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Elisa Gerten Michael Beckmann Matthias Kräkel

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Information and Communication Technology, Hierarchy, and Job Design*

Elisa Gerten
Faculty of Management, Economics and Social Sciences, University of Cologne, Albertus-Magnus-Platz, D-50923 Cologne, Germany; gerten@wiso.uni-koeln.de

Michael Beckmann
Faculty of Business and Economics, University of Basel, Peter Merian-Weg 6, CH-4002 Basel, Switzerland; Institute for Employment Research (IAB), Nuremberg, Germany; IZA Institute of Labor Economics, Bonn, Germany; michael.beckmann@unibas.ch

Matthias Kräkel
Department of Economics, University of Bonn, Adenauerallee 24-42, D-53113 Bonn, Germany; IZA Institute of Labor Economics, Bonn, Germany; m.kraekel@uni-bonn.de

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Abstract

In recent decades, information and communication technology (ICT) has been associated with far-reaching changes in the design of jobs. However, it still remains unclear whether these changes will lead to more centralization or more decentralization in firms. Previous literature on this debate has focused on a strict dichotomy between the two possible directions. In contrast, our theoretical and empirical analyses show that equipping employees with ICT leads to both more centralized *and* more decentralized job-design policies. This finding is particularly pronounced for executive employees, who are granted more work autonomy but also experience more control via stronger monitoring, while non-executive employees only experience more monitoring without receiving more work autonomy. Our theoretical setting is based on a modified principal-agent model. In our empirical approach we apply estimation models that account for both endogeneity and essential heterogeneity, thereby exploiting exogenous geographic variation in our instrumental variable.

Keywords: information and communication technology; centralization; decentralization; monitoring; working from home; marginal treatment effects; essential heterogeneity; instrumental variable

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1 Introduction

Technology has continued to reshape organizational structures and processes over time. In the last decades, advances in information and communication technology (ICT), going hand in hand with declining quality-adjusted prices for ICT and better ICT equipment for employees, have steadily driven changes across a wide range of organizations and industries. At the core of many debates on the optimal design of organizations and jobs is the question of whether better equipment of employees with new technologies, including ICT, will lead to more centralized or decentralized decision authority within firms (e.g., Brynjolfsson 1994, Garicano 2000, Caroli and Van Reenen 2001, Bresnahan et al. 2002, Acemoglu et al. 2007, Colombo and Delmastro 2004, 2008, Bloom et al. 2014). This paper aims to contribute to answering this question by examining the impact of ICT equipment on job design across hierarchical levels. Specifically, we hypothesize that executive and non-executive employees are differently equipped with ICT, such as cellphones, tablet computers, and notebooks, and may therefore experience divergent job designs, with firms applying both centralized and decentralized management practices that can thus coexist simultaneously rather than necessarily substituting each other.

Organizational and job design follow the same logic when it comes to centralization or decentralization of decision authority (e.g., Brickley et al. 2021, part 3; Baron and Kreps 1999, chapter 13; Lazear and Gibbs 2015, part 2). More specifically, organizational design refers to the degree to which decision-making authority is delegated from the top down the hierarchy (e.g., from headquarters to divisions). The centralization-decentralization topic in job design is about the question of whether or not employees at different levels of the hierarchy should be empowered by increasing their degree of self-management or workplace autonomy.[1] Both design types have in common that decentralized decision authority is inherently accompanied by a loss of control. However, in order to balance the benefits of using superior decentralized knowledge against the downside of losing control, firms can complement decentralization with centralized policies such as employee monitoring.

The economic literature is quite inconclusive as to whether ICT tends to promote centralization or decentralization in organizations. This can be explained in large part by the fact that ICT improves the information-processing ability of both superiors and subordinates (e.g., Lawler 1988,

[1] Changing job design does not necessarily imply changing the organizational design or vice versa. It is therefore possible to observe centralization tendencies in job design in firms with a decentralized organizational structure or decentralization tendencies in job design in firms with a centralized organizational structure (Brickley et al. 2021, p. 396).

Gurbaxani and Whang 1991, Guadalupe et al. 2014). ICT supports centralization in the first case and decentralization in the second. Similarly, Garicano (2000) finds that ICT promotes centralization when used to facilitate communication in organizations, while ICT entails decentralization when used to improve individual problem solving. Specifically, to the extent that ICT reduces communication costs, it is likely to support centralized monitoring and employee evaluation. For example, two-way communication via email programs and other types of communication software installed on cellphones or laptops makes it easier for superiors to give instructions to their subordinates regardless of their current location, while simultaneously improving the assessment of an employee's effective contribution to firm profit. In other words, ICT can be expected to bring lower monitoring costs and higher monitoring intensity, thus also favoring a more centralized job design. On the other hand, ICT gives lower-level employees easy access to a wide range of information. Equipping employees with ICT enables them to work with less or even without instructions or interventions from their superiors, thus facilitating autonomous work such as working from home. In this way, ICT can support decentralized decision-making (Garicano 2000, Aghion et al. 2013, Lazear and Gibbs 2015, 190−192).

Most economic studies on the allocation of decision authority within organizations attempt to shed light on these competing predictions by implicitly assuming that centralization and decentralization are substitutes rather than complements in the design of organizations and jobs, so that more decentralization inevitably goes hand in hand with less centralization and vice versa. This traditional view is the starting point of our investigation. The contribution of our paper is threefold. First, both our theoretical and empirical models allow for the possibility that centralization and decentralization coexist in complementary ways in the design of jobs, without ruling out a substitutive relationship. Hence, we see ICT as a potential driver for a simultaneous emergence of centralized and decentralized job-design practices. Second, we explicitly take into account that ICT might entail different effects across hierarchical levels. Specifically, we distinguish between executives (i.e., employees on managerial jobs with personnel responsibility) and non-executive employees in terms of both ICT equipment and effects on job design. In doing so, we differ from studies that either consider the effects of ICT on the allocation of decision authority between two selected managerial levels or make no specific reference to hierarchical differences at all.[2] Finally, with regard to causal inference, we complement empirical studies on the effects of ICT on organizational or job design by accounting not only for conventional endogeneity problems (selection on unobservables) via instrumental variables (IV) / two-stage least squares (2SLS) estimation, but

[2]The latter studies are typically interested in a uniform average effect that is independent of hierarchical level.

also for essential heterogeneity (selection based on unobserved gains) via marginal treatment effects (MTE) estimation. MTE estimation provides us with important additional insights, as it allows us to estimate heterogeneous treatment effects among firms that are more or less likely to equip their employees with ICT. Accounting for essential heterogeneity via MTE estimation is not uncommon in the economics of education and training (e.g., Brinch et al. 2017, Carneiro et al. 2011, 2017, Dorsett and Stokes 2022, Kline and Walters 2016, Kamhöfer et al. 2019), the economics of crime (e.g., Bhuller et al. 2020), health economics (e.g., Basu et al. 2007, Alessie et al. 2020, Gong et al. 2020), as well as the economics of child care (e.g., Cornelissen et al. 2018, Felfe and Lalive 2018, Andresen 2019), but to our knowledge has not yet been applied in organizational economics. However, MTE estimation can be very informative, especially for topics related to organizational or job design, because in addition to revealing effect heterogeneity, the respective slopes of the MTE curves can help to determine whether ICT-induced centralization and decentralization tendencies occur in a complementary or substitutive manner. With our empirical analysis, we thus want to complement the broad field of organisational economics econometrically.

In our study, we measure the degree of decentralization in job design by the prevalence of employee autonomy at work. In our econometric analysis, we specify this point of view by mapping employee autonomy through the firm policy of working from home. Working from home provides an employee with discretion by making use of the employee's local knowledge about various job-related aspects, including the optimal place for task completion, the optimal timing of task completion (e.g., by allowing to adapt task completion to the individual biorhythm), and the individual situation regarding work-life balance (e.g., Bloom et al. 2015, Rupietta and Beckmann 2018). Conversely, we measure the degree of centralization in job design by the intensity to monitor employee effort and performance.[3] By monitoring employee effort and performance through a set of management practices, such as implementing appraisal interviews, setting performance targets or conducting regular performance evaluations, firms can address the concern of losing control that comes from granting employees' autonomy in the workplace.

Both measures of job design can be expected to be related to equipping employees with ICT. For example, ICT enables easy access to important information and supports video conferencing as an alternative to face-to-face meetings, which can make working from home very cost-effective (Bloom et al. 2021). In addition, ICT promotes more effective use of the benefits of autonomous working,

[3]In both our theoretical and empirical analyses, we allow for input and output monitoring; see, e.g., Milgrom and Roberts (1992), chapters 6–7, Khalil and Lawarrée (1995), Prendergast (2002), Colombo and Delmastro (2004), fn. 4, Zhao (2008).

such as getting work done while rested, saving time on commuting between home and work, and saving labor costs by offering more attractive jobs that provide a better work-life balance when working from home (e.g., Bloom et al. 2015). With regard to centralized monitoring, ICT improves the communication between company employees (in particular with their superiors), which leads to better performance evaluation. For example, communication via cellphones, tablet computers, and laptops leads to better information to the firm, how fast and dedicated an employee's reaction is to new suggestions by colleagues or instructions by superiors. In addition, ICT enables the firm to record an employee's communication with customers and suppliers, which further improves performance evaluation.

In the theoretical part of our paper, we consider a modified principal-agent model with hidden action. At the beginning, the firm decides on autonomy and the monitoring intensity and offers the employee an incentive contract based on the firm's performance appraisal system. Thereafter, the employee decides between accepting or rejecting the contract offer and chooses productive effort in case of acceptance. Our main theoretical results show that equipping employees with ICT has different effects (i) across hierarchy levels and (ii) across the two measures of job design, i.e., decentralized autonomy and centralized monitoring. First, equipping executives with ICT is more profitable than equipping non-executives with ICT, as the former possess more human capital and receive higher-powered incentives. Second, as better ICT equipment leads to both additional returns and additional costs, the absolute effect on firm profits, thus, crucially depends on the magnitude of the respective returns and costs. As a consequence, statements on ICT effects on *absolute* firm profits do not offer any insights. For this reason, we measure the *relative* gains of ICT equipment. We first compute the profit changes from higher monitoring and higher autonomy, and then determine how these changes respond to better ICT equipment. Our results show that ICT yields positive relative gains from higher monitoring, both for executive and non-executive employees. Third, ICT leads to positive relative gains from higher autonomy for some, but not all employees. As the effect of a better work-life balance from granted autonomy becomes relevant for executives but not for non-executives under the optimal incentive contract, it is more profitable for the firm to combine ICT with greater autonomy for managers rather than non-managers.

The latter result explains part of our main observation (i) on different ICT effects across hierarchy levels. The remaining part is explained by the fact that ICT equipment has the same costs for both types of employees (e.g., costs for new cellphones and laptops), but lead to higher returns for executives due to their larger human capital, which amplifies the impact of ICT. Recall that ICT equipment is accompanied by a higher monitoring intensity but rather not by more autonomy for non-executives. Hence, ICT leads to more centralized decision authority concerning non-executive employees, irrespective of whether more monitoring or less autonomy is used as centralization measure. Thus, our main observation (ii) does not refer to the non-executives, but to the executives, for whom ICT is accompanied with higher autonomy but also with higher monitoring. Whereas the autonomy result reflects more decentralized decision authority via ICT, the monitoring result reflects more centralization. In this sense, the firm seems to complement higher autonomy for executives with stronger monitoring in order to counter possible negative consequences from a loss of control. In fact, our theoretical findings reveal that the firm uses its performance appraisal system to offer higher-powered incentives to the executives than to the non-executives.

In the empirical part of the paper, we test our theoretical predictions by using employer-level data of the German Linked Personnel Panel and the IAB Establishment Panel of the years 2014 to 2018. Relying on 2SLS and MTE estimation methods, we estimate causal effects of differences in ICT equipment across hierarchical levels on centralized employee monitoring and decentralized autonomy. In order to adequately address the issues of endogeneity and essential heterogeneity, we draw on regional population density as an instrumental variable, thereby exploiting exogenous geographic variation at the district level (401 German districts) to instrument ICT equipment at the firm level.[4] The argument to justify our instrumental variable is that population density is not only a relevant driver of ICT equipment in German firms, but it is also likely to be an exogenous instrument; not least due to the fact that instrument and the variable being instrumented stem from data sources collected at different levels of aggregation.

Our empirical findings show that equipping employees with ICT leads to an increase of centralized monitoring concerning both executives and non-executives, but the former are more affected than the latter. The effects of ICT equipment on decentralized working from home clearly differ across hierarchy levels, because ICT gains in working from home are only detected for executives but not for non-executives. Hence, the empirical findings are consistent with the main theoretical results (i) and (ii). In response to increasing ICT equipment, firms adapt their job design by increasing centralized monitoring across the entire organization, but increasing decentralized au-

[4] In the construction of instrumental variables, other authors also exploit exogenous variation based on regional differences or geographic variation. Examples for such instruments are college availability or the distance to college or school, respectively (Carneiro et al. 2011, 2017, Kamhöfer et al. 2019), as well as the distance to individuals' nearest traineeship provider (Dorsett and Stokes 2022). In the context of instrumenting the firms' use of information technologies and communication technologies, Bloom et al. (2014) rely on the distance between firm location and the SAP headquarter.

tonomy only for their executive employees. In addition, the estimates resulting from our parametric normal MTE model suggest that, while the average firm complements centralized monitoring with decentralized autonomy in response to increasing ICT equipment, both technology-friendly and technology-averse firms tend to view centralized monitoring and decentralized autonomy as substitutive job-design practices. Indeed, the technology-friendly firms prefer the combination 'more monitoring and less autonomy', whereas the technology-averse firms rely on 'more autonomy and less monitoring'. After a series of content-based and method-based robustness checks, the result remains that centralized monitoring increases with the technology affinity of firms, and that this is especially true for executive employees.

Our paper is organized as follows. Section 2 summarizes the related literature. In Section 3, we theoretically analyze the ICT effects on job design. Section 4 describes the data and variables we use. Section 5 contains our baseline estimation models and estimates. Section 6 presents a series of content- and method-based robustness checks. Section 7 provides supplemental empirical evidence on the basic human-capital assumption of our theoretical model. Section 8 concludes.

2 Related Literature

Our paper contributes to various strands of literature. The first strand is the economic literature on optimal job design that typically focuses on multitasking, decision-making authority, and their interplay with incentive pay (e.g., Holmström and Milgrom 1991, Milgrom and Roberts 1992, chapter 12, Itoh 1994). More recent work has extended this discussion by including behavioral effects like intrinsic motivation and task commitment of empowered workers (e.g., Fehr et al. 2013, Bartling et al. 2014, Beckmann et al. 2017, Beckmann and Kräkel 2022). Other related studies show how "good" jobs with a high degree of decentralized decision authority, high efficiency wages, and screening for employee work attitude may endogenously emerge (Bartling et al. 2012). Still other studies consider the coexistence of job autonomy and performance pay (De Varo and Prasad 2015, Bandiera et al. 2021) or multitasking and performance evaluation (Manthei and Sliwka 2019). However, this literature does not consider the effects of ICT equipment on optimal job design.

Secondly, we contribute to the theoretical literature on the allocation of decision authority within firms.[5] Seminal papers in this context are Aghion and Tirole (1997), Garicano (2000),

[5]For example, Bolton and Dewatripont (2012), Gibbons et al. (2012), Aghion et al. (2013), and Garicano and Prat (2013) provide excellent surveys in this field. For a more general survey on the relationship between

Dessein (2002), Dessein and Santos (2006), as well as Garicano and Rossi-Hansberg (2004, 2006a, 2006b, 2012). These papers have a clear focus on organizational design, and thus, emphasize the fundamental trade-off between the use of decentral informational advantages and the loss of control when delegating decision authority. In this context, Garicano (2000), Dessein and Santos (2006), as well as Garicano and Rossi-Hansberg (2004, 2006a, 2006b, 2012) also highlight the role of ICT in determining organizational design and other outcomes such as wage inequality within organizations or organizational growth. However, these studies do not explicitly distinguish between executive and non-executive employees (our result (i)) and do not consider the potential coexistence of complementary measures of job design (our result (ii)).

Building on this literature, Itoh et al. (2008), Dominguez-Martinez et al. (2014) and Barrenechea-Méndez et al. (2016) focus on job design rather than organizational design, and regard autonomy and monitoring not so much as substitutive, but primarily as coexisting firm policies.[6] None of this work, however, discusses the impact of ICT on job design. In contrast, our theoretical model explicitly accounts for the possibility that ICT equipment may affect job design, thereby distinguishing between executives and non-executives (result (i)), while also allowing for the coexistence of decentralized autonomy and centralized monitoring (result (ii)).

Thirdly, we make a substantive contribution to the empirical literature on the impact of ICT on the centralization or decentralization of decision authority within firms. In this strand of literature, the studies of Colombo and Delmastro (2004), Rajan and Wulf (2006), Acemoglu et al. (2007), Guadalupe et al. (2014) as well as McElheran (2014) focus on the ICT effects on organizational design. The authors proxy decentralization with variables such as the span of control, the extent of decentralization between plant manager and corporate superior or between local establishment and corporate parent, the decentralization into profit centers, delayering, and managerial autonomy over investment or employment decisions. By contrast, the ICT effects on job design are empirically investigated in Caroli and Van Reenen (2001) and Bresnahan et al. (2002), dealing with the topic of skill-biased technological and organizational change. Job design is measured here by variables on worker autonomy over the allocation of tasks and the pace of work, the use of teamwork and quality circles, or the extent of general responsibility at the workplace. All these measures reflect decentralized autonomy, thereby assuming that more (less) decentralization implies less (more)

knowledge-based hierarchies and a number of issues, including the evolution of wage inequality, organizational growth and productivity, economic development, the benefits from international trade and offshoring as well as the formation of international production teams, see Garicano and Rossi-Hansberg (2015).

[6]The joint application of workplace autonomy and employee monitoring via performance goals and evaluations is also referred to as Results Only Work Environment (ROWE) in practice (e.g., Kelly et al. 2011, Moen et al. 2011).

centralization.

All these studies are interested in figuring out whether the ICT-induced benefits of decentralization outweigh the associated costs, and most of these studies actually identify a net benefit (e.g., Caroli and Van Reenen 2001, Bresnahan et al 2002, Colombo and Delmastro 2004, Acemoglu et al. 2007, McElheran 2014). There are two exceptions. One is the study by Bloom et al. (2014), who find evidence for both centralization and decentralization depending on whether firms have adopted communication or information technologies. The other study is from Guadalupe et al. (2014), whose findings are consistent with a move toward matrix or centralized M-form organizations, organizational forms with a high emphasis on both centralization and decentralization. Neither study, however, addresses the centralized monitoring of workers, which may coexist with decentralized autonomy (result (ii)). Moreover, none of these studies examines heterogeneous ICT effects between executive and non-executive employees (result (i)).[7]

The paper that comes closest to our study from this strand of literature is Bloom et al. (2014). The authors use measures of both organizational and job design.[8] The outstanding feature of this study compared to all other empirical work of this strand of literature is that the authors are able to separate information technologies from communication technologies, which allows them to obtain separate effects on centralization or decentralization within firms. An important difference to our study is that Bloom et al. (2014) consider centralization and decentralization as substitutive firm policies, while our study does not preclude this approach, but additionally allows for the coexistence of centralized monitoring and decentralized autonomy (result (ii)). In addition, Bloom et al. (2014) consider the ICT-induced shift of decision-making authority from corporate headquarters over plant managers to non-executive workers, while we analyze the ICT effects separately for executive and non-executive employees (result (i)).

Finally, we methodologically contribute to the empirical literature on the ICT effects on the centralization or decentralization of decision authority within firms. Many studies in this strand of literature account in some way for the endogeneity of their explanatory technology variables. Like us, Bresnahan et al. (2002), Acemoglu et al. (2007), and Bloom et al. (2014) estimate instrumental variable models for this purpose. However, none of these studies considers the case of essential heterogeneity. In contrast, by applying both 2SLS and MTE estimation approaches, we do not only

[7]Only Gerten et al. (2019) provide a descriptive analysis on ICT and workplace organization at the employee level, thereby considering differences between hierarchical levels.

[8]Organizational design is measured by a plant manager's span of control and autonomy over capital investment, hiring decisions, the introduction of new products, sales and marketing decisions, while job design is measured by worker autonomy over the pace of work and allocation of production tasks.

account for the endogeneity problem that may be associated with our ICT variable, but additionally address the case that the ICT effect on the job design of executives and non-executives may vary across firms depending on their individual willingness to equip their executives and non-executives with more or less ICT.

3 Theoretical Analysis

We first present our theoretical setting for combining ICT equipment and the firm's choice of job design. In a second step, we solve for the firm's optimal implementation of work incentives, and analyze the relative gains from monitoring and autonomy that are induced by the firm's ICT.

3.1 Model

We consider a situation where a firm wants to hire an employee with monetary reservation value $\bar{u} \geq 0$. As usually assumed in the principal-agent literature, the firm always prefers to hire the employee as long as the latter chooses some positive effort. Both the firm and the employee are assumed to be risk-neutral players. By exerting effort $e \geq 0$ the employee influences the long-term returns of the firm. We assume that the employee's contribution to these returns is described by

$$k \cdot (1 + rI) \cdot (1 + aA) \cdot y(e) \cdot M \tag{1}$$

with $a, k, r > 0$, $I \in [0, 1]$, $A \in \{0, 1\}$, and $0 < M < 1$. The parameter k denotes the productivity of the employee that is based on his knowledge or human capital. r indicates the returns from the firm's ICT equipment. The continuous variable $I \in [0, 1]$ denotes the degree by which the firm equips the employee with ICT.[9] The higher the degree of ICT equipment – i.e., the larger I – the more productive will be the employee at his job, because he can more intensely use a cellphone and a laptop, which improves communication with customers, superiors and colleagues, and grants the employee access to the Internet and, thus, to a huge source of useful information. The parameter a reflects additional returns that accrue to the employee from receiving more autonomy – i.e., the firm chooses $A = 1$ instead of $A = 0$. For example, working from home allows the employee a more effective use of his effort by working when being rested and saving time for commuting.

The function $y(e) \geq 0$ measures the direct impact of effort on long-term returns and is assumed to be monotonically increasing and strictly concave (i.e., $y'(e) > 0$ and $y''(e) < 0$). Furthermore,

[9] Assuming I to be continuous simplifies the comparative-static analysis below as we can apply the envelope theorem.

we assume that $y(0) = 0$. Exerting effort e generates effort costs for the employee that are measured in monetary terms by the function $c(e)$ with $c'(e), c''(e), c'''(e) > 0$ and $c'(0) = 0$.

Finally, the discrete choice variable M indicates the intensity with which the firm measures the employee's performance, i.e., M percent of the employee's tasks are evaluated by the firm's performance appraisal system, whereas the employee's performance at the remaining $1-M$ percent of his tasks is not recorded by the system. As a consequence, only at the M percent of his tasks the employee works hard and exerts effort e induced by the firm's incentive scheme, which will be specified below. At the remaining $1 - M$ percent of his tasks, the employee chooses work-to-rule – being normalized to $e = 0$ in our setting – to save effort costs so that, at these tasks, the employee's contribution to the long-term returns of the firm is zero. In the following, we will refer to the variable M as the firm's *monitoring intensity*. We assume that the firm can choose between two different monitoring intensities, either a low intensity, M_L, leading to low monitoring costs $K_L > 0$ for the firm, or a high intensity, M_H, with $M_H > M_L$ leading to high monitoring costs K_H with $K_H > K_L$.

Introducing ICT (i.e., $I > 0$) leads to costs $I \cdot \kappa$ for the firm with $\kappa > 0$ (e.g., for buying and introducing cellphones, laptops, and tablet PCs). ICT does not only increase the impact of the employee's effort on the returns for the firm via r. It also leads to less costly monitoring of the employee, so that monitoring costs can be cut by the amount $\Delta K > 0$ with $\Delta K < K_L$. ICT allows for easier performance evaluation, for example, because cellphones and laptops can be used by the firm to chat with the employee via emails and communication software, which leads to a better appraisal of an employee's effective contribution to the firm's returns.

Besides the additional returns from more effective working time (via a), granting the employee autonomy ($A = 1$) is assumed to have two further implications. First, autonomy leads to a better work-life balance for the employee, thus yielding extra utility $\Delta u \in (0, \bar{u})$ for him, again measured in monetary terms. Second, granting autonomy leads to a loss of control as monitoring of the employee and assessing his work performance becomes more difficult. To capture this effect, we assume that monitoring costs will rise by $\Delta\hat{K} > 0$ if the firm chooses $A = 1$ instead of $A = 0$. Hence, the firm's overall monitoring costs are $K_H - \Delta K \cdot I + \Delta\hat{K} \cdot A$ if it employs a high monitoring intensity, and $K_L - \Delta K \cdot I + \Delta\hat{K} \cdot A$ if it employs a low intensity.

As (1) describes the employee's contribution to the *long-term* returns of the firm, it cannot be used for incentivizing the employee.[10] Instead, we assume that, for the M percent of the tasks

[10] Alternatively, the employee's contribution to the firm's returns might be too complex to be directly measured and verified by a court; see, e.g., MacLeod (2003) and Herweg et al. (2010).

that are evaluated, the firm can make use of the imperfect but contractible performance signal $s \in \{\underline{s}, \bar{s}\}$, with the probability of $s = \bar{s}$ being increasing in the employee's effort level.[11] Hence, the observation of performance $\bar{s}$ is favorable information about the employee's effort choice in the sense of Milgrom (1981). In particular, we assume that $P(s = \bar{s}|\, e) = e$, such that $P(s = \underline{s}|\, e) = 1 - e$. To ensure that the firm always has imperfect information, the technical restriction $c'(e) = \infty$ if $e \to 1$ is imposed.

The firm wants to maximize expected net profits, $\Pi(I, A, M)$, whereas the employee wants to maximize the expected value of his net income, which comprises his wage $w(s)$ minus effort costs. By imposing the restriction $w(s) \geq 0$ for the wage function, we assume that the employee is protected by limited liability, which excludes the trivial solution that the firm always implements efficient effort.[12] In the following, we will use the parameters k and $\bar{u}$ to differentiate between non-executive and executive employees. Due to more general or industry-specific human capital, executive employees have higher values for k and $\bar{u}$ than non-executive employees.

The timing of events is the following. At the first stage of the game, the firm chooses $I \in [0, 1]$, $A \in \{0, 1\}$, and $M \in \{M_L, M_H\}$, and then offers the wage contract $(w(\underline{s}), w(\bar{s}))$ to the employee. At stage two, the employee observes the firm's choices and accepts or rejects the contract offer. Given that the employee has accepted, he chooses e at stage three. Finally, s is realized and payments are made.

3.2 Optimal Incentives and the Relative Gains of ICT Equipment

For given choices of ICT equipment, I, autonomy, A, monitoring intensity, M, and contract $(w(\underline{s}), w(\bar{s}))$, at stage three the employee chooses effort e to maximize his expected utility

$$EU := e \cdot w(\bar{s}) + (1 - e) \cdot w(\underline{s}) + \Delta u \cdot A - c(e). \tag{2}$$

As this function is strictly concave, the first-order condition

$$w(\bar{s}) - w(\underline{s}) = c'(e) \tag{3}$$

[11]The assumption that a performance signal that is not identical with the agent's output is used to create incentives, is not unusual for principal-agent models; see, among many others, Gjesdal (1982), Grossman and Hart (1983), Kim (1995), MacLeod (2003), and Herweg et al. (2010).

[12]This assumption is often used in contract theory; see, e.g., Sappington (1983), Che and Yoo (2001), Schmitz (2005).

describes the firm's incentive constraint for its contracting problem at stage one. Here, it maximizes expected profits

$$k \cdot (1 + rI) \cdot (1 + aA) \cdot y(e) \cdot M - e \cdot w(\bar{s}) - (1 - e) \cdot w(\underline{s}) \\ - I \cdot \kappa - \left(K - \Delta K \cdot I + \Delta\hat{K} \cdot A\right) \tag{4}$$

subject to the incentive constraint (3), the participation constraint $EU \geq \bar{u}$, and the limited-liability constraint $w(\bar{s}), w(\underline{s}) \geq 0$. We can define

$$R(e) := e \cdot c'(e) - c(e),$$

which is an increasing and convex function with corresponding inverse R^{-1}. The function $R(e)$ describes the employee's expected utility under incentive compatibility and $w(\underline{s}) = \Delta u = 0$. In addition, we can implicitly define $\hat{e}$ by

$$k(1 + rI)(1 + aA)\, y'(\hat{e})M = c'(\hat{e})$$

as the effort level that, for given I, A and M, maximizes the overall surplus. The solution to the firm's contracting problem can then be summarized as follows:

Proposition 1 *Suppose the firm has chosen $I \in [0, 1]$, $A \in \{0, 1\}$, and $M \in \{M_L, M_H\}$.*

(a) If $\bar{u} - \Delta u \cdot A < R(e^*_{(i)})$ with $e^*_{(i)}$ being implicitly described by

$$k(1 + rI)(1 + aA)y'(e^*_{(i)})M = c'(e^*_{(i)}) + e^*_{(i)} \cdot c''(e^*_{(i)}),$$

the firm implements effort $e^*_{(i)}$ and has expected profit

$$\Pi_{(i)}(I, A, M) = k(1 + rI)(1 + aA)\, y(e^*_{(i)})M \\ - e^*_{(i)} \cdot c'(e^*_{(i)}) - \left(K - \Delta K \cdot I + \Delta\hat{K} \cdot A\right) - I\kappa. \tag{5}$$

(b) If $R(e^*_{(i)}) < \bar{u} - \Delta u \cdot A < R(\hat{e})$, the firm implements effort $e^*_{(ii)} = R^{-1}(\bar{u} - \Delta u \cdot A)$ and has expected profit

$$\Pi_{(ii)}(I, A, M) = k(1 + rI)(1 + aA)\, y(e^*_{(ii)})M \\ - c(e^*_{(ii)}) - \left(K - \Delta K \cdot I + \Delta\hat{K} \cdot A\right) - I\kappa - (\bar{u} - \Delta u \cdot A). \tag{6}$$

(c) If $\bar{u} - \Delta u \cdot A > R(\hat{e})$, the firm implements effort $e^*_{(iii)} = \hat{e}$ and has expected profit

$$\Pi_{(iii)}(I, A, M) = k(1 + rI)(1 + aA)\, y(\hat{e})M \\ - c(\hat{e}) - \left(K - \Delta K \cdot I + \Delta\hat{K} \cdot A\right) - I\kappa - (\bar{u} - \Delta u \cdot A). \tag{7}$$

Optimal efforts can be ranked as $e^*_{(i)} < e^*_{(ii)} < e^*_{(iii)}$.

Proof. See Appendix A. ■

Depending on the magnitude of the net reservation value, $\bar{u} - \Delta u \cdot A$, three cases can be distinguished. If $\bar{u} - \Delta u \cdot A$ is small as in result (a), the expected incentive pay will be so large that the participation constraint is non-binding, so that the firm has to leave the employee the strictly positive rent $R(e^*_{(i)}) - (\bar{u} - \Delta u \cdot A)$.[13] As this rent measures the firm's costs of incentivizing the employee, under the optimal contract the firm implements the effort $e^*_{(i)}$ that equates marginal surplus, $k(1 + rI)(1 + aA)y'(e^*_{(i)})M - c'(e^*_{(i)})$, and marginal rent, $R'(e^*_{(i)})$. If $\bar{u} - \Delta u \cdot A$ becomes sufficiently large, the incentive constraint will not imply the participation constraint any longer (result (b)). In that case, the firm has to offer the employee a lot of money to make him sign the labor contract. This money is not paid as fixed salary to the employee but used as incentive pay by the firm, which thus implements a higher effort level than in result (a): $e^*_{(ii)} > e^*_{(i)}$. If the net reservation value $\bar{u} - \Delta u \cdot A$ further increases, the employee's compensation will be so large that the firm implements the effort level that maximizes overall surplus. In both results (b) and (c), the firm exactly offers the amount of money to the employee that makes him just sign the labor contract so that he does not earn a positive rent.

Recall that executive employees have higher productivity parameters k and higher reservation values $\bar{u}$ than non-executive employees. Hence, the findings of Proposition 1 point out that the firm implements higher efforts for executives than for non-executives: Given that high values of k are used as an indicator for executives, our results show that the optimal effort levels $e^*_{(i)}$, $e^*_{(ii)}$, and $e^*_{(iii)}$ weakly increase with k; if high reservation values serve as an indicator for executives, our results show that $e^*_{(i)}$ corresponds to low values of $\bar{u}$, effort $e^*_{(ii)}$ corresponds to intermediate values of $\bar{u}$, and $e^*_{(iii)}$ corresponds to high values of $\bar{u}$ with $e^*_{(i)} < e^*_{(ii)} < e^*_{(iii)}$. All three effort levels are weakly increasing with $\bar{u}$.

As the firm's objective function (4) shows, a direct comparison of the expected profits with high and low monitoring intensity crucially depends on the specific parameter values and, hence, cannot lead to new insights. In particular, a higher monitoring intensity $M_H > M_L$ yields higher implemented effort but also higher monitoring costs $K_H > K_L$. A similar observation holds for autonomy, as more autonomy increases the employee's productivity via a, but also implies additional costs from a loss of control, $\Delta\hat{K}$. However, it is instructive to investigate the relative gains from higher monitoring and more autonomy. For this purpose, we define

$$\Delta\Pi_C(I, A) := \Pi_C(I, A, M_H) - \Pi_C(I, A, M_L)$$

[13]The expression for the rent is obtained by inserting $w(\underline{s}) = 0$ and $w(\bar{s}) = c'(e)$ into $EU - \bar{u}$ with EU being described by (2).

as relative gains from higher monitoring, and

$$\Delta\Pi_C(I,M) := \Pi_C(I,1,M) - \Pi_C(I,0,M)$$

as relative gains from more autonomy for case $C = (i), (ii), (iii)$.

Proposition 2 *ICT equipment has the following impact on profits and relative gains from monitoring and autonomy:*

(a) $\frac{\partial}{\partial I}\Pi_{(iii)}(I,A,M) > \frac{\partial}{\partial I}\Pi_{(ii)}(I,A,M) > \frac{\partial}{\partial I}\Pi_{(i)}(I,A,M)$ *and* $\frac{\partial^2}{\partial I \partial k}\Pi_C(I,A,M) > 0$ *for* $C = (i), (ii), (iii)$.

(b) $\frac{\partial}{\partial I}\Delta\Pi_C(I,A) > 0$ *for* $C = (i), (ii), (iii)$.

(c) $\frac{\partial}{\partial I}\Delta\Pi_{(i)}(I,M) > 0$ *and* $\frac{\partial}{\partial I}\Delta\Pi_{(iii)}(I,M) > 0$. *However,* $\frac{\partial}{\partial I}\Delta\Pi_{(ii)}(I,M) > (<) 0$ *if* a *is sufficiently large (small) compared to* Δu.

(d) Only expected profits $\Pi_{(ii)}(I,A,M)$ *and* $\Pi_{(iii)}(I,A,M)$ *increase with autonomy via* Δu.

Proof. See Appendix A. ■

Recall that executives can be characterized by a higher reservation value $\bar{u}$ or, alternatively, by a higher value of the productivity parameter k compared to non-executives. Thus, result (a) leads to a very robust theoretical prediction. Irrespective of whether we use $\bar{u}$ or k in our analysis, it is more profitable for the firm to equip executives with ICT than non-executives. Hence, if a firm wants to improve its ICT, it should do so especially at higher hierarchy levels.

According to result (b), the relative gains from monitoring will rise if the firm chooses better ICT equipment. The driving force for this finding is that ICT and monitoring are complements in (1) – a higher monitoring intensity implies that the firm implements higher effort, which becomes more productive due to ICT. Thus, in practice, we should observe that better ICT is accompanied by more intense monitoring at both executive and non-executive levels of the hierarchy.

Result (c) addresses the impact of ICT on the relative gains from autonomy. The findings are less clear-cut than those for monitoring. Whereas the relative gains from autonomy will be boosted by ICT if $\bar{u}$ takes low and high values, the relative gains are ambiguous for intermediate values of $\bar{u}$. On the one hand, a large a makes autonomy more profitable for the firm. On the other hand, high values for the extra utility from a better work-life balance, Δu, induce the firm to implement a lower effort level and, thus, render autonomy less profitable. All in all, in practice we should expect a positive influence of ICT on granting employees more autonomy but this effect should not exist for all employees.

Result (d) does not contain a new finding but highlights an important observation from the results of the previous Proposition 1. Recall that autonomy can lead to two positive effects for the firm. First, it increases an employee's productivity (a). Second, it improves the employee's work-life balance (Δu). As each optimal expected profit, $\Pi_C(I, A, M)$, $C = (i), (ii), (iii)$, increases with a, the first effect holds for both executives and non-executives. The second effect, however, is only relevant for employees with intermediate and high reservation values, that is, for executives. The intuition is the following. Executives are costly to hire so that the firm has to offer a lot of money to satisfy their participation constraints. Under the optimal contract, the firm just offers the amount of money that makes the participation constraint bind in the cases (ii) and (iii). Here, a higher utility from a better work-life balance helps to relax the participation constraint so that hiring of executives becomes less costly for the firm. This argument does not hold for non-executives, because they earn positive rents for incentive reasons, so that the profit generated by them is independent of Δu. Therefore, the second effect yields a higher advantage for the firm from granting an executive autonomy. Altogether, if the employee has a high status in the labor market in terms of his reservation value and, thus, clearly belongs to the group of executive employees, the firm will stronger gain from granting this employee autonomy than a non-executive employee.

4 Data and Variables

Our empirical analysis is based on two data sets: the Linked Personnel Panel (LPP) and the IAB Establishment Panel. The LPP is a linked employer-employee data set on human resources, corporate culture, and management practices in German firms (Bellmann et al. 2015, Kampkötter et al. 2016, Ruf et al. 2020). The employer-level data of the LPP marks the primary data set we use to explore the impact of ICT equipment across hierarchical levels on job design. The LPP is representative for German firms with 50 and more employees in the processing industry and the service sector. Since its initial launch in 2012, the survey has been sent to the recipients every two years. Our empirical analysis uses the data of panel waves 2 ($N = 771$), 3 ($N = 846$), and 4 ($N = 769$). The LPP employer survey covers topics on personnel planning and procurement, personnel development, compensation structure, commitment, values, and corporate culture.

All waves of the LPP can be merged with data from the German IAB Establishment Panel. The IAB Establishment Panel is an annual survey of over 15,000 firms of all size classes and industries, which ranks it as being 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 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 us 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.

4.1 Measuring ICT Equipment

We measure ICT equipment by making use of the employers' responses to the question 'What percentage of employees with and without managerial responsibility has your establishment/office equipped with mobile devices such as smart phones, tablet computers or notebooks capable of establishing an Internet connection via the mobile network?'. Smart phones, tablet computers, and notebooks are still the most frequently used forms of ICT in firms.

The fact that these percentages are surveyed separately for executives and non-executives is a unique feature of the LPP, which enables us to shed light on the impact of ICT on job design across hierarchical levels in the first place. Information on ICT equipment across hierarchical levels is available in all considered panel waves. Table 1 displays the main descriptive statistics over time. Here, we find that the proportion of executives and non-executives equipped with ICT has steadily increased, while at the same time there are large differences in ICT equipment between executives and non-executives. In 2014 (2018), 66 (75) percent of executives were equipped with ICT, but only 14 (19) percent of non-executives. In our theoretical model, this unequal deployment of ICT across hierarchical levels is consistent with result (a) of Proposition 2. Here, we explain this phenomenon via superior general or industry-specific human capital, which in turn improves the internal productivity and/or outside options of executives relative to non-executives.

We construct the variable ict^E depicting the proportion of executives equipped with ICT, thus ranging between 0 and 100. Analogously, we construct the variable ict^{NE} measuring the share of ICT-equipped non-executives. These variables focus on technologies that are expected to be closely related to our measures on job design, i.e., centralized monitoring and decentralized working from home. For our empirical analyses, we take the natural logarithms of ict^E and ict^{NE} to address the problem that the actual distributions of the ICT percentages under consideration are skewed

Table 1: Descriptive statistics of the main explanatory variables

Variable	Wave	Hierarchy	Mean	Std. dev.	Range	N
Information and communication technologies						
ICT equipment	2014	Executives	66.07	42.09	0-100	760
(ict^h)		Non-executives	13.76	23.55	0-100	749
	2016	Executives	74.20	38.94	0-100	830
		Non-executives	16.49	25.42	0-100	809
	2018	Executives	74.80	38.79	0-100	759
		Non-executives	18.74	25.79	0-100	744
Centralized monitoring						
Appraisal interview	2016	Executives	62.71	46.94	0-100	831
($interview^h$)		Non-executives	49.11	45.66	0-100	825
	2018	Executives	57.88	47.98	0-100	752
		Non-executives	46.97	45.46	0-100	748
Target agreement	2016	Executives	52.38	48.06	0-100	837
($target^h$)		Non-executives	21.52	37.21	0-100	828
	2018	Executives	46.74	47.79	0-100	756
		Non-executives	20.60	36.49	0-100	751
Performance evaluation	2016	Executives	52.74	49.25	0-100	829
($evaluation^h$)		Non-executives	45.30	45.48	0-100	829
	2018	Executives	47.69	49.00	0-100	751
		Non-executives	44.75	46.25	0-100	755
Decentralized autonomy						
Working from home	2014	Executives	17.05	34.51	0-100	757
(wfh^h)		Non-executives	6.46	19.68	0-100	757
Working from home (D)	2016	Executives	12.54	31.18	0-100	729
($wfh^{D,h}$)		Non-executives	6.44	21.68	0-100	733
Working from home (P)	2016	Executives	2.64	14.21	0-100	722
($wfh^{P,h}$)		Non-executives	0.55	6.27	0-100	724
Working from home (C)	2016	Executives	10.12	27.24	0-100	741
($wfh^{C,h}$)		Non-executives	4.72	17.41	0-100	746

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

Notes. In 2016, information about working from home is given for three functional departments, i.e., (D) distribution and marketing, (P) production, (C) cross-departmental function, administration, and service.

rather than symmetric. Hence, our variables for ICT equipment are defined as

$$ICT_{it}^{h} = \ln(ict_{it}^{h} + 1),$$

where $h \in \{E, NE\}$ and t refers to the panel waves 2, 3 and 4.[14]

In our theoretical model, we argue on the one hand that equipping employees with cellphones, tablet computers, and notebooks makes centralized monitoring less costly, because firms can use these mobile devices as communication tools, which simplifies performance evaluation. On the other hand, however, technologies that promote online information processing, online communication, and virtual collaboration among employees are also likely to support work processes that can be done from home.[15]

4.2 Measuring Centralized Monitoring

Analogous to the ICT-equipment question introduced above, firms are asked in waves 3 and 4 of the LPP employer survey about the prevalence of certain management practices applied in the context of employee performance appraisals, separately for executives and non-executives. Specifically, the survey questions relate to the percentages of employees subject to (1) annual structured appraisal interviews (*interview*), (2) written performance target agreements (*target*), and (3) annual performance evaluations (*evaluation*).

Each of these policies can include components of both input and output control. In this respect, our variables can also incorporate the results of electronic monitoring and human resource analytics, which may be the first intuition when associating ICT equipment with employee monitoring. We regard these three practices of performance appraisal not in the sense of a reduction of employee autonomy, but in the sense of a centralized feedback as well as reward and sanction mechanism, which is why we define these practices as centralized monitoring. Table 1 shows the descriptive statistics of the three monitoring practices, and we can observe major differences between the

[14] In order to ensure that no observations are lost due to taking logs, we add 1 to the respective percentages.

[15] This argument follows Garicano (2000) in the sense that information technologies reduce information costs by positively influencing the flow of information in companies, while communication technologies reduce communication costs by improving the flow of communication. In our case, the use of an ICT variable that captures the equipment with technical devices and is not restricted to the use of specific software (e.g., Enterprise Resource Planning (ERP) as a tool for acquiring information) is appropriate. In this way, we do not exclude any software solution across firms and industries that is used by either executives or non-executives in the flow of information and communication. On the other hand, a focus on a specific technology or software, such as ERP, may make sense to analyze a specific industry (Bloom et al. 2014).

executives and non-executives involved. In 2016, for example, target agreements applied to 52 percent of executive employees and 22 percent of non-executive employees.

In order to create a single measure of centralized monitoring MON^h, $h \in \{E, NE\}$, we sum up the three monitoring practices, separately for executives and non-executives, and then divide by the total number of used monitoring practices, giving us two composite variables normalized between 0 and 100 percent. Analogous to our ICT^h variables, we calculate the natural logarithm of these variables and then obtain

$$MON_{it}^h = \ln\left(\frac{interview_{it}^h + target_{it}^h + evaluation_{it}^h}{3} + 1\right),$$

where t refers to the waves 3 and 4.

MON^h can be interpreted as the intensity of a firm's monitoring of executive and non-executive employees, respectively. According to our theoretical model, ICT^h and MON^h are complements in the firm's returns, implying that better ICT equipment is associated with more intense centralized monitoring. We expect that this applies to both executives and non-executives.

4.3 Measuring Decentralized Autonomy

Our theoretical model predicts that equipping employees with ICT does not only simplify centralized monitoring, but may also promote an employee's autonomy at work. Working from home is a management practice that grants an employee discretion over the place of work and the allocation of working time (e.g., Bloom et al. 2015, Beckmann and Kräkel 2022). As such, working from home has the potential to improve an employee's work-life balance, but, at the same time, it can make it more difficult to monitor employees. Overall, this leads us to refer to working from home as a policy of decentralized autonomy.[16]

In analogy to our variables of ICT and centralized monitoring, we measure a firm's working-from-home policy by the percentage of executives and non-executives who are allowed to make use of the opportunity to work from home. This information is available in panel waves 2 and 3. It is important to note that in wave 3 the relevant question in the questionnaire was modified. Instead of asking about the total percentages, a distinction was made here according to different functional areas, namely distribution and marketing (wfh^D), production (wfh^P)[17], as well as

[16] Other measures on worker autonomy would also be interesting to analyze (e.g., self-managed working time). However, other measures on worker autonomy that are appropriate for both executives and non-executives are not available in our data sets. Moreover, our choice for the variable working from home takes up the current debate on how working from home as a management practice is affected by further ICT deployment in firms.

[17] We are aware of the fact that working from home in the functional area of production is likely to be of minor

cross-departmental function, administration and service (wfh^C). The descriptive statistics are displayed in Table 1. We can see substantial differences between executives and non-executives, with executives having more opportunities to work from home than non-executives.

In order to construct a variable measuring the intensity of working from home, we aggregate the percentages from the survey questions into a single measure WFH_t^h by following the double-standardization approach as applied, for example, in Bresnahan et al. (2002) and Tambe et al. (2012). The first step of this approach is to standardize each of the working-from-home variables according to the general definition $STD(x) = (x - \overline{x})/\sigma_x$, where $\overline{x}$ is the mean and σ_x is the standard deviation of a random variable x. In a second step, we calculate the sum of the values of the standardized variables and then standardize the sum again (required only in wave 3). The resulting variable WFH_t^h can then be written as

$$WFH_t^h = \begin{cases} STD(wfh_t^h) & \text{if } t = 2 \\ STD\{STD(wfh_t^{D,h}) + STD(wfh_t^{P,h}) + STD(wfh_t^{C,h})\} & \text{if } t = 3\,. \end{cases}$$

By construction, WFH_t^h has zero mean and unit variance.[18]

In our theoretical model, we find that firms are more likely to benefit if they increase the autonomy of executives rather than non-executives. This is because autonomy, while increasing the productivity of all employees, only leads to an additional advantage when recruiting executives via improving their work-life balance. Consequently, we expect that equipping employees with ICT will have a mixed effect on decentralized autonomy, primarily by increasing the autonomy of executives, but not the autonomy of non-executives.

5 Identification Strategy and Empirical Results

The identification strategy applied in our empirical analysis is motivated by the econometric approach described in Brave and Walstrum (2014) and Andresen (2018b), which can be illustrated

importance, because production has to take place on-site. This can also be seen in the corresponding descriptive statistics in Table 1. In particular, this applies to non-executive workers. In our empirical analyses, we take into account the low prevalence of working from home in the functional area of production (see Subsection 6.1).

[18] In contrast to our ICT and monitoring variables introduced before, normalizing the working-from-home variables and taking the natural logarithm of the resulting variable would not be appropriate, since the respective percentages in the two panel waves under consideration show significant differences (see Table 1). As a consequence, the working-from-home observations in waves 2 and 3 can only be poorly compared with each other. This problem can be overcome by standardizing the working-from-home variables, separately for both waves, according to the double standardization approach.

as follows.[19] Suppose the true model of the impact of ICT on job design across hierarchical levels can be described by the equation system

$$\begin{aligned} ICT_i^h &= \overbrace{X_i\beta_1^h + \pi^h \tilde{Z}_i}^{\text{observed}} + \overbrace{\theta^h MQ_i + \omega^h \tilde{Z}_i \times MQ_i + \nu_i^h}^{\text{unobserved}} \\ JD_i^h &= \underbrace{X_i\beta_2^h + \gamma^h ICT_i^h}_{\text{observed}} + \underbrace{\delta^h MQ_i + \eta^h ICT_i^h \times MQ_i + \epsilon_i^h}_{\text{unobserved}} \ . \end{aligned} \tag{8}$$

Here, JD_i^h represents either the amount of monitoring MON_i^h or working from home WFH_i^h in firm i and across hierarchical levels h, where $h \in \{E, NE\}$, so $JD^h \in \{MON^h, WFH^h\}$. X_i is a vector of control variables (including time fixed effects) being correlated with or determining ICT_i^h and JD_i^h, while MQ_i represents the quality of management in firm i, which is unobserved by the researcher. Furthermore, $\tilde{Z}$ is a valid instrumental variable (IV) for ICT^h, whereas ν_i^h and ϵ_i^h are idiosyncratic error terms with zero mean and finite variance. Finally, β_1^h, β_2^h, π^h, γ^h, θ^h, δ^h, ω^h, and η^h are the coefficients to be estimated, where γ^h is the coefficient of interest.

Since MQ_i is unobserved, a first simplified approach is to assume $\delta^h = \theta^h = \eta^h = \omega^h = 0$ and estimate the model

$$JD_i^h = X_i\beta^h + \gamma^h ICT_i^h + u_i^h \ , \tag{9}$$

where u_i^h is an idiosyncratic error term with zero mean and finite variance. However, if management quality is correlated with both job design ($\delta^h \neq 0$) and ICT equipment ($\theta^h \neq 0$) across hierarchical levels, the identifying exogeneity assumption $Cov(ICT_i^h, u_i^h \mid X_i) = 0$ is violated, and estimating (9) by conventional ordinary least squares (OLS) will fail to provide an unbiased and consistent parameter estimate of γ^h. The case of $\delta^h \neq 0 \neq \theta^h$ and $\eta^h = 0$ in (8) indicates a typical endogeneity or selection-on-unobservables problem that can be solved by applying two-stage least squares (2SLS), given the existence of a valid instrument for ICT_i^h. Moreover, if $\delta^h \neq 0 \neq \theta^h$ and $\eta^h \neq 0$, the effect of ICT equipment on job design varies throughout firm population according to $\gamma^h + \eta^h \times MQ_i$. This case leads to an estimation problem, which is also referred to as essential heterogeneity (e.g., Heckman et al. 2006a, Basu et al. 2007, Brave and Walstrum 2014, Andresen 2018a) or selection based on unobserved gains (Cornelissen et al. 2016). Under essential heterogeneity, 2SLS will usually fail to provide an unbiased estimate of γ^h. This problem can be solved by estimating the marginal treatment effects (MTE) of ICT equipment for firms with varying levels of management quality (Brave and Walstrum 2014).[20]

[19] In the further course, we omit the time index t, because our identification strategy is based on the use of a valid instrumental variable rather than methods for panel data. For the same reason, we refrain from calling our regression models pooled models.

[20] Strictly speaking, MTE produces heterogeneous ICT effects for firms with a varying unobserved propensity of

Since any variable that is correlated with the firms' decision on ICT equipment across hierarchical levels is also correlated with the unobserved interaction between the ICT-equipment decision and management quality, the presence of essential heterogeneity requires to explicitly model the treatment decision, i.e., the decision to equip high or low shares of executives and non-executives with ICT, as indicated in the first equation of (8). This involves the availability of a continuous IV.[21] Given this continuous IV, Heckman et al. (2006a) have shown that the propensity score, i.e., the selection probability into treatment that is driven by this continuous IV, is a valid instrument to be able to identify both average treatment effects (ATE) and MTE, when both endogeneity and essential heterogeneity are present (Brave and Walstrum 2014).

5.1 Estimating Ordinary Least Squares Effects

5.1.1 OLS Model

We start our empirical analysis assuming $\delta^h = \theta^h = \eta^h = \omega^h = 0$ in (8). The resulting regression model can then be written as

$$JD_i^h = \gamma^h ICT_i^h + X_i \beta^h + \epsilon_i^h \, . \tag{10}$$

As a reference case, equation (10) is estimated by conventional OLS.

In order to choose appropriate control variables X_i that jointly determine our main variables on ICT equipment, employee monitoring and working from home, we draw on the three-legged-stool approach of organizational architecture developed in Brickley et al. (2021, chapter 11). The three-legged-stool approach regards organizational architecture as a coherent system consisting of three complementary components, namely decision-rights assignment, performance evaluation, and rewards. Since two of these components, i.e., employee monitoring and working from home, are at the core of our empirical investigation, it is quite natural to base the choice of control variables on the three-legged-stool approach.

Apart from explaining the complementary components of organizational architecture, Brickley et al. (2021, chapter 11) also argue that organizational architecture itself is determined by business environment (i.e., technology, markets, and regulation) as well as corporate and business-level

adopting ICT equipment, which is assumed to reflect management quality. Furthermore, note that, in theory, the case of $\delta^h \neq 0$ and $\eta^h \neq 0$ is possible without MQ being related to selection into ICT equipment, i.e., $\theta^h = \omega^h = 0$. Here, unobserved effect heterogeneity is present, but this is uncorrelated with selection into treatment. In that case, MTE would not find the heterogeneity.

[21] However, Brinch et al. (2017) develop an approach that requires only a discrete instrument.

strategies. These insights provide us with additional information about the choice of appropriate control variables.

The domain of technology is to some extent covered by our main explanatory variable ICT_i^h. In addition, we use information on the status of a firm's technological equipment, expansion investments, IT investments, and currently realized process innovations to control for the technological determination of job design. In order to control for the market dimension of business environment, we add variables on export rates and self-reported competitive pressure to our set of covariates. As proxies for regulation, we include measures on collective wage bargaining, the existence of works councils, the firms' legal form and their degree of legal and economic independence. Furthermore, we use information on sector affiliation, product innovations, outsourcing, and insourcing as variables measuring corporate strategy, while information on cost and quality leadership strategies represent our measures for business-level strategies.

In terms of measures for organizational architecture other than the policies of employee monitoring and working from home, we add variables on performance pay plans, payments above the level of collective bargaining rates (reflecting the rewards domain) and self-managed working time arrangements, working-time accounts, job rotation, quality circle, and self-directed studies (reflecting the domain of decision-rights assignment) to our set of covariates. Finally, we control for firm size, workforce structure, the existence of continuous training and development plans, as well as the region of a company's location.[22]

5.1.2 OLS Estimation Results

The OLS estimates of γ^h are displayed in Tables 4 (monitoring regressions) and 5 (working-from-home regressions), columns (1) and (2).[23] In the monitoring regressions, the OLS estimates of γ^E and γ^{NE} turn out to be positive and statistically significant at the 1 and 5 percent level, respectively. Although the coefficients appear to be different in magnitude ($\gamma^E = .141$, $\gamma^{NE} = .081$), a test on $\gamma^E = \gamma^{NE}$ shows that we cannot reject the null hypothesis of equal coefficients ($p = .167$). In the working-from-home regressions, γ^E and γ^{NE} do also exhibit a positive sign and are both statistically significant at the 1 percent level. Again, the null hypothesis of equal coefficients for $\gamma^E = .085$ and $\gamma^{NE} = .114$ cannot be rejected ($p = .219$).

[22] A list of the complete set of variables, including their descriptions and summary statistics, can be found in Table 16 in Appendix B.2.

[23] The OLS, 2SLS, and parametric normal MTE regression results for the complete sets of covariates can be found in Appendix B.1, Tables 14 and 15.

The OLS estimates of γ^h can only be interpreted in terms of causal inference if $\delta^h = \theta^h = \eta^h = \omega^h = 0$ in (8), meaning that both ICT_i^E and ICT_i^{NE} are strictly exogenous. However, the exogeneity assumption for the ICT variables is likely to be violated caused by omitted variables (such as MQ_i) including omitted selection, simultaneous causation, and measurement error (Wooldridge 2010, p. 55). All these endogeneity issues imply $\delta^h \neq 0 \neq \theta^h$ in (8). In the present case, omitted variables and omitted selection are the most severe endogeneity issues. Specifically, mobile ICT devices are unlikely to be randomly assigned to both executives and non-executives (see the descriptive statistics displayed in Table 1, which differ substantially between executives and non-executives). In fact, executives and non-executives are likely to differ systematically with respect to the assignment of mobile ICT devices based on observed and unobserved factors. IV estimation provides a solution to these endogeneity issues. While estimating equation (10) using OLS provides us with first insights, it is unlikely to produce meaningful results on which management implications could be built.

5.2 Estimating Two-Stage Least Squares Effects

In order to account for the endogeneity issues that may arise with an OLS estimation of ICT_i^h, we apply a structural model approach and estimate the model parameters using the 2SLS estimation method. Estimating equation system (8) with 2SLS yields unbiased and consistent estimates γ^h for our ICT-equipment variables, provided that $\delta^h \neq 0 \neq \theta^h$ and $\eta^h = 0$ hold. The challenge in this setting is to find an instrument $\tilde{Z}$ that satisfies the validity assumptions of instrument relevance, i.e., $Cov(\tilde{Z}_i, ICT_i^h \,|\, X_i) \neq 0$, and instrument exogeneity or conditional IV independence, i.e., $\tilde{Z}_i \perp \epsilon_i^h, \nu_i^h \,|\, X_i$, meaning that the instrument must be conditionally independent of the unobserved error terms in equation system (8), given that $\omega^h = \eta^h = 0$.

The relevance condition can be easily tested by a first-stage regression of ICT_i^h on $\tilde{Z}_i$ and X_i. However, we cannot directly test the conditional independence assumption. Instead, we seek to find strong indication for the credibility of our instrument "by appealing to economic behavior or introspection" (Wooldridge 2020, p. 497) (see Subsection 5.2.1) and by testing the implications that can be derived from the conditional independence assumption (see Subsection 5.2.3). Overall, therefore, if $\tilde{Z}_i$ has a sizeable effect on ICT_i^h (relevance condition), and if $\tilde{Z}_i$ affects the job-design variables MON_i^h and WFH_i^h exclusively through its effect on ICT_i^h (exclusion restriction as implied by conditional IV independence), then 2SLS will produce IV estimates that can be interpreted as causal effects of ICT equipment on job design.

5.2.1 Population Density as Instrumental Variable

The employer survey of the LPP contains data at the firm level i, and, thus, refers to micro-level indicators of the German economy. In order to find a valid IV, micro-level indicators seem at first glance to be promising IV candidates that are likely to satisfy the relevance condition, especially when the endogenous explanatory variable and the IV originate in the same data set. However, there are also reasonable doubts that micro-level indicators can represent a valid IV, because they are unlikely to be strictly exogenous, meaning that conditional IV independence would not be met. From a methodological point of view, it might therefore be more reasonable to consider indicators at the macro level as a credible IV. This is exactly what is done in recent empirical studies that rely, for example, on information-rich and information-poor regions[24] (Tambe et al. 2012) or IT competition by geographic location (Dewan and Kraemer 2000, Bloom et al. 2012a).

Macro-level data of the German economy can be drawn from various sources. We use the so-called Regional Atlas of Germany ("Regionalatlas Deutschland"), which initially serves the visualization of regional data collected by the German federal authorities in interactive maps.[25] The data are available at the district level j, which is particularly interesting as this allows us to merge the data of the Regional Atlas with our firm-level data via the district identifier.[26]

In our analysis, we use the population density in German districts as IV. This variable measures the number of inhabitants per square kilometre and is available for all needed years. By analogy with ICT_i^h and MON_i^h, we construct a variable $PD_j = \ln(pd_j + 1)$, where pd_j represents the nominal population density in district j, thereby addressing the issue of the skewed distribution of pd_j as well as its wide range of values. We classify population density as an indirect measure of technological adjustment processes in all 401 German districts and thus as a promising candidate to satisfy both conditions of a valid IV.

Figure 1 displays the population density in Germany in 2017 for all 401 districts. The differences between western and eastern Germany, which are attributable to the former division of Germany before 1990, are clearly visible. In addition, other differences between districts can be observed, for example, whether a larger city (e.g., Berlin) is a district in its own right, or whether a district is adjacent to a large city (e.g., Starnberg is a neighboring district to Munich), or whether a district belongs to an economically rich or poor federal state of Germany.[27] The summary statistics of the

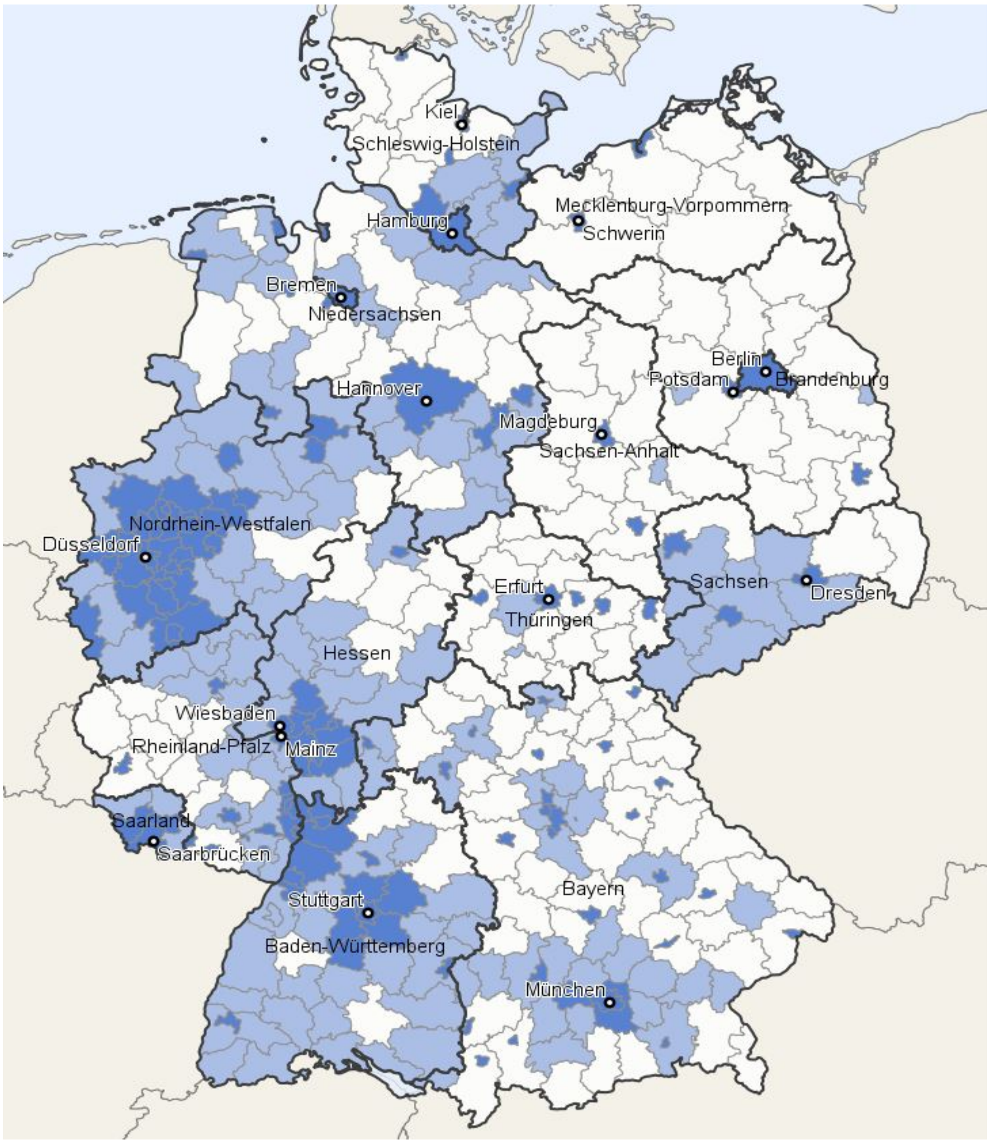
[24] Information-rich regions are high-technology clusters or areas with high worker mobility (Tambe et al. 2012).

[25] In addition, the data on which the interactive maps are based can be drawn in tabular form.

[26] This procedure has already been applied in Beckmann and Kräkel (2022).

[27] For example, Karlsruhe belongs to the economically rich federal state of Baden-Wuerttemberg, whereas Rostock belongs to the economically rather poor federal state of Mecklenburg Western Pomerania.

Figure 1: Population density in Germany in 2017



Source. Regional Atlas Germany, German Federal Statistical Office, 2021, EuroGeographics, and GeoBasis-DE/BKG, 2014.

Note. Districts in white: 36 to 135 inhabitants per sqkm. Districts in light blue: 136 to 407 inhabitants per sqkm. Districts in dark blue: 408 to 4'686 inhabitants per sqkm.

population density variable can be found in Table 2.

Table 2: Descriptive statistics of the instrumental variable

Variable	Wave	Mean	Std. dev.	Range	N
Population density (pd)	2014	665.46	858.95	0-4531	882
	2016	714.29	908.26	0-4668	1011
	2018	716.39	899.49	0-4686	952

Source. German Federal Statistical Office, 2021. Own calculations.

In what follows, we provide a convincing economic narrative or introspection on the relevance and conditional independence of our district-level population density instrument to strengthen its credibility as a valid instrument for the level of ICT equipment in German firms. The results of the corresponding statistical tests are reported in Subsection 5.2.3 after the introduction of the IV model.

A. Instrument Relevance

Starting with the relevance condition, we argue that population density is a relevant instrument for the following reasons. First, it provides information about how many people live in a certain district (district size)[28], and thus about the extent of potential ICT consumption or use. In Germany, the settlement of both people and firms is historically determined[29] and related to regional industrial revolutions.[30] Other industrial reasons of historical settlement are the construction of highways or railway routes[31] and the establishment of high-technology infrastructures.[32] This might explain why some regions in Germany are highly populated (e.g., North Rhine Westphalia, Saarland as well as some areas in Bavaria and Baden Wuerttemberg), while others are sparsely populated (e.g.,

[28] In a similar vein, Combes et al. (2012) use employment density to proxy city size.

[29] Examples include the economic paralysis after World War II, the East-West conflict, and the division of Germany until the fall of the Berlin Wall (Weber 2021). More recently, Peters (2022) showed that the settlement of refugees in the aftermath of World War II had a large and persistent effect on the size of the local population, manufacturing employment and income per capita.

[30] As regional industrial revolutions, we understand the growth of industries such as mining, iron and steel processing in the 19th century, which made the Ruhr area the most important coal and steel region in Europe (Czierpka 2019).

[31] For Germany, Möller and Zierer (2018) found positive causal effects of regional changes in highway kilometers on employment. Using the opening of high-speed railway routes in Germany, Gumpert et al. (2022) examine the response of firm organization to exogenous variation in geographic frictions.

[32] For the U.S., Moretti (2021) analyzes the effect of high-tech clusters on the productivity of top inventors and finds that geographical agglomeration results in significant productivity gains.

Mecklenburg Western Pomerania).

Second, some highly populated German districts might be characterized by the fact that one or more global players are located in that district (e.g., Siemens settled its headquarters in the district of Munich, Deutsche Bank in the district of Frankfurt, both highly populated districts). Nowadays, it is also the local infrastructure and natural environment that make a settlement for people and firms attractive. Thus, population density per district is an informative indicator allowing us to judge whether the regional economic situation in a certain district is rather strong or weak.

Taking both arguments together, we argue first that, in terms of ICT deployment at the district level, the incentive to create a good broadband infrastructure (i.e., good Internet quality) is particularly high in districts with economically strong businesses and high population density.[33] Consequently, we argue that this in turn promotes heavily the competition between businesses, especially in terms of potential exploitable ICT gains. In other words, increased ICT competition between companies in highly populated districts intensifies the incentive to adapt the company's ICT deployment by equipping employees more with ICT. Overall, therefore, a high population density in district j means, on the one hand, a high density of potential ICT users and, on the other hand, a high density of economically strong companies located in this district j. In turn, this encourages local governments to expand the broadband infrastructure in district j and firms to expand the ICT equipment of their employees, the latter due to increasing corporate ICT competition. Hence, we expect a strong positive correlation between population density in district j (PD_j) and ICT equipment of firms i (ICT_i^h) located in district j, i.e., $Cov(PD_j, ICT_i^h \,|\, X_i) > 0$, which would satisfy the relevance condition.

B. Conditional Independence

In order to satisfy the conditional independence assumption, we have to ensure that there is no direct link between the instrument PD_j and our job-design variables MON_i^h and WFH_i^h other than its effect through ICT equipment ICT_i^h. In our case, this restriction is likely to be satisfied, because PD_j is measured at the macro-level (German districts), while MON_i^h and WFH_i^h repre-

[33] Broadband infrastructure (i.e., good vs. bad Internet quality) is an important indicator for economic growth (Czernich et al. 2011) as well as labor market outcomes and productivity of skilled and unskilled workers (Akerman et al. 2015). According to Falck et al. (2014), regional variation in the technical availability of digital subscriber line (DSL) technology points out differences between East and West Germany or urban and rural municipalities. Although the Internet is increasing the market for some companies and start-ups in rural areas (Fabritz 2013, Falck et al. 2016), the particular challenges in Germany lie in the expansion of broadband in rural areas, as the investment interest of telecommunication companies in regions with stagnating population growth is rather low (BMVI 2016).

sent micro-level firm policies. It is very unlikely that firms adapt their job design in direct response to changes in population density. Furthermore, it should be kept in mind that the exogeneity of PD_j only has to be fulfilled conditional on the use of appropriate covariates.

To address any concerns about conditional IV independence, we add appropriate control variables to our estimation model. In the IV context, control variables are used for two reasons (Deuchert and Huber 2017). First, the instrument is not completely random but associated with important confounders. Second, the instrument affects more than one (treatment) variable that is associated with the outcome variable. Since we distinguish between executives and non-executives in terms of ICT equipment, both motives can in principle play a role in our empirical analysis, so we have to take the choice of control variables particularly seriously. Thus, with the choice of control variables we pursue the goal to extract all potential effects of the PD_j instrument on the dependent variables JD_i^h that do not pass through the channel of the explanatory variable ICT_i^h. In this way, we achieve strict exogeneity of the instrument and thus ensure conditional IV independence.[34]

Labor market competition. A first potential concern refers to the argument that local population density might incorporate the effect of labor market competition on the job-design policies of firms.[35] Labor market competition can be measured by local unemployment rates or open job positions.[36] For example, Beckmann and Kräkel (2022) find that local unemployment rates play an important role in determining worker autonomy. When the unemployment rate is low or the number of job openings is high, firms face intense competition to recruit suitable workers. In this setting, firms could offer working-from-home opportunities as a fringe benefit to attract workers and address local labor shortages. In contrast, when the unemployment rate is high or the number of job openings is low, employers gain power over employees and therefore may not see any benefit in changing job-design policies related to working from home. In this case, firms could

[34] If the instrument were completely random, no control variables would be needed. Thus, in the IV context, the purpose of the choice of control variables is to extract potential endogenous variation from the instrument to ensure its exogeneity.

[35] Caroli and Van Reenen (2001) analyze the relationship between employee skills and organizational change and find evidence for a skill-biased organizational change. Furthermore, Bloom et al. (2010, p. 124) emphasize that "when the environment changes because of new technologies and organizational change is required, skilled workers may be better at learning how to cope with the new organizational structures".

[36] Alternatively, Dauth et al. (2022) argue that wages are higher in cities with high population density, because they host more high-quality workers and firms and the matching of workers to firms is more efficient. This implies that cities with high population density are more competitive than cities with low population density due to higher wages and better matching processes.

use their competitive power to introduce stricter monitoring mechanisms.

In order to account for the issue of labor market competition, we add district-level measures on open job positions for certain types of skilled employees (experts and trained professionals) as well as a measure on contemporary local unemployment rates to the set of control variables. In addition, we control for the employment of women in each district, as especially skilled women appreciate working-from-home practices[37] as an important asset in hiring processes. Since the issue of labor market competition applies more to working-from-home policies than to a firm's monitoring activities, the control variables on job openings and female employment are added only to the set of covariates in the working-from-home regressions. However, we include the variable on the district-level unemployment rates to the set of control variables of both monitoring and working-from-home regressions.[38]

Worker's bargaining and self-selection intentions. A second concern associated with the conditional independence of local population density may involve workers' bargaining intentions and the possible self-selection of workers into particular districts or firms. On the one hand, it is possible that workers in highly populated districts start bargaining on certain job-design policies, such as working from home, to relocate in districts with lower rental prices or lower purchase values of land.[39] On the other hand, workers who live in sparsely populated districts could request working from home from their employers to avoid a relocation in districts with higher rental prices and long commuting distances. The workers' incentive to bargain on working from home might also be boosted by the quality of the local IT or broadband infrastructure. In addition, differences in living space must be taken into account, as the feasibility of and demand for working from home appear to depend largely on how much space a worker has at home (Rustin 2021).

We address the issue of real estate market competition by adding district-level information on average purchase values of building land, rental prices, and living space per inhabitant to the set of control variables in our working-from-home regressions. Furthermore, we address the potential selection into certain districts based on local corporate job-design policies by controlling for the firms' use of performance-pay plans. The intuition for this proceeding is based on both the incentive intensity principle and the monitoring intensity principle of agency theory, according to which pay

[37]Mas and Pallais (2020) find that women are more willing to pay for the option to work from home.

[38]The descriptive statistics of the labor-market-competition variables and all other district-level control variables can be found in Table 16 in Appendix B.2.

[39]For instance, in 2018 the average purchase value of land in the district of Munich was € 2,532.57 per square meter. By contrast, the average purchase value of land in Rosenheim, a neighboring district to Munich from which many employees commute to work, was only € 682.23 per square meter.

for performance should accompany both employee monitoring and employee autonomy (Milgrom and Roberts 1992, chapter 7). Finally, we address the issue of regional IT infrastructure by adding a variable that provides general information on a firm's perceived quality of its technical equipment. This information on the technical status of companies is a good indicator for describing the general local IT infrastructure, as it provides insights not only on broadband infrastructure, but also on other IT-related infrastructure, such as the presence of local technical support providers and local educational programs in the IT field. Hence, as far as local broadband infrastructure is concerned, we would expect a low (high) technical status in districts where broadband infrastructure is less (more) advanced. Similarly, with respect to other IT-related infrastructure, we would expect a low (high) technical status in districts where technological support or training is less (more) advanced. We use the performance-pay variable and the variable measuring a firm's technical status as covariates in both the monitoring and the working-from-home regressions to extract the potential effects described above from our population-density IV.

Corporate competition. A final potential concern regarding conditional IV independence rests on the notion that population density reflects to some extent the competitive pressure faced by firms. Competitive pressure may be a key to the choice of a particular firm policy, such as employee monitoring or working from home (Bloom et al. 2013). For example, if a firm chooses to locate in a densely populated district, it faces greater competitive pressures that could lead firms to monitor workforce productivity more closely to identify inefficiencies, maintain market power, and increase profitability. Competition between firms at the district level can be measured by the number of local corporate insolvencies or new business registrations. A low number of corporate insolvencies indicates rather weak competition among firms, while strong competition could lead to a higher number of corporate insolvencies. Similarly, a high number of business registrations indicates that it might be profitable for a young company to start a business. However, these companies face greater competitive pressures than other companies that begin operations in a district with fewer business registrations. Therefore, the former companies may prefer stricter monitoring policies due to greater competitive pressure than the latter companies. Finally, young companies tend to be more decentralized than older companies (Acemoglu et al. 2007) and could therefore respond to competitive pressures with less stringent monitoring practices or a greater focus on delegation and employee autonomy.

In order to account for inter-firm competition, we add district-level variables on corporate insolvencies and business registrations to our set of control variables in the monitoring regressions, as well as firm-level information on self-reported competitive pressure. In addition, we control for firm age in the monitoring and working-from-home regressions. The inclusion of these covariates eliminates the possibility of decontamination of our instrument by competitive pressure. Following Bloom et al. (2010a) and Bloom et al. (2012b), we further control for firm size classes and industry affiliation as the basic determinants of decentralization in the monitoring and working-from-home specifications. Finally, we control for time-fixed effects by including a time dummy variable.

Overall, this introspection leads us to the conviction that population density is a credible and valid instrument. A high population density creates strong incentives for firms to expand their ICT equipment. In contrast, a low population density provides poor incentives for firms to adapt their ICT equipment. Moreover, we argue that population density is not directly related to a firm's monitoring activities or working-from-home policy in any other way than through its impact on ICT equipment. In order to dispel any doubts that may exist in this regard, we apply covariates at the micro (firm) level and macro (district) level to relieve our district-level instrument from potential endogeneity biases. Hence, we are confident that our instrument satisfies not only the relevance condition, but also the conditional independence assumption.

5.2.2 Instrumental Variable Model

In order to address the selection-on-unobservables issue ($\delta^h \neq 0 \neq \theta^h$, $\eta^h = 0$ in (8)), we estimate the following two-stage equation system:

$$ICT_i^h = \pi^h PD_j + X_{i,j}\beta_F^h + \epsilon_{F,i}^h \tag{11}$$

$$JD_i^h = \gamma^h \widehat{ICT}_i^h + X_{i,j}\beta_S^h + \epsilon_{S,i}^h \,, \tag{12}$$

where equation (11) is the first-stage regression and equation (12) is the second-stage structural equation. The parameters are estimated using the parametric 2SLS estimation method, where π^h and γ^h are of particular interest. $X_{i,j}$ includes the firm-level (i) and district-level (j) control variables that have been introduced in Subsection 5.2.1.[40] Finally, $\widehat{ICT}_i^h$ is the estimate of ICT_i^h resulting from (11).

5.2.3 2SLS Estimation Results

The 2SLS estimation results are displayed in Tables 3, 4, and 5. The parameters of the first-stage regressions (11) can be found in panel A of Table 3, where columns (1) and (2) refer to the

[40] For better readability, we uniformly use the symbol X for the covariates and accordingly refrain from labeling the different X-variables in the monitoring and working-from-home regressions differently, such as X^{MON} or X^{WFH}.

employee-monitoring model, and columns (5) and (6) refer to the working-from-home model.[41] Panel B displays the estimated coefficients for PD resulting from a first-stage regression that is augmented with a series of additional control variables to test the conditional independence assumption.

A. Testing Instrument Relevance

As expected, all estimated first-stage coefficients $\widehat{\pi}^h$ reported in panel A are positive and turn out to be highly statistically significant at the 1 percent level, meaning that an increase in population density per district has a strong promoting impact on ICT equipment across hierarchical levels in firms. Moreover, the F-statistics in each specification exceed the critical threshold of 10, thus rejecting the null hypothesis of weak instruments. Hence, the first-stage test statistics indicate that the condition of instrument relevance is satisfied.[42]

[41] The first-stage regressions differ with regard to the number of observations N, which is due to different regressor variables and time periods. Recall that we use panel waves 3 and 4 for the monitoring regressions and panel waves 2 and 3 for the working-from-home regressions.

[42] We estimated the 2SLS models first with heteroskedasticity-robust and second with cluster-robust standard errors. The first approach leads to slightly higher F-statistics than the second approach and thus contributes slightly more to satisfying the relevance condition. The second approach, on the other hand, takes more account of the fact that we use panel data in our analysis, because the standard errors are robust to correlation within panel units over time. With both variants, we obtain similar results for the estimated standard errors of the parameters of interest, which do not change the magnitude and significance level of the estimated coefficients. In the tables, the variant with the heteroskedasticity-robust standard errors is always shown for the 2SLS estimates.

Table 3: First-stage regressions: the impact of population density on ICT equipment

	Monitoring regressions				Working-from-home regressions			
	2SLS	2SLS	Probit ML	Probit ML	2SLS	2SLS	Probit ML	Probit ML
	ICT^{E}	ICT^{NE}	D^{E}	D^{NE}	ICT^{E}	ICT^{NE}	D^{E}	D^{NE}
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A: first-stage estimates for PD according to (11) and (24)							
PD	.132***	.186***	.098**	.167***	.198***	.216***	.141***	.145***
	(.041)	(.045)	(.039)	(.040)	(.057)	(.058)	(.049)	(.050)
F-/χ^2-test	10.373***	16.728***	6.37**	17.21***	11.908***	13.715***	8.20***	8.28***
	[.001]	[.000]	[.011]	[.000]	[.001]	[.000]	[.004]	[.004]
(Pseudo-)R^2	.082	.081	.025	.053	.113	.085	.038	.062
N	1,404	1,404	1,404	1,404	1,345	1,345	1,345	1,345
	Panel B: add X_{OA} and remaining district-level controls							
PD	.161**	.210***	.132**	.163***	.178**	.218***	.155**	.141**
	(.063)	(.068)	(.062)	(.063)	(.073)	(.074)	(.065)	(.066)
H_0: $\widehat{\pi}_A^h = \widehat{\pi}_B^h$	[.535]	[.646]	[.488]	[.940]	[.684]	[.966]	[.738]	[.920]

Sources. Linked Personnel Panel, employer survey 2014/2016/2018, IAB Establishment Panel 2014/2016/2018, German Federal Statistical Office 2020, and BBSR Bonn 2021. Own calculations.

Notes. The values in parentheses (square brackets) represent heteroskedasticity-robust standard errors (p-values). The F-/χ^2-test is a test on instrument relevance. The test on the equality of $\widehat{\pi}_A^h$ and $\widehat{\pi}_B^h$ refers to the estimated coefficients for PD reported in panel A and panel B.

* $p < .10$, ** $p < .05$, *** $p < .01$.

B. Testing Conditional Independence

Following Bhuller et al. (2020), a comparison of the estimated coefficients for PD reported in panels A and B allows us to provide an indirect test of the conditional independence assumption. The test explores what happens if a series of additional control variables is added to the regressor matrix X in the first-stage equation (11). If the instrument PD is (as good as) random, conditional on X, inclusion of the additional control variables should not significantly change the actual first-stage estimates for the instrument PD, as they should be uncorrelated with PD.[43] This is exactly what we observe. Although some coefficients for PD in panel B, i.e., $\widehat{\pi}_B^h$, lose slightly in significance, slipping from the 1 percent to the 5 percent level, they do not deviate appreciably in magnitude from the actual first-stage estimates $\widehat{\pi}_A^h$ reported in panel A. A test on the equality of $\widehat{\pi}_A^h$ and $\widehat{\pi}_B^h$ cannot be rejected in each of the considered specifications displayed in columns (1), (2), (5), and (6). Despite the fact that these test results are not sufficient to prove the conditional independence of PD, they can clearly be interpreted as satisfying a necessary condition for PD to be considered a valid instrument.

C. Second-Stage Estimates

Tables 4 (monitoring regressions) and 5 (working-from-home regressions) display the second-stage estimates of equation (12) in columns (3) and (4).[44] We first see that Wooldridge's score test rejects the null hypothesis of exogenous explanatory variables in all specifications, except for the regression of WFH_i^{NE} on ICT_i^{NE} displayed in column (4) of Table 5. Overall, the test results underline the need for the use of 2SLS estimates to account for the endogeneity of ICT_i^E and ICT_i^{NE}.

Regarding the monitoring regressions, we observe that the ICT effect on employee monitoring is positive and significant at the 5 percent level for executives, and at the 1 percent level for non-executives. The ICT effects for both employment groups are slightly greater than 1.0, meaning that a one percent increase in the proportion of employees equipped with ICT increases the monitoring

[43] As additional control variables, we consider all variables that serve as control variables in our OLS models according to the three-legged stool approach of organizational architecture by Brickley et al. (2021, chapter 11), unless they are already used as control variables in the IV models. We also add the remaining district-level control variables from the working-from-home (monitoring) IV regressions to the monitoring (working from home) IV regressions.

[44] Although our identification strategy relies on IV-based estimation methods rather than panel data models, we additionally estimated fixed effects models to explore the impact of ICT equipment on employee monitoring and working from home. The estimation results are consistent with our baseline 2SLS estimates.

Table 4: ICT equipment and employee monitoring across hierarchical levels

	OLS		2SLS		Parametric Normal MTE	
	MON^E	MON^{NE}	MON^E	MON^{NE}	MON^E	MON^{NE}
	(1)	(2)	(3)	(4)	(5)	(6)
ICT^h	.141***	.081**	1.220**	1.105***		
	(.041)	(.037)	(.503)	(.357)		
D^h					6.435***	2.794***
					(1.768)	(.863)
$\widehat{\lambda}_1^h$					1.144	.547
					(1.271)	(.713)
$\widehat{\lambda}_0^h$					5.239***	2.671***
					(1.442)	(.781)
Controls	X_{OA}	X_{OA}	X	X	X	X
H_0: $\gamma^E = \gamma^{NE}$	[.167]		[.706]			
Score test			[.004]	[.000]		
$\widehat{\rho}_1^h - \widehat{\rho}_0^h$					−4.095**	−2.123**
					(1.837)	(1.040)
R^2	.263	.239				
N	1,192	1,192	1,404	1,404	1,404	1,404

Sources. Linked Personnel Panel, employer survey 2016/2018, IAB Establishment Panel 2016/2018, German Federal Statistical Office 2020, and BBSR Bonn 2021. Own calculations.

Notes. In columns (3) to (6), the IV is PD_j. The set of covariates X_{BSZ} refers to the three-legged-stool approach of organizational architecture developed in Brickley et al. (2021, chapter 11) and contains the firm-level variables introduced in Subsection 5.1.1. The set of covariates X contains firm-level and district-level variables introduced in Subsection 5.2.1. The parameter estimates for D^h represent the ATE. The values in parentheses (brackets) represent standard errors (p-values). In the OLS specifications displayed in columns (1) and (2), the standard errors are clustered at the firm level to allow for correlation within panel units over time (intragroup correlation). In the 2SLS specifications displayed in columns (3) and (4), the standard errors are robust to heteroskedasticity. In the parametric normal MTE models displayed in columns (5) and (6), normal-based bootstrapped standard errors clustered at the firm level (100 replications) are reported to account for the estimated control functions $\widehat{\lambda}_1^h$ and $\widehat{\lambda}_0^h$. The score test is Wooldridge's score test of endogeneity. The statistics on $\widehat{\rho}_1^h - \widehat{\rho}_0^h$ represent a test on essential heterogeneity. The complete regression results are displayed in Appendix B.1, Table 14.

* $p < .10$, ** $p < .05$, *** $p < .01$.

Table 5: ICT equipment and working from home across hierarchical levels

	OLS		2SLS		Parametric Normal MTE	
	WFH^E	WFH^{NE}	WFH^E	WFH^{NE}	WFH^E	WFH^{NE}
	(1)	(2)	(3)	(4)	(5)	(6)
ICT^h	.085***	.114***	.451**	−.014		
	(.014)	(.022)	(.206)	(.157)		
D^h					1.302**	.333
					(.656)	(.706)
$\widehat{\lambda}_1^h$					1.821***	.154
					(.630)	(.639)
$\widehat{\lambda}_0^h$					−.241	−.154
					(.531)	(.480)
Controls	X_{OA}	X_{OA}	X	X	X	X
H_0: $\gamma^E = \gamma^{NE}$	[.219]		[.002]			
Score test			[.049]	[.355]		
$\widehat{\rho}_1^h - \widehat{\rho}_0^h$					2.062**	.309
					(.836)	(.777)
R^2	0.110	0.127				
N	1,193	1,193	1,345	1,345	1,345	1,345

Sources. Linked Personnel Panel, employer survey 2014/2016, IAB Establishment Panel 2014/2016, German Federal Statistical Office 2020, and BBSR Bonn 2021. Own calculations.

Notes. See, Table 4. The complete regression results are displayed in Appendix B.1, Table 15.

* $p < .10$, ** $p < .05$, *** $p < .01$.

intensity by about 1 percent. Both coefficients are not statistically different ($p = .706$).[45] We obtain deviating results for the ICT effects on working from home displayed in columns (3) and (4) of Table 5. For executives, the coefficient is positive and statistically significant at the 5 percent level with a magnitude of .451.[46] However, for non-executives, we obtain a negative, albeit statistically insignificant coefficient, indicating that an increase in ICT equipment among non-executives is not causally related to an increase in the incidence of working from home.[47] The test on equality of coefficients for ICT_i^E and ICT_i^{NE} clearly rejects the null hypothesis of equal coefficients ($p = .002$), implying that ICT equipment increases autonomy only for executives, while it does not promote autonomy for non-executives.

The results of our 2SLS regressions can be summarized as follows. First, ICT equipment increases monitoring for both executives and non-executives, with the ICT effect being slightly, but not significantly, higher for executives than for non-executives. This empirical result is consistent with result (b) predicted in Proposition 2 of our theoretical model. Second, ICT equipment promotes the prevalence of working from home only among executives, but not among non-executives. This finding is in line with results (c) and (d) of Proposition 2 and can be explained by the fact that, under the optimal incentive contracts, improving work-life balance via autonomy is only important concerning executives but not concerning non-executives from the firm's perspective. Overall, this implies that the preference for executives over non-executives in terms of ICT equipment also entails different effects across hierarchical levels in terms of job design. While both groups of employees experience more ICT-induced monitoring, only executives benefit from an ICT-induced increase in autonomy.

[45] The 2SLS estimates are substantially larger than the corresponding OLS estimates. One explanation for this result is measurement error in the endogenous explanatory ICT_i^h variables, biasing the OLS estimates towards zero (e.g., Becker 2016).

[46] The interpretation of the coefficient is that a 1 percent increase in the proportion of ICT-equipped executives increases executive autonomy by .451 standard deviations. This interpretation applies accordingly to the other parameter estimates in the working-from-home regressions.

[47] As noted earlier, Wooldridge's score test does not reject the null hypothesis of exogeneity of ICT_i^{NE}. In this context, one might prefer to resort to the corresponding OLS estimate, which is .114 and highly significant (see column (2)). Nevertheless, we opt for the more conservative 2SLS point estimate in column (4) because, unlike the 2SLS estimate, the OLS estimate is unlikely to be causally interpretable despite the insignificant score test. Another reason for preferring 2SLS estimates is that we want to avoid treating executives and non-executives unequally in terms of estimation strategy.

5.3 Estimating Marginal Treatment Effects

In this subsection, we extend our identification strategy in the sense that we now consider the case of possible effect heterogeneity in addition to standard unobserved heterogeneity. Hence, we account for both $\delta^h \neq 0 \neq \theta^h$ and $\eta^h \neq 0$ in equation system (8). For this purpose, we estimate marginal treatment effects (MTE) of ICT equipment across hierarchical levels on employee monitoring and working from home. In doing so, we examine whether the effects of ICT equipment across hierarchical levels on job design differ within firms with varying levels of unobserved characteristics, such as management quality. For example, if firms with higher management quality (or other unobserved characteristics) are more likely to equip their executive and non-executive employees with ICT and also increase their monitoring activities, the distribution of MTE over the range of the propensity score will indicate this. The methodology of MTE estimation dates back to Björklund and Moffitt (1987) and has been steadily developed by Heckman and Vytlacil (1999, 2001, 2005, 2007), Heckman et al. (2006a), Carneiro et al. (2011), and Brinch et al. (2017), among others.[48]

5.3.1 Foundations of MTE Models

Specifying MTE models requires the dichotomization of our continuous explanatory variables ICT_i^h. We therefore divide the firms into a treatment and a control group according to the extent to which they equip their executives and non-executives with ICT. To keep both groups roughly equal in size, we choose the median of ICT equipment across hierarchical levels h per time period t as the threshold, thus separating firms with high ICT equipment levels ($D_i^h = 1$) from firms with low ICT equipment levels ($D_i^h = 0$). In the following, we refer to the first group as technology-friendly and the second group as technology-averse.

At first sight, collapsing a continuous variable into a binary treatment variable seems to be disadvantageous, because information is lost. On the contrary, however, this potential concern is offset by some important advantages of MTE estimation (e.g., Cornelissen et al. 2016). First, we can use both parametric and semiparametric methods in estimating the MTE, whereas the conventional 2SLS is a purely parametric estimation approach. Second and most importantly, unlike 2SLS, the estimation of MTE takes into account not only selection on unobservables (thus allowing for $\delta^h \neq 0 \neq \theta^h$ in equation system (8)), but also selection on unobserved ICT gains in monitoring and working from home (thus additionally allowing for $\eta^h \neq 0$ in (8)). Hence, while

[48] Excellent surveys on local average treatment effects (LATE) and MTE estimation are provided by Cornelissen et al. (2016) as well as Mogstad and Torgovitsky (2018).

2SLS identifies an overall effect that may hide interesting patterns of treatment heterogeneity, MTE estimation "aims at identifying a continuum of treatment effects along the distribution of the individual unobserved characteristic that drives treatment decisions and allows the identification of a variety of treatment parameters such as ATE, ATT, and ATU under potentially no stronger assumptions than IV estimation" (Cornelissen et al. 2016, p. 48). The binarization of multivalued (treatment) variables is quite common in the MTE literature and is done, for example, in the studies of Carneiro et al. (2011, 2017), Cornelissen et al. (2018), Felfe and Lalive (2018), and Bhuller et al. (2020).

By using a binarized treatment variable D^h, we explicitly address a type of selection mechanism in which firms assign themselves to a treatment and a control group depending on whether they provide ICT to a high or low proportion of their executives and non-executives. This selection mechanism affects our identification strategy in two ways. First, firms are unlikely to select themselves randomly to the treatment or control group, but in systematic ways that have an influence on job design. Second, the selection mechanism is unlikely to be based on observable characteristics alone, but also on firms' expectations of their gains from the treatment or their resistance to treatment, which is unobservable to the researcher. The MTE framework allows us to address these issues and estimate heterogeneous treatment effects in the presence of self-selection (Cornelissen et al. 2016, Andresen 2018a, Schmitz 2022).

The starting point of our MTE estimation is the following potential outcomes model[49]

$$JD_1^h = X\beta_1^h + U_1^h \tag{13}$$

$$JD_0^h = X\beta_0^h + U_0^h \,, \tag{14}$$

where JD_k^h $(k = 0, 1)$ is modelled as a linearly separable function of observed characteristics X and unobserved factors U_k^h. Since the potential outcomes JD_1^h and JD_0^h cannot be observed together for the same firm, the observed outcome JD^h depends on the treatment status D^h, i.e.,

$$JD^h = (1 - D^h) \cdot JD_0^h + D^h \cdot JD_1^h = JD_0^h + (JD_1^h - JD_0^h) \cdot D^h \,. \tag{15}$$

Participation in the treatment D^h is determined by a firm's latent desire to belong to the group of technology-friendly rather than the group of technology-averse firms, $D^{h,*}$, which itself depends on observables $Z = [PD, X]$ and unobservables V, so that

$$D^{h,*} = Z\zeta^h - V^h \,, \quad \text{where } D^h = 1\,[D^{h,*} \geq 0] = 1\,[Z\zeta^h \geq V^h] \,. \tag{16}$$

[49]In the further course of this subsection, we omit the indices i, j and t due to better readability.

Hence, a firm belongs to the group of technology-friendly firms if $Z\zeta^h \geq V^h$.[50]

Equation (16) represents the selection equation, where $Z\zeta^h \geq V^h$ is often called a latent index (Andresen 2019). Due to the negative sign in (16), V^h can be interpreted as unobserved resistance to treatment or cost of participation (e.g., Heckman and Vytlacil 1999, Cornelissen et al. 2016, Andresen 2019, Dorsett and Stokes 2022). The fact that the unobserved error terms in (13), (14), and (16) are allowed to be correlated, conditional on observables, i.e., $U_0^h \not\perp U_1^h \not\perp V^h \,|\, X$ (Heckman et al. 2006a), manifests the problems of endogeneity and essential heterogeneity.

Given that V^h is continuously distributed, selection equation (16) can be expressed as $p^h \geq U_{D^h}$, where $p^h = \Pr(D^h = 1 \,|\, Z) = P^h(Z)$ is the propensity score representing the probability of taking the treatment based on observables, and U_{D^h} is uniformly distributed between 0 and 1 by construction representing the quantiles of V^h (Brave and Walstrum 2014, Cornelissen et al. 2016, Andresen 2018a, 2019, Dorsett and Stokes 2022).[51] Hence, firms will take the treatment ($D^h = 1$) and thus be in the group of technology-friendly firms if their observed encouragement for treatment p^h does not fall below their unobserved resistance for treatment U_{D^h}.

A. Instrument Relevance and Conditional Independence

In order to interpret an MTE in terms of causal inference, the conventional IV assumptions must first be satisfied, i.e., instrument relevance and conditional independence. In the context of MTE estimation, the relevance condition (sometimes also called rank assumption) can formally be expressed as $E[D_z^h - D_{z'}^h \,|\, X] \neq 0$, where D_z^h is a binary indicator for the potential treatment status of a firm for instrument value $PD = z$, and z and z' represent any pair of values of PD. The conditional independence assumption for the MTE case requires that the instrument PD is statistically independent of the unobserved error terms of the outcome and selection equations given X, i.e., $PD \perp (U_0^h, U_1^h, V^h) \,|\, X$.[52] In addition, conditional independence implies the exclusion restriction,

[50] The general modeling of potential outcome equations (13) and (14) is: $JD_k^h = \mu_k^h(X, U_k^h)$, $(k = 0, 1)$, where $\mu_k^h(X, U_k^h)$ is the conditional mean of JD_k^h given X and U_k^h in treatment state k. The general modeling of (16) is: $D^h = \mu_D(Z) > V^h$, where $\mu_D(Z)$ is a function of Z which includes the exogenous covariates X and the instrument PD. Hence, (13), (14), and (16) represent special cases of these general functions.

[51] This is because $D^{h,*} \geq 0 \Leftrightarrow Z\zeta^h \geq V^h \Leftrightarrow F_{V^h}(Z\zeta^h) \geq F_{V^h}(V^h) \Leftrightarrow P^h(Z) \geq U_{D^h} \Leftrightarrow p^h \geq U_{D^h}$, where F_{V^h} is the cumulative distribution function of V^h.

[52] Instead of the conditional independence assumption, some empirical studies on MTE estimation prefer the stronger unconditional or full independence assumption, meaning that the instrument is required to be independent unconditional of the covariates in X, i.e., $(U_0^h, U_1^h, V^h) \perp X, \tilde{Z}$ with $\tilde{Z}$ as instrument (e.g., Giesecke and Schuss 2019, Kamhöfer et al. 2019). See Mogstad and Torgovitsky (2017) for a discussion of the differences between both assumptions.

meaning that population density should affect the firms' job design only through the channel of ICT equipment and not directly in any other way. Conditional independence further implies that the MTE curve, i.e., the relationship between U_0^h, U_1^h, and V^h, must not depend on the instrument PD (Bhuller et al. 2020, Schmitz 2022). The results of statistical tests on the assumptions of instrument relevance and conditional independence are reported in Subsection 5.3.3.

B. Monotonicity and Additive Separability

Apart from the standard IV assumptions, MTE estimation requires the monotonicity (or uniformity) assumption to be met. In the present case, monotonicity requires that all firms that change their treatment status in response to an IV change from $PD = z$ to $PD = z'$ are either all moved into treatment or out of treatment, i.e., $D_z^h \geq D_{z'}^h$, $\forall\, i$, or vice versa. In less technical terms, the monotonicity assumption requires that firms that are already technology-friendly when located in a district with a relatively low population density remain technology-friendly when population density increases, and vice versa for technology-averse firms.[53] Thus, monotonicity rules out the existence of defiers, i.e., firms that do not react in conformity to the instrument, but instead always respond to a change in the instrument in one direction by changing their ICT equipment in the opposite direction. In our case, monotonocity is an intuitively plausible assumption on its own, as it is hard to imagine why a firm should switch from technology-friendly to technology-averse just as population density is increasing.

Assuming monotonicity is necessary, because MTE estimation aims at identifying heterogeneous treatment effects across firms rather than a constant causal effect (Bhuller et al. 2020). It is often pointed out that the monotonicity assumption is satisfied by the latent index model with a linearly separable error term given in equation (16), because $D^{h,*}$ monotonously increases or decreases with higher values of PD (e.g., Vytlacil 2002, Cornelissen et al. 2016, Mogstad et al. 2018). Despite this, the monotonicity assumption can be tested, which is done in Subsection 5.3.3.

Moreover, since our instrument PD is very unlikely to generate full support of the propensity score in both treated and untreated samples within each cell of X, we finally impose the assumption of additive separability between the observed and unobserved parts in the linear potential outcome equations (13) and (14), conditional on $U_{D^h} = u_{D^h}$, i.e., $E[JD_k^h \,|\, X = x, U_{D^h} = u_{D^h}] = X\beta_k^h +$

[53] Bhuller et al. (2020) note that the monotonicity assumtion allows the 2SLS estimate to be interpreted as a LATE. In our case, a 2SLS estimate of D^h could be interpreted as an average causal effect in the subset of firms that would have decided differently in terms of equipping their executives and non-executives with ICT if they were located in a district with a different population density.

$E[U_k^h \,|\, U_{D^h}]$, where $k = 0, 1$. The additive separability assumption allows us to identify the MTE over the common support of the propensity score, unconditional on X. It has two implications. First, the MTE are additively separable in U_{D^h} and X. Second, the shape of the MTE, i.e., the way in which U_1^h and U_0^h are interrelated with V^h, does not depend on X (Andresen 2018a, Schmitz 2022).[54]

C. MTE Estimation

The additive separability assumption allows us to define the MTE to be estimated as the treatment effect at a certain value of U_{D^h}, i.e.,

$$\begin{aligned} MTE(X = x, U_{D^h} = u_{D^h}) &= E[JD_1^h - JD_0^h \,|\, X = x, U_{D^h} = u_{D^h}] \\ &= \underbrace{X(\beta_1^h - \beta_0^h)}_{\text{heterogeneity in observables}} + \underbrace{E[U_1^h - U_0^h \,|\, U_{D^h} = u_{D^h}]}_{\text{heterogeneity in unobservables}} . \end{aligned} \tag{17}$$

In words, the MTE is the marginal effect of treatment conditional on observed firm characteristics X and the propensity not to be treated U_{D^h} (Brave and Walstrum 2014, Cornelissen et al. 2016, Andresen 2018a). The MTE in (17) consists of two components. The first is the average treatment effect $ATE(X) = X(\beta_1^h - \beta_0^h)$, which is the gain of the decision of the average firm with observed characteristics X to select itself to the group of technology-friendly firms. The second component $(U_1^h - U_0^h)$ is the unobserved idiosyncratic gain for this average firm. It indicates that the incremental effect of treatment (high level of ICT equipment) compared to no treatment (low level of ICT equipment) can vary across firms, even after controlling for observables X (Basu et al. 2007).

Given an estimate of the propensity score p^h, the potential outcomes equations (13) and (14) can be expressed by the conditional expectations of JD_1^h and JD_0^h (Heckman et al. 2006b, Brave and Walstrum 2014, Cornelissen et al. 2016), i.e.,

$$E[JD_1^h \,|\, X = x, P^h(Z) = p^h, D^h = 1] = X\beta_1^h + E[U_1^h \,|\, X = x, P^h(Z) = p^h, D^h = 1] \tag{18}$$

$$E[JD_0^h \,|\, X = x, P^h(Z) = p^h, D^h = 0] = X\beta_0^h + E[U_0^h \,|\, X = x, P^h(Z) = p^h, D^h = 0] . \tag{19}$$

The last terms in (18) and (19) denote the confounding endogenous variation in the error terms of the outcome equations (13) and (14). By making use of (15), equations (18) and (19) can be rewritten as

$$E[JD^h \,|\, X = x, P^h(Z) = p^h] = X\beta_0^h + X(\beta_1^h - \beta_0^h)p^h + K(p^h) , \tag{20}$$

[54] Regarding the content and formal representations of the MTE assumptions, see e.g., Heckman and Vytlacil (2005), Heckman et al. (2006a), Brave and Walstrum (2014), Cornelissen et al. (2016), and Andresen (2018a, 2019).

where $K(p^h) = E[U_0^h \mid P^h(Z) = p^h] + p^h \cdot E[U_1^h - U_0^h \mid P^h(Z) = p^h]$ is a nonlinear function of the propensity score p^h capturing heterogeneity along the unobservable resistance to treatment U_{D^h} (Heckman and Vytlacil 2001, 2007, Brave and Walstrum 2014, Cornelissen et al. 2016, Andresen 2018a, Dorsett and Stokes 2022). Equation (20) illustrates that the interaction term between X and p^h identifies $(\beta_1^h - \beta_0^h)$ and that the function $K(p^h)$ does not depend on observable characteristics X. Hence, the MTE curve is shifted by the observables X, while, as mentioned earlier, the slope of the MTE curve does not depend on X (Giesecke and Schuss 2019, Kamhöfer et al. 2019).

The MTE for $X = x$ and $U_{D^h} = p^h$ is given by the derivative of the conditional mean outcome (20) with respect to p^h (e.g., Heckman et al. 2006, Carneiro et al. 2011, Dorsett and Stokes 2022), i.e.,

$$MTE(X = x, U_{D^h} = p^h) = \frac{\partial E[JD^h \mid X = x, P^h(Z) = p^h]}{\partial p^h} = X(\beta_1^h - \beta_0^h) + \frac{\partial K(p^h)}{\partial p^h}\,. \tag{21}$$

MTE estimation can be performed using both parametric and semiparametric methods. In our baseline model described in the next subsection, we apply the parametric normal MTE model and check the robustness of the achieved results in Subsection 6.2.2 by estimating a semiparametric polynomial MTE model.

5.3.2 Parametric Normal MTE Model

Apart from the identifying assumptions discussed above, which are standard in identifying MTE regardless of the underlying estimation method, MTE estimation under the parametric normal model requires an additional assumption with respect to the unobserved error terms in equations (13), (14), and (16). This assumption is a trivariate normal distribution for the error terms, i.e., $(U_0^h, U_1^h, V^h) \sim N(0, \Sigma)$, where Σ is the variance-covariance matrix of the three error terms in which the variance of V^h is normalized to 1 (Heckman et al. 2006b, Brave and Walstrum 2014, Cornelissen et al. 2016).

In the parametric normal MTE model, the estimation of the parameters of the MTE is based on outcome equations (18) and (19), where the last terms in (18) and (19) are given by

$$E[U_1^h \mid X = x, P^h(Z) = p^h, D^h = 1] = -\rho_1^h \frac{\phi(p^h)}{\Phi(p^h)p^h} = \rho_1^h \lambda_1^h \tag{22}$$

$$E[U_0^h \mid X = x, P^h(Z) = p^h, D^h = 0] = \rho_0^h \frac{\phi(p^h)}{\Phi(p^h)(1 - p^h)} = \rho_0^h \lambda_0^h\,. \tag{23}$$

Here, ϕ (Φ) is the probability (cumulative) density function of the standard normal distribution, ρ_1^h (ρ_0^h) denotes the correlation coefficient between U_1^h and V^h (U_0^h and V^h), and λ_1^h and λ_0^h represent the inverse Mills ratios (Heckman et al. 2006b, Brave and Walstrum 2014, Cornelissen et al. 2016).

The assumption of a trivariate normal distribution for U_0^h, U_1^h, and V^h allows us to estimate the MTE over the range of $P^h(Z) \in (0,1)$, thereby applying a two-step control function procedure. The first step is a probit maximum likelihood (ML) estimation of the selection model[55]

$$D^h = Z\zeta^h + v^h \,. \tag{24}$$

From the parameter estimates of (24), we calculate estimates of the inverse Mills ratios λ_1^h and λ_0^h, and add these estimates as control functions to equations (13) and (14) resulting in

$$JD_1^h = X\beta_1^h + \rho_1^h\widehat{\lambda}_1^h + U_1^h \tag{25}$$

$$JD_0^h = X\beta_0^h + \rho_0^h\widehat{\lambda}_0^h + U_0^h \,. \tag{26}$$

In a second step, equations (25) and (26) are then estimated by conventional OLS, where the MTE are calculated according to (17) and (21) as

$$\widehat{MTE}_{PN}(x, u_{D^h}) = X(\widehat{\beta}_1^h - \widehat{\beta}_0^h) + (\widehat{\rho}_1^h - \widehat{\rho}_0^h)\Phi^{-1}(u_{D^h}) \,. \tag{27}$$

The corresponding ATE conditional on X is a special case of (27), yielding $\widehat{ATE}_{PN}(x) = X(\widehat{\beta}_1^h - \widehat{\beta}_0^h) = \widehat{MTE}_{PN}(X = x, U_{D^h} = 0.5)$. Positive (reverse) selection based on unobserved gains would be indicated by $\widehat{\rho}_1^h < \widehat{\rho}_0^h$ ($\widehat{\rho}_1^h > \widehat{\rho}_0^h$), while $\widehat{\rho}_1^h = \widehat{\rho}_0^h$ would indicate no selection on unobserved gains (Heckman et al. 2006b, Cornelissen et al. 2016).

5.3.3 Estimation Results of the Parametric Normal MTE Model

The first-stage probit ML estimates presented in columns (3), (4), (7), and (8) of Table 3, as well as Tables 9, 10, 11, and 12 in Appendix B.1, provide information on the validity of our instrument PD.

A. Testing Instrument Relevance and Conditional Independence

Panel A of Table 3 reports the first-stage estimates of PD according to selection equation (24). Consistent with the corresponding 2SLS estimates, we obtain positive and highly significant effects of PD on D^h, regardless of the hierarchical level. The χ^2-statistics range between 6.37 and 17.21, so they do not always reach the critical rule-of-thumb value of 10.[56] However, as the second-stage

[55]The substitution of V^h for v^h is a consequence of equivalence between the latent index model in (16) and the reduced form (24).

[56]The χ^2-values turn out to be very similar to the corresponding F-values, so we continue to compare the χ^2-statistics with the rule-of-thumb value equal to 10.

ATE-estimates resulting from the parametric normal model are consistent with the corresponding 2SLS estimates based on first-stage estimates in which the F-statistics are always greater than 10, we are confident that our highly significant first-stage estimates, with χ^2 values slightly less than 10, are meaningful and do not compromise the assumption of instrument relevance.

The test on conditional independence proposed in Bhuller et al. (2020) provides similar results as in the 2SLS case. A comparison of the first-stage estimates of PD displayed in panel A with their counterparts resulting from the augmented covariates model reported in panel B of Table 3 shows that the inclusion of the additional control variables do not significantly change the actual first-stage estimates of the instrument PD, implying that the additional variables are uncorrelated with PD. Again, some coefficients of PD in panel B, i.e., $\widehat{\pi}_B^h$, slightly lose in significance, slipping from the 1 percent to the 5 percent level. However, they do not deviate appreciably from the actual first-stage estimates $\widehat{\pi}_A^h$ reported in panel A. The null hypothesis H_0: $\widehat{\pi}_A^h = \widehat{\pi}_B^h$ cannot be rejected in each of the considered specifications displayed in columns (3), (4), (7), and (8), thus providing some support with regard to the conditional independence of our instrument PD.

B. Testing Monotonicity

The monotonicity assumption provides a testable implication according to which the first-stage estimates of the instrument PD should be nonnegative for any subsample (Bhuller et al. 2020). Hence, in order to assess the monotonicity assumption, we run a series of first-stage regressions in which D^h is regressed on the instrument PD and all covariates; however, this is done for specific subsamples rather than for the entire sample. The results of this validity test are reported in Appendix B.1, Tables 9 and 10 for the monitoring regressions, as well as Tables 11 and 12 for the working-from-home regressions. We can see that, in all tables, none of the estimated coefficients for the instrument PD is significantly negative. In fact, the coefficients are either significantly positive or statistically insignificant in all subsamples, which is consistent with the monotonicity assumption.

C. Testing the Exclusion Restriction

Although, as discussed above, the exclusion restriction is an implication of the conditional independence assumption and thus would not need to be tested separately without evidence of violation of the conditional independence assumption, a test is appropriate in our case because we use a binarized treatment variable in our MTE analyses. In this context, Andresen and Huber (2021) show that converting a multivalued endogeneous treatment variable (in our case, ICT^h) to a binary measure (in our case, D^h) violates the exclusion restriction if (a) the instrument affects the multivalued treatment within support areas below and/or above the binarization threshold and (b) such instrument-induced changes in the multivalued treatment affect the outcome variable. The authors show that condition (a) of the violation of the exclusion restriction has testable implications and derive some alternative assumptions to be satisfied in addition to conditional independence and monotonicity. We focus on their Assumption 4 (concentration of compliers at extreme treatment values), according to which all compliers in the population change their treatment from the lowest ($ict_0^h = 0$) to the highest possible treatment value ($ict_1^h = R$) in response to the instrument. This rules out compliers with other treatment margins affected. More formally, Assumption 4 of Andresen and Huber (2021) can be writtten as $I\{ict_1^h \geq r > ict_0^h\} = I\{ict_1^h \geq r^* > ict_0^h\} \, \forall \, r, \, r^* \in \{1, \ldots, R\}$, where I is an indicator function and ict^h is our multivalued treatment variable that is discretely ordered, i.e., $ict^h \in \{0, 1, \ldots, R\}$.[57]

Given conditional independence and monotonicity, a necessary condition for Andresen and Huber's Assumption 4 is that the first stages (complier probabilities) are constant across r. Hence, the hypothesis to be tested is H_0: $\pi_r^h = \pi_{r+1}^h \, \forall \, r < R$, where π_r^h is the first stage effect of our instrument PD on $\Pr(ict^h \geq r)$. H_0 can be tested by making use of a χ^2-test in an equation system in which treatment indicator functions $I\{ict^h \geq r\}$ at different values r are regressed on the instrument PD. If the χ^2-test rejected H_0, this would indicate heterogeneity in the first stage estimates across subgroups, meaning that there would be reason to believe that the exclusion restriction is violated.

Table 13 in Appendix B.1 reports the estimated coefficients $\widehat{\pi}^h$ for the first-stage equation system, where we use the deciles of ict^h as thresholds to create the treatment indicator functions $I\{ict^h \geq r\}$, i.e., $r = ict_{.10}^h, ict_{.20}^h, \ldots, ict_{.90}^h$. Columns (1) and (2) ((3) and (4)) report the estimates for the monitoring (working-from-home) sample, separated for executives and non-executives. In each of the specifications, we see that fixing the threshold for treated and untreated firms at different deciles of ict^h does not change the first-stage effects of PD substantially, which is confirmed by the statistically insignificant test results provided by the χ^2-test on the equality of the first-stage coefficients. We achieve very similar results when we add the monitoring or working-from-home control variables included in X to the model specifications. The most striking difference is that in column (3) the significance level of the coefficients for PD increases when control variables are

[57] Recall that originally ict^h is a percentage ranging between 0 and 100 percent and is thus likely to contain some non-integer values. However, a discretized variable that is ordered, for example, by the deciles of the distribution of ict^h meets the requirements of a discretely ordered multivalued treatment variable.

added to the model.

D. Second-Stage Estimates

The ATE of ICT equipment on monitoring (working from home) can be found in columns (5) and (6) of Table 4 (Table 5). The ATE of ICT equipment on monitoring is positive and highly significant for both executives (6.435) and non-executives (2.794), meaning that switching from the group of technology-averse firms to the group of technology-friendly firms increases monitoring intensity by about 6.44 and 2.79 percent, respectively. In contrast, the corresponding ATE of ICT equipment on working from home is significantly positive only for executives (1.302 standard deviations), while it is insignificant for non-executives (.333 standard deviations). Thus, in terms of statistical significance, the estimated ATE are consistent with the corresponding 2SLS effects displayed in columns (3) and (4) of both tables. With respect to magnitude, however, the ATE deviate to some extent from the respective 2SLS estimates. This can be explained by the fact that the main explanatory variable in the 2SLS models (ICT^h) is continuously scaled, while the treatment variable in the parametric normal MTE models (D^h) is binary. As a consequence, the first stages in the 2SLS models are estimated by OLS, while the parametric normal MTE model uses probit ML estimation in this place.[58]

Of particular interest is another result, according to which the ATE for executives are noticeably larger than the corresponding ATE for non-executives in both the monitoring (6.44 vs. 2.79 percent) and the working-from-home regressions (1.30 vs. .33 standard deviations). Thus, the ICT effect on monitoring is more than twice as high for executives than for non-executives. In the working-from-home case, the ICT effect for executives even exceeds its counterpart for non-executives by a factor of almost 4. Overall, this is a much stronger result than in the 2SLS case, for which we find the larger effect only in the working-from-home regressions.

Columns (5) and (6) of Tables 4 and 5 reveal additional interesting insights with respect to the presence of selection on unobservables and essential heterogeneity. Starting with the monitoring regressions in Table 4, we find that the coefficients of the estimated inverse Mills ratio $\widehat{\lambda}_0^h$ are

[58]Running 2SLS with the binarized treatment variable D^h instead of ICT^h increases the point estimates notably (by a factor of 3 to 4 in absolute terms), thereby causing them to converge in size to their counterparts shown in Tables 4 and 5. In the monitoring (working-from-home) regressions, the point estimates are $\gamma^E = 4.450$, $p = .037$ and $\gamma^{NE} = 3.312$, $p = .002$ ($\gamma^E = 1.661$, $p = .051$ and $\gamma^{NE} = -.059$, $p = .926$), with virtually no change in the significance level. These parameter estimates refute a potential concern, according to which the ATE estimates resulting from the parametric normal MTE model might be driven by collapsing a continuously scaled explanatory variable ICT^h to a binary treatment variable D^h.

positive and highly significant, indicating the relevance of selection on unobservables in the regressions for both employee groups. In addition, we find for both executives and non-executives that $\widehat{\rho}_1^h - \widehat{\rho}_0^h < 0$, indicating essential heterogeneity in the form of positive selection based on unobserved ICT gains. Conversely, in the working-from-home regressions displayed in Table 5, we can confirm the relevance of both selection on unobservables ($\widehat{\lambda}_1^E > 0$) and essential heterogeneity only for the group of executive employees. Unlike the monitoring case, essential heterogeneity appears here in the form of reverse selection based on unobserved gains as $\widehat{\rho}_1^E - \widehat{\rho}_0^E > 0$.

The MTE estimates including the common support areas are plotted separately in Figure 2 for employee monitoring and in Figure 3 for working from home. The light gray error bands correspond to the 90 percent confidence interval, while the dashed line represents the ATE. At first, the figures demonstrate that the propensity score interval indicating common support, i.e., the area of overlaps between treated firms and non-treated firms, is smaller in the executive sample than in the non-executive sample. This applies to both the monitoring and the working-from-home regressions.[59] Nevertheless, in the parametric normal model, the MTE graphs are extrapolated to regions outside the common-support area.

Figure 2 displays the MTE curves for the impact of ICT equipment on centralized monitoring resulting from the parametric normal model, separately for executives and non-executives. The MTE curves illustrate and extend the corresponding tests results on essential heterogeneity (see Table 4 for the test on the significance of $\widehat{\rho}_1^h - \widehat{\rho}_0^h$). Both graphs show a downward-sloping shape of the MTE curve, thus indicating high (low) ICT gains in centralized monitoring in firms with low (high) resistance to high ICT equipment levels. This finding is consistent with the notion of essential heterogeneity in the form of positive selection based on ICT gains, thereby emphasizing the obtained test result, i.e., $\widehat{\rho}_1^h - \widehat{\rho}_0^h < 0$. For the executives, the MTE rank in the statistically significant range ($.01 \leq U_{D^h} \leq .79$) between about 4.86 ($U_{D^h} = .79$) and 15.96 ($U_{D^h} = .01$), with ATE $= 6.44$. The corresponding MTE for the non-executives rank between about 1.74 ($U_{D^h} = 0.69$) and 7.73 ($U_{D^h} = .01$), with ATE $= 2.79$. For both employee groups, we find that the lower the

[59] The common-support graphs per employment group deviate slightly from each other, because the monitoring and working-from-home regressions refer to different panel waves and do not contain the same sets of covariates. For the monitoring regressions on the executive sample, the overlapping propensity scores range between .38 and .82, while for the corresponding non-executive sample the common support area ranges between .12 and .81 (with some interruptions at high and low values). For the working-from-home regressions on the executive sample, the overlapping propensity scores range between .28 and .81 (with a few interruptions at low values), while for the corresponding non-executive sample the common support area ranges between .13 and .79 (also with a few interruptions at high and low values).

Figure 2: Common support and parametric normal MTE model – monitoring

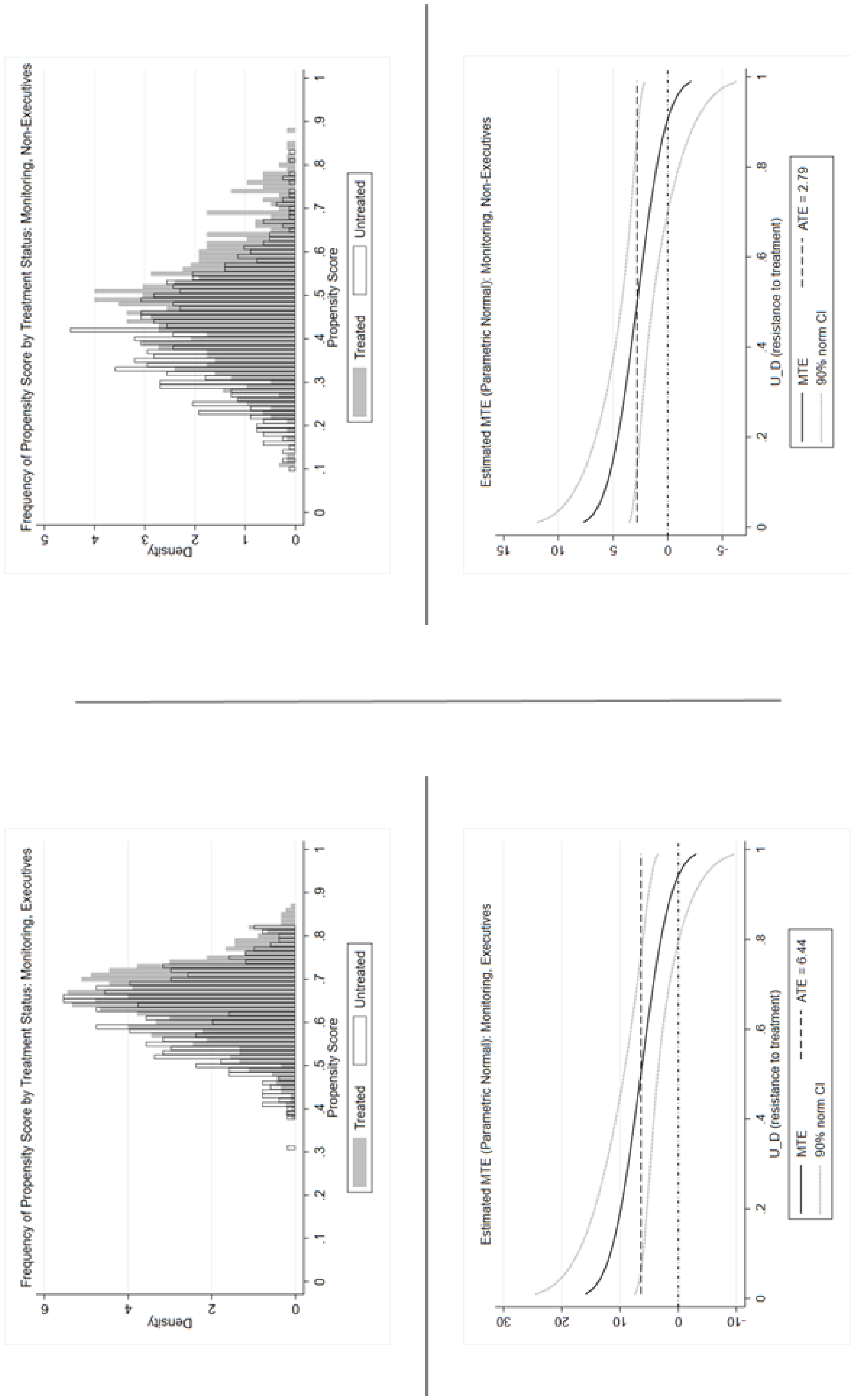
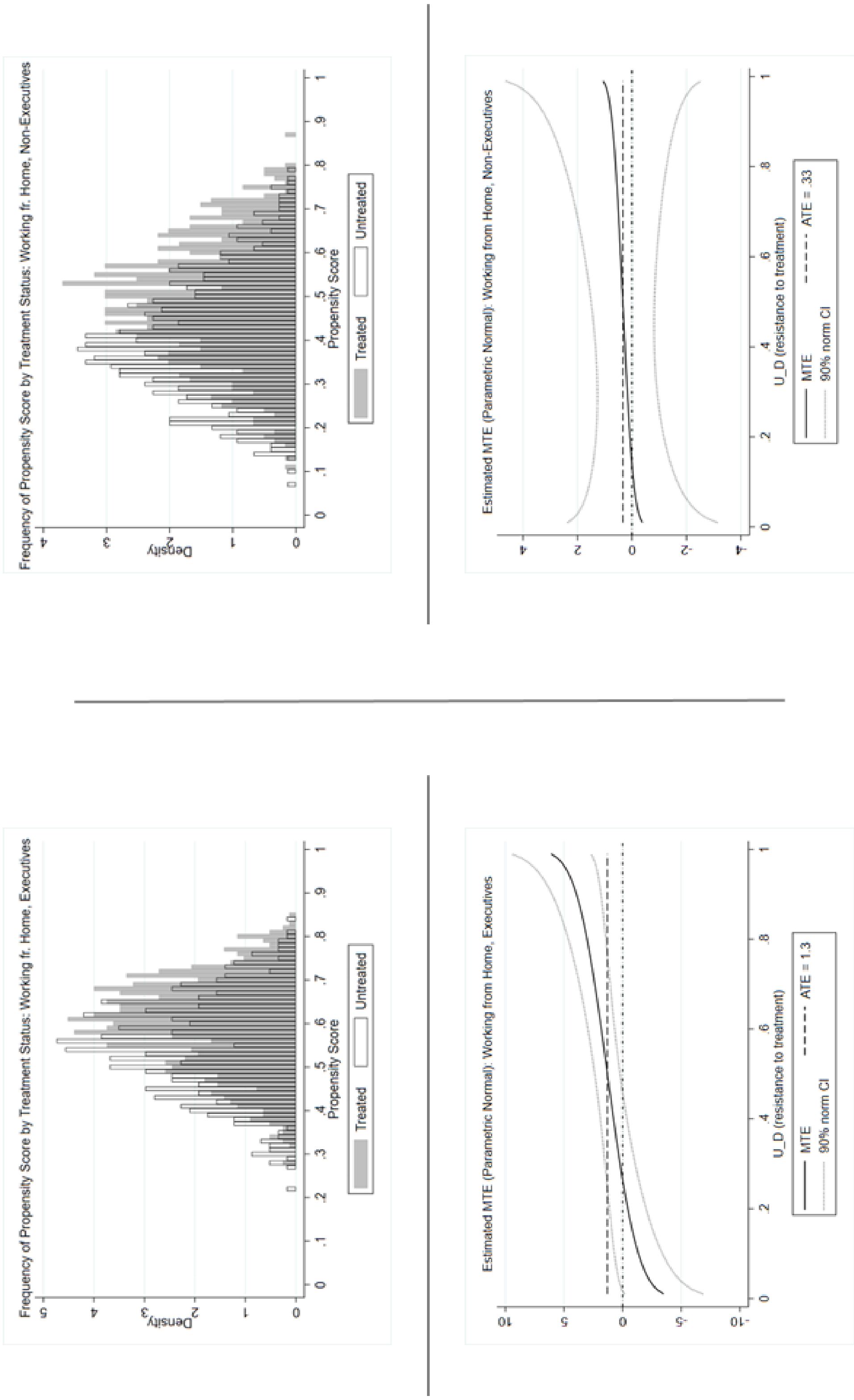


Figure 3: Common support and parametric normal MTE model – working from home



resistance to a high level of ICT equipment, the greater the MTE of ICT equipment on centralized monitoring.

Figure 3 shows the MTE curves for the impact of equipping executives and non-executives with ICT on decentralized autonomy. Both MTE curves exhibit an upward-sloping shape indicating low (high) ICT gains in decentralized autonomy in firms with low (high) resistance to high ICT equipment levels. However, the presence of essential heterogeneity in the form of reverse selection based on ICT gains can only be confirmed for the group of executive employees, which is in line with the corresponding tests on essential heterogeneity mentioned before ($\widehat{\rho}_1^E - \widehat{\rho}_0^E > 0$). Here, the statistically significant MTE range between about 1.19 ($U_{D^h} = .48$) and 6.10 ($U_{D^h} = .99$), with ATE = 1.30. The corresponding MTE for the non-executives range between $-.38$ ($U_{D^h} = .01$) and 1.05 ($U_{D^h} = .99$), with ATE = .33. The MTE for non-executives turn out to be statistically insignificant, with a quite flat MTE curve, thus rejecting the hypothesis of essential heterogeneity in the ICT-effects on decentralized autonomy in the group of non-executive employees.

Comparing the slopes of the MTE curves in the monitoring and working-from-home regressions reveals another interesting implication. For the monitoring case, we find that the MTE of ICT equipment increase with a lower resistance of firms to select themselves into treatment. Conversely, in the working-from-home case, the MTE of ICT equipment increase the more pronounced the resistance of firms to treatment is. This implies that the technology-friendly firms (low U_{D^h}) tend to do a lot of monitoring and grant little autonomy, while the technology-averse firms (high U_{D^h}) grant relatively much autonomy in the form of working from home, but tend to place little emphasis on monitoring. This applies especially for the group of executive employees. On the one hand, we can therefore conclude that firms are indeed adapting their job design in both directions in response to higher ICT equipment, i.e., they are using centralized monitoring and decentralized autonomy as complements. This immediately follows from the positively significant ATE for both monitoring and working from home, representing the ICT-induced effects for the average firm. On the other hand, however, a substitutive use can also be observed. While technology-friendly firms rely on a lot of monitoring with little autonomy, the opposite is true for the technology-averse firms. This additional trade-off between centralized monitoring and decentralized autonomy would have remained undiscovered with the application of 2SLS estimates alone. Overall, we can therefore conclude that our MTE estimations confirm the 2SLS estimates obtained in Subsection 5.2.2 and in some cases deliver valuable additional estimation results.

The MTE results can be summarized as follows. First, in response to increased ICT equipment, firms adapt their job design by increasing both centralized monitoring and decentralized autonomy, which is consistent with our main theoretical result (ii). Second, there are differences across hierarchical levels, meaning that the joint increase in monitoring and autonomy is more pronounced among executives than among non-executives, as the latter only experience closer monitoring and not more working from home in response to more ICT equipment. This finding supports our main theoretical result (i). In addition, the MTE estimates have shown that the ICT-induced monitoring effect for executives is indeed larger than the corresponding effect for non-executives. The observed difference in ICT equipment across hierarchical levels thus entails a conforming difference in the job design of firms. Third, the answer to the question of whether firms use centralized monitoring and decentralized autonomy complementarily or substitutively in response to an increase in ICT equipment depends on the firms' general deployment of technologies. The more technology-friendly (technology-averse) firms are, the more they rely on centralized monitoring (decentralized autonomy). The average firm, on the other hand, uses both job-design policies. Finally, our parametric normal MTE estimates impressively underline the methodological necessity to address not only the conventional endogeneity problem usually associated with ICT use in firms, but also the phenomenon of essential heterogeneity. The MTE estimates provide new information on the existence of treatment heterogeneity and show that technology-friendly and technology-averse firms differ in adapting their job-design policies in response to an increase in ICT equipment.

6 Robustness Checks

In this section, we check the robustness of our baseline regression results obtained in the previous section. We distinguish hereby between content-based and method-based robustness checks.

6.1 Content-Based Robustness Checks

By content-based robustness checks, we mean that we retain the parametric normal MTE estimation method, but make modifications to main variables and samples. Although the 2SLS estimates lead to higher F-statistics that exceed the rule-of-thumb value of 10, we continue our empirical analysis using the MTE estimation approach. By doing so, we address a key methodological issue, according to which 2SLS requires a homogeneous treatment effect for identification of the average treatment effect, while MTE relaxes this assumption. Indeed, since we found evidence of the presence of essential heterogeneity in the previous section, it seems appropriate to conduct the sensitivity analysis using the more informative and flexible MTE method.

We perform the following robustness checks. First, we consider lagged values of our IV PD

instead of the previously used contemporary values. The reason for this modification is to rule out a reverse effect of the endogenous job-design variables JD^h on PD. Second, we clean up the sample by excluding information from districts in which firms are located that are listed on the German stock exchange (DAX-30). This modification follows the intuition that firms with certain patterns of job design may be located in the most economically powerful districts, or may need to adapt more quickly in these districts. In the following, we first explain our approach before discussing the estimation results.[60]

6.1.1 Using Historical Values of Population Density

In this robustness check, the goal is first to learn more about the effect stability of our IV, and second to take more advantage of the linked panel data set by applying historical data to identify a potential reverse effect of job design on the IV. One valuable benefit of the Regional Atlas is that the data for population density can be traced back to 2007. Values on population density can thus be drawn for the respective previous years to the years available in the LPP data set (i.e., 2014, 2016 and 2018). As historical PD, we generate population-density variables for the years 2011, 2013, and 2015 (i.e., PD_{t-3}) and for the years 2007, 2009, and 2011 (i.e., PD_{t-7}). The use of a lagged IV is quite common in the empirical literature (e.g., Möller and Zierer 2018). Moreover, a lagged IV allows us to discover the existence of potential anticipation effects in firms and, if necessary, to learn more about the need to account for these anticipation effects. In this sense, we want to exclude potential reverse effects of job design on the IV. The nature of such reverse effects might originate in a firm's job design, such that a certain job design may attract (deter) people to the district, which then increases (decreases) population density in the district. For example, a firm may adjust its worker autonomy level to improve its corporate image, which in turn may be attractive for more people, and consequently, population density in the district is increasing. The MTE estimates of the monitoring and working-from-home regressions with the inclusion of historical population-density variables can be found in Tables 6 and 7, columns (1) and (2) for PD_{t-3} and columns (3) and (4) for PD_{t-7}.

[60] In a further content-based robustness check, we exclude the variable $WFH^{P,h}$ from the composite variable WFH^h, thereby considering the low relevance of working from home among production jobs. This modification does not change the conclusions drawn in our main specification.

6.1.2 Excluding Potentially Biased Districts

This robustness check refers to the 401 districts in Germany. The aim is to take into account possible selection effects that are due to economically strong districts, in which one of the strongest firms in Germany is located. Our approach follows the intuitive idea that firms with a certain pattern of job design (e.g., high degree of monitoring and working from home) might be located in an economically strong district next to one of the strongest firms in Germany. These firms might have to adapt more quickly in terms of job design than firms in other districts. Potential reasons are a very high competitive pressure or a certain existing pattern of job design in these districts. The selection of such districts is based on our definition of the settlement or location of listed DAX firms in German districts (see Table 17 in Appendix B.2 for more details). Relying on this definition, we remove 17 districts from our MTE models.[61] The removal of these districts leads to a loss in the number of observations from 1,404 to 1,341 for the monitoring regressions and from 1,345 to 1,280 for the working-from-home regressions. The resulting estimates are shown in Tables 6 and 7, columns (5) and (6).

[61] These are Hamburg, Wolfsburg, Bochum, Essen, Düsseldorf, Leverkusen, Bonn, Bad Homburg, Frankfurt am Main, Ludwigshafen, Walldorf, Herzogenaurach, Stuttgart, Munich, Hanover, Heidelberg, and Darmstadt.

Table 6: Content- and method-based robustness checks for the ICT effect on employee monitoring

	Historic PD_{t-3}		Historic PD_{t-7}		Biased districts		CRC model		Semipar. Polyn. MTE	
	MON^E (1)	MON^{NE} (2)	MON^E (3)	MON^{NE} (4)	MON^E (5)	MON^{NE} (6)	MON^E (7)	MON^{NE} (8)	MON^E (9)	MON^{NE} (10)
D^h	8.282***	3.237***	7.416***	2.920***	7.314***	2.765***	6.360***	2.835***	7.675***	3.693***
	(2.193)	(.880)	(1.937)	(.915)	(1.837)	(.856)	(1.364)	(.887)	(1.985)	(1.121)
$\widehat{\lambda}_1^h$	1.627	.714	1.369	.691	1.630	.499				
	(1.532)	(.708)	(1.272)	(.680)	(1.405)	(.747)				
$\widehat{\lambda}_0^h$	6.724***	3.083***	6.036***	2.681***	5.788***	2.705***				
	(1.840)	(.806)	(1.691)	(.820)	(1.554)	(.799)				
$\widehat{v}^h$							−5.139***	−2.511***		
							(1.179)	(.737)		
$D^h \times \widehat{v}^h$							3.941**	1.790**		
							(1.735)	(.796)		
$\widehat{p}^h$									307.605**	−130.189
									(150.879)	(148.943)
$\widehat{p}^{h^2}$									−129.356**	−20.674
									(65.237)	(15.969)
$\widehat{p}^{h^3}$									58.886*	10.890
									(35.653)	(10.787)
Controls	X	X	X	X	X	X	X	X	X	X
							$D^E \times (X - \overline{X})$	$D^{NE} \times (X - \overline{X})$	$X \times \widehat{p}^E$	$X \times \widehat{p}^{NE}$
$\widehat{\rho}_1^h - \widehat{\rho}_0^h$	−5.097**	−2.368**	−4.666**	−1.990**	−4.157**	−2.205**				
	(2.341)	(1.044)	(2.113)	(.979)	(2.085)	(1.113)				
H_0: $\overline{\alpha^E} = \overline{\alpha^{NE}}$							[.014]			
χ^2-test									[.087]	[.392]
N	1,404	1,404	1,395	1,395	1,341	1,341	1,404	1,404	1,404	1,404

Sources. Linked Personnel Panel, employer survey 2016/2018, IAB Establishment Panel 2016/2018, German Federal Statistical Office 2020, BBSR Bonn 2021. Own calculations.
* $p < .10$, ** $p < .05$, *** $p < .01$

Table 7: Content- and method-based robustness checks for the ICT effect on working from home

	Historic PD_{t-3}		Historic PD_{t-7}		Biased districts		CRC model		Semipar. Polyn. MTE	
	WFH^E (1)	WFH^{NE} (2)	WFH^E (3)	WFH^{NE} (4)	WFH^E (5)	WFH^{NE} (6)	WFH^E (7)	WFH^{NE} (8)	WFH^E (9)	WFH^{NE} (10)
D^h	1.289**	.332	1.695**	.642	1.410**	.186	1.570**	.337	2.324***	1.017
	(.651)	(.706)	(.849)	(.715)	(.665)	(.661)	(.703)	(.638)	(.790)	(1.690)
$\widehat{\lambda}_1^h$	1.808***	.158	2.360***	.247	1.429**	.015				
	(.628)	(.638)	(.786)	(.645)	(.597)	(.597)				
$\widehat{\lambda}_0^h$	−.245	−.162	−.199	.148	.156	−.181				
	(.528)	(.481)	(.692)	(.410)	(.480)	(.504)				
$\widehat{v}^h$							−.552	.187		
							(.486)	(.414)		
$D^h \times \widehat{v}^h$							−.574	−.372		
							(.495)	(.773)		
$\widehat{p}^h$									80.160	−16.445
									(74.366)	(98.057)
$\widehat{p}^{h^2}$									−4.867	2.011
									(20.878)	(12.940)
$\widehat{p}^{h^3}$									4.435	2.709
									(11.637)	(9.408)
Controls	X	X	X	X	X	X	X	X	X	X
							$D^E \times (X - \overline{X})$	$D^{NE} \times (X - \overline{X})$	$X \times \widehat{p}^E$	$X \times \widehat{p}^{NE}$
$\widehat{\rho}_1^h - \widehat{\rho}_0^h$	2.054**	.321	2.560**	.099	1.273*	.197				
	(.834)	(.776)	(1.051)	(.703)	(.705)	(.786)				
H_0: $\overline{\alpha^E} = \overline{\alpha^{NE}}$							[.048]			
χ^2-test									[.879]	[.681]
N	1,345	1,345	1,326	1,326	1,280	1,280	1,345	1,345	1,345	1,345

Sources. Linked Personnel Panel, employer survey 2014/2016, IAB Establishment Panel 2014/2016, German Federal Statistical Office 2020, and BBSR Bonn 2021. Own calculations. **Notes.** * $p < .10$, ** $p < .05$, *** $p < .01$

6.1.3 Estimation Results

For both robustness checks, we find that the parameter estimates are very much in line with the results obtained from our baseline parametric normal MTE specifications displayed in columns (5) and (6) of Tables 4 (monitoring regressions) and 5 (working-from-home regressions).[62] This applies to the effect size, the significance level, and the findings on essential heterogeneity. Hence, even after using lagged values of our IV and excluding districts, in which listed DAX firms are located, we find that ICT equipment increases centralized monitoring for both executives and non-executives, while it improves decentralized autonomy only for executives, but not for non-executives. Again, the monitoring effect for executives is much larger than for non-executives. As before, the tests on essential heterogeneity demonstrate that technology-friendly firms increase their monitoring activities for executives at the expense of working from home in response to an increase in ICT equipment, while technology-averse firms react the other way around. Finally, it should be noted that the fact that using lagged values of our IV does not change our baseline MTE results is a further confirmation of the validity of our IV, i.e., the district-level population density PD.

6.2 Method-Based Robustness Checks

In this subsection, we apply two methodological robustness checks to test the vulnerability of our main 2SLS and MTE estimates to alternative estimation strategies. The first approach is a correlated random coefficients (CRC) model, which is sometimes considered an alternative to our IV/2SLS estimation approach discussed in Section 5.2, because, unlike 2SLS, it not only allows us to estimate the ATE but also provides some insights into the pattern of essential heterogeneity (Cornelissen et al. 2016). However, the CRC model is also an interesting alternative to the parametric normal MTE model. As we will see, while the CRC model requires certain linearity assumptions with respect to the reduced-form error term, it does not require the assumption of trivariate normally distributed error terms in the potential outcome and selection models. The second approach is the semiparametric polynomial MTE model, which can be seen as a complement

[62]In this footnote, the notes of Tables 6 and 7 are depicted due to space constraints. In both tables, the IV is PD_{jt-3} in columns (1) and (2), PD_{jt-7} in columns (3) and (4), and PD_j in columns (5) to (10). The set of covariates X is identical to the set applied in the baseline parametric normal MTE estimations (see Tables 4 and 5). The parameter estimates for D^h represent the ATE. The values in parentheses (square brackets) represent bootstrapped standard errors clustered at the firm level (100 replications) to account for the estimated inverse Mills ratios, control functions, and polynomials of the propensity score, respectively (p-values). The bandwidth for the semiparametric polynomial MTE model is .25. The score test is Wooldridge's score test of endogeneity. The χ^2-test is a test on joint significance of $\widehat{p}^{h^2}$ and $\widehat{p}^{h^3}$, providing information on the presence of essential heterogeneity.

to the parametric normal MTE model introduced in Section 5.3. A relative advantage of semiparametric MTE models over their parametric counterparts is that they do not require the assumption of joint normally distributed error terms to identify the MTE. Furthermore, unlike parametric MTE models, semiparametric MTE models do not restrict the MTE curves to be monotonic. On the other hand, however, semiparametric MTE models are more demanding than their parametric counterparts in terms of data. This aspect is important, for example, if the estimation results turn out to be very sensitive to small changes in the data or specification (Cornelissen et al. 2016).

6.2.1 Correlated Random Coefficients Model

The CRC model draws on the observed outcome equation (15) that can be rewritten as

$$JD^h = X\beta_0^h + D^h(X - \overline{X})(\beta_1^h - \beta_0^h) + D^h(U_1^h - U_0^h) + U_0^h \,, \tag{28}$$

where $\overline{X}$ are the sample means of the covariates, which are therefore centered around their respective means. Equation (28) represents a random coefficient model in which the coefficient $\alpha^h = U_1^h - U_0^h$ varies across firms (Cornelissen et al. 2016). After decomposing α^h into its mean $\overline{\alpha^h}$ and the deviation from the mean $\tilde{\alpha}^h = \alpha^h - \overline{\alpha^h}$, equation (28) can be written as

$$JD^h = X\beta_0^h + D^h(X - \overline{X})(\beta_1^h - \beta_0^h) + D^h\overline{\alpha^h} + D^h\tilde{\alpha}^h + U_0^h \,. \tag{29}$$

In this constant coefficient model, centering the covariates around their sample means ensures that $\overline{\alpha^h}$ represents the ATE at means of X (Wooldridge 2015, Cornelissen et al. 2016). If D^h and $\tilde{\alpha}^h$ are positively correlated, the model exhibits selection on unobserved gains, implying that an IV estimation of equation (29) will lead to a biased estimate of the ATE, i.e., $\overline{\alpha^h}$. Equation (29) is referred to as the CRC model (Cornelissen et al. 2016).

Under the assumptions that (i) D^h can be expressed by the reduced form equation (24) and (ii) both sources of unobservables causing selection bias in (29), i.e., U_0^h and $\tilde{\alpha}^h$, are linearly related to the reduced-form error term v^h, so that $E[U_0^h \mid v^h] = \xi^h v^h$ and $E[\tilde{\alpha}^h \mid v^h] = \psi^h v^h$, equation (29) results in

$$E[JD^h \mid X, D^h, v^h] = X\beta_0^h + D^h(X - \overline{X})(\beta_1^h - \beta_0^h) + D^h\overline{\alpha^h} + D^h\psi^h v^h + \xi^h v^h \,. \tag{30}$$

We estimate the parameters of (30) using a control function approach (Wooldridge 2015, Cornelissen et al. 2016). In a first step, we estimate equation (24) by probit ML. From these estimates, we calculate the generalized residuals $\widehat{v}^h = D^h \cdot \widehat{\lambda}^h(Z\zeta^h) - (1 - D^h) \cdot \widehat{\lambda}^h(-Z\zeta^h)$, where

$\widehat{\lambda}^h(Z\zeta^h) = \phi(Z\zeta^h)/\Phi(Z\zeta^h)$ is the estimated inverse Mills ratio. In the second step, we replace v^h in equation (30) by the generalized residual $\widehat{v}^h$ and thus estimate

$$JD^h = X\beta_0^h + D^h \times (X - \overline{X})(\beta_1^h - \beta_0^h) + \overline{\alpha^h} D^h + \psi^h D^h \times \widehat{v}^h + \xi^h \widehat{v}^h + \varepsilon^h \,, \tag{31}$$

where $\widehat{v}^h$ and $D^h \times \widehat{v}^h$ are two control functions included as additional regressors. We can estimate equation (31) by OLS, where $\overline{\alpha^h}$ is the ATE. An estimate of $\xi^h \neq 0$ would indicate the presence of selection on unobservables, while $\psi^h \neq 0$ would indicate selection on unobserved (reversed) gains (Cornelissen et al. 2016), with $\psi^h > 0$ ($\psi^h < 0$) pointing to positive (reversed) gains. The estimates are shown in Tables 6 and 7, columns (7) and (8), for the monitoring and working-from-home regressions, respectively.

6.2.2 Semiparametric Polynomial MTE Model

In addition to the general identifying assumptions described in Section 5.3, semiparametric MTE estimators require an assumption on the support of the estimated propensity score. Specifically, the common support assumption for the propensity score requires the existence of positive frequencies of the estimated propensity score $\widehat{p}^h$ in the range between 0 and 1 for firms that receive treatment ($D^h = 1$) or not ($D^h = 0$). This means that for each X, there must be a treatment group and a control group. Formally, the common support assumption can be expressed as $0 < \Pr(D^h = 1 \,|\, X) < 1$ (Heckman et al. 2006a, Brave and Walstrum 2014). The range of the common support largely depends on the variation in the instrument, meaning that the range over which the MTE can be identified increases with the variation in the instrument (conditional on the included covariates), and thus, the propensity score (Kamhöfer et al. 2019).

In the semiparametric polynomial MTE model, $K(p^h)$ in equation (20) is modelled as a polynomial in the propensity score p^h of degree l. Given an estimate $\widehat{p}^h$, equation (20) then changes to

$$E[JD^h \,|\, X, p^h] = X\beta_0^h + X(\beta_1^h - \beta_0^h)p^h + \sum_{l=1}^{L} \tau_l^h \cdot (p^h)^l \,. \tag{32}$$

The MTE curve for firms with $X = x$ and $U_{D^h} = p^h$ is the partial derivative of equation (32) with respect to p^h, i.e.,

$$\widehat{MTE}_{SP}(x, u_{D^h}) = X(\widehat{\beta_1^h - \beta_0^h}) + \sum_{l=1}^{L} \widehat{\tau}_l^h \cdot l\, (\widehat{p}^h)^{l-1} \,. \tag{33}$$

The MTE (including the ATE) are estimated applying a three-step procedure starting with a probit ML estimation of the reduced form equation (24) to predict the propensity score $\widehat{p}^h = \widehat{D}^h$. In a second step, we run conventional OLS on equation (32) to estimate β_0^h and $(\beta_1^h - \beta_0^h)$. The remaining coefficients of the MTE, i.e., the τ_l^h, are then estimated using local polynomial regressions of $\widehat{JD}^h = JD^h - X\widehat{\beta}_0^h - X(\widehat{\beta_1^h - \beta_0^h})\widehat{p}^h$ on the common support of $\widehat{p}^h$ (Brave and Walstrum 2014).[63]

Equation (32) allows us to test the existence of essential heterogeneity in the context of a semiparametric polynomial MTE model using a test on linearity as developed in Heckman et al. (2006a, 2006b, 2007, 2010). The null hypothesis of this test is $H_0 : \tau_l^h = 0$ for $l = 2, \ldots, L$. Essential heterogeneity is indicated if the test statistic of a χ^2-test on the joint significance of all τ_l^h-parameters except τ_1^h is statistically significant. We fix the degree of the polynomial at $L = 3$. A choice of $L = 2$ would limit the flexibility of the MTE curve, which is then restricted to a straight line. Whether a choice of $L > 3$ is appropriate becomes apparent only after considering the results obtained for $L = 3$.[64] The estimates of the ATE resulting from the semiparametric polynomial MTE model can be found in Tables 6 and 7, columns (9) and (10), for the monitoring and working-from-home regressions, respectively.

6.2.3 Estimation Results

To be clear from the outset, both method-based robustness checks, i.e., the CRC model and the semiparametric polynomial MTE model, support the conclusions resulting from our baseline parametric normal MTE model specifications in the most essential parts, but not in all dimensions. The estimation results for the monitoring regressions are reported in Table 6, columns (7) to (10). They can be summarized as follows. First of all, the test results demonstrate the necessity to account for both endogeneity and essential heterogeneity. In the CRC model, endogeneity is indicated by the highly significant coefficients for the control functions $\widehat{v}^E$ and $\widehat{v}^{NE}$, while essential heterogeneity in the form of positive selection based on unobserved gains is indicated by the significantly positive coefficients of the control functions $D^E \times \widehat{v}^E$ and $D^{NE} \times \widehat{v}^{NE}$. In the semiparametric polynomial model, the χ^2-test on linearity, which is statistically significant in the executives sample, indicates essential heterogeneity. The negative slope over long stretches of U_{D^h} is indicated by the significantly negative parameter estimate of $\widehat{p}^{h^2}$, which, in absolute terms, is

[63] Note that in the case of semiparametric MTE models, the MTE are calculated only at values falling within the common support of the first-stage estimates of the propensity score (Brave and Walstrum 2014).

[64] Apart from setting the degree of the local polynomial, the semiparametric polynomial model allows researchers to make choices on the smoothing of the MTE curve via bandwidths. Setting different bandwidth parameters has also consequences for the magnitude of the ATE to be estimated. We challenged bandwidths ranging between .1 and .5 and choose a medium bandwidth of 0.25. Although we can observe that the effect size of the estimated ATE varies with the choice of bandwidths, we can ascertain that both direction and significance level of the estimated ATE remains stable.

about twice as large as the positive coefficient of $\widehat{p}^{h^3}$.

Second, the ATE of ICT equipment on centralized monitoring is positive and highly significant. This results from both robustness checks and applies to both executive and non-executive employees. Similar to the parametric normal model, the ATE for executives turn out to be about twice as high as the corresponding ATE for non-executives. This results from both the CRC model (6.360 vs. 2.835) and the semiparametric polynomial model (7.675 vs. 3.693). The difference in the ATE for executives and non-executives is statistically significant at the 5 percent level (see the test on $\overline{\alpha^E} = \overline{\alpha^{NE}}$ in column (7), where $p = .014$).

Third, the downward-sloping MTE curves displayed in Figure 4 are consistent with the corresponding MTE curves resulting from the baseline parametric normal model depicted in Figure 2. This applies to both employee groups, although the test on linearity cannot reject the null hypothesis of no essential heterogeneity for the group of non-executives. Both curves have the steepest negative slope in those areas where the MTE are statistically significant, i.e., between $U_{D^E} = .38$ and $U_{D^E} = .65$ for the executives sample, and between $U_{D^{NE}} = .12$ and $U_{D^{NE}} = .52$ for the non-executives sample.[65] These are the areas for firms with a relatively low resistance to treatment, i.e., the technology-friendly firms.[66] At least in this area, essential heterogeneity in the form of positive selection based on unobserved gains is also evident in the sample of non-executives.

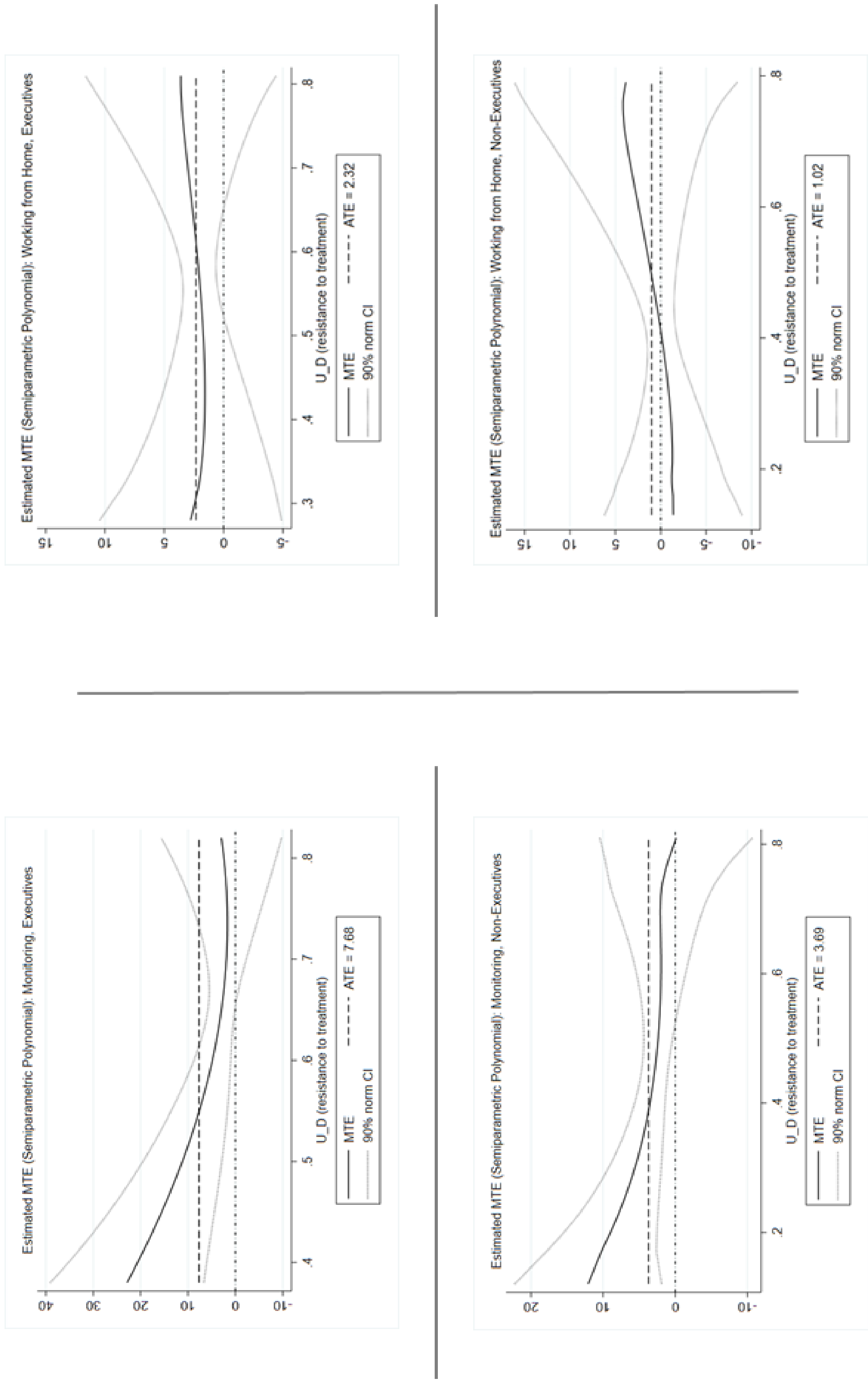
The estimation results for the working-from-home regressions are reported in Table 7, columns (7) to (10). They can be summarized as follows. First, in line with the corresponding parametric normal estimates displayed in Table 5, we also find no evidence for both endogenity and essential heterogeneity here. This applies to both the CRC model and the semiparametric polynomial model.

Second, the ATE of ICT equipment on working from home is positive and highly significant only in the group of executive employees. As a consequence, the ATE for executives is appreciably higher than the corresponding ATE for non-executives (1.570 vs. .337 in the CRC model, 2.324 vs. 1.017 in the semiparametric polynomial model). According to the test on $\overline{\alpha^E} = \overline{\alpha^{NE}}$ in column (7), the difference in the ATE for executives and non-executives is statistically significant at the 5 percent level ($p = .048$). Third, both MTE curves for executives and non-executives show a positive slope, which is relatively flat so that in both cases the null hypothesis of no essential heterogeneity cannot

[65]Unlike in our baseline parametric normal model, in which the MTE graphs are extrapolated to regions outside the common-support area, in the semiparametric polynomial model the MTE are identified only for the observations within the common support.

[66]In the statistically insignificant areas, both MTE curves are flatter and even show a non-monotonic course. The possibility of achieving a non-monotonic course of the MTE curve is often seen as a relative advantage of a semiparametric MTE estimation compared to a parametric MTE estimation.

Figure 4: Semiparametric polynomial MTE model – monitoring and working from home



be rejected (not even in the statistically significant region of the MTE curve for the executives between $U_{D^E} = .52$ and $U_{D^E} = .65$). This was different in our baseline parametric normal model for the group of executives.

Overall, the results of our method-based robustness checks are largely consistent with our baseline parametric normal MTE estimates. In addition, we see that essential heterogeneity is not detectable in all specifications. However, essential heterogeneity is visible in the monitoring regressions and here especially for the technology-friendly firms. The only result from our baseline models that we cannot fully maintain through our method-based robustness checks concerns the ICT-induced use of centralized monitoring and decentralized autonomy as substitutive job-design practices, depending on a firm's degree of technology deployment. Apart from that, our previous results continue to hold. Hence, equipping employees with ICT has different effects across hierarchical levels (main result (i) in our theoretical model) and across the two measures of job design, i.e., decentralized autonomy and centralized monitoring (main result (ii)).

7 Human Capital and ICT Equipment

In this section, we intend to shed more light on the driving force for the differences in ICT equipment between executive and non-executive employees. In our theoretical model, we find that it is more profitable for firms to equip their executives with ICT rather than their non-executives (see result (a) of Proposition 2). The reason for this preferential treatment of executives is a superior endowment of general or industry-specific human capital that improves the internal productivity and the outside options (reservation values) of executives relative to non-executives.

In the following, we translate the theoretical prediction into an econometric model by regressing the known ICT variables ICT_i^h on a set of variables that express the superior quality of human capital and, at the same time, provide indications of effective outside options. The variables in question are district-level measures on open job positions for certain types of skilled labor, i.e., experts (EXP_j) and trained professionals ($PROF_j$).[67] An increase in open job positions in district j for these employees would indicate an increase in the labor demand for these employees and, therefore, an increase in their reservation value. Following this argument and the result (a) of Proposition 2, we expect that, with increasing shares of open job positions for skilled labor, only the share of ICT equipment for executive employees is increasing. The corresponding regression

[67] We have already used these variables as control variables in our 2SLS and MTE analyses to ensure conditional IV independence.

model can be specified as

$$ICT_i^h = \varphi_1^h EXP_j + \varphi_2^h PROF_j + X_i \beta^h + \varepsilon_i^h \,, \tag{34}$$

where EXP_j captures the share of vacancies for employees with at least four years of higher education or equivalent work experience measured against all vacant job positions, and $PROF_j$ is the percentage of open job positions for employees with at least two years of vocational training or comparable qualifications. Hence, the two explanatory variables map both employee skills and outside options for employees at the district level j. As in Section 5.1.1, we follow the three-legged-stool approach of organizational architecture developed in Brickley et al. (2021, chapter 11) for the choice of control variables. We extend this set of covariates with dummy variables measuring those dimensions of monitoring and autonomy with which we constructed the dependent variables of our baseline estimation models (see Sections 4.2 and 4.3).

Consistent with our theoretical model, we expect $\varphi_1^h > 0$ and $\varphi_2^h > 0$ if $h = E$, but no significant relationships with the dependent ICT variable if $h = NE$. Since dependent and main explanatory variables come from different data sets, one of which is at the firm level i and the other at the district level j, we assume that the district-level variables EXP_j and $PROF_j$ contain exogenous variation, so we can estimate equation (34) with conventional OLS. Apart from this, focusing on causality is not compelling at this stage of our analysis.[68]

The estimation results of equation (34) are displayed in Table 8. Here, we can actually see that in the specification for executive employees both coefficients $\widehat{\varphi}_1^E$ and $\widehat{\varphi}_2^E$ exhibit the expected positive sign and are highly statistically significant. An F-test of joint significance of φ_1^E and φ_2^E confirms the relevance of human capital and outside options in determining ICT equipment for executive employees. The F-statistic is highly significant ($F = 4.89$, $p = .007$). On the contrary, neither $\widehat{\varphi}_1^{NE}$ nor $\widehat{\varphi}_2^{NE}$ turns out to be statistically significant in the specification for non-executive employees. In addition, the F-test does not reject the null hypothesis of joint insignificance ($F = 1.14$, $p = .319$). Hence, equipping non-executive employees with ICT does not depend on the human capital and outside options for employees categorized as experts or trained professionals.[69] Finally, a χ^2-test on the equality of coefficients between the two groups of employees, i.e., $\widehat{\varphi}_m^E = \widehat{\varphi}_m^{NE}$, $(m = 1, 2)$, also rejects the null hypothesis of equal coefficients in both cases ($\chi^2 = 3.49$, $p = .061$ and $\chi^2 = 9.93$, $p = .001$). This result is another confirmation of our

[68] In contrast to the 2SLS and MTE models, where we could only use two panel waves due to data availability, we can use data from all three panel waves to estimate equation (34).

[69] For non-executives, other factors could play a role in equipping them with ICT, such as an increasing need for cooperation among non-executives (Gerten 2022).

Table 8: Human capital, outside options, and ICT equipment

	OLS	OLS	
	ICT^E	ICT^{NE}	H_0: $\varphi_m^E = \varphi_m^{NE}$
	(1)	(2)	(3)
EXP	.039***	.012	3.49*
	(.014)	(.014)	[.061]
$PROF$	.028***	$-.007$	9.93***
	(.010)	(.010)	[.001]
Controls	X_{OA}	X_{OA}	
F-test on joint significance of φ_1^h and φ_2^h	4.89***	1.14	
	[.007]	[.319]	
R^2	.145	.177	
N	1,884	1,884	

Sources. Linked Personnel Panel, employer survey 2014/2016/2018, IAB Establishment Panel 2014/2016/2018, German Federal Statistical Office 2020, and BBSR Bonn 2021. Own calculations.

Notes. The values in parentheses (square brackets) represent cluster-robust standard errors (p-values). The standard errors are clustered at the firm level to allow for correlation within panel units over time (intragroup correlation). The test on $\varphi_m^E = \varphi_m^{NE}$ is a χ^2-test. The set of covariates X_{OA} refers to the three-legged-stool approach of organizational architecture developed in Brickley et al. (2021, chapter 11) and contains the firm-level variables introduced in Subsection 5.1.1, extended with dummy variables measuring certain dimensions of employee monitoring and autonomy.

* $p < .10$, ** $p < .05$, *** $p < .01$.

main result in this section, according to which firms prefer to equip executives with ICT, because executives are better endowed with human capital and have better outside options compared to non-executives.

8 Conclusion

Advances in information and communication technology (ICT) have led to changes in firms' optimal job design in the last decades. A still open question is whether these changes ended up in a more centralized or in a more decentralized job design. The previous literature on this topic is typically based on the strict dichotomy that ICT will lead *either* to more centralization *or* to more decentralization in firms, where the vast majority of empirical studies finds evidence consistent with an increase in decentralization. Our paper contributes to this debate by using both a theoretical setting and an empirical approach to allow for a possible deviation from this dichotomy.

To measure centralized and decentralized job-design policies, we consider employee monitoring and autonomy at the workplace. Hence, a more centralized job design is reflected by a high degree of monitoring, whereas decentralization is characterized by a high degree of autonomy. Our theoretical and empirical analyses yield the same main findings. Concerning non-executive employees, increasing ICT equipment in firms leads to clear centralization of job design. However, concerning executive employees, our results disagree with the strict dichotomous view outlined above: increasing ICT equipment yields more decentralized autonomy, but also more centralized monitoring. On the one hand, firms empower executive employees to better use their decentralized information, but, on the other hand, complement empowerment with more intense monitoring (e.g., in combination with higher-powered incentives) to prevent a possible loss of control.

In the theoretical part of our paper, we extend a principal-agent hidden-action model by a firm's choice of ICT equipment. Compared to non-executives, executive employees are more productive in terms of higher human capital and are characterized by a higher reservation value, reflecting their better outside options in the labor market. As mentioned above, both types of employees face larger centralized monitoring when being equipped with more ICT, but crucially differ concerning the degree of decentralized autonomy. The fact that executive employees, contrary to non-executives, are granted more autonomy as a consequence of increased ICT can be explained by two effects. First, productivity gains by autonomy and positive productivity effects due to higher human capital are complements, which favors the equipment of executives with ICT. Second, only the executives' participation constraint is binding under the optimal incentive contract. Thus, granting executives autonomy relaxes their participation constraint via better work-life balance, which lowers the firms' labor costs when employing executive employees.

Our empirical analysis uses the employer survey of the Linked Personnel Panel and the IAB Establishment Panel of the years 2014 to 2018 for about 700 establishments in each wave across Germany. Methodologically, we rely on 2SLS and marginal treatment effects (MTE) estimation methods to establish a causal interpretation of our results and to make conclusions about potential effect heterogeneity. Inspired by some recent empirical studies providing insights of how to instrument ICT appropriately, our instrumental variable exploits geographic variation by making use of information on population density at the district-level.

Analyzing the data reveals some important findings. First, in firms, not all employee groups are equally affected by an adaptation of the job design in response to increased ICT equipment. While executives experience both more centralized monitoring and more decentralized autonomy, non-executives only experience an increase in centralized monitoring, but not in decentralized autonomy. Second, our empirical results clearly point to a joint increase in centralized monitoring and decentralized autonomy induced by ICT, implying that both job-design practices coexist in firms in a complementary way. This is at least true for employees at higher hierarchical levels, i.e., executive employees. While both results are obtained for the average firm, our analysis of the MTE curves reveals an additional finding that refers to firms located at opposite edges of the technological frontier. Specifically, technology-friendly firms respond to an increase in ICT equipment with more centralized monitoring and less decentralized autonomy, while the opposite is true for technology-averse firms. Hence, firms at the edges of the technological frontier adapt their job design in the sense of a substitutive use of centralized monitoring and decentralized autonomy. However, this result applies even more to executives than to non-executives, depends to some extent on the applied estimation strategy, and is not as robust as the other results obtained in our empirical analysis.

In studying our paper, the reader may wonder whether the strong ICT effects on centralized monitoring compared to the corresponding effects on decentralized autonomy might perhaps be driven by the fact that we can use three performance evaluation variables to construct our centralized monitoring variable, but only one working-from-home variable to construct the decentralized autonomy variable. Another concern could be related to the different scaling of the monitoring and autonomy variables, which makes it difficult to compare the ICT effects on centralized monitoring and decentralized autonomy in terms of magnitude. In order to address these potential concerns, we re-run both our 2SLS and MTE regressions with two modifications. First, we standardized each of the three monitoring variables, i.e., appraisal interviews, target agreements, and performance evaluations, to establish comparability with the likewise standardized working-from-home variable. Second, we regressed each standardized monitoring variable on the respective ICT variable (in continuous and binarized form) and estimated both the 2SLS and the MTE effects. The results are unambiguous and apply equally to the 2SLS and MTE estimates. Except for a positive but statistically insignificant ICT effect on target agreements in the group of non-executives, all other monitoring effects turn out to be positive and (highly) significant. Moreover, within both employee groups, the respective monitoring effect is always (significantly) larger than the corresponding working-from-home effect. This is especially true for the ATE resulting from MTE estimation. Hence, as a side result of our empirical analysis, we find evidence that ICT promotes centralized monitoring more than decentralized autonomy. However, we do not want to overemphasize this result and claim that the effects of ICT on centralized monitoring are always larger than on decentralized autonomy. For this, we lack further autonomy variables, e.g., on the share of executives and non-executives with self-managed working time. What we can definitely say, however, is that more ICT leads to more centralized monitoring throughout the organization, whereas firms allow more autonomy to benefit only a part of the workforce, namely those employees at higher hierarchical levels.

In this sense, our theoretical and empirical analysis also provides an update of previous studies that associate higher ICT use in firms mainly with more decentralization (e.g., Caroli and Van Reenen 2001, Bresnahan et al. 2002, Acemoglu et al. 2007). Seemingly, companies are focusing more on centralization in times of digital transformation than on decentralization. Our study can confirm this, at least for the job design of organizations.

Although our paper emphasizes the importance of hierarchical levels to explain the heterogeneity in job-design practices, there is another interesting area of future research by investigating whether the difference in the inter-hierarchical ICT-equipment shares itself has a causal impact on job design or productivity. In this paper, we estimated the effects of ICT equipment on job design among executive and non-executive employees in separate regression models. Yet another effect of ICT equipment on job design or productivity may appear through analyzing the impact of the difference in ICT equipment between executives and non-executives. Based on our findings, another research question could be to analyze the role of centralized (decentralized) job design in a decentralized (centralized) organizational structure.

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Appendix A

Proof of Proposition 1. The proof proceeds similar to the one of Proposition 1 in Kräkel and Schöttner (2010). By replacing $w(\bar{s}) - w(\underline{s})$ with $c'(e)$ according to (3), the corresponding Lagrangian to the firm's problem reads as

$$\begin{aligned}\mathcal{L}(w(\underline{s}), w(\bar{s})) = {} & k(1+rI)(1+aA)\,y(e)\,M - w(\underline{s}) - e \cdot c'(e) \\ & - I \cdot \kappa - \left(K - \Delta K \cdot I + \Delta \hat{K} \cdot A\right) \\ & + \lambda_1 \cdot [w(\underline{s}) + e \cdot c'(e) + \Delta u \cdot A - c(e) - \bar{u}] + \lambda_2 \cdot w(\underline{s})\end{aligned}$$

with $\lambda_1, \lambda_2 \geq 0$ as multipliers satisfying

$$\lambda_1 \cdot [w(\underline{s}) + ec'(e) + \Delta uA - c(e) - \bar{u}] = 0 \quad \text{ and } \quad \lambda_2 \cdot w(\underline{s}) = 0. \tag{35}$$

According to (3), e is a function of $w(\underline{s})$ and $w(\bar{s})$ with

$$\frac{\partial e}{\partial w(\underline{s})} = -\frac{1}{c''(e)} = -\frac{\partial e}{\partial w(\bar{s})}. \tag{36}$$

The first-order conditions yield

$$\begin{aligned}\frac{\partial \mathcal{L}}{\partial w(\underline{s})} = {} & k(1+rI)(1+aA)\,y'(e)\,M\frac{\partial e}{\partial w(\underline{s})} - 1 - [c'(e) + e \cdot c''(e)]\frac{\partial e}{\partial w(\underline{s})} \\ & + \lambda_1 \cdot \left[1 + [c'(e) + e \cdot c''(e)]\frac{\partial e}{\partial w(\underline{s})} - c'(e)\frac{\partial e}{\partial w(\underline{s})}\right] + \lambda_2 = 0 \\ \Leftrightarrow {} & [k(1+rI)(1+aA)\,y'(e)\,M - c'(e) + (\lambda_1 - 1)\,ec''(e)]\frac{\partial e}{\partial w(\underline{s})} = 1 - \lambda_2 - \lambda_1\end{aligned}$$

and

$$\frac{\partial \mathcal{L}}{\partial w(\bar{s})} = [k(1+rI)(1+aA)\,y'(e)\,M - c'(e) + (\lambda_1 - 1)\,ec''(e)]\frac{\partial e}{\partial w(\bar{s})} = 0.$$

From (36), it follows that $1 = \lambda_2 + \lambda_1$. Hence, (35) implies that either (i) only the limited-liability constraint $w(\underline{s}) \geq 0$ (LLC) is binding ($\lambda_1 = 0, \lambda_2 = 1$), or (ii) both LLC and the participation constraint (PC) are binding ($\lambda_1, \lambda_2 > 0$), or (iii) only the PC is binding ($\lambda_1 = 1, \lambda_2 = 0$).

First, consider case (i). Here, $w(\underline{s}) = 0$ and the employee earns a positive rent. Optimal effort $e^*_{(i)}$ is implicitly described by

$$k(1+rI)(1+aA)\,y'(e^*_{(i)})M = c'(e^*_{(i)}) + e^*_{(i)} \cdot c''(e^*_{(i)}), \tag{37}$$

and the firm's expected profit is given by

$$k(1+rI)(1+aA)\,y(e^*_{(i)})M - e^*_{(i)} \cdot c'(e^*_{(i)}) - \left(K - \Delta K \cdot I + \Delta \hat{K} \cdot A\right) - I \cdot \kappa.$$

The non-binding PC implies

$$\bar{u} - \Delta u \cdot A < e^*_{(i)} \cdot c'(e^*_{(i)}) - c(e^*_{(i)}).$$

Next, we turn to case (ii). Again, the LLC is binding – i.e., $w(\underline{s}) = 0$ – but now the employee does not earn a positive rent. Optimal effort $e^*_{(ii)}$ is implicitly described by the binding PC:

$$-e^*_{(ii)} \cdot c'(e^*_{(ii)}) = \Delta u \cdot A - c(e^*_{(ii)}) - \bar{u}. \tag{38}$$

Inserting into the firm's objective function yields optimal profit

$$\begin{aligned}&k(1+rI)(1+aA)\,y(e^*_{(ii)})M - c(e^*_{(ii)})\\ &-\left(K - \Delta K \cdot I + \Delta\hat{K} \cdot A\right) - I \cdot \kappa - (\bar{u} - \Delta u \cdot A).\end{aligned}$$

Finally, case (iii) is considered. As $\lambda_1 = 1$ and $\lambda_2 = 0$, the firm implements effort $e^*_{(iii)}$ being implicitly described by

$$k(1+rI)(1+aA)\,y'(e^*_{(iii)})M = c'(e^*_{(iii)}), \tag{39}$$

leading – together with the binding PC – to expected firm profit

$$\begin{aligned}&k(1+rI)(1+aA)\,y(e^*_{(iii)})M - c(e^*_{(iii)})\\ &-\left(K - \Delta K \cdot I + \Delta\hat{K} \cdot A\right) - I \cdot \kappa - (\bar{u} - \Delta u \cdot A).\end{aligned}$$

As $w(\underline{s}) + e^*_{(iii)} \cdot c'(e^*_{(iii)}) + \Delta u \cdot A - c(e^*_{(iii)}) = \bar{u}$ and $w(\underline{s}) > 0$, we obtain

$$\bar{u} - \Delta u \cdot A > e^*_{(iii)} \cdot c'(e^*_{(iii)}) - c(e^*_{(iii)}).$$

Now, we can rank the implemented efforts for the three cases. Compare (37) with (39). As $e^*_{(i)} \cdot c''(e^*_{(i)})$ is strictly increasing in $e^*_{(i)}$, and $y'(\cdot)$ is a strictly decreasing function, we must have that $e^*_{(i)} < e^*_{(iii)}$. Next, we can rank all three efforts. Solving $\partial\mathcal{L}/\partial w(\bar{s}) = 0$ in case (ii) for the multiplier λ_1 gives

$$\lambda_1 = 1 - \frac{k(1+rI)(1+aA)\,y'(e^*_{(ii)})M - c'(e^*_{(ii)})}{e^*_{(ii)}c''(e^*_{(ii)})}. \tag{40}$$

As $1 = \lambda_2 + \lambda_1$ and $\lambda_1, \lambda_2 > 0$ together imply that $\lambda_1 < 1$, we must have that

$$k(1+rI)(1+aA)\,y'(e^*_{(ii)})M - c'(e^*_{(ii)}) > 0.$$

Due to the strict concavity of the function $k(1+rI)(1+aA)\,y(e)M - c(e)$, this inequality yields $e^*_{(ii)} < e^*_{(iii)}$. From (40) and $\lambda_1 > 0$ we obtain

$$k(1+rI)(1+aA)\,y'(e^*_{(ii)})M - c'(e^*_{(ii)}) - e^*_{(ii)}c''(e^*_{(ii)}) < 0. \tag{41}$$

As $k\,(1+rI)\,(1+aA)\,y\,(e)\,M - e\cdot c'\,(e)$ is a strictly concave function with a maximum at

$$k\,(1+rI)\,(1+aA)\,y'\,(e)\,M - c'\,(e) - e\cdot c''\,(e) = 0,$$

(37) and (41) together yield $e^*_{(ii)} > e^*_{(i)}$. To sum up, we have $e^*_{(iii)} > e^*_{(ii)} > e^*_{(i)}$.

Note that because of the effort ranking and because (38) can be rewritten as $\bar{u} - \Delta u \cdot A = e^*_{(ii)} \cdot c'(e^*_{(ii)}) - c(e^*_{(ii)})$, in case (ii) we have

$$e^*_{(i)} \cdot c'(e^*_{(i)}) - c(e^*_{(i)}) < \bar{u} - \Delta u \cdot A < e^*_{(iii)} \cdot c'(e^*_{(iii)}) - c(e^*_{(iii)}).$$

Proof of Proposition 2. (a) Applying the envelope theorem to (5)–(7) yields

$$\frac{\partial}{\partial I}\Pi_C\,(I,A,M) = kr\,(1+aA)\,y(e^*_C)M + \Delta K - \kappa \tag{42}$$

for $C = (i),(ii),(iii)$. As $e^*_{(i)} < e^*_{(ii)} < e^*_{(iii)}$, we obtain the ranking of the $\frac{\partial}{\partial I}\Pi_C\,(I,A,M)$ as stated in the proposition. Differentiating (42) with respect to k leads to $\frac{\partial^2}{\partial I \partial k}\Pi_C\,(I,A,M) = r\,(1+aA)\,y(e^*_C)M$, which is strictly positive.

(b) Let $e^*_C\,(M) := e^*_C$ denote the implemented effort level under the optimal contract in case $C = (i)\,,(ii)\,,(iii)$, given the monitoring intensity M. Then,

$$\begin{aligned}\Delta\Pi_{(i)}(I,A) = {}& k\,(1+rI)\,(1+aA)\left[y(e^*_{(i)}\,(M_H))M_H - y(e^*_{(i)}\,(M_L))M_L\right] \\ & - \left[e^*_{(i)}\,(M_H)\cdot c'(e^*_{(i)}\,(M_H)) - e^*_{(i)}\,(M_L)\cdot c'(e^*_{(i)}\,(M_L))\right] - \left[K_H - K_L\right].\end{aligned}$$

By applying again the envelope theorem, we obtain

$$\frac{\partial}{\partial I}\Delta\Pi_{(i)}(I,A) = kr\,(1+aA)\left[y(e^*_{(i)}\,(M_H))M_H - y(e^*_{(i)}\,(M_L))M_L\right],$$

which is positive as $M_H > M_L$ and

$$\frac{\partial e^*_{(i)}\,(M)}{\partial M} = -\frac{k(1+rI)(1+aA)y'(e^*_{(i)})}{k(1+rI)(1+aA)y''(e^*_{(i)})M - 2c''(e^*_{(i)}) - e^*_{(i)}c'''(e^*_{(i)})} > 0.$$

The relative gains from higher monitoring in the second case are given by

$$\begin{aligned}\Delta\Pi_{(ii)}(I,A) = {}& k\,(1+rI)\,(1+aA)\left[y(e^*_{(ii)}\,(M_H))M_H - y(e^*_{(ii)}\,(M_L))M_L\right] \\ & - \left[c(e^*_{(ii)}\,(M_H)) - c(e^*_{(ii)}\,(M_L))\right] - \left[K_H - K_L\right]\end{aligned}$$

with

$$\frac{\partial}{\partial I}\Delta\Pi_{(ii)}(I,A) = kr\,(1+aA)\left[y(e^*_{(ii)}\,(M_H))M_H - y(e^*_{(ii)}\,(M_L))M_L\right] > 0$$

as $M_H > M_L$ and $e^*_{(ii)}$ is independent of M. Finally, for the third case, we obtain

$$\Delta\Pi_{(iii)}(I,A) = k\,(1+rI)\,(1+aA)\left[y(e^*_{(iii)}\,(M_H))M_H - y(e^*_{(iii)}\,(M_L))M_L\right] \\ - \left[c(e^*_{(iii)}\,(M_H)) - c(e^*_{(iii)}\,(M_L))\right] - [K_H - K_L]$$

with

$$\frac{\partial}{\partial I}\Delta\Pi_{(iii)}(I,A) = kr\,(1+aA)\left[y(e^*_{(iii)}\,(M_H))M_H - y(e^*_{(iii)}\,(M_L))M_L\right] > 0$$

as

$$\frac{\partial e^*_{(iii)}\,(M)}{\partial M} = -\frac{k\,(1+rI)\,(1+aA)\,y'(e^*_{(iii)})}{k\,(1+rI)\,(1+aA)\,y''(e^*_{(iii)})M - c''(e^*_{(iii)})} > 0.$$

(c) Define $e^*_C\,(A) := e^*_C$ as the implemented effort level in case $C = (i)\,,(ii)\,,(iii)$, given the firm's autonomy decision $A \in \{0,1\}$. Then, the relative autonomy gains in the first case can be written as

$$\Delta\Pi_{(i)}\,(I,M) = k\,(1+rI)\,M\left[(1+a)\,y(e^*_{(i)}\,(1)) - y(e^*_{(i)}\,(0))\right] \\ - \left[e^*_{(i)}\,(1)\cdot c'(e^*_{(i)}\,(1)) - e^*_{(i)}\,(0)\cdot c'(e^*_{(i)}\,(0))\right] - \Delta\hat{K}.$$

According to the envelope theorem, we obtain

$$\frac{\partial}{\partial I}\Delta\Pi_{(i)}\,(I,M) = krM\left[(1+a)\,y(e^*_{(i)}\,(1)) - y(e^*_{(i)}\,(0))\right],$$

which is positive as $a > 0$ and $e^*_{(i)}\,(1) > e^*_{(i)}\,(0)$. The relative autonomy gains in the second case are given by

$$\Delta\Pi_{(ii)}\,(I,M) = k\,(1+rI)\,M\left[(1+a)\,y(e^*_{(ii)}\,(1)) - y(e^*_{(ii)}\,(0))\right] \\ - \left[c(e^*_{(ii)}\,(1)) - c(e^*_{(ii)}\,(0))\right] - \Delta\hat{K} + \Delta u$$

with

$$\frac{\partial}{\partial I}\Delta\Pi_{(ii)}\,(I,M) = krM\left[(1+a)\,y(e^*_{(ii)}\,(1)) - y(e^*_{(ii)}\,(0))\right].$$

As $a > 0$ but $e^*_{(ii)}\,(1) = R^{-1}(\bar{u} - \Delta u) < R^{-1}(\bar{u}) = e^*_{(ii)}\,(0)$ because $R' > 0$, the derivative $\frac{\partial}{\partial I}\Delta\Pi_{(ii)}\,(I,M)$ will be positive if and only if a is sufficiently large compared to Δu. Finally, in the third case,

$$\Delta\Pi_{(iii)}\,(I,M) = k\,(1+rI)\,M\left[(1+a)\,y(e^*_{(iii)}\,(1)) - y(e^*_{(iii)}\,(0))\right] \\ - \left[c(e^*_{(iii)}\,(1)) - c(e^*_{(iii)}\,(0))\right] - \Delta\hat{K} + \Delta u$$

with

$$\frac{\partial}{\partial I}\Delta\Pi_{(iii)}(I,M) = krM\left[(1+a)\,y(e^*_{(iii)}(1)) - y(e^*_{(iii)}(0))\right] > 0$$

as as $a > 0$ and $e^*_{(iii)}(1) > e^*_{(iii)}(0)$.

(d) The claim immediately follows from the inspection of (5)–(7).

Appendix B

B.1 Additional Regression Results

Table 9: Tests for the monotonicity assumption - monitoring regressions, executives

	$\widehat{p}^E_{25}$	$\widehat{p}^E_{50}$	$\widehat{p}^E_{75}$	$\widehat{p}^E_{100}$	Firm size 1	Firm size 2	Firm size 3	Firm size 4	Sector 1	Sector 2
PD	.140	.190	.239	−.057	.178***	.068	.090	−.074	.047	.078
	(.100)	(.161)	(.188)	(.107)	(.069)	(.070)	(.107)	(.136)	(.079)	(.098)
N	351	351	351	348	538	486	238	142	419	371
	Sector 3	Sector 4	Sector 5	Firm founded 1990 or later		Year 2016		Tech status		Pressure 1
				yes	no	yes	no	high	low	
PD	.030	.177*	.250**	.132**	.055	.093*	.101*	.080	.140*	.158
	(.106)	(.106)	(.108)	(.060)	(.063)	(.051)	(.061)	(.050)	(.076)	(.100)
N	239	215	160	659	745	747	657	979	425	207
	Pressure 2	Pressure 3	Performance pay plan		Insolvencies rate		Business registration rate		Unemployment rate	
			yes	no	high	low	high	low	high	low
PD	.084	.099	.066	.124**	.110*	.108*	−.007	.160**	.166***	.060
	(.070)	(.161)	(.057)	(.063)	(.060)	(.163)	(.061)	(.063)	(.061)	(.068)
N	517	680	805	599	694	710	700	704	672	732

Sources. Linked Personnel Panel, employer survey 2014/2016, IAB Establishment Panel 2014/2016, German Federal Statistical Office 2020, and BBSR Bonn 2021. Own calculations. **Notes.** The values in parentheses represent robust standard errors clustered at the firm level. $\widehat{p}^E_{25}$, $\widehat{p}^E_{50}$, $\widehat{p}^E_{75}$, and $\widehat{p}^E_{100}$ denote the 1st, 2nd, 3rd, and 4th quartile of the estimated propensity score. Firm size 1 denotes firms with less than 100 employees, firm size 2 firms with 100-249 employees, firm size 3 firms with 250-499 employees, and firm size 4 firms with 500 and more employees. Sector 1: manufacturing, Sector 2: metal, electronics, vehicle manufacturing, Sector 3: trade, transport, news, Sector 4: firm-related and financial services, Sector 5: ICT and other services. Pressure 1 denotes no or low competitive pressure, Pressure 2 medium competitive pressure, and Pressure 3 high competitive pressure. * $p < .10$, ** $p < .05$, *** $p < .01$

Table 10: Tests for the monotonicity assumption - monitoring regressions, non-executives

	$\widehat{p}^E_{25}$	$\widehat{p}^E_{50}$	$\widehat{p}^E_{75}$	$\widehat{p}^E_{100}$	Firm size 1	Firm size 2	Firm size 3	Firm size 4	Sector 1	Sector 2
PD	.076	.387*	.116	.166	.105	.231***	.172	.228	.128	.130
	(.119)	(.207)	(.225)	(.122)	(.070)	(.073)	(.106)	(.140)	(.087)	(.096)
N	351	351	351	350	538	486	238	142	419	371
	Sector 3	Sector 4	Sector 5	Firm founded 1990 or later		Year 2016		Tech status		Pressure 1
				yes	no	yes	no	high	low	
PD	.148	.082	.394***	.102*	.184***	.172***	.180***	.169***	.188**	.277***
	(.100)	(.101)	(.124)	(.062)	(.064)	(.052)	(.064)	(.052)	(.081)	(.103)
N	239	215	160	659	745	747	657	979	425	207
	Pressure 2	Pressure 3	Performance pay plan		Insolvencies rate		Business registration rate		Unemployment rate	
			yes	no	high	low	high	low	high	low
PD	.222***	.090	.215***	.107*	.180***	.163***	.225***	.103	.148**	.187***
	(.069)	(.062)	(.058)	(.062)	(.060)	(.162)	(.063)	(.063)	(.059)	(.069)
N	517	680	805	599	694	710	700	704	672	732

Sources. Linked Personnel Panel, employer survey 2014/2016, IAB Establishment Panel 2014/2016, German Federal Statistical Office 2020, and BBSR Bonn 2021. Own calculations. **Notes.** The values in parentheses represent robust standard errors clustered at the firm level. $\widehat{p}^E_{25}$, $\widehat{p}^E_{50}$, $\widehat{p}^E_{75}$, and $\widehat{p}^E_{100}$ denote the 1st, 2nd, 3rd, and 4th quartile of the estimated propensity score. Firm size 1 denotes firms with less than 100 employees, firm size 2 firms with 100-249 employees, firm size 3 firms with 250-499 employees, and firm size 4 firms with 500 and more employees. Sector 1: manufacturing, Sector 2: metal, electronics, vehicle manufacturing, Sector 3: trade, transport, news, Sector 4: firm-related and financial services, Sector 5: ICT and other services. Pressure 1 denotes no or low competitive pressure, Pressure 2 medium competitive pressure, and Pressure 3 high competitive pressure. * $p < .10$, ** $p < .05$, *** $p < .01$

Table 11: Tests for the monotonicity assumption - working from home regressions, executives

	$\widehat{p}^E_{25}$	$\widehat{p}^E_{50}$	$\widehat{p}^E_{75}$	$\widehat{p}^E_{100}$	Firm size 1	Firm size 2	Firm size 3	Sector 1	Sector 2	Sector 3
PD	.125	$-.053$	.550**	$-.102$	.217***	.127	.068	.141	.110	.056
	(.128)	(.188)	(.219)	(.203)	(.080)	(.085)	(.118)	(.091)	(.105)	(.136)
N	337	336	336	335	507	461	377	428	363	223
	Sector 4	Sector 5	Firm founded 1990 or later		Year 2016		Tech status		Performance pay plan	
			yes	no	yes	no	high	low	yes	no
PD	.243*	.239	.142**	.141	.170**	.108	.078	.250***	.226***	.056
	(.131)	(.203)	(.072)	(.088)	(.074)	(.066)	(.062)	(.092)	(.073)	(.073)
N	203	128	609	736	669	676	977	368	776	569
	Open positions for professionals		Female employment		Living space		Rental prices		Unemployment rate	
	high	low	high	low	high	low	high	low	high	low
PD	.154**	.069	.068	.195**	.190*	.097	.054	.202***	.111*	.126
	(.073)	(.078)	(.073)	(.099)	(.101)	(.068)	(.009)	(.068)	(.064)	(.109)
N	669	676	660	685	650	695	531	814	648	697

Sources. Linked Personnel Panel, employer survey 2014/2016, IAB Establishment Panel 2014/2016, German Federal Statistical Office 2020, and BBSR Bonn 2021. Own calculations. **Notes.** The values in parentheses represent robust standard errors clustered at the firm level. $\widehat{p}^E_{25}$, $\widehat{p}^E_{50}$, $\widehat{p}^E_{75}$, and $\widehat{p}^E_{100}$ denote the 1st, 2nd, 3rd, and 4th quartile of the estimated propensity score. Firm size 1 denotes firms with less than 100 employees, firm size 2 firms with 100-249 employees, firm size 3 firms with 250 and more employees. Sector 1: manufacturing, Sector 2: metal, electronics, vehicle manufacturing, Sector 3: trade, transport, news, Sector 4: firm-related and financial services, Sector 5: ICT and other services. Not displayed in the table: coefficients (cluster robust standard errors) for open positions for experts: high: .807 (.074) $N = 655$, low: .058 (.106) $N = 690$. Coefficients (cluster robust standard errors) for purchase value of land: high: .002 (.132) $N = 672$, low: .219*** (.084) $N = 673$. * $p < .10$, ** $p < .05$, *** $p < .01$

Table 12: Tests for the monotonicity assumption - working from home regressions, non-executives

	$\widehat{p}^E_{25}$	$\widehat{p}^E_{50}$	$\widehat{p}^E_{75}$	$\widehat{p}^E_{100}$	Firm size 1	Firm size 2	Firm size 3	Sector 1	Sector 2	Sector 3
PD	.053	.460**	.291	.173	.196**	.110	.149	.330***	.065	.109
	(.131)	(.193)	(.184)	(.195)	(.086)	(.088)	(.118)	(.110)	(.098)	(.140)
N	337	336	336	336	507	461	377	428	363	223
	Sector 4	Sector 5	Firm founded 1990 or later		Year 2016		Tech status		Performance pay plan	
			yes	no	yes	no	high	low	yes	no
PD	−.033	.187	.092	.243***	.143*	.158**	.142**	.132	.239***	.058
	(.130)	(.208)	(.076)	(.087)	(.074)	(.069)	(.065)	(.101)	(.074)	(.076)
N	203	128	609	736	669	676	977	368	776	569
	Open positions for professionals		Female employment		Living space		Rental prices		Unemployment rate	
	high	low	high	low	high	low	high	low	high	low
PD	.169**	.171**	.107	.243**	.241**	.086	.101	.192***	.084*	.269**
	(.074)	(.076)	(.076)	(.100)	(.100)	(.072)	(.115)	(.074)	(.067)	(.110)
N	669	676	660	685	650	695	531	814	648	697

Sources. Linked Personnel Panel, employer survey 2014/2016, IAB Establishment Panel 2014/2016, German Federal Statistical Office 2020, and BBSR Bonn 2021. Own calculations. **Notes.** The values in parentheses represent robust standard errors clustered at the firm level. $\widehat{p}^E_{25}$, $\widehat{p}^E_{50}$, $\widehat{p}^E_{75}$, and $\widehat{p}^E_{100}$ denote the 1st, 2nd, 3rd, and 4th quartile of the estimated propensity score. Firm size 1 denotes firms with less than 100 employees, firm size 2 firms with 100-249 employees, firm size 3 firms with 250 and more employees. Sector 1: manufacturing, Sector 2: metal, electronics, vehicle manufacturing, Sector 3: trade, transport, news, Sector 4: firm-related and financial services, Sector 5: ICT and other services. Not displayed in the table: coefficients (cluster robust standard errors) for open positions for experts: high: .085 (.077) $N = 655$, low: .118 (.105) $N = 690$. Coefficients (cluster robust standard errors) for purchase value of land: high: .304** (.134) $N = 672$, low: .149* (.090) $N = 673$. * $p < .10$, ** $p < .05$, *** $p < .01$

Table 13: Tests for the exclusion restriction within a binarized treatment framework

	Monitoring regressions		Working-from-home regressions	
Hierarchy level h	E	NE	E	NE
	Probit ML PD (1)	Probit ML PD (2)	Probit ML PD (3)	Probit ML PD (4)
$I\{ict^h \geq ict^h_{.10}\}$	.102**		.080*	
	(.043)		(.044)	
$I\{ict^h \geq ict^h_{.20}\}$	.070*		.077**	
	(.036)		(.035)	
$I\{ict^h \geq ict^h_{.30}\}$	.088***	.056*	.076**	
	(.032)	(.032)	(.033)	
$I\{ict^h \geq ict^h_{.40}\}$	.082***	.086***	.069**	.078**
	(.031)	(.031)	(.030)	(.031)
$I\{ict^h \geq ict^h_{.50}\}$	.082***	.104***	.054*	.114***
	(.031)	(.030)	(.030)	(.031)
$I\{ict^h \geq ict^h_{.60}\}$	.082***	.116***	.054*	.108***
	(.031)	(.030)	(.030)	(.030)
$I\{ict^h \geq ict^h_{.70}\}$	.082***	.121***	.054*	.122***
	(.031)	(.031)	(.030)	(.031)
$I\{ict^h \geq ict^h_{.80}\}$	.082***	.145***	.054*	.123***
	(.031)	(.034)	(.030)	(.032)
$I\{ict^h \geq ict^h_{.90}\}$	.082***	.120***	.054*	.090**
	(.031)	(.038)	(.030)	(.040)
χ^2-test on equality of coefficients	[.659]	[.354]	[.712]	[.606]
N	1,404	1,404	1,345	1,345

Sources. Linked Personnel Panel, employer survey 2016/2018, IAB Establishment Panel 2016/2018, German Federal Statistical Office 2020, and BBSR Bonn 2021. Own calculations.

Notes. The specifications in Columns (1) to (4) additionally contain an intercept, but no control variables. The values in parentheses (square brackets) represent robust standard errors clustered at the firm level (p-values). Since the treatment group in the regressions with $I\{ict^h \geq ict^h_{.40}\}$ (monitoring regressions, column (1)) and $I\{ict^h \geq ict^h_{.50}\}$ (working-from-home regressions, column (3)) as the dependent variable only includes firms that equip all their executives with ICT, the estimated coefficients for PD in the subsequent regressions are identical. These regression models are then no longer included in the χ^2-test on the equality of coefficients. For the group of non-executives (columns (2) and (4)), no firms are represented in the respective control group in the regressions in which the threshold is set at smaller deciles, so that the dependent variable then shows no variation here.

* $p < .10$, ** $p < .05$, *** $p < .01$.

Table 14: Complete regression results - monitoring

	OLS		2SLS		Parametric Normal MTE	
	MON^E	MON^{NE}	MON^E	MON^{NE}	MON^E	MON^{NE}
	(1)	(2)	(3)	(4)	(5)	(6)
ICT^h	.141***	.081**	1.220**	1.105***		
	(.041)	(.037)	(.503)	(.357)		
D^h					6.435***	2.794***
					(1.768)	(.863)
					Treated	**Treated**
Firm size classes						
Firm size 100-249	.084	−.077	.110	.094	.259	.256
	(.133)	(.129)	(.195)	(.146)	(.216)	(.175)
Firm size 250-499	.304*	.131	.318	.355**	.841***	.782***
	(.163)	(.171)	(.279)	(.171)	(.272)	(.207)
Firm size >500	.506***	.436**	.605**	.195	1.010***	.883***
	(.182)	(.203)	(.286)	(.259)	(.226)	(.249)
Sector affiliation						
Metal, electronics,	.176	.304*	.280*	.152	.197	.129
vehicle manufacturing	(.154)	(.175)	(.160)	(.157)	(.162)	(.171)
Trade, transport, news	.409**	.375**	.714***	.365*	.174*	.214
	(.169)	(.179)	(.250)	(.190)	(.207)	(.258)
Firm-related/financial	.453**	.688***	.172	.315*	.021	.448*
services	(.186)	(.188)	(.179)	(.191)	(.243)	(.235)
ICT and other services	.433*	.504**	1.145***	.539**	.277	.329
	(.227)	(.225)	(.425)	(.234)	(.326)	(.267)
Year						
2016	.117	.017	.198*	.340**	.163	−.127
	(.085)	(.082)	(.119)	(.157)	(.099)	(.149)
Region affiliation						
Eastern Germany	−.070	.210				
	(.158)	(.160)				
Southern Germany	.141	.246				
	(.159)	(.161)				
Western Germany	.010	−.003				
	(.156)	(.158)				

	OLS		2SLS		Parametric Normal MTE	
	MON^E	MON^{NE}	MON^E	MON^{NE}	MON^E	MON^{NE}
	(1)	(2)	(3)	(4)	(5)	(6)
Self-reported competition						
Low competition	.001	−.249	−.360	−.584*	−.157	−.512
	(.260)	(.254)	(.402)	(.300)	(.345)	(.397)
Medium competition	−.354	−.523**	−.898**	−.741***	−.419	−1.039***
	(.238)	(.216)	(.417)	(.276)	(.325)	(.340)
High competition	−.319	−.426**	−.822**	−.935***	−.444	−1.004***
	(.236)	(.214)	(.408)	(.302)	(.318)	(.357)
Innovation						
Product innovation 1	.005	−.001				
	(.125)	(.123)				
Product innovation 2	.227**	.208*				
	(.111)	(.121)				
Product innovation 3	.313**	.205				
	(.134)	(.147)				
Process innovation	.136	.085				
	(.124)	(.127)				
Tech-status						
Status	.208***	.174**	.220**	.154*	.167	.244***
	(.073)	(.071)	(.093)	(.090)	(.103)	(.093)
Other						
Export rate	.002	−.000				
	(.002)	(.002)				
Performance pay plan	.512***	.627***	.532***	.466***	.771***	.553***
	(.115)	(.111)	(.183)	(.177)	(.160)	(.186)
SMWT	.240**	.197*				
	(.109)	(.105)				
Collective wage	−.027	−.146				
bargaining	(.142)	(.143)				
Works council	.068	−.092				
	(.133)	(.128)				
Legal form	−.189	.061				
	(.295)	(.276)				
Independence	−.468***	−.319**				
	(.114)	(.127)				

	OLS		2SLS		Parametric Normal MTE	
	MON^{E}	MON^{NE}	MON^{E}	MON^{NE}	MON^{E}	MON^{NE}
	(1)	(2)	(3)	(4)	(5)	(6)
Expansion investments	.002	−.001				
	(.001)	(.001)				
IT investments	−.138	.145				
	(.113)	(.112)				
Outsourcing	.131	−.222				
	(.256)	(.242)				
In-sourcing	−.341	−.103				
	(.273)	(.284)				
Cost leadership	−.058	−.133				
	(.218)	(.204)				
Quality leadership	.106	.045				
	(.109)	(.112)				
Working time accounts	.044	−.099				
	(.137)	(.137)				
Job rotation	.181	.342***				
	(.128)	(.132)				
Quality circle	.132	.059				
	(.118)	(.124)				
Learn	.395***	.439***				
	(.114)	(.113)				
Payments above	.088	.085				
	(.129)	(.133)				
Skill	.006***	.008***				
	(.002)	(.002)				
Fixed-term workers	.001	−.000				
	(.004)	(.005)				
Part-time workers	−.005	−.013***				
	(.003)	(.003)				
Female workers	.007**	.012***				
	(.003)	(.003)				
Temporary agency	−.001	−.003				
workers	(.008)	(.006)				
Apprentices	−.001	.002				
	(.013)	(.014)				
Training	.738***	.484**				
	(.226)	(.206)				

	OLS		2SLS		Parametric Normal MTE	
	MON^E	MON^{NE}	MON^E	MON^{NE}	MON^E	MON^{NE}
	(1)	(2)	(3)	(4)	(5)	(6)
Firm age			.022**	.041***	.011	.037***
			(.009)	(.011)	(.008)	(.012)
Corporate insolvencies			−.000	−.002	−.000	−.001
			(.003)	(.003)	(.002)	(.003)
Business registrations			−.001	−.003	.003	.005
			(.003)	(003)	(.003)	(.003)
Unemployment			−.008	.031	.003	.002
			(.026)	(.027)	(.027)	(.030)
					Untreated	**Untreated**
Firm size 100-249					−.281	.182
					(.301)	(.171)
Firm size 250-499					−.435	.240
					(.396)	(.216)
Firm size >500					.453	−.414
					(.358)	(.352)
Firm age					.042***	.043***
					(.010)	(.011)
Metal, electronics,					.412*	.061
vehicle manufacturing					(.237)	(.200)
Trade, transport, news					.494**	.364**
					(.233)	(.179)
Firm-related/financial					−.770*	.207
services					(.421)	(.211)
ICT and other services					1.508***	.695***
					(.390)	(.238)
2016					.308**	−.279**
					(.154)	(.139)
Status					.094	.205***
					(.151)	(.078)
Performance pay plan					.310	.527***
					(.204)	(.193)
Corporate insolvencies					.001	.001
					(.004)	(.003)
Business registrations					−.011*	−.008**
					(.005)	(.003)

	OLS		2SLS		Parametric Normal MTE	
	MON^{E}	MON^{NE}	MON^{E}	MON^{NE}	MON^{E}	MON^{NE}
	(1)	(2)	(3)	(4)	(5)	(6)
Low competition					.126	−.481
					(.465)	(.318)
Medium competition					−.381	−.167
					(.427)	(.286)
High competition					−.423	−.468
					(.420)	(.312)
Unemployment					−.028	.032
					(.043)	(.032)
R^2	.263	.239				
N	1,192	1,192	1,404	1,404	1,404	1,404

Sources. Linked Personnel Panel 2016/2018, IAB Establishment Panel 2016/2018, German Federal Statistical Office 2020, and BBSR Bonn 2021.

Notes. * $p < .10$, ** $p < .05$, *** $p < .01$.

Table 15: Complete regression results - working from home

	OLS		2SLS		Parametric Normal MTE	
	WFH^E	WFH^{NE}	WFH^E	WFH^{NE}	WFH^E	WFH^{NE}
	(1)	(2)	(3)	(4)	(5)	(6)
ICT^h	.085***	.114***	.451**	−.014		
	(.014)	(.022)	(.206)	(.157)		
D^h					1.302**	.333
					(.656)	(.706)
					Treated	**Treated**
Firm size classes						
Firm size 100-249	.038	.064	.008	.079	.017	.080
	(.067)	(.063)	(.078)	(.098)	(.100)	(.157)
Firm size 250-499	.073	.069	−.098	.131*	−.028	.190
	(.099)	(.104)	(.140)	(.079)	(.140)	(.163)
Firm size >500	.184	.252	.114	.384***	.156	.503**
	(.150)	(.164)	(.165)	(.137)	(.185)	(.220)
Sector affiliation						
Metal, electronics,	−.106	−.151**	−.040	−.036	−.069	−.026
vehicle manufacturing	(.081)	(.076)	(.075)	(.075)	(.114)	(.152)
Trade, transport, news	.024	−.147	.087	−.198***	.119	−.213
	(.110)	(.099)	(.121)	(.067)	(.156)	(.131)
Firm-related/financial	.129	.098	.053	.044	−.110	.172
services	(.114)	(.114)	(.096)	(.092)	(.133)	(.178)
ICT and other services	.215	.333	.304	.089	.458*	.482
	(.179)	(.276)	(.195)	(.151)	(.250)	(.455)
Year						
2016	.001	.008	−.143	.023	−.402***	.049
	(.054)	(.053)	(.094)	(.062)	(.134)	(.121)
Region affiliation						
Eastern Germany	−.226**	−.112				
	(.095)	(.092)				
Southern Germany	−.233*	.017				
	(.121)	(.127)				

	OLS		2SLS		Parametric Normal MTE	
	WFH^{E}	WFH^{NE}	WFH^{E}	WFH^{NE}	WFH^{E}	WFH^{NE}
	(1)	(2)	(3)	(4)	(5)	(6)
Western Germany	$-.082$	.100				
	(.102)	(.100)				
Self-reported competition						
Low competition	.111	.299**				
	(.140)	(.136)				
Medium competition	.077	.147				
	(.123)	(.103)				
High competition	.131	.235**				
	(.121)	(.103)				
Innovation						
Product innovation 1	$-.076$	$-.021$				
	(.067)	(.069)				
Product innovation 2	.017	$-.004$				
	(.068)	(.068)				
Product innovation 3	.014	.021				
	(.109)	(102)				
Process innovation	.026	.036				
	(.070)	(.065)				
Tech-status						
Status	.002	$-.015$	$-.022$	.019	$-.092$	$-.036$
	(.040)	(.042)	(.053)	(.047)	(.096)	(.096)
Other						
Export rate	.002	.001				
	(.001)	(.001)				
Performance pay plan	.079	.047	.023	.193***	$-.085$	.209
	(.058)	(.053)	(.110)	(.069)	(.132)	(.142)
Collective wage	$-.023$	$-.010$				
bargaining	(.083)	(.088)				
Works council	.018	$-.016$				
	(.064)	(.067)				
Legal form	.103	$-.012$				

	OLS		2SLS		Parametric Normal MTE	
	WFH^{E}	WFH^{NE}	WFH^{E}	WFH^{NE}	WFH^{E}	WFH^{NE}
	(1)	(2)	(3)	(4)	(5)	(6)
	(.175)	(.089)				
Independence	$-.284^{***}$	$-.207^{**}$				
	(.092)	(.098)				
Expansion investments	.000	$-.000$				
	(.000)	(.000)				
IT investments	.006	$-.042$				
	(.059)	(.062)				
Outsourcing	$-.107$	.012				
	(.140)	(.172)				
In-sourcing	$-.030$	$-.237^{*}$				
	(.221)	(.134)				
Cost leadership	$-.053$	.129				
	(.107)	(.145)				
Quality leadership	$.204^{***}$	$.164^{**}$				
	(.074)	(.074)				
Appraisal interviews	.072	$.087^{**}$				
	(.060)	(.045)				
Target agreements	.050	$.084^{**}$				
	(.062)	(.041)				
Development plans	.060	$.150^{**}$				
	(.070)	(.064)				
Performance appraisals	.057	.062				
	(.067)	(.056)				
Distribution systems	.126	$-.054$				
	(.138)	(.111)				
Evaluation rounds	$-.068$	.012				
	(.099)	(.113)				
Payments above	$-.004$	$-.091$				
	(.088)	(.099)				
Skill	.001	$.002^{*}$				
	(.001)	(.001)				
Fixed-term workers	.000	.000				
	(.002)	(.002)				
Part-time workers	$-.003^{**}$	$-.001$				

	OLS		2SLS		Parametric Normal MTE	
	WFH^E	WFH^{NE}	WFH^E	WFH^{NE}	WFH^E	WFH^{NE}
	(1)	(2)	(3)	(4)	(5)	(6)
	(.001)	(.001)				
Female workers	.001	−.000				
	(.002)	(.002)				
Temporary agency	−.002	.004				
workers	(.003)	(.004)				
Apprentices	−.000	−.005				
	(.007)	(.009)				
Training	−.012	−.180**				
	(.069)	(.082)				
Firm age			.002	.000	.001	.015
			(.004)	(.005)	(.007)	(.013)
Open positions: experts			−.021	.011	−.047**	.013
			(.018)	(.016)	(.021)	(.030)
Open positions: profes-			−.007	−.002	−.020	−.007
sionals			(.009)	(.008)	(.015)	(.015)
Female employment			.018**	.012*	.043***	.019
			(.009)	(.006)	(.014)	(.013)
Living space			.008	.012	.007	.018
			(.011)	(.008)	(.013)	(.016)
Purchase value of land			.000	.001**	.001	.001
			(.000)	(.000)	(.001)	(.001)
Rental prices			.055	−.006	.072	−.008
			(.045)	(.037)	(.062)	(.070)
Unemployment			.005	−.002	.001	−.001
			(.014)	(.009)	(.017)	(.020)
					Untreated	**Untreated**
Firm size 100-249					.159**	.078
					(.064)	(.074)
Firm size 250-499					.137	.035
					(.109)	(.055)
Firm size >500					.323**	.155
					(.140)	(.117)
Firm age					−.001	−.006

	OLS		2SLS		Parametric Normal MTE	
	WFH^E	WFH^{NE}	WFH^E	WFH^{NE}	WFH^E	WFH^{NE}
	(1)	(2)	(3)	(4)	(5)	(6)
					(.004)	(.006)
Metal, electronics,					.004	−.070
vehicle manufacturing					(.077)	(.070)
Trade, transport, news					−.156*	−.125*
					(.085)	(.064)
Firm-related/financial					.111	.006
services					(.159)	(.110)
ICT and other services					−.114	−.091
					(.129)	(.087)
2016					.148	.000
					(118)	(.047)
Status					.055	.037
					(.056)	(.050)
Performance pay plan					.245**	.090
					(.102)	(.090)
Open positions: experts					.022	.002
					(.019)	(.017)
Open positions: profes-					.009	.002
sionals					(.009)	(.007)
Female employment					.002	.004
					(.010)	(.006)
Living space					.016	.007
					(.015)	(.007)
Purchase value of land					.001	.000
					(.001)	(.001)
Rental prices					−.029	.034
					(.051)	(.029)
Unemployment					.001	.006
					(.016)	(.010)
R^2	.110	.127				
N	1,193	1,193	1,345	1,345	1,345	1,345

Sources. Linked Personnel Panel 2014/2016, IAB Establishment Panel 2014/2016, German Federal Statistical Office 2020, and BBSR Bonn 2021. **Notes.** * $p < .10$, ** $p < .05$, *** $p < .01$.

B.2 Additional Descriptive Statistics

Table 16: Definitions and descriptive statistics of all variables

Variable	Definition	Mean	Std.-dev.	Min-Max	Data
	Dependent and main explanatory 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	74.202	38.935	0–100	
	– Non-executives	16.487	25.422	0–100	
Employee monitoring					
Appraisal interviews	Share of executive or non-executive workers that the firm has conducted structured appraisal interviews with at least once a year				LPP
	– Executives	62.716	46.943	0–100	
	– Non-executives	49.116	45.667	0–100	
Target agreements	Share of executive or non-executive workers for that target agreements are available in written form				LPP
	– Executives	52.388	48.061	0–100	
	– Non-executives	21.520	37.212	0–100	
Performance appraisals	Share of executive or non-executive workers for that performance appraisals are issued				LPP
	– Executives	52.747	49.253	0–100	

Variable	Definition	Mean	Std.-dev.	Min-Max	Data
	– Non-executives	45.307	45.481	0–100	
Distribution system	Share of executive or non-executive workers for that distribution recommendations are issued				LPP
	– Executives	5.159	21.808	0–100	
	– Non-executives	4.734	20.336	0–100	
Evaluation rounds	Share of executive or non-executive workers for that evaluation rounds are meant				LPP
	– Executives	7.496	26.043	0–100	
	– Non-executives	5.778	21.930	0–100	
Employee autonomy					
Working from home (D)	Share of executive or non-executive workers in the functional area *Distribution and Marketing* that can make use of the opportunity to work at home (eligible workers)				LPP
	– Executives	12.541	31.184	0–100	
	– Non-executives	6.442	21.684	0–100	
Working from home (P)	Share of executive or non-executive workers in the functional area *Production* that can make use of the opportunity to work at home (eligible workers)				LPP
	– Executives	2.641	14.216	0–100	
	– Non-executives	0.555	6.273	0–100	

Variable	Definition	Mean	Std.-dev.	Min-Max	Data
Working from home (C)	Share of executive or non-executive workers in the functional area *Cross-Departmental Function, Administration, and Service* that can make use of the opportunity to work at home (eligible workers)				LPP
	– Executives	10.129	27.247	0–100	
	– Non-executives	4.729	17.410	0–100	
Instrumental variable					
Population density	Number of inhabitants per square kilometre (sqkm) for all 401 districts in Germany, and the years 2014, 2016, and 2018	714.297	908.269	0–4668.1	RA
Population density (3y)	Number of inhabitants per square kilometre (sqkm) for all 401 districts in Germany, and the years 2011, 2013, and 2015	698.410	884.136	0–4531.2	RA
Population density (7y)	Number of inhabitants per square kilometre (sqkm) for all 401 districts in Germany, and the years 2007, 2009, and 2011	713.736	891.237	37.6–4282.2	RA
	Used covariates based on Brickley et al. (2021)				
Competition					
No competition	Dummy variable indicating firms with no competitive pressure	0.031	0.175	0–1	IAB BP
Low competition	Dummy variable indicating firms with low competitive pressure	0.089	0.286	0–1	IAB BP
Medium competition	Dummy variable indicating firms with medium competitive pressure	0.360	0.480	0–1	IAB BP
High competition	Dummy variable indicating firms with high competitive pressure	0.517	0.500	0–1	IAB BP

Variable	Definition	Mean	Std.-dev.	Min-Max	Data
Export rate	Export share based on total sales (%)	17.385	25.781	0-100	IAB BP
Regulation					
Collective wage bargaining	Dummy variable indicating firms that commit to collective wage bargaining at the industry or firm level	0.600	0.490	0–1	IAB BP
Works council	Dummy variable indicating firms with a works council	0.618	0.485	0–1	IAB BP
Legal form	Dummy variable indicating firms that are privately owned	0.042	0.202	0–1	IAB BP
Independence	Dummy variable indicating firms that are independent	0.748	0.433	0–1	IAB BP
Technology					
Tech-status	Dummy variable indicating that the status of a firm's technological equipment is (1) out-of-date, (2) low, (3) medium, (4) high, or (5) state-of-the-art	3.886	0.749	1–5	IAB BP
Expansion investments	Share of expansion investments	24.817	32.880	0–100	IAB BP
IT investments	Dummy variable indicating firms with IT investments in the previous year	0.622	0.485	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	0.349	0.477	0–1	IAB BP
Strategy					

Variable	Definition	Mean	Std.-dev.	Min-Max	Data
Out-sourcing	Dummy variable indicating firms in which parts of the firm were closed down or relocated with other company units between 1 July 2015 and 30 June 2016, or separated and continued as independent businesses	0.028	0.166	0–1	IAB BP
In-sourcing	Dummy variable indicating firms in which there were organizational developments that resulted in the integration of other establishments or establishment units into the firm	0.022	0.148	0–1	IAB BP
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	0.583	0.493	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	0.321	0.467	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	0.137	0.344	0–1	IAB BP
Cost leadership	Dummy variable indicating firms that apply a cost-leadership strategy	0.056	0.230	0–1	LPP

Variable	Definition	Mean	Std.-dev.	Min-Max	Data
Quality leadership	Dummy variable indicating firms that apply a quality-leadership strategy	0.309	0.462	0–1	LPP
Manufacturing	Dummy variable indicating firms in the manufacturing industry	0.300	0.458	0–1	LPP
Metal, electronics, vehicle manufacturing	Dummy variable indicating firms in the metal working sector, in the electrical industry or in vehicle manufacturing	0.268	0.443	0–1	LPP
Trade, transport, news	Dummy variable indicating firms in the trade, traffic, or news sector	0.165	0.371	0–1	LPP
Firm-related/financial services	Dummy variable indicating firms that offer firm-related or financial services	0.147	0.355	0–1	LPP
IC and other services	Dummy variable indicating firms that offer information and communication services or other services	0.118	0.323	0–1	LPP
Decision rights					
SMWT	Dummy variable indicating firms that offer trust-based working hours/self-managed working hours (without operational timekeeping)	0.394	0.488	0–1	IAB BP
Working time accounts	Dummy variable indicating firms that offer working time accounts to their employees	0.823	0.381	0–1	IAB BP
Job rotation	Dummy variable indicating firms that release staff and cover the expenses in full or in part for job rotation	0.196	0.397	0–1	IAB BP

Variable	Definition	Mean	Std.-dev.	Min-Max	Data
Quality circle	Dummy variable indicating firms that release staff and cover the expenses in full or in part for quality circles, workshop circles, learning workshop, and continuous improvement teams	0.223	0.416	0–1	IAB BP
Learn	Dummy variable indicating firms that release staff and cover the expenses in full or in part for self-directed study (e.g. by means of computer-aided self-learning programs or reference books)	0.364	0.481	0–1	IAB BP
Reward and performance development					
Performance pay plan	Dummy variable indicating firms that have a salary system with variable proportions	0.574	0.494	0–1	LPP
Payments above	Dummy variable indicating firms that pay wages above the collective bargaining rate	0.357	0.479	0–1	IAB BP
Development plans	Dummy variable indicating firms that have development plans for employees	0.446	0.497	0–1	LPP
Workforce structure					
Fixed-term workers	Share of workers with a fixed-term contact (%)	6.844	11.829	0–100	IAB BP
Part-time workers	Share of part-time workers (%)	16.710	21.326	0–100	IAB BP
Female workers	Share of female workers (%)	32.807	24.737	0–97.402	IAB BP
Temporary agency workers	Share of temporary agency workers (%)	3.669	7.906	0–91.228	IAB BP
Apprentices	Share of apprentices (%)	4.235	4.683	0–40.659	IAB BP

Variable	Definition	Mean	Std.-dev.	Min-Max	Data
Skill	Share of employees for skilled jobs, requiring a vocational qualification or comparable training on the job or relevant professional experience, or requiring a university degree	75.769	24.344	0–100	IAB BP
Workforce training					
Training	Dummy variable indicating firms that offer further training	0.916	0.277	0–1	IAB BP
Region affiliation					
Northern Germany	Dummy variable indicating firms that are located in Northern Germany	0.190	0.392	0–1	LPP
Eastern Germany	Dummy variable indicating firms that are located in Eastern Germany	0.190	0.392	0–1	LPP
Southern Germany	Dummy variable indicating firms that are located in Southern Germany	0.190	0.392	0–1	LPP
Western Germany	Dummy variable indicating firms that are located in Western Germany	0.190	0.392	0–1	LPP
Firm size classes					
Firm size 1–49	Dummy variable indicating firms with 1–49 employees covered by social security	0.030	0.172	0–1	LPP
Firm size 50–99	Dummy variable indicating firms with 50–99 employees covered by social security	0.339	0.473	0–1	LPP
Firm size 100–249	Dummy variable indicating firms with 100–249 employees covered by social security	0.353	0.478	0–1	LPP

Variable	Definition	Mean	Std.-dev.	Min-Max	Data
Firm size 250–499	Dummy variable indicating firms with 250–499 employees covered by social security	0.159	0.366	0–1	LPP
Firm size 500+	Dummy variable indicating firms with 500+ employees covered by social security	0.117	0.321	0–1	LPP
Firm age					
Firm age	Dummy variable indicating a firm's age	1992.008	7.053	1987–2014	LPP
Used covariates based on our introspection in subsection 5.2.1					
Corporate competition					
Corporate insolvencies	Number of corporate insolvencies per 10,000 companies subject to sales tax for all 401 districts in Germany	62.979	26.073	11.5–169.3	RA
Business registrations	Number of business registrations without takeovers per 10,000 inhabitants for all 401 districts in Germany	69.927	19.409	34.6–168.7	RA
Labour market competition					
Unemployment	Average share of unemployed in the civilian labor force for all 401 districts in Germany	6.967	2.982	1.3–15.1	RA
Open job positions for experts	Share of vacancies with the requirement level *Experts* in the total number of vacancies (%) for all 401 districts in Germany; *Expert*: at least four years of higher education or equivalent work experience	7.540	2.913	2.8–20.3	BBSR

Variable	Definition	Mean	Std.-dev.	Min-Max	Data
Open job positions for professionals	Share of vacancies with the requirement level *Professional* in the total number of vacancies (%) for all 401 districts in Germany; *Professional*: at least two years of vocational training or comparable qualification	67.285	3.975	35.8–78.7	BBSR
Female employment	Share of female employees covered by social security in the total number of employees covered by social security (%) for all 401 districts in Germany	46.871	3.881	30.9–57.9	BBSR
Real estate market competition					
Living space	Average living space per inhabitant in square meters (sqm) for all 401 districts in Germany	46.240	4.352	36.2–68.6	BBSR
Purchase value of land	Average purchase value (in euro) per square meter of building land for all 401 districts in Germany	133.001	158.228	8.47–1732.33	IT.NRW
Rental prices	Class of average demanded rent per square meter (i.e. below 4 euro, 4-5 euro, 1 euro steps until 17 euro and more) for all 401 districts in Germany	3.856	1.708	2–12	BBSR

Sources. Linked Personnel Panel 2016 (LPP), IAB Establishment Panel 2016 (IAB BP), German Federal Statistical Office 2020, and BBSR Bonn 2021 (RA, IT.NRW); data format: raw.

Notes. Own calculations. The data is merged via firm-level or district-level indicators and depicted in this table for the year 2016.

Table 17: Considered DAX companies and corresponding districts

Listed DAX Company	District name	District code
Adidas	Herzogenaurach	9572
Allianz	Munich	9162
BASF	Ludwigshafen	7314
Bayer	Leverkusen	5316
Beiersdorf	Hamburg	2000
BMW ST	Munich	9162
Continental	Hannover	3241
Covestro	Leverkusen	5316
Daimler	Stuttgart	8111
Deutsche Bank	Frankfurt	6412
Deutsche Börse	Frankfurt	6412
Deutsche Post	Bonn	5314
Deutsche Telekom	Bonn	5314
E.ON	Dusseldorf	5111
Fresenius	Bad Homburg	6434
Fresenius Medical Care	Bad Homburg	6434
Heidelberg Cement	Heidelberg	8221
Henkel	Dusseldorf	5111
Merck	Darmstadt	6411
Münchener Rück	Munich	9162
RWE	Essen	5113
SAP	Walldorf	8226
Siemens	Munich	9162
Volkswagen	Wolfsburg	3103
Vonovia	Bochum	5911
Wirecard	Munich	9162

Source. DGWZ 2021.

Notes. In a content-based robustness check (see Subsection 6.1.2), we remove these 17 districts from our MTE estimations.