Yes
County x year FE	Yes	Yes	Yes	Yes
Industry x year FE	Yes	Yes	Yes	Yes
Firm x year FE	Yes	Yes	Yes	Yes
Obs	32,428,714	32,428,709	32,428,709	32,428,714
R2	0.67	0.67	0.66	0.67

Table 6
Profit sharing and RWI

The dependent variable is an establishment's residual wage inequality (HWI). RWI captures wage differences among employees with similar characteristics in the same occupation-task group. Profit sharing is measured as the number of employees who participate in profit sharing in an establishment, divided by the establishment's total number of employees. The regression models are estimated on the employee-year level for the survey sample (Section 4.5). T-statistics based on robust standard errors clustered at the establishment level are presented in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. A detailed description of all variables can be found in Appendix B.

	(1)	(2)	(3)	(4)
profit sharing	0.0064***	0.0064***	0.0023***	0.0016***
	(4.75)	(4.67)	(8.21)	(5.70)
$\log(\text{empl})_{estab}$				0.0012***
				(13.76)
Year FE	No	Yes	Yes	Yes
County x year FE	No	No	Yes	Yes
Industry x year FE	No	No	Yes	Yes
Obs	3,257,088	3,257,088	3,256,666	3,256,666
R2	0.10	0.10	0.54	0.56

Table 7
Financial performance and RWI

The dependent variable is a firm's residual wage inequality (RWI). RWI captures wage differences among employees with similar characteristics in the same occupation-task group. The measure for financial performance is indicated in each column. The regression models are estimated on the employee-year level. T-statistics based on robust standard errors clustered at the firm level are presented in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. A detailed description of all variables can be found in Appendix B.

	(1)	(2)	(3)	(4)
ebitda/assets	0.0049***			
	(4.42)			
ebit/assets		0.0030***		
		(3.43)		
net income/assets			0.0036**	
			(2.34)	
cash flow/assets				0.0043***
				(2.93)
log(total assets)	0.0021***	0.0018***	0.0021***	0.0021***
	(18.94)	(16.95)	(17.82)	(18.76)
leverage	-0.0015***	-0.0012***	-0.0013***	-0.0016***
	(-3.45)	(-3.34)	(-2.88)	(-3.56)
tangibility	-0.0099***	-0.0077***	-0.0080***	-0.0097***
	(-13.41)	(-13.79)	(-11.54)	(-12.68)
cash holdings	-0.0020*	-0.0013	-0.0019	-0.0019*
	(-1.90)	(-1.57)	(-1.64)	(-1.77)
listing dummy	0.0025**	0.0016**	0.0023*	0.0024**
	(2.16)	(1.98)	(1.91)	(2.09)
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Industry x year FE	Yes	Yes	Yes	Yes
Obs	25,125,090	18,536,099	20,533,326	25,046,989
R2	0.50	0.40	0.52	0.50

Appendices

A. The KldB2010 occupational classification scheme

A.1. Description

The KldB2010 occupational classification scheme is published by the Institute for Employment Research (Institut für Arbeitsmarkt- und Berufsforschung, IAB). KldB stands for "Klassifikation der Berufe" (classification of occupations), and 2010 indicates the version of the classification scheme.

The KldB2010 scheme uses five digits to define occupations, and its structure is as follows: the first digit indicates the occupational area, the first two digits the occupational main group, the first three digits the occupational group, and the first four digits the occupational sub-group. The fifth digit specifies the task level on a scale from one to four: one stands for unskilled or semi-skilled tasks, two for skilled tasks, three for complex tasks, and four for highly complex tasks.[32] The combination of occupational subgroup and task level defines a suboccupation-task group, but not all task levels exist for all groups. In total, there are 10 occupational groups, 37 occupational main groups, 144 occupational groups, 700 occupational sub-groups, and 1,286 suboccupation-task groups.

To illustrate the classification scheme, consider occupational group 2: Occupations in production of raw materials and goods, and manufacturing. For this occupational group, there are nine main groups, for example, 22: Occupations in plastic-making and -processing, and wood-working and -processing, 23: Occupations in paper-making and -processing, printing, and in technical media design, and 24: Occupations in metal-making and -working, and in metal

[32] Level one requires "no vocational qualification, or regular one-year vocational training," two "at least two years of vocational training, also graduation from vocational school," three "qualification as master craftsman or technician or equivalent technical school or college graduation, also graduation from a professional academy or university bachelor's degree," and four "completed university studies of at least four year" (Paulus and Matthes, 2013).

construction. The last main group is further divided into five occupational groups, for example, 241: Occupations in metal-making, 243: Occupations in treatment of metal surfaces, and 242: Occupations in metalworking. The last occupational group is then divided into six sub-groups, for example, 2421: Occupations in metalworking: non-cutting, 2422: Occupations in metalworking: grinding, and 2423: Occupations in metalworking: cutting. For the last sub-group, the classification scheme distinguishes two task levels: 24232: Occupations in metalworking: cutting—skilled tasks and 24233: Occupations in metalworking: cutting—complex tasks.[33]

The KldB2010 three-plus-fifth-digit classification, which we use in our main analyses, is a combination of the 3-digit occupational group and the fifth digit, which indicates the task level. This scheme distinguishes 144 occupational groups with up to four task levels, which yields 431 occupation-task groups. The full list of these groups is shown in A.2. We use the five-digit classification scheme, which distinguishes all 1,286 occupations, as the robustness test in Table 3.

[33]Please note that "unskilled or semi-skilled tasks" and "highly complex tasks" do not exist for 2423: Occupations in metalworking: cutting.

A.2. List of occupations (KldB2010 three-plus-fifth digit)

111-1	Occupations in farming - unskilled/semiskilled tasks
111-2	Occupations in farming - skilled tasks
111-3	Occupations in farming - complex tasks
111-4	Occupations in farming - highly complex tasks
112-1	Occupations in animal husbandry - unskilled/semiskilled tasks
112-2	Occupations in animal husbandry - skilled tasks
112-3	Occupations in animal husbandry - complex tasks
112-4	Occupations in animal husbandry - highly complex tasks
113-2	Occupations in horsekeeping - skilled tasks
113-3	Occupations in horsekeeping - complex tasks
113-4	Occupations in horsekeeping - highly complex tasks
114-1	Occupations in fishing - unskilled/semiskilled tasks
114-2	Occupations in fishing - skilled tasks
114-3	Occupations in fishing - complex tasks
114-4	Occupations in fishing - highly complex tasks
115-1	Occupations in animal care - unskilled/semiskilled tasks
115-2	Occupations in animal care - skilled tasks
115-3	Occupations in animal care - complex tasks
115-4	Occupations in animal care - highly complex tasks
116-2	Occupations in vini- and viticulture - skilled tasks
116-3	Occupations in vini- and viticulture - complex tasks
116-4	Occupations in vini- and viticulture - highly complex tasks
117-1	Occupations in forestry, hunting and landscape preservation - unskilled/semiskilled tasks
117-2	Occupations in forestry, hunting and landscape preservation - skilled tasks
117-3	Occupations in forestry, hunting and landscape preservation - complex tasks
117-4	Occupations in forestry, hunting and landscape preservation - highly complex tasks
121-1	Occupations in gardening - unskilled/semiskilled tasks
121-2	Occupations in gardening - skilled tasks
121-3	Occupations in gardening - complex tasks
121-4	Occupations in gardening - highly complex tasks
122-2	Occupations in floristry - skilled tasks
122-3	Occupations in floristry - complex tasks
122-4	Occupations in floristry - highly complex tasks
211-1	Occupations in underground and surface mining and blasting engineering - unskilled/semiskilled tasks
211-2	Occupations in underground and surface mining and blasting engineering - skilled tasks
211-3	Occupations in underground and surface mining and blasting engineering - complex tasks
211-4	Occupations in underground and surface mining and blasting engineering - highly complex tasks
212-1	Conditioning and processing of natural stone and minerals, production of building materials - unskilled/semiskilled tasks
212-2	Conditioning and processing of natural stone and minerals, production of building materials - skilled tasks
212-3	Conditioning and processing of natural stone and minerals, production of building materials - complex tasks
213-1	Occupations in industrial glass-making and -processing - unskilled/semiskilled tasks
213-2	Occupations in industrial glass-making and -processing - skilled tasks
213-3	Occupations in industrial glass-making and -processing - complex tasks
214-1	Occupations in industrial ceramic-making and -processing - unskilled/semiskilled tasks
214-2	Occupations in industrial ceramic-making and -processing - skilled tasks
214-3	Occupations in industrial ceramic-making and -processing - complex tasks
221-1	Occupations in plastic- and rubber-making and -processing - unskilled/semiskilled tasks
221-2	Occupations in plastic- and rubber-making and -processing - skilled tasks
221-3	Occupations in plastic- and rubber-making and -processing - complex tasks
221-4	Occupations in plastic- and rubber-making and -processing - highly complex tasks
222-1	Occupations in colour coating and varnishing - unskilled/semiskilled tasks
222-2	Occupations in colour coating and varnishing - skilled tasks
222-3	Occupations in colour coating and varnishing - complex tasks
222-4	Occupations in colour coating and varnishing - highly complex tasks
223-1	Occupations in wood-working and -processing - unskilled/semiskilled tasks
223-2	Occupations in wood-working and -processing - skilled tasks
223-3	Occupations in wood-working and -processing - complex tasks
223-4	Occupations in wood-working and -processing - highly complex tasks

231-1	Technical occupations in paper-making and -processing and packaging - unskilled/semiskilled tasks
231-2	Technical occupations in paper-making and -processing and packaging - skilled tasks
231-3	Technical occupations in paper-making and -processing and packaging - complex tasks
231-4	Technical occupations in paper-making and -processing and packaging - highly complex tasks
232-2	Occupations in technical media design - skilled tasks
232-3	Occupations in technical media design - complex tasks
232-4	Occupations in technical media design - highly complex tasks
233-2	Occupations in photography and photographic technology - skilled tasks
233-3	Occupations in photography and photographic technology - complex tasks
233-4	Occupations in photography and photographic technology - highly complex tasks
234-1	Occupations in printing technology, print finishing, and book binding - unskilled/semiskilled tasks
234-2	Occupations in printing technology, print finishing, and book binding - skilled tasks
234-3	Occupations in printing technology, print finishing, and book binding - complex tasks
234-4	Occupations in printing technology, print finishing, and book binding - highly complex tasks
241-1	Occupations in metal-making - unskilled/semiskilled tasks
241-2	Occupations in metal-making - skilled tasks
241-3	Occupations in metal-making - complex tasks
241-4	Occupations in metal-making - highly complex tasks
242-1	Occupations in metalworking - unskilled/semiskilled tasks
242-2	Occupations in metalworking - skilled tasks
242-3	Occupations in metalworking - complex tasks
242-4	Occupations in metalworking - highly complex tasks
243-1	Occupations in treatment of metal surfaces - unskilled/semiskilled tasks
243-2	Occupations in treatment of metal surfaces - skilled tasks
243-3	Occupations in treatment of metal surfaces - complex tasks
243-4	Occupations in treatment of metal surfaces - highly complex tasks
244-1	Occupations in metal constructing and welding - unskilled/semiskilled tasks
244-2	Occupations in metal constructing and welding - skilled tasks
244-3	Occupations in metal constructing and welding - complex tasks
244-4	Occupations in metal constructing and welding - highly complex tasks
245-1	Occupations in precision mechanics and tool making - unskilled/semiskilled tasks
245-2	Occupations in precision mechanics and tool making - skilled tasks
245-3	Occupations in precision mechanics and tool making - complex tasks
245-4	Occupations in precision mechanics and tool making - highly complex tasks
251-1	Occupations in machine-building and -operating - unskilled/semiskilled tasks
251-2	Occupations in machine-building and -operating - skilled tasks
251-3	Occupations in machine-building and -operating - complex tasks
251-4	Occupations in machine-building and -operating - highly complex tasks
252-1	Technical occupations in the automotive, aeronautic, aerospace and ship building industries - unskilled/semiskilled tasks
252-2	Technical occupations in the automotive, aeronautic, aerospace and ship building industries - skilled tasks
252-3	Technical occupations in the automotive, aeronautic, aerospace and ship building industries - complex tasks
252-4	Technical occupations in the automotive, aeronautic, aerospace and ship building industries - highly complex tasks
261-2	Occupations in mechatronics, automation and control technology - skilled tasks
261-3	Occupations in mechatronics, automation and control technology - complex tasks
261-4	Occupations in mechatronics, automation and control technology - highly complex tasks
262-2	Technical occupations in energy technologies - skilled tasks
262-3	Technical occupations in energy technologies - complex tasks
262-4	Technical occupations in energy technologies - highly complex tasks
263-1	Occupations in electrical engineering - unskilled/semiskilled tasks
263-2	Occupations in electrical engineering - skilled tasks
263-3	Occupations in electrical engineering - complex tasks
263-4	Occupations in electrical engineering - highly complex tasks
271-3	Occupations in technical research and development - complex tasks
271-4	Occupations in technical research and development - highly complex tasks
271-2	Occupations in technical research and development - skilled tasks
272-2	Draftspersons, technical designers, and model makers - skilled tasks
272-3	Draftspersons, technical designers, and model makers - complex tasks
272-4	Draftspersons, technical designers, and model makers - highly complex tasks
273-2	Technical occupations in production planning and scheduling - skilled tasks
273-3	Technical occupations in production planning and scheduling - complex tasks

273-4	Technical occupations in production planning and scheduling - highly complex tasks
281-1	Occupations in textile making - unskilled/semiskilled tasks
281-2	Occupations in textile making - skilled tasks
281-3	Occupations in textile making - complex tasks
281-4	Occupations in textile making - highly complex tasks
282-2	Occupations in the production of clothing and other textile products - skilled tasks
282-3	Occupations in the production of clothing and other textile products - complex tasks
282-4	Occupations in the production of clothing and other textile products - highly complex tasks
282-1	Occupations in the production of clothing and other textile products - unskilled/semiskilled tasks
283-1	Occupations in leather- and fur-making and -processing - unskilled/semiskilled tasks
283-2	Occupations in leather- and fur-making and -processing - skilled tasks
283-3	Occupations in leather- and fur-making and -processing - complex tasks
283-4	Occupations in leather- and fur-making and -processing - highly complex tasks
291-2	Occupations in beverage production - skilled tasks
291-3	Occupations in beverage production - complex tasks
291-4	Occupations in beverage production - highly complex tasks
292-1	Occupations in the production of foodstuffs, confectionery and tobacco products - unskilled/semiskilled tasks
292-2	Occupations in the production of foodstuffs, confectionery and tobacco products - skilled tasks
292-3	Occupations in the production of foodstuffs, confectionery and tobacco products - complex tasks
292-4	Occupations in the production of foodstuffs, confectionery and tobacco products - highly complex tasks
293-1	Cooking occupations - unskilled/semiskilled tasks
293-2	Cooking occupations - skilled tasks
293-3	Cooking occupations - complex tasks
293-4	Cooking occupations - highly complex tasks
311-2	Occupations in construction scheduling and supervision, and architecture - skilled tasks
311-3	Occupations in construction scheduling and supervision, and architecture - complex tasks
311-4	Occupations in construction scheduling and supervision, and architecture - highly complex tasks
312-2	Occupations in surveying and cartography - skilled tasks
312-3	Occupations in surveying and cartography - complex tasks
312-4	Occupations in surveying and cartography - highly complex tasks
321-1	Occupations in building construction - unskilled/semiskilled tasks
321-2	Occupations in building construction - skilled tasks
321-3	Occupations in building construction - complex tasks
321-4	Occupations in building construction - highly complex tasks
322-1	Occupations in civil engineering - unskilled/semiskilled tasks
322-2	Occupations in civil engineering - skilled tasks
322-3	Occupations in civil engineering - complex tasks
322-4	Occupations in civil engineering - highly complex tasks
331-1	Floor layers - unskilled/semiskilled tasks
331-2	Floor layers - skilled tasks
331-3	Floor layers - complex tasks
332-1	Painters & varnishers, plasterers, occ. in waterp. of build., preservation of structures & wooden build. comp.- unskilled/semiskilled tasks
332-2	Painters & varnishers, plasterers, occ. in waterproofing of buildings, preservation of structures & wooden build. comp. - skilled tasks
332-3	Painters & varnishers, plasterers, occ. in waterproofing of buildings, preservation of structures & wooden build. comp. - complex tasks
333-1	Occupations in interior construction & dry walling, insulation, carpentry, glazing, roller shutter & jalousie inst. - unskilled/semiskilled tasks
333-2	Occupations in interior construction & dry walling, insulation, carpentry, glazing, roller shutter & jalousie installation - skilled tasks
333-3	Occupations in interior construction & dry walling, insulation, carpentry, glazing, roller shutter & jalousie installation - complex tasks
341-2	Occupations in building services engineering - skilled tasks
341-3	Occupations in building services engineering - complex tasks
341-4	Occupations in building services engineering - highly complex tasks
342-1	Occupations in plumping, sanitation, heating, ventilating, and air conditioning - unskilled/semiskilled tasks
342-2	Occupations in plumping, sanitation, heating, ventilating, and air conditioning - skilled tasks
342-3	Occupations in plumping, sanitation, heating, ventilating, and air conditioning - complex tasks
342-4	Occupations in plumping, sanitation, heating, ventilating, and air conditioning - highly complex tasks
343-1	Occupations in building services and waste disposal - unskilled/semiskilled tasks
343-2	Occupations in building services and waste disposal - skilled tasks
343-3	Occupations in building services and waste disposal - complex tasks
343-4	Occupations in building services and waste disposal - highly complex tasks
411-3	Occupations in mathematics and statistics - complex tasks
411-4	Occupations in mathematics and statistics - highly complex tasks

412-3	Occupations in biology - complex tasks
412-4	Occupations in biology - highly complex tasks
412-2	Occupations in biology - skilled tasks
413-3	Occupations in chemistry - complex tasks
413-4	Occupations in chemistry - highly complex tasks
413-1	Occupations in chemistry - unskilled/semiskilled tasks
413-2	Occupations in chemistry - skilled tasks
414-3	Occupations in physics - complex tasks
414-4	Occupations in physics - highly complex tasks
414-2	Occupations in physics - skilled tasks
421-2	Occupations in geology, geography and meteorology - skilled tasks
421-3	Occupations in geology, geography and meteorology - complex tasks
421-4	Occupations in geology, geography and meteorology - highly complex tasks
422-2	Occupations in environmental protection engineering - skilled tasks
422-3	Occupations in environmental protection engineering - complex tasks
422-4	Occupations in environmental protection engineering - highly complex tasks
423-2	Occupations in environmental protection management and environmental protection consulting - skilled tasks
423-3	Occupations in environmental protection management and environmental protection consulting - complex tasks
423-4	Occupations in environmental protection management and environmental protection consulting - highly complex tasks
431-2	Occupations in computer science - skilled tasks
431-3	Occupations in computer science - complex tasks
431-4	Occupations in computer science - highly complex tasks
432-4	Occupations in IT-system-analysis, IT-application-consulting and IT-sales - highly complex tasks
432-3	Occupations in IT-system-analysis, IT-application-consulting and IT-sales - complex tasks
433-3	Occupations in IT-network engineering, IT-coordination, IT-administration and IT-organisation - complex tasks
433-4	Occupations in IT-network engineering, IT-coordination, IT-administration and IT-organisation - highly complex tasks
434-2	Occupations in software development and programming - skilled tasks
434-3	Occupations in software development and programming - complex tasks
434-4	Occupations in software development and programming - highly complex tasks
511-2	Technical occupations in railway, aircraft and ship operation - skilled tasks
511-3	Technical occupations in railway, aircraft and ship operation - complex tasks
511-4	Technical occupations in railway, aircraft and ship operation - highly complex tasks
512-2	Occupations in the inspection and maintenance of traffic infrastructure - skilled tasks
512-3	Occupations in the inspection and maintenance of traffic infrastructure - complex tasks
512-4	Occupations in the inspection and maintenance of traffic infrastructure - highly complex tasks
513-1	Occupations in warehousing and logistics, in postal and other delivery services, and in cargo handling - unskilled/semiskilled tasks
513-2	Occupations in warehousing and logistics, in postal and other delivery services, and in cargo handling - skilled tasks
513-3	Occupations in warehousing and logistics, in postal and other delivery services, and in cargo handling - complex tasks
513-4	Occupations in warehousing and logistics, in postal and other delivery services, and in cargo handling - highly complex tasks
514-2	Service occupations in passenger traffic - skilled tasks
514-3	Service occupations in passenger traffic - complex tasks
515-3	Occupations in traffic surveillance and control - complex tasks
515-4	Occupations in traffic surveillance and control - highly complex tasks
515-2	Occupations in traffic surveillance and control - skilled tasks
516-3	Management assistants in transport and logistics - complex tasks
516-4	Management assistants in transport and logistics - highly complex tasks
516-2	Management assistants in transport and logistics - skilled tasks
521-2	Driver of vehicles in road traffic - skilled tasks
522-2	Drivers of vehicles in railway traffic - skilled tasks
523-3	Aircraft pilots - complex tasks
523-4	Aircraft pilots - highly complex tasks
524-3	Ship's officers and masters - complex tasks
524-4	Ship's officers and masters - highly complex tasks
524-2	Ship's officers and masters - skilled tasks
525-2	Drivers and operators of construction and transportation vehicles and equipment - skilled tasks
525-1	Drivers and operators of construction and transportation vehicles and equipment - unskilled/semiskilled tasks
525-3	Drivers and operators of construction and transportation vehicles and equipment - complex tasks
531-1	Occupations in physical security, personal protection, fire protection and workplace safety - unskilled/semiskilled tasks
531-2	Occupations in physical security, personal protection, fire protection and workplace safety - skilled tasks
531-3	Occupations in physical security, personal protection, fire protection and workplace safety - complex tasks

531-4	Occupations in physical security, personal protection, fire protection and workplace safety - highly complex tasks
532-2	Occupations in police and criminal investigation, jurisdiction and the penal institution - skilled tasks
532-3	Occupations in police and criminal investigation, jurisdiction and the penal institution - complex tasks
532-4	Occupations in police and criminal investigation, jurisdiction and the penal institution - highly complex tasks
532-1	Occupations in police and criminal investigation, jurisdiction and the penal institution - unskilled/semiskilled tasks
533-2	Occupations in occupational health and safety administration, public health authority, and disinfection - skilled tasks
533-3	Occupations in occupational health and safety administration, public health authority, and disinfection - complex tasks
533-4	Occupations in occupational health and safety administration, public health authority, and disinfection - highly complex tasks
541-1	Occupations in cleaning services - unskilled/semiskilled tasks
541-2	Occupations in cleaning services - skilled tasks
541-3	Occupations in cleaning services - complex tasks
611-2	Occupations in purchasing and sales - skilled tasks
611-3	Occupations in purchasing and sales - complex tasks
611-4	Occupations in purchasing and sales - highly complex tasks
612-3	Trading occupations - complex tasks
612-4	Trading occupations - highly complex tasks
612-2	Trading occupations - skilled tasks
613-2	Occupations in real estate and facility management - skilled tasks
613-3	Occupations in real estate and facility management - complex tasks
613-4	Occupations in real estate and facility management - highly complex tasks
621-1	Sales occupations in retail trade (without product specialisation) - unskilled/semiskilled tasks
621-2	Sales occupations in retail trade (without product specialisation) - skilled tasks
621-3	Sales occupations in retail trade (without product specialisation) - complex tasks
621-4	Sales occupations in retail trade (without product specialisation) - highly complex tasks
622-2	Sales occupations (retail trade) selling clothing, electronic devices, furniture, motor vehicles and other durables - skilled tasks
623-1	Sales occupations (retail) selling foodstuffs - unskilled/semiskilled tasks
623-2	Sales occupations (retail) selling foodstuffs - skilled tasks
624-2	Sales occupations (retail) selling drugstore products, pharmaceuticals, medical supplies and healthcare goods - skilled tasks
625-2	Sales occupations (retail) selling books, art, antiques, musical instruments, recordings or sheet music - skilled tasks
625-3	Sales occupations (retail) selling books, art, antiques, musical instruments, recordings or sheet music - complex tasks
625-4	Sales occupations (retail) selling books, art, antiques, musical instruments, recordings or sheet music - highly complex tasks
631-2	Occupations in tourism and the sports (and fitness) industry - skilled tasks
631-3	Occupations in tourism and the sports (and fitness) industry - complex tasks
631-4	Occupations in tourism and the sports (and fitness) industry - highly complex tasks
632-2	Occupations in hotels - skilled tasks
632-3	Occupations in hotels - complex tasks
632-1	Occupations in hotels - unskilled/semiskilled tasks
632-4	Occupations in hotels - highly complex tasks
633-1	Gastronomy occupations - unskilled/semiskilled tasks
633-2	Gastronomy occupations - skilled tasks
633-3	Gastronomy occupations - complex tasks
633-4	Gastronomy occupations - highly complex tasks
634-1	Occupations in event organisation and management - unskilled/semiskilled tasks
634-2	Occupations in event organisation and management - skilled tasks
634-3	Occupations in event organisation and management - complex tasks
634-4	Occupations in event organisation and management - highly complex tasks
711-4	Managing directors and executive board members - highly complex tasks
712-4	Legislators and senior officials of special interest organisations - highly complex tasks
713-2	Occupations in business organisation and strategy - skilled tasks
713-3	Occupations in business organisation and strategy - complex tasks
713-4	Occupations in business organisation and strategy - highly complex tasks
714-1	Office clerks and secretaries - unskilled/semiskilled tasks
714-2	Office clerks and secretaries - skilled tasks
714-3	Office clerks and secretaries - complex tasks
714-4	Office clerks and secretaries - highly complex tasks
715-2	Occupations in human resources management and personnel service - skilled tasks
715-3	Occupations in human resources management and personnel service - complex tasks
715-4	Occupations in human resources management and personnel service - highly complex tasks
721-2	Occupations in insurance and financial services - skilled tasks
721-3	Occupations in insurance and financial services - complex tasks

721-4	Occupations in insurance and financial services - highly complex tasks
722-2	Occupations in accounting, controlling and auditing - skilled tasks
722-3	Occupations in accounting, controlling and auditing - complex tasks
722-4	Occupations in accounting, controlling and auditing - highly complex tasks
723-2	Occupations in tax consultancy - skilled tasks
723-3	Occupations in tax consultancy - complex tasks
723-4	Occupations in tax consultancy - highly complex tasks
731-4	Occupations in legal services, jurisdiction, and other officers of the court - highly complex tasks
731-2	Occupations in legal services, jurisdiction, and other officers of the court - skilled tasks
731-3	Occupations in legal services, jurisdiction, and other officers of the court - complex tasks
732-1	Occupations in public administration - unskilled/semiskilled tasks
732-2	Occupations in public administration - skilled tasks
732-3	Occupations in public administration - complex tasks
732-4	Occupations in public administration - highly complex tasks
733-2	Occupations in media, documentation and information services - skilled tasks
733-3	Occupations in media, documentation and information services - complex tasks
733-4	Occupations in media, documentation and information services - highly complex tasks
811-2	Doctors' receptionists and assistants - skilled tasks
811-3	Doctors' receptionists and assistants - complex tasks
812-2	Laboratory occupations in medicine - skilled tasks
812-3	Laboratory occupations in medicine - complex tasks
812-4	Laboratory occupations in medicine - highly complex tasks
813-1	Occupations in nursing, emergency medical services and obstetrics - unskilled/semiskilled tasks
813-2	Occupations in nursing, emergency medical services and obstetrics - skilled tasks
813-3	Occupations in nursing, emergency medical services and obstetrics - complex tasks
813-4	Occupations in nursing, emergency medical services and obstetrics - highly complex tasks
814-4	Occupations in human medicine and dentistry - highly complex tasks
815-4	Occupations in veterinary medicine and non-medical animal health practitioners - highly complex tasks
815-2	Occupations in veterinary medicine and non-medical animal health practitioners - skilled tasks
816-4	Occupations in psychology and non-medical psychotherapy - highly complex tasks
816-3	Occupations in psychology and non-medical psychotherapy - complex tasks
817-2	Occupations in non-medical therapy and alternative medicine - skilled tasks
817-3	Occupations in non-medical therapy and alternative medicine - complex tasks
817-4	Occupations in non-medical therapy and alternative medicine - highly complex tasks
818-4	Occupations in pharmacy - highly complex tasks
818-2	Occupations in pharmacy - skilled tasks
818-3	Occupations in pharmacy - complex tasks
821-1	Occupations in geriatric care - unskilled/semiskilled tasks
821-2	Occupations in geriatric care - skilled tasks
821-3	Occupations in geriatric care - complex tasks
821-4	Occupations in geriatric care - highly complex tasks
822-2	Occupations providing nutritional advice or health counselling, and occupations in wellness - skilled tasks
822-3	Occupations providing nutritional advice or health counselling, and occupations in wellness - complex tasks
822-4	Occupations providing nutritional advice or health counselling, and occupations in wellness - highly complex tasks
823-1	Occupations in body care - unskilled/semiskilled tasks
823-2	Occupations in body care - skilled tasks
823-3	Occupations in body care - complex tasks
824-2	Occupations in funeral services - skilled tasks
824-3	Occupations in funeral services - complex tasks
824-4	Occupations in funeral services - highly complex tasks
825-2	Technical occupations in medicine, orthopaedic and rehabilitation - skilled tasks
825-3	Technical occupations in medicine, orthopaedic and rehabilitation - complex tasks
825-4	Technical occupations in medicine, orthopaedic and rehabilitation - highly complex tasks
831-1	Occupations in education and social work, and pedagogic specialists in social care work - unskilled/semiskilled tasks
831-2	Occupations in education and social work, and pedagogic specialists in social care work - skilled tasks
831-3	Occupations in education and social work, and pedagogic specialists in social care work - complex tasks
831-4	Occupations in education and social work, and pedagogic specialists in social care work - highly complex tasks
832-1	Occupations in housekeeping and consumer counselling - unskilled/semiskilled tasks
832-2	Occupations in housekeeping and consumer counselling - skilled tasks
832-3	Occupations in housekeeping and consumer counselling - complex tasks

833-4	Occupations in theology and church community work - highly complex tasks
833-2	Occupations in theology and church community work - skilled tasks
833-3	Occupations in theology and church community work - complex tasks
841-4	Teachers in schools of general education - highly complex tasks
841-3	Teachers in schools of general education - complex tasks
842-3	Teachers for occupation-specific subjects at vocational schools and in-company instructors in vocational training - complex tasks
842-4	Teachers for occupation-specific subjects at vocational schools and in-company instructors in vocational training - highly complex tasks
843-4	Teachers and researcher at universities and colleges - highly complex tasks
844-4	Teachers at educational institutions other than schools (except driving, flying and sports instructors) - highly complex tasks
844-2	Teachers at educational institutions other than schools (except driving, flying and sports instructors) - skilled tasks
844-3	Teachers at educational institutions other than schools (except driving, flying and sports instructors) - complex tasks
845-3	Driving, flying and sports instructors at educational institutions other than schools - complex tasks
845-4	Driving, flying and sports instructors at educational institutions other than schools - highly complex tasks
911-4	Occupations in philology - highly complex tasks
912-4	Occupations in the humanities - highly complex tasks
912-3	Occupations in the humanities - complex tasks
913-4	Occupations in the social sciences - highly complex tasks
913-1	Occupations in the social sciences - unskilled/semiskilled tasks
913-2	Occupations in the social sciences - skilled tasks
913-3	Occupations in the social sciences - complex tasks
914-4	Occupations in economics - highly complex tasks
921-2	Occupations in advertising and marketing - skilled tasks
921-3	Occupations in advertising and marketing - complex tasks
921-4	Occupations in advertising and marketing - highly complex tasks
922-3	Occupations in public relations - complex tasks
922-4	Occupations in public relations - highly complex tasks
923-2	Occupations in publishing and media management - skilled tasks
923-3	Occupations in publishing and media management - complex tasks
923-4	Occupations in publishing and media management - highly complex tasks
924-2	Occupations in editorial work and journalism - skilled tasks
924-3	Occupations in editorial work and journalism - complex tasks
924-4	Occupations in editorial work and journalism - highly complex tasks
931-2	Occupations in product and industrial design - skilled tasks
931-3	Occupations in product and industrial design - complex tasks
931-4	Occupations in product and industrial design - highly complex tasks
932-2	Occupations in interior design, visual marketing, and interior decoration - skilled tasks
932-3	Occupations in interior design, visual marketing, and interior decoration - complex tasks
932-4	Occupations in interior design, visual marketing, and interior decoration - highly complex tasks
933-2	Occupations in artisan craftwork and fine arts - skilled tasks
933-3	Occupations in artisan craftwork and fine arts - complex tasks
933-4	Occupations in artisan craftwork and fine arts - highly complex tasks
934-2	Artisans designing ceramics and glassware - skilled tasks
934-3	Artisans designing ceramics and glassware - complex tasks
935-2	Artisans working with metal - skilled tasks
935-3	Artisans working with metal - complex tasks
935-4	Artisans working with metal - highly complex tasks
936-2	Occupations in musical instrument making - skilled tasks
936-3	Occupations in musical instrument making - complex tasks
936-4	Occupations in musical instrument making - highly complex tasks
941-4	Musicians, singers and conductors - highly complex tasks
941-3	Musicians, singers and conductors - complex tasks
942-4	Actors, dancers, athletes and related occupations - highly complex tasks
942-2	Actors, dancers, athletes and related occupations - skilled tasks
942-3	Actors, dancers, athletes and related occupations - complex tasks
943-3	Presenters and entertainers - complex tasks
943-4	Presenters and entertainers - highly complex tasks
943-2	Presenters and entertainers - skilled tasks
944-2	Occupations in theatre, film and television productions - skilled tasks
944-3	Occupations in theatre, film and television productions - complex tasks
944-4	Occupations in theatre, film and television productions - highly complex tasks

945-2	Occupations in event technology, cinematography, and sound engineering - skilled tasks
945-3	Occupations in event technology, cinematography, and sound engineering - complex tasks
945-4	Occupations in event technology, cinematography, and sound engineering - highly complex tasks
946-2	Occupations in stage, costume and prop design, - skilled tasks
946-3	Occupations in stage, costume and prop design, - complex tasks
946-4	Occupations in stage, costume and prop design, - highly complex tasks
947-4	Technical and management occupations in museums and exhibitions - highly complex tasks
947-2	Technical and management occupations in museums and exhibitions - skilled tasks
947-3	Technical and management occupations in museums and exhibitions - complex tasks
011-4	Commissioned officers - highly complex tasks
012-3	Senior non-commissioned officers and higher - complex tasks
013-2	Junior non-commissioned officers - skilled tasks
014-2	Armed forces personnel in other ranks - skilled tasks

Appendix B
Definition of Variables

Variable	Description
Wage and AKM components	
wage	Imputed real log daily wage. The base year for the inflation adjustment using the Consumer Price Index is 2010. Source: BeH.
person FE	Person fixed effect from the AKM-type regression. The implementation and interpretation of the AKM-type regression are explained in detail in Section 3.3.1.
establishment FE	Establishment fixed effect from the AKM-type regression. The implementation and interpretation of the AKM-type regression are explained in detail in Section 3.3.1.
Xb	Combination of life cycle and aggregate factors from the AKM-type regression. The implementation and interpretation of the AKM-type regression are explained in detail in Section 3.3.1.
residual (wage)	Residual wage from the AKM-type regression. The implementation and interpretation of the AKM-type regression are explained in detail in Section 3.3.1.
Occupational characteristics	
HWI	Variance of wages within an occupation-task group and establishment. The calculation of the horizontal wage inequality (HWI) is explained in Section 3.2.
RWI	Variance of residual wages within an occupation-task group and establishment. The calculation of the residual wage inequality (RWI) is explained in detail in Section 3.2.
analytical nonroutine tasks	Fraction of analytical nonroutine tasks in an occupation. Source: Dengler, Matthes and Paulus (2014).
interactive nonroutine tasks	Fraction of interactive nonroutine tasks in an occupation. Source: Dengler, Matthes and Paulus (2014).
occupational complexity	Level of task complexity of an occupation-task group according to the KldB2010 occupational classification scheme. *1* stands for unskilled/semi-skilled tasks, *2* for skilled tasks, *3* for complex tasks, and *4* for highly complex tasks. Source: BeH, BHP.
Establishment characteristics	
HWI_{estab}	Mean within occupation-task group variance of wages within an establishment. The calculation of the horizontal wage inequality (HWI) is explained in detail in Section 3.2.
RWI_{estab}	Mean within occupation-task group variance of residual wages within an establishment. The calculation of the residual horizontal wage inequality (HWI) is explained in detail in Section 3.2.

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Variable	**Description**
number of occupation-task groups	Number of occupation-task groups using the first three digits plus the fifth digit of the KldB 2010 classification scheme. Source: BeH.
empl_{estab}	Number of full-time employees in an establishment. Source: BeH, BHP.
analytical nonroutine tasks_{estab}	Mean fraction of analytical nonroutine tasks in an establishment. Source: BeH, Dengler, Matthes and Paulus (2014).
interactive nonroutine tasks_{estab}	Fraction of interactive nonroutine tasks in an establishment. Source: BeH, Dengler, Matthes and Paulus (2014).
occupational $\text{complexity}_{estab}$	Mean occupational complexity in an establishment. Source: BeH, BHP.
profit sharing	Number of employees in an establishment who participate in profit sharing, divided by total number of employees of the establishment. Source: BP.
written employee assessment	Dummy variable that indicates whether the establishment conducts written assessments of employees. Source: BP.
written employee targets	Dummy variable that indicates whether an establishment has written target agreements with employees. Source: BP.
Firm characteristics	
HWI_{firm}	Mean within occupation-task group variance of wages within a firm. The calculation of the horizontal wage inequality (HWI) is explained in detail in Section 3.2.
RWI_{firm}	Mean within occupation-task group variance of residual wages within a firm. The calculation of the residual horizontal wage inequality (HWI) is explained in detail in Section 3.2
empl_{firm}	Number of full-time employees in a firm. Source: BeH, BHP, Orbis-ADIAB.
multi-establishment firm	Dummy indicating whether the establishment belongs to a firm with multiple establishments. Source: Oribs-ADIAB.
number of establishments	Number of establishments that belong to a firm. Source: Oribs-ADIAB.
analytical nonroutine tasks_{firm}	Mean fraction of analytical nonroutine tasks in a firm. Source: BeH, Orbis-ADIAB, Dengler, Matthes and Paulus (2014).
interactive nonroutine tasks_{firm}	Fraction of interactive nonroutine tasks in a firm. Source: BeH, Orbis-ADIAB, Dengler, Matthes and Paulus (2014).
occupational complexity_{firm}	Mean occupational complexity in a firm. Source: BeH, Orbis-ADIAB.
ebitda to assets_{firm}	Ratio of a firm's ebitda to total assets. Source: Orbis.
ebit to assets_{firm}	Ratio of a firm's ebit to total assets. Source: Orbis.

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Appendix B continued

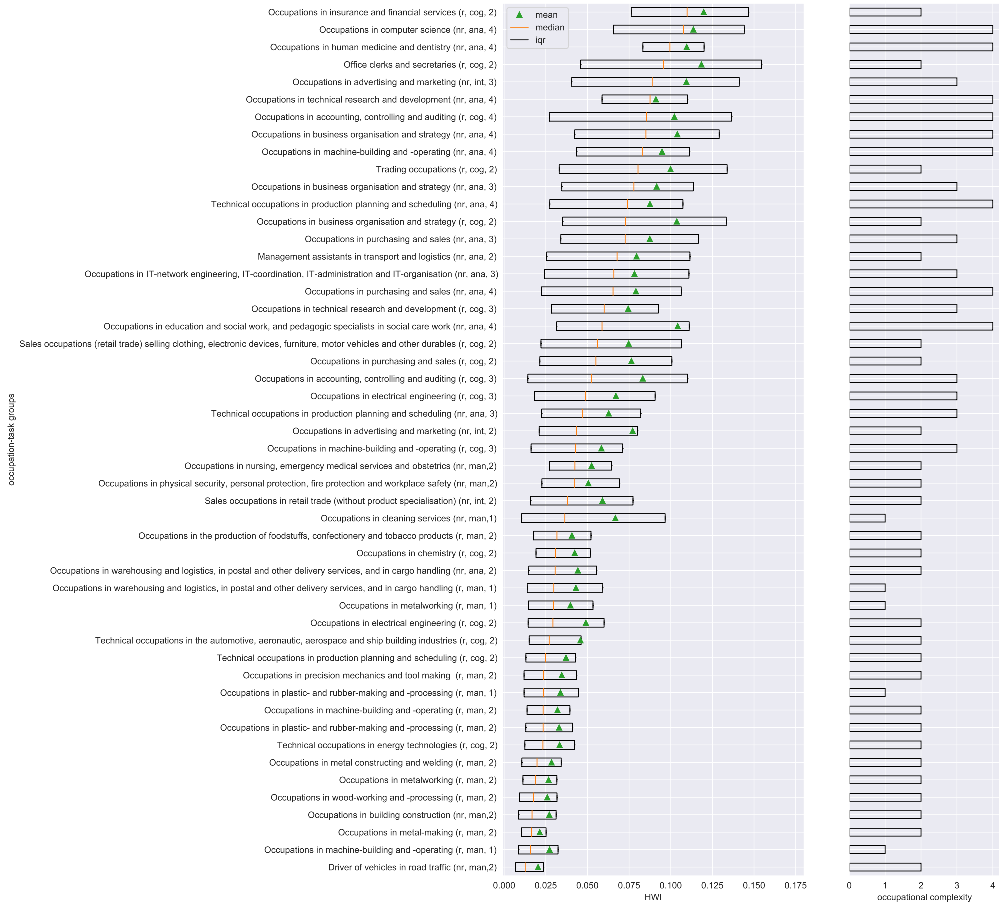
Variable	Description
net income to assets$_{firm}$	Ratio of a firm's net income to total assets. Source: Orbis.
cash flow to assets$_{firm}$	Ratio of a firm's cash flow to total assets. Source: Orbis.
log(total assets)	Natural logarithm of a firm's total assets (CPI-adjusted to the base year 2010). Source: Orbis.
leverage	Ratio of a firms' debt to the sum of debt and shareholders' funds. Debt is defined as the sum of loans and long-term debt. Source: Orbis.
tangibility	Ratio of a firm's tangible assets to its total assets. Source: Orbis.
cash holdings	Ratio of a firm's cash holdings to its total assets. Source: Orbis.
listing dummy	Dummy indicating whether the firm is listed on a stock exchange. Source: BeH, BHP, Orbis.

BeH stands for Beschäftigten-Historik provided by the Institute of Employment Research, *BHP* for Betriebshistorik Panel provided by the Institute of Employment Research, *BP* for Betriebspanel provided by the Institute of Employment Research, and *Orbis* for the Orbis database by Bureau van Dijk.

Appendix C

Horizontal wage inequality and occupation-task groups

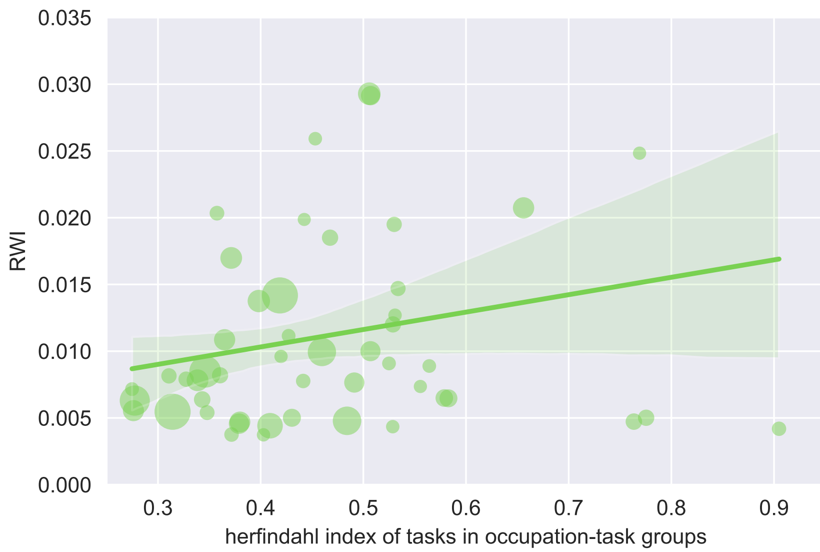
This figure shows the horizontal wage inequality (HWI) in different occupation-task groups. We limit this analysis to the 50 most common occupation-task groups in our sample; they account for approximately 70% of the employee-years. The occupation-task groups are sorted by the median value of the HWI measure. A detailed description of all variables can be found in Appendix B.



Appendix D

RWI and unobserved task heterogeneity within occupation-task groups

This figure illustrates the relation between task heterogeneity and residual wage inequality (RWI) in different occupation-task groups. RWI captures wage differences among employees with similar characteristics in the same occupation-task group. We limit this analysis to the 50 most common occupation-task groups in our sample; they account for approximately 70% of the employee-years. We measure the task heterogeneity of an occupation-task group by the Herfindal index of the fraction of analytical nonroutine tasks, interactive nonroutine tasks, cognitive routine tasks, manual nonroutine tasks, and manual routine tasks. A detailed description of all variables can be found in Appendix B.



Appendix E

Firm size, task complexity, and RWI: controlling for mean occupation size

This table repeats the analysis shown in Table 4 controlling for occupation size, measured as the logarithm of the mean number of emplozees in an occupation in a firm. The dependent variable is a firm's residual wage inequality (RWI). RWI captures wage differences among employees with similar characteristics in the same occupation-task group. The task-based measures, which follow Autor, Levy and Murnane (2003), capture the average share of analytical nonroutine and interactive nonroutine tasks in a firm. Occupational complexity is based on the fifth digit of the KldB2010 occupational classification scheme and captures the average task complexity level of occupation-task groups in a firm. The regression models are estimated on the employee-year level. T-statistics based on robust standard errors clustered at the firm level are presented in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. A detailed description of all variables can be found in Appendix B.

	(1)	(2)	(3)	(4)
$\log(\text{empl})_{firm}$	0.0010***			
	(5.69)			
analytical nonroutine tasks_{firm}		0.025***		
		(22.25)		
interactive nonroutine tasks_{firm}			0.018***	
			(10.42)	
occupational complexity_{firm}				0.0061***
				(21.32)
$\log(\text{mean occupation empl})_{firm}$	0.0011***	0.0020***	0.0020***	0.0021***
	(5.99)	(23.02)	(21.49)	(22.76)
Year FE	Yes	Yes	Yes	Yes
County x year FE	Yes	Yes	Yes	Yes
Industry x year FE	Yes	Yes	Yes	Yes
Obs	69,250,918	69,250,918	69,250,918	69,250,918
R2	0.45	0.47	0.45	0.47