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Measuring workers' financial incentives

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Abstract

We propose a novel measure for workers' financial incentives based on within-establishment wage differences among similar workers from the same occupation. This measure captures all forms of incentive pay that lead to worker-employer-specific pay premiums, including explicit (e.g., bonuses) and implicit forms (e.g., tournaments). We estimate the measure using a linked worker-establishment-firm dataset that covers 31 million workers in Germany. For validation, we exploit survey-based information on performance pay and variation in monitoring costs due to occupational characteristics, establishment size, and task complexity and show that the measure behaves as theoretically predicted. Applying the measure yields evidence that workers' incentives positively correlate with firms' performance and innovativeness, which supports a positive relationship between incentives and effort.

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1. Introduction

Pay methods that reward workers' performance, which we refer to as incentive pay, are potentially important for the motivation of workers and, as a consequence, for firms' performance and innovativeness (Lazear and Rosen, 1981; Baker, Jensen and Murphy, 1988; Manso, 2011). However, while generally accepted measures for incentive-provision to top management have been developed and frequently explored in the financial economics literature (Murphy, 2013; Edmans, Gabaix and Jenter, 2017), empirical assessments of incentive provision to workers are limited (Prendergast, 1999).

This paper proposes an indirect approach to measuring workers' financial incentives based on within-establishment wage differences. Our measure exploits that wage policies that provide monetary rewards for performance lead to worker-employer-specific wage premiums and more dispersed wages among otherwise comparable workers (Seiler, 1984; Lemieux, MacLeod and Parent, 2009). This indirect measurement approach captures all incentive schemes, including job-promotion tournaments, performance-related base-wage adjustments, or bonuses (see Lazear, 2018, for an overview). This is an important feature because many schemes are not explicitly written down in contracts (Bloom and Van Reenen, 2011).

Our measure is based on wage differences among workers with similar characteristics who work in the same occupation. Focusing on comparable workers enables us to filter out confounding wage determinants. Most importantly, workers' characteristics can affect wages via multiple channels, and more dispersed workforce characteristics can cause wage differences that are unrelated to incentive pay (Mueller, Ouimet and Simintzi, 2017). However, wage differences among workers with similar characteristics may not necessarily reflect differences in incentives if they work in different occupations and perform different tasks (MacLeod and Parent, 2012; Mueller, Ouimet and Simintzi, 2015).

We calculate our incentive-pay measure for all establishments of a firm using a novel dataset that links employee and establishment-level information from the German social security system with firm-level information from the Orbis database by Bureau van Dijk. The sample includes data on 17 million workers, 206,000 establishments, and 88,000 firms between 2010 and 2016. These comprehensive employer-employee data allow us to apply a model with additive fixed effects for workers and establishments in the spirit of Abowd, Kramarz and Margolis (1999) (henceforth AKM).[1] Within this framework, we decompose wage differences within an establishment into differences that are related to workers' observable and (for the researcher) unobservable characteristics and residual wage differences among workers with similar characteristics.

Residual wages in the AKM model are independent of firm or establishment-specific pay premiums, observable time-variant worker characteristics (e.g., age), and unobservable time-invariant worker characteristics (e.g., ability).[2] They include, among other things, wage premiums which are idiosyncratic in the sense that they are specific to an employer-employee combination. Incentive schemes that link workers' performance to their wages lead to employer-employee-specific wage premiums. Thus, the residual wage component in the AKM model is conceptually linked to incentive pay (see Section 2.1 for a detailed discussion).

Our decomposition of the overall within-establishment wage differences, measured as the variance of workers' log average daily wages, reveals that workers' characteristics are responsible for about 85.6% of wage differences within establishments. The remaining 14.4% can be interpreted as residual wage differences among workers with similar characteristics.[3] We use occupations to identify workers who perform similar tasks because worker-specific tasks are not included in our dataset. Accordingly, we split differences in residual wages into those that arise either within and across occupations and find that 85.8% of the residual wage differences arise within occupations. This within-occupation variation of residual wages, which we use as a measure for incentive pay, accounts for 23% of the wage differences within occupations and 13% of the wage differences within establishments.

[1]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., Card, Heining and Kline, 2013; Card et al., 2018; Song et al., 2019). Recently, it is also applied in financial economics (e.g., Matveyev, 2017; Babina et al., 2019; He and le Maire, 2019).

[2]Martins (2008), among others, highlights that most of the empirical research measures wage dispersion using residuals from wage regressions that only control for observable worker characteristics. However, not taking into account unobserved worker heterogeneity may potentially lead to biased results. Wage differences that are due to unobserved worker characteristics may simply reflect standard remuneration of productive worker attributes that occur in competitive labor markets.

[3]Relatedly, Song et al. (2019) investigate the rise of wage inequality in U.S. firms over time and find that residual wage differences account for about 25% of wage inequality within U.S. firms between 2007 and 2013.

To validate our measure, we first make use of additional survey data on profit-sharing policies of establishments that are available for a smaller sample. Despite the fact that this sample only covers one dimension of incentive pay, it is reassuring that we find a strong and positive correlation between our measure and the share of employees participating in a profit-sharing scheme.

For our second validation approach, we analyze how our incentive-pay measure varies with monitoring costs. Intuitively, the alignment of interests between employers and employees and, thus, the importance of incentive pay are higher in firms or establishments with high monitoring costs. The models of Lazear and Rosen (1981) and Prendergast (2002) also predict that incentive pay will be more common if monitoring costs are high. Our dataset allows us to approximate monitoring costs by occupational characteristics, size differences of establishments between and within firms, and the tasks performed within an establishment.

Regarding occupational characteristics, we find that the measure for incentive pay is higher in occupations with more cognitive and nonroutine tasks (e.g., chartered accountants or management consultants) and lower in occupations with more manual tasks (e.g., road makers or motor vehicle drivers). This finding indicates that incentive pay increases with task complexity, which makes monitoring more costly.

We then turn to establishment characteristics and find that the incentive-pay measure increases with establishment size. Comparing the decile of the smallest establishments to the decile of the largest ones, our measure more than doubles. To mitigate concerns that unobservable heterogeneity between firms drives this finding, we alternatively focus on firms with multiple establishments and show that the same patterns exist when we compare smaller and larger establishments within the same firms. We also find that the incentive-pay measure is more pronounced in establishments with more complex tasks and that the effects of size and task complexity reinforce each other.

The last step is to apply our measure and investigate how workers' financial incentives are related to firm outcomes. We start by showing that workers' incentives correlate with financial performance in terms of higher EBIT, EBITDA, net income, and cash flow per employee. When we turn to operating characteristics, we find that firms with higher incentives for workers have more sales and value added per employee. For operating efficiency, the results are less clear as we find higher inventory turnover in high-incentive firms but no differences with regard to asset turnover. As a third application, we examine firms' innovativeness and find that workers' incentives are correlated with more patents per employee and higher degree of patent quality, as indicated by more citations. We find no differences for the generality of patents, but high-incentive firms exhibit a higher patent originality. Although our setting makes it difficult to draw causal inferences, these results indicate that workers' incentives are highly correlated with firm outcomes.

Our first contribution to the literature is the development of a novel measure for workers' incentive pay. In contrast to the incentives for top management,[4] the measurement of incentives on the worker level is still very challenging, and the literature mostly relies on survey-based measures for small samples, often single firms (Gibbons, 1998; Lazear, 2018). Our incentive-pay measure can be estimated for all firms or establishments with worker-level wage information. In addition, survey-based measures typically focus on specific forms of incentive pay.[5] Our measure is more general and captures all pay methods that lead to worker-specific wage premiums. Lastly, our measure is based on administrative data, which cannot be manipulated or selectively reported by firms, and captures the extent, not only the existence, of incentive pay.

Our second contribution is an analysis of the relationship between workers' incentives and firm outcomes. The literature that focuses explicitly on incentive pay and firm outcomes is limited, with a few notable exceptions. Lazear (2000) investigates one company that replaced fixed hourly rates by piece rates and finds substantial productivity increases. Similarly, Shearer (2004) examines one tree-planting firm and finds that workers who were randomly assigned to the piece-rate group became more productive, which also increased the firm's profitability. Recently, Breza, Kaur and Shamdasani (2018) conduct an experiment with Indian manufacturing workers and show that performance

[4]Examples of studies that analyze the incentive pay of CEOs or other top managers are Jensen and Murphy (1990), Hall and Liebman (1998), Aggarwal and Samwick (2003), and Frydman and Saks (2010). Murphy (2013) and Edmans, Gabaix and Jenter (2017) provide an overview of the executive compensation literature.

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

pay reduces output if the productivity of coworkers cannot be easily observed. Kim and Ouimet (2014) focus on profit sharing in the form of employee stock ownership plans (ESOPs) and document a positive effect on productivity and firm performance, at least for small ESOPs. For innovation, Manso (2011) and Hellmann and Thiele (2011) show theoretically that workers' incentives are crucial for innovation.

Lastly, we also add to the literature on wage inequality within firms. Using data from Portugal, Martins (2008) measures the overall pay dispersion after controlling for worker heterogeneity and finds a negative relation to firm performance. Mahy, Rycx and Volral (2011) find a hump-shaped relationship between wage dispersion and productivity in Belgian firms. Mueller, Ouimet and Simintzi (2017) measure within-firm wage inequality as pay differences between hierarchy levels of a firm (which is conceptually similar to our "between-occupations" inequality) and find that these differences are associated with larger firms and higher performance.[6] We complement these studies by decomposing the overall within-establishment wage inequality, using the within-occupation variance of residual wages as a measure for incentive pay, and linking this measure to firm outcomes.

2. Theoretical background of the incentive-pay measure

This section describes the development of the incentive-pay measure. We explain how we adjust wages for workers' characteristics using two-way fixed effects regressions, measure within-establishment wage differences, and decompose these differences to derive our incentive-pay measure.

2.1. Confounding wage determinants

Incentive pay is certainly not the only determinant of workers' wages. First, the characteristics of workers can affect wages via multiple channels that are unrelated to incentive pay. Examples include return to education (Katz and Murphy, 1992) or assortative matching, that is, the sorting of high-wage workers into high-wage firms (Abowd, Kramarz and Margolis, 1999; Card, Heining

[6] Mueller, Ouimet and Simintzi explain this result by differences in managerial talent. Our finding that more than 96% of the wage inequality between occupations comes from differences in workers' characteristics supports their conclusion.

and Kline, 2013; Song et al., 2019). Second, firm and establishment-level factors are likely to play an important role. Empirical evidence has documented the impact of establishment size (Bloom et al., 2018), family ownership (Ellul, Pagano and Schivardi, 2018), and financial leverage (Hanka, 1998), among other factors, on workers.

To filter out these confounding effects, we rely on a two-way fixed effect regression model in the spirit of AKM that allows us to decompose workers' wages into a worker-specific component, an establishment-specific component, and a residual wage. Under the assumptions of the AKM model,[7] the residual wage is unaffected by a worker's characteristics and establishment-specific wage premiums. Technically, we assume that the log real daily wage $y_t^{i,j}$ is an additively separable function of a time-invariant worker fixed effect α^i, an establishment fixed effect ψ^j[8], an index of time-varying observable characteristics βX_t^i, and a residuum $r_t^{i,j}$. X_t^i includes an unrestricted set of year dummies and quadratic and cubic terms in age fully interacted with educational attainment.[9] In order to identify ψ^j, the following regression model is estimated on the largest connected set of establishments that are linked by worker transitions from 2010 to 2017:

$$y_t^{i,j} = \alpha^i + \psi^j + \beta X_t^i + r_t^{i,j}. \tag{1}$$

The error term $r_t^{i,j}$ is the residual wage of individual i at establishment j. This residual captures, among other things, wage premiums, which are idiosyncratic in the sense that they are specific to a worker-establishment combination. Incentive pay affects the residual wage component in the AKM model because it links workers' performance to their wages, which leads to worker-

[7]We are aware of the debates around the "conditional random mobility" assumption. The estimates of the fixed effects are biased if workers' mobility across establishments systematically depends on components other than worker or firm fixed effects. Andrews et al. (2012) show that the bias decreases in the number of worker transitions across employers. In our data, worker mobility is high as we use the universe of German administrative data to estimate the AKM model. Using the same data, Lochner, Seth and Wolter (2020) show that the bias is small and rather constant over time. Song et al. (2019) draw a similar conclusion using U.S. data.

[8]For notational convenience, we suppress the dependence of subscript j on worker i and t, such that j = J(i,t).

[9]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.

establishment-specific wage premiums.[10] Other factors that can influence this component are drifts in the portable component of workers' earning power or measurement errors (see CHK for a more detailed discussion).

We use the parameter estimates of the AKM-type regression in Equation 1 to adjust the wage for worker characteristics,

$$y_t^{i,j} - \beta X_t^i = \alpha^i + \psi^j + r_t^{i,j}, \tag{2}$$

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

Equation 2 represents the wage after controlling for observable worker characteristics (βX_t^i). Equation 3 represents the wage after controlling for all observable and unobservable (α^i) characteristics that are related to a specific worker.

2.2. Within-establishment wage differences and worker characteristics

Next, we calculate the within-establishment wage differences[11] among workers with the same characteristics. We start by measuring the overall wage differences within an establishment-year as the variance of workers' log daily wages,

$$var_t^j(y_t^{i,j}) = \frac{1}{N_t^j} \sum_i (y_t^{i,j} - \bar{y}_t^j)^2, \tag{4}$$

where $y_t^{i,j}$ is the log daily wage of a worker i employed at establishment j in year t. We then decompose the overall within-establishment wage differences into differences that are related to workers' characteristics and differences in residual wages among workers with similar characteristics. This is important for the construction of our incentive-pay measure because higher overall wage differences within establishments could be related to more dispersed characteristics of workers and not their incentives. Technically, we use the parameter estimates from the AKM-type regression in Equation 1 to decompose the within-establishment variances of workers' wages into components related to

[10] More generally, those idiosyncratic wage premiums arise "in models in which there is an idiosyncratic productivity component associated with each potential job match, and workers receive some share of the rents from a successful match" (CHK, p. 987). In these models, the worker-firm-specific rent sharing can be interpreted as firms' incentive provision to workers.

[11] For the construction of our establishment-specific incentive-pay measure, we are only interested in wage differences within, not across, establishments.

workers' characteristics and differences in the residual wage:

$$
\begin{aligned}
var_t^j(y_t^{i,j}) = {} & var_t^j(\alpha^i) + var_t^j(\beta X_t^i) + var_t^j(r_t^{i,j}) \\
& + 2cov(\alpha^i, \beta X_t^i) + 2cov(\beta X_t^i, r_t^{i,j}) + 2cov(\alpha^i, r_t^{i,j}).
\end{aligned} \tag{5}
$$

Likewise, we can write the within-establishment variances of the wages adjusted for workers' observable characteristics as

$$
var_t^j(y_t^{i,j} - \beta X_t^i) = var_t^j(\alpha^i) + var_t^j(r_t^{i,j}) + 2cov(\alpha^i, r_t^{i,j}). \tag{6}
$$

The within-establishment variance of the wages, adjusted for workers' observable and unobservable characteristics, equals the variance of the residual wages:

$$
var_t^j(y_t^{i,j} - \beta X_t^i - \alpha^i) = var_t^j(r_t^{i,j}). \tag{7}
$$

$Var_t^j(r_t^{i,j})$ captures wage differences among workers with similar characteristics as it is net of all observable and unobservable worker characteristics.

2.3. Wage differences within and between occupations

The next step is to distinguish wage differences within and between occupations. This is important for the construction of our measure because wage differences across occupations could be due to the fact that workers, even if seemingly similar in skills, perform different tasks (MacLeod and Parent, 2012; Mueller, Ouimet and Simintzi, 2015). Those wage differences between tasks can, for instance, be related to the multiplier effects of a task in a firm (Rosen, 1981; Gabaix and Landier, 2008). Because our data do not include worker-specific tasks, we focus on wage differences among workers within the same occupation to measure incentives. We decompose wage differences within an establishment into within- and between-occupation components,

$$
var_t^j(y_t^{i,j}) = \underbrace{var_t^j(\bar{y}_t^{o,j})}_{\text{between-occupation component}} + \underbrace{\sum_o w_t^{o,j} \cdot var_t^{o,j}(y_t^{i,j})}_{\text{within-occupation component}}, \tag{8}
$$

where o denotes an occupation.[12] $var_t^j(\bar{y}_t^{o,j})$ captures the variance of workers'

[12] We measure occupations based on the first three digits of the Classification of Occupa-

wages between occupations within an establishment. $w_t^{o,j}$ denotes the fraction of workers employed in occupation o at establishment j in year t. $var_t^{o,j}(y_t^{i,j})$ measures the wage dispersion within occupation o and establishment j. Using the same approach, we decompose wages after controlling for workers' observable characteristics and residual wages, which are net of workers' observable and unobservable characteristics, into within and between-occupation components. We can write the decomposition for the residual wage variation as

$$var_t^j(r_t^{i,j}) = \underbrace{var_t^j(\bar{r}_t^{o,j})}_{\text{between-occupation component}} + \underbrace{\sum_o w_t^{o,j} \cdot var_t^{o,j}(r_t^{i,j})}_{\text{within-occupation component}} . \tag{9}$$

2.4. The incentive-pay measure

Financial incentives increase the sensitivity of wages to worker-specific performance, which leads to idiosyncratic wage premiums. Thus, wages among otherwise comparable workers will be more dispersed if incentive pay is more common in an establishment (Seiler, 1984; Lemieux, MacLeod and Parent, 2009). We measure workers' incentives as the variation of residual wages within an establishment and occupation, that is, $var_t^{o,j}(r_t^{i,j})$ in Equation 9. This measure is not affected by wage differences that are related to workers' characteristics since we use the variation of residual wages. In addition, using only the variation within occupations ensures that differences in wage levels or pay policies between occupations do not affect our measure. The indirect nature of our measurement approach ensures that we capture all incentive schemes that lead to employee-employer-specific wage premiums, such as job-promotion tournaments, performance-related base-wage adjustments, or bonuses.

3. Estimation of the incentive-pay measure

This section describes the data and their preparation. After that, we present the decomposition of wage differences into its components (which results in our measure) along with descriptive statistics.

tions 1988 (KldB 1988), which distinguishes between 341 different occupations.

3.1. Worker-level data

The core of our dataset is the employee history file (Beschäftigten-Historik, BeH). This administrative matched employer-employee data is provided by the Institute for Employment Research (Institut für Arbeitsmarkt- und Berufsforschung, IAB). The BeH originates from earnings records of the German social security system and includes person-level information on total earnings, days worked at each job, education, occupation, industry, and part-time or full-time status.[13]

The data preparation largely follows the steps conducted by CHK and Bellmann et al. (2020). The starting point is the universe of full-time jobs held by workers aged 20 to 60 from 2010 to 2017.[14] While CHK examine male workers in Western Germany, we include both male and female workers in Eastern and Western Germany. We exclude marginal employment and apprenticeship. We identify the main job held by each worker in a given year, that is, the job with the highest total wage sum (including bonus payments). For all these jobs, we calculate the average daily wage by dividing the total earnings by the total duration of the main job. Wages in the BeH are censored to a time- and region-specific threshold.[15] 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). The resulting dataset consists of over 161 million worker-establishment years, around 31 million unique workers, and more than 2.1 million establishments. The AKM-type regression model is estimated on the largest connected set of establishments that are linked by worker transitions.

[13]For further details on the dataset, please refer to the technical report by Antoni, Ganzer and vom Berge (2016).

[14]The administrative data originates from the social security system; therefore, the IEB data do not include employment spells of civil servants and self-employed workers.

[15]The so-called contribution assessment ceiling ("Beitragsbemessungsgrenze") varies between 5,500 and 6,350 EUR per month in West Germany and between 4,650 and 5,700 EUR per month in East Germany for our sample period.

3.2. Firm-establishment-level data

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 Bureau van Dijk (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. 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.[16] Firm-level financial data comes from the BvD Orbis database and information on the three-digits industry codes (Classification of Industries 2008) of establishments is obtained from the IAB establishment history panel (Betriebs-Historik-Panel, BHP).[17]

We exclude firms with fewer than 20 employees in any sample year to ensure that firm-years with very few observations do not distort the calculation of our wage dispersion measures.[18] We also exclude employee-establishment-years that are not linked to a firm.[19] 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. Table A displays details on the definitions and data sources of variables. The final sample covers 72,394,909 worker-years, 16,868,872 million unique workers, 206,287 establishments, and 87,580 firms between 2010 and 2016.

3.3. Decomposition of within-establishment wage differences

We start by decomposing the overall wage differences within establishments into the variances and covariances of the parameter estimates from the AKM-

[16] 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. We exclude establishment-years that are not uniquely assigned to one firm.

[17] We largely follow the steps by Jäger, Schoefer and Heining (2019) to clean the firm-level financial data from Orbis and check its internal consistency. The most important deviation from their procedure is that we only consider the financial data in firm-years that report both total assets and sales.

[18] Song et al. (2019) use the same threshold.

[19] See Antoni et al. (2018) for details on the representativity of the linked firm-establishment dataset for the German labor market.

type regression.[20] Table 1 shows that differences in observable worker characteristics account for 2.5% ($\frac{0.119-0.116}{0.119}$) of the wage dispersion within establishments, whereas differences in observable and unobservable characteristics are responsible for about 86% ($\frac{0.119-0.017}{0.119}$) of this dispersion. The remaining 14% arise from wage differences after accounting for workers' characteristics.[21]

— Table 1 about here —

We further split wage differences into within- and between-occupations components. We use three-digits occupational codes according to the Classification of Occupations (KldB) from 1988. This classification scheme distinguishes between 341 different occupations. Table 2 presents the results, which are also illustrated in Figure 1. We find that wage differences within and between occupations are almost equally important (46% versus 54%, repectively). However, when we do the same decomposition after adjusting wages for observable and unobservable worker characteristics, we find that 86% of the residual wage differences arise from pay differences within occupations. Overall, the residual wage variance within occupations, which we use as a measure for incentive pay, accounts for 12.6% of the within-establishment wage differences.

— Table 2 about here —
— Figure 1 about here —

3.4. Descriptive statistics

Table 3 provides descriptive statistics. On average, a worker earns a log daily wage of 4.607 EUR in a given year. This corresponds to an average yearly income of 36,566 EUR (monthly: 3,047 EUR) for a full-time employee. The median worker is employed at an establishment with 170 full-time employees,

[20] The overall wage variance when considering wage differences within and between establishments is 0.280 in our sample. Lochner, Seth and Wolter (2020) report a variance of log daily earnings of 0.291 for the universe of German establishments in the same time period. The similarity of these values helps to mitigate concerns that our focus on establishments that are linked to a firm in the ORBIS-ADIAB dataset (cf. Section 3.2) reduces the generalizability of our sample.

[21] Related to our findings, Song et al. (2019) show that wage differences after controlling for worker characteristics account for approximately 25% of the wage dispersion within U.S. firms (from 2007 to 2013). Hence, the role of "residual" wage differences seems to be slightly more pronounced for U.S. firms.

16 occupations, and 7.1% highly complex tasks. Furthermore, about 47% of workers are employed in firms with more than one establishment.

— Table 3 about here —

4. Verification of the incentive-pay measure

This section presents verification tests that analyze how our incentive-pay measure is related to survey-based data on profit sharing and monitoring costs.

4.1. Survey data on profit sharing

To validate our incentive-pay measure, we first use survey data on the use of profit-sharing programs within German establishments. In particular, we rely on information from the IAB establishment panel (Betriebspanel, BP)—a representative establishment survey—which, in 2011, 2013, and 2015, directly asked establishments to specify the fraction of employees that participated in profit sharing.[22] For legal reasons, we cannot link the survey data with information on firm structure. Hence, we only observe employee-establishment information in the survey sample.

To test whether a higher extent of profit sharing within establishments is correlated with more dispersed wages among seemingly similar workers, we regress the measure for incentive pay on the fraction of employees who participate in a profit-sharing program. We use the following regression specification:

$$var_t^{o,j}(r_t^{i,j}) = \alpha + \beta profit\_sharing_t^j + \gamma log(size_t^j) + \lambda^j \cdot \tau_t + \kappa^j \cdot \tau_t + \pi^o \cdot \tau_t + \epsilon, \tag{10}$$

where $var_t^{o,j}(r_t^{i,j})$ is the occupation variance of residual wages within establishments, $profit\_sharing_t^j$ is the share of employees within an establishment who participate in a profit-sharing program, λ^j denotes establishment-industry dummies (based on three-digit WZ2008 industries), κ^j establishment-county dummies (based on "Landkreise"), π^o occupation dummies, and τ_t year dummies. α is a constant, and ϵ is the error term. We estimate this model on the worker-year level and cluster standard errors at the establishment-level.

[22] We observe information on profit sharing for about 3.5 million employee-years, 2.1 million employees, and 18,454 establishments. On average, 36.4% of employees participate in the establishment's profit-sharing program. For further details on the dataset, please refer to the technical report by Bechmann et al. (2017).

The results are shown in Table 4. We start with a simple specification that only includes year fixed effects in Column 1. The coefficient estimate for β in this specification implies that our incentive-pay measure increases by 49%, relative to the sample mean,[23] for an establishment that newly introduces profit sharing for all employees. In Columns 2 and 3, we add more fixed effects to control for county-year-, industry-year-, and occupation-year-specific factors. The coefficient estimates for β are positive and highly statistically significant in both specifications, but their magnitude is smaller. They imply that our incentive-pay measure increases by 12% to 17%, again relative to the sample mean, for an establishment that newly introduces profit sharing for all employees. The specification in Column 4, in which we control for establishment size, leads to similar results. Overall, it is reassuring to see this positive correlation between profit sharing and our incentive-pay measure despite the fact that the latter is more general and not limited to profit sharing.

— Table 4 about here —

4.2. Variation in monitoring costs

Our second verification strategy uses occupational characteristics, establishment size, and the complexity of tasks performed in an establishment as proxies for monitoring costs and tests how they are related to our measure for incentive pay.

4.2.1. Theory

Interests of employers and workers diverge because employers want workers to maximize their efforts, but workers' utility is negatively related to effort (Ross, 1973). This divergence of interests creates agency problems, especially if monitoring costs are high and workers have a great deal of discretion in choosing their effort level (Holmstrom, 1979). There are two potential solutions: monitoring and pay methods that reward worker performance. The personnel economics literature suggests that the monitoring costs of a specific firm play an important role in the choice between monitoring and incentive pay (Brown, 1990; Drago and Heywood, 1995; Heywood, Siebert and Wei, 1997; Barth et al., 2008). However, incentive pay is also not costless for firms, for

[23]The mean of the incentive-pay measure for the survey data sample is 0.0135 and the standard deviation is 0.00987.

instance because such pay policies can lead to the manipulation of performance measures or the deceiving of customers (Baker, Gibbons and Murphy, 1994). Consequently, firms with low monitoring costs might be better off monitoring workers instead of incentivizing them.[24] The model of Prendergast (2002) also predicts that firms use more incentive pay if monitoring is costly, and the theory on delayed payments by Lazear (1981) suggests that experience-earnings profiles are steeper when monitoring is more costly.

4.2.2. Occupational characteristics and incentive pay

The extent of the agency problems between employers and workers is, among other factors, determined by the characteristics of workers' occupations (Holmstrom and Milgrom, 1991). Accordingly, firms choose compensation policies that fit occupational characteristics (Holmstrom and Milgrom, 1994; MacLeod and Parent, 2012). What we exploit for our test is the theoretical prediction that incentive pay is more likely in occupations that involve complex tasks because these tasks are hard to monitor due to greater uncertainty regarding workers' optimal actions (Prendergast, 2002).

To assess the complexity of tasks, we rely on the classification approach proposed by Autor, Levy and Murnane (2003). They distinguish between routine and nonroutine tasks, that is, whether the optimal actions to carry out tasks follow an explicit procedure. Furthermore, they distinguish between cognitive and manual tasks. Nonroutine cognitive tasks (e.g., managing others or research) are the most complex because the optimal actions do not follow a strict procedure. Accordingly, occupations with mainly nonroutine cognitive tasks are the hardest to monitor. Information on the main task of occupations and their task composition were obtained from Dengler, Matthes and Paulus (2014).[25]

To investigate how the task complexity of occupations affects incentive pay, we sort occupations by their variance of residual wages.[26] Figure 2 (a)

[24]See Pendleton (2006) for a more comprehensive overview of monitoring costs and incentive pay. In a related context, Fahlenbrach (2009) shows that CEOs' pay-for-performance sensitivity increases with monitoring costs.

[25]Dengler, Matthes and Paulus follow the approach of Autor, Levy and Murnane and classify tasks of occupations into nonroutine analytical, nonroutine interactive, routine cognitive, nonroutine manual, and routine manual. We combine analytical nonroutine and interactive nonroutine tasks into one category, which we refer to as cognitive nonroutine tasks, and rely on the classification from 2013.

[26]The occupation-level residual wage variance is calculated as the employee weighted aver-

presents the 10 occupations with the highest and the 10 with the lowest value of incentive pay.[27] In line with theoretical predictions, eight of the 10 occupations with the highest value of incentive pay have mainly cognitive, nonroutine tasks (e.g., journalists and management consultants). The other two occupations are chartered accountants and electrical engineers, who perform mainly cognitive tasks that follow a routine. Among the 10 occupations with the lowest value of incentive pay, we find only occupations with mainly manual tasks. Four of them follow a routine (e.g., printers and bricklayers) while the other six do not (e.g., motor vehicle drivers and road makers). This comparison shows that our measure for incentive pay is, as theoretically predicted, higher in occupations with complex tasks that are costly to monitor.

— Figure 2 about here —

In Panel B of Figure 2, we illustrate the relation between occupations' task composition and incentive pay. The horizontal axis shows the fraction of cognitive nonroutine tasks (Subfigure b), cognitive routine tasks (c), manual nonroutine tasks (d), or manual routine tasks (e) of an occupation. The vertical axis shows the level of incentive pay, that is, the average variance of residual wages within an occupation. 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 cognitive nonroutine tasks of an occupation has the strongest positive relationship with incentive pay. The fraction of routine cognitive tasks shows a weaker but still positive relationship. For nonroutine and routine manual tasks, we detect a negative relationship. These findings again show that our incentive-pay measure is higher in occupations with tasks that are costly to monitor.

4.2.3. Establishment size and incentive pay: Graphical analysis

In addition to occupational characteristics, the size of an establishment likely affects how costly it is to monitor workers. Garen (1985), for instance, develops a model in which compensation contracts differ between large and small firms because of their differences in monitoring costs. An important

age of all establishment-occupation residual wage variances. Please note that we focus on the one hundred largest occupations, which account for approximately 90% of the worker-years in our dataset, for the analysis of occupational characteristics.

[27] Appendix B shows the corresponding figure for the top 10 and bottom 10 industries.

ingredient of his model is that larger firms have higher costs of acquiring information about workers and lower accuracy when screening workers.

We start by analyzing the relationship between size and within-establishment wage differences in Figure 3 and focus on our measure for incentive pay in the following paragraph. We sort establishments into deciles based on their number of full-time employees and calculate the mean value of the within-establishment variance of wages for each decile. The variance of wages within establishments increases monotonically from about 0.101 in the smallest decile (average of 19.9 employees) to about 0.156 in the largest decile (average of 10,259 employees). The illustration shows that differences in workers' characteristics are responsible for about 80% of the higher wage variance in the largest establishments, of which one-fifth is attributable to observable worker characteristics and four-fifths to unobservable worker characteristics. The remaining 20% is related to the higher residual wage variance in the largest establishments.[28]

— Figure 3 about here —

Figure 4 presents the results for within- and between-occupation wage differences. Subfigure(a) shows that the within-occupation wage variance increases monotonically in size, whereas the between-occupation wage variance is relatively constant over deciles 1 to 8 and increases only in the upper two deciles, that is, for establishments with more than 719 employees. The results for wages net of observable characteristics, in Subfigure (b), are very similar. Subfigure (c) shows the size patterns for our incentive-pay measure, that is, the variance of residual wages within occupations. While the between-occupation residual wage variance decreases slightly in size, we find a strong increase of incentive pay from the smallest to the largest establishment decile (0.010 vs. 0.023). This finding shows that our measure for incentive pay is, as theoretically predicted, more common in larger establishments that have higher monitoring costs.

— Figure 4 about here —

[28]These results support the conclusion of Mueller, Ouimet and Simintzi (2017) that the higher wage inequality in larger firms is related to differences in managerial talent. Furthermore, they are consistent with Song et al. (2019), who show that the rise in within-firm inequality in the U.S. is most pronounced in the largest firms.

4.2.4. Establishment size and incentive pay: Regression analysis

To quantify the relationship between establishment size and incentive pay, we regress the within-occupation variance of residual wages, $var_t^{o,j}(r_t^{i,j})$, on an establishment's number of full-time employees, $size_t^j$. We also include county-year, industry-year, and occupation-year fixed effects to control for time effects, economic development on the county level, industry-specific time trends, and occupation-related factors. The regression specification for worker i in occupation o of establishment j and year t can be written as

$$var_t^{o,j}(r_t^{i,j}) = \alpha + \beta log(size_t^j) + \lambda^j \cdot \tau_t + \kappa^j \cdot \tau_t + \pi^o \cdot \tau_t + \epsilon, \qquad (11)$$

where λ^j denotes establishment-industry dummies (based on three-digit WZ2008 industries), κ^j establishment-county dummies (based on "Landkreise"), π^o occupation dummies, and τ_t year dummies. α is a constant, ϵ is the error term, and β is the coefficient of interest. We estimate this model on the worker-year level and cluster standard errors at the firm level.

The results are presented in the first three columns of Table 5. We show a specification with year fixed effects in Column 1 and add county-year and industry-year fixed effects in Column 2. The full specification, as in Equation 11, can be found in Column 3. The coefficient estimate for size is positive and statistically significant at the 1% level in all three specifications. The magnitude of β varies between 0.0021 and 0.0022, which indicates that the incentive-pay measure is about 14% higher, relative to the sample mean, for an establishment that has twice as many employees.

Next, we use the establishment structure of multi-establishment firms to estimate a specification that additionally includes firm-year fixed effects.[29] These additional fixed effects ensures that the estimation of the parameter of interest, β, is based on size differences between establishments within the same firm. This within-firm estimation controls for all time-constant and time-varying firm-specific factors and helps to mitigate concerns that small and large firms could differ along dimensions that are unrelated to incentive pay. The regression specification for worker i in occupation o of establishment j and year t

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

can be written as

$$var_t^{o,j}(r_t^{i,j}) = \alpha + \beta log(size_t^j) + \lambda^j \cdot \tau_t + \kappa^j \cdot \tau_t + \pi^o \cdot \tau_t + \eta^k \cdot \tau_t + \epsilon, \qquad (12)$$

where η^k denotes firm dummies.

The results are presented in the last two columns of Table 5. We show a specification without occupation fixed effects in Column 4 and the full specification, as in Equation 12, in Column 5. The coefficient estimates for size, which are statistically significant at the 1% level, are 0.0017 in both specifications. These estimates are comparable to the previous specifications without firm-year fixed effects and indicate that the incentive-pay measure is about 11% higher, relative to the sample mean, for an otherwise identical establishment of the same firm that has twice as many employees.

4.2.5. Establishment task complexity and incentive pay

In addition to size, monitoring costs may also be affected by the complexity of tasks that are performed in an establishment. In contrast to Section 4.2.2, which investigates how the task complexity of an occupation affects the occupation-level incentive pay, we analyze how the fraction of complex tasks in an establishment affects its level of incentive pay in this subsection. The theoretical prediction is that incentive pay will be more important in establishments with a high fraction of complex tasks because those tasks are more costly to monitor (Prendergast, 2002). To test this prediction, we rely on the specifications in Equations 11 and 12 and use $highly\ complex_t^j$, that is, the number of employees who perform highly complex tasks in an establishment divided by its total employees, as an independent variable.[30]

Table 6 presents the results. The coefficient estimates for task complexity are positive and statistically significant at the 1% level in all specifications. The magnitude of β varies between 0.0022 and 0.0031, which indicates that the level of incentive pay increases by 15% to 21%, relative to the sample mean, if the fraction of employees who perform highly complex tasks in the establishment increases by 10%. These results show once more that our incentive-pay measure is more common in establishments with higher monitoring costs.

[30]The number of employees who perform highly complex tasks comes from the BHP and is based on the last digit of the five-digit Classification of Occupations 2010.

— Table 6 about here —

Next, we include both establishment-level proxies for monitoring costs, that is, $size_t^j$ and $highly\ complex_t^j$, and their interaction term in the same regression to investigate their joint influence on incentive pay.[31] The results are reported in Table 7. The coefficient estimates for $highly\ complex_t^j$ and $size_t^j$ are positive and highly statistically significant in all specifications. Their magnitude is comparable, albeit somewhat smaller for size, to our previous results in Tables 5 and 6. The positive and highly significant coefficient estimates for the interaction terms indicate that the effects of size and task complexity reinforce each other regarding their impact on our incentive-pay measure. Overall, the results in this subsection show that our incentive pay varies as expected with establishment size and task complexity.

— Table 7 about here —

5. Incentive pay and firm outcomes

In this section, we apply our measure to investigate how workers' incentives are related to firm outcomes. After explaining the related theory and our empirical design, we present the results for financial performance, operating performance and efficiency, and innovativeness.

5.1. Theory

The theoretical literature shows that there can be ambiguous effects of incentive pay on workers' efforts. On the one hand, if fairness considerations prevailed, wage differences among similar workers in the same occupation could demoralize workers and lead to less expended effort (Akerlof and Yellen, 1990). If this holds true, we expect to find lower financial performance, operating performance, and efficiency, as well as less innovativeness in firms with high incentive-pay for workers. On the other hand, theories on incentive pay such as the tournament theory (Lazear and Rosen, 1981) predict that more incentive pay increases workers effort. Accordingly, we expect a positive effect of incentive pay on performance and innovativeness. A third possibility is that

[31] The regression specifications follow Equations 11 and 12, and we center all interacted variables at their sample means to make the interpretation easier.

incentive pay has no significant effect on workers' behavior and firm outcomes, for example, because the relative importance of incentive pay for total compensation tends to be smaller for workers compared to the top management.[32]

5.2. Empirical design

We use cross-sectional regressions to shed light on the relation between workers' incentives and firm outcomes. These models will not allow us to draw causal inferences, but they help identifying firm outcomes that correlate with incentive pay. The regression specification for worker i in occupation o of establishment j at firm k and year t can be written as

$$Outcome_t^k = \beta var_t^{o,j}(r_t^{i,j}) + \vec{\gamma}\vec{C}_t^k + \lambda^j \cdot \tau_t + \epsilon, \tag{13}$$

where $Outcome_t^k$ is the outcome variable of firm k in year t and $var_t^{o,j}(r_t^{i,j})$ the incentive-pay measure. $\vec{C}^k$ 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, and λ^j establishment-industry dummies. Since we observe the 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 proxies to measure firms' financial performance. These are EBITDA, EBIT, net income, and cash flow. All proxies are scaled by the total number of employees, and we take their natural logarithm (please see Appendix A for details on their construction). Table 8 presents the results. We show the full regression model, as in Equation 13, and a specification without industry times year fixed effects for each dependent variable. For all financial performance proxies and specifications, we find a positive and statistically

[32] Lemieux, MacLeod and Parent (2009), for instance, find that 37.5% of workers 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 most workers' compensation. 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).

significant coefficient estimate for β. In terms of economic magnitude, the estimates imply that a one-standard-deviation increase in incentive pay is related to a 5% higher EBITDA. The respective numbers for EBIT, net income, and cash flow are 3%, 5%, and 3%, respectively. These results show that incentive pay is positively correlated with firms' financial performance. Although we are careful not to draw causal inferences, this positive correlation is difficult to reconcile with a negative morale effect of incentive pay and more in line with a positive relationship between incentives and effort.

— Table 8 about here —

5.4. Operating performance and efficiency

To measure firms' operating performance, we use sales per employee and value added per employee, again in log terms. To approximate operating efficiency, we use the asset turnover ratio and the inventory turnover ratio. Details on the construction of the variables can be found in Appendix A. Table 9 shows the results. For operating performance, we find robust evidence for a positive correlation with incentive pay. In terms of economic magnitude, the coefficient estimates indicate that a one-standard-deviation increase in incentive pay is related to 2% more sales per employee and 7% more value added per employee. The results for operating efficiency are more ambiguous. We find a positive, but, in terms of statistical significance, relatively weak correlation between incentive pay and inventory turnover. Our second proxy for operating efficiency, asset turnover, seems to be uncorrelated to incentive pay. To conclude, incentive pay seems to be related to operating performance, but not operating efficiency. One possible explanation for this finding is that the rewards of incentive-pay schemes are typically tied to output rather than the input-output ratio, which determines efficiency. The positive correlation between incentive pay and operating efficiency is again difficult to reconcile with a negative morale effect of incentive pay and more in line with the view that workers' effort is higher in firms with more incentive pay.

— Table 9 about here —

5.5. Innovativeness

We apply four patent-based measures to measure the innovativeness of a firm. The first measure is the number of patents, which captures the quantity of innovation that is produced by a firm. The second measure is the number of citations per patent, which is a proxy for the quality of a firm's innovations. We take the logarithm of both variables. The last two measures capture the generality and originality of a firm's patents.[33] The results are shown in Table 10. We find a positive correlation between incentive pay and both the quantity and quality of innovation. The coefficient estimates indicate that a one-standard-deviation increase in incentive pay is related to 24% more patents and 2.5% more citations per patent. We find no relation between patent generality and incentive pay, but incentives are positively correlated with patent originality. Taken together, these results show that the quantity and quality of innovation is higher in firms with more incentive pay, which is again in line with a positive relationship between workers' effort and incentive pay, but not a negative morale effect.

— Table 10 about here —

6. Conclusion

The use of financial incentives and its consequences are well documented for top management, but relatively little is known about incentives in the context of non-managerial workers. The main challenge here is the measurement of incentive pay, especially when the incentive schemes are not explicitly written down as contracts (Bloom and Van Reenen, 2011).

This paper proposes an indirect estimation method for incentive pay. Incentive schemes that reward worker performance lead to idiosyncratic wage premiums and more dispersed wages among otherwise comparable workers within the same establishment of a firm (Seiler, 1984; Lemieux, MacLeod and Parent, 2009). We exploit this relationship and use wage differences among workers with similar characteristics who work in the same occupation as a measure for incentive pay. Our measure captures all forms of incentive pay that lead to worker-specific pay premiums, including explicit (e.g., bonuses) and implicit forms (e.g., promotion tournaments or performance-related base-wage adjustments). We validate the measure by showing that it is positively

[33] Generality measures how often the patent is cited outside its core field, while originality is related to its citations of patents from other fields.

correlated with survey-based data on profit sharing and that it varies with monitoring costs as predicted by theory (e.g., Prendergast, 2002).

We apply our measure to firms' financial performance, operating performance and efficiency, and innovativeness. Incentive pay is positively correlated with different proxies for financial and operating performance, but not with operating efficiency. Firms with more incentive pay have a higher quantity and quality of innovations, as shown by their higher number of patents and citations. Although we are careful not to draw causal inferences, these positive correlations are difficult to reconcile with a negative morale effect of incentive pay. By contrast, they are in line with the view that incentive pay has a positive effect on workers' effort. The application of our measure for different firm outcomes, such as employee satisfaction, corporate social responsibility, or product quality, seems a promising area for future research to better understand the interaction between workers, incentives, 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 worker characteristics ("wages - Xb"), and wages after controlling for observable and unobservable worker characteristics ("residual wages") into between-occupation and within-occupation components. The exact values of the decomposition can be found in Table 2. A detailed description of all variables can be found in Appendix A.

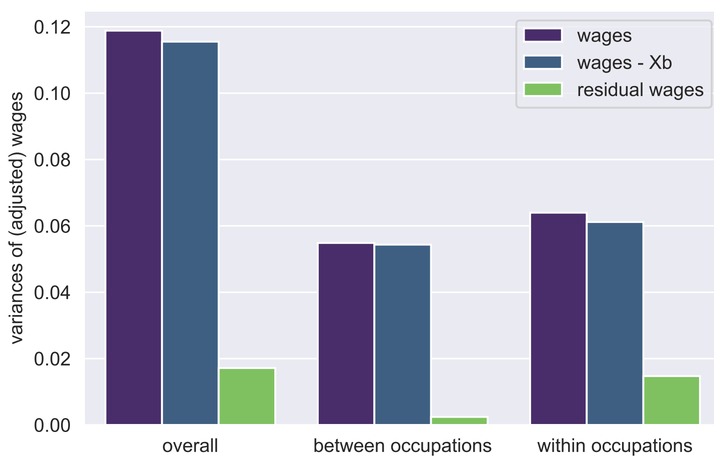
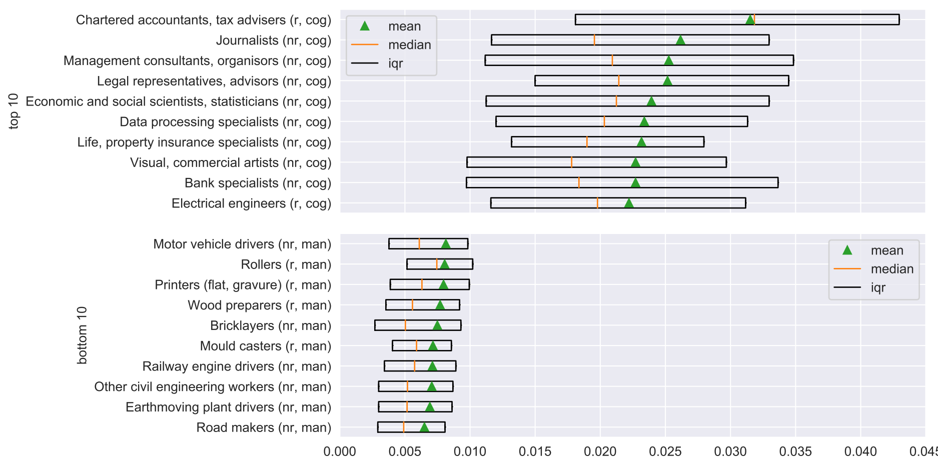


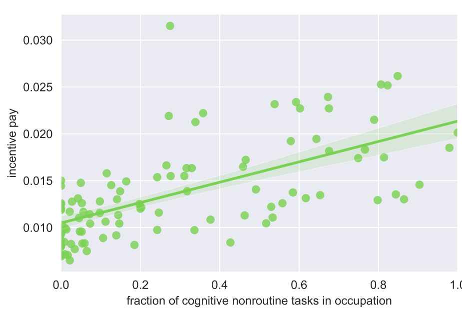
Figure 2
The incentive-pay measure and occupations

This figure shows the incentive-pay measure in different occupations. We limit this analysis to the 100 most common occupations in our sample; they account for approximately 90% of the employee-years. Subfigure (a) presents the 10 occupations with the highest and the 10 with the lowest values of the incentive-pay measure. In the brackets, we classify the main task of the occupation following the approach of Autor, Levy and Murnane (2003). *nr* denotes a nonroutine task, *r* a routine task, *cog* a cognitive task, *man* a manual task. Subfigures (b) to (e) illustrate the relation between the task classification of an occupation and incentive pay by a linear regression line with a 90% confidence interval. A detailed description of all variables can be found in Appendix A.

(a) Occupations with highest/lowest values of the incentive-pay measure

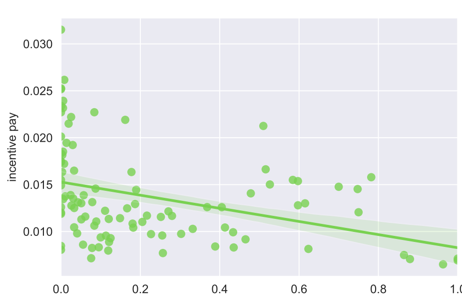


(b) %Cognitive nonroutine



(c) %Cognitive routine

(d) %Manual nonroutine



(e) %Manual routine

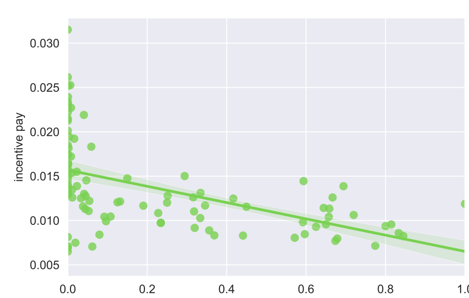


Figure 3

Within-establishment wage differences and size

This figure presents, for each establishment-size decile, the mean value of the within-establishment variance of wages, wages after controlling for observable worker characteristics (wages - Xb), and wages after controlling for observable and unobservable worker characteristics (residual wages). To construct the establishment-size deciles, we sort establishments based on their number of full-time employees. A detailed description of all variables can be found in Appendix A.

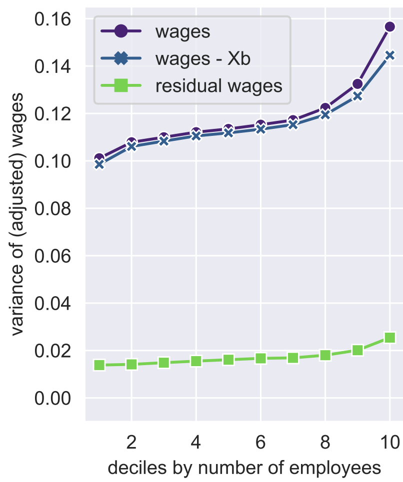
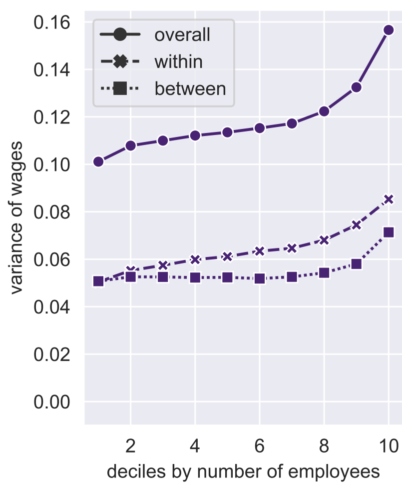


Figure 4

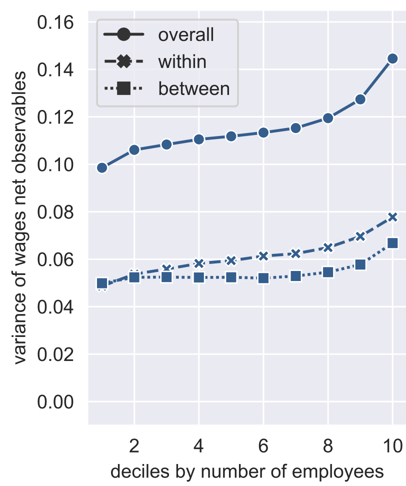
Within-establishment wage differences and size: within vs. between occupations

This figure presents, for each establishment-size decile, the decomposition of the mean value of the within-establishment variance into between- and within-occupation components, as stated in Equation 8. We decompose the within-establishment variance of wages in Subfigure (a), wages after controlling for worker observables ("wages - Xb") in Subfigure (b), and wages after controlling for observable and unobservable worker characteristics ("residual wages") in Subfigure (c). To construct the establishment-size deciles, we sort establishments based on their number of full-time employees. A detailed description of all variables can be found in Appendix A.

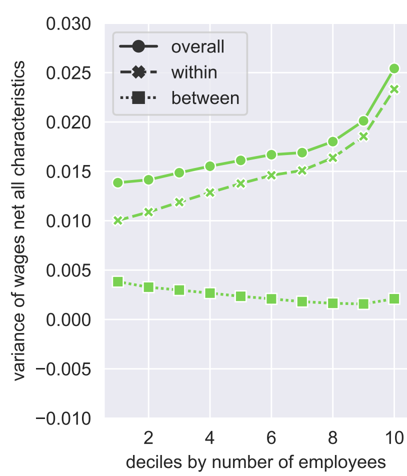
(a) wages



(b) wages - Xb



(c) residual wages



Tables

Table 1
Decomposition of within-establishment wage differences

This table presents the decomposition of the within-establishment variance of wages, wages after controlling for observable worker characteristics (wages - Xb), and wages after controlling for observable and unobservable worker characteristics (residual wages) into the variances and covariances of the parameter estimates from the AKM-type regression, as stated in Equation 5. A detailed description of all variables can be found in Appendix A.

	var(wages)		var(wages - Xb)		var(residual wages)	
	mean	share	mean	share	mean	share
total	0.119	1.000	0.116	1.000	0.017	1.000
var(person FE)	0.098	0.823	0.098	0.846	-	-
var(Xb)	0.009	0.077	-	-	-	-
var(residual)	0.017	0.144	0.017	0.149	0.017	1.000
2cov(person FE, Xb)	-0.006	-0.049	-	-	-	-
2cov(person FE, residual)	0.001	0.005	0.001	0.005	-	-
2cov(Xb, residual)	-0.000	-0.000	-	-	-	-

Table 2
Wage differences within and between occupations

This table presents the decomposition of the within-establishment variance of wages, wages after controlling for observable worker characteristics (wages - Xb), and wages after controlling for observable and unobservable worker characteristics (residual wages) into a between-occupation and a within-occupation component, as stated in Equation 8. A detailed description of all variables can be found in Appendix A.

	var(wages)		var(wages - Xb)		var(residual wages)	
	mean	share	mean	share	mean	share
total	0.119	1.000	0.116	1.000	0.017	1.000
between occupations	0.055	0.462	0.054	0.470	0.002	0.142
within occupations	0.064	0.538	0.061	0.530	0.015	0.858

Table 3
Descriptive statistics

This table presents descriptive statistics The sample consists of 72,394,909 employee-years, 16,868,872 individual employees, 206,287 establishments, and 87,580 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 A.

	Obs	Mean	SD	25th	50th	75th
wage	72,394,909	4.607	0.529	4.272	4.601	4.929
incentive pay	72,303,233	0.015	0.013	0.006	0.011	0.020
empl	72,394,909	1282	4933	63	170	525
number of occupations	72,394,909	22	19	9	16	30
highly complex	62,076,764	0.123	0.151	0.024	0.071	0.163
multi-establishment firm	72,394,909	0.467	0.499	0.000	0.000	1.000
number of establishments	72,394,909	44	262	1	1	5
log(sales per employee)$_{firm}$	37,092,970	12.283	1.089	11.724	12.306	12.978
log(value added per employee)$_{firm}$	20,604,518	11.900	0.604	11.531	11.836	12.213
asset turnover$_{firm}$	37,079,990	2.014	1.696	0.872	1.560	2.605
inventory turnover$_{firm}$	4,390,189	16.652	47.540	7.666	9.816	16.427
log(ebitda per employee)$_{firm}$	28,662,733	9.751	1.322	9.072	9.836	10.567
log(ebit per employee)$_{firm}$	19,928,555	9.089	1.489	8.208	9.203	10.101
log(net income per employee)$_{firm}$	20,601,912	8.865	1.765	7.883	9.076	10.170
log(cash flow per employee)$_{firm}$	29,190,845	9.422	1.436	8.685	9.541	10.375
log(patents)$_{firm}$	12,092,979	2.024	1.618	0.693	1.792	3.761
log(citations per patent)$_{firm}$	9,091,795	0.768	0.581	0.288	0.693	1.170
patent originality$_{firm}$	9,059,462	0.257	0.126	0.198	0.259	0.313
patent generality$_{firm}$	7,710,157	0.111	0.105	0.000	0.106	0.160

Table 4
Survey-based profit sharing and the incentive pay measure

The dependent variable is the incentive pay measure. Profit sharing is measured as the number of employees who participate in profit sharing in an establishment, divided by the establishment's total number of employees. The regression models are estimated on the worker-year level for the survey sample (Section 4). T-statistics, presented in parentheses, are based on robust standard errors clustered at the firm level. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively. A detailed description of all variables can be found in Appendix A.

	(1)	(2)	(3)	(4)
profit sharing	0.0066***	0.0023***	0.0023***	0.0016***
	(4.63)	(8.40)	(8.43)	(6.12)
log(empl)				0.0012***
				(13.43)
Year FE	Yes	Yes	Yes	Yes
County x year FE	No	Yes	Yes	Yes
Industry x year FE	No	Yes	Yes	Yes
Occupation x year FE	No	No	Yes	Yes
Obs	3,471,500	3,471,073	3,270,294	3,270,294
R2	0.10	0.56	0.57	0.59

Table 5

Establishment size and the incentive-pay measure

The dependent variable is the incentive-pay measure. Establishment size is the natural logarithm of an establishment's number of employees. The regression is estimated on the worker-year level. T-statistics, presented in parentheses, are based on robust standard errors clustered at the firm level. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively. A detailed description of all variables can be found in Appendix A.

	(1)	(2)	(3)	(4)	(5)
log(empl)	0.0022***	0.0022***	0.0021***	0.0017***	0.0017***
	(15.34)	(20.57)	(20.93)	(12.83)	(13.24)
Year FE	Yes	Yes	Yes	Yes	Yes
County x year FE	No	Yes	Yes	Yes	Yes
Industry x year FE	No	Yes	Yes	Yes	Yes
Occupation x year FE	No	No	Yes	No	Yes
Firm x year FE	No	No	No	Yes	Yes
Obs	72,303,233	72,278,553	70,047,561	33,725,471	32,825,318
R2	0.09	0.37	0.39	0.67	0.67

Table 6
Task complexity and the incentive-pay measure

The dependent variable is the incentive-pay measure. Highly complex is the number of employees who perform highly complex tasks in the establishment, divided by the establishment's total number of employees. The regression is estimated on the worker-year level.T-statistics, presented in parentheses, are based on robust standard errors clustered at the firm level. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively. A detailed description of all variables can be found in Appendix A.

	(1)	(2)	(3)	(4)	(5)
highly complex	0.031***	0.023***	0.022***	0.027***	0.027***
	(22.62)	(18.95)	(17.85)	(13.17)	(15.80)
Year FE	Yes	Yes	Yes	Yes	Yes
County x year FE	No	Yes	Yes	Yes	Yes
Industry x year FE	No	Yes	Yes	Yes	Yes
Occupation x year FE	No	No	Yes	No	Yes
Firm x year FE	No	No	No	Yes	Yes
Obs	62,001,286	61,999,806	59,774,022	28,934,771	28,037,024
R2	0.14	0.37	0.38	0.68	0.68

Table 7
Establishment size, task complexity, and the incentive-pay measure

The dependent variable is the incentive-pay measure. Highly complex is the number of employees who perform highly complex tasks in the establishment, divided by the establishment's total number of employees. Establishment size is the natural logarithm of an establishment's number of employees. Highly complex and establishment size are centered at their sample means. The regression is estimated on the worker-year level. T-statistics, presented in parentheses, are based on robust standard errors clustered at the firm level. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively. A detailed description of all variables can be found in Appendix A.

	(1)	(2)	(3)	(4)	(5)
highly complex	0.028***	0.022***	0.022***	0.028***	0.028***
	(26.76)	(21.08)	(19.91)	(13.52)	(18.13)
log(empl)	0.0017***	0.0019***	0.0019***	0.0013***	0.0013***
	(12.10)	(19.77)	(19.56)	(10.60)	(11.09)
highly complex x log(empl)	0.0053***	0.0060***	0.0058***	0.0056***	0.0056***
	(6.52)	(12.81)	(12.74)	(9.94)	(12.02)
Year FE	Yes	Yes	Yes	Yes	Yes
County x year FE	No	Yes	Yes	Yes	Yes
Industry x year FE	No	Yes	Yes	Yes	Yes
Occupation x year FE	No	No	Yes	No	Yes
Firm x year FE	No	No	No	Yes	Yes
Obs	62,001,286	61,999,806	59,774,022	28,934,771	28,037,024
R2	0.20	0.42	0.43	0.69	0.69

Table 8
The incentive-pay measure and financial performance

The dependent variables are indicated in each column. Incentive pay is the within-occupation variance of residual wages. T-statistics, presented in parentheses, are based on robust standard errors clustered at the firm level. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively. A detailed description of all variables can be found in Appendix A.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	log(ebitda per empl)		log(ebit per empl)		net income per empl		cash flow per empl	
incentive pay	3.46**	3.58**	2.24**	2.56**	4.08**	4.11**	2.38*	2.35*
	(2.00)	(2.12)	(2.09)	(2.54)	(2.05)	(2.12)	(1.72)	(1.71)
log(total assets)	0.26***	0.27***	0.28***	0.28***	0.29***	0.29***	0.29***	0.30***
	(20.38)	(22.43)	(18.51)	(20.54)	(17.18)	(17.17)	(27.71)	(28.27)
leverage	-0.28***	-0.28***	-0.26***	-0.27***	-0.74***	-0.73***	-0.043	-0.042
	(-3.60)	(-4.22)	(-5.46)	(-5.98)	(-8.86)	(-9.18)	(-0.69)	(-0.70)
tangibility	1.10***	1.09***	-0.053	-0.047	-0.39***	-0.37***	1.42***	1.42***
	(9.97)	(11.13)	(-0.59)	(-0.55)	(-2.94)	(-2.88)	(15.46)	(16.03)
cash holdings	0.81***	0.79***	1.04***	1.03***	1.35***	1.36***	1.44***	1.44***
	(6.29)	(6.63)	(8.55)	(9.01)	(7.95)	(8.04)	(11.30)	(11.49)
listing dummy	-0.054	-0.077	0.076	0.050	0.69***	0.69***	0.75***	0.73***
	(-0.40)	(-0.58)	(0.52)	(0.36)	(5.09)	(5.10)	(6.76)	(6.65)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry x year FE	No	Yes	No	Yes	No	Yes	No	Yes
Obs	26,219,833	26,219,833	18,177,285	18,177,285	19,315,827	19,315,827	26,899,737	26,899,737
R2	0.49	0.52	0.44	0.45	0.45	0.47	0.53	0.54

Table 9

The incentive-pay measure, operating performance, and operating efficiency

The dependent variables are indicated in each column. Incentive pay is the within-occupation variance of residual wages. T-statistics, presented in parentheses, are based on robust standard errors clustered at the firm level. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively. A detailed description of all variables can be found in Appendix A.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	log(sales per empl)		log(value added per empl)		asset turnover		inventory turnover	
incentive pay	1.65**	1.61**	5.67***	5.71***	-0.35	-0.32	177*	169*
	(2.05)	(2.15)	(10.52)	(10.73)	(-0.29)	(-0.27)	(1.79)	(1.77)
log(total assets)	0.20***	0.20***	0.17***	0.17***	-0.34***	-0.34***	-5.47***	-5.19***
	(20.17)	(24.78)	(32.41)	(33.47)	(-25.05)	(-27.05)	(-4.07)	(-3.79)
leverage	0.053	0.054*	-0.10***	-0.10***	-0.23***	-0.22***	-2.03	2.92
	(1.59)	(1.65)	(-5.60)	(-5.74)	(-3.78)	(-3.79)	(-0.36)	(0.51)
tangibility	-0.47***	-0.48***	-0.21***	-0.21***	-1.41***	-1.42***	-13.3	-11.4
	(-6.81)	(-7.47)	(-6.41)	(-6.66)	(-12.04)	(-12.32)	(-1.33)	(-1.19)
cash holdings	0.019	0.0035	0.17***	0.16***	-0.61***	-0.63***	-0.64	-2.75
	(0.24)	(0.05)	(3.55)	(3.56)	(-3.95)	(-4.21)	(-0.04)	(-0.14)
listing dummy	-0.23***	-0.23***	-0.15***	-0.14***	-0.55***	-0.55***	-0.46	-0.43
	(-2.85)	(-3.19)	(-3.78)	(-3.86)	(-6.75)	(-6.87)	(-0.15)	(-0.12)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry x year FE	No	Yes	No	Yes	No	Yes	No	Yes
Obs	31,378,491	31,378,491	18,923,319	18,923,319	31,378,491	31,378,491	3,997,080	3,997,080
R2	0.63	0.64	0.43	0.44	0.46	0.47	0.21	0.31

Table 10
The incentive-pay measure and innovativeness

The dependent variables are indicated in each column. Incentive pay is the within-occupation variance of residual wages. T-statistics, presented in parentheses, are based on robust standard errors clustered at the firm level. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively. A detailed description of all variables can be found in Appendix A.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	log(patents)		log(citations per patent)		patent generality		patent originality	
incentive pay	18.3***	18.1***	1.77***	2.11***	0.025	0.032	0.39**	0.33**
	(4.98)	(4.88)	(2.58)	(2.74)	(0.16)	(0.21)	(2.46)	(2.15)
log(total assets)	0.49***	0.50***	0.080***	0.087***	0.0021	0.00090	0.0011	0.00067
	(10.07)	(10.53)	(7.58)	(8.52)	(0.88)	(0.37)	(0.46)	(0.26)
leverage	-0.0042	0.014	-0.047	-0.026	-0.031**	-0.025*	-0.00079	-0.0041
	(-0.03)	(0.10)	(-1.02)	(-0.53)	(-2.30)	(-1.83)	(-0.04)	(-0.24)
tangibility	-0.78***	-0.76***	-0.32***	-0.30***	-0.049**	-0.052**	-0.068***	-0.064**
	(-2.66)	(-2.75)	(-3.22)	(-3.03)	(-2.17)	(-2.32)	(-2.73)	(-2.52)
cash holdings	0.12	0.040	0.035	-0.069	0.012	0.013	0.012	0.0085
	(0.38)	(0.14)	(0.28)	(-0.55)	(0.41)	(0.44)	(0.43)	(0.28)
listing dummy	0.94***	0.93***	0.069*	0.068*	-0.0048	-0.0043	0.013	0.013*
	(4.84)	(4.81)	(1.72)	(1.72)	(-0.57)	(-0.50)	(1.55)	(1.73)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry x year FE	No	Yes	No	Yes	No	Yes	No	Yes
Obs	11,149,039	11,149,039	8,493,414	8,493,414	8,464,069	8,464,069	7,290,409	7,290,409
R2	0.71	0.73	0.59	0.68	0.16	0.27	0.28	0.39

Appendix A
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 (Beschäftigten-Historik).
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 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 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 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 2.1.
Establishment characteristics	
incentive pay	Within-occupation variance of residual wages. The calculation of the incentive-pay measure is explained in detail in Section 2.
empl	Number of full-time employees in an establishment. Source: BeH, BHP (Betriebshistorik Panel).
number of occupations	Number of occupations according to the first three digits of the Classification of Occupations 1988 (KldB 1988). Source: BeH.
highly complex	Number of (full-time and part-time) employees who perform highly complex tasks divided by the (full-time and part-time) total employees. This variable is based on the last digit of the five-digit Classification of Occupations 2010 and is available from 2011 on. Source: BeH, BHP.
profit sharing	Number of employees who participate in profit sharing divided by number of employees. Source: BP (Betriebs Panel).
Firm characteristics	
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.

continued on next page

Appendix A continued

Variable	Description
log(sales per employee)$_{firm}$	Natural logarithm of the ratio of a firm's sales to the total number of full-time employees. Sales is CPI-adjusted to the base year 2010. Source: BeH, BHP, Orbis.
log(value added per employee)$_{firm}$	Natural logarithm of the ratio of a firm's value added to the total number of full-time employees. Value added is calculated as operating revenue minus material expenses. Both variables are CPI-adjusted to the base year 2010. Source: BeH, BHP, Orbis.
asset turnover$_{firm}$	Ratio of a firm's sales to total assets. Source: BeH, BHP, Orbis.
inventory turnover$_{firm}$	Ratio of a firm's costs of goods sold to inventories. Source: BeH, BHP, Orbis.
log(ebitda per employee)$_{firm}$	Natural logarithm of the ratio of a firm's EBITDA to the total number of full-time employees. EBITDA is CPI-adjusted to the base year 2010. Source: BeH, BHP, Orbis.
log(ebit per employee)$_{firm}$	Naural logarithm of the ratio of a firm's EBIT to the total number of full-time employees. EBIT is CPI-adjusted to the base year 2010. Source: BeH, BHP, Orbis.
log(net income per employee)$_{firm}$	Natural logarithm of the ratio of a firm's net income to the total number of full-time employees. Net income is CPI-adjusted to the base year 2010. Source: BeH, BHP, Orbis.
log(cash flow per employee)$_{firm}$	Natural logarithm of the ratio of a firm's cash flow to the total number of full-time employees. Cash flow is CPI-adjusted to the base year 2010. Source: BeH, BHP, 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 does so in at least one year during our sample period. Source: BeH, BHP, Orbis.
log(citations per patent)$_{firm}$	Natural logarithm of the ratio of a firm's forward citations to filed patents. Source: Orbis.
patent generality$_{firm}$	Average degree to which patents at the firm-year level are cited by patents in different International Patent Classifications. Source: Orbis.
patent originality$_{firm}$	Average degree to which patents filed by a firm in a given year cite other patents in different International Patent Classifications. 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.

continued on next page

Appendix A continued

Variable	Description
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

The incentive-pay measure and industries

This figure shows the incentive-pay measure in different industries. We limit this analysis to the 100 most common industries in our sample; they account for approximately 87% of the employee-years. The figure presents the 10 industries with the highest and the 10 industries with the lowest values of the incentive-pay measure. A detailed description of all variables can be found in Appendix A.