Does Progress in Information and Communication Technology Foster Organizational Control?*

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Abstract

Organizational control of employees in firms can be characterized through the dimensions of monitoring and employee autonomy, so that high organizational control is defined by high monitoring and low employee autonomy. It is unclear whether progress in information and communication technology leads to more or less organizational control. As a specific example, we consider the widespread use of mobile information and communication technology (MICT) in firms in recent years. Our theoretical and empirical analyses show that MICT leads to more monitoring at all hierarchy levels but only boosts the autonomy of executives. Thus, MICT has different effects on organizational control across hierarchical levels. Primarily executives are granted autonomy to better utilize their higher human capital and to save labor costs by offering them a preferred work-life balance. Overall, MICT fosters organizational control, but the results on executives document that firms partially benefit from combining seemingly contradicting management practices.

Keywords: monitoring; working from home; marginal treatment effects; essential heterogeneity; instrumental variable.

JEL classification: D2; J3; L2; M5.

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"The telescreen received and transmitted simultaneously. Any sound that Winston made, above the level of a very low whisper, would be picked up by it, moreover, so long as he remained within the field of vision which the metal plaque commanded, he could be seen as well as heard." (George Orwell *Nineteen Eighty-Four*, p. 6)

1 Introduction

Technology has continued to reshape organizational structures and processes over time, which is particularly true for advances in information and communication technology (ICT). In this paper, we consider the impact of ICT on the organizational control of employees. High organizational control is characterized by high monitoring intensity and a low degree of employee autonomy.[1] It is an open question whether advances in ICT generally lead to more or less organizational control. On the one hand, ICT can better reveal employees' contributions to firm success and allow for closer communication with superiors, which improves monitoring. On the other hand, ICT can grant employees access to better knowledge (e.g., via the Internet), leading to more autonomy. Since technological progress is an ongoing process, we have to clearly define the technological change we want to address. As a specific case, we thus focus on the equipment of employees with mobile information and communication technology (MICT) in recent years (e.g., smartphones, tablet computers, and notebooks).[2] This application is also at the core of many technology-driven debates on the optimal design of jobs in organizations (e.g., Garicano 2000, Caroli and Van Reenen 2001, Bresnahan et al. 2002, Acemoglu et al. 2007, Bloom et al. 2014, Labro et al. 2023).

The contribution of our paper is threefold. First, most of the previous studies on the organizational control of employees implicitly assume that more monitoring goes hand in hand with less employee autonomy and vice versa, so that a firm consistently either increases or decreases its organizational control. On the contrary, both our theoretical and empirical models also allow for the possibility that high monitoring and a high degree of employee autonomy coexist in a complementary way. Hence, we see MICT as a potential driver for a simultaneous emergence of seemingly contradicting management practices. Second, we explicitly take into account that MICT might

[1]For this characterization, see, for example, the industrial relations literature: "The greater the flexibility, the greater the risk of opportunism, and vice versa, because it is assumed that flexibility requires greater worker autonomy, which entails less organizational control" (Salesina 2025, p. 58, referring to Marsden 1999). A similar characterization can be found in the management literature (e.g., Bloom et al. 2014, Langfred and Rockmann 2016, van Triest and Wiliams 2024) and in the economics literature (e.g., Kala 2024).

[2]The importance of these MICT devices is highlighted by Kalyani et al. (2025), pp. 1319–1320.

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 MICT equipment and MICT impact on organizational control. In doing so, we differ from studies that either consider the effects of MICT on organizational control between two selected managerial levels or make no specific reference to hierarchical differences at all.[3] Finally, with regard to causal inference, we complement empirical studies on the effects of MICT on organizational control by accounting not only for conventional endogeneity problems (selection on unobservables), but also for essential heterogeneity (selection based on unobserved gains). For this purpose, we employ the estimation of marginal treatment effects (MTE) models. 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 MICT. To the best of our knowledge, accounting for essential heterogeneity has not been applied in organizational economics so far.

In our econometric analysis, we measure employee autonomy through the management practice of working from home. Working from home provides employees with discretion by making use of their local knowledge about various job-related aspects, including the optimal place for task completion, the optimal timing of task completion (e.g., by allowing employees to adapt task completion to their individual biorhythm), and the individual situation regarding work-life balance (e.g., Bloom et al. 2015). Hence, a high degree of employee autonomy is given if an employee has large discretion about deciding to work from home. We empirically measure monitoring intensity through the use of appraisal interviews, target agreements, and performance evaluation. Thus, we consider both input and output monitoring, with a high degree of monitoring being associated with an intensive use of appraisal interviews, target agreements, and performance evaluation.

The two dimensions of organizational control (monitoring, employee autonomy) and employees' MICT equipment can be expected to interact. For example, MICT 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, MICT promotes more effective use of the benefits of autonomous working, 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).

[3]The latter studies are typically interested in a uniform average effect that is independent of hierarchical level. Only Gerten et al. (2019) provide a rather descriptive analysis on MICT and workplace organization at the employee level, thereby considering differences between hierarchical levels.

With regard to monitoring, MICT improves the communication between employees (in particular with superiors), which leads to better performance evaluation. For example, communication via smartphones, tablet computers and laptops provides the firm with better information on how quickly and committed an employee reacts to new suggestions from colleagues or instructions from superiors. In addition, MICT 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, monitoring intensity and MICT equipment, 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 MICT (i) has different effects on organizational control across hierarchy levels and (ii) leads to a combination of higher monitoring and more autonomy as seemingly contradicting management practices.

Result (i) on different MICT effects across hierarchy levels refers to more MICT equipment and higher employee autonomy for executives than for non-executives. This finding can be explained by the following rationale. MICT equipment has the same costs for both types of employees (e.g., costs for new smartphones and laptops), but lead to higher returns for executives due to their larger human capital and higher-powered incentives. Hence, it is more profitable for the firm to equip executives with MICT than non-executives. As this productivity effect is amplified by higher working autonomy, the firm benefits more from applying autonomy to executives than to non-executives. This different treatment of executives and non-executives is supported by a second effect: Under the optimal incentive contract, only the participation constraint of the executives is binding but not the one of the non-executives. Hence, granting executives autonomy and, thus, a better work-life balance relaxes their participation constraint, which lowers the firm's labor costs. The same effect does not hold for non-executives, who earn a positive rent for incentive reasons. A better work-life balance would only increase this rent.

Our theoretical results show that a better MICT equipment yields positive gains from higher monitoring, both for executive and non-executive employees. In other words, MICT favors higher organizational control in terms of monitoring for *all* employees irrespective of their hierarchical rank. Thus, our main result (ii) on the combination of seemingly contradicting management practices *exclusively* refers to the executives, for whom MICT is accompanied with more employee autonomy but also with higher monitoring. The intuition for this finding can be explained as follows. More autonomy particularly increases the productivity of executives due to their larger human capital, and, in order to secure these productivity gains, higher autonomy is complemented by increased monitoring. The exploiting and securing of higher productivity gains from executives is also related to the firm's induced incentives. In fact, our theoretical findings show that the firm uses its performance appraisal system to offer higher-powered incentives to the executives rather than to the non-executives.

In the empirical part of the paper, we test our theoretical predictions using large-scale representative employer-level survey data from the German Linked Personnel Panel and the IAB Establishment Panel of the years 2014 to 2018. Relying on MTE estimation methods that allow for identifying heterogeneous treatment effects, we estimate the causal effects of differences in MICT equipment across hierarchical levels on employee autonomy and monitoring. To adequately address the issues of both endogeneity and essential heterogeneity, we make use of an additional data set, the INKAR database, and construct a composite instrumental variable (IV) based on three geographical measures providing information about local population density and the number of students in STEM disciplines. We show that this IV is positively related to technological innovation, which argues for its relevance in promoting MICT equipment. To satisfy the assumption of conditional independence, we leverage the technological domain of our IV and remove possible contaminating effects, particularly agglomeration and labor supply effects, by using appropriate control variables. The conditional independence of our IV therefore rests on the assumption that its drivers are unrelated to the firms' practices of organizational control after controlling for observable confounders of agglomeration economies, labor supply, and other related firm- and district-level characteristics.

Our empirical findings are consistent with the predictions of our main theoretical results (i) and (ii). First, we can observe substantial differences across hierarchical levels in the equipment of MICT, meaning that executive employees are much more equipped with MICT than non-executive employees. Second, equipping employees with MICT results in different effects on organizational control across hierarchical levels, where the effects for executives are more pronounced than those for non-executives (result (i)). Third, firms use different combinations of employee autonomy and monitoring in response to increasing MICT equipment. For executives, MICT equipment promotes both employee autonomy and monitoring. In contrast, for non-executives, MICT only promotes monitoring, not employee autonomy (result (ii)). These findings imply that MICT indeed fosters organizational control of employees – at least in the monitoring dimension. Finally, we also find differences between executive and non-executive employees with regard to the presence of essential heterogeneity, which we observe more pronounced for executives (result (i)).

Our paper is related to the literature that analyzes the loss of control in hierarchies. Firms often become large to generate economies of scale or scope. However, such firm growth will lead to a loss of control if a hierarchy's span of control increases. Williamson (1967), Calvo and Wellisz (1978), Qian (1994), Acemoglu and Newman (2002), and Chen (2017), among many others, analyze how limits on workers' autonomy and optimal monitoring can increase organizational control and finally results into optimal firm size. We add to this discussion by theoretically and empirically investigating, how MICT influences organizational control via autonomy and monitoring.

Furthermore, our paper contributes to a broader discussion in the empirical literature whether ICT leads to more centralization or to more decentralization in firms, which is comparable to more or to less organizational control. This discussion includes both the analysis of organizational design (i.e., interaction between organizational units like headquarters and divisions) and the analysis of job design (i.e., interaction between superiors and subordinated employees within the same organizational unit). Rajan and Wulf (2006), Acemoglu et al. (2007) as well as McElheran (2014) focus on the ICT effects on organizational design. By contrast, the ICT effects on job design are empirically investigated in Caroli and Van Reenen (2001) and Bresnahan et al. (2002). 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. The outstanding feature of this study compared to all other empirical work 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 management practices, while our study does not preclude this approach, but additionally allows for the coexistence of employee autonomy and monitoring to optimize organizational control (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 effects separately for executive and non-executive employees (result (i)). Moreover, different to all these papers, we extend the analysis by considering MICT (instead of ICT), which includes up-to-date technical devices such as smartphones. Our paper is also related to Labro et al. (2023), who find that ICT primarily entails centralization tendencies. However, in contrast to our paper, Labro et al. (2023) exclusively focus on predictive analytics as a measure for ICT. Furthermore, the authors do not explicitly distinguish between executive and non-executive employees.

Finally, we methodologically contribute to the empirical literature on the effects of ICT on organizational control. 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 MTE estimation approaches, we do not only account for the endogeneity problems that may be associated with our MICT variables, but additionally address the case that the MICT effect on the organizational control 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 MICT.

2 Theoretical analysis

We first present our theoretical setting for combining MICT equipment and the firm's choice of organizational control. 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 MICT.

2.1 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 MICT equipment. The continuous variable $I \in [0, 1]$ denotes the degree by which the firm equips the employee with MICT. The higher the degree of MICT equipment – i.e., the larger I – the more productive will be the employee at his job, because he can more intensely use a smartphone 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, 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 $K_H > K_L$.

The two variables A and M specify the organizational control that is optimally chosen by the firm. If the firm prefers $A = 1$ to $A = 0$, it will implement high autonomy as management practice. If the firm chooses $M = M_H$ instead of $M = M_L$, it will employ a high monitoring intensity. The combination $(A, M) = (0, M_H)$ characterizes a firm with high organizational control. Concerning monitoring intensity M, expression (1) reflects that the firm's performance appraisal system is based on input and output monitoring.

Introducing MICT (i.e., $I > 0$) leads to costs $I \cdot \kappa$ for the firm with $\kappa > 0$ (e.g., for buying and introducing smartphones, laptops, and tablet PCs). MICT 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 $\Delta K < K_L$. MICT allows for easier performance evaluation, for example, because smartphones 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 organizational control as employees enjoy higher discretion and assessing their 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.[4] Instead, we assume that, for the M percent of the tasks 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. 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 $P\left(s = \bar{s} \middle| e\right) = e$, such that $P\left(s = \underline{s} \middle| e\right) = 1 - e$. 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.[5] 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.

[4] 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., Herweg et al. (2010).

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

2.2 Optimal incentives and the relative gains of MICT equipment

For given choices of MICT 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

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

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

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

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:[6]

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

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

[6] All proofs are relegated to the appendix.

(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 $e^*_{(i)} < e^*_{(ii)} < e^*_{(iii)}$.

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 $R(e^*_{(i)}) - (\bar{u} - \Delta u \cdot A)$.[7] 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

[7] 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).

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 organizational control, $\Delta\hat{K}$. However, it is instructive to investigate the relative gains from higher monitoring and more autonomy. For this purpose, we define

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

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 *MICT 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.

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 MICT than non-executives. Hence, if a firm wants to improve its MICT, 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 MICT equipment. Intuitively, MICT and monitoring are complements in (1) – a higher monitoring intensity implies that the firm implements higher effort, which becomes more productive due to MICT. Thus, in practice, we should observe that better MICT is accompanied by more intense monitoring at both executive and non-executive levels of the hierarchy.

Result (c) addresses the impact of MICT 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 MICT 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 MICT on granting employees more autonomy but this effect should not exist for all employees.

Result (d) does not contain a new finding but summarizes 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 executives, the firm will stronger gain from granting this employee autonomy than a non-executive employee.

To sum up, Proposition 2 highlights the interplay of MICT equipment and optimal organizational control, leading to two main findings. (i) Equipping employees with MICT has different effects across hierarchy levels. The firm benefits more from equipping executives with MICT than non-executives. In addition, the firm strongly favors autonomy for executives but not for non-executives. (ii) Equipping employees with MICT leads to a combination of seemingly contradicting management practices. In particular, it is optimal for the firm to employ high autonomy (i.e., low organizational control) and high monitoring (i.e., high organizational control) to executives. This combination is optimal for the firm, because a high monitoring intensity secures the large productivity gains of executives stemming from high human capital and autonomy, which are further amplified by a higher MICT equipment.

3 Data and variables

The dependent and treatment variables of our empirical analysis stem from two data sets: the employer survey of 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 (Kampkötter et al. 2016). It is representative for German firms with 50 and more employees in the manufacturing and service sector. Since its initial launch in 2012, the LPP employer survey has been sent to recipients every two years. The data from the corresponding employee survey is collected in the subsequent uneven years, starting in 2013. Our empirical analysis makes use of the data from 2014, 2016, and 2018, i.e., panel waves 2, 3, and 4.[8]

All waves of the LPP can be merged with the 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 firm-level information, such as employment and workforce structure, wage bills, sales, investments, international trade, product and process innovations, organizational change, and worker representation. The LPP companies are drawn as a sub-sample from the IAB Establishment Panel.

A special feature of the LPP employer survey is that, unlike other firm-level data sets, information is available separately by hierarchical level for both our treatment and outcome variables. This additional information enables us to enrich the ongoing debate on the influence of MICT on organizational control with the hierarchy aspect.

[8]We leave aside the information collected during the COVID-19 pandemic period (panel wave 5 from 2020) in order to avoid possible pandemic-related biases in our estimation results. In panel wave 1, information on our core variables was not collected. In the most recent panel wave 6, there is only information on the monitoring variables, but none on working from home and MICT.

3.1 Measuring MICT equipment

We measure the firms' MICT equipment by making use of the employers' responses to the survey 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?'*. Smartphones, tablet computers, and notebooks are still the most frequently used forms of MICT in firms. Information on MICT equipment across hierarchical levels is available in all considered panel waves.

Table 1 shows that the proportion of executives and non-executives equipped with MICT has steadily increased and that executives are equipped with MICT much more frequently than non-executives. In 2018, for example, 75 percent of executive employees were equipped with MICT, but only 19 percent of non-executive employees. This finding is consistent with our theoretical result (a) of Proposition 2, according to which firms find it more profitable to equip executives with MICT than non-executives.

Since our MTE estimation approach introduced in Section 4 requires binary treatment variables, we binarize our MICT variables by dividing the firms into a treatment and a control group based on the extent to which they equip their executives and non-executives with MICT. To keep both groups roughly equal in size, we choose the respective median of MICT equipment for executives ($h = E$) and non-executives ($h = NE$) per time period t as the threshold, thus separating firms with high MICT equipment levels ($MICT^h = 1$) from firms with low MICT equipment levels ($MICT^h = 0$). Hence, our MICT treatment variables are defined as

$$MICT^h = \begin{cases} 1 & \text{if } mict^h \geq mict^h_{0.5} \\ 0 & \text{if } mict^h < mict^h_{0.5}\,, \end{cases}$$

where $mict^h$ denotes our original MICT variable measured in percentages and $mict^h_{0.5}$ represents the median of the $mict^h$-distribution. In the following, we refer to the treatment group as MICT-friendly and the control group as MICT-averse. The binarization of multivalued (treatment) variables is quite common in the MTE literature and is done, for example, in the studies of Cornelissen et al. (2018) and Bhuller et al. (2020).

In our theoretical model, we argue on the one hand that equipping employees with smartphones, tablet computers and notebooks makes 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

Table 1: Descriptive statistics of the key variables

Variable	Wave	Hierarchy	Mean	Std. dev.	Range	N
Mobile information and communication technology						
MICT equipment	2014	Executives	66.07	42.09	0–100	760
($mict^h$)		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
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
Employee 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. N denotes the number of observations. Std. dev. abbreviates standard deviation.

done at home. Hence, the $MICT^h$ variables focus on technologies that are expected to be closely related to our measures on organizational control, i.e., monitoring and employee autonomy in the form of working from home.

3.2 Measuring monitoring

In panel waves 3 and 4 of the LPP employer survey, firms are asked about the prevalence of 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, who are subject to (a) annual structured appraisal interviews (*interview*), (b) written performance target agreements (*target*), and (c) annual performance evaluations (*evaluation*).

Each of these practices 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 MICT equipment with monitoring. We regard the three practices of performance appraisal not in the sense of a reduction of employee autonomy, but in the sense of hierarchical feedback or reward and sanction mechanisms, which is why we define these practices as monitoring. Table 1 shows for all three monitoring practices that executive employees are affected more frequently than non-executive employees.

To create an overall measure of monitoring, we aggregate the percentages from the survey questions into a composite measure MON^h, $h \in \{E, NE\}$, by making use of the double-standardization approach as applied, for example, in Bresnahan et al. (2002) and Tambe et al. (2012). The resulting variable can then be written as

$$MON^h = STD\{STD(interview^h) + STD(target^h) + STD(evaluation^h)\}\,.$$

By construction, MON^h has zero mean and unit variance and can be interpreted as the firms' intensity to monitor their executive and non-executive employees. According to our theoretical model, $MICT^h$ and MON^h are complements in the firm's returns, implying that better MICT equipment is associated with more intense monitoring. We expect that this applies to both executives and non-executives.

3.3 Measuring employee autonomy

We measure the degree of employee autonomy based on the percentage of executives and non-executives who can make use of the option to work from home. Working from home is a management practice that grants employees discretion over their place of work and their allocation of working time (e.g., Bloom et al. 2015, Beckmann and Kräkel 2022). As such, working from home has the potential to improve employees' work-life balance, but it can also make it more difficult to monitor employees. Overall, this leads us to refer to working from home as a corporate policy of employee autonomy.

Information on the prevalence of working from home is available in panel waves 2 and 3 of the LPP employer survey. It is important to note that in wave 3 the respective question in the questionnaire was modified. Instead of asking about the overall percentage, respondents were asked about the proportion of working from home in the functional areas of distribution and marketing (wfh^D), production (wfh^P), as well as 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.

To construct an overall variable measuring the intensity of working from home, we proceed in analogy to the composite monitoring variable by applying the double-standardization approach. The resulting variable WFH^h can then be generated as

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

where t is a time index. Again, WFH^h has zero mean and unit variance.

In our theoretical model, we find that firms are more likely to benefit if they increase the autonomy for executives rather than the autonomy for non-executives in response to an increase in MICT equipment. This is because autonomy yields higher productivity gains for executives and it only relaxes the participation constraints of executives. Consequently, we expect that equipping employees with MICT will have a mixed effect on employee autonomy, primarily increasing the autonomy of executives but not the autonomy of non-executives.

4 Identification strategy

Our identification strategy relies on the estimation of marginal treatment effects (MTE). Specifically, we estimate the MTE of MICT equipment on monitoring and employee autonomy in the form of working from home, separately for executive and non-executive employees. MTE estimation allows us to account not only for unobserved heterogeneity or endogeneity (often referred to as selection on unobservables), but also for essential heterogeneity (also referred to as selection on unobserved gains).

4.1 A generalized Roy model framework

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), Brinch et al. (2017), as well as Mogstad et al. (2018), among others.[9] The starting point of our MTE estimation is the potential outcomes model for the determination of organizational control

$$OC_1^h = X\beta_1^h + U_1^h \tag{8}$$

$$OC_0^h = X\beta_0^h + U_0^h \,, \tag{9}$$

where $OC_j^h \in \{MON_j^h, WFH_j^h\}$ $(j = 0, 1)$ is modeled as a linearly separable function of observed characteristics X and unobserved factors U_j^h. Since the potential outcomes OC_1^h and OC_0^h cannot be observed together for the same firm, the observed outcome OC^h depends on the treatment status $MICT^h$ and can thus be expressed by the switching regression model

$$OC^h = (1 - MICT^h) \cdot OC_0^h + MICT^h \cdot OC_1^h = OC_0^h + (OC_1^h - OC_0^h) \cdot MICT^h \,. \tag{10}$$

Participation in the treatment is determined by a firm's latent desire to belong to the group of MICT-friendly ($MICT^h = 1$) rather than the group of MICT-averse ($MICT^h = 0$) firms, which itself depends on observables $Z = [PDS, X]$ and unobservables V, so that

$$MICT^{h,*} = Z\zeta^h - V^h \,, \quad \text{where } MICT^h = 1\,[MICT^{h,*} \geq 0] = 1\,[Z\zeta^h \geq V^h] \,, \tag{11}$$

and PDS is a valid instrumental variable (IV), which will be introduced in the following Section 4.2. Hence, a firm belongs to the group of MICT-friendly firms if $Z\zeta^h \geq V^h$. Due to the negative sign in selection equation (11), V^h can be interpreted as unobserved resistance to treatment or cost of participation (e.g., Heckman and Vytlacil 1999, Cornelissen et al. 2016). Since the model structure allows the treatment $MICT^h$ to depend on OC_1^h and OC_0^h, the error terms in (8), (9), and (11) are correlated conditional on observables, i.e., $U_0^h \not\perp U_1^h \not\perp V^h \,|\, X$ (Heckman et al. 2006a, Brinch et al. 2017), which manifests the issues of endogeneity and essential heterogeneity.

Given that V^h is continuously distributed, selection equation (11) can be expressed as $p^h \geq U_{MICT^h}$, where $p^h = \Pr(MICT^h = 1 \,|\, Z) = P^h(Z)$ is the propensity score representing the probability of taking the treatment based on observables, and U_{MICT^h} is uniformly distributed

[9] An excellent survey on MTE estimation is provided by Cornelissen et al. (2016). For a more general overview on the estimation of treatment effects using instrumental variables, see Mogstad and Torgovitsky (2024).

between 0 and 1 by construction representing the quantiles of V^h (Brave and Walstrum 2014, Cornelissen et al. 2016). Hence, firms will take the treatment ($MICT^h = 1$) and thus select themselves into the group of MICT-friendly firms if their observed encouragement for treatment p^h does not fall below their unobserved resistance for treatment U_{MICT^h}.

By using a binarized treatment variable $MICT^h$, we explicitly address a type of selection mechanism in which firms assign themselves to a treatment or control group, depending on whether they provide MICT 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 organizational control. Second, the selection mechanism is unlikely to be based on observable characteristics alone, but also on the 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 2018).

4.2 Instrumental variable (IV) and identifying assumptions

To find a valid IV for MICT equipment, we follow the growth model developed by Galor and Weil (2000). In this model, technological progress is determined by population size and human capital (see also Klasen and Nestmann 2006). We refer to these determinants by combining variables that capture regional population size on the one hand and regional labor supply on the other, when specifying our IV. More precisely, our IV combines district-level information on population density, i.e., the number of inhabitants per square kilometer, and the number of students in science, technology, engineering, or mathematics (STEM disciplines). The latter can be interpreted as a measure of the future labor force potential in high-skilled technology-related occupations and thus as a special case within the theoretical framework of Galor and Weil (2000).[10]

The approach of constructing IVs by using regional-level information is quite common in the empirical literature and has been applied, for example, in Dewan and Kraemer (2000), Bloom et al. (2012a), and Tambe et al. (2012). We use the so-called INKAR database to gain the information necessary to construct our IV (as well as most control variables). The INKAR data is available at the district level, which allows us to merge the data with our firm-level observational data via the

[10]Similar to us, Basher and Lagerlöf (2008) proxy human capital by the number of employees who are employed in science and technology occupations where tertiary education is usually required.

district identifier.[11]

To address the skewed distribution as well as the wide value range of both the population-density variable pd_k and the STEM-students variable $stem_k$, we follow Kitamura and Lagerlöf (2020) and take the natural logarithm of both variables, thus generating the variables $PD_k = \ln(pd_k + 1)$ and $STEM_k = \ln(stem_k + 1)$, where k indexes the 401 German districts. We have access to a second variable providing information on population density, so we additionally use this information to construct our IV. This second variable $Dtype_k$ is an ordinal variable ranging between 1 and 4, where 1 indicates a sparsely populated rural district, 2 represents a rural district with densification tendencies, 3 stands for an urban district, and 4 indicates a district-free large city. Hence, by highlighting the dichotomy between urban and rural areas, $Dtype_k$ provides us with information on the type of districts. Unlike population density, $Dtype_k$ explicitly emphasizes the fact that the levels of population density are higher in cities than in rural areas (Kitamura and Lagerlöf 2020).

Obviously, PD_k and $Dtype_k$ are highly positively correlated by construction. Moreover, since universities (of applied sciences) are usually located in large, densely populated cities, $STEM_k$ is also likely to be highly correlated with PD_k and $Dtype_k$. To avoid serious collinearity problems and in analogy to our dependent variables on organizational control, we construct our composite IV by making use of the double standardization approach, i.e.,

$$PDS_k = STD\{STD(PD_k) + STD(Dtype_k) + STD(STEM_k)\}\,.$$

Again, PDS_k has zero mean and unit variance by construction. The summary statistics of the variables entering our IV can be found in Table 2.

To be able to interpret the MTE estimates in terms of causal inference, the identifying assumptions of instrument relevance, conditional independence, monotonicity, and additive separability must be satisfied (e.g., Vytlacil 2002, Heckman and Vytlacil 2005, Heckman et al. 2006a, Cornelissen et al. 2016).

(i) Instrument relevance

Our relevance condition can be expressed formally as $E[MICT^h_z - MICT^h_{z'} \mid X] \neq 0$, where $MICT^h_z$ is a binary indicator for the potential treatment status of a firm for instrument value $PDS = z$, with z and z' representing any pair of values of PDS. To explain the relevance of our population density variables PD_k and $Dtype_k$ for the MICT affinity in firms $MICT^h$, we resort to agglomeration economies and economic growth theory (e.g., Galor and Weil 2000, Klasen and Nestmann 2006,

[11] Detailed information about the INKAR database can be found at https://www.inkar.de.

Table 2: Descriptive statistics of the variables entering the instrumental variable

Variable	Wave	Mean	Std. dev.	Min–Max	N
Population density (pd)	2014	700.15	887.09	36.5–3,837.5	721
	2016	751.11	944.79	36.3–4,668.1	846
	2018	754.28	929.92	36.8–4,055.0	769
District type ($Dtype$)	2014	2.67	1.07	1–4	719
	2016	2.64	1.10	1–4	844
	2018	2.65	1.11	1–4	769
STEM students ($stem$)	2014	5,053.83	11,696.96	0–63,759	721
	2016	5,991.43	13,148.33	0–67,414	846
	2018	5,869.13	12,970.27	0–69,967	769

Source. INKAR database. Own calculations.

Notes. N denotes the number of observations. Std. dev. abbreviates standard deviation.

Bolter and Robey 2020). This literature argues that denser markets facilitate the creation of knowledge about the use of new technologies, help to reduce communication costs, and increase market size as well as the demand for innovation. To explain the relevance of the $STEM_k$-component of our instrument PDS_k, we build on the impact of changes in the relative supply of skilled labor on the use of new technologies (e.g., Acemoglu 1998, 2002, Kiley 1999, San 2023). This literature emphasizes a market size effect, according to which a relative increase in the expected future supply of employees with STEM qualifications promotes the diffusion of technologies that are complementary to these qualifications. Bolter and Robey (2020) combine these lines of reasoning and note that firms located in densely populated areas have access to a large labor market, and are thus more willing to invest in new technologies such as MICT. Hence, we expect that our composite PDS-instrument will be a relevant driver of equipping both executive and non-executive employees with MICT. In Section A1.1 of the Supplemental Appendix, we provide a more extensive discussion on the relevance of our IV. In Section A2.1, we empirically test the assumption of instrument relevance.

(ii) Conditional independence

The conditional independence or unconfoundedness assumption requires that our PDS-instrument is statistically independent from the unobserved error terms in the outcome equations (8) and (9) as well as the selection equation (11), conditional on a set of covariates X, i.e., $PDS \perp (U_0^h, U_1^h, V^h) \mid X$. Not least because of our reasoning on instrument relevance, the assumption of strict exogeneity or unconditional independence of PDS seems unrealistic, even if we take into account that our dependent variables do not measure, for example, the productivity of a geographical location or related regional outcomes, but the firms' level of organizational control. In the absence of an IV that is not completely random, the only way for us to exploit exogenous variation in our IV is to use appropriate control variables that help satisfy the exclusion restriction by cleaning up PDS from those agglomeration, labor supply, and other confounding effects on MON^h and WFH^h that go beyond the direct technology-related effect of PDS on the treatment variable $MICT^h$. Our set of control variables comprises both firm-level information collected in the LPP employer survey and the IAB Establishment Panel as well as district-level information stemming from the INKAR database.[12] Each of the control variables included serves the purpose of eliminating influences that drive changes in the PDS instrument, which are not unrelated to the firms' practices of organizational control, without removing the technological information from PDS.[13] In Section A1.2 of the Supplemental Appendix, we extensively discuss the set of covariates that we include in our econometric models to extract PDS from potentially contaminating regional and firm-specific confounders. In Sections A2.1 and A2.2, we provide suggestive evidence on the validity of the conditional independence assumption and the exclusion restriction for a binarized treatment variable. In Section A3.5, we relax the exclusion restriction and test the consequences of slight violations of the exclusion restriction on the estimated parameters.

(iii) Monotonicity

The monotonicity or uniformity assumption requires that all firms altering their treatment status in response to an IV-change from $PDS = z$ to $PDS = z'$ are either all moved into treatment or out of treatment, i.e., $MICT^h_z \geq MICT^h_{z'}$ or vice versa. Hence, firms that are already MICT-friendly when located in districts with relatively low values of PDS remain MICT-friendly when PDS increases and vice versa for MICT-averse firms. 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 MICT equipment in the opposite direction. In our case, monotonocity is an intuitively plausible assumption on its own, as it is hard

[12]The descriptive statistics of all firm-level and district-level control variables can be found in Table A1 in Section A4 of the Supplemental Appendix.

[13]Deuchert and Huber (2017) describe a second reason for the use of control variables in the IV context. The IV affects more than one (treatment) variable that is associated with the outcome variable. Since we distinguish between the MICT equipment of executives ($MICT^E$) and non-executives ($MICT^{NE}$) in our analysis, this motive is also important for us to be able to achieve instrument exogeneity.

to imagine why firms should switch from MICT-friendly to MICT-averse just as the IV components of population density and the number of STEM students start to increase. 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). The monotonicity assumption can be tested, which is done in Section A2.3 of the Supplemental Appendix.

(iv) Additive separability

Since our PDS-instrument 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 (8) and (9), conditional on $U_{MICT^h} = u_{MICT^h}$, i.e., $E[OC_j^h \,|\, X = x, U_{MICT^h} = u_{MICT^h}] = X\beta_j^h + E[U_j^h \,|\, U_{MICT^h}]$, where $j = 0, 1$. 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_{MICT^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 2018).

4.3 Marginal treatment effects (MTE) estimation

The MTE definition requires the specification of the conditional expectations of U_1^h and U_0^h (Brinch et al. 2017), i.e.,

$$k_j(p^h, x) = E(U_j \,|\, X = x, U_{MICT^h} = p^h)\,, \quad j = 0, 1\,, \tag{12}$$

and

$$k(p^h, x) = k_1(p^h, x) - k_0(p^h, x) = E(U_1 - U_0 \,|\, X = x, U_{MICT^h} = p^h)\,. \tag{13}$$

Applying (13) and the additive separability assumption, gives the MTE definition as the expected treatment effect conditional on X and U_{MICT^h}, i.e.,

$$MTE(x, p^h) = E[OC_1^h - OC_0^h \,|\, X = x, U_{MICT^h} = p^h] = X(\beta_1^h - \beta_0^h) + k(p^h, x)\,. \tag{14}$$

Under the identifying assumptions introduced in Section 4.2, the MTE in (14) is defined as the treatment effect at a certain value of U_{MICT^h} (Cornelissen et al. 2016). It is additive separable into an observed component $X(\beta_1^h - \beta_0^h)$, which is the gain of the decision of the average firm with observed characteristics X to select itself into the group of MICT-friendly firms (heterogeneity in observables), and an unobserved component $k(p^h, x)$ measuring the idiosyncratic gains in organizational control for this average firm, conditional on X and the unobserved propensity not to be treated U_{ID^h} (heterogeneity in unobservables). Since conditioning on $U_{MICT^h} = p^h$ is equivalent to conditioning on the intersection of $P^h(Z) = p^h$ and $MICT^h = 0$, the MTE defined in (14) can be interpreted as the average effect of treatment for firms who are indifferent between participation in treatment and non-participation (Cornelissen et al. 2016, Brinch et al. 2017).

MTE estimation can be realized by applying the local instrumental variable (LIV) approach described in Heckman and Vytlacil (1999) among others, or by the separate approach developed in Heckman and Vytlacil (2007). In our empirical analysis, we apply the separate approach that identifies the observed and unobserved components $X\beta_j^h + k_j(p^h, x)$, $(j = 0, 1)$, separately for the treated and untreated firms (Brinch et al. 2017). The reason for preferring the separate over the LIV approach is the higher vulnerability of the LIV approach to misspecification. For example, Andresen (2018) shows that LIV is quite sensitive to the choice of the estimation method for the selection model. Furthermore, LIV turns out to be very sensitive to the specification of the covariates in X when estimating the slope of the MTE curve (Devereux 2022).

Applying the separate approach allows the potential outcome equations (8) and (9) to be expressed by the conditional expectations of OC_1^h and OC_0^h given $P^h(Z)$ and X (Heckman et al. 2006b, Brave and Walstrum 2014, Cornelissen et al. 2016, Brinch et al. 2017, Andresen 2018, Devereux 2022), i.e.,

$$E[OC_1^h \,|\, P^h(Z) = p^h, X = x, MICT^h = 1] = X\beta_1^h + K_1(p^h, x) \tag{15}$$

$$E[OC_0^h \,|\, P^h(Z) = p^h, X = x, MICT^h = 0] = X\beta_0^h + K_0(p^h, x)\,, \tag{16}$$

where $K_1(p^h, x) = E[U_1^h \,|\, U_{MICT^h} \leq p^h, X = x]$ and $K_0(p^h, x) = E[U_0^h \,|\, U_{MICT^h} > p^h, X = x]$ denote the confounding endogenous variation in the error terms of the outcome equations (8) and (9). Following Brinch et al. (2017), differentiating K_1 and K_0 with respect to p^h and rearranging results in

$$k_1(p^h, x) = p^h \frac{\partial K_1(p^h, x)}{\partial p^h} + K_1(p^h, x) \tag{17}$$

and

$$k_0(p^h, x) = -(1 - p^h) \frac{\partial K_0(p^h, x)}{\partial p^h} + K_0(p^h, x)\,. \tag{18}$$

MTE estimation can be performed using both parametric and semiparametric methods. We estimate both parametric normal and semiparametric MTE models, where we make use of the former in our baseline specifications and the latter in our sensitivity analysis.

4.4 Parametric normal MTE model

In addition to the identifying assumptions mentioned earlier, MTE estimation under the parametric normal model requires a trivariate normal distribution for the error terms in equations (8), (9), and (11), 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 and 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 model, MTE estimation is based on outcome equations (15) and (16), where K_1 and K_0 are given by

$$K_1(p^h, x) = -\rho_1^h \frac{\phi(p^h)}{\Phi(p^h)p^h} = \rho_1^h \lambda_1^h \tag{19}$$

$$K_0(p^h, x) = \rho_0^h \frac{\phi(p^h)}{\Phi(p^h)(1-p^h)} = \rho_0^h \lambda_0^h \,. \tag{20}$$

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, Andresen 2018).

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[14]

$$MICT^h = Z\zeta^h + v^h \,. \tag{21}$$

From the parameter estimates of (21), we calculate estimates of the inverse Mills ratios λ_1^h and λ_0^h, and add these estimates as control functions to equations (8) and (9) resulting in

$$OC_1^h = X\beta_1^h + K_1(p^h, x) + U_1^h = X\beta_1^h + \rho_1^h \widehat{\lambda}_1^h + u_1^h \tag{22}$$

$$OC_0^h = X\beta_0^h + K_0(p^h, x) + U_0^h = X\beta_0^h + \rho_0^h \widehat{\lambda}_0^h + u_0^h \,, \tag{23}$$

where u_1^h and u_0^h are analogous to v^h. In a second step, MTE estimation of equations (22) and (23) using the separate approach of the parametric normal model leads to (see Brinch et al. 2017, Andresen 2018, Devereux 2022)

$$\widehat{MTE}_{PN}(x, p^h) = X(\widehat{\beta}_1^h - \widehat{\beta}_0^h) + \widehat{k}_1(p^h, x) - \widehat{k}_0(p^h, x) = X(\widehat{\beta}_1^h - \widehat{\beta}_0^h) + (\widehat{\rho}_1^h - \widehat{\rho}_0^h)\Phi^{-1}(p^h) \,. \tag{24}$$

Essential heterogeneity in the form of positive (reversed) 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).

[14] The substitution of V^h for v^h is a consequence of equivalence between the latent index model in (11) and the reduced form (21).

5 Empirical results

This section comprises the results of our empirical analyses, starting with direct and suggestive tests of the identifying assumptions in Section 5.1 and ending with a series of robustness checks for our baseline MTE estimates in Section 5.3. A detailed representation can be found in Sections A2 and A3 of the Supplemental Appendix. The main part of this section is devoted to the results of our MTE estimation approach displayed in Section 5.2.

5.1 Assessment of instrument validity

To obtain meaningful and reliable treatment effect estimates from MTE estimation, the validity tests must be consistent with the respective identifying assumptions. While the assumptions of instrument relevance and monotonicity are directly testable, we can only obtain indicative evidence for the conditional independence assumption and the IV exclusion restriction, which can be regarded as necessary but not sufficient conditions for their validity.

Tables 3 (panel A) and 4 (lower part) show the test statistics for the relevance condition. As expected, the first-stage estimates of PDS turn out to be highly significant with a positive sign, regardless of the applied sample. The corresponding χ^2-test statistics range between 15.47 and 27.85 in our trimmed baseline sample (Table 4) and between 10.80 and 19.43 in the untrimmed sample (Table 3), which we refer to in some of our robustness checks. In all cases, therefore, the critical rule-of-thumb value of 10 is surpassed, thus rejecting the null hypothesis of weak instruments and confirming the assumption of instrument relevance.

Our indirect test on conditional independence is based on Bhuller et al. (2020) and results from the comparison of the estimates displayed in panels A and B of Table 3. The test explores the consequences of adding further covariates to the regressor matrix X in the first-stage equation (21). If the instrument PDS is as good as random conditional on X, the inclusion of additional covariates should not significantly change the magnitude of the first-stage estimates of the PDS-instrument, as they are expected to be uncorrelated with PDS. A test on the equality of coefficients confirms that adding a series of district- and firm-level covariates to the original first-stage specifications does not virtually change the magnitude of the respective PDS estimates (p-values range between 0.760 and 0.961), which may serve as an indication of conditional independence.

Furthermore, we test whether the binarization of our PDS-instrument violates the IV exclusion restriction, as pointed out in Angrist and Imbens (1995). According to the results of a test developed in Andresen and Huber (2021), we find no indication for such a violation (see Figure

Table 3: First-stage regressions: the effect of PDS on $MICT^h$

Control model MTE model	Monitoring model Monitoring regressions		Autonomy model Working-from-home regressions	
Estimation method	Probit ML	Probit ML	Probit ML	Probit ML
Dependent variable	$MICT^E$	$MICT^{NE}$	$MICT^E$	$MICT^{NE}$
	(1)	(2)	(3)	(4)
	Panel A: First-stage estimates according to (21)			
PDS	0.191***	0.155***	0.243***	0.290***
	(0.048)	(0.047)	(0.070)	(0.065)
χ^2-test	15.43***	10.80***	12.11***	19.43***
	[0.000]	[0.001]	[0.000]	[0.000]
N	1,423	1,423	1,340	1,340
	Panel B: Panel A plus additional covariates at the firm and district level			
PDS	.201***	.137*	.240***	.293***
	(.076)	(.075)	(.085)	(.073)
N	1,275	1,275	1,197	1,197
H_0: $\widehat{\zeta}^{h,A}_{PDS} = \widehat{\zeta}^{h,B}_{PDS}$	[.848]	[.760]	[.935]	[.961]

Sources. Linked Personnel Panel, employer survey 2014/2016/2018, IAB Establishment Panel 2014/2016/2018, INKAR database, various years.

Notes. The values in parentheses (square brackets) represent robust standard errors clustered at the district level (p-values). The χ^2-test is a test on instrument relevance. The test on the equality of $\widehat{\zeta}^{h,A}_{PDS}$ and $\widehat{\zeta}^{h,B}_{PDS}$ refers to the estimated coefficients for PDS reported in panel A and panel B. N denotes the number of observations. The additional firm-level covariates of the augmented first-stage regressions displayed in panel B include variables on a firm's market environment, regulatory conditions, strategies, workforce composition, and product innovations. The additional district-level covariates include variables on employment structures, mobility trends, local gross-domestic products, child care facilities, and commuting distances. Finally, the augmented first-stage regressions for the monitoring (autonomy) model includes the model-specific, previously excluded covariates from the autonomy (monitoring) model.

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

A1 and the corresponding test results in the Supplemental Appendix), which can be regarded as suggestive evidence. Finally, our monotonicity test is based on the theoretical implication that the first-stage estimates of the instrument PDS should be nonnegative for any subsample (Bhuller et al. 2020). Our first-stage regression results reported in Tables A2 to A5 of the Supplemental Appendix are consistent with this implication.

5.2 MTE estimation of MICT on organizational control

Table 4 contains the treatment effects of MICT equipment on monitoring and employee autonomy resulting from our baseline parametric normal MTE models. In our baseline specifications, we restrict the econometric analysis to a trimmed sample in which one percent of the observations were trimmed at each tail of the propensity score distributions to avoid limited common support. In fact, the common support graphs displayed in Figure A2 of the Supplemental Appendix indicate little overlap at the tails of the propensity score distributions, so trimming is an appropriate response. Columns (1) and (2) of Table 4 report the average treatment effects (ATE) as well as the average treatment effects for the treated (ATT) and the untreated (ATUT) firms for the monitoring model, separately for executive and non-executive employees. Columns (3) and (4) show the corresponding effects resulting from the autonomy model, where WFH^E and WFH^{NE} represent the dependent variables. The H_0-tests reported in the medium part of the table represent one- and two-sided tests on essential heterogeneity and heterogeneous average treatment effects.

Our estimation results show that equipping employees with MICT increases both employee autonomy and monitoring for executives, while non-executives only experience more intensive monitoring, but do not receive greater autonomy. For the executives, all treatment effects in the monitoring and autonomy models prove to be statistically significant (at least at the 5 percent level), while statistically significant treatment effects for the non-executives are only found in the monitoring model, but not in the autonomy model.[15] Moreover, in both models of organizational control, the estimated treatment effects turn out to be higher for executives than for non-executives, which is supported by the profiles of the MTE curves in Figure 1. Overall, these findings have two implications. First, the effect of equipping employees with MICT on organizational control differs

[15]For example, the ATE of MICT equipment on monitoring is positive and highly significant for both executives (1.445) and non-executives (1.026), meaning that switching from the group of MICT-averse firms to the group of MICT-friendly firms increases monitoring intensity by about 1.5 or 1.0 standard deviations, respectively. In contrast, the corresponding ATE of MICT equipment on working from home is significantly positive only for executives (1.128 standard deviations), while it is insignificant for non-executives (0.155 standard deviations).

Table 4: Treatment effects of MICT on organizational control: baseline model

Control model	Monitoring model		Autonomy model	
Econometric model	Parametric Normal MTE		Parametric Normal MTE	
Dependent variable	MON^E	MON^{NE}	WFH^E	WFH^{NE}
	(1)	(2)	(3)	(4)
ATE	1.445***	1.024**	1.179**	0.262
	(0.444)	(0.468)	(0.509)	(0.435)
ATT	1.692***	1.348**	0.925**	0.247
	(0.492)	(0.535)	(0.468)	(0.337)
ATUT	1.125***	0.610	1.505**	0.282
	(0.423)	(0.487)	(0.593)	(0.600)
Tests on essential heterogeneity and heterogeneous treatment effects				
H_0: $\widehat{\rho}_1^h - \widehat{\rho}_0^h = 0$	−1.056**	−0.875	1.291**	0.310
	(0.528)	(0.579)	(0.574)	(0.527)
H_0: ATT $\leq$ ATUT	[0.013]**	[0.045]**		
H_0: ATUT $\leq$ ATT			[0.017]**	[0.465]
Test on instrument relevance: first-stage estimates according to (21)				
PDS	0.265***	0.188***	0.311***	0.359***
	(0.051)	(0.047)	(0.071)	(0.068)
χ^2-test	26.14***	15.47***	18.86***	27.85***
	[0.000]	[0.000]	[0.000]	[0.000]
N	1,393	1,395	1,313	1,313

Sources. See Table 3. Own calculations.

Notes. The estimates are based on a trimmed sample in which 1 percent of the observations have been trimmed at each tail of the propensity score distributions because of limited common support. The set of covariates contains firm-level and district-level variables introduced in Section A1.2 of the Supplemental Appendix. The values in parentheses represent bootstrapped standard errors clustered at the district level (200 replications) to account for the inclusion of estimated control functions. The values in square brackets represent p-values. The parameters $\widehat{\rho}_1^h$ and $\widehat{\rho}_0^h$ are the coefficients of the estimated inverse Mills ratios $\widehat{\lambda}_1^h$ and $\widehat{\lambda}_0^h$ according to equations (22) and (23). Negative (positive) differences indicate essential heterogeneity in the form of positive (reversed) selection based on unobserved MICT gains. Furthermore, a negative (positive) sign for $\widehat{\rho}_1^h - \widehat{\rho}_0^h = 0$ is equivalent to downward (upward) sloping MTE curves. N denotes the number of observations. The MTE regression models have been estimated by applying the user-written Stata do-file 'mtefe' developed by Martin Eckhoff Andresen (Andresen 2018).

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

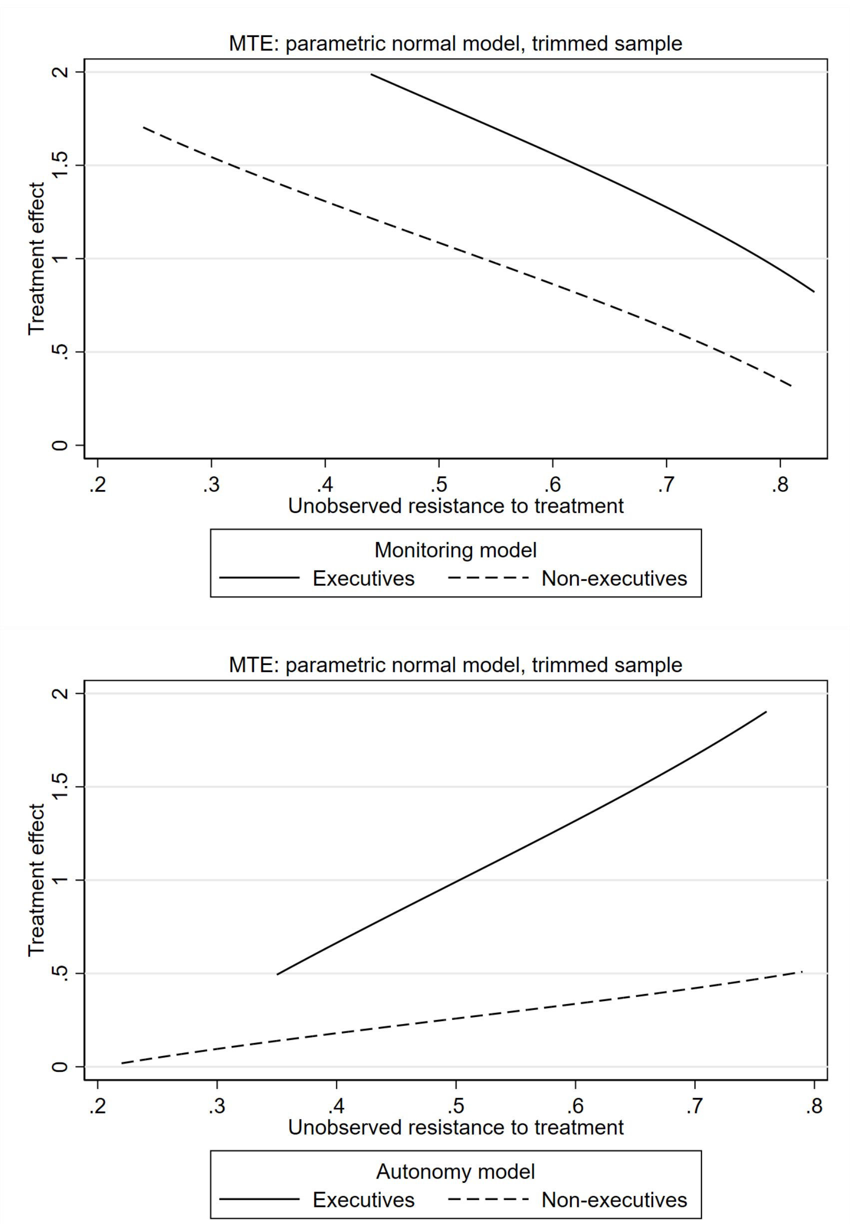
across hierarchical levels, which is consistent with result (i) of our theoretical model. Second, firms combine a high monitoring intensity with high employee autonomy in response to increasing MICT equipment, at least for executive employees. This latter finding is quite surprising, as recent empirical studies of MICT usage on organizational or job design tend to identify either clear decentralization trends (e.g., Caroli and Van Reenen 2001, Bresnahan et al. 2002, Acemoglu et al. 2007) – comparable with low organizational control – or clear centralization trends (e.g., Labro et al. 2023) – comparable with high organizational control. Nevertheless, our empirical finding is consistent with result (ii) of our theoretical model and is to some extent also in line with the centralization result obtained in Labro et al. (2023), as we find monitoring to be more prevalent in firms than employee autonomy that is restricted to executive employees.

Finally, our estimation results demonstrate the existence of essential heterogeneity and heterogeneous treatment effects, with differences again between the monitoring and autonomy models and between executive and non-executive employees. As Figure 1 shows, the MTE curves for both groups of employees are downward sloping in the monitoring model, while they are upward sloping in the autonomy model.[16] The achieved orders of the estimated treatment effects, i.e., ATUT < ATE < ATT for the monitoring model and the opposite order ATUT > ATE > ATT for the autonomy model, are in line with the MTE curves. The tests on heterogeneous treatment effects are consistent with the tests on essential heterogeneity, except for the specification for the non-executives in the monitoring model, where the test on heterogeneous treatment effects indicates statistical significance. Once again, these findings show substantial differences between executives and non-executives, thus additionally supporting result (i) of our theoretical analysis.

The estimated orders of ATT, ATE and ATUT as well as the resulting MTE curves imply that with increasing affinity for MICT, companies intensify their monitoring activities while at the same time reducing employee autonomy. Put differently, MICT-friendly firms (low U_{MICT^h}) tend to do a lot of monitoring and grant little autonomy (high organizational control), while MICT-averse firms (high U_{MICT^h}) grant relatively much autonomy in the form of working from home but tend to place little emphasis on monitoring (low organizational control). This applies especially to executive employees and then points to a certain substitution between monitoring and employee autonomy depending on the firms' MICT affinity. However, due to the positively significant treatment effects obtained in the monitoring and autonomy models, it is still the case that companies with increasing MICT equipment use monitoring and employee autonomy as complementary man-

[16]The detailed individual MTE curves, which additionally contain the confidence intervals and the ATE functions for each of the four MTE models, can be found in Figure A3 of the Supplemental Appendix.

Figure 1: Marginal treatment effect curves: baseline specification



agement practices. In this respect, this additional finding is also consistent with results (i) and (ii) from our theoretical model.

5.3 Sensitivity analysis

In this section, we present the results of some robustness checks of our baseline MTE regression results obtained in Section 5.2. A more detailed version of all sensitivity checks can be found in Section A3 of the Supplemental Appendix. We proceed in six steps. First, we rerun our parametric normal MTE regressions using the untrimmed sample. In a second step, we exclude observations originating from districts that may be biased or unrepresentative because particularly large companies are headquartered there. The next steps comprise the specification of alternative estimation models to our baseline parametric normal MTE models. Specifically, we estimate correlated random coefficients (CRC) models described in Wooldridge (2015) and Cornelissen et al. (2016), using both the untrimmed sample (step 3) and the trimmed sample (step 4), as well as semiparametric MTE models (step 5). Both estimation models are attractive candidates for a robustness check because, unlike our baseline parametric normal MTE models, they do not require the assumption of trivariate normally distributed error terms in the potential outcome and selection equations. Another benefit of the CRC model is that it conveniently allows us to perform statistical tests on the equality of the estimated ATEs resulting for executive and non-executive employees, which is valuable for us because it helps us to strengthen the explanatory power with respect to our theoretical result (i). An additional benefit of semiparametric MTE models is that they do not restrict the MTE curves to be monotonic. Finally, in step six, we test whether our parameter estimates are affected by relaxing the assumption that our IV PDS perfectly satisfies the exclusion restriction (Berkovitz et al. 2012, Riquelme et al. 2013).

The analyses in Section A3 demonstrate that the estimation results of all robustness checks are consistent with our baseline MTE estimates presented in Section 5.2. In addition, the CRC models provide statistical confirmation for our observation that the MICT effects are higher for executives than for non-executives. This applies to both the effects on monitoring and the effects on employee autonomy, as indicated by the statistically significant ATE differences between executives and non-executives displayed in the middle part of Tables A6 and A7. However, higher ATE for executives than for non-executives can only be determined in the semiparametric model estimates for the autonomy model, but not for the monitoring model. This means that only the ATE differences in the autonomy model prove to be robust in all sensitivity checks carried out, which is in line with result (i) of our theoretical model. Finally, after applying the fractionally resampled Anderson-Rubin (FAR) test, which allows for a slight violation of the orthogonality or exogeneity assumption, we are still able to draw valid conclusions about the impact of MICT equipment on monitoring and employee autonomy across hierarchical levels, even if the exclusion restriction is slightly violated.

6 Conclusion

Advances in information and communication technology lead to considerable changes in firms' optimal job design. A still open question is whether these changes result in higher or lower organizational control. We address this fundamental question by considering the dissemination of mobile information and communication technology (MICT) among employees in the last years. The previous literature on this topic is typically based on the strict dichotomy that MICT will lead *either* to more centralization – comparable to higher organizational control – *or* to more decentralization – comparable to lower organizational control – 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 organizational control, we consider monitoring and employee autonomy, with high organizational control being defined by a high monitoring intensity and a low degree of employee autonomy. Our theoretical and empirical analyses yield the same main findings. Concerning non-executive employees, increasing MICT equipment in firms leads to clearly higher organizational control. However, concerning executive employees, our results disagree with the strict dichotomous view outlined above. Increasing MICT equipment yields more employee autonomy (i.e., lower organizational control), but also more monitoring (i.e., higher organizational control). On the one hand, firms empower executive employees to better utilize their skills, but, on the other hand, complement empowerment with more intense monitoring and 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 optimal choice of MICT equipment and organizational control. 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 monitoring when being equipped with more MICT, but crucially differ concerning the degree of employee autonomy. The fact that executive employees, contrary to non-executives, are granted more autonomy as a consequence of increased MICT can be explained by two effects. First, relative productivity gains by autonomy and positive productivity effects due to higher human capital favor the equipment of executives with MICT. 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 makes use of three German observational and regional data sets at the firm and district level. Methodologically, we rely on marginal treatment effects (MTE) estimation to establish a causal interpretation of our results and to draw conclusions about possible effect heterogeneity. Our instrumental variable (IV) exploits geographic variation by making use of information on population density and future labor force participation in high-skilled technology-related occupations (number of students in STEM disciplines).

The empirical findings are consistent with our theoretical predictions. First, executive employees are much more equipped with MICT than non-executive employees. Second, equipping employees with MICT results in different effects on organizational control across hierarchical levels. The effects for executives are more pronounced than those for non-executives, in particular with respect to autonomy (result (i)). Third, firms use high monitoring and high employee autonomy as complements in designing jobs in response to increasing MICT equipment (result (ii)). This applies primarily to executive employees, while non-executives only experience an increase in monitoring, but not in autonomy. Fourth, our empirical analysis proves the relevance of heterogeneous treatment effects as well as the appearance of essential heterogeneity, suggesting that, to some extent, firms substitute between monitoring and employee autonomy, depending on their affinity to MICT. However, this does not change our overall finding, according to which firms use both practices of organizational control as complements in response to an increase in MICT, at least for executive employees.

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Appendix

Proof of Proposition 1. By replacing $w(\bar{s}) - w(\underline{s})$ with $c'(e)$ according to (3), the corresponding Lagrangian to the firm's problem reads as

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

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

$$\lambda_1 \cdot [w(\underline{s}) + ec'(e) + \Delta uA - c(e) - \bar{u}] = 0 \quad \text{and} \quad \lambda_2 \cdot w(\underline{s}) = 0. \tag{25}$$

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

$$\frac{\partial e}{\partial w(\underline{s})} = -\frac{1}{c''(e)} = -\frac{\partial e}{\partial w(\bar{s})}. \tag{26}$$

The first-order conditions yield

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

$$\Leftrightarrow [k(1+rI)(1+aA)\,y'(e)\,M - c'(e) + (\lambda_1 - 1)\,ec''(e)]\frac{\partial e}{\partial w(\underline{s})} = 1 - \lambda_2 - \lambda_1$$

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 (26), it follows that $1 = \lambda_2 + \lambda_1$. Hence, (25) 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

$$k(1+rI)(1+aA)\,y'(e^*_{(i)})M = c'(e^*_{(i)}) + e^*_{(i)} \cdot c''(e^*_{(i)}), \tag{27}$$

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:

$$-e^*_{(ii)} \cdot c'(e^*_{(ii)}) = \Delta u \cdot A - c(e^*_{(ii)}) - \bar{u}. \tag{28}$$

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

$$k\,(1+rI)\,(1+aA)\,y'(e^*_{(iii)})M=c'(e^*_{(iii)}),\tag{29}$$

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 (27) with (29). 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

$$\lambda_1=1-\frac{k\,(1+rI)\,(1+aA)\,y'(e^*_{(ii)})M-c'(e^*_{(ii)})}{e^*_{(ii)}c''(e^*_{(ii)})}.\tag{30}$$

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 (30) and $\lambda_1>0$ we obtain

$$k\,(1+rI)\,(1+aA)\,y'(e^*_{(ii)})M-c'(e^*_{(ii)})-e^*_{(ii)}c''(e^*_{(ii)})<0.\tag{31}$$

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

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

(27) and (31) 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 (28) 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

$$\frac{\partial}{\partial I}\Pi_C\left(I,A,M\right) = kr\left(1+aA\right)y(e_C^*)M + \Delta K - \kappa \tag{32}$$

for $C = (i),(ii),(iii)$. As $e_{(i)}^* < e_{(ii)}^* < e_{(iii)}^*$, we obtain the ranking of the $\frac{\partial}{\partial I}\Pi_C\left(I,A,M\right)$ as stated in the proposition. Differentiating (32) with respect to k leads to $\frac{\partial^2}{\partial I\partial k}\Pi_C\left(I,A,M\right) = r\left(1+aA\right)y(e_C^*)M$, which is strictly positive.

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

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

By applying again the envelope theorem, we obtain

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

which is positive as $M_H > M_L$ and

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

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

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

with

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

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

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

with

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

as

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

(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

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

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

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

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,

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

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).

Supplemental Appendix

A1 Detailed discussion on instrument validity

A1.1 Instrument relevance

There are various arguments within agglomeration economies and economic growth theory postulating a strong positive link between population density and technological innovations. First, based on Malthusian theory and historical observations, periods with (without) technological progress have been found to be associated with increasing (stable) population sizes (Ashraf and Galor 2011). The second argument is learning, meaning that knowledge generation and accumulation about the development and adoption of new technologies is facilitated in denser markets (Puga 2010). Third, population density promotes the development and diffusion of new technologies by reducing the cost of workplace communication and information exchange, increasing the size of markets and opportunities for specialization, and creating the necessary demand for innovation (Klasen and Nestmann 2006, Puga 2010). This will encourage local governments to expand transport and telecommunication infrastructures in the districts concerned (Bolter and Robey 2020), while companies will have an incentive to increase the MICT equipment of their employees. Consequently, we expect a strong positive correlation between district-level population density and MICT equipment of firms. This applies to both indicators of population density.

To explain the relevance of the STEM component of our IV, we build on the theoretical link between relative labor supply and technological progress (e.g., Acemoglu 1998, 2002, Kiley 1999, San 2023), where it is argued that an increase in the relative supply of skilled labor reduces the wage premium for skilled workers relative to unskilled workers (substitution effect), but also leads to an expansion of the market for technologies that are complementary to skilled labor (market size effect). For our research question, the market size effect implies that a relative increase in the expected future supply of employees with STEM qualifications promotes the diffusion of mobile technologies, which are assumed to be complementary to these qualifications. We therefore hypothesize a strong positive relationship between the number of graduates from MICT-friendly STEM degree programs in a certain district and the proportion of employees equipped with MICT in firms located in this district.

Bolter and Robey (2020) combine both arguments stating that firms located in densely populated areas have access to a large labor market and are more likely to invest in new technologies because they know they can find the required workers here. Based on the technology relatedness derived for all variables entering our composite instrument PDS, we expect a strong positive correlation with the MICT treatment variable, which would satisfy the relevance condition.

A1.2 Conditional independence

Since our PDS-instrument consists of variables that provide information on technology intensity, agglomeration economies, and future labor supply, it is unlikely to be uncorrelated with the error terms of the potential outcome equations (8) and (9), making it difficult for us to exploit exogenous variation based on regional and firm differences in our PDS-instrument to instrument MICT equipment. Endogeneity in the instrument may arise primarily due to some unobserved agglomeration or labor supply characteristics that drive both the PDS instrument and the dependent job-design variables MON^h and WFH^h. In the following paragraphs A to F, we will extensively discuss the set of covariates that we include in our econometric models to extract our IV PDS from potentially contaminating regional and firm-specific confounders in a manner sufficient to exploit exogenous variation in PDS to instrument MICT equipment.

A. Labor market competition

A first concern regarding the exogeneity assumption of our PDS-instrument relates to the argument that, in addition to the effect on technology, measures of local population density and the amount of future technology-related labor supply may also encompass the effect of labor market competition on the firms' policies of organizational control. Specifically, companies located in larger cities and urban areas with a high population density are more likely to face intense competition for suitable MICT-friendly employees than firms in rural areas with a low population density. Since firms can be expected to respond to labor market competition, for example, by adapting their policies of organizational control, our econometric models must include proxies for labor market competition to rid the PDS-instrument of possible contamination induced by effects of labor market competition.

We capture the impact of labor market competition on both our IV and the dependent organizational control variables by controlling for local unemployment rates and the presence of open job positions for skilled workers in firms. Low unemployment rates and many vacant job positions indicate a high level of labor market competition. In this case, firms could offer work-from-home options to attract workers and address local labor shortages. In contrast, when unemployment rates are high or the number of job openings is low, employers gain bargaining power over employees, which might encourage them to adopt stricter monitoring practices. Controlling for local unemployment and job openings extracts these effects of labor market competition from our PDS-instrument, reducing concerns about IV endogeneity. For the same reason, we control for the share of skilled employees in firms and the total number of students of universities (of applied sciences) per district. These measures are included to remove the impact of the level of employee qualification of our IV without eliminating its relationship with technology. A PDS-instrument that is free of employment and skill effects measures the technology affinity of the future labor force through its component 'number of STEM students', while also influencing the affinity of firms to equip their executive and non-executive employees with MICT.

B. Competitive pressure (firm selection)

Another potential concern regarding conditional IV independence rests on the notion that a measure containing information on population density reflects to some extent the level of competitive pressure faced by firms. Competitive pressure, in turn, can be a key to the choice of a particular firm policy, such as monitoring or working from home (Bloom et al. 2013). In the agglomeration economics literature, this argument is referred to as 'firm selection' (e.g., Puga 2010, Combes et al. 2012). For example, if a firm is located in a densely populated district, it faces substantial competitive pressure that may encourage management to adapt the level of organizational control by increasing monitoring to identify inefficiencies, maintain market power, or achieve competitive advantage.

We measure the competitive pressure among businesses at the district level by the number of business registrations per district. 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 pressure than other companies that begin operations in a district with fewer business registrations and might, therefore, prefer stricter monitoring. On the other hand, young companies tend to use less organizational control than older companies (Acemoglu et al. 2007) and could therefore respond to competitive pressure with a greater focus on practices of employee autonomy such as working from home. Hence, to account for inter-firm competition, we also control for the firms' age. Furthermore, we include a set of dummy variables indicating different levels of firms' self-reported competitive pressure. Our final control variable for competitive pressure is the firms' annual change of total employment, where a negative change indicates a problematic economic firm situation. The inclusion of these covariates should eliminate the possible decontamination of our PDS instrument by the effects of competitive pressure.

C. Local telecommunication infrastructure

Although the purpose of our IV is to instrument firms' MICT equipment, we have to exclude a special type of MICT-related effect, namely the possibility that our IV contains effects caused by local telecommunications infrastructure. This is because firms are not unlikely to adapt their practices of organizational control based on the quality of the local telecommunications structure. For example, local or supra-regional governments may give preference to urban, more densely populated areas over rural, less densely populated areas when deciding on the expansion of telecommunications structures. This disparity between districts could result in firms in districts with a high-quality telecommunication infrastructure being more (less) likely to use the work-from-home (monitoring) option than firms in districts with a low-quality telecommunication infrastructure, violating the exogeneity assumption for our PDS-instrument.

To ensure the exclusion of the quality-of-telecommunications infrastructure interpretation without eliminating the technology relatedness of our IV, we enlarge our set of covariates by adding two dummy variables providing self-reported information about a firm's general quality of technical equipment (usage of superior or state-of-the-art technologies). The technical status of businesses is a suitable indicator for describing the general local telecommunications infrastructure, as it provides information not only on broadband infrastructure, but also on other MICT-related infrastructure, such as the existence of local technical support providers and local educational programs in the MICT field. In all cases, we expect a positive correlation with the technical status of firms.

D. Agglomeration economies: productivity advantages

Generally speaking, agglomeration economies refer to performance advantages of larger cities relative to less densely populated rural regions. However, if firms in urban high-performing regions show systematic differences in their practices of organizational control compared to firms located in rural, low-performing regions, then the exogeneity of our IV (which is partially based on population density) is not guaranteed, which would also violate the conditional independence assumption.

In the agglomeration economies literature, the local value added per employee and local wage levels are considered appropriate measures of agglomeration economies in the form of local performance differences. In addition, some studies note that productivity and wages are higher in larger and densely populated cities relative to rural and less densely populated areas (e.g., Glaeser 2010, Puga 2010). Since firms located in more productive regions can be expected to behave differently with respect to organizational control than firms located in less productive regions, we need to control for regional productivity differences to extract potential endogenous variation in the form of productivity effects from our PDS-instrument. Our productivity measure is defined as the ratio of the annual value added and the annual wage, both measured per employee and district. The use of this measure should help to sufficiently disentangle our IV from the variation associated with local productivity differences.

E. Agglomeration economies: employee mobility and residence decisions

Another issue that challenges the exogeneity assumption of our PDS-instrument concerns the mobility of workers and their choice of residence. In particular, people are likely to differ systematically in terms of their preferred place of residence. Some employees prefer to live in large cities, while others are drawn to less densely populated rural regions. However, it is not unlikely that employees' residence decisions depend on whether or not their employers offer the option of working from home. For example, employees who currently live in densely populated districts but plan to move to less densely populated districts, where rents, housing prices, or land purchase prices are relatively low, could begin negotiations with their employers about the option of working from home. Analogously, employees living in sparsely populated districts and at a great distance from their place of work could request from their employers the option to work from home in order to avoid long commuting times or moving to districts with high housing prices. In these cases, our IV, based in part on local population density, would likely capture the effect of individual residence preferences on the opportunity to work from home, and would then be endogenous, unless the regression model contains suitable control variables to account for these residence preferences.

We address the issue of employees' residence preferences by adding district-level information on average purchase values of building land, living space per inhabitant, and the balance of inbound and outbound commuters to the set of control variables in our working-from-home regressions. Since female employees are expected to be particularly interested in work-from-home options due to family and childcare responsibilities, we add variables with firm-level and district-level information on the respective shares of female employees to the set of covariates. We add these control variables only to our working-from-home regressions but not to the monitoring regressions, as mobility and residence decisions are only relevant if employers permit their workers to perform their tasks outside the firm location. This specification enables us to extract the effects of worker mobility and residence preferences from our IV, so that PDS affects WFH^h only through its effect on $MICT^h$, but not through its association with worker mobility and housing preferences.

F. Additional firm characteristics and time fixed effects

Following the monitoring intensity principle described in Milgrom and Roberts (1992, chapter 7), we address the potential selection into certain districts based on local corporate job-design policies by controlling for the firms' usage of performance pay plans. The monitoring intensity principle predicts that firms that apply performance pay plans are likely to increase their efforts to monitor their employees. Since the assumption of a complementary relationship with pay for performance refers only to monitoring practices, but not to employee autonomy, we add a control variable for the use of performance pay plans only to the regression equations of the monitoring model. Moreover, we follow Bloom et al. (2012b) and control for firm size classes and industry affiliation as fundamental determinants in the debate about centralization or decentralization in organizational and job design. For example, since larger firms are typically headquartered in densely populated urban regions and are likely to differ from smaller firms not only in terms of digitalization (Forman et al. 2005, 2008, Goldfarb and Tucker 2019), but also in terms of their policies of organizational control, it is necessary to disentangle our PDS-instrument from the effect of firm size. Finally, by including a time dummy variable, we control for time-fixed effects and ensure that our estimation results do not suffer from neglecting temporal trends.

A2 Assessment of instrument validity

A2.1 Testing instrument relevance and conditional independence

Panel A of Table 3 reports the first-stage estimates of PDS, i.e., $\widehat{\zeta}^{h,A}_{PDS}$, obtained from the selection model (21) using the untrimmed sample. Despite the fact that we have two treatment variables ($MICT^E$ and $MICT^{NE}$), four first-stage estimations are required because information from different panel waves is available for the monitoring and the autonomy model and the sets of control variables are not identical. For the same reason, we also have four different graphs of common support instead of two (see Figure A2).

For comparison, panel B in Table 3 displays the first-stage estimates $\widehat{\zeta}^{h,B}_{PDS}$ obtained from a probit ML regression of $MICT^h$ on PDS and the augmented set of covariates. As additional firm-level covariates, we include variables measuring a firm's market environment as well as its regulatory conditions, corporate strategies, workforce composition, and product innovations. At the district level, we additionally control for regional employment structures, mobility trends, local gross-domestic products, child care facilities, and commuting distances. Finally, the extended set of covariates includes those model-specific monitoring or working-from-home covariates that were excluded in the respective other MTE model (see our discussion on covariates in Section A1.2).

A comparison of the first-stage estimates $\widehat{\zeta}^{h,A}_{PDS}$ and $\widehat{\zeta}^{h,B}_{PDS}$ shows that the respective effect sizes are very close and hardly deviate from each other. This observation is confirmed by a test on the equality of $\widehat{\zeta}^{h,A}_{PDS}$ and $\widehat{\zeta}^{h,B}_{PDS}$. The null hypothesis H_0: $\widehat{\zeta}^{h,A}_{PDS} = \widehat{\zeta}^{h,B}_{PDS}$ cannot be rejected in any of the four first-stage model specifications, where the estimated p-values range between 0.760 and 0.961. The null hypothesis on effect-size equality can therefore clearly not be rejected in all four cases considered, implying that the additional covariates are indeed uncorrelated with PDS. Despite the fact that these test results are not sufficient to prove the conditional independence of our PDS-instrument, they can clearly be interpreted as satisfying a necessary condition for PDS to be considered a valid instrument.

A2.2 Testing the exclusion restriction for a binarized treatment variable

Andresen and Huber (2021) discuss assumptions satisfying the IV exclusion restriction in case of a binarized treatment variable. The authors also derive testable implications of their assumptions and develop the respective statistical tests. We focus on Andresen and Huber's Assumption 3 implying that all compliers are captured by the threshold used for binarization. The null hypothesis to be tested is then H_0: $\theta_{j+1} - \theta_j \geq 0, \forall j^* > j > 0$ and $\theta_j - \theta_{j+1} \geq 0, \forall J > j \geq j^*$, where θ_j denotes the first-stage estimate of the instrument PDS on $P(mict^h_D \geq j)$ and $mict^h_D$ is a multivalued, discretized treatment variable with $mict^h_D \in \{0, 1, \ldots, J\}$ (Andresen and Huber 2021, p. 539, 547). Furthermore, in our case, $j \in \{1, \ldots, J\}$ denotes the deciles of the distribution of the original percentage variable $mict^h$, i.e., $J = 10$. Finally, j^* is the selected threshold value in the support of $mict^h_D$, which in our case is the median of the $mict^h$-distribution. A rejection of H_0 indicates the presence of non-threshold compliance, i.e., the sample includes firms that respond to the instrument but are not induced to cross the threshold j^*, so point identification is usually lost (Andresen and Huber 2021, p. 548).

Figure A1 shows the effect of our PDS-instrument on the extent to which executives and non-executives are equipped with MICT, where the extent is measured in deciles rather than percentages. It is noticeable that the dashed line indicating the threshold for the formation of the binarized treatment is close to the mode of the θ_j-estimates in each case, which at least visually does not indicate violations of the exclusion restriction. This impression is confirmed by the results of the formal hypotheses tests. The respective null hypothesis cannot be rejected for any of the models considered (monitoring model, executives: $p = 0.594$; monitoring model, non-executives:

$p = 0.722$; autonomy model, executives: $p = 0.578$; autonomy model, non-executives: $p = 0.839$). Note, however, that not rejecting Andresen and Huber's Assumption 3 does not inevitably imply the validity of the exclusion restriction. The non-rejection is just a necessary, but not a sufficient condition for the validity of the exclusion restriction in case of a binarized treatment variable (Andresen and Huber 2021).[17]

A2.3 Testing monotonicity

The monotonicity assumption provides us with a testable implication, according to which the first-stage estimates of the instrument PDS should be nonnegative for any subsample (Bhuller et al. 2020). Hence, to assess the monotonicity assumption, we run a series of first-stage regressions, in which $MICT^h$ is regressed on the instrument PDS 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 Tables A2 and A3 for the monitoring regressions as well as Tables A4 and A5 for the working-from-home regressions. We can observe that in all the tables, none of the estimated coefficients for the instrument PDS is significantly negative. In fact, the coefficients are either positive and statistically significant or statistically insignificant in all subsamples, which is consistent with the monotonicity assumption.

A3 Sensitivity analysis

A3.1 MTE estimates for the untrimmed sample

In our first robustness check, we repeat the MTE estimates from our parametric normal baseline specifications but apply them to the complete untrimmed sample. The estimation results are reported in columns (1) and (2) of Table A6 for the monitoring model and Table A7 for the autonomy model. The estimates confirm our baseline results. Due to the extrapolation of the estimated MTE to outside the area of common support, the ranges between the ATT and ATUT estimates are greater, and the estimated ATEs turn out to be larger (except for the executive employees in the autonomy model) than in the trimmed baseline specifications. The corresponding MTE curves can be found in the upper panel of Figure A4.

Overall, the parametric normal MTE estimates for the untrimmed sample confirm the findings

[17] To test the exclusion restriction in case of a binarized treatment variable, we applied the user-written Stata do-file 'mvttest' developed by Martin Eckhoff Andresen.

of the baseline MTE estimates with respect to results (i) and (ii) of our theoretical model. First, the MICT effects for executives are larger than for non-executives. This applies not only to the autonomy model, but also to the monitoring model and includes the extent of essential heterogeneity. Second, executives experience both more monitoring and more autonomy through the use of MICT, while non-executives are only confronted with more monitoring without more autonomy.

A3.2 Excluding potentially biased districts

The aim of this robustness check is to address possible selection effects attributable to economically strong districts in which the largest and most successful German companies are headquartered. Our approach follows the intuitive idea that firms with a certain pattern of organizational control (e.g., high degree of monitoring and working from home) might be located in an economically powerful district next to one of the largest and most successful German companies. These firms may have to adapt their practices of organizational control more quickly than their competitors in other districts, for example, because of high competitive pressure or existing organizational control patterns in these districts. We therefore clean up the sample for observations from districts that may be biased or unrepresentative due to the location of powerful multinational companies.

The districts were selected on the basis of the settlement or location of companies that are listed as DAX-30 companies on the German Stock Exchange. In total, we removed 17 districts from our MTE models, namely Hamburg (Beiersdorf), Wolfsburg (Volkswagen), Bochum (Vonovia), Essen (RWE), Düsseldorf (E.ON, Henkel), Leverkusen (Bayer, Covestro), Bonn (Deutsche Post, Deutsche Telekom), Bad Homburg (Fresenius, Fresenius Medical Care), Frankfurt am Main (Deutsche Bank, Deutsche Börse), Ludwigshafen (BASF), Walldorf (SAP), Herzogenaurach (Adidas), Stuttgart (Daimler), Munich (Allianz, BMW, Münchener Rück, Siemens, Wirecard), Hannover (Continental), Heidelberg (Heidelberg Cement), and Darmstadt (Merck). The removal of these districts entailed an additional loss in the number of observations. The resulting MTE estimates are shown in Tables A6 and A7, columns (3) and (4). In particular, the empirical findings are again consistent with our results (i) and (ii) from the theoretical model.

A3.3 Correlated random coefficients (CRC) model

The CRC model draws on the observed outcome equation (10) that can be transformed to the estimation model (see Wooldridge 2015, Cornelissen et al. 2016)

$$OC^h = X\beta_0^h + MICT^h \times (X - \overline{X})(\beta_1^h - \beta_0^h) + \overline{\alpha}^h MICT^h + \psi^h MICT^h \times \widehat{v}^h + \xi^h \widehat{v}^h + \varepsilon^h \,, \quad (33)$$

where $\widehat{v}^h$ and $MICT^h \times \widehat{v}^h$ are two control functions included as additional regressors, and $X - \overline{X}$ denotes the set of covariates centered around their means. The control function approach proceeds in two steps (Wooldridge 2015, Cornelissen et al. 2016). In a first step, we estimate equation (21) by probit ML. From these estimates, we calculate the generalized residuals $\widehat{v}^h$. In the second step, we estimate equation (33) 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 gains (Cornelissen et al. 2016), with $\psi^h > 0$ ($\psi^h < 0$) pointing to positive (reversed) gains.

The estimation results of the CRC models are shown in Tables A6 and A7, columns (5) to (8) for the monitoring and autonomy models. In both tables, columns (5) and (6) report the parameter estimates for the untrimmed samples, while columns (7) and (8) show the estimation results for the trimmed samples. The ATEs estimated by the CRC models are very similar to their counterparts obtained from the corresponding parametric normal MTE models (baseline models and robustness checks). Therefore, we can draw the same conclusions to empirically support our theoretical predictions (i) and (ii). Furthermore, a one-sided test on H_0: $\overline{\alpha}^E \leq \overline{\alpha}^{NE}$ additionally confirms previous observations, according to which the ATEs for executives are larger than those for non-executives, which stretches the validity range of our result (i) from the theoretical model even further by extending it to the monitoring case.

A3.4 Semiparametric MTE model

As before in the parametric cases, we apply the separate approach version of the semiparametric MTE model instead of the LIV version. This is because the semiparametric LIV model is at risk to produce biased estimates even in the absence of misspecification (Devereux 2022). Our semiparametric MTE model is based on the conditional expectations of OC_1^h and OC_0^h described in equations (15) and (16). The estimation process starts with the double residual regression approach developed in Robinson (1988) and is precisely described in Andresen (2018). The baseline regression model is

$$OC_j^h = X\beta_j^h + K_j(p^h, x) + \epsilon_j^h \,, \quad j = 0, 1 \,. \tag{34}$$

The next steps are the estimation of $K_j(p^h, x)$ and the subsequent calculation of $k_j(p^h, x)$ according to (17) and (18), which then allows us to identify the MTE estimate as

$$\widehat{MTE}_{SP}(x, p^h) = X\left(\widehat{\beta_1^h - \beta_0^h}\right) + k_1\widehat{(p^h, x)} - k_0\widehat{(p^h, x)} \,. \tag{35}$$

The estimated treatment effects resulting from our semiparametric MTE models can be found in Tables A6 and A7, columns (9) and (10).

The estimates are in line with previous results, but deviate from these results in one specific detail. While in the autonomy model the treatment effects for the executives still exceed their counterparts for the non-executives, the corresponding effects for the non-executives are now even slightly higher than the treatment effects for the executives. A look at the MTE curve for the non-executives in the monitoring model can at least partially explain this finding (see Figure A4 in Section A4). The MTE curve for the non-executives in the monitoring model turns out to be U-shaped, while all other semiparametrically estimated MTE curves show a monotonically increasing (autonomy model) or decreasing (monitoring model) path. As a consequence, at least the ATUT and possibly also the ATE are higher than would be expected from a monotonously decreasing path. Despite the fact that semiparametric MTE estimates tend to be more sensitive to small changes in the data or specification than their parametric counterparts (Cornelissen et al. 2016), we take the results of this robustness check very seriously. Overall, however, this still leaves us with the conclusion that the MICT effects on employee autonomy are higher for executives than for non-executives, which is consistent with the prediction from our theoretical model and thus confirms result (i).

A3.5 Fractionally resampled Anderson-Rubin (FAR) test

The FAR test is based on the modified resampled fraction $f_N = 1/2 - \kappa/\sqrt{N}$, where N denotes sample size (Riquelme et al. 2013). The authors recommend choosing the value for κ so that $0.20 \leq \kappa \leq 0.25$. Given the unrestricted sample sizes $N = 1,423$ in the monitoring model and $N = 1,340$ in the autonomy model, we choose $\kappa = 11$ and a number of 100,000 replications for both models. The FAR test yields the following p-values for the validity of the null hypothesis that MICT equipment has no significant effect on monitoring and employee autonomy: monitoring model, executives: $p = 0.036$, non-executives: $p = 0.099$, autonomy model, executives: $p = 0.105$, non-executives: $p = 0.420$. These test statistics imply that even with slight violations of the exogeneity assumption of our IV PDS, the MICT effects on monitoring remain statistically significant at the 5 percent (executives) or 10 percent (non-executives) level, while the MICT effect on employee autonomy for the executives only proves to be statistically significant at the 10.5 percent level and remains statistically insignificant for the non-executives. Overall, therefore, the results of the FAR test suggest that we can draw valid conclusions about the impact of MICT equipment on organizational control across hierarchical levels, even if the exclusion restriction is slightly violated.

A4 Additional tables and figures

Table A1: Definitions and descriptive statistics of all variables

Variable	Definition	Mean	Std.-dev.	Min-Max	Data
	Dependent and main explanatory variables				
Information and communication technology					
mict	Percentage of workers being equipped with mobile devices (smartphones, tablet computers, notebooks) capable of establishing a mobile Internet connection				LPP
	– Executives	74.202	38.935	0–100	
	– Non-executives	16.487	25.422	0–100	
Monitoring					
Appraisal interviews	Percentage of workers with structured appraisal interviews				LPP
	– Executives	62.716	46.943	0–100	
	– Non-executives	49.116	45.667	0–100	
Target agreements	Percentage of workers with written target agreements				LPP
	– Executives	52.388	48.061	0–100	
	– Non-executives	21.520	37.212	0–100	
Performance appraisals	Percentage of workers with performance appraisals				LPP
	– Executives	52.747	49.253	0–100	
	– Non-executives	45.307	45.481	0–100	
Employee autonomy					
Working from home (D)	Percentage of workers in the functional area *Distribution and Marketing* having the opportunity to work from home				LPP
	– Executives	12.541	31.184	0–100	
	– Non-executives	6.442	21.684	0–100	

Variable	Definition	Mean	Std.-dev.	Min-Max	Data
Working from home (P)	Percentage of workers in the functional area *Production* having the opportunity to work from home				LPP
	– Executives	2.641	14.216	0–100	
	– Non-executives	0.555	6.273	0–100	
Working from home (C)	Percentage of workers in the functional area *Cross-Departmental Function, Administration, and Service* having the opportunity to work from home				LPP
	– Executives	10.129	27.247	0–100	
	– Non-executives	4.729	17.410	0–100	
Instrumental variables					
Population density	Number of inhabitants per square kilometer and district	751.11	944.79	36.3–4668.1	INKAR
District type	Ordinal variable ranging between 1 and 4. 1: sparsely populated rural district, 2: rural district with densification tendencies, 3: urban district, 4: district-free large city	2.64	1.10	1–4	INKAR
STEM students	Number of students in science, technology, engineering, or mathematics	5,991.4	13,148.3	0–67,414	INKAR
	Firm-level covariates				
No competition	Dummy variable indicating firms with no competitive pressure	0.031	0.175	0–1	IAB EP
Low competition	... with low competitive pressure	0.089	0.286	0–1	IAB EP
Medium competition	... with medium competitive pressure	0.360	0.480	0–1	IAB EP
High competition	... with high competitive pressure	0.517	0.500	0–1	IAB EP

Variable	Definition	Mean	Std.-dev.	Min-Max	Data
Technical status	Ordinal 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 EP
Manufacturing	Dummy variable indicating firms in the manufacturing industry	0.300	0.458	0–1	LPP
Metal, electronics, vehicle manufacturing	... in the metal working sector, in the electrical industry or in vehicle manufacturing	0.268	0.443	0–1	LPP
Trade, transport, news	... in the trade, traffic, or news sector	0.165	0.371	0–1	LPP
Firm-related / financial services	... that offer firm-related or financial services	0.147	0.355	0–1	LPP
ICT / other services	... that offer ICT or other services	0.118	0.323	0–1	LPP
Performance pay	Dummy variable indicating firms that have a salary system with variable proportions	0.574	0.494	0–1	LPP
Women firm	Percentage of female workers	32.807	24.737	0–97.402	IAB EP
Skill	Percentage of skilled employees, requiring at least a vocational qualification or professional experience	75.769	24.344	0–100	IAB EP
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	... with 50–99 employees ...	0.339	0.473	0–1	LPP
Firm size 100–249	... with 100–249 employees ...	0.353	0.478	0–1	LPP

Variable	Definition	Mean	Std.-dev.	Min-Max	Data
Firm size 250–499	... with 250–499 employees ...	0.159	0.366	0–1	LPP
Firm size 500+	... with 500+ employees ...	0.117	0.321	0–1	LPP
Firm age	Year of firm foundation	1992.008	7.053	1987–2014	LPP
Vacant jobs	Dummy variable indicating open job positions for skilled workers	0.355	.479	0–1	IAB EP
Δ workforce	Firms' annual change of total employment	1.067	125.704	−2363–2517	IAB EP
	District-level covariates (401 German districts)				
Business registrations	Number of business registrations per 10,000 inhabitants	69.927	19.409	34.6–168.7	INKAR
Unemployment rate	Average percentage of unemployed in the civilian labor force	6.967	2.982	1.3–15.1	INKAR
Productivity	Ratio of annual value added and annual wage (per employee and district)	1.970	0.147	1.538–2.919	INKAR
Women district	Percentage of female employees in the total number of employees covered by social security	46.871	3.881	30.9–57.9	INKAR
Living space	Average living space per inhabitant in square meters	46.240	4.352	36.2–68.6	INKAR
Purchase value of land	Average purchase value per square meter of building land (in euro)	133.001	158.228	8.47–1732.33	INKAR
Commuter balance	Balance of inbound and outbound commuters	−5.342	25.716	−147.4–64.1	INKAR

Sources. LPP: Linked Personnel Panel, employer survey, IAB EP: IAB Establishment Panel, INKAR: INKAR database.

Notes. The descriptive statistics for 2016 are reported. Own calculations.

Figure A1: Effects of the instrument PDS on MICT usage (measured in deciles of $mict^h$)

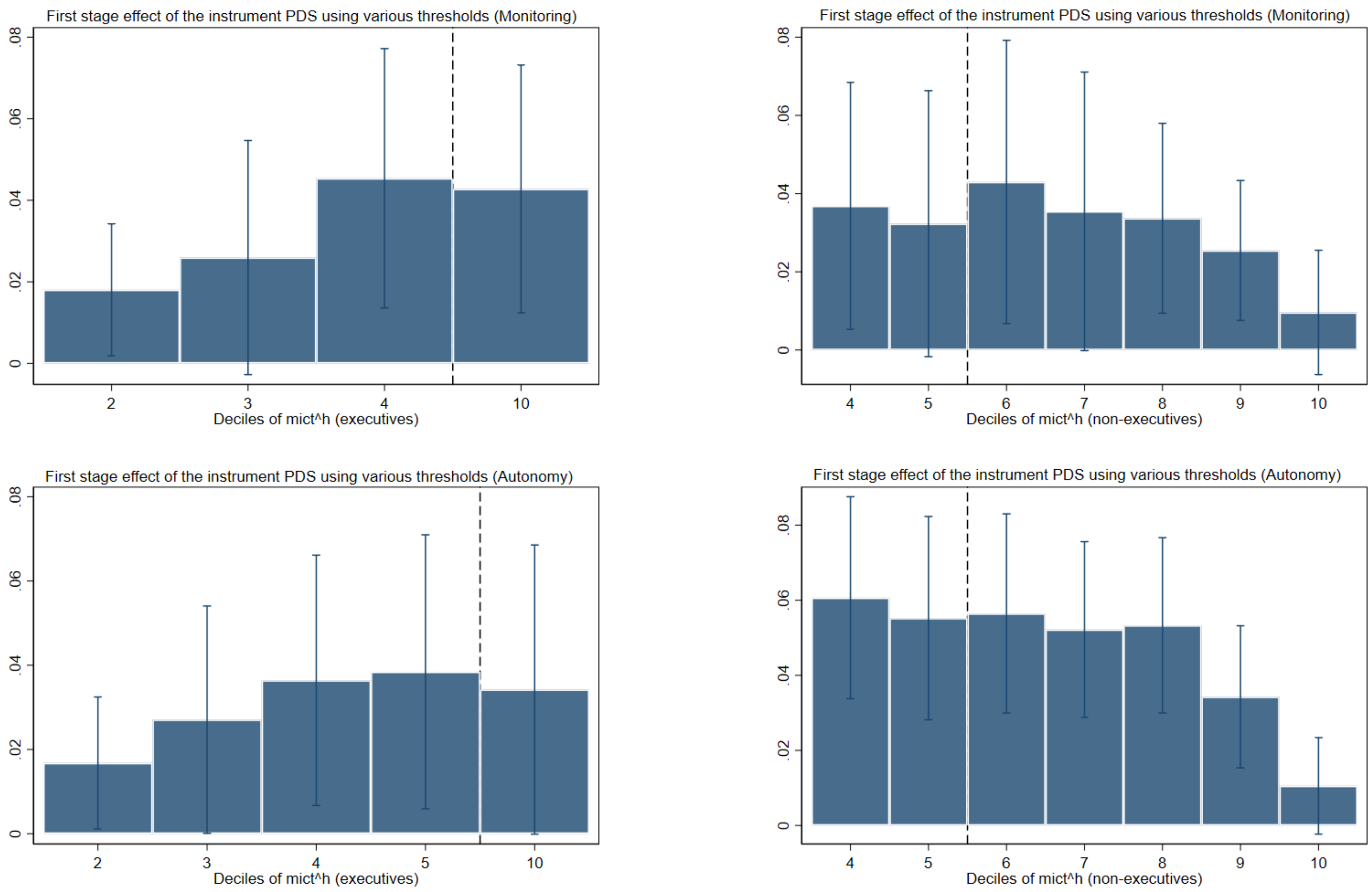

Table A2: Tests for the monotonicity assumption - monitoring regressions, executives

	100-249	250-499	500+	Metal	Trade	Fin. service	ICT service	Low comp.	Medium comp.	High comp.
PDS	0.175*	0.149	0.044	0.274***	0.150	0.153	0.405***	0.226**	0.196**	0.197***
	(0.095)	(0.139)	(0.172)	(0.099)	(0.141)	(0.123)	(0.143)	(0.106)	(0.085)	(0.067)
N	492	246	144	378	243	219	160	208	526	689
	Unemployment		Business registrations		Skilled workers		Students		Δ workforce	
	high	low	high	low	high	low	high	low	≥ 0	< 0
PDS	0.261***	0.090	0.122	0.163*	0.191***	0.193***	0.197**	0.127	0.152**	0.267***
	(0.055)	(0.102)	(0.098)	(0.085)	(0.067)	(0.075)	(0.093)	(0.109)	(0.062)	(0.072)
N	688	735	708	715	711	712	710	713	897	526
	Vacant jobs		Firm founded		Performance pay		Productivity		Technical status	
	yes	no	≥ 1990	< 1990	yes	no	high	low	high	low
PDS	0.239***	0.172**	0.305***	0.108	0.217***	0.167**	0.198***	0.240***	0.188***	0.193**
	(0.072)	(0.069)	(0.068)	(0.075)	(0.068)	(0.070)	(0.074)	(0.068)	(0.065)	(0.085)
N	574	849	663	760	817	606	699	724	993	430

Sources. See Table 3.

Notes. The values in parentheses represent robust standard errors clustered at the district level. Not displayed are the PDS estimates for firms belonging to the 1st, 2nd, 3rd, and 4th quartile of the estimated propensity score. Each of them is positive, but not always statistically significant. Also not displayed is the PDS estimate for observations of the year 2016, which is highly significant with a positive sign. In the top panel, the first three columns refer to firm size classes. The next four columns refer to industries, i.e., Metal: metal, electronics, vehicle manufacturing; Trade: trade, transport, news; Fin. service: firm-related and financial services; ICT service: ICT and other services. Low, medium and high comp. denote no/low, medium, high competitive pressure. The PDS estimates for the respective counter-categories are not listed in the table for reasons of space. They are all positively significant. The threshold for distinguishing between the 'high' and 'low' categories is the respective median. Definitions and descriptive statistics for all control variables can be found in Table A1.

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

Table A3: Tests for the monotonicity assumption - monitoring regressions, non-executives

	100-249	250-499	500+	Metal	Trade	Fin. service	ICT service	Low comp.	Medium comp.	High comp.
PDS	0.250***	−0.044	0.553**	0.158	0.089	−0.136	0.439***	0.116	0.245***	0.098
	(0.079)	(0.138)	(0.235)	(0.109)	(0.139)	(0.124)	(0.141)	(0.129)	(0.078)	(0.079)
N	492	246	144	378	243	219	160	208	526	689
	Unemployment		Business registrations		Skilled workers		Students		Δ workforce	
	high	low	high	low	high	low	high	low	≥ 0	< 0
PDS	0.221***	0.026	0.195**	0.014	0.170**	0.152**	0.190**	0.020	0.188***	0.109
	(0.056)	(0.093)	(0.082)	(0.096)	(0.071)	(0.069)	(0.081)	(0.117)	(0.058)	(0.081)
N	688	735	708	715	711	712	710	713	897	526
	Vacant jobs		Firm founded		Performance pay		Productivity		Technical status	
	yes	no	≥ 1990	< 1990	yes	no	high	low	high	low
PDS	0.110	0.206***	0.145*	0.140**	0.223***	0.080	0.064	0.226***	0.172***	0.169*
	(0.083)	(0.065)	(0.075)	(0.069)	(0.061)	(0.082)	(0.076)	(0.068)	(0.053)	(0.101)
N	574	849	663	760	817	606	699	724	993	430

Sources. See Table 3. **Notes.** See Table A2. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A4: Tests for the monotonicity assumption - working from home regressions, executives

	100-249	250-499	500+	Metal	Trade	Fin. service	ICT service	Low comp.	Medium comp.	High comp.
PDS	0.201	0.187	0.851***	0.488***	0.464***	0.308	−0.220	0.133	0.132	0.345***
	(0.123)	(0.168)	(0.305)	(0.137)	(0.169)	(0.189)	(0.275)	(0.235)	(0.105)	(0.098)
N	459	234	143	362	222	202	128	156	489	695
	Unemployment		Business registrations		Skilled workers		Students		Δ workforce	
	high	low	high	low	high	low	high	low	≥ 0	< 0
PDS	0.091	0.314***	0.146	0.213*	0.280**	0.191**	0.230	0.381***	0.066	0.592***
	(0.108)	(0.109)	(0.126)	(0.111)	(0.110)	(0.096)	(0.142)	(0.141)	(0.096)	(0.108)
N	669	671	663	677	669	671	665	675	834	506
	Vacant jobs		Firm founded		Productivity		Technical status			
	yes	no	≥ 1990	< 1990	yes	no	high	low		
PDS	0.255*	0.242***	0.200*	0.267**	0.314***	0.160	0.197**	0.344***		
	(0.137)	(0.081)	(0.112)	(0.106)	(0.096)	(0.109)	(0.086)	(0.129)		
N	412	928	606	734	665	675	972	368		
	Living space		Purchase value		Commuter balance		Women district		Women firm	
	high	low	high	low	high	low	high	low	high	low
PDS	0.325***	0.168	0.221	0.296***	0.113	0.307*	0.171	0.288***	0.196**	0.288***
	(0.116)	(0.121)	(0.163)	(0.115)	(0.115)	(0.157)	(0.106)	(0.109)	(0.098)	(0.103)
N	655	685	668	672	667	673	657	683	669	671

Sources. See Table 3. **Notes.** See Table A2. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A5: Tests for the monotonicity assumption - working from home regressions, non-executives

	100-249	250-499	500+	Metal	Trade	Fin. service	ICT service	Low comp.	Medium comp.	High comp.
PDS	0.373***	0.144	0.367	0.290**	0.182	0.338*	−0.493	−0.111	0.191*	0.443***
	(0.109)	(0.171)	(0.322)	(0.140)	(0.205)	(0.177)	(0.332)	(0.258)	(0.104)	(0.104)
N	459	234	143	362	222	202	128	156	489	695
	Unemployment		Business registrations		Skilled workers		Students		Δ workforce	
	high	low	high	low	high	low	high	low	≥ 0	< 0
PDS	0.352***	0.348***	0.292**	0.314***	0.343***	0.277***	0.224**	0.343**	0.309***	0.331***
	(0.106)	(0.097)	(0.114)	(0.116)	(0.103)	(0.092)	(0.121)	(0.140)	(0.076)	(0.109)
N	669	671	663	677	669	671	665	675	834	506
	Vacant jobs		Firm founded		Productivity		Technical status			
	yes	no	≥ 1990	< 1990	yes	no	high	low		
PDS	0.253**	0.312***	0.239**	0.404***	0.390***	0.268***	0.311***	0.261*		
	(0.126)	(0.083)	(0.100)	(0.111)	(0.088)	(0.102)	(0.081)	(0.142)		
N	412	928	606	734	665	675	972	368		
	Living space		Purchase value		Commuter balance		Women district		Women firm	
	high	low	high	low	high	low	high	low	high	low
PDS	0.416***	0.185**	0.328**	0.249**	0.174*	0.136	0.317***	0.352***	0.272**	0.282***
	(0.128)	(0.092)	(0.132)	(0.118)	(0.104)	(0.131)	(0.091)	(0.111)	(0.112)	(0.086)
N	655	685	668	672	667	673	657	683	669	671

Sources. See Table 3. **Notes.** See Table A2. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure A2: Common support plots

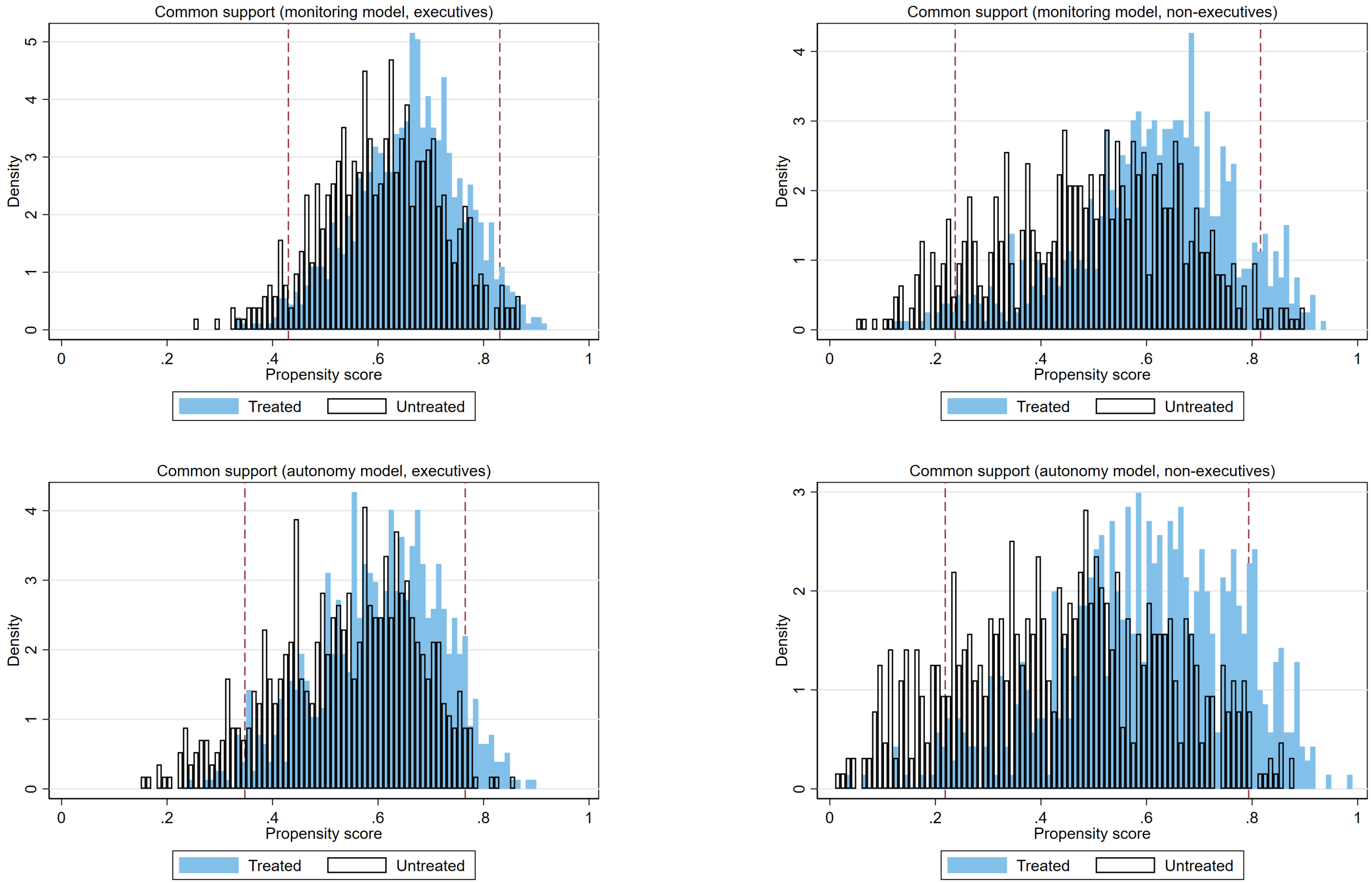

Figure A3: MTE curves: parametric normal model, trimmed sample

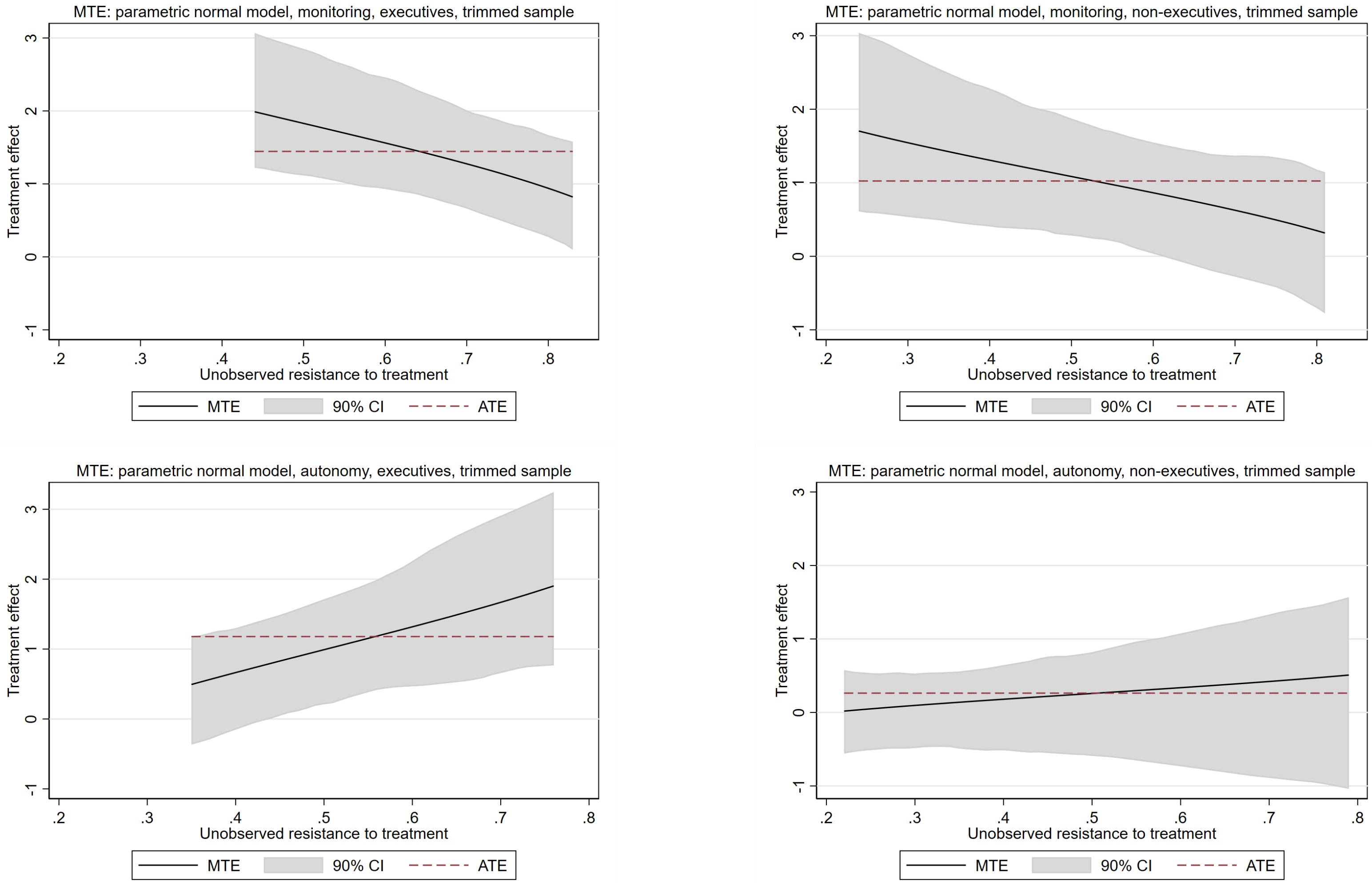

Table A6: Treatment effects of MICT on organizational monitoring: robustness checks

Robustness check	Original sample		Biased districts		CRC model		CRC model		Semiparametric MTE	
Dependent variable	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)
ATE	2.507**	1.523**	1.664***	0.835**	2.515***	1.521**	1.837***	1.089**	1.431***	1.744**
	(1.031)	(0.631)	(0.500)	(0.426)	(0.674)	(0.652)	(0.502)	(0.517)	(0.492)	(0.746)
ATT	3.378**	2.391**	1.872***	1.181**					1.692***	2.044**
	(1.344)	(0.955)	(0.538)	(0.468)					(0.512)	(0.889)
ATUT	0.954	0.419	1.388***	0.402					1.096**	1.360*
	(0.981)	(0.769)	(0.487)	(0.478)					(0.544)	(0.804)
Test on the equality of ATEs between executives and non-executives										
H_0: $\overline{\alpha}^E \leq \overline{\alpha}^{NE}$						[.042]**		[.056]*		
Tests on essential heterogeneity and heterogeneous treatment effects										
H_0: $\widehat{\rho}_1^h - \widehat{\rho}_0^h = 0$	−1.491*	−1.187	−0.924*	−0.914*						
	(0.880)	(0.778)	(0.555)	(0.531)						
$MICT^h \times \widehat{v}^h$					1.501**	1.085	1.068**	0.803		
					(0.664)	(0.708)	(0.507)	(0.526)		
H_0: ATT ≤ ATUT	[.042]**	[.055]*	[.031]**	[.029]**					[.069]*	[.209]
Test on instrument relevance										
χ^2-test	15.43***	10.80***	24.98***	17.67***	15.43***	10.80***	26.14***	15.47***	26.14***	15.47***
	[0.000]	[0.001]	[0.000]	[0.000]	[0.000]	[0.001]	[0.000]	[0.000]	[0.000]	[0.000]
N	1,423	1,423	1,331	1,331	1,423	1,423	1,393	1,395	1,393	1,395

Sources. Linked Personnel Panel, employer survey 2016/2018, IAB Establishment Panel 2016/2018, INKAR database, various years. Own calculations.

Notes. See Table 4.

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

Table A7: Treatment effects of MICT on employee autonomy: robustness checks

Robustness check	Original sample		Biased districts		CRC model		CRC model		Semiparametric MTE	
Dependent variable	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)
ATE	1.125*	0.365	1.037**	−0.146	1.269**	0.363	1.097**	0.258	1.134**	0.733
	(0.651)	(0.499)	(0.491)	(0.471)	(0.555)	(0.484)	(0.455)	(0.385)	(0.537)	(0.514)
ATT	0.080	0.229	0.849*	−0.022					0.777	0.386
	(0.710)	(0.480)	(0.445)	(0.344)					(0.493)	(0.437)
ATUT	2.548**	0.515	1.277**	−0.283					1.590**	1.131
	(1.217)	(0.819)	(0.579)	(0.670)					(0.675)	(0.705)
	Test on the equality of ATEs between executives and non-executives									
H_0: $\overline{\alpha}^E \leq \overline{\alpha}^{NE}$						[0.028]**		[0.021]**		
	Tests on essential heterogeneity and heterogeneous treatment effects									
H_0: $\widehat{\rho}_1^h - \widehat{\rho}_0^h = 0$	1.584*	0.265	0.946*	−0.092						
	(0.906)	(0.551)	(0.530)	(0.572)						
$MICT^h \times \widehat{v}^h$					−0.746	−0.300	−0.610	−0.319		
					(0.590)	(0.604)	(0.472)	(0.469)		
H_0: ATUT $\leq$ ATT	[0.041]**	[0.372]	[0.048]**	[0.712]					[0.033]**	[0.080]*
	Test on instrument relevance									
χ^2-test	12.11***	19.43***	19.78***	22.71***	12.11***	19.43***	18.86***	27.85***	18.86***	27.85***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
N	1,340	1,340	1,249	1,248	1,340	1,340	1,313	1,313	1,313	1,313

Sources. Linked Personnel Panel, employer survey 2014/2016, IAB Establishment Panel 2014/2016, INKAR database, various years. Own calculations.

Notes. See Table 4.

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

Figure A4: MTE curves: robustness checks