Technology and Performance Pay in Organizations

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Abstract

In this paper, I draw on established theories in labor and organizational economics to explain theoretically that information and communication technologies (ICT) increase task complexity and worker interdependencies (i.e., non-routine or team tasks), and thus the need to adapt incentive schemes either towards individual or collective performance pay, or fixed wages. To date, there has been little literature addressing the changes in the compensation system that may result from the proliferation of modern technologies in the workplace. This paper aims to close this research gap. Using unique German panel data on management practices from the years 2014 to 2018, I apply the bracketing-property approach to emphasize that equipping workers with ICT leads to adaptations in the compensation system. Both the theoretical and empirical framework advance the literature on ICT and incentives by showing that ICT equipment in lower layers in a hierarchy increases the prevalence of collective performance pay, while there is no such effect in higher layers.

Keywords: information and communication technology, incentives, team tasks, worker interdependencies, hierarchy, bracketing property
JEL: J33, M12, M52, O33

1 Introduction

Firm performance crucially depends on the right incentive scheme. For many years, firms focused on bonuses tied to individual performance to raise productivity. More recently, fixed wages only or collective performance incentive schemes such as profit-sharing or team incentives appear to be more beneficial (Sliwka 2020, Grunau et al. 2021). Widely discussed reasons why some firms shy away from individual performance pay are multitasking distortions (Hong et al. 2019), workers' social preferences or traits (Bandiera et al. 2005, Donato et al. 2017), or the lack of objective performance measures (Manthei and Sliwka 2019). However, these factors alone fail to capture recent extensive technology adaptions in firms and their impact on performance incentive schemes. It is well known that firms adapt their organizational and job design to maintain competitive advantages in a digital economy (Bresnahan et al. 2002, Gerten et al. 2022). Yet the effects of an immersive technological work environment on potential adaptions in performance incentive schemes are only partially understood.

This paper studies the technological equipment of workers in the workplace and its impact on performance incentive schemes. I show that an increase in collective performance pay depends not only on workers' equipment with information and communication technologies (ICT), but also on the layer in a knowledge-based hierarchy at which ICT has been introduced. In addition to studies that primarily focus on subgroups of workers or on a specific firm type, average changes in incentive schemes should be examined to obtain a more comprehensive picture of the recent ICT expansion in firms that reveal differences between managerial and non-managerial employees.[1] A key implication of my study is that collective performance pay (based on team/divisional and/or organizational performance) accumulate while equipping workers at lower layers in a hierarchy with ICT (i.e., workers without managerial responsibilities). I explain this phenomenon theoretically by relying on established theories in labor and organizational economics, and coupling them with theories on incentive pay. Further, I test my hypotheses in an empirical setting.

Specifically, I study the effect of equipping managerial and non-managerial workers with mobile information and communication technologies on performance incentives schemes in German firms that applied incentive pay between the years 2014 to 2018.[2] I use established German employer level

[1] In the literature, there is a growing number of field experiments studying the performance effects of bonus schemes. Each field experiment concentrates on a specific firm or a specific job type. This paper, however, studies ICT equipment and potential effects on the prevalence of individual or collective performance pay using representative data of over 700 establishments located in Germany. See, Sliwka (2020) to get a short overview of field experiments in the domain of performance pay.

[2] By mobile information and communication technologies, I refer to mobile tools capable to establish an Internet

data from the Linked Personnel Panel (LPP) and the IAB Establishment Panel to document that ICT equipment among non-managerial workers increases the prevalence of collective performance pay for these workers. For managerial workers, I do not find a change in the prevalence of a more individual or collective performance pay.

In the first part of the paper, I motivate my research idea by following three theoretical literature branches that, taken together, suggest that ICT equipment among workers might affect either individual or collective performance pay, or the prevalence of fixed wages, and that potential ICT effects on performance incentive schemes differentiate across hierarchical levels.

First, I rely on theories in labor economics. The skill-biased technological change (SBTC) framework assumes that technology is complementary to skilled workers (Acemoglu 1998; Goldin and Katz 1998).[3] In addition, according to the routine-biased technological change (RBTC), rapid improvements in digital technologies, such as information and communication technologies (ICT) and artificial intelligence (AI), are biased toward replacing labor in routine tasks (Acemoglu and Autor 2011; Autor et al. 2003, 2006, 2008; Autor et al. 2015; Brynjolfsson and McAfee 2011, 2014; Goos et al. 2009, 2014; Gregory et al. 2022). If technological progress is complementary with non-routine tasks, workers are forced to adjust quickly in terms of skills, competencies, flexibility, and cooperation abilities (Caines et al. 2017; Mobius and Schoenle 2006). New human resource management practices are required, such as problem solving teams and meetings (Bartel et al. 2007; Boning et al. 2007), to face arising task complexity in the workplace.

Second, I consider theories in organizational economics. While implementing technologies, firms go through a process of organizational redesign and they change their organizational practices (Bresnahan et al. 2002; Bloom et al. 2014). Simultaneously, firms change worker policies that define the design of jobs (Gerten et al. 2022). In a knowledge-based hierarchy, the deployment of technologies forces decentralizing measures, such as dropping hierarchical layers or granting more autonomy to workers, leading to greater control spans and larger (autonomous) teams (Garicano 2000; Garicano and Rossi-Hansberg 2006, 2015).

Based on these findings stemming from theories in labour and organizational economics, I argue that, first, the spread of technologies and the complementary task complexity (i.e., non-routine tasks) increases in-person interactions or worker interdependencies in a firm (i.e., team tasks). Second, the referred increase in team size (due to larger control spans) is consistent with

connection such as laptops, smartphones, and tablets. In the literature, mobile ICT are categorized as remote working technologies (OECD 2021), meaning technologies that allow to work autonomous and remote, independent of working time and working place.

[3] See, Acemoglu and Autor (2011) and Acemoglu and Restrepo (2018) for an extensive literature review.

this reasoning, which predicts an ICT-induced increase in interdependencies between workers in an organization. I explain this phenomenon by introducing the team-biased technological change (TBTC), a technical change that is biased towards team tasks. Team tasks reflect tasks that, by their construction, require interdependencies between workers in lower and/or higher layers.

Third, I link the principles of incentive pay to the previously mentioned theories in labor and organizational economics. Implementing ICT in the workplace improves the information-processing ability of superiors (Guadalupe et al. 2014), centralizing communication in organizations (Garicano 2000), and centralized monitoring across hierarchical levels (Gerten et al. 2022). A firm might devote resources to improve measurement of performance, but it is generally costly to reduce the error variance of the performance measure (Milgrom and Roberts 1992, p. 226). However, the availability of cheap ICT (Brynjolfsson and McAfee 2011, 2014) and the increasingly precise information technologies deliver (Westerman 2019) render performance measurement more affordable and attractive. The increasing demand for quantified workplaces (Moore and Woodcock 2021), data-driven management (Blader et al. 2020; Brynjolfsson and McElheran 2016) and resource fluidity matches (Westerman 2019) stimulate firms to invest in such monitoring practices.[4] Technologies might allow for a better differentiation between high- and low-performing workers and, in the case of differentiation, individual bonus payments increase (Kampkötter and Sliwka 2018).

Relying on the complementary character between measuring performance and setting intense incentives (Milgrom and Roberts 1992, p. 227), I argue that firms consequently increase individual incentives while they improve the accuracy of performance measurement with technologies. Or, in other words, following the incentive intensity principle (Milgrom and Roberts 1992, p. 221), the optimal intensity of incentives depends on the precision with which performance is assessed. Following this principle, I argue that firms add more precise indicators in performance incentive schemes allowing them to increase individual performance.

However, observing the concept of a knowledge-based hierarchy and the SBTC, RBTC, and TBTC, I argue that firms adapt performance incentive schemes due to the changing nature of tasks[5] and the complementary relationship between technology adaption and decentralization.[6]

[4]According to Kampkötter and Sliwka (2018), a firm should invest more in accurate measurement or use stricter evaluators, when the marginal returns to a worker's effect are larger, which should be the case at higher hierarchical levels.

[5]Incentives might be introduced to enhance idea creation or creativity (Gibbs et al. 2017), and thus, to cope better with increasing task complexity and worker interdependencies.

[6]See, Holmstrom and Milgrom (1991), Jensen and Meckling (1992), Prendergast (2002), Itoh et al. (2008), and Rantakari (2008). These studies argue that incentives must be stronger, while delegating decision-making authority. A similar result has been found in Colombo and Delmastro (2004, 2008), Wulf (2007), and De Varo and Prasad

On the one hand, increasing team sizes, task complexity and worker interdependencies make performance measurement imprecise and firms might refrain to offer individual incentives. On the other hand, the new challenges in the workplace in terms of team tasks could lead firms to adapt their incentive scheme towards collective performance pay or fixed wages only.[7] Considering the latter, the prevalence of collective performance pay such as team/divisional and/or organizational incentives, should dominate.

In the second part of the paper, I present empirical evidence that is consistent with the pattern of the theoretical considerations and with earlier findings in empirical studies. I apply two data sets that are representative for German establishments of the processing industry and service sector. First, I use the Linked Personnel Panel, which combines employer with employee data on human resources, corporate culture, and management practices in German establishments. Second, I combine the LPP data with the data of the Establishment Panel of the Institute for Employment Research allowing me to add further information on the determinants of employment in German establishments.

In order to account for multiple sources of endogeneity, I construct a panel data set using four waves of the LPP employer survey from the year 2012 to 2018. I measure the prevalence of ICT by the proportion of managerial and non-managerial workers equipped with mobile ICT. Performance incentive schemes are measured by shares in percentage of individual, team/divisional, and organizational performance pay in the overall performance incentive scheme, thereby distinguishing between managerial and non-managerial workers. My identification strategy exploits the bracketing property of fixed effects and lagged dependent variables models, thereby allowing me to account for omitted variables biases, including omitted selection, and simultaneous causation. The empirical results can be interpreted as causal.

My contribution to the literature is manifold: First, I take up a still unexplored research question on the effects of ICT deployment in firms on performance incentive schemes. In doing so, I differ from other studies that tend to investigate productivity effects after the implementation of performance pay or the conditions under which performance pay works best. Second, I develop a theoretically grounded mechanism - called team-based technological change - that underpins

(2015), where the latter find a positive (negative) relationship between individual incentive pay and delegation of worker authority for simple (complex) jobs in non-managerial occupations.

[7] I rely here on literature arguing that teamwork is pervasive in the workplace, and both productivity and team composition is affected by team incentives (Bandiera et al. 2013). Moreover, I orientate this paper partly on the paper from Englmaier et al. (2018). Here, the authors study non-routine analytical and interactive team tasks in a field experiment, and show that team bonus may affect a team's outcome positively under specific conditions.

my empirical findings on potential ICT effects on performance incentive systems, especially with regard to increasing collective performance pay at lower layers in a hierarchy. In this sense, I differ from other studies in labor economics that tend to emphasize the role of SBTC or RBTC only, or from studies in organisational economics that analyse concepts in a knowledge-based hierarchy without considering the SBTC or RBTC. Clearly, the aim here is to develop a theoretical approach that reconciles current findings in business administration with established theories in labour and organisational economics. Third, the data I use allow me to distinguish between managerial and non-managerial employees, so that it is possible to align my results with recent findings of other studies, in which ICT forces structural changes, especially in lower layers. Fourth, the empirical framework allows me to interpret my results as causal.

The paper proceeds as follows: In Section 2, the theoretical background is discussed. Section 3 provides an overview of the data set, the variables used, and descriptive statistics. In Section 4, the empirical strategy is described in detail. The results can be found in Section 5. Section 6 reports selected robustness checks, and Section 7 a complementary analysis. Finally, Section 8 concludes.

2 Theoretical background

In this section, I show how mainstream theories in labor and organizational economics can be merged to team and incentive theories to explain potential effects of ICT equipment on pay for performance. With the consideration of performance pay, I want to explain the importance of existing team theories and deliver a novel theoretical idea on how these theories contribute to predict the prevalence of individual or collective performance pay offered to ICT-equipped workers. In addition, I show how the theory on knowledge-based hierarchies can be extended by an analysis of worker interdependencies and that this novel extension derived from personnel economics helps to explain recent findings in labor and organizational economics.

2.1 Technological change in labor and organizational economics

First, I highlight how theories on the skill-biased technological change (SBTC) and the routine-biased technological change (RBTC) interact with organizational economic theories of centralization and decentralization in firms. The studies from Acemoglu (1999), Acemoglu (2002), Acemoglu and Autor (2011), and Autor et al. (2003, 2006, 2008), are the baseline to describe theoretically current trends on the labor market originating in technologies that affect the acquisition and communication of knowledge (i.e., information and communication technologies). To explain and relate organizational economic theories to labor market frameworks, I rely heavily on the studies from Garicano (2000), and Garicano and Rossi-Hansberg (2006, 2015). Finally, I introduce in this section the concept of the team-biased technological change (TBTC) allowing me to link the theories in labor and organizational economics to the principle of incentive pay. A graphical illustration of the following proceeding can be found in Figure 1.

Skill-biased and routine-biased technological change During the 1980s, a large literature noticed a remarkable growth of employment shares in high-skill, high-wage occupations relative to low-skill, low-wage occupations. Employment growth was mainly determined by the share of employment in occupations above the median skill level, and the share of employment in occupations below the median declined (Acemoglu 1998). One explanation of this pattern could be the relative demand for skills that is linked to technology (i.e., the skill bias of technical change). The SBTC framework is based on the so-called canonical model[8], which includes at least two skill groups (i.e., high-skill and low-skill workers) performing two distinct and imperfectly substitutable occupations. A main assumption of the model is that technology takes a factor-augmenting form, indicating that new technologies evoke greater skill demands, and, thus, are more complementary to high-skill workers than to less-skill workers (Goldin and Katz 2008), unless the increase in the supply of skilled workers compensates the skill bias[9]. This phenomenon has since been labeled wage (or job) polarization.

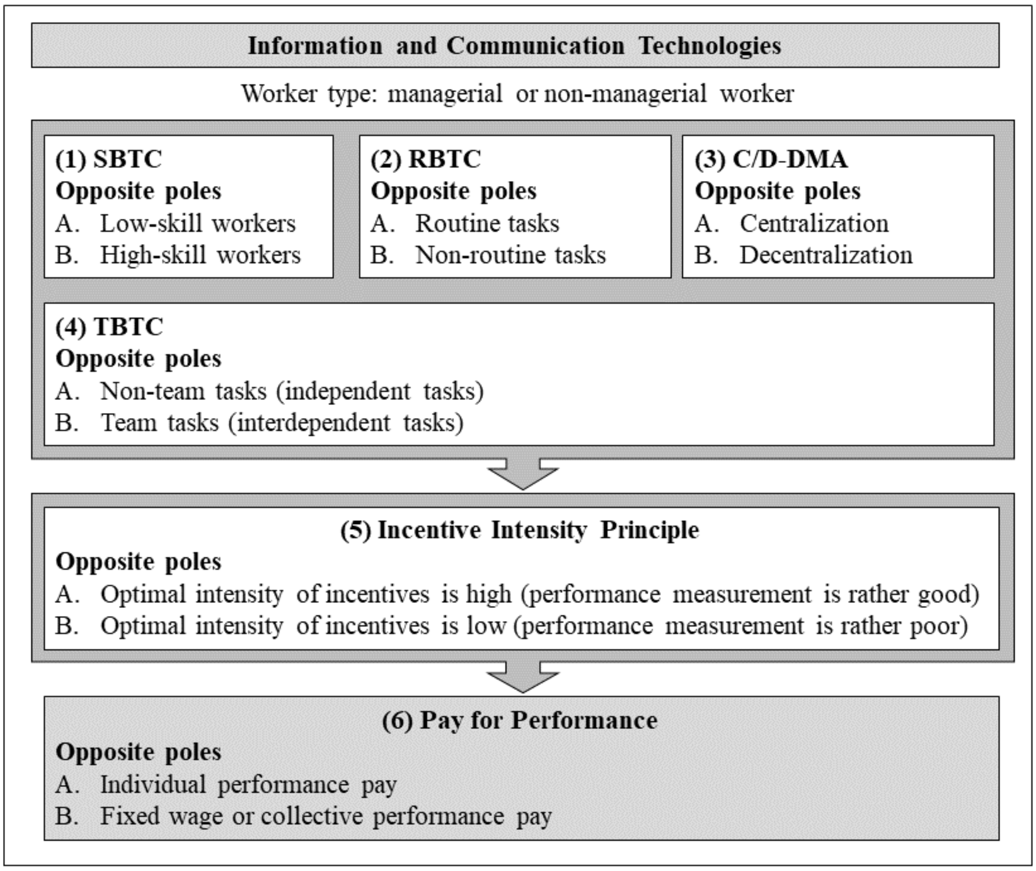
During the 1990s, however, the monotone employment growth in occupational skill showed a different pattern of job polarization. Relative employment growth could not only be found at high-skill percentiles, but also at low-skill percentiles, whereas relative employment growth at intermediate-percentiles was negative (Acemoglu and Autor 2011; Goos et al. 2009). The underlying mechanism affects workers in the middle of the skill distribution negatively. In the subsequent decade, there was a disproportionate employment growth at the lowest skill percentiles (Acemoglu and Autor 2011). As conventional theories of changes in the return to skill fail to explain this finding, researchers developed two other explanations to understand the changing structure of the supply and demand for skills.[10] Autor et al. (2003, 2006) proposed that improvements in the productivity of ICT could be one source of explanation. Together with Acemoglu and Autor (2011), they emphasized the necessity to analyze the "task content" of occupations and developed

[8]See, Acemoglu and Autor (2011, p. 1098) for an extensive description of the canonical model.

[9]See, Acemoglu (2002) for an extensive survey of the skill-biased technological change.

[10]See, Acemoglu and Autor (2011, pp. 1075 ff.), for more details.

Figure 1: Technological change in labour and organizational economics



Source. Own generation. **Note.** SBTC: skill-biased technological change. RBTC: routine-biased technological change. C/D-DMA: centralized or decentralized decision-making authority. TBTC: team-biased technological change. Information and communication technologies lead to either the opposite pole A or B, and with consideration of the incentive intensity principle, to different performance incentive schemes.

a task-based approach.[11] Other theories partly explained the findings with changing returns to managerial activities (Gabaix and Landier 2008).

With the emergence of the task-based approach, researchers found a structure of substitution between tasks in the production process, independent of skill-levels, that may explain the transformation on the labor market. From the 1980s to this day, the rapid declining price in the real cost of implementing ICT accelerates the automation of tasks previously performed by human labor, and makes labor gradually redundant (e.g., Brynjolfsson and McAfee 2011, 2014; Autor et al. 2015; Acemoglu and Autor 2011).

To adequately analyze current changes in job polarization, Autor et al. (2003) and Acemoglu and Autor (2011, p. 1076) differ between routine and non-routine tasks, by which they mean tasks that are (not) sufficiently specified to be executed by a machine. The terminology of the routine-biased technological change (RBTC) refers to the following definition: Non-routine (routine) tasks are relatively hard (easy) to automate, and thus, the relative demand for workers performing complementary non-routine (routine) tasks is increasing (decreasing) (Goos et al. 2014; Gregory et al. 2022). Moreover, two major sub-categories for non-routine tasks have been introduced: abstract and manual tasks. The former require competencies in problem-solving, intuition, persuasion, creativity, and are complementary to computer technology, whereas the latter are characterized by interpersonal and environmental adaptability, and consequently, require in-person interactions, but less formal education relative to non-routine abstract tasks (Acemoglu and Autor 2011, p. 1077; Autor and Dorn 2009). According to one of the latest studies on the automation of tasks (Acemoglu and Restrepo 2018), humans have a comparative advantage in new and more complex tasks, and in these cases, new technologies complement, rather than substitute, human labor. Until today, a shift in technology constantly alter the range of tasks, because there is an ongoing "race" between automation processes and the creation of new tasks that allow firms to adapt their production and employment processes.

Clearly, the SBTC can be seen as a subgroup of the RBTC: If new tasks are characterized by a high complexity (i.e., non-routine tasks), high-skill workers are favored, while automation substitutes capital for labor in tasks, where workers with a lower formal education tend to have a comparative advantage (i.e., routine tasks) (Acemoglu and Restrepo 2018, p. 1519). The assumption that high-skill workers have a comparative advantage in new and more complex tasks, whereas

[11] Some studies have shown that relying on a task-based framework instead of a factor-based framework provides a more powerful force toward stability. A task-based model is more successful in describing the future path of technological change (Acemoglu and Autor 2011; Acemoglu and Restrepo 2018).

low-skill workers have a comparative advantage in less complex tasks, is depicted in (1) and (2) in Figure 1, leading to two opposite poles (A) low-skill workers and (B) high-skill workers for the SBTC, and (A) routine tasks and (B) non-routine tasks for the RBTC. Low-skill workers do not have a competitive advantage in new and complex tasks, until new and complex tasks become more "standarized" and thus "productively performable" by low-skill workers (Acemoglu and Restrepo 2018, p. 1520).[12]

(De)centralization of decision-making authority Many papers analyze the job or task polarization discussed in Section 2.1 in isolation from organizational economics, and vice versa. Consequently, mainstream organizational economic theories are not or not sufficiently incorporated into labor market frameworks. A first attempt is Garicano and Rossi-Hansberg (2015) who investigate the interaction between organization and the economy. They base their investigation on the concept of knowledge-based hierarchies, which has been earlier introduced in Garicano (2000) and Garicano and Rossi-Hansberg (2006).

Garicano (2000) starts by developing a model that investigates the organization of knowledge in production. In production processes, physical resources, knowledge about how to use them, and time are required. A primary assumption is that a worker must spend a specific unit of time to solve a problem in order to produce. If the worker is able to solve the problem, she produces, otherwise she does not. In the latter case, the worker has to reach out to a more knowledgeable worker to solve the problem. This process involves communication costs. In the production floor, the workers normally work on the most common or easiest problems. In higher floors of the hierarchy, workers (i.e., managers) have then more time to apply their more exceptional knowledge to solve harder problems, and only lead or manage other workers "by exception" (Garicano and Rossi-Hansberg 2006). Consequently, workers specialize in production solving, and managers in problem solving. This key characteristic of the knowledge-based hierarchy is similar to the definition of the skill-biased technological change. In both models, workers are divided into two sub-groups, where they specialize in either production problems or solving problems (regarding the knowledge-based hierarchy), or in either low-skill or high-skill levels (regarding the SBTC). Assuming that low-skill

[12] Acemoglu and Restrepo (2018) allow in their task-based model the case that low-skill workers' productivity increases over time. This might be due to a standardization of new and complex tasks in a firm in a later time period, or, as they have mentioned in their study, to an additional acquisition of human capital through training, on-the-job-learning, or schooling (e.g., Galor and Moav 2000; Goldin and Katz 2008; Beaudy et al. 2016). Moreover, the link between low-skill workers and non-routine tasks can also be drawn by considering non-routine manual tasks (see, Acemoglu and Autor 2011, p. 1077).

workers specialize in production problems and high-skill workers in solving problems, the theory of knowledge-based hierarchies can easily be linked to the SBTC.

The relationship between the knowledge-based hierarchy and the RBTC is more difficult to explain. According to the theory of knowledge-based hierarchies, less knowledgeable workers deal with routine production tasks. However, these so-called routine production tasks might not be the same as the routine tasks in the RBTC. Recall that the RBTC defines a routine task as a task that is easy to be executed by a machine. The more the worker works on routine tasks, the higher the probability that her work can be automated, independent of the worker's hierarchical level (Acemoglu and Restrepo 2018). The theory on knowledge-based hierarchies defines routine tasks as tasks that require less knowledge. It only makes a distant statement on the degree of automation, when referring to the offshoring-probability of tasks (Garicano and Rossi-Hansberg 2015).[13] However, it makes a further statement that is not included either in the SBTC nor in the RBTC. That is, the worker's marginal value of ability for the organization is increasing, when her control span increases.[14]

Suppose now an organization can add layers to its hierarchy, doing so would decrease the control span of workers and increase the communication required to solve problems (i.e., the distance to knowledge to solve the problem is increasing). This is induced by the general understanding of the knowledge-based hierarchy: Workers with the same cognitive skills are segmented, and thus, located in the same position in the knowledge-based hierarchy (Garicano 2000; Garicano and Rossi-Hansberg 2006). Each time the worker, independent of the hierarchical level she is located at, needs help to solve a problem, communication costs incur and communication ripples sequentially from the bottom to the top of the hierarchy (and back) (Garicano and Rossi-Hansberg 2015). If an organization removes now layers from its hierarchy, control spans would increase and communication costs would decrease (i.e., the distance to knowledge to solve the problem is decreasing). The marginal production of the worker and her former manager (they are located now at the same hierarchical floor) differentiate only by their talent, not by the talent of their supervisor

[13]That means that, according to the RBTC, workers in all hierarchical floors may face a probability of (a partial) automation. Thus, routine tasks can be found in all hierarchical floors, and not only at the bottom of the hierarchy, as it is defined in the theory of knowledge-based hierarchies (KBH). This observed difference in "routine" tasks needs a further explanation in the literature. In this paper, I define routine tasks (according to RBTC) as tasks that face automation, non-routine manual tasks (according to RBTC) as routine production tasks (according to KBH), and non-routine abstract tasks (according to RBTC) as problem solving tasks (according to KBH).

[14]This additional assumption is important to explain in Section 2.2 the relation of the theories in labor and organizational economics to team and incentive theories.

(Garicano and Rossi-Hansberg 2015, p. 10). The former manager of the worker loses from the decreased distance to the worker, while the worker is better off and experiences a reduction in wage inequality relative to the former manager.[15] According to Garicano and Rossi-Hansberg (2015), the mid-level workers, like the manager in this example, could be worse off.

What enables organizations to reduce layers from its hierarchy? What is a potential enabler of such a process described above? As in the theories of the RBTC and the SBTC, the changing process can be explained by the impact of information and communication technologies. In this case, they affect the hierarchy and the knowledge acquired, and not the specificity of tasks or the demand of skill levels, as in Section 2.1. The impact of ICT is explained in the theoretical model in Garicano (2000).

Decreases in the communication costs (due to cheaper and better communication technologies) lead to a cheaper transmission of knowledge. Workers rely more on problem solvers at higher layers, because the knowledge can be transferred at low costs from the top to the bottom of the hierarchy. In this case, the decision-making authority is "centralized" at higher hierarchical levels (i.e., centralization). In Figure 1, centralization (A) is one of the opposite poles depicted in (3).

Cheaper acquisition of knowledge (due to cheaper and better information technologies) enables worker at all organizational layers to solve a higher number of problems on their own. The discretionality of all workers is increasing and workers in the production floor need to reach out less to their managers. In this case, the decision-making authority is "decentralized" at lower hierarchical levels (i.e., decentralization). In Figure 1, decentralization (B) is the other opposite pole depicted in (3).

Both ICT effects reduce the demand for managers in organizations (Garicano and Rossi-Hansberg 2015). Moreover, the same mechanism casts "a shadow" on production workers, because the wage inequality between them and top performers at the very high level of a hierarchy (Garicano and Rossi-Hansberg (2015) call them "superstars") is increasing due to technology-induced specialization effects (or the skill bias of technical change as described in Section 2.1). Under these conditions, the pattern of potential ICT effects on workers in a knowledge-based hierarchy is similar to the pattern described in the section on the RBTC and SBTC. Both edges of the distribution of workers (i.e., the low-skill/high-skill workers in labor economics, and the production worker/problem solver in organizational economics) are positively affected by the spread of

[15]However, the wage inequality between the worker and her new supervisor is larger than it has been before between the worker and her former manager. That is, because the new supervisor is more knowledgeable (i.e., is higher skilled) than the former manager.

information and communication technologies. The managers or mid-skill workers are negatively affected.

Team-biased technological change The referred theories in labor and organizational economics show that ICT reduce the demand for mid-skill workers (or managers) in organizations, leading to a decrease in the distance between low-skill (production workers) and high-skill workers (problem solvers) to access problem-solving knowledge. Assume an organization with only two layers: High-skill workers (problem solvers) are located in the upper layer, low-skill workers (production workers) in the lower layer. The result of a decentralization process is a compression of specific knowledge towards the two layers and a new allocation of tasks either to the production workers or the problem solvers. In such a setting, an organization can highly benefit from the marginal value of ability of their "superstars", because the control span of the superstars is increasing (Garicano and Rossi-Hansberg 2015, and see Section 2.1). Moreover, organizations profit from higher educated workers at lower layers, because they can work on more complex tasks.[16]

With regard to the characteristics of ICT and the theory of knowledge-based hierarchies, a worker in the lower layer might behave in two distinct ways: If she is able to solve the problem (with or without the help of information technologies), (i) she produces (namely, Q), otherwise she does not. In the latter case (ii), I assume now that she uses communication technologies to reach out to a more knowledgeable worker (a) in the same layer and the same organizational unit, or (b) in the same layer, but a different organizational unit, or (c) in the upper layer in order to produce Q. According to Garicano and Santos (2004), only the workers with the hardest problems are in need of advice from high-skill workers. In some cases, however, the problem (or task) to solve is not one of the most difficult problems, but just one for which the worker (here, worker i) faces an interdependency I in the same or upper layer. Worker i might be working on a task that needs an interaction between worker i and worker j in the same layer, and/or between worker i and manager m in the upper layer by task construction. The logic (i) and (ii) might be depicted as follows:

[16] Having higher educated workers at lower layers is a general cause of decentralized growth, as well as larger control spans or larger teams (see, for more detail, Caliendo et al. 2015; Caliendo and Rossi-Hansberg 2012; Caroli and Van Reenen 2001; Garicano and Hubbard 2007; Rajan and Wulf 2006).

$$
Q_{ijm} = \begin{cases} 1 & \text{if } I_{ij} = I_{im} = I_{ijm} = 0, \quad \textit{the worker } i \textit{ solves the problem alone.} \\ 1 & \text{if } I_{ij} = 1, \quad \textit{the worker } i \textit{ solves the problem together with worker } j. \\ 1 & \text{if } I_{im} = 1, \quad \textit{the worker } i \textit{ solves the problem together with manager } m. \\ 1 & \text{if } I_{ijm} = 1, \quad \textit{the worker } i \textit{ solves the problem together with worker } j \textit{ and manager } m. \\ 0 & \text{otherwise.} \end{cases}
$$

Here, I argue that technological progress is complementary with task complexity and task interdependency (i.e., the complexity of the task itself and worker interdependencies increase with the share of ICT-equipped workers)[17], and workers are forced to adjust quickly in terms of coordination and cooperation. If workers face interdependencies (ii), they solve the problem horizontally in an organization, and/or they choose to reach out to workers located at the upper layer.[18] If workers do not face interdependencies (i), they solve the problem on their own (i.e., they work on independent tasks). In other words, if the worker is not capable to solve the problem alone, she reaches out to a member of the hierarchy to solve the problem together in a team.[19] Intuitively, I assume here the case of having heterogeneous workers, independent of the layer; otherwise the other team member cannot contribute to the solution of the problem or the interdependency cannot exit.[20]

[17]Equipping workers with ICT opens opportunities to work with new and complex software tools requiring new skills and competencies (Gibbs 2017). Additionally, working speed and multitasking is increasing (Lazear and Gibbs 2015, p. 174; Lindbeck and Snower 2000).

[18]I assume here that horizontal coordination is not only needed between individual tasks or workers, but also between organizational units (Lazear and Gibbs 2015, p. 180).

[19]This process might be especially true in lower layers (i.e., workers in lower layers are the workers that reach out for help) and when standardization of tasks is increasing (i.e., low-skill workers work only on similar tasks than high-skill workers after a certain time period or standardization). In this case, the worker i in the lower layer knows exactly to which team member (worker j or manager m) she has to reach out to get the work done.

[20]The assumption in Garicano and Rossi-Hansberg (2006) is different. Here, the lowest layer of a team is a set of equally knowledgeable production workers and they work on routine problems. However, the definition of "routine problems" remains unclear in terms of automation or other characteristics, such as worker interdependencies. In my paper, I assume that in the case of equally knowledgeable production workers in lower layers, the work could be done by one single worker as this worker possesses all the information that is needed to solve the problem. There would be no interdependencies. The worker would only reach out to the manager in the case of no production (i.e., there would only be vertical interdependencies, however, no horizontal interdependencies). Even in the case of specialization, the workers might work on tasks acquiring different levels of interdependencies by construction. Next to Garicano and Rossi-Hansberg (2006), there are other studies focusing on team theories. The study of Fuchs et al. (2015, p. 663) analyzes the optimal matching between questions and expertise in depth and state that "team

These assumptions allow me to approach the theories in labor economics and to distinguish between two different types of tasks: Tasks that rely more on an efficiently-working team, and tasks that rely more on individual work (see, the opposite poles (A) and (B) in (5) in Figure 1). In this paper, I call them team tasks and non-team tasks and argue that ICT leads, in some cases, to more team tasks, and, in others, to more non-team tasks. To ease the understanding, I name this classification team-biased technological change (TBTC) (see, Figure 1), a technical change that is biased towards team tasks. Importantly, it is no classification in terms of educational skills (SBTC), but rather a sub-category in the "routinization" of tasks (RBTC). Concretely, it refers to a simple task design characteristic that appears throughout the hierarchy and is independent of the skill-level, such as the needed in-person interactions or interdependencies in a heterogeneous group of workers to solve a problem in an organisation.[21]

Both characteristics of ICT drive the TBTC. The cheaper acquisition of information makes low-level workers more knowledgeable and they can constantly improve their interdependencies (i.e., they get cheaper access to information on current task updates and the work done by others)[22], whereas improvements in communication technologies allow a better and faster coordination and cooperation process between workers (Impink et al. 2020).[23]

The questions that remain is what type of task is affected by the TBTC, and are there any differences between a worker-worker or worker-manager interdependency. To answer the former ques-

production is most effective when the most knowledgeable agents [...] are matched with the least knowledgeable ones [...]. Agents with intermediate knowledge, in contrast, contribute to team production the least." Garicano and Prat (2013) give insights on decision-making in teams, the costs of teams, and what kind of businesses should adapt teams. Kräkel (2017) mentions one possibility that firms might prefer self-organizing teams, because, under non-delegation, agents are forced into inefficient matches, but under delegation, they voluntarily form efficient matches, and according to Flores-Fillol et al. (2017), overall delegation of decision-making is positively associated with team work.

[21] See, Acemoglu and Autor 2011, p. 1077 for an example in non-routine manual tasks. Lazear and Gibbs (2015, p. 180) discuss the case of task complementarity, the need to separate tasks and the emergence of teams.

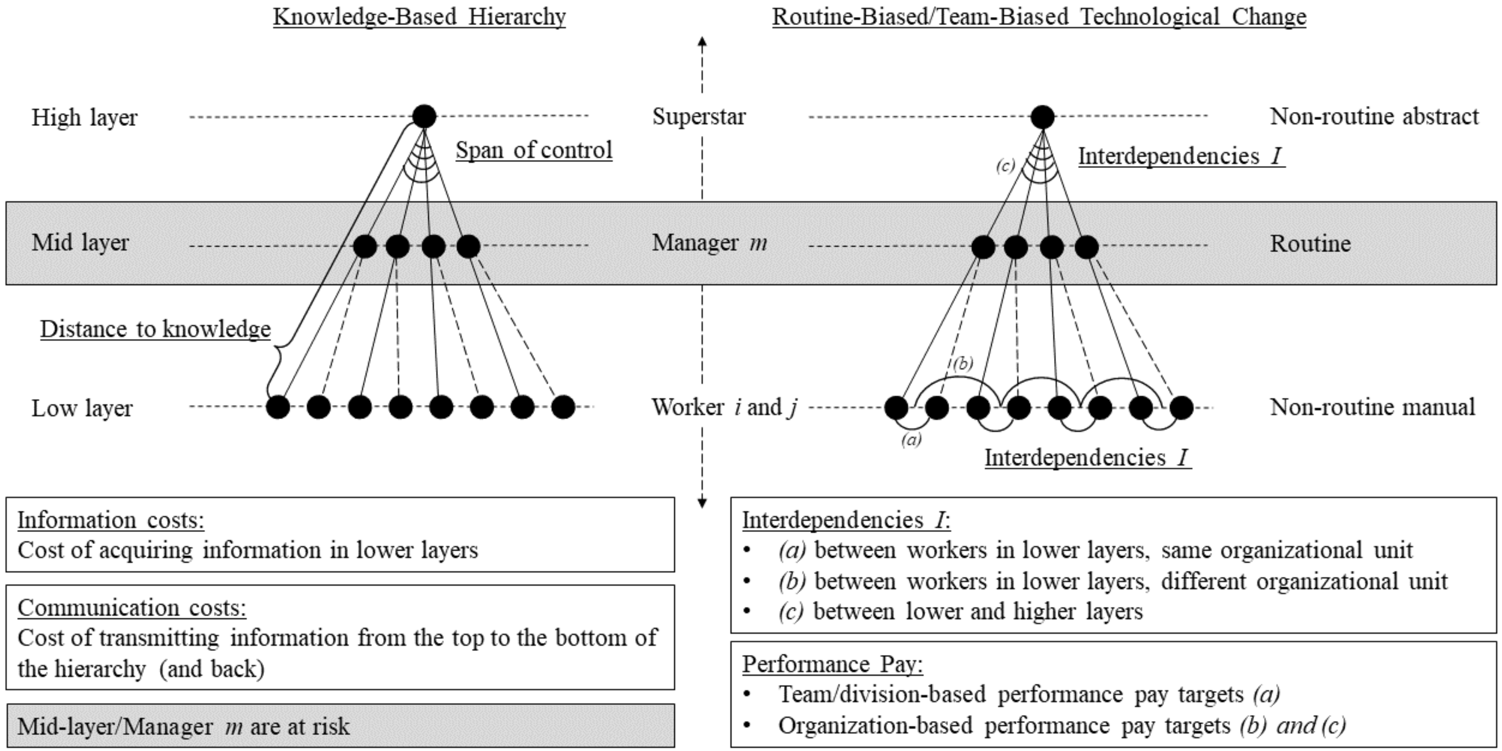
[22] According to Blader et al. (2020) and Brynjolfsson and McElheran (2016), data-driven management or decision-making gains in importance. The higher the levels of information technology, and the more educated the workers are (what they are in a decentralized organization), the better practices can be adjusted in order to generate greater benefit. Lazear and Gibbs (2015, p. 192) bring up an example on statistical process control (SPC) that provides workers in manufacturing with real-time production data, and, thus, with real-time feedback on how to test potential remedies.

[23] According to Impink et al. (2020, p. 183), "knowledge workers rely on email, meetings, and, in many cases, instant messenger software to collaborate with others. As a consequence, electronic communications are able to capture valuable [...] information on the underlying interactions among employees within a team, across functional groups (internally), and with partners and customers (externally)."

tion, I rely on Acemoglu and Autor (2011, p. 1076-1077), who differentiate between non-routine abstract and non-routine manual tasks. Recall that abstract tasks require analytical capabilities, whereas manual tasks require situational adaptability and in-person interactions. Intuitively, manual tasks seem to be more prone for high levels of in-person interdependencies than abstract tasks. However, that does not mean that the high-level worker is less important when it comes to interdependencies. On the contrary: Decentralized organizations with large control spans (or large teams) heavily rely on their "superstars" to manage and control low-skill workers to solve the hardest problems (i.e., a worker-manager interdependency might have a greater value to the organization than a worker-worker interdependency).[24] The explained logic can be found in Figure 2, showing the relationship between the span of control, the distance to knowledge, and worker interdependencies.

[24]However, I argue that the general task construction is built in such a way that worker-worker interdependencies are primarily exploited, before worker-manager interdependencies are generated. Recall that in production processes time is required, but time is limited. The more the workers are able to solve problems on their own, the more time managers have to apply their exceptional knowledge to solve harder problems (Garicano 2000). Moreover, I argue that, in some cases, workers might feel a resistance to reach out to their manager/superior, and that this resistance to contact does not come without any costs (Edmondson and Lei 2014). In such a case, the resistance-to-contact costs must be added to the communication costs.

Figure 2: Control span, knowledge, and interdependencies



Source. Own generation. **Note.** Depiction of the control span, the distance to knowledge, and worker interdependencies considering relevant theories in labor and organizational economics (i.e., theory on the routine-biased technological change and the knowledge-based hierarchy). The interdependencies I are shown here between worker i and worker j, and between worker i and manager m. They are representative for the team-biased technological change, the technical change towards more relevant and complex interdependencies. Mid-layer workers (or managers m) are shown in gray, because they are at risk according to the theories used in Section 2.1.

2.2 The relation to performance incentive schemes

Drawing main hypotheses about the relationship between ICT equipment and performance incentive schemes requires to combine theories in labor and organizational economics to theories on incentives. In a first step, I rely on Milgrom and Roberts (1992) to introduce the incentive-intensity principle, and to construct the optimal intensity of incentives. In a second step, I merge the incentive-intensity principle to the theories mentioned in Section 2.1 to hypothesize whether ICT equipment leads to a higher prevalence of individual performance pay, collective performance pay, or fixed wages.

The incentive-intensity principle Assume that worker i must exert an effort e at personal cost $C(e)$ to serve the interests of the employer and produce profit $P(e)$. The effort e cannot be directly observed and might be contaminated by random events beyond the control of worker i (Milgrom and Roberts 1992, pp. 214 ff.). The employer is able to observe $z = e + x$, where x is a random variable and depicts the noise between e and the observed z. Thus, the compensation (i.e., wage w) of worker i can be written as follows:

$$w_i = \alpha + \beta(e_i + x) \tag{1}$$

I use α to measure the base salary, and β to measure the intensity of the individual incentive provided to worker i. The higher the value of β, the stronger the incentive for worker i to increase her effort e_i (Milgrom and Roberts 1992, p. 216). Note that w_i varies not only with e_i, but also with the random event x. With $\beta \neq 0$, the random event x imposes risk on the worker i. The worker's certain equivalent CE takes the following form (Milgrom and Roberts 1992, p. 217):

$$CE_i = \alpha + \beta(e_i) - C(e_i) - \frac{1}{2} r_i \beta^2 Var(x) \tag{2}$$

Note that r is the absolute risk aversion of worker i (Milgrom and Roberts 1992, p. 217). The output-based contract is efficient and realizable under the incentive constraint: $\beta - C'(e_i) = 0$, that is, the marginal gains from effort e_i are equal to the marginal personal costs of worker i. It is helpful to consider the incentive-intensity principle to determine how intense the individual incentive should be. According to Milgrom and Roberts (1992, p. 221), the optimal intensity can be written in the following form:

$$\beta = \frac{P'(e_i)}{[1 + r_i V C''(e_i)]} \quad \text{with} \quad V = Var(x) \tag{3}$$

The optimal intensity of incentives is determined by four factors, namely the profitability of eliciting extra effort ($P'(e_i)$), the risk aversion of the worker i (r_i), the precision with which the performance of worker i is measured (i.e., low measurement precision corresponds to high values of V), and the responsiveness of effort e_i to incentives (i.e., the responsiveness is inversely proportional to $C''(e_i)$). To determine the optimal intensity of individual incentives in this paper, ICT equipment and a worker's interdependencies must influence at least one of these four factors.

Technological change, team tasks, and incentives To analyze the relationship between ICT and performance incentive schemes, I rely on theoretical assumptions made in Milgrom and Roberts (1992) and De Varo and Prasad (2015), and on the theories in labor and organizational economics discussed in Section 2.1. From the incentive-intensity principle described in this section, I know that the third factor of the incentive-intensity principle is the precision with which performance is measured. If performance measurement is highly imprecise, the variance V in equation (3) is high, and strong individual incentives should not be used. On the other hand, if performance measurement is precise, the variance V in equation (3) is low, and strong individual incentives can be used. Using this basic assumption defined in Milgrom and Roberts (1992), I argue that the effect of ICT on the optimal intensity of incentive is twofold:

First, performance measurement can be improved by "devoting resources to that objective" (Milgrom and Roberts 1992, p. 226), mainly by a closer monitoring. Introducing ICT makes a closer monitoring more attractive, because it leads to a less costly monitoring of the worker. Moreover, a firm might combine ICT with a more intense monitoring throughout the hierarchy, when it experiences a loss of control due to granting autonomy to workers (i.e., decentralization of decision-making) as assessing the worker's performance becomes more difficult (Gerten et al. 2022). In both cases, performance measurement is improving, the variance V is decreasing, and strong incentives are likely to be optimal (Milgrom and Roberts 1992).

Assuming that the effort of worker i can easily and, with the help of ICT, precisely be measured, individual incentives can be stronger. In this case, I draw the line between ICT and the opposite pole (A) in (1)-(6) in Figure 1[25], and formulate the hypothesis:

Hypothesis 1: *Equipping workers with ICT leads to a better performance measurement, and, thus, to a higher intensity of individual incentives.*

[25] That means that ICT in combination with low-skill workers, routine tasks, centralization, and non-team tasks might be prone to individual performance pay.

Second, relying on the theories in labor and organizational economics mentioned in Section 2.1, ICT may lead to an increase in task complexity and worker interdependencies (i.e., an increase in team tasks according to the TBTC), especially in lower layers in a knowledge-based hierarchy (Garicano and Rossi-Hansberg 2015) and among low-skill workers performing non-routine manual tasks (Acemoglu and Autor 2011). I argue that this increase in task complexity and worker interdependencies increase the variance V (i.e., the output of worker i is an increasingly noisy measure), and ultimately make it less likely that strong individual incentives are offered. In other words, the effort e_i includes the ICT-induced worker interdependencies between worker i, worker j, and manager m (namely, I_{ij}, I_{im}, and I_{ijm}), if $I_{ij} \neq 0$, $I_{im} \neq 0$, and $I_{ijm} \neq 0$. With $I_{ij} \neq 0$, $I_{im} \neq 0$, and $I_{ijm} \neq 0$, V is increasing, β is decreasing, and the relationship between ICT and individual incentives should be negative.[26]

This result is in line with De Varo and Prasad (2015, p. 298), who argue that the relationship between delegation and incentive pay is negative for *complex* jobs, but positive for *simple* jobs.[27] They define a job as complex if "tasks vary sufficiently in terms of their expected return relative to the second best surplus from effort", "if output is a sufficiently noisy measure of effort", and "if the variation in risk across tasks is high enough that preferences between the principal and agent diverge with respect to task selection." According to this definition, the completion of a task that relies on a set of ICT-induced worker interdependencies can be classified as a *complex* job, and ICT should show a negative relationship with individual incentive pay.

In the case of delegation (i.e., decentralization of decision-making authority), however, it is not unlikely that employers offer an output-based contract, so that worker i focuses more on task returns than on her private benefits (De Varo and Prasad 2015, p. 302).[28] To address increasing

[26]Interdependencies I are hard to observe or to measure precisely, they contribute to the noise making individual performance measurement less reliable, and thus affect the optimal β in equation (3). In Figure 2, I show the different interdependencies I (a) between workers, (b) between organizational units, and (c) between hierarchical layers.

[27]In their principal-agent model, De Varo and Prasad (2015) argue that, in the case of *simple* jobs, there is no conflict of interest, and both the principal and the agent prefer the high risk-return task, H (with normally-distributed returns of R), instead of the low risk-return task, L (with normalized returns of 0), given that the mean of R is larger than zero. However, in the case of *complex* jobs, the risk-averse agent might prefer task L, instead of task H (because of a high variance in R, while performing task H). In this case, incentives must be weakened to induce the agent to select task H.

[28]See, De Varo and Prasad (2015), Holmstrom and Milgrom (1991), Jensen and Meckling (1992), Prendergast (2002), and Itoh et al. (2008) for more theoretical details.

task complexity and worker interdependencies in the output-based contract offered to workers, the employer could adapt the performance incentive scheme in two ways:

First, the employer can switch to incentives that do not reward individual performance, but rather collective performance. In other words, the employer could choose to reward team/division-based output, and organizational output, and offer collective performance pay. To detect the role of collective performance pay in an organization that depends on worker interdependencies, I consider the assumptions in Section 2.1 that can also be found in Figure 2. I differ between different types of interdependencies I (see, Figure 2), (a) between workers in lower layers and in the same organizational unit, (b) between workers in lower layers, but in different organizational units, and (c) between workers in lower and higher layers. Relying on this separation of interdependencies, I argue that team/division-based performance pay should target interdependencies of type (a), and organization-based performance pay should target interdependencies of type (b) and (c). In both cases, an increase in ICT-induced worker interdependencies should lead to an increase in the respective performance incentive scheme, and thus, ICT should show a positive relationship with collective incentive pay.

Second, there might be some cases in which the employer wants to refrain from using incentive pay to address increasing task complexity and worker interdependencies, and offers only fixed wages. Following this reasoning, ICT should show a positive relationship with the implementation of fixed wages only.

According to this reasoning, I link ICT with the opposite pole (B) in (1)-(6) in Figure 1[29] and generate the hypothesis:

Hypothesis 2: *Equipping workers with ICT leads to an increase in task complexity and team tasks (i.e. interdependencies between worker i and worker j, and/or between worker i and manager m), and, thus, to a lower intensity of individual incentives, and/or to a higher intensity of collective incentives, or to fixed wages.*

Furthermore, relying on the findings in Acemoglu and Autor (2011) and Garicano and Rossi-Hansberg (2015) that show differences between high/low-skill workers or workers located at high/low layers in a knowledge-based hierarchy, I extend hypothesis 2 with the following statement:

[29]That means that ICT in combination with high-skill workers, non-routine tasks, decentralization, and team tasks might be prone to collective performance pay or fixed wages.

Hypothesis 2 (extended): *The effect of ICT on performance incentive schemes is stronger for workers in lower layers than for workers in higher layers.*

In the next part of the paper, I formulate an adequate empirical model and use panel data to analyze the potential effects of ICT equipment on performance incentive schemes, that is, the prevalence of individual performance pay, collective performance pay, and fixed wages.

3 Data, variables and descriptive statistics

3.1 Data sets

My empirical analysis is based on two data sets that are representative for German establishments of the processing industry and service sector. First, I use the Linked Personnel Panel, which combines employer with employee data on human resources, corporate culture, and management practices in German establishments (Bellmann et al. 2015, Kampkötter et al. 2016). I use the employer-level data of the LPP to explore the impact of ICT equipment among managerial and non-managerial employees on performance incentive schemes. The LPP employer survey has been launched in 2012 and sent to its recipients every two years. It covers topics on personnel planning and procurement, personnel development, compensation structure, commitment, values, and corporate culture.

Second, I combine the LPP data with the data of the Establishment Panel of the Institute for Employment Research allowing me to add further information on the determinants of employment in German establishments. The IAB Establishment Panel is an annual survey of over 15,000 firms of all size classes and industries. It can be ranked as the most comprehensive establishment-level data set in Germany (Fischer et al. 2009). The firms are selected from a parent sample of all German firms employing at least one employee covered by social security. This parent sample can be considered as complete, because firms in Germany are required by law to report the number of employees covered by social security. The IAB Establishment Panel is approximately proportional to the national level of employment and therefore representative for the German economy. It provides me with additional information on labor market topics, such as employment and workforce structure, wage bills, sales, investments, international trade, product and process innovations, organizational change, worker representation as well as vocational and continuing training. The LPP companies are drawn as a sub-sample from the IAB Establishment Panel.

For my empirical analysis, I use panel data from the first four waves of the LPP employer survey from the years 2012 to 2018 and combine these data with the corresponding panel waves of the IAB Establishment Panel. Of particular importance for my analysis are waves 2 ($N = 771$), 3 ($N = 846$), and 4 ($N = 769$) of the LPP's employer-level survey, because these waves contain information on the ICT equipment of managerial and non-managerial employees.

3.2 Measuring mobile technologies

I measure the prevalence of mobile ICT by the proportion of managerial and non-managerial workers equipped with mobile ICT, such as laptops, tablets, and smartphones that are capable to establish an Internet connection. The percentages of ICT equipped managerial and non-managerial workers are surveyed separately making the LPP data set unique in terms of ICT equipment in the workplace. As already mentioned, information on ICT equipment across hierarchical levels is available in panel waves 2, 3 and 4. Table 1 displays the main descriptive statistics over time.

The proportion of managerial and non-managerial workers equipped with ICT has steadily increased, while at the same time there are large differences in ICT equipment between the two employment groups. In 2014 (2018), 66 (75) percent of managerial workers were equipped with mobile ICT, but only 14 (19) percent of non-managerial workers. I explain these differences by different general or industry-specific human capital (Gerten et al. 2022) and by hierarchy-specific risk aversion, which in turn affects the productivity level of managerial and non-managerial workers, and thus, the incentive to equip managerial workers with ICT in higher shares than non-managerial workers.

I construct the variable ICT^{M} depicting the proportion of managerial workers equipped with ICT. Analogously, I construct the variable ICT^{NM} measuring the share of ICT-equipped non-managerial workers. Both variables range between 0 and 100 percent. Due to the skewed distributions of both variables, they enter the regressions in logs (natural logarithm). On the one hand, the ICT variables focus on remote technologies that are expected to be closely related to measures on organizational structure (Bloom et al. 2014) and job design (Gerten et al. 2022), such as the establishment of a cooperative and decentralized work environment. On the other hand, these technologies allow for a more precise and centralized monitoring (Lemieux et al. 2009, Gerten et al. 2022) or a better differentiation between employees.

In both cases, I assume productivity effects.[30] Consequently, I expect them to affect established

[30]The impact of IT on productivity has long been studied, and previous studies have shown that information technology leads to adaptions in worker skills (Autor et al. 1998, Autor 2003, Caroli and van Reenen 2001, Goldin and Katz 1998), in human resource management practices (Bresnahan et al. 2002), and makes production processes

Table 1: Descriptive statistics

Variable	Wave	Hierarchy	Mean	Std. dev.	Range	*N*
ICT equipment	2014	Managerial workers	66.07	42.09	0-100	760
		Non-managerial workers	13.76	23.55	0-100	749
	2016	Managerial workers	74.20	38.94	0-100	830
		Non-managerial workers	16.49	25.42	0-100	809
	2018	Managerial workers	74.80	38.79	0-100	759
		Non-managerial workers	18.74	25.79	0-100	744
PFP	2014	none	0.61	0.48	0-1	771
	2016	none	0.57	0.49	0-1	844
	2018	none	0.55	0.49	0-1	768
PFP (individual)	2014	Managerial workers	20.46	28.91	0-100	727
		Non-managerial workers	21.11	34.62	0-100	752
	2016	Managerial workers	18.05	27.30	0-100	796
		Non-managerial workers	20.43	33.86	0-100	815
	2018	Managerial workers	16.23	27.01	0-100	711
		Non-managerial workers	20.40	35.10	0-100	741
PFP (team)	2014	Managerial workers	10.45	18.96	0-100	719
		Non-managerial workers	8.72	21.35	0-100	753
	2016	Managerial workers	10.00	19.90	0-100	796
		Non-managerial workers	7.64	19.01	0-100	815
	2018	Managerial workers	10.66	21.64	0-100	711
		Non-managerial workers	7.81	21.30	0-100	741
PFP (organisation)	2014	Managerial workers	27.32	33.37	0-100	723
		Non-managerial workers	13.68	27.90	0-100	755
	2016	Managerial workers	25.67	33.49	0-100	797
		Non-managerial workers	11.92	25.39	0-100	815
	2018	Managerial workers	25.27	34.69	0-100	711
		Non-managerial workers	11.98	26.66	0-100	741
PFP (collective)	2014	Managerial workers	37.76	39.56	0-100	719
		Non-managerial workers	22.28	35.56	0-100	752
	2016	Managerial workers	35.71	39.53	0-100	796
		Non-managerial workers	19.56	33.09	0-100	815
	2018	Managerial workers	35.94	40.91	0-100	711
		Non-managerial workers	19.80	34.59	0-100	741

Source. Linked Personnel Panel 2014/2016/2018, employer survey. Own calculations.

Notes. Collective performance pay is constructed by summing up the performance pay shares of the components *team* and *organisation*.

performance incentive schemes. In terms of task complexity in the workplace, equipping employees with ICT should be closely related to possible tendencies to equip workers with specific software applications. Software applications can complement workers in non-routine tasks. In some cases, software applications render tasks more complex and increase the demand for cooperation. Moreover, I assume that managerial and non-managerial workers need different software applications, especially regarding their appointed tasks and responsibilities. Despite potential differences in software applications, it is very probable that these software applications are installed on similar hardware devices, such as mobile information and communication technologies.

In Table 2, a simple pooled OLS regression on ICT in the respective group - managerial or non-managerial workers equipped with ICT, i.e., ICT^{M} and ICT^{NM} - on possible determinants is presented.

more efficient (Athey and Stern 2002, Bartel et al. 2007, Brynjolfsson and Hitt 2003, Hubbard 2003).

Table 2: What are possible determinants of ICT equipment?

Dependent Variable:	ICT^{M}		ICT^{NM}	
Model:	OLS		OLS	
	(1)		(2)	
Market competition				
Low competition	-.150	(.117)	-.284***	(.107)
Medium competition	.149	(.122)	-.191	(.121)
High competition	.052	(.131)	-.072	(.123)
Regulation				
Collective wage bargaining	-.0409	(.093)	-.036	(.090)
Works council	.046	(.089)	.029	(.087)
Technology status				
Tech-status 2	.123	(.714)	1.115***	(.405)
Tech-status 3	.136	(.678)	.955***	(.364)
Tech-status 4	.342	(.677)	1.053***	(.362)
Tech-status 5	.302	(.681)	1.153***	(.371)
Strategy				
Product innovation 1	.131	(.093)	.109	(.091)
Product innovation 2	.228**	(.093)	.097	(.095)
Product innovation 3	.185*	(.105)	.084	(.106)
Process innovation	.243*	(.135)	.123	(.154)
Cost leadership	.100	(.121)	.044	(.136)
Quality leadership	-.012	(.073)	.091	(.071)
Export rate	.000	(.001)	-.000	(.001)
Metal, electronics, vehicle manufacturing	-.266***	(.096)	-.188*	(.098)
Trade, transport, news	-.110	(.110)	.233*	(.125)
Firm-related/financial services	.244*	(.129)	.291**	(.135)
IC and other services	-.169	(.157)	.203	(.162)
Decision rights				
SMWT	.139**	(.065)	.178**	(.070)
Working time accounts	.104	(.100)	-.061	(.098)
Long-term working time accounts	.045	(.076)	.031	(.090)
Performance evaluation				

Dependent Variable:	ICT^M		ICT^{NM}	
Model:	OLS		OLS	
	(1)		(2)	
Appraisal interviews	-.056	(.097)	.063	(.091)
Target agreements	.243***	(.082)	.162**	(.079)
Performance appraisals	.209**	(.088)	.020	(.086)
Distribution system	-.006	(.113)	.097	(.124)
Evaluation rounds	-.068	(.108)	-.188*	(.111)
Reward and performance development				
Payments above	-.052	(.085)	-.156*	(.089)
Development plans	-.053	(.074)	.104	(.074)
Workforce structure				
Female workers	-.012***	(.002)	-.013***	(.001)
Temporary agency workers	.002	(.004)	-.007**	(.003)
Low-skilled workers	-.001	(.001)	-.007***	(.001)
High-skilled workers	.008***	(.001)	.024***	(.002)
Region affiliation				
Eastern Germany	-.299***	(.103)	-.313***	(.106)
Southern Germany	-.102	(.112)	.134	(.120)
Western Germany	-.030	(.104)	.034	(.108)
Firm size classes				
Firm size 50–99	.135	(.234)	-.001	(.242)
Firm size 100–249	.275	(.238)	-.025	(.247)
Firm size 250–499	.464*	(.246)	.113	(.253)
Firm size 500+	.417*	(.250)	.309	(.262)
Wave 3	.287***	(.067)	.243***	(.067)
Wave 4	.434***	(.110)	.461***	(.104)
R^2	.135		.216	
Obs	2'052		2'052	
Groups	1'234		1'234	

Sources. Linked Personnel Panel (LPP), employer survey (2014, 2016, 2018), and IAB Establishment Panel (2014, 2016, 2018). Own calculations. **Notes.** Tech-status 2–5 refer to dummy variables indicating that the status of a firms' technological equipment is less than satisfactory (Tech-status 2), satisfactory (Tech-status 3), more than satisfactory (Tech-status 4), or state-of-the-art (Tech-status 5). Product innovation 1–3 refer to dummy variables indicating firms that did improve or further develop a product or service which had previously been part of the portfolio (Product innovation 1), that did start to offer a product or service that had been available on the market before (Product innovation 2), or that have started to offer a completely new product or service (Product innovation 3). SMWT refers to a dummy variable indicating firms that offer trust-based working hours/self-managed working time (SMWT). See, Table 12 in the Appendix for more details. The values in parentheses represent robust standard errors clustered at the firm level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

In column (1), ICT equipment of managerial workers is positively correlated with a corporate strategy based on innovation, and a job design based on performance appraisals. Moreover, firm size (i.e., firms with more than 250 employees) seems to determine the equipment of managerial workers with ICT. In column (2), we see that ICT equipment of non-managerial workers is positively correlated with the status of a firm's technological equipment, and with the service sector trade, transport, and news. It shows a negative correlation when firms face low market pressure, or when firms issue pay above the collective bargaining rate, implement a forced distribution system[31], or employ temporary agency workers. This is also true when the share of low-skilled workers is high.

Other factors correlate with ICT equipment of both employment groups. For example, the presence of decision rights assignment (i.e., self-managed working time) and performance evaluation (i.e., target agreements) correlate positively with ICT equipment, independent of the hierarchical level. In Eastern Germany, mobile ICT equipment seems to be less common, as well as in the metal working sector, in the electrical industry, or in vehicle manufacturing. In the service sector, however, the correlation is positive. The share of high-skilled workers is positively correlated with mobile ICT equipment, whereas the share of female workers seems to undermine an increase in ICT equipment (or vice versa).

Apart from providing some interesting information on similarities and differences in the determination of ICT equipment for managerial and non-managerial employees, these conditional correlations are useful for the choice of the set of covariates to be applied in the regression analyses. Moreover, they are informative to see whether or not there is sufficient variation in ICT^{M} and ICT^{NM} based on a series of potential determinants of ICT equipment.

[31] A forced distribution system is "a performance appraisal system that forces supervisors to distribute a predetermined percentage of employees in categories based on their employees' performance relative to other employees' performance" (Moon et al. 2016, p. 166).

3.3 Measuring performance pay

To measure performance pay and the composition of performance incentive schemes, I concentrate on different measures of the LPP employer-level survey. First, I rely on the survey question '*Does your establishment/office have a salary system with variable proportions?*'[32] to capture the existence of performance pay in firm i at time t. From this information, I generate the variable

$$PFP_{it} = \begin{cases} 0 & \text{if firms do not pay for performance,} \\ 1 & \text{if firms pay for performance}\,. \end{cases}$$

Performance pay has been applied in more than 50% of the surveyed German firms in the years 2014 to 2018 (see, Table 1). In 2014, 61% of the firms choose a salary system that allows the inclusion of variable pay. Until 2018, the average share has slightly decreased to 55%.

With the usage of performance incentive scheme, a firm can choose if variable pay is offered to managerial workers only, or to both managerial and non-managerial workers. Zooming in on non-managerial employees, the share of this employment group receiving variable pay has slightly increased over the years (2014: 58%, 2018: 60%). Over all three waves of the panel, the share of variable pay relative to the basic or fixed salary is higher for the managerial workers (about 10%) than for the non-managerial workers (about 7%).

Performance incentive schemes can be designed differently and in accordance with the job design and the organizational structure of a firm (Lazear and Gibbs 2015). Typically, various criteria of performance measurement can be considered. The LPP employer-level survey asks what proportion of variable pay is based on the components of individual performance ($PFP_{it}^{h,indiv}$), team or divisional performance ($PFP_{it}^{h,team/div}$), and organizational success ($PFP_{it}^{h,orga}$). The survey assumes an additive structure of the performance incentive schemes, and differentiates between managerial (M) and non-managerial (NM) workers ($h \in \{M, NM\}$) (Grunau et al. 2021). Following this structure, I generate the following variable

$$PFP_{it}^{hs} = \begin{cases} 0 & \text{if firms do not pay for performance,} \\ > 0 & \text{if firms pay for performance of type } s \text{ at hierarchical level } h\,. \end{cases}$$

The variable PFP_{it}^{hs} equals zero if performance pay is not applied in firm i at time t. The value of PFP_{it}^{hs} is greater than zero if firms pay for performance of type s at hierarchical level h. Here, s reflects a performance incentive scheme that is based on either individual performance, team/divisional performance, or organizational success.

[32]Variable proportions means here the existence of variable components in a salary system.

In a next step, I generate a variable grouping performance pay based on team/divisional performance and organizational success to be used as a counterpoint to individual performance pay $PFP_{it}^{h,indiv}$, i.e.,

$$PFP_{it}^{h,coll} = PFP_{it}^{h,team/div} + PFP_{it}^{h,orga}.$$

Here, $PFP_{it}^{h,coll}$ is a proxy for collective performance pay in firm i at time t at hierarchical level h. The idea behind merging the two variables $PFP^{h,team}$ and $PFP^{h,orga}$ is that both variables reflect performance incentives directed at a more or less large group of employees. Thus, both variables express performance incentives directed toward collaboration and cooperation. I want to contrast the composite variable $PFP^{h,coll}$ with the variable $PFP^{h,indiv}$, where individual performance pay has a very different objective than collective performance pay, because it encourages competition among employees. Moreover, cooperation and competition are precisely those opposing dimensions that have been addressed in my theoretical considerations.

In analogy to ICT^{M} and ICT^{NM}, the $PFP^{h,s}$ variables enter the regressions in logs (natural logarithm) to account for their skewed distributions.

4 Identification strategy

In order to estimate meaningful cause-and-effect relationships, my identification strategy must explicitly account for the fact that the explanatory variables ICT^{M} and ICT^{NM} are unlikely to be exogenous.[33] A first obstacle in achieving parameter estimates that can be interpreted in terms of causal inference is time-constant unobserved heterogeneity that is associated with an omitted variables bias if not taken into account. A common example for a time-invariant unobserved firm characteristic is management quality.[34] Management quality is likely to be correlated with both the choice of equipping managerial and non-managerial employees with ICT and the decision on the composition of performance pay. Hence, the omission of this variable would be associated with biased and inconsistent parameter estimates, unless the estimation strategy accounts for the omission. Estimating fixed effects (FE) models can effectively counter time-invariant omitted variables bias.

[33] Since the focus of my empirical investigation is on the effects of ICT equipment on the composition of performance pay rather than on its existence, I explain my identification strategy for the composition case. The procedure is analogous for the existence case.

[34] I assume here that management quality depicts an unobservable factor that might explain why some firms are more productive than others (see, Tambe et al. 2012).

The identifying assumption of the FE model is that any kind of unobserved heterogeneity is time-invariant. The conditional independence assumption of the FE model can then be written as

$$E(PFP^{hs}_{it}(ICT^h)|X_{it}, \mu_i, ICT^h_{it}) = E(PFP^{hs}_{it}(ICT^h)|X_{it}, \mu_i)\,, \tag{4}$$

where X is a matrix of time-varying covariates including time fixed effects, and μ_i represents unobserved firm characteristics. Assuming (4), the estimation of the FE model

$$PFP^{hs}_{it} = \alpha^{FE} ICT^h_{it} + X_{it}\beta^{FE} + \mu_i + u_{it}\,, \tag{5}$$

where u_{it} is an idiosyncratic error term with mean zero and finite variance, provides causal effects of α^{FE} and β^{FE}, where α^{FE} is the parameter of interest.

A second source of endogeneity is simultaneous or reverse causality, leading to simultaneity bias if left untreated. In the present case, reverse causation is not unlikely to occur as changes in the composition of performance pay, for the sake of achieving certain corporate goals, can also be associated with subsequent changes in the ICT equipment of managerial and non-managerial employees to support these goals. Specifying a lagged dependent variable (LDV) model accounts for simultaneous causation. The LDV model can the be written as

$$PFP^{hs}_{it} = \gamma^{LDV} PFP^{hs}_{it-1} + \alpha^{LDV} ICT^h_{it} + X_{it}\beta^{LDV} + \varepsilon_{it}\,, \tag{6}$$

where ε_{it} is an idiosyncratic error term with mean zero and finite variance, and γ^{LDV}, α^{LDV}, and β^{LDV} are the parameters to be estimated.

The identifying assumption of the LDV model is that any time-varying unobserved characteristics can be captured by the included LDV PFP^{hs}_{it-1}. The conditional independence assumption of the LDV model can be written as

$$E(PFP^{hs}_{it}(ICT^h)|PFP^{hs}_{it-1}, X_{it}, ICT^h_{it}) = E(PFP^{hs}_{it}(ICT^h)|PFP^{h}_{it-1}, X_{it})\,. \tag{7}$$

Concerns regarding time-invariant unobserved heterogeneity and simultaneous causation can be tackled separately by estimating equations (5) and (6). In order to interpret the results, I can make use of the bracketing property of the two models developed in Angrist and Pischke (2009, pp. 182-184). The bracketing-property approach states that if (7) is correct, the FE estimate tends to overestimate the true causal effect in absolute terms. However, if (4) is correct, the LDV estimate tends to underestimate the true causal effect in absolute terms (Angrist and Pischke 2009, pp. 184-185, Ding and Li 2019). Hence, the estimates of α^{FE} and α^{LDV} bracket the causal effect of interest.[35]

[35] Recently, the bracketing-property approach has also been applied, for example, in Falk et al. (2018), Kampkötter and Sliwka (2018), and Beckmann and Kräkel (2022).

Recall that conditional independence assumption (4) is restricted to time-invariant unobserved heterogeneity, and thus does not solve the problem of an omitted variables bias in case of time-varying omitted variables, while conditional independence assumption (7) is too rigorous if PFP^{hs}_{it-1} fails to sufficiently capture the relevant omitted variables. In order to address potentially remaining endogeneity issues, I exploit the richness of my large-scale linked employer data sets by conditioning on a rich set of potential time-varying confounders. By doing so, I aim to address concerns related to time-varying omitted variables, including omitted selection. In the present case, the last mentioned endogeneity problem results from the fact that firms are unlikely to select themselves randomly to a regime, where equipping managerial and non-managerial employees with ICT are made more or less intense.

In order to choose appropriate covariates that jointly determine PFP^{hs} and ICT^{h}, I draw on the three-legs-stool approach of organizational architecture developed in Brickley et al. (2021, chapter 11). The three-legged-stool approach relates organizational architecture, which is a coherent system consisting of three complementary components (decision-rights assignment, performance evaluation, and rewards), to corporate and business-level strategies as well as business environment, i.e., technology, market, and regulation. Since my core variables PFP^{hs} (ICT^{h}) reflects the rewards (technology) dimension, it is quite natural to base the choice of covariates on this three-legged-stool approach.

In addition to the main explanatory variable ICT^{h} that covers to some extent the domain of technology, the status of a firm's technological equipment provides information on the technologies' degree of modernity ranging from out-of-date to state-of-the-art. Moreover, I add data on export rates and self-reported competitive pressure to control for the market dimension of business environment. In order to proxy the dimension of regulation, I include measures on collective wage bargaining and the existence of works councils. In addition, information on sector affiliation and product innovations are a good fit to proxy corporate strategies, while information on cost and quality leadership strategies represent attractive measures on business-level strategies.

In terms of measures for organizational architecture, I add variables on payments above the level of collective bargaining rates (reflecting the rewards domain), as well as self-managed working time arrangements and (long-term) working-time accounts (reflecting the domain of decision-rights assignment). Finally, I control for the dimension of performance evaluation by including measures on appraisal interviews, performance target agreements, performance appraisals, forced distribution system, and evaluation rounds. Finally, I add measures on firm size, workforce structure, the existence of development plans, and the region of a company's location to the set of covariates.[36]

By complementing the bracketing-property approach of the FE and the LDV model with conditioning on a set of potential confounders, my identification strategy allows me to eliminate or at least mitigate estimation biases caused by omitted variables, simultaneous causation, and selectivity. Overall, therefore, I am confident that my identification strategy will contribute significantly to being able to draw conclusions in terms of causal inference.

5 Estimation results

In this section, I present and discuss my estimation results obtained from the application of the bracketing-property approach in combination with selection on observables. The first part of this section deals with the impact of ICT equipment of managerial and non-managerial employees on the existence of performance pay plans. The second part focuses on the impact of ICT equipment on the composition of performance pay plans (provided that a performance pay plan exists), separated for managerial and non-managerial employees.

5.1 ICT equipment and the existence of performance pay

First, I analyze the effect of ICT equipment on the existence of performance pay by following equation (5) and (6). The dependent variable is here the dummy variable of performance pay (PFP_{it}) indicating the existence of a salary system with variable proportions. The independent variable is ICT^h.

Table 3 shows in columns (1) and (2) pooled OLS estimations, in columns (3) and (4) an FE model on an unrestricted sample, and in columns (5) to (8) either the FE model or the LDV model on a restricted sample. In the estimation models in columns (5) to (8), I lose some observations due to the construction of the LDV.[37] In order to make the FE model in columns (5) and (7) comparable to the LDV model in columns (6) and (8), the sample is in these estimations *restricted*. However, as the FE model does not originally contain a lagged dependent variable (that leads here to a loss of over 300 observations), it is informative to estimate the same FE model on an *unrestricted* sample (here, in columns (3) and (4)).

[36]A list of the complete set of variables, including their descriptions and summary statistics, can be found in Table 12 in the Appendix

[37]Recall that my empirical analysis refers to the panel waves 2, 3, and 4. However, panel wave 1 is also not unimportant as this wave is used to construct the LDV. The loss of observations is attributable to the fact that my data set is an unbalanced panel exhibiting a certain degree of attrition (panel mortality).

Table 3: ICT equipment and the existence of performance pay

Model:	*OLS*	*OLS*	*FE*	*FE*	*FE*	*LDV*	*FE*	*LDV*
Hierarchy:	*M*	*NM*	*M*	*NM*	*M*	*M*	*NM*	*NM*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$ln(ICT^h)$	.022***	.024***	.002	.025*	.001	.009	.022	.015*
	(.008)	(.008)	(.013)	(.013)	(.014)	(.008)	(.014)	(.008)
PFP_{t-1}						.406***		.407***
						(.029)		(.029)
Controls	yes	yes	yes	yes	yes	yes	yes	yes
R^2	.209	.210	.060	.066	.071	.360	.076	.361
Obs	1'911	1'911	1'911	1'911	1'440	1'440	1'440	1'440
Groups	1'188	1'188	1'188	1'188	822	822	822	822

Sources. Linked Personnel Panel (LPP), employer survey, waves 2014, 2016, 2018, and IAB Establishment Panel, waves 2014, 2016, 2018. Own calculations.

Notes. The dependent variable is the dummy PFP. The independent variable is ICT^h, indicating the equipment in information and communication technologies of managerial or non-managerial workers. The values in parentheses represent robust standard errors clustered at the firm level to allow for intragroup correlation. In the FE estimations, R^2 is the R^2-within.

* $p < 0.10$, *** $p < 0.01$.

In columns (1) and (2), both OLS-estimates are positive and statistically significant at the 1% level. However, the boundaries of the causal ICT effect for the managerial employees in columns (5) and (6) are not significant. In columns (7) and (8) showing the FE- and LDV-estimation results for the non-managerial employees, only α^{LDV} is positive and statistically significant at the 10% level. Considering the FE model in the *unrestricted* sample, α^{FE} for the non-managerial employees in column (4) is positive and statistically significant at the 10% level. Independent of the sample size, both point estimates of the FE model have a similar magnitude (i.e., for the *unrestricted* sample, α^{FE} equals .025, and for the *restricted* sample, α^{FE} equals .022), and are slightly higher than α^{LDV} which equals to .015. Hence, a one-percent increase in the proportion of non-managerial employees equipped with ICT increases the probability of changing from a fixed wage system to a performance pay system by about .015 to .025.

Therefore, I conclude that there is evidence that ICT equipment of non-managerial employees affects the existence of performance pay. However, I do not find causal evidence in terms of statistically significant brackets in the *restricted* sample, but sufficient evidence while considering the LDV estimate in the *restricted* sample and the FE estimate in the *unrestricted* sample.

5.2 ICT equipment and the composition of performance pay

In my main specification, I estimate, at first, equation (5) using the random effects (RE) tobit model, because my dependent variable PFP^{hs} is left-censored at zero.[38] Using an RE tobit model implies treating μ_i as an unobserved time-invariant individual random effect. In a second step, I estimate the FE model using the *unrestricted* sample (see, e.g., Section 5.1). The estimation results of the RE tobit and FE model are depicted in Table 4, separated for managerial employees (columns (1), (3), (5), and (7)) and non-managerial employees (columns (2), (4), (6), and (8)). In addition, I distinguish between the schemes of performance pay based on individual output (columns (1) and (2)), on team/divisional output (columns (3) and (4)), and organizational output (columns (5) and (6)). In columns (7) and (8), estimation results are shown for the dependent variable measuring collective performance pay $PFP_{it}^{h,coll}$.

[38] A fixed effects tobit model would lead here to inconsistent estimates (e.g., Baltagi 2013).

Table 4: RE Tobit and FE

Hierarchy:	*M*	*NM*	*M*	*NM*	*M*	*NM*	*M*	*NM*
Scheme:	*individual*	*individual*	*team*	*team*	*organization*	*organization*	*collective*	*collective*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Model:	**Random-Effects Tobit Models**							
$ln(ICT^h)$	.205***	.442***	.220**	.475**	.218***	.525***	.202***	.479***
	(.076)	(.094)	(.093)	(.120)	(.066)	(.102)	(.067)	(.097)
LC/RC	1'142/0	1'306/0	1'339/0	1'538/0	992/0	1'424/0	939/0	1'314/0
Model:	**Fixed Effects Model (unrestricted sample)**							
$ln(ICT^h)$	.028	.046	.040	.075**	.037	.152***	.038	.179***
	(.049)	(.046)	(.037)	(.036)	(.053)	(.045)	(.056)	(.051)
R^2	.087	.067	.035	.060	.046	.049	.044	.066
Controls	yes	yes	yes	yes	yes	yes	yes	yes
Obs	1'911	1'911	1'911	1'911	1'911	1'911	1'911	1'911
Groups	1'188	1'188	1'188	1'188	1'188	1'188	1'188	1'188

Sources. Linked Personnel Panel (LPP), employer survey, waves 2014, 2016, 2018, and IAB Establishment Panel, waves 2014, 2016, 2018. Own calculations.

Notes. The dependent variable is $ln(PFP^{hs})$. h indicates the hierarchical level (i.e., managerial or non-managerial worker) and s the scheme of performance pay (i.e., individual, team, organizational, or collective based performance pay). The independent variable is ICT^h, indicating the equipment in information and communication technologies of managerial or non-managerial workers. The values in parentheses represent standard errors (for RE tobit) or robust standard errors clustered at the firm level to allow for intragroup correlation (for FE). LC/RC indicates left-censored/right-censored. R^2 is the R^2-within.

** $p < 0.05$, *** $p < 0.01$.

In the RE tobit case, the estimated parameters are positive and statistically significant at the 1% or 5% level (see, columns (1) to (8)), independent of the hierarchical level of the worker (managerial or non-managerial) or the incentive scheme (individual, team/divisional, or organizational performance pay). The parameters range between .202 to .525. One estimation pattern remains stable across all incentive schemes, namely a higher ICT effect for non-managerial workers than for managerial workers in terms of the estimate's magnitude. In columns (5) and (6), for example, a change in ICT^{M} (ICT^{NM}) by one percent leads to a change in $PFP^{M,orga}$ ($PFP^{NM,orga}$) by .218 (.525) percent.

Using the FE model in the *unrestricted* sample, I find positive and statistically significant results at the 1% or 5% level in columns (4), (6), and (8) (see, Table 4). The estimate of .075 for $PFP^{NM,team/div}$ is the lowest in terms of magnitude, followed by .152 for $PFP^{NM,orga}$, and .179 for $PFP^{NM,coll}$. The estimation results of the FE model using the *unrestricted* sample are a first indication that an increase in ICT equipment leads to an increase in collective performance pay, especially for non-managerial workers.

Table 5 displays the estimation results of the FE model (5) and the LDV model (6) that constitutes the bracketing-property approach.

Table 5: Bracketing Property

Hierarchy:	*M*	*NM*	*M*	*NM*	*M*	*NM*	*M*	*NM*
Scheme:	*individual*	*individual*	*team*	*team*	*organization*	*organization*	*collective*	*collective*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Model:	**Fixed Effects Model**							
$ln(ICT^h)$	.067	.054	.045	.076**	.055	.128***	.038	.173***
	(.055)	(.052)	(.043)	(.038)	(.057)	(.048)	(.062)	(.054)
R^2	.091	.072	.057	.095	.061	.071	.064	.099
Model:	**Lagged Dependent Variable Model**							
$ln(ICT^h)$	.020	.086***	.038	.093***	.057*	.128***	.050	.157***
	(.030)	(.033)	(.025)	(.025)	(.032)	(.029)	(.034)	(.034)
$ln(PFP^{hs}_{t-1})$	.343***	.376***	.335***	.238***	.401***	.335***	.411***	.321***
	(.030)	(.031)	(.032)	(.034)	(.030)	(.033)	(.030)	(.031)
R^2	.295	.253	.256	.157	.344	.237	.363	.252
Controls	yes	yes	yes	yes	yes	yes	yes	yes
Obs	1'377	1'377	1'377	1'377	1'377	1'377	1'377	1'377
Groups	789	789	789	789	789	789	789	789

Sources. Linked Personnel Panel (LPP), employer survey, waves 2014, 2016, 2018, and IAB Establishment Panel, waves 2014, 2016, 2018. Own calculations.

Notes. The dependent variable is PFP^{hs} (or $PFP^{h,coll}_{it}$ in Columns (7) and (8)). h indicates the hierarchical level (i.e., managerial or non-managerial worker) and s the scheme of performance pay (i.e., individual, team, organizational, or collective based performance pay). The independent variable is ICT^h, indicating the equipment in information and communication technologies of managerial or non-managerial workers. The values in parentheses represent robust standard errors clustered at the firm level to allow for intragroup correlation. R^2 is the R^2-within. The estimates of the control variables are displayed in the Appendix.

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

First of all, the parameter estimates for managerial employees are statistically insignificant (except in column (5) for $PFP^{M,orga}$, where α^{LDV} is positive and statistically significant at the 10% level). But this does not hold for non-managerial employees. Specifically, I find causal bracketing effects of ICT equipment on team/divisional performance pay, on organizational performance pay, and on collective performance pay. In columns (4), (6), and (8), all point estimates α^{FE} and α^{LDV} are positive and statistically significant at the 1% level (except in column (4) for $PFP^{NM,team/div}$, where α^{FE} is statistically significant at the 5% level). For individual performance pay for non-managerial employees, only α^{LDV} in column (2) is positive and statistically significant at the 1% level.

The FE estimate of .076 in column (4) is lower than its LDV counterpart of .093. However, the range disappears in column (6), where both estimates α^{FE} and α^{LDV} equal the causal ICT effect of .128 on organizational performance pay. Considering the dependent variable collective performance pay $PFP_{it}^{h,coll}$, I can see that according to the bracketing-property approach of the FE and the LDV model, the causal ICT effect ranges between .157 (α^{LDV}) and .173 (α^{FE}).[39]

The estimation results imply that equipping non-managerial workers with ICT causally promotes collective performance pay, and thus, according to the theoretical considerations in Section 2, cooperation among non-managerial workers rather than competition. Relying on the results in Table 5, I state that firms support a cooperative behavior of non-managerial workers by increasing the part of performance pay that is based on team/divisional and organizational output, or in other words, by increasing collective performance pay.

6 Robustness checks

The aim of this section is to check the robustness of my estimation results discussed in the previous Section 5. Recall that my identification strategy so far explicitly addresses endogeneity issues resulting from time-invariant omitted variable, simultaneous or reverse causation, and omitted selection. However, the informativeness of my estimation results might additionally be subject to other econometric problems. The first is serial correlation in panel data that might be associated with inefficient parameter estimates. The second is sample selection, which is an issue here, because my dependent variables are only observed in firms making use of a pay-for-performance system. In the previous analyses, firms without a performance-pay system entered my analyses with a value of zero, meaning that these firms rely on fixed wages rather than pay for performance. In the

[39]Consider Table 11 for the complete regression results including control variables.

remainder of the analysis in this section, I consider that firms do not randomly decide whether or not to use a pay-for-performance system.

6.1 Testing and correcting for serial correlation

A first robustness check refers to the internal validity of the FE and LDV estimates displayed in Table 5. In the context of panel data models, internal validity is often threatened by serially correlated error terms leading to a violation of the assumption of no serial correlation in the idiosyncratic errors, i.e., $E(u_{it}, u_{it'}) = 0 \; \forall \; t \neq t'$. Serial correlation in the idiosyncratic errors causes the standard errors of the estimated coefficients to be biased and the estimated coefficients to be less efficient (Drukker 2003). I test for serial correlation using Wooldridge's test for autocorrelation in panel data (Wooldridge 2002, chapter 10.6.3, Drukker 2003).

The starting point of Wooldridge's test is the first-differenced (FD) version of equation (5), i.e.,

$$\Delta PFP_{it}^{hs} = \alpha^{FD} \Delta ICT_{it}^{h} + \Delta X_{it} \beta^{FD} + \Delta u_{it} \, , \tag{8}$$

where Δ is the first-difference operator. Under the null hypothesis of no first-order autocorrelation among the u_{it}, the residuals from regression (8) should have a first-order autocorrelation of $-.5$, i.e., $Corr(\Delta \widehat{u}_{it}, \Delta \widehat{u}_{it-1}) = -.5$. The Wooldridge test regresses the residuals $\Delta \widehat{u}_{it}$ from (8) on their lags $\Delta \widehat{u}_{it-1}$ and performs a Wald test that the coefficient on the lagged residuals $\Delta \widehat{u}_{it-1}$ is equal to $-.5$. In order to account for the within-panel correlation in the regression of $\Delta \widehat{u}_{it}$ on $\Delta \widehat{u}_{it-1}$, the variance–covariance matrix of the estimators is adjusted for clustering at the panel level (Drukker 2003). The results of Wooldridge's test of first-order autocorrelation in panel data are displayed in the upper panel of Table 6. The test cannot reject the null hypothesis of no first-order autocorrelation for the specifications displayed in columns (1) to (4), while it detects significant first-order autocorrelation for the specifications displayed in columns (5) to (8).

Table 6: Testing for serial correlation

Hierarchy:	*M*	*NM*	*M*	*NM*	*M*	*NM*	*M*	*NM*
Scheme:	*individual*	*individual*	*team*	*team*	*organization*	*organization*	*collective*	*collective*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Model:	**(1) Test for Serial Correlation in Panel Data**							
with $ln(ICT^h)$	2.055	2.388	2.719	2.393	8.857	5.886	10.214	11.678
	[.153]	[.123]	[.100]	[.123]	[.003]	[.016]	[.001]	[.000]
Obs	734	752	730	752	733	754	730	751
Groups	516	523	516	523	517	523	516	522
Model:	**(2) Testing for Serial Correlation after Pooled OLS using LDV**							
LDV:	**no**							
$\widehat{u}_{t-1}$	.367***	.393***	.339***	.282**	.416***	.380***	.427***	.339***
	[8.58]	[9.24]	[7.45]	[5.87]	[10.20]	[8.16]	[10.42]	[7.76]
LDV:	**yes**							
$\widehat{u}_{t-1}$	.114	-.396***	-.250	-.106	-.128	-.267	-.125	-.177
	[0.77]	[-2.64]	[-1.64]	[-0.58]	[-1.11]	[-1.58]	[-1.10]	[-1.17]
Obs	734	722	730	722	732	724	730	721
Groups	516	508	516	508	516	508	516	507
Controls	yes	yes	yes	yes	yes	yes	yes	yes

Sources. Linked Personnel Panel (LPP), employer survey, waves 2014, 2016, 2018, and IAB Establishment Panel, waves 2014, 2016, 2018. Own calculations. **Notes.** The first model shows the Wooldridge test for serial correlation in panel data. The null hypothesis of no serial correlation is rejected in columns (5)-(8). The second model shows a test for serial correlation after estimation by pooled OLS (Wooldridge 2010, p.198-199). $\widehat{u}_{t-1}$ is estimated and included in pooled OLS estimations. After the inclusion of the LDV $ln(PFP^{hs}_{t-1})$, the null hypothesis of no serial correlation is only rejected in column (2). The values in brackets represent in Model (1) p-values and in Model (2) t statistics on $\widehat{u}_{t-1}$. ** $p < 0.05$, *** $p < 0.01$.

In order to address the problem of serially correlated errors, Cameron and Trivedi (2010, p. 336) argue that estimating the parameters by making use of cluster-robust standard errors that require only independence across clusters (here firms), while allowing for within-cluster correlation over time, will suffice in short panels. The linked data set I apply comprises of three panel waves and can thus be considered as a short panel. Recall that the FE estimates displayed in Table 5 are already estimated using robust standard errors clustered at the firm level to allow for correlation within panel units over time (intragroup correlation). Therefore, no additional action is required at this point. Applying cluster-robust standard errors, however, will not suffice to achieve internal validity in LDV models with serially correlated error terms. In addition to this, a common problem in LDV models is that the coefficient of the LDV (here γ^{LDV}) tends to be biased upward, while the coefficients of the contemporary explanatory variables, i.e., α^{LDV} and β^{LDV} tend to be biased downward when estimated with pooled OLS. Moreover, if the idiosyncratic errors of the LDV model are serially correlated, the biases do not even disappear in large samples, so in case of serial correlation, the pooled OLS estimates are also inconsistent. Apart from serially correlated error terms, whether or not estimating an LDV model with pooled OLS is problematic depends on whether the stationarity condition $\left|\gamma^{LDV}\right| < 1$ is satisfied (Maddala and Rao 1973, Keele and Kelly 2006, Wilkins 2018).

In order to address this issue, I first perform a test on serial correlation according to Wooldridge (2010, p. 198-199) that can be applied in the context of LDV regression models. The first step is a pooled OLS estimation of

$$PFP_{it}^{hs} = \alpha^{POLS} ICT_{it}^{h} + X_{it}\beta^{POLS} + \varepsilon_{it} \,. \tag{9}$$

In a second step, the lagged residuals from equation (9) are then included as an additional regressor to (6), i.e.,

$$PFP_{it}^{hs} = \gamma^{LDV} PFP_{it-1}^{hs} + \alpha^{LDV} ICT_{it}^{h} + X_{it}\beta^{LDV} + \rho^{LDV}\widehat{u}_{it-1} + \varepsilon_{it} \,. \tag{10}$$

A t-test on $\rho^{LDV} = 0$ provides information on whether the error terms in (10) are serially correlated or not. If $\rho^{LDV} \neq 0$, the null hypotheses of no serial correlation must be rejected. The results of this Wooldridge test are displayed in the lower panel of Table 6. They show that the inclusion of the LDV PFP_{it-1}^{hs} mostly makes the coefficient ρ^{LDV} statistically insignificant, with one exception (see column (2)). For this reason, I decided to correct the estimates of my main LDV models for serial correlation.[40]

[40] In Angrist and Pischke (2009), correcting for serial correlation in the LDV model is not part of the recommendation. In this sense, I do not use this specification in my baseline model.

I re-estimate equation (6) by means of the Newey-West estimator using standard errors that are robust to heteroskedasticity and first-order autocorrelation (HAC standard errors). This procedure provides consistent parameter estimates for γ^{LDV}, α^{LDV}, and β^{LDV}. The results of this robustness check are displayed in Table 7.

Table 7: Correcting for serial correlation

Hierarchy:	*M*	*NM*	*M*	*NM*	*M*	*NM*	*M*	*NM*
Scheme:	*individual*	*individual*	*team*	*team*	*organization*	*organization*	*collective*	*collective*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Model:	**Lagged Dependent Variable Model with HAC Standard Errors**							
$ln(ICT^h)$	.020	.086***	.038	.093***	.057*	.128***	.050	.157***
	(.030)	(.033)	(.025)	(.025)	(.032)	(.029)	(.034)	(.034)
$ln(PFP^{hs}_{t-1})$	.343***	.376***	.335***	.238***	.401***	.335***	.411***	.321***
	(.029)	(.030)	(.031)	(.034)	(.028)	(.031)	(.028)	(.029)
Controls	yes	yes	yes	yes	yes	yes	yes	yes
Obs	1'377	1'377	1'377	1'377	1'377	1'377	1'377	1'377

Sources. Linked Personnel Panel (LPP), employer survey, waves 2014, 2016, 2018, and IAB Establishment Panel, waves 2014, 2016, 2018. Own calculations.

Notes. Newey-West estimations. The values in parentheses represent Newey-West standard errors.

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

It can be seen that the parameters of interest, i.e., γ^{LDV} and α^{LDV}, do not change compared to the baseline results depicted in Table 5. Moreover, the standard errors do only slightly change compared to the baseline results, so none of the estimated coefficients gain or loose in terms of statistical significance. I also observe that the stationarity condition $\left|\gamma^{LDV}\right| < 1$ is fulfilled. Overall, therefore, applying the Newey-West estimator does not compromise the internal validity of my main result.

Although the robustness check using the Newey-West estimator with HAC standard errors is important, the problem of a downward biased ICT effect α^{LDV} is not so critical in the present case as it seems, because, according to the bracketing-property approach, α^{LDV} is the lower bound of the true causal effect $\widehat{\alpha}$. In this respect, the following applies: If the underestimated lower bound of the causal effect is already statistically significant, then the precisely estimated lower bound, and thus the causal effect, should be statistically significant, provided that the upper bound is also statistically significant. Recall that I am more interested in proving the existence of a causal effect than in determining the exact magnitude of that causal effect.

6.2 Testing and correcting for sample selection bias

In Sections 4 and 5, I addressed a selection problem that refers to the main explanatory variables ICT^{M} and ICT^{NM} (omitted selection). However, in the present case, there might be another selection problem that is related to the dependent variables PFP^{hs}. More precisely, in order to obtain unbiased and consistent parameter estimates, I have to account for the fact that firms are unlikely to select themselves randomly into certain remuneration regimes. In contrast, it is much more likely that firms make well-considered decisions with regard to the introduction of a performance-pay system and the composition of the variable pay components. In this context, I have to correct for the fact that a considerable number of firms deliberately do not make use of a performance-pay system, and thus cannot make decisions about the composition of variable pay components. Failure to account for this situation carries the risk that the obtained parametric estimates are biased due to sample selection bias. Since my identification strategy heavily relies on the bracketing property of the FE and the LDV model, I have to account for sample selection bias in both models.

With regard to address potential sample selection bias in the context of FE models, I rest on the procedures suggested in Wooldridge (2010, chapter 19.9.2). A first step is to test whether or not a sample selection bias is present at all. For this purpose, I add the lagged selection indicator

PFP_{it-1} to the FE model specified in equation (5), i.e.,

$$PFP_{it}^{hs} = \alpha^{FE} ICT_{it}^{h} + X_{it}\beta^{FE} + \delta^{FE} PFP_{it-1} + \mu_i + u_{it}\,, \tag{11}$$

and estimate equation (11) using the FE within estimator. Recall that, at this stage, PFP^{hs} includes the information of firms that pay fixed wages to their employees and do not have established a pay-for-performance system. The null hypothesis of the test on sample selection bias is that u_{it} is uncorrelated with PFP_{it-1}, meaning that sample selection in the previous time period $t-1$ should not be significant in equation (11) at time t, which is equivalent to $\delta^{FE} = 0$. Hence, a simple t-test on $\delta = 0$ provides information on whether sample selection bias is present or not. The test results are quite clear. In each of the PFP^{hs}-regressions, δ^{FE} turns out to be statistically different from zero, implying that I need to correct for sample selection bias.

The procedure to correct for sample selection bias in an FE context is as follows: In a first step, I estimate the pooled probit model

$$\begin{aligned} PFP_{it} &= \psi_1^{FE}\overline{PFP}_{it} + \alpha_1^{FE} ICT_{it}^{h} + X_{it}\beta_1^{FE} + \overline{Z}_i\theta_1^{FE} + \epsilon_{it} \\ &= Z_{it}^{FE}\eta_1^{FE} + \overline{Z}_i\theta_1^{FE} + \epsilon_{it}\,, \end{aligned} \tag{12}$$

where $Z_{it}^{FE} = [\overline{PFP}_{it}, ICT_{it}^{h}, X_{it}]$ and $\eta_1^{FE} = [\psi_1^{FE}, \alpha_1^{FE}, \beta_1^{FE}]$. $\overline{Z}_i$ represents the averages of all covariates over time, i.e., $\overline{Z}_i = [\overline{\overline{PFP}}_i, \overline{ICT_i^{h}}, \overline{X}_i]$. By including $\overline{Z}_i$ I apply a Mundlak approach (Mundlak 1978), thereby addressing the fact that the present case is about the correction of a sample selection bias in a FE context.

$\overline{PFP}_{it}$ is a group-specific mean of PFP_{it} that serves as a technical instrumental variable. The categories for generating the group-specific mean values are firm size classes and sector affiliation. $\overline{PFP}_{it}$ is positively correlated with PFP_{it} by construction, but there is no reason to expect that the average proportion of pay-for-performance firms in a certain cell representing a certain firm size class-industry sector combination has an influence on a firm's probability of having established a performance-pay system in any other way than through its effect on PFP_{it}. In other words, $\overline{PFP}_{it}$ satisfies the relevance condition by construction and should also meet the exogeneity assumption regarding the determination of PFP_{it}, thus representing a valid instrument for PFP_{it}.[41]

From equation (12), I predict the inverse Mills ratio for the firms using a performance-pay system, i.e., $\widehat{\lambda}_{it}^{FE} = \widehat{\lambda}_{it}^{FE}(Z^{FE}\eta_1^{FE}, \overline{Z}\theta_1^{FE}) = \phi(Z_{it}^{FE}\eta_1^{FE} + \overline{Z}_i\theta_1^{FE} + \epsilon_{it})/\Phi(Z_{it}^{FE}\eta_1^{FE} + \overline{Z}_i\theta_1^{FE} + \epsilon_{it})$, where $\phi(\cdot)$ is the standard normal probability density function, and $\Phi(\cdot)$ is the standard normal cumulative distribution function.

[41] To be precise, $\overline{\overline{PFP}}_i$, i.e., the group-specific mean of $\overline{PFP}_{it}$ over time, can additionally be interpreted as a technical instrumental variable.

The second step is a pooled OLS regression using the selected sample of firms with a performance-pay system, i.e.,

$$\begin{aligned} PFP_{it}^{hs} &= \alpha_2^{FE} ICT_{it}^h + X_{it}\beta_2^{FE} + \pi_{21}^{FE}\overline{ICT_i^h} + \pi_{22}^{FE}\overline{X}_i + \varphi_2^{FE}\widehat{\lambda}_{it}^{FE} \\ &\quad + \sum_{k=1}^{3}\sum_{t=2}^{4}\xi_{2k}^{FE} T_t \times \widehat{\lambda}_{it}^{FE} + u_{it} \quad \forall\, PFP_{it} = 1\,, \end{aligned} \tag{13}$$

where T_t denotes time dummies for the periods 2, 3, and 4. Since equation (13) entails the predicted inverse Mills ratio $\widehat{\lambda}^{FE}$ resulting from the first-step regression (12) and its interactions with the time dummies, I estimate the parameters of equation (13) using bootstrapped standard errors clustered at the firm level.

Regarding potential sample selection bias in the context of a LDV model, I estimate a conventional Heckman sample selection model (Heckman 1976, 1979) augmented with the LDV. The regression model of interest is

$$PFP_{it}^{hs} = \gamma^{LDV} PFP_{it-1}^{hs} + \alpha^{LDV} ICT_{it}^h + X_{it}\beta^{LDV} + \varepsilon_{it} \quad \forall\, PFP_{it} = 1\,, \tag{14}$$

meaning that PFP_{it}^{hs} is only observed in pay-for-performance firms. The selection model is specified as

$$\begin{aligned} PFP_{it} &= \psi_1^{LDV}\overline{PFP}_{it} + \gamma_1^{LDV} PFP_{it-1}^{hs} + \alpha_1^{LDV} ICT_{it}^h + X_{it}\beta_1^{LDV} + \epsilon_{it} \\ &= Z_{it}^{LDV}\eta_1^{LDV} + \epsilon_{it}\,, \end{aligned} \tag{15}$$

where $Z_{it}^{LDV} = [\overline{PFP}_{it}, PFP_{it-1}^{hs}, ICT_{it}^h, X_{it}]$ and $\eta_1^{LDV} = [\psi_1^{LDV}, \gamma_1^{LDV}, \alpha_1^{LDV}, \beta_1^{LDV}]$. The error terms ε and ϵ are assumed to be normally distributed with mean zero and variance σ^2 and 1, respectively, i.e., $\varepsilon \sim N(0, \sigma^2)$ and $\epsilon \sim N(0, 1)$. Furthermore, ε is allowed to be correlated with ϵ, i.e., $corr(\varepsilon, \epsilon) = \rho$. If $\rho \neq 0$, OLS estimates of the parameters in equation (14) would be biased. The procedure of correcting for sample selection in equation (14) using Heckman's two-step estimator is similar to the two-step procedure explained above for the case of correcting for sample selection in the context of the FE model. In a first step, equation (15) is estimated using probit maximum likelihood (ML). From these estimates, inverse Mills ratio for firms with a performance-pay system is calculated, i.e., $\widehat{\lambda}_{it}^{LDV}(Z^{LDV}\eta_1^{LDV}) = \phi(Z^{LDV}\eta_1^{LDV})/\Phi(Z^{LDV}\eta_1^{LDV})$. The second step is then an OLS estimation of (14) extended by inverse Mills ratio and its interactions with the time dummies as control functions, i.e.,

$$\begin{aligned} PFP_{it}^{hs} &= \gamma_2^{LDV} PFP_{it-1}^{hs} + \alpha_2^{LDV} ICT_{it}^h + X_{it}\beta_2^{LDV} + \varphi_2^{LDV}\widehat{\lambda}_{it}^{LDV} \\ &\quad + \sum_{k=1}^{3}\sum_{t=2}^{4}\xi_{2k}^{LDV} T_t \times \widehat{\lambda}_{it}^{LDV} + \varepsilon_{it} \quad \forall\, PFP_{it} = 1\,. \end{aligned} \tag{16}$$

The regression results of equations (13) and (16) are displayed in Table 8. Again, I apply bootstrapped standard errors clustered at the firm level to account for the inclusion of the estimated control functions $\widehat{\lambda}_{it}^{LDV}$ and $T_t \times \widehat{\lambda}_{it}^{LDV}$.

Table 8: Sample selection bias

Hierarchy:	*M*	*NM*	*M*	*NM*	*M*	*NM*	*M*	*NM*
Scheme:	*individual*	*individual*	*team*	*team*	*organization*	*organization*	*collective*	*collective*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Model:	**(1) Pooled OLS**							
$ln(ICT^h)$	-.022	.113**	.102*	.133***	.066	.161***	.060	.197***
	(.058)	(.057)	(.057)	(.046)	(.055)	(.055)	(.048)	(.059)
$\widehat{\lambda}^{FE,h}$	.045	-.391	.934***	.411	-.226	-.203	.237	-.145
	(.373)	(.372)	(.315)	(.319)	(.258)	(.359)	(.215)	(.376)
$\widehat{\lambda}^{FE,h}$ x T_2	-.303	-.230	-.453	-.318	.350	.182	.050	.076
	(.408)	(.425)	(.342)	(.361)	(.303)	(.421)	(.243)	(.432)
$\widehat{\lambda}^{FE,h}$ x T_3	.241	.179	-.793**	-.734**	.309	-.266	-.214	-.549
	(.398)	(.482)	(.365)	(.358)	(.319)	(.431)	(.265)	(.462)
Model:	**(2) Heckman Two Step Estimations**							
$ln(ICT^h)$	-.037	.085	.065	.136***	.049	.174***	.039	.209***
	(.053)	(.053)	(.054)	(.043)	(.052)	(.049)	(.044)	(.050)
$ln(PFP^{hs}_{t-1})$	.229***	.421***	.276***	.228***	.261***	.416***	.197***	.337***
	(.059)	(.057)	(.055)	(.056)	(.058)	(.061)	(.057)	(.058)
$\widehat{\lambda}^{LDV,h}$	-.535	.805	-.159	-.332	.387	.997	.393	.558
	(.528)	(.687)	(.520)	(.575)	(.443)	(.681)	(.432)	(.739)
$\widehat{\lambda}^{LDV,h}$ x T_2	.231	-1.299*	.540	.394	-.430	-1.148	-.150	-.712
	(.526)	(.702)	(.519)	(.611)	(.395)	(.701)	(.366)	(.735)
$\widehat{\lambda}^{LDV,h}$ x T_3	.762	-.826	.284	.093	-.124	-1.341*	-.203	-1.044
	(.616)	(.746)	(.564)	(.671)	(.479)	(.771)	(.431)	(.812)
$\widehat{\lambda}^{LDV,h}$ x T_4	.615	-.885	.940	.694	-.479	-1.055	-.056	-.573
	(.566)	(.688)	(.579)	(.582)	(.445)	(.763)	(.414)	(.756)

Sources. Linked Personnel Panel (LPP), employer survey, waves 2014, 2016, 2018, and IAB Establishment Panel, waves 2014, 2016, 2018. Own calculations. **Notes.** In Model (1), selected observations equal to 775, and groups to 500. In Model (2), the number of observations equals to 1'377, selected observations to 775, and groups to 789. The values in parentheses represent in Model (1)/(2) bootstrap standard errors with 253/254 replications. Controls are added to all estimations. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The estimates of the pooled OLS and the augmented Heckman two-step model, both specified to correct for sample selection bias, are consistent with my baseline estimates displayed in Table 5. Most importantly, the positive and statistically significant impact of ICT equipment on collective performance pay in the group of non-managerial employees remains in place. In this group, the ICT effect on team- or division-based performance pay ($PFP^{NM,team/div}$) and performance pay based on organizational success ($PFP^{NM,orga}$) turns out to be highly significant, and this also applies to the ICT effect on the composite variable of collective performance pay ($PFP^{NM,coll}$).

Note that after accounting for sample selection bias, the estimated ICT effects $\hat{\alpha}_2^{FE}$ and $\hat{\alpha}_2^{LDV}$ are very close to each other. This finding shows that the causal ICT effect on the composition of incentive pay for non-managerial employees is narrowly bounded at about .135 for team-based performance pay, .170 for performance pay based on organizational success, and .200 for the composite variable of collective performance pay. The interpretation, illustrated by the example of collective performance pay, is that a 10 percent increase in the share of ICT equipment for non-managerial workers raises the share of collective performance for this group by about 2 percent. This result is not only statistically, but also economically significant. The finding that $\hat{\alpha}_2^{LDV}$ turns out to be slightly larger than $\hat{\alpha}_2^{FE}$, rather than the reverse as expected, can be attributed to the applied procedure of correcting for sample-selection bias.

A final result of this robustness check is that the parameters of the estimated control functions $\widehat{\lambda}_{it}^{LDV}$ and $T_t \times \widehat{\lambda}_{it}^{LDV}$ mostly turn out to be statistically insignificant. This implies that the presumed sample selection problem in the present case is not as large as feared or that the sample selection problem can already be substantially reduced by applying the bracketing-property approach in combination with conditioning on a set of potential confounders.

7 Complementary analysis

7.1 Excluding firms without performance pay

In the analysis so far, I have always considered the respective components of incentive compensation in relation to fixed wages, but not the relations of the individual components to each other. Thus, the reference group to the firms that use certain forms of variable, performance-based compensation has so far consisted of those firms that do not use any form of performance-based compensation. In a further step, I examine the effects of equipping employees with ICT on the composition of performance pay, focusing on the extent of collective performance pay in relation to the extent of individual performance pay. The analysis therefore focuses on the question of whether equipping employees with ICT across hierarchical levels leads to a shift in the components of incentive pay. Does ICT equipment promote a shift in the pay-for-performance components in favor of collective performance pay and at the expense of individual performance pay? Or does the shift occur in favor of individual performance pay? In the first case, ICT would promote cooperation among employees. In the opposite case, ICT would strengthen competition among employees.

This adjusted approach excludes firms without a performance-pay system, implying that almost half of the firms would be dropped from the analysis from the outset. Another argument, which also argues against a hasty exclusion of firms without a pay-for-performance system, comes from the fact that it has been observed recently that firms abolish individual performance pay and instead either return to fixed wages or substitute individual performance pay with collective performance pay (Sliwka 2020).

For this reason, I construct two new dependent variables, one explicitly focusing on the relationship between individual and collective performance pay and one that does not exclude firms without a performance-pay system. Both variables are defined in such a way that they express the opposing objectives of performance-pay systems, thus relating cooperation incentives to competition incentives.

The first variable is constructed as follows:

$$PFP_{it}^{h,O} = \begin{cases} 1 & \text{if } PFP_{it}^{h,coll} > PFP_{it}^{h,indiv} \\ 0 & \text{if } PFP_{it} = 0 \\ -1 & \text{if } PFP_{it}^{h,coll} \leq PFP_{it}^{h,indiv}. \end{cases}$$

Hence, $PFP_{it}^{h,O}$ is an ordinally scaled variable, where increasing values express an increasing degree of cooperation incentive. The strongest cooperation incentives are set by firms in which collective performance incentives play a greater role than individual performance incentives. These companies are assigned the value 1. In the opposite case, i.e., when individual performance incentives equal or exceed collective performance incentives, a firm increases competition among its employees. These firms are assigned the value -1. Firms that do not use pay for performance occupy a position between these two poles and are therefore assigned the value 0.

The second variable is a dummy variable separating firms with a focus on inducing cooperation among their employees from firms that especially induce competition among their employees, i.e.,

$$PFP_{it}^{h,D} = \begin{cases} 1 & \text{if } PFP_{it}^{h,coll} > PFP_{it}^{h,indiv} \\ 0 & \text{if } PFP_{it}^{h,coll} \leq PFP_{it}^{h,indiv} . \end{cases}$$

This variable explicitly addresses an argument mentioned above, according to which some firms have changed their remuneration system by substituting individual performance incentives with collective performance incentives. This change can be interpreted as a shift in corporate thinking with regard to setting performance incentives away from competitive incentives and toward collaborative incentives.

When the ordinal variable $PFP_{it}^{h,O}$ is used as dependent variable, I resort to the original bracketing-property approach developed in Angrist and Pischke (2009) and deliberately refrain from applying a selection correction, because, in this case, the focus is on the change in performance incentives through wage policy as a whole. If, on the other hand, the dummy variable $PFP_{it}^{h,D}$ is used as dependent variable, the selection correction again plays a significant role, because, in this case, the shift in performance incentives in firms with incentive pay systems is to be emphasized. Hence, the regressions with $PFP_{it}^{h,O}$ as dependent variable are performed according to equations (5) and (6), where the FE model is estimated using robust standard errors clustered at the firm level and the LDV model is estimated using the Newey-West estimator to account for serial correlation. On the contrary, the regressions with $PFP_{it}^{h,D}$ as dependent variable are performed according to equations (13) and (16), thus addressing the sample selection issue. The corresponding regression results are displayed in Table 9.

The estimates displayed in columns (1) and (2) refer to the FE and LDV regressions, where $PFP_{it}^{h,O}$ is the dependent variable. For managerial employees, the estimation results remain statistically insignificant. For non-managerial employees, the FE estimates are only statistically significant, if the unrestricted sample is used. In this case, there is indeed a causal effect of ICT equipment on $PFP_{it}^{h,O}$, which is bounded by statistically significant FE and LDV estimates, i.e., $\widehat{\alpha} \in [\widehat{\alpha}^{LDV} = .031, \widehat{\alpha}^{FE} = .047]$.

Columns (3) and (4) display the estimates referring to the second stages of the pooled OLS and LDV regressions, where $PFP_{it}^{h,D}$ is the dependent variable and corrections for sample selection bias have been made. For managerial employees, only the pooled OLS coefficient for ICT equipment turns out to be statistically significant at the 10% level, but not the corresponding LDV coefficient resulting from Heckman's sample selection model. For non-managerial employees, however, I obtain parameter estimates that are statistically significant at the 5% level in both models, the pooled OLS

Table 9: Excluding firms without performance pay

Hierarchy:	*M*	*NM*	*M*	*NM*
Variable:	*ordinal*	*ordinal*	*dummy*	*dummy*
	(1)	(2)	(3)	(4)
Model:	**(1) FE (unrestricted sample)**			
$ln(ICT^h)$	.008	.047**		
	(.017)	(.021)		
Model:	**(2) FE (restricted sample)**		**(1) Pooled OLS**	
$ln(ICT^h)$	.003	.030	.024*	.029**
	(.019)	(.023)	(.013)	(.013)
$\widehat{\lambda}^{FE,h}$			.094	.014
			(.087)	(.082)
$\widehat{\lambda}^{FE,h}$ x T_2			.076	.023
			(.093)	(.091)
$\widehat{\lambda}^{FE,h}$ x T_3			-.005	-.132
			(.110)	(.093)
Model:	**(3) LDV with HAC s.e.**		**(2) Heckman 2S.**	
$ln(ICT^h)$	.016	.031**	.022	.031**
	(.011)	(.013)	(.014)	(.012)
$ln(PFP^h_{t-1})$	.292***	.326***	.290***	.304***
	(.030)	(.030)	(.051)	(.058)
$\widehat{\lambda}^{LDV,h}$			.003	-.020
			(.180)	(.141)
$\widehat{\lambda}^{LDV,h}$ x T_2			.122	.041
			(.175)	(.141)
$\widehat{\lambda}^{LDV,h}$ x T_3			.061	-.138
			(.193)	(.156)
$\widehat{\lambda}^{LDV,h}$ x T_4			.051	-.008
			(.184)	(.152)

Sources. Linked Personnel Panel (LPP), employer survey, waves 2014, 2016, 2018, and IAB Establishment Panel, waves 2014, 2016, 2018. Own calculations. **Notes.** For the ordinal variable: *Obs* equals to (1) 1'911, (2) 1'372, and (3) 1'372. For the dummy variable: *Obs* equals to (1) 772, and (2) 772.The values in parentheses represent firm-level-clustered (for ordinal) and bootstrap (for dummy) standard errors with (1) 256 or (2) 245 replications. Controls are added to all estimations. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

model corrected for sample selection bias and the LDV model resulting from Heckman's sample selection model. According to these estimates, the causal effect of ICT equipment on $PFP_{it}^{h,D}$ ranges between .029 and .031, i.e., $\widehat{\alpha}_2 \in [\widehat{\alpha}_2^{POLS} = .029, \widehat{\alpha}_2^{LDV} = .031]$.

The estimation results obtained from both models suggest the following. For non-managerial employees, ICT is changing the compensation policy of firms in such a way that cooperation incentives are increasing relative to competition incentives. ICT thus creates a shift in the composition of variable incentive pay components in favor of collective incentive pay and at the expense of individual incentive pay. This confirms my theoretical considerations that ICT promotes a job design characterized by complex, non-routine tasks, as well as interdependent tasks. In such an environment, it is therefore important for employees to work more collaboratively in order to be able to solve the challenging tasks. Companies support such changing work requirements by adapting their reward system and focusing more on cooperation incentives than on competition incentives. For the composition of incentive pay, this means that a shift is taking place away from individual incentive pay and toward collective incentive pay.

No reliable statements can be made in this regard for managerial employees. Here, the ICT effects on the composition of incentive pay are statistically insignificant in the majority of cases. This could be explained by the fact that ICT enables more competition among managerial employees for some firms and more cooperation for others. In the overall effect, these opposing effects balance each other out.

7.2 Endogeneity of managerial vs. non-managerial workers to ICT

Another assumption I have made so far in my analysis is that managerial and non-managerial workers are exogenous to the deployment of information and communication technology in firms. However, there might be potential endogeneity of managerial versus non-managerial workers that is attributable to the continuous spread of ICT in firms. In Section 2, I discussed this case theoretically in which technology may reduce the demand for middle-skilled management or middle-skilled workers on the one hand (Acemoglu and Autor 2011, Garicano and Rossi-Hansberg 2015), and increase the demand for high-skilled and low-skilled workers on the other hand (Acemoglu and Autor 2011, Goos et al. 2009).

Consequently, I want to analyze empirically if the demand for managerial and non-managerial workers is endogenous to the deployment of ICT, and if such a potential endogeneity of managerial versus non-managerial workers to ICT is biasing my results of the main specification in Section 5.2. More concretely, I first regress a proxy of labor demand for both employment groups on ICT

Table 10: Endogeneity of managerial vs. non-managerial workers to ICT

Hierarchy:	*M*	*NM*	*M*	*NM*
Variable:	$search^{SN,M}$	$search^{SN,NM}$	$search^{HH,M}$	$search^{HH,NM}$
	(1)	(2)	(3)	(4)
$ln(ICT^h)$	.003	.009**	.012**	.022***
	(.003)	(.004)	(.005)	(.006)
Controls	yes	yes	yes	yes
R^2	.103	.122	.216	.069
Obs	2'029	2'029	2'029	2'029

Sources. Linked Personnel Panel (LPP), employer survey, waves 2014, 2016, 2018, and IAB Establishment Panel, waves 2014, 2016, 2018. Own calculations.

Notes. OLS estimates are shown. The dependent variables are $search^{SN,h}$ (i.e., labor search via social networks) and $search^{HH,h}$ (i.e., labor search via headhunters). The independent variable is $ln(ICT^h)$, indicating the equipment in information and communication technologies of managerial or non-managerial workers. $h = (M, NM)$. The values in parentheses represent robust standard errors clustered at the firm level.

** $p < .05$, *** $p < .01$.

equipment using information on labor search via social networks and professional headhunters for the concerned employment groups (i.e., managerial and non-managerial workers). I rely on two employer survey questions of the Linked Personnel Panel '*In the last two years, have you directly approached candidates who were employed by another employer via social networks such as XING, LinkedIn or similar?*' and '*In the last two years, have you recruited candidates who were employed by another employer through a private employment agency or a recruitment consultancy?*'.[42] Referring to a subsequent survey question ('*Were these candidates for positions with management responsibility or for positions without management responsibility?*'), I am able to distinguish between managerial and non-managerial workers and construct the variables $search^{SN,h}$ (i.e., labor search via social networks) and $search^{HH,h}$ (i.e., labor search via headhunters) with $h = (M, NM)$ (see, Table 12 in the Appendix for descriptive statistics). The results of OLS estimations can be found in Table 10.

[42]These questions obviously relate to job poaching. Poaching can be considered as a type of labour mobility between firms as a result of active recruitment by the hiring firm against the will of the sending firm (Stockinger and Zwick 2017). It is an indicator of competition between companies in the labour market. In this paper, the questions reflect the attempt to recruit workers who are very important for the firm, and thus show the need for both employment groups, i.e. managerial and non-managerial workers.

The empirical results confirm a conditional relationship between equipping managerial and non-managerial workers with ICT and labor search for both employment groups. ICT equipment leads to an increase in labor search via professional headhunters for managerial workers (see, Column (2) in Table 10), and an increase in labor search via social networks and professional headhunters for non-managerial workers (see, Column (3) and (4) in Table 10).

In a second step, I want to address potential endogeneity of managerial versus non-managerial workers to ICT in my main specification in Section 5.2 by including both variables $search^{SN,h}$ and $search^{HH,h}$ as control variables in the respective empirical model. In addition, the conditional correlation between labor search and ICT equipment indicates the necessity to add the labor search variables to my estimation model. After including the labor search variables as additional controls, I do not discover substantial changes. In other words, my empirical results remain robust, allowing me to conclude that the composition of pay for performance is affected by the deployment of ICT in firms, shifting towards a more collective performance pay for non-managerial workers who are predominantly located at lower layers of the hierarchy.

8 Conclusion

In this paper, I examine the question, whether or not the existence of pay-for-performance plans, and especially the composition of pay for performance, is affected by a firm policy according to which workers are equipped more or less extensively with ICT. Specifically, I am interested in identifying a potential causal effect of ICT equipment on a firm's pay-for-performance plan, thereby distinguishing between managerial and non-managerial employees.

For this purpose, I draw on established theories in labor economics (i.e., skill-biased technological change, routine-biased technological change) and organizational economics (i.e., the role of technology in determining the centralization or decentralization of organizations) and combine the major insights of these theories to develop the foundations of a theoretical approach that I call the team-biased technological change. I then confront the implications resulting from the team-biased technological change with the implications resulting from the incentive intensity principle to derive two rival hypotheses according to which equipping employees with ICT increases the importance of performance pay plans that either focus on individual or on collective performance pay. Finally, a third hypothesis relates to differences across hierarchical levels, i.e., between managerial and non-managerial workers.

In the empirical part of the paper, I aim at testing my three theoretical hypotheses by making use of large-scale firm-level panel data on management practices in Germany. In order to identify a cause-and-effect relationship between ICT equipment and the existence and composition of pay for performance, I rely on the bracketing-property approach developed in Angrist and Pischke (2009), while conditioning on a rich set of potential confounders. My main empirical result is that equipping workers in lower, non-managerial layers of the hierarchy with ICT increases the prevalence of collective performance pay, while there is no such effect in higher, managerial layers. This result turns out to be robust to first-order serial correlation and sample selection. Hence, my empirical strategy explicitly addresses the most severe endogeneity issues (i.e., omitted variables bias including omitted selection, selectivity bias caused by reverse or simultaneous causation, and sample selection bias) as well as concerns with regard to efficiency.

My empirical results suggest that digital transformation in general and ICT in particular have the potential to change the nature of work in a way that places more emphasis on jobs and tasks, where characteristics such as collaboration, cooperation, teamwork and interdependent work gain in importance. According to my estimation results, this does especially apply to jobs and tasks performed by non-managerial workers, who are predominantly located at lower layers of the hierarchy. However, if workers at lower hierarchical levels have more and more to collaborate with co-workers and if task completion requires more and more interdependent work, equipping non-managerial workers with ICT will also contribute to increase the task complexity for these workers. The finding that equipping managerial employees with ICT does apparently not have an impact on the composition of their performance pay-plans may be explained by the presence of possible opposite effects, meaning that ICT equipment in this group may promote individual performance pay in some firms and collective performance pay in others. It would be promising to conduct complementary studies that explicitly explore these potentially diverse ICT effects on the performance-pay plans of managerial workers. Building on the empirical results of my investigation, one could, for example, hypothesize that equipping managerial employees with ICT tends to promote collective performance pay in firms with a corporate culture that is based on values such as cooperation, mutual assistance, or fault tolerance, whereas ICT tend to increase individual performance pay in corporate cultures based on performance measurement and competition.

Opposite ICT effects on the performance-pay plans of managerial employees may also be presumed for employees located at different managerial layers of the hierarchy. For example, if it can be assumed that virtually all top managers are compensated with some form of collective performance pay, while this is not necessarily true for lower management levels, then ICT could diminish the relative importance of collective performance pay in top management in favor of individual performance pay, for example, because ICT improves individual performance measurement. At middle and lower management levels, on the other hand, cooperation between divisions or departments could be more important than at upper management levels, so that the ICT effect on cooperation dominates the ICT effect on individual performance measurement and collective performance pay thus increases more than individual performance pay.

Overall, the results of my analysis complement the theoretical and empirical literature on the ICT effects on job design or organizational architecture. Specifically, the study points out that technologies used in companies in the age of digital transformation will change job design in such a way that independent work will continue to lose importance, while interdependencies at the workplace will increase in importance. This development places special demands on both companies and their employees. Employees will work less on their own, but will be increasingly involved in team solutions. In addition to technical qualifications, skills that are necessary for interpersonal interactions will also be in demand. In turn, companies will have to adapt or expand their job design and, if necessary, even their corporate culture. The digital transformation will entail more collaboration and cooperation efforts, at least for non-managerial workers. This process should be accompanied by an adjustment of the remuneration system in terms of a stronger relative importance of collective performance pay.

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Appendix

Complete regression results

Table 11: Complete regression results: Bracketing Property

Hierarchy:	*M*	*NM*	*M*	*NM*	*M*	*NM*	*M*	*NM*
Scheme:	*individual*	*individual*	*team*	*team*	*organization*	*organization*	*collective*	*collective*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Model:	**Fixed Effects Model**							
$ln(ICT^h)$	.067	.054	.045	.076**	.055	.128***	.038	.173***
	(.055)	(.052)	(.043)	(.038)	(.057)	(.048)	(.062)	(.054)
Market competition								
Low competition	-.045	-.028	.238	.342*	-.170	-.101	-.080	.055
	(.222)	(.228)	(.190)	(.186)	(.233)	(.196)	(.236)	(.215)
Medium competition	-.216	-.034	.142	.261	-.219	-.106	-.155	-.011
	(.251)	(.219)	(.214)	(.179)	(.229)	(.197)	(.238)	(.208)
High competition	-.396	-.271	-.018	.160	-.167	-.036	-.157	-.059
	(.275)	(.237)	(.218)	(.181)	(.280)	(.230)	(.287)	(.248)
Regulation								
Collective wage bargaining	.188	.364	.347	.424	-.035	.366	-.037	.405
	(.372)	(.304)	(.248)	(.292)	(.389)	(.310)	(.384)	(.348)
Works council	.615	.231	.795*	.809*	.099	.429	.334	1.108**
	(.392)	(.467)	(.427)	(.433)	(.436)	(.444)	(.517)	(.530)
Technology status								
Tech-status 2	-.165	.101	-.211	-.604	.945	-.171	1.037	-.309
	(.565)	(.656)	(.606)	(.430)	(.616)	(.301)	(.668)	(.383)
Tech-status 3	-.255	-.202	-.255	-.503**	-.221	-.183	-.247	-.439*
	(.262)	(.251)	(.228)	(.221)	(.271)	(.205)	(.300)	(.257)
Tech-status 4	-.261	-.170	-.095	-.313	-.021	.002	.013	-.134
	(.220)	(.205)	(.198)	(.192)	(.219)	(.179)	(.255)	(.218)

Hierarchy:	*M*	*NM*	*M*	*NM*	*M*	*NM*	*M*	*NM*
Scheme:	*individual*	*individual*	*team*	*team*	*organization*	*organization*	*collective*	*collective*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Strategy								
Product innovation 1	-.049	.090	.007	-.041	.046	.166	.033	.064
	(.198)	(.183)	(.170)	(.188)	(.201)	(.160)	(.205)	(.209)
Product innovation 2	.052	.311	.010	.056	-.056	.294	-.058	.332
	(.222)	(.204)	(.172)	(.198)	(.195)	(.185)	(.203)	(.220)
Product innovation 3	.268	.234	-.120	-.226	-.157	.129	-.207	.004
	(.250)	(.244)	(.220)	(.202)	(.213)	(.204)	(.242)	(.227)
Process innovation	-.047	-.059	-.114	-.052	-.042	.547*	-.037	.411
	(.342)	(.333)	(.343)	(.309)	(.304)	(.315)	(.350)	(.368)
Cost leadership	.142	-.025	.310	.304	-.043	-.041	.196	.143
	(.293)	(.299)	(.243)	(.209)	(.310)	(.261)	(.305)	(.262)
Quality leadership	-.168	-.177	-.269*	-.091	.002	-.009	-.049	-.061
	(.192)	(.206)	(.145)	(.138)	(.151)	(.164)	(.156)	(.188)
Export rate	-.0101	-.014	.001	-.003	-.006	-.007	-.007	-.008
	(.008)	(.009)	(.004)	(.006)	(.007)	(.006)	(.007)	(.007)
Metal, electronics, etc.	.957	1.204	.371	.516	.870	.509	.854	.617
	(.640)	(.777)	(.393)	(.480)	(.657)	(.468)	(.708)	(.577)
Firm-related services, etc.	4.604***	5.193***	-1.248*	2.273***	1.576*	1.545**	-.346	2.533***
	(.930)	(1.011)	(.690)	(.740)	(.939)	(.772)	(1.032)	(.897)
IC and other services	4.485***	5.017***	-1.338*	2.190***	1.329	1.107	-.533	2.045**
	(.961)	(1.025)	(.709)	(.754)	(.959)	(.804)	(1.055)	(.931)
Decision rights								
SMWT	.089	-.056	-.019	-.070	-.228	-.102	-.219	-.148
	(.187)	(.183)	(.160)	(.147)	(.167)	(.161)	(.176)	(.179)
Working time accounts	-.127	-.155	-.259	-.256	-.006	-.251	-.102	-.285

Hierarchy:	*M*	*NM*	*M*	*NM*	*M*	*NM*	*M*	*NM*
Scheme:	*individual*	*individual*	*team*	*team*	*organization*	*organization*	*collective*	*collective*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	(.289)	(.259)	(.246)	(.217)	(.272)	(.204)	(.302)	(.241)
Long-term working time accounts	-.227	.306	.011	.383*	.292	.199	.192	.464*
	(.222)	(.203)	(.220)	(.199)	(.216)	(.225)	(.234)	(.246)
Performance evaluation								
Appraisal interviews	.215	-.222	.200	.070	-.199	.065	-.116	.057
	(.172)	(.186)	(.154)	(.143)	(.205)	(.171)	(.219)	(.185)
Target agreements	-.050	-.022	.292*	.162	-.087	-.081	.098	.003
	(.193)	(.190)	(.162)	(.162)	(.188)	(.170)	(.204)	(.197)
Performance appraisals	.367**	.377**	.015	-.067	.415**	-.108	.475***	-.123
	(.168)	(.159)	(.137)	(.129)	(.167)	(.150)	(.181)	(.171)
Distribution system	.073	-.134	.060	.028	-.063	.171	-.177	.104
	(.297)	(.274)	(.260)	(.250)	(.244)	(.267)	(.276)	(.324)
Evaluation rounds	.237	-.053	.014	.227	.088	.514*	-.110	.599**
	(.291)	(.241)	(.257)	(.196)	(.288)	(.289)	(.304)	(.291)
Reward and performance development								
Payment above	.479*	.150	.068	.037	.355*	-.116	.352	-.087
	(.249)	(.219)	(.179)	(.153)	(.200)	(.151)	(.220)	(.191)
Development plans	.356*	.051	-.293	-.248	.033	-.061	-.143	-.190
	(.184)	(.179)	(.180)	(.150)	(.184)	(.161)	(.212)	(.185)
Workforce structure								
Low-skilled workers	-.002	-.000	-.002	-.001	.003	-.004	.000	-.006
	(.006)	(.005)	(.004)	(.004)	(.006)	(.005)	(.007)	(.006)
High-skilled workers	.001	.002	.0155	.000	-.000	-.009	.007	-.012
	(.012)	(.011)	(.010)	(.011)	(.010)	(.010)	(.010)	(.010)
Female workers	-.003	-.015	-.0170	.002	-.011	.010	-.012	.009

Hierarchy:	*M*	*NM*	*M*	*NM*	*M*	*NM*	*M*	*NM*
Scheme:	*individual*	*individual*	*team*	*team*	*organization*	*organization*	*collective*	*collective*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	(.014)	(.011)	(.012)	(.009)	(.013)	(.012)	(.014)	(.012)
Temporary agency workers	-.009	-.025**	-.000	-.012**	-.008	.008	-.011	-.002
	(.012)	(.010)	(.010)	(.006)	(.009)	(.008)	(.010)	(.009)
Firm size classes								
Firm size 1-49	.783	-.177	.346	.081	.271	.248	.517	-.037
	(.488)	(.454)	(.323)	(.333)	(.394)	(.489)	(.389)	(.526)
Firm size 50-99	.431	-.736	.192	.023	.353	.020	.426	-.220
	(.572)	(.560)	(.421)	(.396)	(.452)	(.599)	(.494)	(.618)
Firm size 100-249	-.400	-2.178***	.173	-1.209**	-.344	-.998	-.497	-1.637**
	(.749)	(.710)	(.618)	(.576)	(.670)	(.740)	(.729)	(.797)
Firm size 250-499	-1.256	-2.028	-.058	-.530	-1.342	-.768	-1.421	-.637
	(.928)	(.764)	(.864)	(.917)	(.870)	(.866)	(.939)	(1.003)
Wave								
Wave 3	-.133	-.033	.005	-.024	-.046	-.045	.006	-.054
	(.109)	(.105)	(.086)	(.085)	(.098)	(.092)	(.100)	(.107)
Wave 4	-.403*	-.006	-.040	.022	-.089	.019	-.069	-.077
	(.223)	(.177)	(.170)	(.148)	(.218)	(.181)	(.219)	(.179)
R^2	.091	.072	.057	.095	.061	.071	.064	.099
Model:	**Lagged Dependent Variable Model**							
$ln(ICT^h)$	.020	.086***	.038	.093***	.057*	.128***	.050	.157***
	(.030)	(.033)	(.025)	(.025)	(.032)	(.029)	(.034)	(.034)
$ln(PFP^{hs}_{t-1})$	.343***	.376***	.335***	.238***	.401***	.335***	.411***	.321***
	(.030)	(.031)	(.032)	(.034)	(.030)	(.033)	(.030)	(.031)
Market competition								

Hierarchy:	*M*	*NM*	*M*	*NM*	*M*	*NM*	*M*	*NM*
Scheme:	*individual*	*individual*	*team*	*team*	*organization*	*organization*	*collective*	*collective*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Low competition	.108	.052	-.001	.215	-.121	.149	-.043	.229
	(.169)	(.178)	(.145)	(.138)	(.179)	(.156)	(.185)	(.174)
Medium competition	-.097	.033	-.008	.164	-.185	.081	-.111	.140
	(.163)	(.175)	(.154)	(.143)	(.162)	(.145)	(.180)	(.173)
High competition	-.327**	-.106	-.179	.006	-.091	.084	-.116	-.011
	(.165)	(.173)	(.150)	(.134)	(.168)	(.151)	(.181)	(.176)
Regulation								
Collective wage bargaining	-.055	.048	-.063	-.086	-.278**	-.190*	-.252*	-.227*
	(.120)	(.124)	(.107)	(.107)	(.128)	(.110)	(.137)	(.129)
Works council	.028	.008	.105	-.071	.029	-.061	.021	-.094
	(.107)	(.114)	(.097)	(.093)	(.115)	(.100)	(.124)	(.116)
Technology status								
Tech-status 2	-.573	-.815	-.242	-.624	-.368	-.269	-.369	-.435
	(.573)	(.642)	(.413)	(.454)	(.649)	(.604)	(.716)	(.650)
Tech-status 3	-.624	-1.099*	-.444	-.651	-.712	-.692	-.737	-.719
	(.527)	(.601)	(.373)	(.420)	(.583)	(.551)	(.652)	(.593)
Tech-status 4	-.796	-1.159*	-.353	-.559	-.627	-.703	-.596	-.659
	(.524)	(.598)	(.373)	(.419)	(.580)	(.550)	(.648)	(.590)
Tech-status 5	-.738	-1.139*	-.358	-.495	-.424	-.601	-.457	-.548
	(.536)	(.607)	(.383)	(.430)	(.591)	(.558)	(.660)	(.600)
Strategy								
Product innovation 1	.045	.143	.021	.038	.091	.264**	.125	.270**
	(.121)	(.121)	(.102)	(.102)	(.127)	(.107)	(.131)	(.127)
Product innovation 2	.143	.341***	.135	.028	.272**	.195*	.313**	.246*
	(.121)	(.130)	(.106)	(.111)	(.123)	(.115)	(.132)	(.136)

Hierarchy:	*M*	*NM*	*M*	*NM*	*M*	*NM*	*M*	*NM*
Scheme:	*individual*	*individual*	*team*	*team*	*organization*	*organization*	*collective*	*collective*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Product innovation 3	.222	.239	.217*	.128	.128	.271*	.130	.328**
	(.142)	(.150)	(.130)	(.123)	(.145)	(.138)	(.156)	(.156)
Process innovation	.040	.324	.183	.263	.005	.270	.036	.338
	(.190)	(.237)	(.187)	(.203)	(.186)	(.207)	(.199)	(.242)
Cost leadership	-.014	-.062	.167	.036	.187	-.063	.236	-.060
	(.183)	(.190)	(.160)	(.133)	(.202)	(.156)	(.211)	(.175)
Quality leadership	-.042	.060	.009	.034	.078	.180*	.068	.132
	(.104)	(.112)	(.085)	(.089)	(.103)	(.100)	(.107)	(.113)
Export rate	.000	.000	-.001	.000	.000	.000	.000	.000
	(.001)	(.002)	(.001)	(.001)	(.002)	(.002)	(.002)	(.002)
Metal, electronics, etc.	-.104	-.029	-.254**	-.132	-.245**	-.165	-.302**	-.213*
	(.112)	(.120)	(.102)	(.100)	(.118)	(.107)	(.126)	(.125)
Trade, transport, etc.	-.036	.213	.001	.121	-.167	-.048	-.168	.042
	(.133)	(.150)	(.130)	(.129)	(.149)	(.126)	(.158)	(.150)
Firm-related services etc.	-.096	.113	.240*	-.056	-.218	.024	-.086	.037
	(.151)	(.162)	(.144)	(.133)	(.159)	(.146)	(.169)	(.166)
IC and other services	.285	.340	.110	-.073	-.200	-.008	-.210	-.021
	(.183)	(.220)	(.173)	(.164)	(.232)	(.204)	(.246)	(.225)
Decision rights								
SMWT	.236**	.092	.206**	.194**	.234**	.183*	.282**	.328***
	(.103)	(.109)	(.090)	(.087)	(.104)	(.094)	(.111)	(.108)
Working time accounts	.072	-.012	.167*	.098	.011	-.065	.089	.037
	(.122)	(.125)	(.098)	(.088)	(.131)	(.107)	(.136)	(.119)
Long-term working time accounts	-.281**	.007	.020	.206	-.005	-.020	-.021	.145

Hierarchy:	*M*	*NM*	*M*	*NM*	*M*	*NM*	*M*	*NM*
Scheme:	*individual*	*individual*	*team*	*team*	*organization*	*organization*	*collective*	*collective*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	(.116)	(.122)	(.120)	(.115)	(.130)	(.127)	(.138)	(.144)
Performance evaluation								
Appraisal interviews	.096	-.164	.142	.027	-.154	.016	-.067	.017
	(.108)	(.109)	(.098)	(.092)	(.122)	(.102)	(.132)	(.117)
Target agreements	.267**	.126	.280***	.150*	.430***	.146	.484***	.234**
	(.106)	(.106)	(.087)	(.088)	(.113)	(.096)	(.120)	(.112)
Performance appraisals	.374***	.448***	.163*	.043	.425***	.143	.463***	.097
	(.106)	(.110)	(.084)	(.085)	(.115)	(.104)	(.119)	(.114)
Distribution system	.100	.135	.341**	.308*	.067	.084	.100	.206
	(.177)	(.201)	(.164)	(.170)	(.174)	(.167)	(.184)	(.199)
Evaluation rounds	.215	.219	.024	.182	-.132	.185	-.087	.311
	(.173)	(.183)	(.158)	(.155)	(.173)	(.168)	(.188)	(.196)
Reward and performance development								
Payments above	.244**	.039	.084	.094	.270**	.280***	.267**	.256**
	(.124)	(.121)	(.108)	(.100)	(.114)	(.100)	(.125)	(.120)
Development plans	.178*	.101	.037	.067	.119	-.025	.135	.034
	(.101)	(.107)	(.096)	(.090)	(.107)	(.094)	(.115)	(.109)
Workforce structure								
Low-skilled workers	.001	.000	.001	.001	.002	-.001	.003	-.001
	(.001)	(.001)	(.001)	(.001)	(.002)	(.001)	(.002)	(.002)
High-skilled workers	.005	.003	.003	.000	.005	.003	.005	.000
	(.003)	(.004)	(.003)	(.003)	(.003)	(.004)	(.003)	(.004)
Female workers	-.005***	-.003	-.004**	-.001	-.001	.000	-.003	-.001
	(.002)	(.002)	(.001)	(.001)	(.002)	(.001)	(.002)	(.002)
Temporary agency workers	-.007	-.011**	.002	-.004	-.011**	-.007*	-.011**	-.009**

Hierarchy:	*M*	*NM*	*M*	*NM*	*M*	*NM*	*M*	*NM*
Scheme:	*individual*	*individual*	*team*	*team*	*organization*	*organization*	*collective*	*collective*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	(.004)	(.004)	(.004)	(.003)	(.004)	(.003)	(.005)	(.004)
Region affiliation								
Eastern Germany	-.039	.064	.080	.099	.181	.052	.156	.080
	(.123)	(.128)	(.111)	(.104)	(.137)	(.120)	(.148)	(.137)
Southern Germany	.204	.178	.184	.131	.335**	.115	.376**	.196
	(.126)	(.146)	(.129)	(.124)	(.151)	(.148)	(.157)	(.166)
Western Germany	.093	.105	.077	.004	.458***	-.022	.425***	.000
	(.124)	(.136)	(.110)	(.106)	(.143)	(.125)	(.150)	(.142)
Firm size classes								
Firm size 50-99	.298	.016	.012	.131	.049	.043	-.082	-.037
	(.204)	(.217)	(.193)	(.157)	(.235)	(.206)	(.243)	(.242)
Firmm size 100-249	.512**	.171	.084	.282*	.130	.119	-.002	.116
	(.200)	(.214)	(.198)	(.160)	(.234)	(.211)	(.244)	(.245)
Firm size 250-499	.548**	.080	.223	.299*	.336	.200	.235	.217
	(.215)	(.231)	(.217)	(.180)	(.252)	(.228)	(.263)	(.265)
Firm size 50+	.642***	.106	-.144	.061	.396	.206	.147	.126
	(.238)	(.262)	(.238)	(.209)	(.269)	(.263)	(.277)	(.298)
Wave								
Wave 3	-.102	-.003	-.006	-.054	-.005	-.003	.071	-.036
	(.107)	(.112)	(.093)	(.089)	(.108)	(.098)	(.116)	(.115)
Wave 4	-.303**	-.027	-.133	-.131	-.101	.051	-.081	-.073
	(.142)	(.149)	(.132)	(.126)	(.142)	(.136)	(.152)	(.157)
R^2	.295	.253	.256	.157	.344	.237	.363	.252
Controls	yes	yes	yes	yes	yes	yes	yes	yes
Obs	1'377	1'377	1'377	1'377	1'377	1'377	1'377	1'377
Groups	789	789	789	789	789	789	789	789

Hierarchy:	*M*	*NM*	*M*	*NM*	*M*	*NM*	*M*	*NM*
Scheme:	*individual*	*individual*	*team*	*team*	*organization*	*organization*	*collective*	*collective*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)

Sources. Linked Personnel Panel (LPP), employer survey, waves 2014, 2016, 2018, and IAB Establishment Panel, waves 2014, 2016, 2018. Own calculations. **Notes.** * $p < .10$, ** $p < .05$, *** $p < .01$

Additional descriptive statistics

Table 12: Definitions and descriptive statistics of all variables

Variable	Definition	Mean	Std.-dev.	Min-Max	Data
	(1) Main explanatory and dependent variables				
Information and communication technology					
ICT	Share of executive or non-executive workers that the firm has equipped with mobile devices such as smart phones, tablet computers or notebooks capable of establishing an Internet connection via the mobile network				LPP
	– Executives	71.764	40.117	0–100	
	– Non-executives	16.328	25.021	0–100	
Performance Pay					
Performance pay plan	Dummy variable indicating firms that have a salary system with variable proportions	0.574	0.494	0–1	LPP
Performance pay (organization)	Share of executive or non-executive workers receiving a performance pay that is based on organizational success				LPP
	– Executives	26.084	33.837	0–100	
	– Non-executives	12.519	26.641	0–100	
Performance pay (team)	Share of executive or non-executive workers receiving a performance pay that is based on team/divisional success				LPP
	– Executives	10.362	20.180	0–100	
	– Non-executives	8.053	20.538	0–100	

Variable	Definition	Mean	Std.-dev.	Min-Max	Data
Performance pay (individual)	Share of executive or non-executive workers receiving a performance pay that is based on individual success				LPP
	– Executives	18.259	27.791	0–100	
	– Non-executives	20.646	34.504	0–100	
(2) Used covariates based on Brickley et al. (2021)					
Market Competition					
No competition	Dummy variable indicating firms with no competitive pressure	.206	.405	0–1	IAB BP
Low competition	Dummy variable indicating firms with low competitive pressure	.143	.351	0–1	IAB BP
Medium competition	Dummy variable indicating firms with medium competitive pressure	.274	.446	0–1	IAB BP
High competition	Dummy variable indicating firms with high competitive pressure	.375	.484	0–1	IAB BP
Regulation					
Collective wage bargaining	Dummy variable indicating firms that commit to collective wage bargaining at the industry or firm level	.596	.490	0–1	IAB BP
Works council	Dummy variable indicating firms with a works council	.634	.481	0–1	IAB BP
Technology Status					
Tech-status 1	Dummy variable indicating that the status of a firm's technological equipment is out-of-date	.002	.050	0–1	IAB BP
Tech-status 2	Dummy variable indicating that the status of a firm's technological equipment is less than satisfactory	.028	.165	0–1	IAB BP

Variable	Definition	Mean	Std.-dev.	Min-Max	Data
Tech-status 3	Dummy variable indicating that the status of a firm's technological equipment is satisfactory	.266	.442	0–1	IAB BP
Tech-status 4	Dummy variable indicating that the status of a firm's technological equipment is more than satisfactory	.524	.499	0–1	IAB BP
Tech-status 5	Dummy variable indicating that the status of a firm's technological equipment is state-of-the-art	.178	.383	0–1	IAB BP
Strategy					
Product innovation 1	Dummy variable indicating firms that did improve or further develop a product or service which had previously been part of the portfolio	.215	.411	0–1	IAB BP
Product innovation 2	Dummy variable indicating firms that did start to offer a product or service that had been available on the market before	.229	.420	0–1	IAB BP
Product innovation 3	Dummy variable indicating firms that have started to offer a completely new product or service in the last business year of 2015 for which a new market had to be created	.157	.364	0–1	IAB BP
Process innovation	Dummy variable indicating firms that did develop or implement procedures in the last business year of 2015 which have noticeably improved production processes or services	.055	.228	0–1	IAB BP

Variable	Definition	Mean	Std.-dev.	Min-Max	Data
Cost leadership	Dummy variable indicating firms that apply a cost-leadership strategy	.062	.242	0–1	LPP
Quality leadership	Dummy variable indicating firms that apply a quality-leadership strategy	.297	.457	0–1	LPP
Export rate	Export share based on total sales (%)	17.940	25.907	0-100	IAB BP
Manufacturing	Dummy variable indicating firms in the manufacturing industry	.307	.461	0–1	LPP
Metal, electronics, vehicle manufacturing	Dummy variable indicating firms in the metal working sector, in the electrical industry or in vehicle manufacturing	.271	.444	0–1	LPP
Trade, transport, news	Dummy variable indicating firms in the trade, traffic, or news sector	.164	.370	0–1	LPP
Firm-related/financial services	Dummy variable indicating firms that offer firm-related or financial services	.152	.360	0–1	LPP
IC and other services	Dummy variable indicating firms that offer information and communication services or other services	.103	.304	0–1	LPP
Decision rights					
SMWT	Dummy variable indicating firms that offer trust-based working hours/self-managed working hours (without operational timekeeping)	.410	.491	0–1	IAB BP
Working time accounts	Dummy variable indicating firms that offer working time accounts to their employees	.820	.383	0–1	IAB BP

Variable	Definition	Mean	Std.-dev.	Min-Max	Data
Long-term working time accounts	Dummy variable indicating firms that offer long-term working time accounts to their employees to be used, for example, for sabbaticals	.172	.377	0–1	IAB BP
Performance Evaluation					
Appraisal interviews	Dummy variable indicating that the firm has conducted structured appraisal interviews with at least once a year	.699	.458	0–1	LPP
Target agreements	Dummy variable indicating that target agreements are available in written form	.615	.486	0–1	LPP
Performance appraisals	Dummy variable indicating that performance appraisals are issued	.640	.479	0–1	LPP
Distribution system	Dummy variable indicating that distribution recommendations are issued	.076	.265	0–1	LPP
Evaluation rounds	Dummy variable indicating that evaluation rounds are issued	.099	.299	0–1	LPP
Reward and performance development					
Payments above	Dummy variable indicating firms that pay wages above the collective bargaining rate	.348	.476	0–1	IAB BP
Development plans	Dummy variable indicating firms that have development plans for employees	.457	.498	0–1	LPP
Workforce structure					
Female workers	Share of female workers (%)	32.402	24.591	0–98.181	IAB BP
Temporary agency workers	Share of temporary agency workers (%)	3.712	7.955	0–100	IAB BP

Variable	Definition	Mean	Std.-dev.	Min-Max	Data
Low-skilled workers	Share of employees for skilled jobs, requiring a vocational qualification or comparable training on the job or relevant professional experience	20.075	26.059	0–100	IAB BP
High-skilled workers	Share of employees for skilled jobs, requiring a university degree	10.554	15.546	0–99.04	IAB BP
Region affiliation					
Northern Germany	Dummy variable indicating firms that are located in Northern Germany	.195	.396	0–1	LPP
Eastern Germany	Dummy variable indicating firms that are located in Eastern Germany	.360	.480	0–1	LPP
Southern Germany	Dummy variable indicating firms that are located in Southern Germany	.189	.391	0–1	LPP
Western Germany	Dummy variable indicating firms that are located in Western Germany	.254	.435	0–1	LPP
Firm size classes					
Firm size 1–49	Dummy variable indicating firms with 1–49 employees covered by social security	.033	.178	0–1	LPP
Firm size 50–99	Dummy variable indicating firms with 50–99 employees covered by social security	.338	.473	0–1	LPP
Firm size 100–249	Dummy variable indicating firms with 100–249 employees covered by social security	.342	.474	0–1	LPP
Firm size 250–499	Dummy variable indicating firms with 250–499 employees covered by social security	.170	.376	0–1	LPP

Variable	Definition	Mean	Std.-dev.	Min-Max	Data
Firm size 500+	Dummy variable indicating firms with 500+ employees covered by social security	.114	.318	0–1	LPP
	(3) Covariates additionally used in Section 7.2				
Labor search via social networks	Dummy variable indicating that firms approached executive or non-executive candidates (who were in employment with another employer) directly via social networks, such as XING, LinkedIn, or other, in the last two years				LPP
	– Executives	.099	.299	0–1	
	– Non-executives	.115	.319	0–1	
Labor search via headhunters	Dummy variable indicating that firms recruited executive or non-executive candidates (who were in employment with another employer) through a private employment agency or an recruitment consultancy in the last two years				LPP
	– Executives	.229	.420	0–1	
	– Non-executives	.178	.382	0–1	

Sources. Linked Personnel Panel (LPP), employer survey, waves 2014, 2016, 2018, and IAB Establishment Panel, waves 2014, 2016, 2018. Own calculations; data format: raw.

Notes. Own calculations.