Horizontal Wage Inequality within Firms

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Abstract

This paper sheds new light on firms' horizontal wage inequality (HWI), that is, wage differences among employees who perform similar tasks. Using employee-level data for 87,440 German firms, we find that HWI accounts for half of the within-firm wage inequality. Three-quarters of HWI results from heterogeneous employee characteristics. The remaining quarter is higher in occupations with more task complexity, larger firms, larger establishments within firms, and establishments with profit sharing and stringent employee assessment, and it is positively correlated with profitability and innovativeness. Our results point to incentive pay as a plausible explanation for HWI among employees with similar characteristics.

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1. Introduction

Within-firm wage inequality can arise because employees who perform different tasks earn different wages ("vertical wage inequality," henceforth VWI) or due to wage differences among employees with similar tasks ("horizontal wage inequality," HWI). While VWI is well documented in the financial economics literature (Mueller, Ouimet and Simintzi, 2017a,b),[1] surprisingly little is known about HWI. How relevant is HWI for within-firm wage inequality? What fraction of HWI is explained by heterogeneous employee characteristics? Can monetary rewards for employee performance, which we refer to as incentive pay, explain the part that is not related to employee characteristics? And how is HWI connected to firm outcomes?

To shed light on these questions, we use a novel dataset that links employee-level information from the German social security system with firm-level data from Bureau van Dijk's Orbis database. We measure HWI as the variance of log wages of employees in the same occupation and establishment for a sample that covers 16,630,960 employees, 205,858 establishments, and 87,440 firms between 2010 and 2016. Using a fine-grained occupational classification scheme, which differentiates 431 occupations from 144 occupational groups and up to four levels of task complexity within these groups, enables us to identify employees who perform similar tasks within firms.[2]

We find that HWI accounts for half of the within-establishment wage differences. The importance of HWI raises the question of why firms pay employees who perform similar tasks differently, especially because wage inequality is a hotly debated topic among regulators, policy makers, and the general public. First, HWI can result from the within-occupation heterogeneity of employee characteristics if these characteristics affect wages in competitive labor markets. Examples for such characteristics include ability, experience, and education, which ultimately determine an employee's productivity (Katz and Murphy, 1992). Second, HWI can result from wage policies of firms that lead to employee-employer-specific wage premiums such as incentive-pay schemes.

[1]Mueller, Ouimet and Simintzi measure within-firm wage inequality as wage differences between the hierarchy levels of a firm, which corresponds to VWI.

[2]Examples of occupational groups are occupations in computer science, office clerks and secretaries, or drivers of vehicles in road traffic. Appendix A.1 provides a description of the classification scheme, and Appendix A.2 the complete list of all 431 occupations.

To decompose HWI into components related to the remuneration of heterogeneous employee characteristics and employee-employer-specific wage adjustments, we estimate 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 Abowd, Kramarz and Margolis (1999) (henceforth AKM).[3] In this model, the remuneration for an employee's characteristics is captured by control variables and an employee fixed effect that is identified by employees who switch employers over time. This unobserved, permanent wage component (such as return to schooling or innate ability) is specific to an employee but not to an employee-employer combination. We find that three-quarters of the overall HWI is related to the remuneration for heterogeneous employee characteristics within occupations.[4]

The remaining quarter of the HWI, which we refer to as residual HWI, is related to employee-employer-specific wage adjustments. A potential explanation for such wage adjustments is provided by incentive-pay schemes. Examples of incentive pay include merit-based pay, bonus payments, or piece rates (Lazear, 2018). Incentive pay, which links employees' wages to their performance, creates dispersed wages within occupations due to performance differences across employees and over time (Seiler, 1984; Lemieux, MacLeod and Parent, 2009). Alternative explanations for employee-employer-specific wage adjustments are provided by idiosyncratic match effects between employees and employers that occur if employees' productivity differs across firms, for example, due to complementarities or drifts in the portable component of employees' earnings power (see CHK for a detailed discussion).

Our empirical framework does not directly allow us to decompose residual HWI into incentive pay and other factors, such as match effects. However, two alternative empirical strategies enable us to shed light on the role of incentive pay. We start by analyzing the relationship between residual HWI and

[3]We use an implementation of the AKM model that is similar to Card, Heining and Kline (2013) (henceforth CHK). The AKM model is widely used in labor economics (e.g., CHK; Card et al., 2018; Song et al., 2019) and, more recently, in financial economics (e.g., Matveyev, 2017; Babina et al., 2019; He and le Maire, 2019).

[4]As a side result, we show that VWI is nearly exclusively explained by differences in employee characteristics. This result supports the conclusions of Mueller, Ouimet and Simintzi (2017b), who document that wage differences across hierarchy levels are associated with larger firms and higher firm performance and explain this result by means of differences in managerial talent.

establishment-level characteristics that are based on survey data for a smaller sample. These characteristics are the existence of profit-sharing programs, written employee assessments, and written employee targets in an establishment. If residual HWI reflects incentive pay, we would expect to find a positive correlation with profit sharing, which is one component of incentive pay. For employee assessments and targets, we would also expect to find a positive correlation because both the measurement of employee performance and the existence of objective evaluation criteria are key ingredients of incentive-pay schemes. The fact that we indeed find a strong positive correlation between all three characteristics and residual HWI is in line with the view that residual HWI captures incentive pay.

After that, we exploit that incentive-pay schemes are conceptually linked to monitoring cost. Firms can use incentive pay to reduce their agency conflicts with employees (Ross, 1973), which is especially important when monitoring is costly because employees' actions are difficult to observe or because of uncertainty about their optimal actions (Holmstrom, 1979; Prendergast, 2002). We first approximate uncertainty about optimal actions by considering the task complexity of an occupation. For the measurement of task complexity, we rely on the classification scheme of Autor, Levy and Murnane (2003) and the occupational complexity according to our occupational classification scheme. We find that residual HWI is higher in occupations with high complexity and more analytical and interactive tasks that do not follow a routine (e.g., engineering and science) and lower in occupations with mainly manual tasks (e.g., cleaning and vehicle driving).[5] Second, we use firm size as a proxy for uncertainty about employees' actions (Garen, 1985). We find that residual HWI increases monotonically with size and more than doubles when comparing the smallest firm decile to the largest. These results document a positive relationship between residual HWI and monitoring cost, which again points to incentive pay as a plausible explanation for residual HWI.

When we regress residual HWI on firm size in a model with county times year and industry times year fixed effects, the coefficient estimate for firm size, which is statistically significant at the 1% level, shows that residual HWI is

[5] Among the largest 50 occupations, the five with the highest residual HWI 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).

about 12.5% higher, relative to its mean, for a firm that has twice as many employees. We also find that a one-standard-deviation increase in the fraction of analytical nonroutine tasks is associated with a 19.7% higher residual HWI, which is again statistically significant at the 1% level. The corresponding values for interactive nonroutine tasks and occupational complexity are 10.1% and 17.1%, respectively. To mitigate concerns about unobservable firm heterogeneity, we alternatively focus on multi-establishment firms and show that the same patterns exist when we add firm times year fixed effects and compare the size and task complexity of different establishments within the same firms.

Lastly, we link residual HWI to firm outcomes. Incentive pay, which, according to our previous findings, is captured by residual HWI, is potentially important for the motivation of employees and, therefore, for firms' performance and innovativeness (Lazear and Rosen, 1981; Baker, Jensen and Murphy, 1988; Manso, 2011). We find a positive correlation between residual HWI and EBITDA, EBIT, net income, and cash flow, all scaled by total assets. For instance, a one-standard-deviation increase in residual HWI is associated with a seven-percent increase in EBIT, relative to its mean. For firm innovativeness, we find that a one-standard-deviation increase in residual HWI is associated with a one-third increase in patents. Residual HWI is also correlated with more patents per employee and a higher degree of patent quality, as indicated by more overall citations and more citations per patent. Although our setting makes it difficult to draw causal inferences, these results are in line with the view that residual HWI captures incentive-provision to employees, which increases their motivation and, ultimately, firm profitability and innovativeness.

Robustness tests address potential concerns regarding our occupational classification, the AKM model, and the role of unions. First, we conduct all empirical tests using the five-digit classification of KldB2010, which distinguishes 1,286 occupations (instead of the 431 occupations in our baseline classification scheme). Despite a substantially smaller number of employees per occupation, all the results are very similar to our main specification. Second, we discuss the "conditional random mobility" assumption of the AKM model and approximate the importance of heterogeneous employee characteristics for HWI without the AKM model. For this purpose, we estimate the average within-employee variance of wages over time and compare it to the overall wage variation within occupations. We find that wage inequality after controlling for heterogeneous employee characteristics accounts for one quarter of the overall HWI, which is nearly identical to our AKM model-based estimation. Lastly, we show that unionization has a positive impact on residual HWI, but this relationship disappears when we control for establishment size. This finding mitigates concerns that our results are not representative for economies with lower unionization rates than Germany.

Our paper contributes to the literature on within-firm wage inequality. Mueller, Ouimet and Simintzi (2017a) and Mueller, Ouimet and Simintzi (2017b) measure within-firm wage inequality as pay differences between hierarchy levels of a firm, which corresponds to what we call VWI. In their first paper, they show that firm growth leads to more within-firm pay inequality. In the second paper, they document that firms that have higher pay inequality are, on average, larger and have higher valuations and stronger operating performance. Song et al. (2019) document the importance of wage differences within firms for the overall wage inequality in the economy. Other studies that are related to within-firm wage inequality include, for instance, Martins (2008), Barth et al. (2012), Green and Zhou (2019), and Gartenberg and Wulf (2020), but none of these focus on HWI.

We complement this literature by showing that (i) HWI accounts for half of the overall wage inequality within establishments, (ii) remuneration for heterogeneous employee characteristics explains three-quarters of the overall HWI, (iii) incentive pay is a plausible explanation for residual HWI, that is, wage inequality after controlling for heterogeneous employee characteristics, and (iv) this residual HWI is linked to better firm performance and higher innovativeness. These findings suggest that firms use HWI to incentivize employees and overcome agency conflicts. In this regard, we document a "bright" side of wage differences among employees that should not be overlooked in the debate on wage inequality.

We also contribute to the labor and finance literature by pointing out a potentially novel way to measure employee incentive pay. While generally accepted proxies for incentive-provision to top management have been developed and frequently explored in the financial economics literature,[6] empirical assess-

[6] Examples of studies that analyze the incentive pay of CEOs or other top managers are Jensen and Murphy (1990), Aggarwal and Samwick (2003), and Frydman and Saks (2010). Murphy (2013) and Edmans, Gabaix and Jenter (2017) provide an overview of the executive

ments of incentive pay in the context of employees is difficult (Prendergast, 1999), and the literature mostly relies on survey-based measures for small samples, often single firms (Gibbons, 1998; Lazear, 2018). Our results suggest that residual HWI captures employees' financial incentives. This measure has multiple advantages over survey-based measures. First, it can be estimated for all firms or establishments with employee-level wage information. Second, survey-based measures typically focus on specific forms of incentive pay.[7] Residual HWI is more general and captures all pay methods that lead to employee-specific wage premiums, including implicit incentive-pay schemes and those formally written down in contracts (Bloom and Van Reenen, 2011). Third, residual HWI is based on administrative data, which cannot be manipulated or selectively reported by firms. Lastly, residual HWI captures the extent, not only the existence, of incentive pay.

2. Sample and 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. Similar to CHK and Bellmann et al. (2020), who use the same data source, we only include full-time jobs (excluding marginal employment and apprenticeship) held by employees aged 20 to 60 from 2010 to 2017. We then calculate the average daily wage by dividing the total earnings by the total duration of the main employment spell.[9]

compensation literature.

[7] Lemieux, MacLeod and Parent (2009), for instance, use questions from the Panel Study of Income Dynamics to identify employees who received performance pay in the form of bonuses, commissions, or piece rates.

[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

The occupation information includes the job title of an employee at a firm for a particular year. The employers allocate occupation codes to each of their employees in each year 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 levels of task complexity within occupational groups. Because not all complexity levels exist for all occupations, our final dataset includes 431 unique occupations 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 recently available ORBIS-ADIAB dataset, which provides a linking table between the IAB internal (system-free) establishment identifiers and the firm identifiers by BvD. Comprehensive documentation of the linking process is provided by Antoni et al. (2018). 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] 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

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 classification of KldB2010 distinguishes 1,286 occupations in our sample, which reduces the number of employees per occupation substantially. Nevertheless, we repeat our analyses using the five-digit classification scheme when we address robustness in Section 6.1.

[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% 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.

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% of employees work in firms with more than one establishment.

3. Measurement and decomposition of HWI

3.1. Measurement of HWI

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% of the overall wage inequality in the economy.[13]

To distinguish wage differences among employees with similar tasks from those among employees with different tasks, we would ideally use information on the exact tasks of employees. However, this information is not available. As an alternative approach to identify employees who perform similar tasks,

[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.

we rely on a fine-grained occupational classification scheme with 431 occupations that differentiates various degrees of task complexity within occupations (see Section 2 for more details). 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. 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.

3.2. Decomposition of HWI

To better understand its determinants, we decompose the overall 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.

3.2.1. The AKM model

The AKM model assumes that the log real daily wage $y_t^{i,j}$ is an additively separable function of a time-invariant employee fixed effect α^i, an establishment fixed effect ψ^j[14], an index of time-varying observable characteristics X_t^i, and an error term $r_t^{i,j}$. X_t^i includes an unrestricted set of year dummies and quadratic and cubic terms in age[15] fully interacted with educational attainment. In order to estimate the parameters, we run the following regression model on the largest connected set of establishments that are linked by employee transitions from 2010 to 2017:

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

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

[15] 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.

The error term $r_t^{i,j}$ is the residual wage of employee i at establishment j. It captures employee-employer-specific wage adjustments that can exist because of incentive-pay schemes that reward the performance of individual employees, idiosyncratic match effects between employees and employers, for example, due to complementarities between employers and employees, drifts in the portable component of employees' earning power, or measurement errors (see CHK, p. 987, for a more detailed discussion).

The AKM model estimates the remuneration for an employee's characteristics by means of control variables (βX_t^i) and an employee fixed effect (α^i) that is identified by employees who switch employers over time.[16] This unobserved, permanent wage component is specific to an employee, but not to an employee-employer combination. A critical assumption of the AKM model is conditional random mobility, which we discuss when we address robustness in Section 6.2.

3.2.2. Variance decomposition

We use the parameter estimates from Equation 3 to decompose the variance of wages into a component that is related to remuneration for heterogeneous employee characteristics and the variation of residual wages. The variance decomposition of overall wages within establishments can be written as follows:

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

The results are reported in Table 2 and graphically illustrated in Figure 1. For the overall wage inequality within establishments, nearly 85% is explained by the heterogeneity of employee characteristics. Most of the explanatory power derives from employee fixed effects, not from observable, time-variant

[16] 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% of all employees switch employers at least once.

employee characteristics. For HWI, we find that remuneration for heterogeneous employee characteristics accounts for about three-quarters of the wage variation within occupations. Again, most of the explanatory power derives from employee fixed effects. The variance of the residuum component accounts for about one-quarter of the HWI. For VWI, we find an even higher explanatory power of heterogeneous employee characteristics, which account for over 95% of the wage variance between occupations.[17]

4. Residual HWI and incentive pay

The residual HWI, which accounts for one-quarter of the overall HWI, captures the part of the HWI that cannot be explained by remuneration for heterogeneous employee characteristics. The residual HWI of an establishment j or firm f in year t can be written as

$$\begin{aligned} Residual\ HWI_t^j &= \sum_o w_t^{o,j} \cdot var_t^{o,j}(r_t^{i,j}) \\ Residual\ HWI_t^f &= \sum_o w_t^{o,f} \cdot var_t^{o,f}(r_t^{i,j}), \end{aligned} \tag{5}$$

where $w_t^{o,j}$ is the fraction of employees in occupation o at establishment j in year t, $w_t^{o,f}$ the fraction of employees in occupation o at firm f in year t, $var_t^{o,j}(y_t^{i,j})$ the residual wage dispersion within occupation o and establishment j, and $var_t^{o,f}(y_t^{i,j})$ the residual wage dispersion within occupation o and firm f.

This component of the HWI is related to employee-employer-specific wage adjustments, which can result from incentive-pay schemes that reward the performance, idiosyncratic match effects, or other factors discussed in Section 3.2.1. Our empirical framework does not allow us to decompose residual HWI directly into incentive pay and those other factors. As an alternative approach to shed light on the role of incentive pay for residual HWI, we exploit differences in the characteristics of establishments (profit sharing, employee assessment, and employee targets) that are based on survey data and the fact that incentive pay is conceptually linked to monitoring cost. Although neither

[17] 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.

of these two approaches will allow us to exclude other factors as potential determinants, they will enable us to understand better the importance of incentive pay for residual HWI.

4.1. Residual HWI and survey-based establishment characteristics

For this test, we rely on information from the IAB establishment panel (Betriebspanel, BP). In this representative survey, establishments are asked multiple questions, including the fraction of employees that participate in profit sharing, the existence of written employee assessment, and whether or not employees have clear, written targets.[18] For legal reasons, we cannot link the survey data with information on firm structures. Hence, we only observe employee-establishment information in the survey sample.

4.1.1. Profit sharing

We first use survey data on the use of profit-sharing programs in establishments. If residual HWI captures incentive pay, we expect it to be higher in establishments with more profit-sharing.

We observe information on profit sharing for about 3.3 million employee-years, 2.0 million employees, and 16,553 establishments. On average, 37% of employees participate in the establishment's profit-sharing program. To test whether a greater extent of profit sharing in establishments is correlated with residual HWI, we regress residual HWI on the fraction of employees who participate in a profit-sharing program using the following regression specification:

$$Residual\ HWI_t^j = \alpha + \beta profit\ sharing_t^j + \gamma log(emp_t^j) + \lambda^j \cdot \tau_t + \kappa^j \cdot \tau_t + \epsilon_t^j, \tag{6}$$

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 the three-digit WZ2008 industry classification), 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.

[18] The technical report by Bechmann et al. (2017) provides further details on the dataset. The question on profit sharing was asked in 2011, 2013, and 2015. The questions on written employee assessment and written targets were asked in 2011 and 2013.

The results are shown in Panel A of Table 3. We start with a simple specification without fixed effects in Column 1. The coefficient estimate for β is 0.0064 with a t-value of 4.75 in this specification, which implies that residual HWI increases by 49.2%, relative to its mean,[19] for a hypothetical establishment that changes the share of employees participating in a profit-sharing program from zero to one. The coefficient estimate remains unchanged when we add year fixed effects in Column 2. The magnitude of the coefficient estimate drops to 0.0023, but the statistical significance increases (t-value of 8.21 versus 4.67) 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).

4.1.2. Written employee assessments and targets

The establishments were also asked whether written employee assessments and written target agreements with employees exist. Both aspects of human resource management are indirectly related to incentive pay: employees' wages can only be linked to their performance if their performance is measured and if there are objective criteria that determine their performance. Thus, comprehensive employee assessment and target-setting are key ingredients of incentive-pay schemes. Bloom and Van Reenen (2011) provide more background on incentive pay and human resource management.

We observe information on employee assessment and target setting for about 2.2 million employee-years, 1.6 million employees, and 14 thousand establishments. On average, 77% of employees experience written employee assessments. The corresponding percentage for written employee targets is 69%. In terms of methodology, we follow Equation 6 and replace $profit\_sharing_t^j$ with $written\_employee\_assessment_t^j$ and $written\_employee\_targets_t^j$.

The results for employee assessment are shown in Panel B of Table 3. We again start with a simple specification without fixed effects in Column 1. The coefficient estimate for β is 0.0034 with a t-value of 3.88, which implies that residual HWI increases by 26.2%, relative to its mean,[20] for an establishment that introduces written employee assessments. The coefficient estimate re-

[19]The mean of the residual HWI for the survey data sample on profit sharing is 0.013, and the standard deviation is 0.0097.

[20]The mean of the residual HWI for the survey data sample on written employee assessments and written target agreements is 0.013, and the standard deviation is 0.0098.

mains unchanged when we add year fixed effects in Column 2. The magnitude of the coefficient estimate drops substantially once we control for county-year- and industry-year fixed effects in Column 3, and it becomes statistically insignificant when we additionally control for establishment size in Column 4. These results point to a positive correlation between residual HWI and the existence of formal employee assessment. However, this correlation seems to be substantially driven by the size differences between establishments.

In Panel C of Table 3, we focus on written employee targets using the same regression specifications as for profit sharing and employee assessments. The coefficient estimate of 0.0039 (t-value 4.05) in Column 1 indicates that residual HWI increases by 30%, relative to its mean, when an establishment introduces written employee targets. The coefficient estimates is unchanged when we introduce year-fixed effects in the next column. In Column 3, we add county-year and industry-year fixed effects, which reduces the coefficient estimate to 0.0014 (t-value 4.28). Additionally controlling for establishment size further reduces the estimate to 0.00074 (t-value 2.16). These results indicate that residual HWI is positively correlated with the existence of written employee targets.

4.2. Residual HWI and monitoring costs

Our second strategy to shed light on the relevance of incentive pay for residual HWI exploits that incentive pay is conceptually linked to monitoring cost. In our tests, we rely on variations in monitoring cost due to occupational characteristics and the size of establishments.

4.2.1. Conceptual framework

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 pay methods that reward employee performance. Their relative attractiveness depends on the monitoring costs of a firm. If monitoring costs are low, the firm is likely better off monitoring its employees instead of using incentive-pay schemes, which also come at a cost for firms.[21]

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

However, if monitoring costs are high, incentive pay becomes more attractive for firms than monitoring. In this context, the model of Prendergast (2002) predicts that the use of incentive pay should increase with monitoring cost, and the model of Lazear (1981) suggests that age-earnings profiles should increase with monitoring cost. The empirical literature, which finds that the use of incentive pay increases with monitoring cost, provides support for these predictions (e.g., Brown, 1990; Drago and Heywood, 1995; Barth et al., 2008).

What determines monitoring cost? Two important factors that we can exploit in our empirical tests are the observability of employees' actions and uncertainty about their optimal actions (Holmstrom, 1979; Prendergast, 2002). The observability of employees' actions depends, among other characteristics, on the size of an establishment. Garen (1985) develops a model in which compensation contracts differ between large and small firms because of their differences in monitoring costs. An important ingredient of his model is that larger firms have higher costs of acquiring information about employees and lower accuracy when screening employees. Uncertainty about optimal actions is closely related to the characteristics of employees' tasks (Holmstrom and Milgrom, 1991), and firms choose compensation policies that fit those characteristics (Holmstrom and Milgrom, 1994; MacLeod and Parent, 2012). In this context, the Prendergast (2002) model predicts that incentive pay is more likely in occupations that involve complex tasks that are more difficult to monitor due to greater uncertainty regarding employees' optimal actions.

4.2.2. Task complexity of occupations: Descriptive evidence

To assess the task complexity of an occupation, we rely on two classification schemes. First, we use the scheme proposed by Autor, Levy and Murnane (2003), who distinguish between routine and nonroutine tasks, that is, whether or not the optimal actions to carry out tasks follow an explicit procedure. Furthermore, they distinguish between analytical, interactive, and manual tasks. 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. Overall, Autor, Levy and Murnane distinguish five types of tasks: analytical nonroutine, interactive nonroutine, cognitive routine (which is a combination of analytical and interactive routine), manual nonroutine, and manual routine.

Task complexity is highest in nonroutine analytical and nonroutine interactive tasks, followed by routine cognitive tasks, and lowest in nonroutine and routine manual tasks.[22] 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 within occupational sub-groups (see Appendix A for more details).

We first sort occupations by their median residual HWI in Figure 2(a).[23] 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 residual HWI 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 residual HWI have mainly manual tasks (four routine, one nonroutine).

Figures 2(b) to (f) illustrate the relation between occupations' task composition and residual HWI. 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% confidence interval. We find that the fraction of analytical nonroutine tasks and interactive nonroutine tasks has a positive relationship with residual HWI.[24] For all other tasks, we detect a flat or negative relationship. These results indicate that residual HWI is higher in occupations with more complex tasks that are more costly to monitor due to their higher uncertainty about optimal actions.

4.2.3. Firm/establishment size: Descriptive evidence

Next, we present a graphical analysis of the relationship between the different types of wage inequality and firm size. In Figure 3, we sort firms into

[22] 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. We use the classification from 2013.

[23] The occupation-level residual wage variance 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% of the employee-years in our dataset, for the analyses in Figure 2.

[24] These patterns cannot be explained by higher task heterogeneity in occupations with analytical or interactive tasks. Appendix C shows that the relationship between (residual) HWI and task concentration is flat or even slightly positive.

deciles based on their number of full-time employees and calculate, for each decile, the average within-establishment variance of overall and residual wages.

Figure 3(a) shows that the variance of wages within firms increases monotonically with their size, from about 0.108 in the smallest decile, with an average of 32 employees, to about 0.152 in the largest decile, with an average of 50,625 employees. When we split the overall wage inequality into HWI and VWI, we find that VWI is responsible for slightly more than half of the overall wage inequality in the smallest firms. For the largest firms, their relative importance reverts, and HWI contributes slightly more to the overall wage inequality than does VWI. This shift in the relative importance of HWI and VWI exists because HWI increases monotonically with establishment size, while VWI is relatively flat for the first nine deciles but increases substantially in the tenth decile.

In Figure 3(b), we focus on residual wage inequality, that is, the wage inequality after adjusting for remuneration of heterogeneous employee characteristics. Similar to overall wage inequality, residual wage inequality increases with firm size, from about 0.0138 in decile one to 0.0265 in decile ten. All of this increase is driven by residual HWI, which more than doubles from decile one to ten, while residual VWI declines with size. Using establishment size instead of firm size in Figures 3(c) and (d) leads to similar results. These findings provide further support for the view that residual HWI captures incentive pay since the observability of employees' actions is lower in larger firms, which increases their monitoring cost and their need for incentive pay to mitigate agency problems.

4.2.4. Regression analysis

We conduct regressions to further analyze the relationship between residual HWI, task complexity, and firm size. First, we regress the residual HWI of a firm, which is calculated over all its employees and establishments, on the number of full-time employees:

$$Residual\ HWI_t^f = \alpha + \beta log(emp_t^f) + \lambda^f \cdot \tau_t + \kappa^f \cdot \tau_t + \epsilon_t^f, \tag{7}$$

where $log(emp_t^f)$ is the size of firm f in year t, α a constant, and ϵ the error term. We also 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 are presented in Column 1 of Table 4. The coefficient estimate for $log(emp_t^f)$ is positive and statistically significant at the 1% level. The magnitude of β is 0.0020, which indicates that the residual HWI is about 12.5% higher, relative to its mean, for a firm that has twice as many employees.[25]

In Columns 2 to 4, we analyze our measures for task complexity. Similar to our descriptive analysis in Section 4.2.2, 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. The regression specification follows Equation 7, except that we replace $log(emp_t^f)$ with our task complexity measures. For all measures, we find that residual HWI 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% higher residual HWI, relative to its mean. The corresponding values for interactive nonroutine and occupational complexity are 10.1% and 17.1%. In Column 5, we include all measures for size and task complexity in the regression at the same time. All of them remain positive and statistically significant at the 1% level.

Next, we use the establishment structure of 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.[26] 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

[25] 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 to the regression model in Column 1. It turns out that, on average, about half of the firm-size effect originates from larger occupations in larger firms.

[26] See Giroud and Mueller (2015) for a similar approach in the context of labor reallocation within firms.

analysis can be written as

$$Residual\ HWI_t^j = \alpha + \beta log(emp_t^j) + \lambda^j \cdot \tau_t + \kappa^j \cdot \tau_t + \eta^f \cdot \tau_t + \epsilon_t^j, \quad (8)$$

where $log(emp_t^j)$ is the size of establishment j in year t and $\eta^f \cdot \tau_t$ a firm-year fixed effect. The results are reported in Table 5. We find that residual HWI is higher in larger establishments and those that have more complex tasks. The magnitudes of the estimates for β are similar to the ones we documented before. Overall, our results show that residual HWI increases with firms' monitoring cost, which is in line with the view that it captures incentive pay. However, while our findings show that incentive pay is highly relevant for residual HWI, our empirical approach does not enable us to conclude that match effects or other potential determinants play no role.

5. Residual HWI and firm outcomes

After presenting evidence that residual HWI captures incentive-pay schemes, we analyze the link between residual HWI and firm performance and innovativeness.

5.1. Conceptual framework

The theoretical literature suggests that residual HWI can have ambiguous effects on employees' efforts. On the one hand, if fairness considerations prevailed, wage differences in the same occupation could demoralize employees and lead to less expended effort (Akerlof and Yellen, 1990). If this holds true, we expect to find lower performance and innovativeness in firms with higher residual HWI. On the other hand, theories such as the tournament theory (Lazear and Rosen, 1981) predict that more incentive pay increases employee effort, and Hochberg and Lindsey (2010) shows that firms in which employee stock options have higher implied incentives perform better. Manso (2011) and Hellmann and Thiele (2011) show theoretically that employee incentives are important for firm innovation. Accordingly, we expect a positive effect of incentive pay on performance and innovativeness. A third possibility is that incentive pay has no significant effect on employee behavior or firm outcomes, for example, because the relative importance of incentive pay for employees' total compensation is smaller compared to the top management.[27]

5.2. Empirical design

Our regression models exploit cross-sectional and time-series variation in residual HWI and firm outcomes. The regression specification for firm f and year t can be written as

$$Outcome_t^f = \alpha + \beta residual\ HWI_t^f + \vec{\gamma}\vec{C}_t^f + \lambda^f \cdot \tau_t + \epsilon_t^f, \tag{9}$$

where $Outcome_t^f$ is the outcome variable 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. Because we observe firm outcomes only at the firm level and not at the establishment level, it is not possible to exploit differences between establishments within firms for these tests.

5.3. Financial performance

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 6 presents the results. For all measures, we find a positive and statistically significant coefficient estimate for β. In terms of economic magnitude, the estimates imply that a one-standard-deviation increase in residual HWI is related to a 7.7% higher EBITDA, 6.7% higher EBIT, 8.2% higher net income, and 4.8% higher cash flow. Although we are careful not to draw causal inferences, these results are difficult to reconcile with a negative morale effect of incentive pay and more in line with a positive relationship between incentives and employee effort.

[27] Lemieux, MacLeod and Parent (2009), for instance, report that 37.5% of employees in their sample received performance pay in any given year of their employment relationship. However, less than 10% did so in more than half of those years, indicating that performance pay is not a major component of the compensation for most employees. By contrast, Guay, Kepler and Tsui (2019) report that the base salary accounts for less than 15% of the total compensation for the average CEO. The literature largely supports the view that such large managerial incentives lead to behavioral adjustments (e.g., Bergstresser and Philippon, 2006; Coles, Daniel and Naveen, 2006; Kale, Reis and Venkateswaran, 2009; Armstrong and Vashishtha, 2012).

5.4. Innovativeness

We apply three patent-based measures, which are based on the Orbis Intellectual Property database, to approximate the innovativeness of a firm: number of patents, number of citations, and number of citations per patent (please see Appendix B for details about the construction of the variables). We use the natural logarithm for all of these measures. While the first measure allows us to shed light on the amount of innovations of a firm, the citation-based measures capture their quality. The results are shown in Table 7. The coefficient estimates for β are all positive and statistically significant, which indicates that residual HWI is related to more and better innovation production. The coefficient estimates indicate that a one-standard-deviation increase in residual HWI is related to 36.6% more patents, 60.8% more citations, and 4.8% more citations per patent. These results are again in line with the view that incentive pay increases employee efforts, which is beneficial for firm innovativeness.

6. Robustness

6.1. More detailed occupational classification scheme

The choice of the occupational classification scheme involves the trade-off between higher accuracy of the classification and more observations per establishment-occupation-year. Our main scheme is based on the KldB2010 three-plus-fifth-digit classification and distinguishes 144 occupational groups with up to four levels of complexity, which yields 431 occupations (see Appendix A for details about the classification scheme). Alternatively, we use the full five-digit classification scheme of KldB2010, which distinguishes 700 occupational sub-groups with up to four levels of complexity, yielding 1,286 occupations. The advantage of this scheme is that employees in the same occupation are even more likely to conduct the same tasks than in our main classification scheme. In other words, the more fine-grained the occupational classification scheme is, the less likely it is that wage variations within occupations capture 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 firm-occupation-years.

We first decompose the within-establishment wage differences using the five-digit KldB2010 occupational classification in Appendix D: Table 1. The corresponding decomposition for our baseline three-plus-fifth-digit classification is shown in Table 1. The outcome of the decomposition is very similar for both classification schemes. The total wage variation within establishments, which is unaffected by the occupational classification scheme, is 0.118. For the five-digit scheme, the within-occupation wage variance is 0.055, which implies that HWI accounts for 46.6% of the overall wage variance. The corresponding numbers for the three-plus-fifth-digit scheme are 0.058 and 49.2%, respectively. Thus, only 2.6 percentage points are additionally attributed to HWI when using the more detailed classification scheme. The fraction of HWI that can be explained by heterogeneous employee characteristics is also very similar for both classification schemes (75.0% vs. 74.9%). This outcome mitigates concerns that our baseline results are biased by a measurement error of VWI as HWI due to too-broadly-defined occupations.

We then re-run all our analyses using the residual HWI based on the full five-digit occupational classification scheme.[28] We start with our survey-based analyses of establishment characteristics (see Table 3). The results for the five-digit industry classification are reported in Appendix D: Table 2. Comparing the models in Columns 1 without any fixed effects shows identical coefficient estimates for both occupational classifications. The coefficient estimates in the other models are also highly similar. Next, we focus on how monitoring costs affect residual HWI. The firm-level analysis of Table 4 is replicated in Appendix D: Table 3. The coefficient estimates are very similar in both tables. The differences for the establishment-level results are similarly small (see Table 5 and Appendix D: Table 4). Lastly, we repeat our analysis of how residual HWI affects firm outcomes using the more detailed occupational classification scheme. Both for financial performance (see Table 6 and Appendix D: Table 5) and innovativeness (see Table 7 and Appendix D: Table 6), we find very little difference between the two classification schemes. These results help to mitigate concerns that our baseline occupational classification is too broad.

[28] Our measures for the average fraction of analytical nonroutine and interactive nonroutine tasks in a firm are not available for the full five-digit occupational classification scheme. Therefore, we continue using the variables defined for the first three plus the fifth digit of the occupation classification scheme.

6.2. Conditional random mobility assumption of the AKM model

The AKM model assumes "conditional random mobility," which means that employee mobility across establishments does not depend on factors other than worker and establishment fixed effects. If employee mobility across establishments depended systematically on other components, the estimates of the fixed effects would be biased. In this regard, Andrews et al. (2012) show that the bias decreases with the number of employee transitions across employers. 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% lower compared to our baseline estimation, and the variance of the employee fixed effects is 4% lower. The correlation between the fixed effects when using bias correction is 35%, as compared to 33% in our baseline AKM regression.[29] The very similar results using 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 systematic bias. This conclusion is in line with AKM, CHK, or Song et al. (2019).

6.3. Estimation approach without the AKM model

Here we present an alternative approach to estimate how much of HWI is explained by heterogeneous employee characteristics. Instead of the fixed effects approach in the AKM model, we decompose the wage variance within an occupation and establishment into the variation within employees over time and the variation between employees. Under the assumption that the characteristics of an employee remain constant over our six-year estimation period and that age-earnings effects are negligible for this short-term period, this within-employee variation controls for employee characteristics without requiring the conditional random mobility assumption of the AKM model. We find that within-employee wage variation is responsible for 22% of the overall within-occupation variation in an establishment. This figure is very similar to the share of residual HWI, which is 25% according to our AKM estimation.

[29] 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.

6.4. The role of union wage bargaining

Compared to many other countries, unionization rates in Germany are comparatively high. Thus, one potential concern with our results is that they are driven by union wage bargaining, which might make them less representative for other countries. To investigate how unionization affects our findings, we rely on establishment-level survey data on the existence of a union wage bargaining contract (see Section 4.1 for a description of the survey). In Panel A of Appendix E, we focus on the existence of any wage bargaining contract, either directly between the establishment and the union ("Haustarifvertrag") or on the industry-level ("Branchentarifvertrag"). We find that union wage bargaining is positively correlated with residual HWI in Columns 1 to 3. However, once we control for establishment size in Column 4, this positive correlation disappears, and the coefficient estimate for wage bargaining is very close to zero. When we distinguish between bargaining contracts at the establishment and industry level in Panel B, we find the same patterns. In the first three columns, both establishment- and industry-level bargaining exhibits a positive correlation with residual HWI, which disappears when we control for establishment size. These results suggest that union wage bargaining has no direct impact on residual HWI, which mitigates concerns that our results could be less representative for countries with lower unionization rates.

7. Conclusion

This paper aims to answer four questions: How relevant is HWI for overall within-firm wage inequality? What fraction of HWI is explained by the within-occupation heterogeneity of employee characteristics such as ability? Can incentive-pay schemes explain the remaining part that is not related to employee characteristics? And how is HWI connected to firm outcomes?

Using a newly available dataset that links employee-, establishment-, and firm-level information from Germany, we find that (i) HWI accounts for half of the overall wage inequality within establishments, (ii) heterogeneous employee characteristics explain three-quarters of the overall HWI, (iii) incentive pay is a plausible explanation for residual HWI, that is, wage inequality after controlling for heterogeneous employee characteristics, and (iv) this residual HWI is linked to better firm performance and higher innovativeness.

These findings suggest that there are at least two reasons that firms pay unequal wages to employees who perform similar tasks. The first reason is related to the heterogeneity of employee characteristics, such as ability, experience, or education. While remuneration for characteristics that are linked to productivity are typically not targeted by regulation, "equal pay for equal work" laws ban wage discrimination based on gender, race, or religion in many jurisdictions. Disentangling HWI that results from remuneration for productivity-related employee characteristics from HWI that derives from discrimination seems an interesting area for future research. The second reason for unequal wages of employees who perform similar tasks is to incentivize them and overcome agency conflicts. This incentive function points to a bright side of wage inequality that should not be overlooked in the public debate.

The application of residual HWI as proxy for incentive pay provides an interesting avenue for further investigation. Although the calculation of our measure requires linked employee-employer data, such datasets are becoming increasingly available to researchers. Using residual HWI as complement or substitute to survey data to measure incentive pay will hopefully provide a more comprehensive understanding of the interplay between incentives, employees, and 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) and a horizontal (within-occupation) 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.

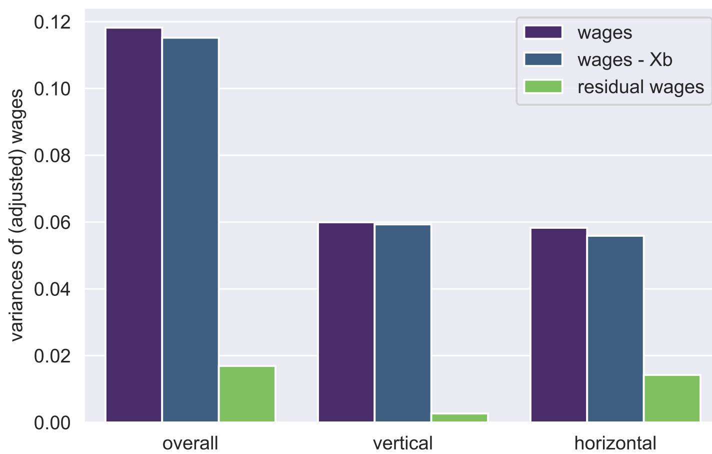
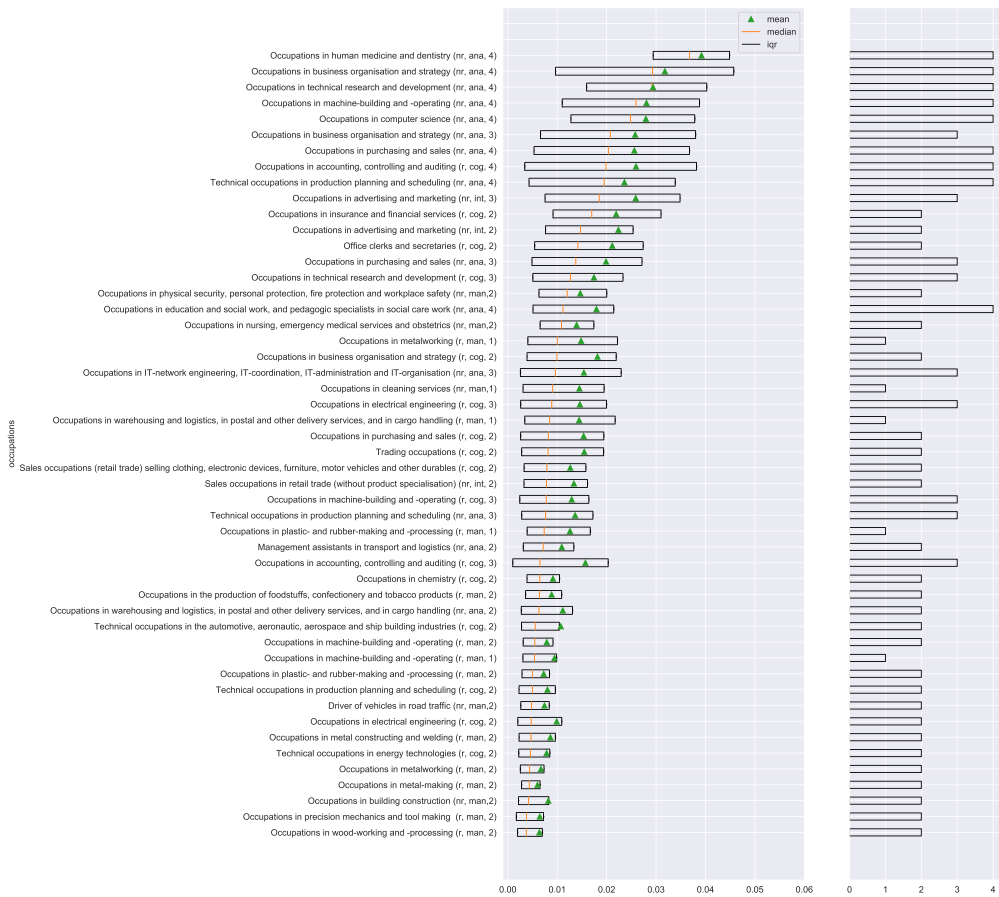


Figure 2
Residual HWI and occupations

This figure shows the residual horizontal wage inequality (HWI) in different occupations. We limit this analysis to the 50 most common occupations in our sample; they account for approximately 70% of the employee-years. Subfigure (a) presents the occupations 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 occupational complexity 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 residual HWI



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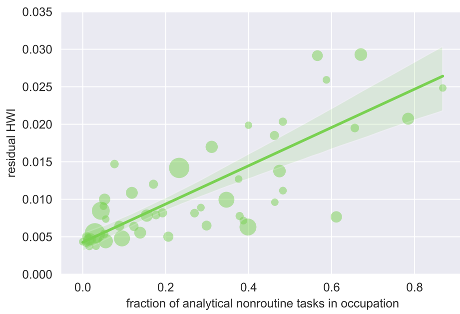
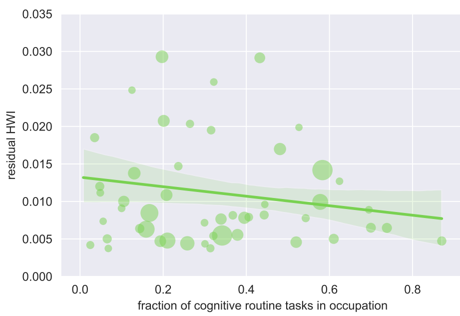
(b) analytical nonroutine tasks

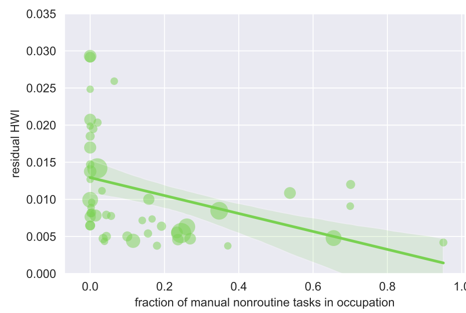


(c) interactive nonroutine tasks

(d) cognitive routine tasks



(e) manual nonroutine tasks



(f) manual routine tasks

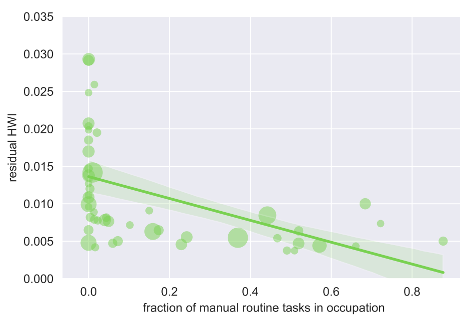
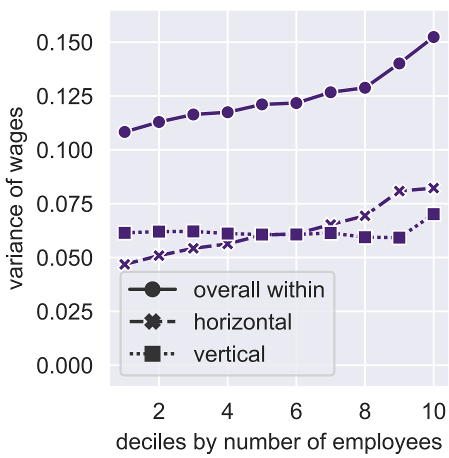


Figure 3
Size and within wage inequality

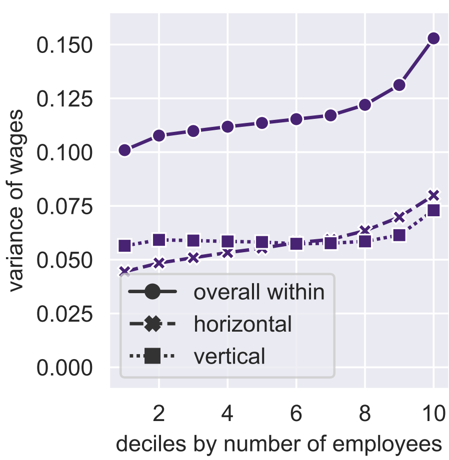
This figure presents, for each size decile, the decomposition of the mean value of the within-establishment variance into a horizontal and a vertical component, as stated in Equation 2. In Subfigures (a) and (b), size and wage inequality are measured on the firm level. In Subfigures (c) and (d), the measurement is on the establishment level. Residual wage inequality captures wage differences due to employee-employer-specific wage adjustments. 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.

(a) wage inequality$_{firm}$



(b) residual wage inequality$_{firm}$

(c) wage inequality$_{estab}$



(d) residual wage inequality$_{estab}$

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
residual HWI_{estab}	69,175,635	0.014	0.013	0.006	0.011	0.019
residual HWI_{firm}	69,268,888	0.016	0.012	0.007	0.013	0.022
number of occupations	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
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
$\log(\text{patents})_{firm}$	10,535,797	2.050	1.607	0.693	1.946	3.850
$\log(\text{citations})_{firm}$	8,063,862	2.770	2.169	0.693	2.565	4.673
$\log(\text{citations per patent})_{firm}$	8,063,862	0.620	0.531	0.122	0.560	0.997

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 occupations (HWI), and the within-establishment variance of wages between occupations (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
Profit sharing, human resources management, and residual HWI

The dependent variable is an establishment's residual horizontal wage inequality (HWI). Residual HWI captures wage differences among employees in the same occupation due to employee-employer-specific wage adjustments. 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. Written employee assessment is a dummy variable that indicates whether an establishment conducts written assessments of employees. Written employee targets is a dummy variable that indicates whether an establishment uses written target agreements with employees. Profit sharing, written employee assessment, and written employee targets are based on survey data (see Section 4.1 for more details.) The regression models are estimated on the employee-year level. 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)
Panel A: Profit sharing				
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
Panel B: Written employee assessments				
written employee assessment	0.0034***	0.0034***	0.00075**	-0.00013
	(3.88)	(3.80)	(2.29)	(-0.38)
$\log(\text{empl})_{estab}$				0.0014***
				(12.23)
Year FE	No	Yes	Yes	Yes
County x year FE	No	No	Yes	Yes
Industry x year FE	No	No	Yes	Yes
Obs	2,197,831	2,197,831	2,197,660	2,197,660
R2	0.02	0.03	0.54	0.56
Panel C: Written employee targets				
written employee targets	0.0039***	0.0039***	0.0014***	0.00074**
	(4.05)	(3.92)	(4.28)	(2.16)
$\log(\text{empl})_{estab}$				0.0013***
				(12.06)
Year FE	No	Yes	Yes	Yes
County x year FE	No	No	Yes	Yes
Industry x year FE	No	No	Yes	Yes
Obs	2,197,526	2,197,526	2,197,355	2,197,355
R2	0.03	0.04	0.55	0.56

Table 4

Firm size, task complexity, and residual HWI

The dependent variable is a firm's residual horizontal wage inequality (HWI). Residual HWI captures wage differences among employees in the same occupation 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 a firm. Occupational complexity is based on the fifth digit of the KldB2010 occupational classification scheme and captures the average complexity of occupations 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)	(5)
log(empl)$_{firm}$	0.0020***				0.0019***
	(20.81)				(20.22)
analytical nonroutine tasks$_{firm}$		0.024***			0.015***
		(22.00)			(9.21)
interactive nonroutine tasks$_{firm}$			0.017***		0.012***
			(10.04)		(6.66)
occupational complexity$_{firm}$				0.0055***	0.0016***
				(19.46)	(3.98)
Year FE	Yes	Yes	Yes	Yes	Yes
County x year FE	Yes	Yes	Yes	Yes	Yes
Industry x year FE	Yes	Yes	Yes	Yes	Yes
Obs	69,250,918	69,250,918	69,250,918	69,250,918	69,250,918
R2	0.44	0.42	0.40	0.42	0.47

Table 5
Establishment size, task complexity, and residual HWI

The dependent variable is an establishment's residual horizontal wage inequality (HWI). Residual HWI captures wage differences among employees in the same occupation 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 occupational classification scheme and captures the average complexity of occupations 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)	(5)
log(empl)$_{estab}$	0.0017***				0.0018***
	(13.11)				(14.84)
analytical nonroutine tasks$_{estab}$		0.031***			0.023***
		(12.71)			(8.25)
interactive nonroutine tasks$_{estab}$			0.021***		0.018***
			(9.49)		(9.50)
occupational complexity$_{estab}$				0.0075***	0.0015***
				(12.29)	(2.67)
Year FE	Yes	Yes	Yes	Yes	Yes
County x year FE	Yes	Yes	Yes	Yes	Yes
Industry x year FE	Yes	Yes	Yes	Yes	Yes
Firm x year FE	Yes	Yes	Yes	Yes	Yes
Obs	32,428,714	32,428,709	32,428,709	32,428,714	32,428,709
R2	0.67	0.67	0.66	0.67	0.68

Table 6
Residual HWI and financial performance

The dependent variables are indicated in each column. Residual HWI captures wage differences among employees in the same occupation due to employee-employer-specific wage adjustments. 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	ebit/assets	net income/assets	cash flow/assets
residual HWI_{firm}	0.68***	0.40***	0.26**	0.30***
	(4.33)	(3.44)	(2.36)	(2.97)
log(total assets)	-0.014***	-0.0088***	-0.0048***	-0.0090***
	(-14.83)	(-11.27)	(-7.10)	(-13.09)
leverage	-0.057***	-0.051***	-0.051***	-0.031***
	(-8.77)	(-13.93)	(-15.53)	(-8.83)
tangibility	0.12***	0.011**	-0.000095	0.091***
	(12.34)	(2.06)	(-0.02)	(16.90)
cash holdings	0.11***	0.12***	0.100***	0.11***
	(8.23)	(11.92)	(13.14)	(14.35)
listing dummy	-0.037***	-0.035***	0.0070	0.0094*
	(-4.96)	(-3.69)	(1.26)	(1.93)
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	0.25	0.20	0.21	0.21

Table 7
Residual HWI and innovativeness

The dependent variables are indicated in each column. Residual HWI captures wage differences among employees in the same occupation due to employee-employer-specific wage adjustments. 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)
	log(patents)	log(citations)	log(citations/patent)
residual HWI$_{firm}$	26.0***	39.6***	3.92**
	(4.65)	(3.89)	(2.28)
log(total assets)	0.47***	0.57***	0.074***
	(15.40)	(12.73)	(7.80)
leverage	0.12	-0.24	-0.039
	(1.01)	(-0.81)	(-0.74)
tangibility	-0.19	-0.73	-0.19*
	(-0.82)	(-1.48)	(-1.81)
cash holdings	-0.0012	-0.68	-0.022
	(-0.01)	(-1.51)	(-0.18)
listing dummy	0.63***	0.70***	0.058
	(4.24)	(2.94)	(1.48)
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Industry x year FE	Yes	Yes	Yes
Obs	9,771,810	7,544,733	7,544,733
R2	0.80	0.84	0.73

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 complexity 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.[30] The combination of occupational sub-group and task complexity defines an occupation, but not all levels of task complexity exist for all occupational sub-groups. In total, there are 10 occupational groups, 37 occupational main groups, 144 occupational groups, 700 occupational sub-groups, and 1,286 occupations.

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

[30]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 levels of task complexity: 24232: Occupations in metalworking: cutting—skilled tasks and 24233: Occupations in metalworking: cutting—complex tasks.[31]

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 level of task complexity. This scheme distinguishes 144 occupational groups with up to four levels of complexity, which yields 431 occupations. The full list of occupations in this classification scheme is shown in A.2. We use the five-digit classification scheme, which distinguishes all 1,286 occupations, as the robustness test in Section 6.1.

[31]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 3.2.1.
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 3.2.1.
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 3.2.1.
residual (wage)	Residual wage from the AKM-type regression. The implementation and interpretation of the AKM-type regression are explained in detail in Section 3.2.1.
Occupational characteristics	
HWI	Variance of wages within an occupation and establishment. The calculation of the horizontal wage inequality (HWI) is explained in Section 3.1.
residual HWI	Variance of residual wages within an occupation and establishment. The calculation of the residual horizontal wage inequality (HWI) is explained in Section 3.2.2.
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	Task complexity within an occupational sub-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 variance of wages within an establishment. The calculation of the horizontal wage inequality (HWI) is explained in detail in Section 3.1.
residual HWI_{estab}	Mean within-occupation variance of residual wages within an establishment. The calculation of the residual horizontal wage inequality (HWI) is explained in detail in Section 3.1.
number of occupations	Number of occupations using the first three digits plus the fifth digit of the KldB 2010 classification scheme. Source: BeH.

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Variable	Description
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.
Bargaining contract	Dummy variable that indicates whether an establishment is covered by a firm- or industry-level union wage bargaining contract ("Tarifvertrag"). Source: BP.
Bargaining contract_{estab}	Dummy variable that indicates whether an establishment is covered by an establishment-level union wage bargaining contract ("Haustarifvertrag"). Source: BP.
Bargaining $\text{contract}_{industry}$	Dummy variable that indicates whether an establishment is covered by an industry-level union wage bargaining contract ("Branchentarifvertrag"). Source: BP.
Firm characteristics	
HWI_{firm}	Mean within-occupation variance of wages within a firm. The calculation of the horizontal wage inequality (HWI) is explained in detail in Section 3.1.
residual HWI_{firm}	Mean within-occupation variance of residual wages within a firm. The calculation of the residual horizontal wage inequality (HWI) is explained in detail in Section 3.1
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).

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Appendix B continued

Variable	Description
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.
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(patents)$_{firm}$	Natural logarithm of a firm's filed patents plus one. The number of filed patents is set to zero if the firm does not file a patent in the given year but in at least one year during our sample period. Source: BeH, BHP, Orbis.
log(citations)$_{firm}$	Natural logarithm of a firm's forward citations to filed patents. Source: Orbis.
log(citations per patent)$_{firm}$	Natural logarithm of the ratio of a firm's forward citations to filed patents. 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 B

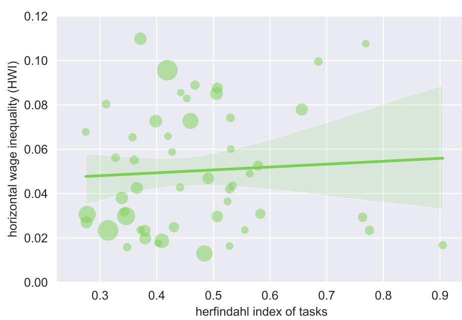
Horizontal wage inequality and occupations

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

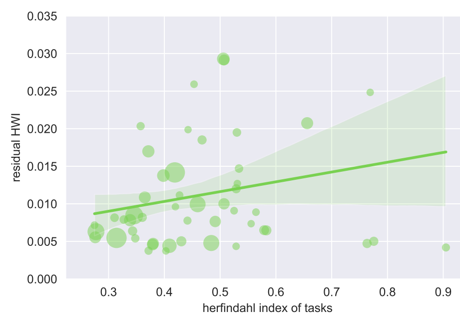
Appendix C
Horizontal wage inequality, occupations, and task heterogeneity

This figure illustrates the relation between task heterogeneity and the horizontal wage inequality (HWI) in different occupations. We limit this analysis to the 50 most common occupations in our sample; they account for approximately 70% of the employee-years. We measure the task heterogeneity of an occupation 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.

(a) HWI



(b) residual HWI



Appendix D. Results for five-digit KldB2010 classification

Appendix D: Table 1
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 occupations (HWI), and the within-establishment variance of wages between occupations (VWI) using the five-digit KldB2010 occupational classification scheme, which distinguishes 1,286 occupations. Our baseline decomposition in Table 2 uses the first three digits plus the fifth digit of the KldB2010 classification and distinguishes 426 occupations. 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	0.055	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

Appendix D: Table 2

Survey-based profit sharing, human resources management, and residual HWI: five-digit KldB2010

The dependent variable is an establishment's residual horizontal wage inequality (HWI) using a more granular definition of 1,286 occupations based on the full five digits of the Kldb2010. Residual HWI captures wage differences among employees in the same occupation due to employee-employer-specific wage adjustments. 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. Written employee assessment is a dummy variable indicating that the establishment conducts written assessments of employees. Written employee targets is a dummy indicating that the establishment defines written target agreements with employees. The regression models are estimated on the employee-year level for the survey sample (Section 4.1). 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)
Panel A: Profit sharing				
profit sharing	0.0064***	0.0064***	0.0023***	0.0015***
	(4.76)	(4.69)	(8.20)	(5.60)
$\log(\text{empl})_{estab}$				0.0013***
				(14.38)
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	0.55	0.57
Panel B: Written employee assessments				
written employee assessment	0.0034***	0.0034***	0.00070**	-0.00020
	(3.87)	(3.80)	(2.16)	(-0.59)
$\log(\text{empl})_{estab}$				0.0014***
				(12.74)
Year FE	No	Yes	Yes	Yes
County x year FE	No	No	Yes	Yes
Industry x year FE	No	No	Yes	Yes
Obs	2,197,831	2,197,831	2,197,660	2,197,660
R2	0.02	0.03	0.55	0.57

Continued on next page

Appendix D: Table 2 continued

Panel C: Written employee targets				
written employee targets	0.0039***	0.0038***	0.0013***	0.00065*
	(3.98)	(3.86)	(4.13)	(1.94)
$\log(\text{empl})_{estab}$				0.0013***
				(12.56)
Year FE	No	Yes	Yes	Yes
County x year FE	No	No	Yes	Yes
Industry x year FE	No	No	Yes	Yes
Obs	2,197,526	2,197,526	2,197,355	2,197,355
R2	0.03	0.04	0.55	0.57

Appendix D: Table 3

Firm size, task complexity, and residual HWI: five-digit KldB2010

The dependent variable is a firm's residual horizontal wage inequality (HWI), which we calculate based on the five-digit KldB2010 occupational classification scheme. This scheme distinguishes 1,286 occupations, compared to 426 in our baseline classification scheme. Residual HWI captures wage differences among employees in the same occupation 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 a firm. Occupational complexity is based on the fifth digit of the KldB2010 occupational classification scheme and captures the average complexity of occupations 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)	(5)
log(empl)$_{firm}$	0.0020***				0.0019***
	(21.35)				(20.86)
analytical nonroutine tasks$_{firm}$		0.023***			0.015***
		(21.04)			(9.11)
interactive nonroutine tasks$_{firm}$			0.016***		0.011***
			(9.73)		(6.63)
occupational complexity$_{firm}$				0.0052***	0.0013***
				(18.29)	(3.20)
Year FE	Yes	Yes	Yes	Yes	Yes
County x year FE	Yes	Yes	Yes	Yes	Yes
Industry x year FE	Yes	Yes	Yes	Yes	Yes
Obs	69,250,918	69,250,918	69,250,918	69,250,918	69,250,918
R2	0.45	0.43	0.41	0.42	0.47

Appendix D: Table 4

Establishment size, task complexity, and residual HWI: five-digit KldB2010

The dependent variable is an establishment's residual horizontal wage inequality (HWI), which we calculate based on the five-digit KldB2010 occupational classification scheme. This scheme distinguishes 1,286 occupations, compared to 426 in our baseline classification scheme. Residual HWI captures wage differences among employees in the same occupation 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 occupational classification scheme and captures the average complexity of occupations 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)	(5)
log(empl)$_{estab}$	0.0017***				0.0018***
	(13.03)				(14.71)
analytical nonroutine tasks$_{estab}$		0.030***			0.023***
		(12.38)			(8.23)
interactive nonroutine tasks$_{estab}$			0.020***		0.018***
			(9.32)		(9.45)
occupational complexity$_{estab}$				0.0072***	0.0013**
				(11.82)	(2.23)
Year FE	Yes	Yes	Yes	Yes	Yes
County x year FE	Yes	Yes	Yes	Yes	Yes
Industry x year FE	Yes	Yes	Yes	Yes	Yes
Firm x year FE	Yes	Yes	Yes	Yes	Yes
Obs	32,428,714	32,428,709	32,428,709	32,428,714	32,428,709
R2	0.67	0.67	0.66	0.67	0.68

Appendix D: Table 5

Residual HWI and financial performance: five-digit KldB2010

The dependent variables are indicated in each column. Residual horizontal wage inequality (HWI) captures wage differences among employees in the same occupation due to employee-employer-specific wage adjustments. It is calculated based on the five-digit KldB2010 occupational classification scheme. This scheme distinguishes 1,286 occupations, compared to 426 in our baseline classification scheme. 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	ebit/assets	net income/assets	cash flow/assets
residual HWI$_{firm}$	0.69***	0.42***	0.27**	0.32***
	(4.48)	(3.54)	(2.35)	(3.07)
log(total assets)	-0.014***	-0.0089***	-0.0048***	-0.0091***
	(-14.94)	(-11.30)	(-7.11)	(-13.13)
leverage	-0.057***	-0.051***	-0.051***	-0.031***
	(-8.74)	(-13.92)	(-15.53)	(-8.83)
tangibility	0.12***	0.011**	-0.000088	0.091***
	(12.42)	(2.07)	(-0.02)	(16.95)
cash holdings	0.11***	0.12***	0.100***	0.11***
	(8.22)	(11.92)	(13.14)	(14.35)
listing dummy	-0.037***	-0.035***	0.0070	0.0093*
	(-4.96)	(-3.70)	(1.26)	(1.91)
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	0.25	0.20	0.21	0.21

Appendix D: Table 6

Residual HWI and innovativeness: five-digit KldB2010

The dependent variables are indicated in each column. Residual horizontal wage inequality (HWI) captures wage differences among employees in the same occupation due to employee-employer-specific wage adjustments. It is calculated based on the five-digit KldB2010 occupational classification scheme. This scheme distinguishes 1,286 occupations, compared to 426 in our baseline classification scheme. 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)
	log(patents)	log(citations)	log(citations/patent)
residual HWI$_{firm}$	27.3***	41.0***	4.20**
	(4.81)	(3.98)	(2.45)
log(total assets)	0.46***	0.57***	0.073***
	(15.12)	(12.48)	(7.72)
leverage	0.12	-0.24	-0.039
	(1.01)	(-0.81)	(-0.73)
tangibility	-0.18	-0.71	-0.19*
	(-0.78)	(-1.44)	(-1.79)
cash holdings	-0.00036	-0.69	-0.022
	(-0.00)	(-1.51)	(-0.18)
listing dummy	0.63***	0.69***	0.058
	(4.22)	(2.92)	(1.47)
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Industry x year FE	Yes	Yes	Yes
Obs	9,771,810	7,544,733	7,544,733
R2	0.80	0.84	0.73

Appendix E

Union wage bargaining contracts and residual HWI

The dependent variable is an establishment's residual horizontal wage inequality (HWI), which we calculate based on the five-digit KldB2010 occupational classification scheme. This scheme distinguishes 1,286 occupations, compared to 426 in our baseline classification scheme. Residual HWI captures wage differences among employees in the same occupation due to employee-employer-specific wage adjustments. Bargaining contract is a dummy variable that equals one if the establishment has an establishment-level bargaining contract or is part of an industry-level bargaining contract. The union wage bargaining variables are based on survey data (see Section 4.1 for more details.) The regression models are estimated on the employee-year level. 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)
Panel A: Union wage bargaining contract				
bargaining contract	0.0036***	0.0036***	0.0011***	0.000013
	(4.25)	(4.19)	(4.98)	(0.06)
$\log(\text{empl})_{estab}$				0.0013***
				(16.56)
Year FE	No	Yes	Yes	Yes
County x year FE	No	No	Yes	Yes
Industry x year FE	No	No	Yes	Yes
Obs	7,860,633	7,860,633	7,859,484	7,859,484
R2	0.02	0.03	0.53	0.55
Panel B: Separate analyses of estab. and ind.-level bargaining contracts				
bargaining contract_{estab}	0.0056***	0.0056***	0.00093**	-0.000084
	(2.65)	(2.63)	(2.34)	(-0.22)
bargaining $\text{contract}_{industry}$	0.0031***	0.0031***	0.0012***	0.000045
	(3.77)	(3.73)	(5.16)	(0.20)
$\log(\text{empl})_{estab}$				0.0013***
				(16.49)
Year FE	No	Yes	Yes	Yes
County x year FE	No	No	Yes	Yes
Industry x year FE	No	No	Yes	Yes
Obs	7,860,633	7,860,633	7,859,484	7,859,484
R2	0.03	0.04	0.53	0.55