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HR analytics: A centralizing or decentralizing force?

Johannes Lehmann*

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Abstract

This study empirically analyzes the relationship between the application of HR analytics and the assignment of decision-making authority in Swiss establishments. From a theoretical standpoint the direction of this relationship is ex-ante unclear as opposing forces are at work simultaneously. While HR analytics can reduce the local information advantage or even take over decision-making processes, acting as a centralizing force, it can also generate additional local information and dampen the hidden action problem, resulting in the decentralization of decision-making processes. The empirical results, relying on doubly robust ATE estimations, are in line with a decentralizing force of HR analytics. More precisely, a comprehensive measure of decision rights as well as operational and strategic decisions are more decentralized in establishments that apply HR analytics. Overall the findings suggest that Swiss establishment combine the use of HR analytics with employee empowerment and do not use it to create a dystopian work environment as feared by proponents of *digital taylorism*.

Keywords: HR analytics, people analytics, decision-rights assignment, authority in organizations, doubly robust ATE estimation **JEL classification:** L22, M12, M50, M54

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1 Introduction

The digital transformation deeply changes the environment businesses operate in. Subsumed under the term human-resource analytics (HR analytics), the increasing use of digital technologies and data analytics also affects the field of human resources.¹ Comprehensive in nature, HR analytics ranges from more basic tools, for example, included in enterprise resource planning software, to cutting-edge technologies such as artificial intelligence, machine learning and Internet of Things sensors (e.g., Aral et al., 2012; Davenport, 2018; Shet et al., 2021). Practical applications range from Starbucks using a scheduling software that analyzes data including weather and pedestrian patterns (Tursunbayeva et al., 2022), Tesco reusing its customer analytics tool to better understand its employees, McDonalds leveraging information about management behavior and staff attitude to optimize restaurant performance (Angrave et al., 2016; Sparrow et al., 2016), to an offshore drilling company using statistical analyses to compare the success of their graduate program with competitors (Rasmussen and Ulrich, 2015). These practical examples show that HR analytics can provide new insights into employee behavior and the inner workings of companies. Through this, it has the power to impact the organization of establishments and various business outcomes (e.g., Van Den Heuvel and Bondarouk, 2017; Giermindl et al., 2022). Against this background, the present paper investigates the relationship between the application of HR analytics and the hierarchical level to which decision-rights are assigned in companies.

In the definition of HR analytics, I follow Marler and Boudreau (2017, p. 15), who define it as a HR practice enabled by information technology that uses descriptive, visual, and statistical analyses of data related to HR processes, human capital, organizational performance, and external economic benchmarks to establish business impact and enable data-driven decision-making. This definition is widely applied in the HR analytics literature (e.g., Tursunbayeva et al., 2018; Álvarez-Gutiérrez et al., 2022; Bonilla-Chaves and Palos-Sánchez, 2023). HR analytics is, therefore, a process lying at the intersection between information technology and personnel management. For the present study, the inclusiveness of the present definition is appealing, namely that the outcome dimension of HR analytics is characterized very broadly.² While the term HR analytics focuses on the analytics part, the collection of data is inherently part of this process (e.g., Falletta and Combs, 2020). I measure HR analytics as the presence of artificial intelligence or data analytics tools as a supporting means to collect information that can be used during the

¹HR analytics is also known under the terms workforce analytics, human capital analytics, or people analytics (Huselid, 2018; Bonilla-Chaves and Palos-Sánchez, 2023).

 $^{^{2}}$ The inclusiveness of this definition of HR analytics is not unique but also visible in other definitions such as Sakib et al. (2024).

implementation of employee development or performance evaluation. This measure of HR analytics only includes people already working for the establishment, therefore, excluding the recruitment process.

The outcome of interest captures the distribution of decision-making authority within establishments. This concept reflects the degree of centralization present in establishments, as centralization indicates on which level in the hierarchical order the locus of decisionmaking authority lies (Pugh et al., 1968; Galbraith, 1973; Camps and Luna-Arocas, 2009; Wang and Feeney, 2016). In essence, centralization describes a continuum, where in highly centralized organizations, decision-making power is held by very few, and in decentralized organizations by most employees (Tata and Prasad, 2004). Another closely related concept is job autonomy, which refers to the degree of decision-making authority of specific employees (Hackman and Oldham, 1975; Zhao and Wu, 2023). In the present investigation, decision-making authority denotes an index which classifies establishments from decentralized to centralized. This index is based on information about a comprehensive list of decision types, covering nine different areas. Additionally, the empirical investigation also considers specifically operational and strategic decisions.

From a theoretical perspective, the relationship between HR analytics and the assignment of decision-making authority in establishments is ambiguous. HR analytics acts as a decentralizing force as it dampens the hidden action problem through its function as a monitoring tool. Additionally, the data-generating processes connected to HR analytics can potentially produce local information which increases the information asymmetry between higher and lower hierarchical levels, leading to more decision-delegation. Conversely, HR analytics functions as a centralizing force when it reduces the local information advantage by providing information about work processes to higher hierarchical levels or when refined tools take over decision-making processes that were previously delegated to lower level employees. These theoretical findings lead to the formulation of two rival hypotheses, anticipating that HR analytics is associated with either centralization or decentralization, depending on which forces outweigh the others.

To empirically test these two rival hypotheses I use a data source that we collected by ourselves and call the *Swiss Employer Survey* (SES). The SES is a cross-sectional establishment survey that contains information about a wide range of business topics in Swiss establishments. The final data set consists of 479 observations. The estimation approach relies on a selection-on-observables approach and combines inverse probability weighting (IPW) with regression models for the potential outcome equations. The combination of these two approaches lead to a doubly robust average treatment effect (ATE) estimator. The empirical results uncover a statistically significant relationship between the application of HR analytics and more decentralized establishments. In other words, the use of HR analytics is more likely to occur in establishments where decision-making authority is delegated to lower levels of the hierarchy. This result holds for a broad measure of decision-making authority and for both explicitly operational and strategic decisions. On a more granular level, the relationship is visible for decision-rights in the areas of work planning, task definition, and regarding investments in machinery or equipment. For decision rights in general as well as for specifically operational decisions, the results are in line with a shift away from the top management and towards non-managerial employees. For specifically strategic decision rights from the top managements to the lower and middle management.

These baseline results are largely robust to a variety of robustness checks. To be precise, I apply an alternative methodological approach consisting of causal forests, reestimate the baseline model with different trimming and weighting specifications, and exclude a part of the sample whose contact information was collected via web scraping. All robustness checks qualitatively support the baseline result. The results for strDRA show the largest degree of sensitivity as they become partially statistically insignificant.

The interest of researchers in the topic of HR analytics has been growing over the past decade. Sakib et al. (2024) show that there has been an annual increase of close to 10% in the number of published articles between 2008 and 2023. While many researchers paint a very positive picture about the future of HR analytics (e.g., Sharma and Sharma, 2017; Van Den Heuvel and Bondarouk, 2017), others are more pessimistic. This pessimism is visible regarding possible negative effects for employees (Giermindl et al., 2022; Tursunbayeva et al., 2022), but also regarding a possible lack of effectiveness (Angrave et al., 2016).

The main drawback of the present literature investigating HR analytics is the lack of rigorous empirical studies (Rasmussen and Ulrich, 2015; Marler and Boudreau, 2017; Van Den Heuvel and Bondarouk, 2017; Greasley and Thomas, 2020; Shet et al., 2021; Giermindl et al., 2022; Bonilla-Chaves and Palos-Sánchez, 2023). A large part of the existing literature consists of conceptual paper, literature reviews, and case studies (Giermindl et al., 2022). From this follows that not much is known about the processes through which HR analytics influences organizational design and other business outcomes (Huselid, 2018; Shet et al., 2021). Álvarez-Gutiérrez et al. (2022, p. 129) put it provocatively, noting that the existing literature would appear to be more promotional than descriptive. Others put it more optimistically, for example, Bonilla-Chaves and Palos-Sánchez (2023, p. 5) observe indications that some quantitative empirical studies in HR analytics are beginning

to emerge. One notable exception is the study by Aral et al. (2012) who provide causal evidence for a productivity effect of a complementary system consisting of HR analytics, performance pay, and information technology. Overall, however, the HR analytics literature is still in its emerging stage and needs more empirical analyses to mature.³

As stated above, HR analytics lays at the intersection of HR-processes and digital technologies. While there are, to the best of my knowledge, no other empirical papers investigating the relationship between HR analytics and decision-rights assignment, various studies have been conducted in these adjacent field, namely investigating the relationship between HR practices or digital technologies and changes in the hierarchical structure of establishments.

Relating to the connection between HR-practices and decision-rights assignment, there are, for example, papers investigating the decentralizing effects of high-performance work systems (Colombo et al., 2007), high-involvement mangement (Zoghi and Mohr, 2011), or self-managed teams (Tata and Prasad, 2004).

Additionally there is a wide range of papers investigating the link between the application of digital technologies and the degree of centralization present in companies.⁴ Most closely related to the present paper is the study by Labro et al. (2023), who investigate the effects of predictive analysis on decision-rights assignment. However, this study is different in that it investigates the usage of predictive analysis in a general and not specifically related to HR-processes. They find that the application of predictive analytics is related to a centralization of decision-making authority.

This paper has two main contribution to the existing literature in the field of HR analytics. First, it grounds the empirical analysis on a theoretical foundation. More specifically, the analysis combines different theoretical aspects into an overarching framework and tests them empirically. The second and main contribution is the provision of empirical evidence in the field of HR analytics. As illustrated, the HR analytics literature is still in an emerging state and suffers from a scarcity of empirical studies. This study helps to reduce this gap in the literature by providing empirical evidence on the relationship between the application of HR analytics and the assignment of decision-making authority within establishments.

The remainder of the paper is structured as follows. Section 2 describes the theoreti-

³Closely related to the HR analytics literature is a strand of literature focusing on electronic performance monitoring. However, this literature is also still in its early stages (Ravid et al., 2020; Siegel et al., 2022). ⁴Examples are plentiful and range from investigations of the effects of investments into ICT (Hitt and Brynjolfsson, 1997), the level of present ICT capital (Mocetti et al., 2017), the diffusion of technologies (Acemoglu et al., 2007), the usage of information and communication technology (Bloom et al., 2014), the digital transformation (Yang et al., 2024), the application of enterprise resource planning software (Doherty et al., 2010), the usage of robotics (Dixon et al., 2021), to equipping employees with ICT (Gerten et al., 2022).

cal framework and derives the hypotheses. Section 3 introduces the data set (3.1), the variables of interest (3.2), and presents descriptive statistics (3.3). Section 4 provides information about the empirical approach (4.1), the control variables (4.2), the applied weighting strategy (4.3), and reasons to trim the computed weights (4.4). Section 5 discusses the balance statistics (5.1), common support assumption (5.2), as well as the baseline estimation results (5.3) and from where in the hierarchy these relationships emerge (5.4). Section 6 tests the sensitivity of the empirical results. Finally, section 7 concludes.

2 Theoretical framework

This section theoretically examines the relationship between HR analytics and the assignment of decision rights in establishments. Building on these theoretical considerations, it concludes with the derivation of the hypotheses.

The arguments mainly rely on agency theory. Therefore, the starting point is a simple principal-agent model. Two defining features of the relationship between the principal and the agent are that the agent has more information than the principal and that there is a conflict of interest between the two actors.

The information asymmetry arises because the agent has more knowledge, for example, about the production process, the workflow, the applied technology, and his specific actions. Consequently, the agent has more localized information, based on which they can make more informed and more productive decisions than the principal. Thus, it can make sense for a principal to delegate decision rights to the agent and avoid noisy communication between the two actors (e.g., Dessein, 2002). An additional consequence of the present information asymmetry is that the principal cannot directly observe the agent's effort. This lack of total control over the agent, combined with the fact that the interests of the two are not necessarily aligned, results in agents making decisions that maximize their own utility and not the utility of the establishment, for example, by reducing their effort. A phenomenon termed the *hidden action problem*.

The principal now faces the challenge of maximizing the utility of the establishment in deciding on the ideal level of delegation. In doing so, they need to consider that an increase in the delegation of decision-making authority increases the level of utilized local knowledge but, at the same time, increases the possibility of counter-productive behavior by the agent (e.g., Jensen and Meckling, 1992; Hitt and Brynjolfsson, 1997; Acemoglu et al., 2007). All else equal, the level of delegation increases with the information advantage of the agent and decreases when the principal suspects a higher degree of diverging interests (Labro et al., 2023). When a principal decides to introduce HR analytics into

this model-establishment the optimization problem changes which potentially affects the ideal level of decision-rights assignment. Whether this leads to increased centralization or decentralization is not clear ex-ante, as there are four different and opposing forces working simultaneously. The following paragraphs discuss the nature of these forces.

In its essence HR analytics consists of data analytics enabling data-driven decision-making regarding HR processes. From this follows that the application of HR analytics inherently generates new information. The data can include both information about workflows and the way employees act.

When HR analytics generates information about the actions of employees it functions as a monitoring tool. Examples of such HR applications are plentiful and range from analyses of data contained in human capital management (HCM) software (Aral et al., 2012), human resource management systems (HRMS) (Shet et al., 2021), to real-time HR dashboards (Álvarez-Gutiérrez et al., 2022) and, increasingly, data from more dubious and invasive sources such as sociometric sensors or voice analysis software (Falletta and Combs, 2020). Employers use monitoring tools to incentivize employees to act in ways that benefit the establishments and not the employees themselves. In this sense, control instruments help align the employees' actions with the goals of the establishment and decrease the agency problems arising from the information asymmetry, i.e. they dampen the hidden action problem (e.g., Camps and Luna-Arocas, 2009; Mocetti et al., 2017; Sharma and Sharma, 2017). As Gerten et al. (2022) summarize, policies such as employee monitoring can be used to balance the benefits of using the available local knowledge with the associated losses of control. Thus, HR analytics can act as a decentralizing force, as it reduces hidden action problems through employee monitoring.

As stated before, HR analytics not only generates additional information about the actions of employees but also about, for example, workflows, production processes, or customer interactions. This is the case when the aforementioned HR softwares are in use (e.g. HCM, HRMS, or HR dashbords), but also when data from external sources, such as the weather or pedestrian patterns (Tursunbayeva et al., 2022) is compiled and analyzed. The effect HR analytics has on the organizational architecture through the provision of this information depends on the actor who can profit most from these newly available information. If the application of HR analytics increases the provision of information to employees in higher hierarchical position and/or decreases the difficulty of transmitting existing local information up the hierarchy, a decrease in the local information advantage will follow (e.g., Bloom et al., 2014; Labro et al., 2023). This follows the argument that the access to high-quality data diminishes the uneven distribution of information, consequently decreasing the information asymmetry between principal and agent. Such developments have been linked to changes in decision-making processes in firms, for example, in connection with the introduction of new information technology (e.g., Jensen and Meckling, 1992; Acemoglu et al., 2007; Mocetti et al., 2017; Szukits and Móricz, 2024). An example is Bloom et al. (2014), who show that when the introduction of new information technology leads to a reduction in the communication cost, the centralization of decision-making power follows. Thereby, the application of HR analytics can act as a centralizing force. The reverse is true, if lower level employees can profit more from the additional information than the employees who work higher up in the hierarchy. As this would suggest an increase in the local information advantage, increased delegation should follow. Due to the information advantage of the agents, it is plausible that the data-generating processes associated with HR analytics can produce information that is valuable to lower level employees. For example, Aral et al. (2012) argue that HCM provides feedback to employees which helps them to better understand KPIs or strategic goals.⁵



Figure 1: Theoretical framework

Giermindl et al. (2022) propose a fourth possible channel through which HR analytics influences decision-rights assignment in establishments. They argue that refined applications of HR analytic tools, including machine learning or AI, could take over decisionmaking processes themselves. This would result in a situation, described by the literature as *digital taylorism*, where employees are limited to performing tasks assigned, designed,

⁵Additionally, Labro et al. (2023) make this argument in regard to predictive analysis.

and controlled by these new HR analytics tools (e.g., Holford, 2019; Faraj et al., 2018). Through this, the application of HR analytics might shift decision-making power away from low-level employees, leading to a more centralized workplace. A commonly cited example are gig economy companies that use algorithms to automatically terminate underperforming employees without any human involvement (O'Connor (2016); Schildt, 2017; Giermindl et al., 2022).

Figure 1 summarizes these four different lines of argument. If HR analytics reduces the local information advantage or if self-learning algorithms take over decision-making processes, it acts as a centralizing force. However, if HR analytics dampens the hidden action problem or generates additional local information, it acts as a decentralizing force. From a theoretical perspective, HR analytics could therefore shift decision-making authority both upwards and downwards in the hierarchy. As the empirical analysis examines the overall relationship between HR analytics and the allocation of decision rights, it will uncover the net effect resulting from the simultaneous action of all these forces. The theoretical considerations lead to the formulation of the following two rival hypotheses:

Centralization Hypothesis: The application of HR analytics is positively related to the centralization of decision-making authority if the reduction of the local information advantage and the effect of self-learning algorithms taking over decision-making outweigh the decentralizing forces.

Decentralization Hypothesis: The application of HR analytics is positively related to the decentralization of decision-making authority if the reduction of the hidden action problem and the provision of additional local information outweigh the centralizing forces.

3 Data, variables, and descriptive statistics

3.1 Data and sampling process

This study relies on establishment-level data to investigate the present research question of interest.⁶ The applied data set has been collected as a primary data set by the chair of Human Resources and Organization at the University of Basel and covers establishments with at least 10 employees. We refer to this data set as the *Swiss Employer Survey* (SES). It is based on a cross-sectional survey covering information of the year 2020 or 2022.

The SES was conducted in two steps. In a first step, we contacted a representative sample of 10'000 establishments.⁷ The contact with the establishments was established by letter.

⁶Each spatially separated organizational unit of an enterprise is considered a distinct establishment. In the following, I will use the terms establishment, business, firm, and company equivalently.

⁷The Swiss Federal Statistical Office (SFSO) provided this sample and the addresses of the establish-

Establishments that did not react at first contact received a second letter which was intended as a reminder. Unfortunately, the response rate did not meet our goals and reached about six percent, including establishments which did not provide all information of interest (the target was a 'typical' response rate of about 20%). The main reason for this was that the timing of the survey coincided with the heights of the Covid-19 pandemic, a time where establishments certainly had other concerns than participating in our survey. After excluding observations which did not provide the necessary information for the present empirical analysis, this first part of the sample comprises 313 observations.⁸

In a second step, we increased the sample size by contacting a sample of establishments whose information we acquired via web scraping. To accomplish this, we first manually compiled a list of employer and industry associations. Subsequently, the contact details of the member companies listed on the association's websites were extracted either manually (for smaller associations) or automatically using a Python script (for larger associations). The compiled sample included the e-mail addresses of the establishments, which we used to establish contact. This approach allowed us to increase the sample size of the present study by 166 establishment observations that meet the exclusion restrictions of the SFSO sample.⁹ This brings the total number of observations to 479.

The SES covers a wide range of topics with a focus on the technological development of Swiss companies. Most importantly, it includes information on the use of HR analytics and a nine-item question on the distribution of decision-making authority within organizations. Furthermore, it provides information on workforce structure, corporate culture and strategies, the application of digital technologies, personnel planning, performance measurement, remuneration policies, and additional general information. The availability of a broad set of supplementary information about the establishments is of special importance in the present case, since the estimation approach relies on a selection-onobservables approach. The broad nature of the SES allows to control for a variety of covariates to move the estimated relationship closer to the true underlying effect.

There are two main problems following from the present sampling and surveying process. First, that the survey took place during the Covid-19 pandemic, and second, that a subsample relies on information from establishments that are not part of the sample provided by the SFSO, but which we identified through web scraping. Lehmann and Beckmann

ments. In the drawing of the sample, larger establishments were disproportionately represented to ensure a sufficient coverage of this group. The sample excludes establishments which are active in public administration, farming, and the mining sector.

⁸The relevant literature shows that even though low response rates can be associated with the presence of nonresponse bias, this relationship is not strong (e.g., Curtin et al., 2000; Keeter et al., 2000; Groves, 2006; Groves and Peytcheva, 2008; Brick, 2013).

⁹The sample restrictions refer to the exclusion of establishments which are active in public administration, farming, and the mining sector, as well as establishments with less than 10 employees.

(2024) examine whether the descriptive results of the SES are close to comparable data sets from Switzerland conducted before the Covid-19 pandemic. Finding similar results, they conclude that there is no fundamental bias in the data set. Section 6.3 of the sensitivity analysis addresses possible heterogeneity between the two subsamples. It does this by comparing the mean values of the included variables between the two subsamples and by reestimating the baseline models without the web scraped subsample.

Table A2 in the appendix provides descriptive statistics for all variables of interest.

3.2 Variables of interest

The outcome variables of interest focus on the hierarchical level to which decision-rights are assigned in companies. Table 1 shows the exact structure of the survey question that the SES poses regarding decision rights-assignment and introduces the abbreviations for the items (column (4)). The establishments provide information about the specific hierarchical level (non-managerial employees; lower and middle management; or top management) that mainly makes the decisions in nine distinct areas. The broadness of the covered areas reflect that decision-rights assignment within companies is a multifaceted object. The survey items include decisions about typical supervisory activities, such as work planning and definition of tasks, as well as decisions regarding very specific duties such as the replenishment of materials and supplies or customer contact. In addition, there is information on strategic decisions, such as investments in machinery and equipment, and the granting of compensation, bonuses and promotions.

	Non- managerial employees	Lower and middle manage- ment	Top man- agement	Abbreviation
	(1)	(2)	(3)	(4)
Work planning Definition of tasks Pace of work Sequence of work Customer contact Quality control of work Replenishment of materials and supplies	0000000	000000	0000000	WP Def Pace Seq Cust Qual Repl
Investments in machinery or equipment Award of compensation, bonus & promotions	0	0	\bigcirc	Inv Award

To combine the available information of these nine distinct items into more comprehensive measures of decision-rights assignment within a specific establishment, this analysis makes use of the double standardization approach or double-z-score. *Standardization* (STD) implies the subtraction of the mean of a variable and the division by its standard deviation, resulting in a variable that has a mean of zero and a standard deviation of one by construction. The double-standardization procedure now adds up different standardized variables and standardizes this sum a second time. The goal of this transformation is the construction of an overarching index reflecting the dimension of interest through information present in different indicators.¹⁰ The index for decision rights assignment (DRA) includes all nine items present in table 1 and takes the following form:

$$DRA_{j} = STD\{STD(WP_{j}) + STD(Def_{j}) + STD(Pace_{j}) + STD(Seq_{j}) + STD(Cust_{j}) + STD(Qual_{j}) + STD(Repl_{j}) + STD(Inv_{j}) + STD(Award_{j})\},\$$

where j refers to the establishment. Decisions made at a lower hierarchical level are coded as smaller values, therefore, a low value of DRA indicates a high degree of decentralization.¹¹

To gain a more granular insight into the assignment of the decision-making authority within establishments the empirical analysis does not only concentrate on DRA but further separates this indicator. To achieve this, I follow a similar approach as Camps and Luna-Arocas (2009) and differentiate between strategic and operational decision-making.¹² Where strategic decision-making has a more global impact, while operational decisions focus more on the day-to-day activities. Regarding the nine items present in DRA and depicted in table 1, I classify the first seven items as part of the operational decision-making and the last two as belonging to the strategic dimension.

From this follows, through the double-standardization process, that the indicator measuring the centralization regarding operational decisions (opDRA) is defined as:

$$opDRA_{j} = STD\{STD(WP_{j}) + STD(Def_{j}) + STD(Pace_{j}) + STD(Seq_{j}) + STD(Cust_{j}) + STD(Qual_{j}) + STD(Repl_{j})\},\$$

¹⁰The double standardization procedure is very commonly used in the personnel economics literature. Examples include Hitt and Brynjolfsson (1997); Bresnahan et al. (2002); Tambe et al. (2012); and Beckmann and Kräkel (2022).

¹¹The underlying variables, before standardization, take the value one if the establishment selected *non-managerial employees*, two represents *lower and middle management*, and three *top management*.

¹²The idea of differentiating between different types of decisions is well established. For example, Hitt and Brynjolfsson (1997) differentiate between structural and individual decentralization and Tata and Prasad (2004) distinguish between macro- and micro-level decentralization. Van Den Heuvel and Bondarouk (2017) also talk about operational and strategic decision-making in the context of HR analytics.

and for strategic decisions (strDRA) it takes the following form:

$$strDRA_{i} = STD\{STD(Inv_{i}) + STD(Award_{i})\}.$$

In addition to the three aggregated variables (i.e., DRA, opDRA, and strDRA), the baseline empirical analysis also considers the standardized versions of the nine underlying items in order to identify potential drivers of the effects observed for the aggregated variables.

The explanatory variable of interest captures the presence of artificial intelligence or data analytics tools as a supporting means to collect information that can be used during the implementation of employee development or performance evaluation. In other words, this variable is a binary measure indicating the presence of data-based measures which are used in personnel management, where personnel management covers the areas of performance evaluations and employee development. In the following this variables is denoted as HRA, which is short for HR analytics.

3.3 Descriptive statistics

This section presents descriptive insight into the dependent and explanatory variables of interest. To ensure that the descriptive statistics calculated from the SES are representative of the Swiss business sector, they include sampling weights. The weighting procedure calibrates the underlying sample to mirror the effective distribution of Swiss establishments. It takes geographical characteristics, the specific industry and the number of employees into account.¹³

Figure 2 shows the distribution of the outcome variable of interest in the establishment population. More specifically, it depicts the hierarchical level to which the establishments assign the decision-making power for all nine items that define DRA. Not surprisingly, it reveals significant differences in the hierarchical levels responsible for decision-making across the various areas. At first glance, a notable contrast emerges between operational and strategic decisions, with strategic decisions being predominantly the responsibility of the top management. For instance, in 97% of establishments, the top management oversees decisions related to the award of compensation, bonuses, and promotions. Similarly, in 91% of establishments, they are in charge of investment decisions concerning machinery or equipment. In contrast, the seven items capturing operational decision-making show greater variability between the hierarchical levels. Non-managerial employees are most

¹³While the use of survey weights in the estimation of regression models is not seen as universally beneficial, its use for the presentation of descriptive results is less contested (e.g., Solon et al., 2015; Bollen et al., 2016). Section 4.3 discusses the weighting process in more detail.



Figure 2: Distribution of decision rights

Source: Swiss Employer Survey (SES); own calculations. Notes: Number of observations: 479. Shares include sample weights.

often responsible for decisions related to the replenishment of materials and supplies, taking charge in 54% of establishments. Meanwhile, decisions on quality control and the sequence of work fall primarily under the control of the lower and middle management (both in close to 60% of establishments), as do decisions regarding work planning, pace of work, and definition of tasks (all around 55%). Finally, decisions regarding customer contact is distributed most evenly across the hierarchical levels. In summary, while top management almost consistently oversees strategic decisions, the assignment of decision rights regarding operational matters varies significantly across Swiss establishments.

Regarding the explanatory variables of interest, about 15% of establishments utilize HR analytics, as they collect data that can be used during the implementation of employee development or performance evaluations. While the adoption of HR analytics is not yet widespread in Swiss establishments, a significant number of employees are nonetheless affected by its application. This underscores the relevance of the current investigation for a broader public in Switzerland.

Figure 3: Degree of centralization by treatment status (*HRA*)



Source: Swiss Employer Survey (SES); own calculations. Notes: Number of observations: 479. Calculations include sample weights. Section 3.2 defines *HRA*, *DRA*, *opDRA*, and *strDRA*.

Figure 3 presents the mean values of three composite variables (i.e., *DRA*, *opDRA*, and *strDRA*) separated by treatment status. Specifically, the figure contrasts the mean values between establishments that utilize HR analytics and those that do not. A lower observed mean value indicates that the decision-making authority lays further down the hierarchy. While the absolute levels of the standardized means are not inherently insightful, the figure demonstrates that, across all three variables, decision-making authority tends to be situated at a lower hierarchical level in establishments where HR analytics is present. This observation provides preliminary support for the hypothesis that the implementation of HR analytics is linked to a greater delegation of decision rights. However, while informative, this descriptive finding does not substitute for more rigorous econometric analysis, as it does not account for potential confounding factors.

4 Empirical methodology

4.1 Estimation approach

The starting point of our empirical analysis are two regression models used to predict outcomes for all observations (Cameron and Trivedi, 2022, p. 1292):

$$DRA_{1,i} = X_i\beta_1 + U_{1,i} \quad \text{if } HRA_i = 1$$
 (1)

$$DRA_{0,i} = X_i\beta_0 + U_{0,i} \quad \text{if } HRA_i = 0,$$
 (2)

where DRA_1 and DRA_0 represent the dependent variables on decision-rights assignment, i.e., DRA, opDRA, and strDRA. The index *i* denotes the respective firm. HRA is a binary treatment variable indicating a firm's utilization of HR analytics. All of these variables of interest were introduced in section 3.2. X is the matrix of control variables which will be discussed in section 4.2, while the vectors β_1 and β_0 represent the parameters to be estimated. Finally, U_1 and U_0 denote stochastic error terms with zero mean and finite variance.

I am interested in estimating the average treatment effect (ATE) of HR analytics utilization on the level of decision-rights assignment in Swiss companies. For this purpose, I apply a doubly robust estimation strategy for the ATE developed in Robins et al. (1994). The doubly robust ATE estimator combines inverse probability weighting (IPW) with the specified regression models for the potential outcomes (1) and (2).

This estimation strategy is a three-step approach. The first step is a probit maximum likelihood estimation of the parameters of the treatment probability model

$$p(X_i) = Pr(HRA = 1 | X = X_i) = HRA_i = \Phi(X_i\beta),$$
 (3)

where Φ is the cumulative distribution function of the standard normal distribution. These estimates, define the propensity score $\hat{p}(X_i)$ and the IPWs (Austin, 2011; Austin and Stuart, 2015). After estimating the propensity scores, the analysis enforces common support within the sample.¹⁴

The second step estimates the regression models (1) and (2) and predicts the treatmentspecific outcomes $\widehat{DRA}_{1,i} = x'_i \hat{\beta}_1$ and $\widehat{DRA}_{0,i} = x'_i \hat{\beta}_0$ for the entire sample to impute the unobserved counterfactual (Cameron and Trivedi, 2022, p. 1292). The third step

¹⁴Common support ensures that the analysis only includes observations with comparable counterparts. This is achieved by excluding non-treated observations with a propensity score lower than the lowest one associated with a treated observation, and by excluding treated observations with a propensity score higher than the highest one associated with a non-treated observation.

incorporates the first two steps and estimates the potential outcomes by including a weighted residual term (Cameron and Trivedi, 2022, p. 1296). The doubly robust ATE is then computed by the difference of these weighted averages (e.g., Funk et al., 2011; Abdia et al., 2017; Cameron and Trivedi, 2022, p. 1296).

This three-step procedure provides consistent estimates that can be interpreted in terms of causal inference if the stable unit treatment value assumption (SUTVA), the conditional independence assumption (CIA), and the common support assumption (CSA) are satisfied (e.g., Imbens, 2004; Austin, 2011; Li, 2013; Abdia et al., 2017; Narita et al., 2023).

For the present empirical analysis, CIA is the most critical assumption. This is because the analysis can only draw on cross-sectional data. However, in order to convincingly estimate causal ATEs within the scope of a selection-on-observables approach such as doubly robust ATE estimation, the availability of a comprehensive panel data set including pre-treatment control variables and post-treatment outcome variables would be required. Although it appears unlikely that the ATEs resulting from the doubly robust estimator can be interpreted in terms of causal inference, the doubly robust property makes this estimator superior to parametric OLS or other semiparametric estimators such as IPW.

The doubly robust property means that the estimator provides consistent ATEs even if either the regression models for the potential outcomes (1) and (2) or the IPW model (3) is incorrectly specified (Funk et al., 2011; Abdia et al., 2017). In contrast, OLS and IPW require correct specification of the assumed functional form for the outcome model (OLS) or the treatment probability model (IPW) (Cameron and Trivedi, 2022, p. 1295).¹⁵

4.2 Control variables

As discussed in the previous section, the econometric modeling approach applied in this analysis relies on selection-on-observables. Consequently, the validity of the econometric results depends critically on the inclusion of the appropriate control variables. To reduce ambiguity within the selection process of the covariates, this analysis grounds it on a solid theoretical framework. Specifically, it employs the three-legged stool framework as developed by Brickley et al. (2021). Central to this model is the concept of organizational architecture, which is viewed as a coherent system consisting of three interrelated components (or stool legs): the assignment of decision rights, the reward system, and the performance evaluation system. This organizational architecture is, in turn, shaped by the strategic choices, which are in themselves influenced by the broader business environment. The business environment comprises the technological factors, markets, and regulatory conditions an establishment faces.

¹⁵This chapter closely follows Lehmann and Beckmann (2024).

The core of this theoretical framework encompasses both the dependent and explanatory variables of interest. On the one hand, decision rights assignment is a distinct component, on the other hand, *HRA* relates to both the performance-evaluation and the reward system, as it both incorporates aspects of performance assessment as well as personnel development. Through this, the three-legged stool model presents itself as a natural candidate to aid in the selection process of the covariates. Following Brickley et al. (2021), the choice of the covariates will supplement information within the present stool-legs of the organizational architecture, cover the applied strategy, as well as the three elements that characterize the business environment.

To account for the technological dimension, the covariates include a standardized measure based on an establishment's self-assessment of its technological state. Furthermore, a composite variable is incorporated, constructed using the double standardization approach. This composite variable integrates information on the proportion of employees and managerial staff equipped with mobile devices, the share of total training expenses allocated to technology-induced training, the percentage of recruitments requiring digital skills, and the proportion of investments directed towards digital equipment.¹⁶ The market environment is captured by a standardized measure of the competitive pressure an establishment faces, along with its geographic location, which accounts for local demand conditions. The geographic location is classified according to Switzerland's seven greater regions (e.g., Espace Mittelland, Région lémanique, Ticino). The regulatory environment is represented by the legal form of the company (private vs. capital company), the presence of an in-house employee representation (works council), and a dummy variable indicating whether the establishment operates independently or as part of a larger organization.

The strategic decisions dimension includes the industry in which the establishment operates (sixteen NOGA classes aggregated into nine categories, see table A2) and two dummy variables that capture the establishment's make-or-buy strategies over the past five years (internal and external expansion strategies, business unit sales, and outsourcing decisions). Two dummy variables indicating the use of performance targets and performance evaluations complement the coverage of the performance-evaluation system. The reward system is supplemented by the existence of a pay-for-performance scheme.¹⁷

¹⁶This measure of digital affinity aligns closely with the taxonomy of digital-intensive sectors developed by Calvino et al. (2018), which combines indicators such as ICT investment, ICT intermediates purchases, robot usage, ICT specialists, and online sales. Furthermore, it is applied in Lehmann and Beckmann (2024).

¹⁷The variables covering the performance-evaluation and the reward system, i.e. performance targets, performance evaluations, and pay-for-performance schemes, could mediate the effect between HRA and DRA. However, as simple OLS-regressions do not reveal a significant relationship between HRA and any of these variables, this does not seem to be the case. Still, their inclusion in the regression model is the

Lastly, the analysis includes additional general covariates, namely, the existence of company supported further training measures, the number of employees at the establishment (six size classes), and a dummy indicator reflecting that the survey was conducted at two different points in time.

Table A2 in the appendix provides descriptive statistics for all control variables.

4.3 Sampling weights

The use of sampling weights is discussed controversially in the literature. On the one hand, survey weights may be essential to avoid bias when estimating population means and they can mitigate potential non-response bias that may result from low response rates. On the other hand, their unnecessary use can lead to an inefficient estimator without reducing bias (Brick, 2013; Solon et al., 2015; Bollen et al., 2016; Busemeyer et al., 2022). In response, the literature urges researchers to check whether the estimated results are overly sensitive to the chosen approach, namely by reporting both weighted and unweighted estimates, as this serves as a useful test against model misspecification (e.g., Solon et al., 2015).

Overall, the inclusion of sampling weights seems appropriate in the present situation, since the main goal of the investigation is to produce estimates representative for the Swiss Economy.¹⁸ In addition, reliable information is available on the population distribution of the characteristics considered in the weighting procedure. However, to address the points raised by the literature the empirical analysis covers both possibilities. The baseline estimation process (section 5) incorporates sampling weights. Additionally, section 6.2 checks whether the ATE estimates are driven by the applied sample weighting procedure by reporting unweighted estimates. While the estimation results without sampling weights produce lower coefficients and are not statistically significant the suggested direction of the results, and with this the underlying message, is consistent with the baseline approach.

The weighting process calibrates the underlying sample to fit the actual distribution of Swiss establishments with more than ten employees regarding the geographical location (seven Swiss greater regions), sector (sixteen sections according to the NOGA classification 2008), and number of employed people (three company size classes: small, medium, and large establishments).

more cautious approach, as any possible mediated effects are absorbed. A reestimation of the baseline models without these control variables results in almost identical coefficients.

¹⁸In other words, the main goal of the inclusion of sampling weights in the present analysis is not the reduction of non-response bias but the estimation of representative results.

4.4 Trimming

Treated companies with a propensity score close to zero and non-treated companies with a propensity score close to one can receive very large IPWs. Extreme weights can also be generated by the sample weighting procedure when a firm belongs to an under-sampled part of the firm population. If, as in the present case, both IPW and sample weighting are combined, the presence of extreme weights can be exacerbated because both weights are multiplied with each other. The existence of extreme weights can negatively impact the precision of the ATE estimate (Austin and Stuart, 2015). In such cases, trimming extreme weights (i.e., setting weights below and above a certain threshold value equal to the weight at the selected threshold) can effectively reduce the sampling variance of ATE estimates. However, this comes at the cost of an increased mean square error and generally leads to a deterioration in the achieved covariate balance (e.g., Cole and Hernan, 2008; Potter and Zheng, 2015).

Since trimming weights always entails the mentioned trade-off, there are various viable options to set the cutoff percentiles for trimming. The trimming thresholds most commonly discussed in the literature are the 1^{st} and 99^{th} percentile, the 2.5^{th} and 97.5^{th} percentile as well as the 95^{th} and 5^{th} percentile (e.g., Stürmer et al., 2010; Lee et al., 2011; Austin and Stuart, 2015; Thoemmes and Ong, 2016; Hashimoto and Yasunaga, 2022). Section 5.1 will discuss the impact of these various trimming thresholds on the covariate balance and argue for the optimal trimming cutoff in the present case. Additionally, section 6.2 checks if the applied approach has a large impact on the estimation results by reestimating the baseline results with differing trimming thresholds.

5 Empirical analysis

5.1 Balance diagnostics

Intuitively speaking, the goal of IPW is to create a synthetic sample which balances the observed covariates across the treatment variable. The level of achieved balance is, therefore, a crucial indicator about the goodness of the IPW. It follows that for an analysis applying IPW it is important to investigate the obtained balance and find the optimal modeling approach before the coefficients of interest are estimated. The most widely used approach to quantify the remaining level of covariance imbalance after IPW is to report the absolute standardized mean differences (ASMD) (e.g., Austin, 2011; Li, 2013; Austin and Stuart, 2015; Abdia et al., 2017; Narita et al., 2023). As indicated by the name, the ASMD detects differences in the means of covariates between the subgroups of treated and non-treated observations. A high level of ASMD after weighting could imply that the propensity score model is not correctly specified (Austin, 2011). In the literature, different thresholds for ASMD are considered acceptable. For example, Abdia et al. (2017) tolerate differences up to 20%. More commonly, however, a threshold of 10% is regarded as viable (e.g., Austin and Stuart, 2015). In any case, the modeling approach should aim to minimize the remaining imbalance between covariates, all else being equal.

The upper part of table 2 presents summary statistics for the ASMD for different model specifications. Column (1) presents the ASMDs before the weighting took place, i.e., in the unaltered original data set. Columns (2) - (5) show the values after weighting and enforcing common support with different trimming cutoffs. In column (2) no trimming of the weights takes place. In columns (3) - (5) the weights are trimmed at the $1^{st}/99^{th}$, $2.5^{th}/97.5^{th}$, or $5^{th}/95^{th}$ percentile, respectively.

	Pre- weighting (1)	Post- weighting (2)	Post- weighting (3)	Post- weighting (4)	Post- weighting (5)
Trimming percentiles			$1^{st}/99^{th}$	$2.5^{th}/97.5^{t}$	$^{h} 5^{th}/95^{th}$
Average ASMD Highest ASMD №>0.1	$0.069 \\ 0.264 \\ 8$	$0.060 \\ 0.186 \\ 7$	$0.045 \\ 0.154 \\ 3$	$0.039 \\ 0.102 \\ 1$	$0.042 \\ 0.109 \\ 2$
N_{P} non-treated observations N_{P} treated observations N_{P} observations	413 66 479	$377 \\ 65 \\ 442$	$378 \\ 65 \\ 443$	$379 \\ 65 \\ 444$	$376 \\ 65 \\ 441$

Table 2: Covariate balance diagnostics (ASMD)

Source: Swiss Employer Survey (SES); own calculations.

Notes: ASMD refers to the absolute standardized mean difference. Common support is enforced in columns (2) - (5).

Prior to applying the weights, eight covariates display an ASMD exceeding 10%, with the highest ASMD being 26%, attributed to the variable *Level of digitalization*. While weighting the observations and enforcing common support decreases the highest ASMD, it remains above 10% but below 20% in all of the four specifications in columns (2) -(5). Using the 2.5th and 97.5th percentiles as a cutoff minimizes all three of the depicted summary statistics. Namely, the associated average ASMD (0.039), the maximum ASMD (0.102), as well as the number of covariates exceeding the threshold of 10% is lower than in any other specification. The only covariate slightly breaching an ASMD of 10% is the variable *wave*. Even though, the differences are sometimes small (e.g., compare column (4) to column (5)) these cutoffs are clearly best suited to minimizes the difference in the distributions of the observed covariates across the treatment variable. The baseline estimation approach, therefore, uses the 2.5th and 97.5th percentiles as trimming cutoffs.

5.2 Common support

The lower part of table 2 reports the number of observations excluded due to enforcing common support. This reduces the sample size from 479 to between 441 to 444 observations, indicating that depending on the specification between 38 and 35 observations are outside of the area of common support. The variation in the number of observations lost across the four different trimming levels is minimal.

Figure 4 provides information on the distribution of propensity scores for the observations within common support for the chosen baseline trimming cutoff at the 2.5^{th} and 97.5^{th} percentiles. It achieves this by showing the density functions of the propensity scores for establishments that adopt HR analytics and those that do not. For the empirical analysis to yield meaningful results, a substantial overlap between these two distributions is desirable (Busso et al., 2014). Subplot (a) presents the density functions prior to enforcing common support, while subplot (b) depicts them after common support has been enforced.







Overall, the plots reveal that although the mass of the PDF for establishments without HR analytics lies a little bit further to the left, there is a substantial degree of overlap between the two distributions even before enforcing common support. Comparing the two subplots shows that in subplot (b) the right tail of the distribution depicting observations with HR analytics is clipped, a look at table 2 indicates that this observation relates to the one treated observation that is excluded. Furthermore, the left tail of the distribution without HR analytics becomes steeper. This reflects the impact of the 34 non-treated

observations that are dropped. Overall the PDFs provide convincing evidence that the there is no problem regarding common support in the present empirical investigation.

5.3 Baseline regression results

This section presents the doubly robust ATE estimation results regarding the empirical relationship between the application of HR analytics and decision rights assignment within establishments. As discussed in section 2, from a theoretical perspective HR analytics can act both as a decentralizing and centralizing force. The present econometric approach measures the net effect over the centralizing and decentralizing forces which are at work simultaneously. Since higher hierarchical levels are coded as higher numbers, a positive coefficient would associate HRA with increased centralization, while a negative coefficient would associate HRA with increased decentralization.

The upper part of table 3 presents the estimated relationship between the treatment variable HRA and the three composite outcomes of interest covering all types of decisions (DRA), and focusing on operational (opDRA) or strategic (strDRA) decisions.

The results indicate a negative and significant effect for all three composite variables at least on a 5% level. The application of HRA, therefore, exhibits a statistically significant relationship with decision rights being present on lower hierarchical levels in establishments. The presence of HRA is associated with a downward shift in the hierarchical level on which decisions are made by 0.320 standard deviations. The same interpretation applies to specifically operational (-0.265 standard deviations) and strategic decisions (-0.296 standard deviations).

The bottom two parts of table 3 now show the relationship between HR analytics and each of the nine underlying items, to explore at a more granular level where the observed relationships for the aggregate variables emerge from. For the individual items only one of the estimated coefficients is positive, this is regarding decisions about the pace of work. However, this coefficient is small and clearly not statistically significant (*p*-value = 0.85). All eight other depicted coefficients are negative. Three of the items seem to be the main drivers of the observed effects for the composite variables, as their coefficients are statistically significant. Among these three items are two belonging to the operational dimension (*Work planning* and *Definition of tasks*) and one who is part of the strategic dimension (*Investments in machinery or equipment*).

Composite DRA	I.	$\begin{array}{ccc} HRA & HRA \\ (1) & (2) \end{array}$		$\begin{array}{c} HRA\\ (3)\end{array}$	l		
DRA	-0.3	320***					
op DRA $str DRA$	(0	.120)		-0.265^{**} (0.115)		-0.296*	**
						(0.120)
Operational DRA	$\begin{array}{c} HRA \\ (1) \end{array}$	HRA (2)	HRA (3)	HRA (4)	HRA (5)	HRA (6)	HRA (7)
Work planning	-0.296^{**} (0.142)						
Definition of tasks	()	-0.451^{***} (0.156)					
Pace of work		()	0.023 (0.118)				
Sequence of work			()	-0.101 (0.114)			
Customer contact				(-)	-0.238 (0.145)		
Quality control					()	-0.025 (0.143)	
Replenishment						(0.2.20)	-0.155 (0.146)
Strategic DRA		$\begin{array}{c} HRA \\ (1) \end{array}$				$\begin{array}{c} HRA\\ (2) \end{array}$	
Investments		-0.424^{***} (0.158)					
Award		、				-0.065 (0.109)	

Table 3: Average treatment effects: HR analytics and decision rights assignment

Source: Swiss Employer Survey (SES); own calculations.

Notes: N = 444. *, **, and *** represent statistical significance at the 10%, 5%, and 1% level, respectively. Each entry in the table refers to a separate estimation. The values in parentheses are robust standard errors. Table 2 denotes the balance statistics. Calculations include sample weights and IPW. *HRA* abbreviates HR-Analytics and *DRA* decision rights assignment. Table A1 depicts the full regression results for the three models visible in the uppermost panel.

Overall the ATEs resulting from the doubly robust estimation approach provide strong evidence for the hypothesis that the application of HR analytics is related to delegating decision rights to lower levels in the hierarchical structure of establishments. From a theoretical perspective, this suggests that the effects of a reduction of the hidden action problem and an increase in the local information advantage dominate the centralizing forces (i.e., reductions in the local information advantage and HRA tools that take over decisions).

5.4 Differences between hierarchical levels

This section investigates where in the hierarchical structure the relationship between HR analytics and decision-rights assignment emerges from. In other words, it examines which hierarchical levels assume greater decision-making authority and which experience a reduction in their decision-making responsibilities. To achieve this, the nine items included in the construction of the three composite variables of interest (DRA; opDRA; strDRA) are redesigned such that they do not take the three different hierarchical levels (see table 1) into account but reflect the presence of decision-making authority on each hierarchical level through a dummy. These dummies take the following form:

$$Item_{TM,j} = \begin{cases} 1 & \text{if } Item_j = Top \text{ management} \\ 0 & \text{if } Item_j = Lower \text{ and } middle \text{ management} \\ 0 & \text{if } Item_j = Non-managerial \text{ employees}}, \end{cases}$$
$$Item_{LM,j} = \begin{cases} 0 & \text{if } Item_j = Top \text{ management} \\ 1 & \text{if } Item_j = Lower \text{ and } middle \text{ management} \\ 0 & \text{if } Item_j = Non-managerial \text{ employees}}, \end{cases}$$
$$Item_{NM,j} = \begin{cases} 0 & \text{if } Item_j = Top \text{ management} \\ 0 & \text{if } Item_j = Top \text{ management} \\ 0 & \text{if } Item_j = Lower \text{ and } middle \text{ management} \\ 1 & \text{if } Item_j = Lower \text{ and } middle \text{ management} \\ 1 & \text{if } Item_j = Non-managerial \text{ employees}}. \end{cases}$$

Item refers to all nine question items as table 1 defines them, j identifies the observation, TM refers to top management, LM to lower and middle management, and NM to non-managerial employees. $Item_{TM}$, $Item_{LM}$, and $Item_{NM}$ are dummy indicators which measure if decision-making power is present at the respective hierarchical level. The analysis now constructs three versions of DRA (DRA_{TM} , DRA_{LM} , and DRA_{NM}) as well as for opDRA ($opDRA_{TM}$, $opDRA_{LM}$, $opDRA_{NM}$) and strDRA ($strDRA_{TM}$, $opDRA_{LM}$, and $strDRA_{NM}$) following the double standardization procedure, including the respective newly constructed dummy variables.

Table 4 presents the regression results. The first part of the table shows the results for the composite variable DRA at each of the three hierarchical levels, while the second and third part of the table focus on specifically operational (opDRA) and strategic decisions (strDRA), respectively. A positive coefficient signifies a positive relationship between HRA and decisions-making power being located at the specific hierarchical level. Since the explanatory variable of interest (HRA) does not change the balance diagnostics as table 2 presents them still apply.

	HRA	HRA	HRA
	(1)	(2)	(3)
DRA_{TM}	-0.258**		
	(0.111)		
DRA_{LM}		0.065	
		(0.126)	
DRA_{NM}			0.302^{**}
			(0.138)
$opDRA_{TM}$	-0.175		
	(0.110)		
$opDRA_{LM}$		-0.069	
		(0.141)	
$opDRA_{NM}$			0.319**
			(0.148)
$strDRA_{TM}$	-0.331**		
	(0.134)		
$strDRA_{LM}$		0.328^{**}	
		(0.140)	
$strDRA_{NM}$			0.065
			(0.075)

Table 4: Average treatment effects: Differences between hierarchical levels

Source: Swiss Employer Survey (SES); own calculations.

Notes: N = 444. *, **, and *** represent statistical significance at the 10%, 5%, and 1% level, respectively. Each entry in the table refers to a distinct estimation. The values in parentheses represent robust standard errors. The balance statistics are denoted in table 2. Calculations include sample weights and IPW. *HRA* abbreviates HR-Analytics and *DRA* decision rights assignment.

The estimated coefficients for HRA are statistically significant at the 5% level in the regressions with DRA_{TM} and DRA_{NM} as outcome variables, showing a negative effect for the former and a positive effect for the latter. This result is in line with a reallocation of decision-making authority away from top management and towards non-managerial

employees for the broad measure of decision-rights assignment.

For operational decisions as measured by opDRA, the effects align closely with those for DRA as they are in line with a similar shift in decision-making authority from top management and towards non-managerial employees. While the former negative effect for $opDRA_{TM}$ is marginally not statistically significant (p=0.11), the positive effect for $opDRA_{NM}$ is statistically significant.

For strDRA the results are consistent with a shift of decision-making authority away from the top management, since the regarding coefficient in the model with $strDRA_{TM}$ is negative and statistically significant. However, a contrasting dynamic to the results for DRA and opDRA is observed in regard to the effect on the lower and middle management, as the effect for $strDRA_{LM}$ is large in magnitude and statistically significant. This signifies that strategic decision-making authority is primarily reallocated to the lower and middle management and not to the non-managerial employees. The non-significance of $strDRA_{NM}$ is also consistent with descriptive evidence that non-managerial employees are rarely involved in strategic decisions.

In summary, the empirical evidence is consistent with the interpretation that decision making authority is shifted away from the top management, for all three composite measures. For DRA and opDRA the reallocation of authority seems to benefit mostly non-managerial employees, while for strategic decisions the lower and middle managements experiences increases in decision-making authority.

6 Sensitivity analysis

6.1 Causal forest

In order to test the robustness of the baseline results, this section uses a different methodological approach to estimate the coefficients of interest. Specifically, I estimate ATEs using generalized causal forests.¹⁹

At an intuitive level, a causal forest consists of a large number of trees. Each tree partitions the sample into subgroups (leaves) based on covariate conditions, with the aim of creating subgroups that are as homogeneous as possible with respect to the outcome. To ensure diversity among the trees, to decorrelate them, and to avoid overfitting, each tree is built using a random subset of observations and covariates, and causal forests use an honest approach: some observations are left out during the tree-building process and are only

¹⁹Wager and Athey (2018) and Athey et al. (2019) derive the applied estimation approach. Athey and Wager (2019) present a use-case example including coding information for R. Labro et al. (2023) is an example of the application of generalized causal forests within the management literature.

used to estimate of the treatment effect. Finally, the causal forest estimates the ATEs by aggregating the predictions of all the trees. Following Wager and Athey (2018) and Athey et al. (2019) the present approach constructs one forest to model treatment assignment and another one to estimate the outcome in the absence of treatment effects. These two are then combined in a manner similar to how propensity score matching combines a selection model with an outcome model to estimate the treatment effects of interest (Labro et al., 2023).²⁰

The first panel of table 5 presents the estimated coefficients for the models with DRA (column 1), opDRA (column 2), and strDRA (column 3) as the dependent variables. These results are generally consistent with the baseline results, as the estimated coefficients are all negative and similar in magnitude to the baseline estimation. More specifically, the coefficient in columns (1) and (3) is slightly lower and the coefficient in column (2) is marginally higher than in the baseline models. However, the associated standard errors are larger than in the baseline models. As a result, the effects in columns (1) and (2) are only significant at the 10% level, and the effect in column (3) is marginally insignificant with an associated *p*-value of 0.118.

Thus, although the statistical significance is lower than in the baseline model, the estimated results remain qualitatively similar. They support the decentralization hypothesis, indicating that the application of HR analytics is linked to decentralization within establishments.

6.2 Different weighting and trimming procedures

The choices regarding weighting and trimming inherently affect the estimated coefficients of interests. Even if the modelling applied in the baseline estimation seems appropriate, it is important to examine alternative specifications to see if the obtained estimates are highly sensitive to these choices. In this vein this subsection investigates if the obtained effect estimates are driven by the chosen weighting approach and trimming threshold.

The second panel of table 5 shows the estimation results following from estimations omitting sampling weights (column 1), and with three different trimming threshold, namely without any trimming (column 2), trimming the highest and lowest percentile (column

²⁰There are several tuning parameters involved in the growth of the forest. As in Athey and Wager (2019), I determine all tuning parameters through a cross-validation procedure. Additionally, to account for the relatively small sample size, I grow a relatively large number of trees (5000) in each forest. As encouraged by Athey and Wager (2019) and derived by Basu et al. (2018), I first grow a *pilot random forest* that includes all the features of interests and subsequently reestimate the ATEs using only the covariates that turn out to be important, i.e., those most frequently used to partition the sample in the trees of the *pilot forest*. While the estimated coefficients are slightly lower when the *pilot forest* is omitted, the underlying message of the results remains consistent.

		Causa	l forest	
	HRA (1)	H	(<i>RA</i>)	$\begin{array}{c} HRA\\ (3) \end{array}$
DRA	-0.299^{*} (0.162)			
opDRA		-0. (0.	279* 153)	
strDRA				-0.239 (0.153)
Nº	479	2	179	479
	Diffe	rent Trimming an	d Weighting Approa	ches
	No sample weights (1)	No trimming (2)	1st & 99th Perc. (3)	5th & 95th Perc. (4)
DRA	-0.175 (0.122)	-0.323^{***} (0.112)	-0.326^{***} (0.116)	-0.293^{**} (0.126)
opDRA	-0.131 (0.116)	-0.279^{***} (0.107)	-0.278^{**} (0.111)	-0.239^{*} (0.123)
strDRA	-0.203 (0.131)	-0.268^{**} (0.118)	-0.281^{**} (0.118)	-0.283^{**} (0.123)
Nº	394	442	443	441
	Si	ubsample: Swiss fe	ederal statistical offic	e
	HRA (1)	H	(RA)	$\begin{array}{c} HRA \\ (3) \end{array}$
DRA	-0.241^{*} (0.123)			
opDRA		-0.	218*	
strDRA		(0.	120)	-0.165 (0.109)
Nº	292	c 2	292	292

Table 5: Sensitivity Analysis

Source: Swiss Employer Survey (SES); own calculations.

Notes: *, **, and *** represent statistical significance at the 10%, 5%, and 1% level, respectively. Each entry in the table refers to a distinct estimation. The values in parentheses represent robust standard errors. \mathbb{N}° denotes to the number of observations, HRA refers to HR-Analytics and DRA to decision rights assignment.

3), and trimming at the 5^{th} and 95^{th} percentile (column 4). Each depicted coefficient refers to a distinct estimation. As discussed in section 5.1 the balance diagnostics for the three trimming thresholds applied in this section are not as convincing as for the choosen baseline specification. This is especially the case for the specification without any trimming (column 2). For the specification omitting sampling weights the observed balance diagnostics are very credible as the highest ASMD amounts to 0.041. The number of observations omitted to achieve common support is, however, larger than in the other specifications, the number of retained observations is 394.

The coefficients in column (1) reveal that the effects estimated without sampling weights are of a smaller magnitude than in the baseline specification. This observation indicates that within the population of establishments who answered the survey the observed effect is lower than when these are reweighted to fit the actual distribution of establishment characteristics within the Swiss economy regarding industry, number of employees, and geographical characteristics. As the point estimates are clearly negative and the suggestive evidence following from this alternative approach still fits with the baseline results, I do not classify the statistical insignificance as greatly affecting the persuasiveness of the baseline results.

Furthermore, all coefficients in columns (2) - (4) are statistically significant and negative. Additionally, the magnitude of the coefficients is relatively similar to the baseline results. The baseline effects for both DRA and opDRA lie between those shown here with the three alternative trimming thresholds. For strDRA the baseline trimming approach leads to a slightly higher coefficient estimate than in the other three specifications. This deviation is, however, only minor. These findings indicate that the trimming approach chosen for the baseline specification does not drive the results.

Overall, this robustness check supports the baseline result, namely that the application of HR analytics is related to decentralization tendencies in establishments. This indicates that the results are not overly sensitive to adjustments in the weighting and trimming strategy.

6.3 Subsampling

One drawback of the data gathering process is that part of the sample relies on contact information collected via web scraping.²¹ This section tries to analyze if any problems arise from this setting. It does this in two steps. First, it looks at differences in the mean values of the variables of interest and the control variables in the two subsamples. Additionally, it also reestimates the baseline specification within the subsample of the

²¹Section 3.1 discusses the data gathering process.

data set whose contact information came from the SFSO.

Table A2 in the appendix depicts descriptive statistics of all included variables. Among others, it depicts the mean values in the whole data set (column (1)), as well as in the subsets of observations contacted from information stemming from web scraping (column (2)) and from the SFSO (column (3)). A comparison for the variables of interest does not reveal big divergences of the means between the two subsamples. Among the control variables a considerable difference exists with regard to the number of employees. The web scraped sample incorporates a higher share of smaller establishments, especially with 10-19 employees. This was to be expected, at least to a certain degree, since the sample of the SFSO oversampled larger establishments. Furthermore, the web scraped part of the sample contains a larger share of establishments belonging to the NOGA classes I and R (hospitality and entertainment), while the SFSO part of the sample is more strongly represented in NOGA classes P and Q (education and health/social service). This indicates that a larger number of companies from NOGA classes I and R are organized in industry associations which publicly provide contact information, while the reverse is true for companies from NOGA classes P and Q. This seems very plausible. As the overall differences are not very pronounced, this comparison of the mean values does not reveal a big problem of the underlying sampling process.

Furthermore, the lowermost panel in table 5 shows the results of the reestimation of the baseline specification only within the SFSO sample. The number of observations here amounts to 313 observations before enforcing common support and 292 after enforcing common support. The balance diagnostic do not indicate substantial differences in the covariates after weighting and trimming at the 2.5% and 97.5% percentile. The maximum ASMD amounts to 0.101. The estimated coefficients are again negative for all three composite versions of DRA, but they are smaller than in the baseline specification. While the estimated coefficient for HRA with DRA and opDRA as dependent variables are statistically significant at the 10% level, this is marginally not the case for strDRA (p-value = 0.13). This comparison indicates that the effect size in the SFSO sample is smaller than in the overall sample. However, this difference is not very pronounced. The omission of part of the sample also results in a loss of statistical power which can partly explain the non-significant effect estimate for strDRA.

Overall the results in this sensitivity analysis show that the web scraped part of the sample is not systematically different and that it does not massively skew the observed baseline results.

7 Conclusion

New digital technologies and data analytic tools change the way we work. This development does also affect the area of human resource management. Under the umbrella term HR analytics data analytic tools influence the way supervisors manage their employees. As this is a relatively new trend empirical evidence is scarce in this research area. In this paper I try to shed light on the relationship between HR analytics and the decision rights assignment within establishments by theoretically and empirically investigating this relationship.

From a theoretical perspective it is unclear if HR analytics leads to a more centralized or decentralized organizational architectures as opposing forces are at work simultaneously. Advanced digital tools have the ability to take over decision-making authority, resulting in more centralized establishments. Additionally, HR analytics can influence the information asymmetry between principal and agent. On the one hand, if it provides people in higher hierarchical positions with more reliable information about the workflows, it decreases the informational advantage of lower-level employees, which leads to less reasons to delegate decisions. On the other hand, the newly available data can also be informative to lower-level employees, maybe even increasing their information advantage. Finally, HR analytics, through its function as monitoring tool, dampens the hidden action problem, decreasing the possibility of counter productive actions by the employees and, therefore, increasing the incentive of managers to delegate decision rights.

To test empirically whether the centralizing or decentralizing forces dominate, I use a novel cross-sectional observational data set of Swiss establishments that we collected by ourselves and call the *Swiss Employer Survey* (SES). The estimation approach relies on a selection-on-observables approach that combines inverse probability weighting (IPW) with regression models for the potential outcome equations.

The empirical results support the decentralization hypothesis, as establishments which make use of HR analytics are more decentralized. The result holds for a composite measure of decision-rights assignment (DRA), as well as for operational (opDRA) and strategic decisions (strDRA). For DRA and opDRA the results align with a reallocation of decision-making authority away from the top management towards non-managerial employees. In contrast, the effects for strDRA are consistent with a shift of decision rights from the top managements to the lower and middle management. This divergence in the results between strDRA and opDRA is not surprising, as strategic decision rights are typically present in higher levels of the hierarchy as operational decisions. From a theoretical perspective, these results suggest that the dampening of the hidden action problem and the increase in the local information advantage dominate the centralizing forces (i.e., reductions in the local information advantage and HRA tools that take over decisions).

These findings contrast with the study of Labro et al. (2023) who observe a centralizing effect of predictive analysis. This difference is, however, not surprising since they do not specifically investigate the usage of predictive analysis in regard to HR processes. While the theoretical channels are likely similar the importance of the individual channels do not need to be identical.

The results suggest that, at least at the present time, Swiss establishments predominantly combine HR analytics with employee empowerment through the delegation of decision-rights. From an employee perspective this result can inspire optimism, as it does not seem that data analytics tools are used to create a dystopian work environment as feared by proponents of the new *digital taylorism*.

To check the sensitivity of the results I conduct several robustness checks. First, I apply a different methodological approach and re-estimate the coefficients of interests by implementing causal forests. Second, a variety of different trimming and weighting approaches are tested. Last, only the subsample of the data set consisting of establishments whose contact data was provided by the Swiss federal statistical office estimates the effects. All robustness checks qualitatively support the baseline result that the application of HR analytics is related to more decentralization in establishments. The results for strDRAshow the largest degree of sensitivity as they become partially statistically insignificant.

While this paper provides valuable empirical evidence in the field of HR analytics, a key limitation is that the results cannot be interpreted as causal estimates. Although the applied estimation approach extends beyond conventional OLS-regressions, the cross-sectional nature of the data and reliance on a selection-on-observables approach prevent causal interpretation.

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Appendix

	DRA	opDRA	strDRA
	(1)	(2)	(3)
HRA	-0.320***	-0.265**	-0.296**
	(0.120)	(0.115)	(0.120)
State of techn. equipment	0.131^{**}	0.167^{***}	-0.045
	(0.056)	(0.052)	(0.061)
Level of digitalization	-0.098*	-0.091	-0.063
<u> </u>	(0.057)	(0.060)	(0.047)
Performance targets	-0.166	-0.063	-0.365***
č	(0.156)	(0.170)	(0.109)
Performance pay	-0.250**	-0.276**	-0.036
	(0.115)	(0.112)	(0.124)
Performance evaluations	-0.029	0.079	-0.321**
	(0.202)	(0.218)	(0.141)
Further training	-0.341**	-0.449***	0.158
-	(0.159)	(0.163)	(0.133)
Competitive pressure	0.103	0.112^{*}	0.018
	(0.069)	(0.061)	(0.083)
Location: Espace Mittelland	0.169	0.190	0.013
	(0.167)	(0.171)	(0.173)
Location: Région lemanique	0.653^{***}	0.755^{***}	-0.003
	(0.206)	(0.199)	(0.201)
Location: Nortwestern Sw.	-0.379*	-0.362*	-0.214
	(0.217)	(0.194)	(0.271)
Location: Eastern Sw.	0.058	0.050	0.047
	(0.160)	(0.165)	(0.199)
Location: Ticino	0.072	0.136	-0.151
	(0.197)	(0.225)	(0.260)
Location: Central Sw.	-0.188	-0.152	-0.184
	(0.201)	(0.199)	(0.185)
Capital company	0.157	0.115	0.188
	(0.152)	(0.145)	(0.174)
Works council	0.179	0.235^{*}	-0.081
	(0.140)	(0.133)	(0.141)
Legally independent	0.231	0.170	0.274
	(0.181)	(0.158)	(0.193)
Strategy: Expansion	-0.083	-0.128	0.089
	(0.116)	(0.124)	(0.098)
Strategy: Reduction	0.192	0.235^{*}	-0.038
	(0.138)	(0.134)	(0.146)
10-19 employees	0.559	0.479	0.471
	(0.352)	(0.314)	(0.384)
20-29 employees	0.622^{**}	0.531^{**}	0.531
	(0.316)	(0.269)	(0.394)
30-49 employees	0.263	0.159	0.41
	(0.327)	(0.271)	(0.427)
50-99 employees	0.115	0.06	0.208
	(0.350)	(0.297)	(0.427)
100-249 employees	0.304	0.255	0.272
	(0.317)	(0.258)	(0.446)

Table A1: Overview: Full regression results

Continued on the next page...

	DRA	opDRA	strDRA
	(1)	(2)	(3)
NOGA class: C, D & E	0.221	0.127	0.362
	(0.338)	(0.301)	(0.351)
NOGA class: F	0.654^{*}	0.732**	0.065
	(0.375)	(0.327)	(0.419)
NOGA class: G & H	0.301	0.229	0.337
	(0.347)	(0.305)	(0.369)
NOGA class: I & R	0.593	0.579	0.299
	(0.402)	(0.371)	(0.381)
NOGA class: K & L	0.618^{*}	0.514	0.564
	(0.373)	(0.344)	(0.365)
NOGA class: J & M	0.505	0.468	0.324
	(0.351)	(0.314)	(0.368)
NOGA class: N	0.187	0.148	0.194
	(0.412)	(0.379)	(0.402)
NOGA class: P & Q	0.651^{*}	0.631^{*}	0.343
-	(0.369)	(0.325)	(0.379)
Wave	-0.018	-0.022	0.004
	(0.141)	(0.140)	(0.116)
Intercept	-0.535	-0.467	-0.426
-	(0.546)	(0.494)	(0.620)

... Table A1 continued

Source: Swiss Employer Survey (SES); own calculations.

Notes: N = 444. *, **, and *** represent statistical significance at the 10%, 5%, and 1% level, respectively. The values in parentheses are robust standard errors. Table 2 denotes the balance statistics. Calculations include sample weights and IPW. *HRA* abbreviates HR-Analytics and *DRA* decision rights assignment.

Variables of interest	Total (1)	$\frac{\underline{\text{Mean}}}{\text{WebScraping}}$ (2)	$\begin{array}{c} \mathrm{SFSO} \\ (3) \end{array}$	$ \frac{\text{SD}}{\text{Total}} $ (4)	$\frac{\text{Minimum}}{\text{Total}} $ (5)	Maximum Total (6)
HRA	0.138	0.108	0.153	0.345	0	1
DRA	0	0.112	-0.059	1	-4.407	2.124
opDRA	0	0.103	-0.055	1	-2.308	2.337
strDRA	0	0.073	-0.039	1	-7.884	0.328
WP	2.084	2.169	2.038	0.635	1	3
Def	2.301	2.355	2.272	0.558	1	3
Pace	1.952	1.988	1.933	0.663	1	3
Seq	1.927	1.946	1.917	0.635	1	3
Cust	1.948	1.928	1.958	0.792	1	3
Qual	2.129	2.223	2.08	0.603	1	3
Repl	1.541	1.566	1.527	0.658	1	3
Inv	2.871	2.898	2.856	0.377	1	3
Award	2.952	2.964	2.946	0.242	1	3

Table A2: Descriptive statistics of the included variables

Continued on the next page...

Variables of interest	Total	<u>Mean</u> WebScraping	SFSO	<u>SD</u> Total	<u>Minimum</u> Total	<u>Maximum</u> Total
	(1)	(2)	(3)	(4)	(5)	(6)
Control variables						
State of techn. equipment	0	-0.119	0.063	1	-3.177	1.776
Level of digitalization	0	-0.155	0.082	1	-1.785	4.228
Performance targets	0.885	0.898	0.879	0.319	0	1
Performance pay	0.351	0.325	0.364	0.478	0	1
Performance evaluations	0.873	0.825	0.898	0.334	0	1
Further training	0.883	0.837	0.907	0.322	0	1
Competitive pressure	0	0.057	-0.03	1	-1.27	1.27
Location: Espace Mittelland	0.24	0.259	0.23	0.428	0	1
Location: Région lemanique	0.127	0.12	0.131	0.334	0	1
Location: Nortwestern Sw.	0.152	0.169	0.144	0.36	0	1
Location: Eastern Sw.	0.127	0.145	0.118	0.334	0	1
Location: Ticino	0.092	0.072	0.102	0.289	0	1
Location: Central Sw.	0.1	0.12	0.089	0.301	0	1
Location: Zurich	0.161	0.114	0.185	0.368	0	1
Capital company	0.697	0.735	0.677	0.46	0	1
Works council	0.307	0.253	0.335	0.462	0	1
Legally independent	0.8	0.837	0.78	0.401	0	1
Strategy: Expansion	0.559	0.512	0.585	0.497	0	1
Strategy: Reduction	0.15	0.187	0.131	0.358	0	1
10-19 employees	0.159	0.331	0.067	0.366	0	1
20-29 employees	0.148	0.12	0.163	0.356	0	1
30-49 employees	0.171	0.127	0.195	0.377	0	1
50-99 employees	0.223	0.169	0.252	0.417	0	1
100-249 employees	0.18	0.157	0.192	0.384	0	1
> 249 employees	0.119	0.096	0.131	0.324	0	1
NOGA class: C, D & E	0.219	0.193	0.233	0.414	0	1
NOGA class: F	0.15	0.187	0.131	0.358	0	1
NOGA class: G & H	0.079	0.06	0.089	0.271	0	1
NOGA class: I & R	0.119	0.235	0.058	0.324	0	1
NOGA class: J & M	0.081	0.078	0.083	0.274	0	1
NOGA class: K & L	0.079	0.078	0.08	0.271	0	1
NOGA class: N	0.063	0.048	0.07	0.243	0	1
NOGA class: P & Q	0.171	0.102	0.208	0.377	0	1
NOGA class: S	0.038	0.018	0.048	0.19	0	1
Wave	0.347	1	0	0.476	0	1

...Table A2 continued

Source: Swiss Employer Survey (SES); raw data.

Notes: N = 479. The table depicts the mean values of the overall sample (*Total*), and two subsamples divided by method of contact (*SFSO & WebScraping*). SD denotes the standard deviation, while Minimum and Maximum denote the lowest and highest values in the data set.