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Employer Review Platforms – Do the Rating Environment and Platform Design affect the Informativeness of Reviews? Theory, Evidence, and Suggestions**

Abstract

Online employer review platforms (ERPs) enable employees to evaluate their current and former companies anonymously online. Job-seekers can use the aggregated reviews to obtain information about potentially attractive companies and thus limit the number of suitable companies. However, the matching process between job-seekers and companies can only be effective if the information provided on ERPs is representative and can be trusted. This paper investigates specific characteristics of ERPs using the two large ERPs *Kununu* and *Glassdoor* as examples. It is argued that the ERP environment is very different from the well-known and -studied reputation system environment of online marketplaces, and that specific factors can potentially bias reviews on ERPs. Based on a new data set containing the *Kununu* and *Glassdoor* reviews of 114 major German employers, it is analyzed if and how design aspects of ERPs and other specific factors affect reviews. Results show that overall (and industry-specific), average review scores on *Kununu* and *Glassdoor* differ significantly from each other. Further results indicate that factors such as employees' awareness of their impact on a company's reputation also affect reviews. Suggestions are made on how ERPs could reduce the influence of these factors in order to present the aggregated information more effectively.

Keywords: employer reviews, reputation, work standards, rating systems, online marketplaces. (JEL: C81, M50, M51, M54)

Introduction

The success story of e-commerce is closely linked to the successful establishment of various online rating (or reputation) systems. These rating systems enable users of online marketplaces such as *eBay*, *Amazon*, or *Airbnb* to assess the trustworthiness of other users and the quality of the products and services offered. In this way, online marketplaces can carry out transactions that would not have been possible without the existence of well-functioning rating systems that minimize transaction costs (Luca, 2017; Tadelis, 2016).

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In the course of the steady growth and continuous improvement of online marketplaces, the benefits of online-based rating systems for human resource management (HRM) were also recognized. Accordingly, in the mid-2000s, the first online employer review platforms (ERPs) were launched. In the years before, several platforms such as *Monster*, *JobScout24*, or *StepStone* had already been established for job placement and to maintain business contacts via the internet, enabling employees and companies to get in touch with each other (Grund, 2006).

ERPs like the Austrian company *Kununu* and the US-company *Glassdoor* have greatly expanded their range of services since the founding years and are recording continuous growth. The information obtained via ERPs differs from information provided by the companies themselves, e.g., at job fairs or official websites, and reflects a broader spectrum of individual opinions. Since the information voluntarily provided on ERPs can reduce information asymmetries between employees and companies during the process of finding a job, the quality of employee-job matches can be improved.[1] ERPs also have the potential to enhance the relationship between a company and its current employees. As a result of the digital transformation, employees in many companies are faced with changes in their work-life setup (Schwarzmüller et al., 2018). Companies can get important feedback on how to successfully manage these changes through the information provided on ERPs.

Since each individual review only reflects the subjective judgement of a single employee and thus has limited information content, a higher number of reviews allows drawing better conclusions regarding the actual quality of a company. By aggregating as many individual reviews as possible, ERPs promise greater transparency on the labor market. It seems likely that after a successful job search, employees will recommend ERPs and use them repeatedly, especially the more accurately the company information provided on ERPs corresponds to the actual conditions (experienced) in a company. However, it remains an open question whether and how the concrete design of an ERP influences the reviews and how representative the reviews really are for a company's workforce as a whole.

When evaluating their current or former company on an ERP, employees often provide more sensitive information compared to rating completed transactions or purchased products on *eBay* or *Amazon*. For online marketplaces, several studies identify review influencing factors such as the reciprocity between the buyer and the seller (Ye et al., 2014; Bolton et al., 2013), the gender of the reviewer (Craciun & Moore, 2019) or emotional expressions in reviews (Kim & Gupta, 2012). A further but yet uninvestigated question is therefore whether specific factors on ERPs may potentially bias employees' aggregate reviews. The aim of this article is to fill this research gap by analyzing and comparing the average review scores on *Kununu* and *Glassdoor* systematically for different industries and, in the case of *Kununu*, for

1 Grund (2006) discusses the implications of matching theory for the employee recruitment process via the internet in detail.

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different subgroups of employees and reviews. The results show that the average review scores on *Glassdoor* are significantly better than those on *Kununu*. It is argued that these discrepancies result from differences in ERP designs which lead to different perceived levels of anonymity and differences in self-selection. It is further theoretically explained and, wherever possible, empirically demonstrated that the time of posting a review, socially influenced preferences, and employees' awareness of their impact on a company's reputation can affect the reviews of different subgroups.

This paper has the following contributions: First, ERP operators gain insights that can help to improve the existing ERP designs and thereby attract further customers in form of companies and employees. Second, employees, job-seekers, and other stakeholders can gain information on aspects that should be considered when interpreting the contents of ERPs. And third, as this is one of the first papers that examine the ERP environment in detail, I hope that this paper provides a stepping stone for future research on particular characteristics of ERPs.

The remainder of the paper is organized as follows. The second section gives a brief summary of related literature on ERPs. The third section addresses the main differences between the rating systems of online marketplaces and ERPs. The fourth section describes the review systems of *Kununu* and *Glassdoor*, the data set, and addresses the ERP range and usage behavior of employees and companies. In the fifth section, specific factors that can influence ERP reviews are examined both theoretically and empirically. Suggestions on how to minimize the impact of these factors are presented in the sixth section. The last section concludes by pointing out a number of limitations and outlining a research agenda.

Literature on Employer Review Platforms

In recent years, ERPs have been increasingly used not only by employees and companies but also for research purposes. This section aims to provide a brief overview of these studies and some exemplary findings, without any claim to completeness. The first subsection presents studies that use the information provided on ERPs for a variety of research objectives. Thereafter, studies examining explicit design features of ERPs or addressing questions regarding the reliability of ERP reviews are presented.

Using ERP Data for Research

So far, there is a small but growing number of studies that use the information available on ERPs as a data source for different research questions. The majority of these studies (Marinescu et al., 2021; Huang et al., 2020; Dabirian et al., 2016; Luo et al., 2016; Moniz, 2015; Moniz & de Jong, 2014) rely on data from *Glassdoor* but other recently published studies (Hoon et al., 2019; Kollitz et al., 2019; Könsgen et al., 2018; Abel et al., 2017) also use *Kununu* as their data source.

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A large number of studies (Könsgen et al., 2018; Abel et al., 2017; Luo et al., 2016; Dabirian et al., 2017; Moniz, 2015; Moniz & de Jong, 2014) also use text mining tools in order to categorize the reviews in regard to their linguistic content.

The results of Huang et al.'s (2020) study show that employees' business outlooks collected from *Glassdoor* are well suited to predict the future operating performance of companies. The studies of Luo et al. (2016), Moniz (2015) and Huang et al. (2015) examine the relation between ERP contents and the financial performance of companies. The results of all three studies indicate that there is a positive correlation between a company's review score on ERPs and Tobin's q. Following the "Dieselgate" scandal, Hoon et al. (2019) examine more than 1,000 *Kununu* reviews of *Volkswagen* employees and find that they showed no increasingly destructive voice behavior towards their company after the scandal, but that the amount of constructive voice behavior decreased. Kollitz et al. (2019) use company review scores from *Kununu* as an external measure of employer reputation in a study on the recruitment strategies of family businesses. The authors find that below-average recruitment practices predict poor employee ratings on *Kununu*.

Studies on the Validity of Reviews and Specific ERP Designs

The scientific literature dealing with the specific characteristics of ERPs is limited. Marinescu et al. (2021) refer to the fact that the existing literature has not yet investigated to what extent the online review behavior of employees differs from the relatively well studied online review behavior of consumers (e.g., Dorner et al., 2020; Filippas et al., 2018; Bolton et al., 2013).

By comparing the *Glassdoor* review scores of US federal agencies' employees, Landers et al. (2019) examine the construct validity of the reviews on *Glassdoor*. The authors find that the general job satisfaction information provided on *Glassdoor* can be considered valid as the values from *Glassdoor* correlate moderately with the values from the official survey.

The only study that examines a concrete design feature of an ERP is Marinescu et al. (2021). *Glassdoor* requires its users to provide work-related information in return for unrestricted access to the available information. According to *Glassdoor* this "Give to get policy" is intended to ensure that the written reviews reflect a wide range of opinions. The results of Marinescu et al. (2021) show that the "Give to get policy" caused a slight but significant increase of 2.6 (2.9 %) in the proportion of rather moderate 3 (4) star reviews compared to voluntary reviews. The share of the worst (best) 1 (5) star ratings decreased significantly by 3.6 (2.1 %). Following the interpretation of Marinescu et al. (2021), the non-monetary incentive to provide a review results in reviews reflecting a more representative picture of employee opinions in the aggregate.

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Differences between the Rating Systems of ERPs and Online Marketplaces

As previously mentioned, the scientific literature on rating systems of online marketplaces identifies various factors that can influence the contents of reviews. Addressing existing differences between the rating systems of online marketplaces and the rating systems of ERPs is helpful in order to determine whether and which of these factors are also relevant for the reviews on ERPs. Following the discussion in this section, the fifth section turns to examine factors that can specifically affect reviews on ERPs in more detail.

What is the Subject of the Review?

On internet platforms like *eBay*, *Amazon*, or *Yelp*, users evaluate products purchased or services. In general, one-time transactions are rated. Users of these platforms, therefore, have little reason to assume that they will suffer negative consequences as a result of their review. In contrast, on *Kununu* and *Glassdoor*, employees evaluate an organization to which they actually belong or have belonged in the past. The submission of a review on an ERP obviously has a stronger potential to cause negative consequences that affect the reviewing person afterwards. In the case of current employees, the organization in question has a direct influence on the economic situation of the respective employee. In this relatively sensitive review environment, other factors can have an impact on the provided contents of reviews compared to online marketplaces.

Users of online marketplaces in general rate a relatively homogeneous product or service. Although it is possible that different attributes may be taken into account when posting a review, in most cases, the number of the attributes is relatively small. In contrast, the users of ERPs evaluate a complex company. In a company, employees work in different business units, have different colleagues and supervisors, and deal with different tasks. The subject area evaluated on ERPs is therefore much more heterogeneous than on online marketplaces.

What are the Motives for Providing a Review?

A greater similarity between the rating systems of ERPs and online marketplaces can be found in terms of the potential motives that encourage users to submit a review. First of all, it is plausible that people who provide a review are guided by the motive to contribute to a public good in both review environments. The users of online marketplaces and ERPs are therefore aware that they benefit from a large pool of reviews when making their own decisions and want to contribute to this pool in order to increase the amount of information available.

However, on online marketplaces such as *eBay* (buyers and sellers) or *Airbnb* (hosts and guests), reviews are provided by both market sides. Every user who provides

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a review has his/her own account with a nickname and can also receive reviews from transaction partners. Due to these accounts, the users of online marketplaces are often identifiable at least in terms of their gender or skin color. Several studies (Cui et al., 2020; Edelman et al., 2017; Ayres et al., 2015; Doleac & Stein, 2013; Nunley et al., 2011) show that this partial identifiability allows for discrimination. On *Amazon,* users have accounts as well which can incentivize them to provide reviews that are as informative as possible. Every user can mark reviews from other users that she regards as helpful. Users whose reviews have been particularly often marked as helpful can receive special benefits from *Amazon* by being included in an exclusive club of product testers (Dorner et al., 2020). Since employees provide reviews on ERPs on a completely anonymous basis (accounts are invisible for other users), problems such as discrimination do not play a role. Nevertheless, the missing possibility to mark existing reviews as helpful also reduces the incentive to provide highly informative reviews.

Although ERPs pursue economic interests, they can, in the broader sense be assigned to a commons-based peer production environment (Benkler, 2006). Algan et al. (2013) use the example of the online encyclopedia *Wikipedia* to investigate motives that tempt individuals to engage in such commons-based peer production environments. Using an online experiment in which *Wikipedia* authors acted as test participants, the authors show that the number of contents that the test participants had contributed to *Wikipedia* was strongly related to their preference for reciprocal exchange, their social image interest, and their altruistic preferences. Therefore, an individual's motivation to submit a review on an ERP can also be explained by intrinsic motivation (see e.g., Poch & Martin, 2015; Bitzer et al., 2007; Tedjamulia et al.; 2005; Kreps, 1997) and reciprocity (see e.g., Jochims, 2016; Fehr & Gächter, 1998).

ERP Characteristics, Data Set, and Descriptive Statistics

Kununus and Glassdoors Rating Systems

On *Kununu* and *Glassdoor*, employees can rate companies in different categories by using a five-star scale. On *Kununu*, stars can be awarded in 13 categories such as working atmosphere, supervisor behavior and working conditions. On *Glassdoor*, in addition to the overall rating, stars can be awarded in five other categories such as work/life balance and career opportunities. On both ERPs, employees can describe individual experiences using text comments and indicate whether they would recommend their current or former company. Reviews can be submitted by active and former employees as well as trainees, interns and applicants.

The submission of reviews takes place anonymously. Employees who wish to leave a review must, however, register with a valid E-mail address on the respective ERP. *Kununu* and *Glassdoor* have established various technical and manual testing procedures to ensure that the reviews are written by actual employees and meet

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the codes of conduct. Furthermore, both ERPs promise that they never delete or change the contents of reviews as long as these reviews met the codes of conduct.[2] When writing a review on *Kununu* and *Glassdoor*, various information may be deliberately omitted, especially if a piece of information allows identification. A difference between the two ERPs is, that the location of the company to be reviewed must always be indicated on *Kununu*, while on *Glassdoor* this information can be deliberately omitted. On both ERPs, reviews can be filtered by different employee subgroups, review score, and on *Kununu*, by the time period (i.e. reviews written in the last month, the last 6 or 12 months).

On both ERPs, companies can choose between free and paid company profiles, whereby the paid variants include far more options. Companies being active on the respective ERP are marked accordingly.

Company-related information is freely accessible to every user on *Kununu*. In addition to all reviews, employer responses to reviews and company profiles (if existent) can be viewed for free. *Glassdoor* users are initially presented with only a limited amount of user-generated content for each company. While users can, for example, see the average review score, only a limited number of reviews can be viewed in detail.

Kununu's unique characteristic is the connection to the career-oriented social networking service *XING*, established in January 2013. The connection to *XING* appears quite advantageous for *Kununu*. Employees who have a *XING* profile but have not yet been active on an ERP will be approached by *XING* to use *Kununu*.

Data Set

This section explains the data set, which is used in the subsequent section to present descriptive statistics on the ERP range and the ERP usage behavior of companies and employees in Germany. In the fifth section, the data set is used to perform more detailed statistical tests and a regression analysis that investigates potential bias factors that may affect the reviews on ERPs. The aim of these investigations is to gain deeper insights into the specific characteristics of ERPs, which are not covered by the literature presented in the second section.

The dataset contains several indicators from *Glassdoor* and *Kununu* and key figures for 114 companies. The companies were selected on the basis of the biennial report of the German Monopolies Commission (Monopolkommission, 2018). In terms of domestic net product, the report contains the largest companies in Germany for the

2 See videos (in German) on *Kununus*' review control system (https://kununugmbh.zendesk.com/hc/de/articles/115004243929-Wie-sorgt-kununu-für-echte-Bewertungen-wie-funktioniert-die-Bewertungskontrolle-) and codes of conduct (https://kununugmbh.zendesk.com/hc/de/articles/115004235245-Warum-gibt-es-auf-kununu-Regeln-wie-lauten-diese-) and *Glassdoors*' community guidelines (https://help.glassdoor.com/article/Community-Guidelines/en_US) (all three sources accessed June 06, 2020).

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reporting years 2016 and 2014. The partial geographical limitation to the largest European economy, Germany, allows a detailed analysis of the two ERPs and at the same time ensures a sufficiently large data basis.

The data set contains the number of employees in Germany for the year 2016 (2014) for 108 (97) companies. In 2016, these companies thus employed at least 3.636.987 people, which corresponds to more than 8.28 % of the employed German residents during that time period.[3] In order to enable a uniform comparison of the ERPs and companies, all data from *Kununu* and *Glassdoor* were collected within one week (April 6–9, 2020).

For *Kununu*, the total number of reviews, the number of reviews for the last 12 months, the average review score, the recommendation rate, the number of employer responses, and the number of active months on *Kununu* were collected for each company. In order to enable a detailed analysis, data on the number of reviews, the average review score, and the recommendation rate were also collected for the following subsets: current and former employees, executives and non-executives, and reviews with and without employer responses. Due to limited filter functions for *Glassdoor*, only the total number of reviews, the average review score, the recommendation rate and the number of active months on *Glassdoor* were collected for each company. Since the recommendation rates correlate strongly with the average review scores (*Kununu*: $r = 0.92$, p-value < 0.001; *Glassdoor*: $r = 0.83$, p-value < 0.001), only the average review scores are used in the further analyses.

For both ERPs, it was also recorded whether the companies were marked as active employers on the respective ERP. The companies were assigned to one of eleven (clustered) industries based on their indicated economic sector (see Appendix A1).[4] For all figures, tables, regressions, and significance tests in this paper, only those companies were considered for which at least 10 reviews had been submitted on the respective ERP.

ERP Range and Usage of Companies and Employees in Germany

With approximately 60 million reviews, salary reports, and insights on more than one million companies and 50 million different visitors per month, *Glassdoor* is currently (mid-2020) one of the world's largest ERPs.[5] More than 7,000 companies are customers of *Glassdoor* and make use of the available recruitment and advertising

3 According to the Federal Statistical Office of Germany (2019), there were 43,900,000 employed German residents in December 2016.

4 Throughout this paper, due to lack of space, only the first-mentioned industries of the clustered industries are mentioned in figures, tables, and the text.

5 It should be noted that the job search engine *Indeed* has the largest number of company reviews for worldwide locations. However, since *Indeed's* number of reviews for companies in Germany is much lower and the filter functions are less advanced than on *Kununu* and *Glassdoor*, this paper refrains from taking a closer look at *Indeed*.

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opportunities.[6] In 2015, the platform was already actively used by 433 (87 %) of the Fortune 500 companies (Barnes et al., 2015).

In German-speaking countries, *Kununu* is the largest ERP with more than 4.1 million reviews on more than 946,000 companies.[7] As of May 2020, *Kununu* has been active in German-speaking countries for more than 12 years and has therefore been present in this region much longer compared to *Glassdoor* (since January 2015). In addition to *Kununu* and *Glassdoor*, there are further ERPs in German-speaking countries which are not taken into account in this paper due to the much lower user numbers (see Reuter & Junge, 2017).

In the following, several indicators collected directly from both ERPs for selected companies and their employees are presented by using the data set. In this way, a more detailed picture of the current ERP usage behavior of employees and companies in Germany is provided. As mentioned above, for reviews on *Kununu* there is a need to indicate a company's location. As this is not the case for *Glassdoor*, for the companies included in the data set only a comparatively small proportion of the total reviews can be clearly attributed to company locations in Germany.

Figure 1 shows whether the companies in the dataset are marked as active employers on *Kununu* and/or *Glassdoor*. Only 9 out of 114 companies (7.89 %) are not active on either of the two ERPs. Of the 114 companies considered, 88 (77.19 %) are active on *Kununu* and 79 (69.30 %) on *Glassdoor*.

Table 1 presents values of several indicators on *Kununu* and *Glassdoor* ordered by company sizes. The number of reviews for German locations is considerably higher for *Kununu*. As it is not mandatory to indicate the location of the company when submitting a review on *Glassdoor*, Table 1 also presents the numbers of reviews relating to worldwide locations which are, on average, much higher. For the companies considered, less than 5 % of the reviews on *Glassdoor* can be clearly identified with locations in Germany. Even when considering all reviews in German (language), the number of these reviews accounts, on average, for less than 10 % of the worldwide reviews for *Glassdoor* (location indicated and not indicated).

6 The information was extracted from the 'about us' section on the *Glassdoor* website (https://www.glassdoor.com/about-us/, https://www.glassdoor.com/about-us/recruit-holdings-announces-completion-of-glassdoor-acquisition/, both accessed June 06, 2020).

7 The information was extracted from the main section on the *Kununu* website (https://www.kununu.com/, accessed June 06, 2020).

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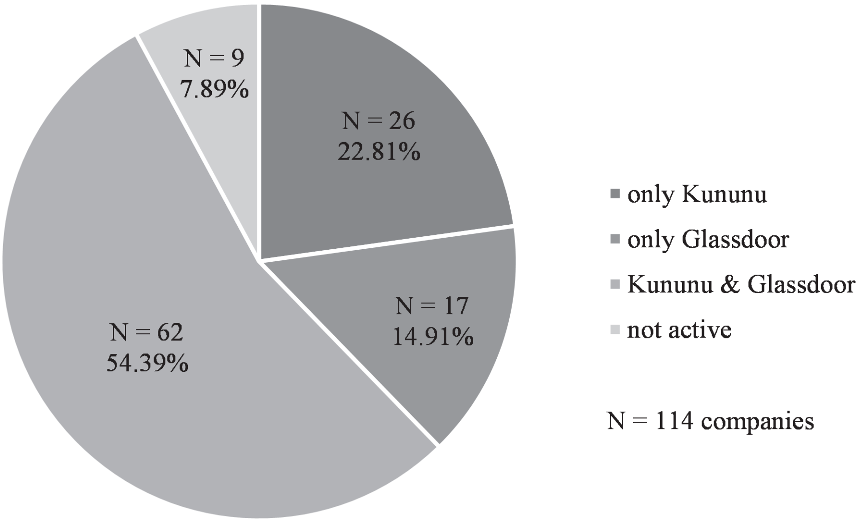
Figure 1. ERP activities of the companies.



Notes: Unpaired t-tests (unequal variances) for the following industries: automotive, building, logistics, all. Unpaired t-tests (equal variances) for the following industries: consumables, energy, finance, health, media, pharma, retail, technology. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

On average, less than 10 % of reviews on *Kununu* received responses from the respective companies. Moreover, more than 40 % of the companies use the response function only to a very limited extent. A closer comparison of the average review scores of reviews with and without employer responses shows that the companies use the response function primarily to respond to reviews with a below-average star rating. Considering companies that have responded on at least 10 reviews, the mean review score is significantly worse (unpaired t-test (unequal variances), *p*-value < 0.01, N = 65 companies) for reviews with responses (mean = 3.33, sd = 0.54) than for reviews without responses (mean = 3.64, sd = 0.26).

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Table 1: ERP Usage Characteristics for Kununu and Glassdoor Ordered by Company Size (Employees in Germany in 2016).

Company Size (in 2016)		<10.000	10.000 – 19.999	20.000 – 49.999	>=50.000	All Sizes
Companies	*N*	35	39	20	20	114
	%	30.70	34.21	17.54	17.54	100.00
Kununu						
Reviews (full period)	Mean	453.80	547.21	861.90	2123.75	850.32
	Median	374.00	463.00	880.50	1720.00	534.00
	(sd)	(331.32)	(430.75)	(535.29)	(1567.73)	(961.41)
	N	35	39	20	20	114
Reviews (last 12 months)	Mean	96.97	116.38	172.35	525.90	192.08
	Median	56.00	108.00	147.50	386.50	116.50
	(sd)	(75.90)	(86.08)	(250.95)	(432.43)	(251.92)
	N	35	39	20	20	114
Employer Respons-es	Mean	50.94	48.54	75.50	195.80	79.84
	Median	8	19	26.50	66.50	23.50
	(sd)	(94.95)	(93.85)	(96.85)	(237.35)	(140.29)
	N	35	39	20	20	114
Companies with <10 Employer Re-sponses	*N*	19	16	8	6	49
	% per Group	54.29	41.03	40.00	30.00	42.98
Companies marked as Active Employers	*N*	25	32	14	17	88
	% per Group	71.43	82.05	70.00	85.00	77.19
Glassdoor						
Reviews (Germany)	Mean	62.80	83.24	95.60	270.10	112.43
	Median	30.00	37.00	56.00	224.00	46.50
	(sd)	(101.82)	(228.79)	(95.14)	(190.40)	(183.03)
	N	35	37	20	20	112
Reviews (language: German)	Mean	142.66	149.24	162.70	488.15	210.11
	Median	68.00	77.00	98.00	347.00	85.00
	(sd)	(272.28)	(256.99)	(162.64)	(381.97)	(301.05)
	N	35	37	20	20	112
Reviews (Worldwide)	Mean	3223.14	2918.61	1154.80	2023.95	2542.41
	Median	216.00	287.50	240.00	1230.00	417.00
	(sd)	(7407.77)	(8963.95)	(1762.12)	(2334.07)	(6726.01)
	N	35	38	20	20	113
Companies marked as Active Employers	*N*	22	25	14	18	79
	% per Group	62.86	64.10	70.00	90.00	69.30

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Possible Bias Factors affecting Reviews on ERPs

The third section has emphasized that the review environment of ERPs differs considerably from the review environment of online marketplaces, especially with regard to the subject of the review. Below, four factors that can bias the (aggregate) reviews on ERPs are identified and examined. The sequence of these factors is chosen with regard to their presumed impact on average reviews where those factors considered to have the biggest influence are examined first.

Perceived Level of Anonymity

ERPs state that they are concerned with ensuring the highest possible degree of anonymity for their users. These efforts are quite understandable from a scientific point of view. For example, Brutus and Derayeh (2002) and Antonioni (1994) show that a high degree of anonymity encourages honest employer evaluations.

Even if ERPs try to guarantee a high degree of anonymity, it seems questionable whether this is perceived by ERP users accordingly. In particular, employees who work for relatively small companies may fear that they could be identified through the submission of a review.[8]

If employees have the ambition to write a review that is as informative as possible, they often not only award stars in different categories, but also write text commentaries in which they describe their individual job-related experiences. The submitted experiences could potentially harm the rated company.[9] If an employee is concerned that the publication of her work-related experience will enable her identification and could cause negative consequences for the company, she could deliberately limit her review to more positive experiences. As Cloos et al. (2019) experimentally show, the willingness to accept disclosure of information to other people depends strongly on the concrete content of this information. Further, the results of several experimental studies (Cloos et al., 2019; Benndorf & Normann, 2018; Schudy & Utikal, 2017) suggest that between 10 and 20 % of participants generally refuse to share their private information with others. Transferred to ERPs, this implies that employees with concerns about the consequences of their shared work-related experiences could deliberately refrain from writing text commentaries and/or specifying the location of their employer. In the case of too strong concerns, they could also decide completely against the submission of a review.

8 Media reports in which German employers could clearly assign negative reviews to individual employees can be found online. In one case, this even resulted in dismissal (see (in German): https://www.waz.de/wirtschaft/noten-fuer-den-chef-kann-man-job-bewertungsportalen-trauen-id214021731.html, https://www.handelsblatt.com/unternehmen/beruf-und-buero/the_shift/arbeitgeber-bewertung-im-netz-kantinenessen-lecker-kollegen-nett-chef-bloed/21086920.html, both accessed June 06, 2020).

9 See Pfeffer et al. (2014) on negative word-of-mouth dynamics in social media networks.

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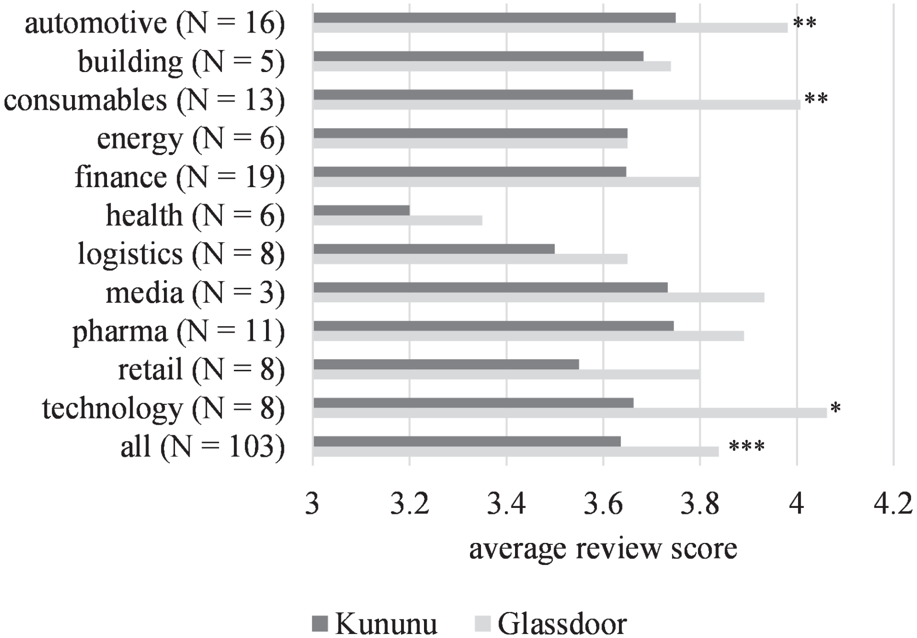
As mentioned earlier, employees who submit a review on *Glassdoor* can choose not to disclose their company's location and obviously often decide against a disclosure. As shown in Table 1, the number of reviews on *Glassdoor* written in German is almost twice as high as the number of reviews written in German and additionally indicating a company location.[10]

Unlike on *Glassdoor*, employees on *Kununu* are required to indicate the location of their company when providing a review. For reviews with an indicated company location, it, therefore, seems likely that these reviews reflect a wider range of opinions when provided on *Kununu* than when provided on *Glassdoor*. In order to test whether the perceived level of anonymity can have an influence, *Kununu's* and *Glassdoor's* average review scores for reviews with an indicated company location (in Germany) are compared below.

Figure 2. Mean review scores for Kununu and Glassdoor ordered by industry.



Notes: Unpaired t-tests (unequal variances) for the following industries: automotive, building, finance, health, logistics, pharma, all. Unpaired t-tests (equal variances) for the following industries: consumables, energy, retail, technology. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

10 It is of course possible that some of the reviews in German refer to company locations in Austria, Switzerland, and other countries. However, it is assumed here that these reviews represent only a negligible percentage share, since most of the locations of the companies in the data set are in Germany, and Germany also has considerably more employed inhabitants than Austria and Switzerland.

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Figure 2 depicts the mean review scores on *Kununu* and *Glassdoor* for each industry. With the exception of the energy industry, the average review score is always higher on *Glassdoor* than on *Kununu*. The differences are significant for the automotive (unpaired t-test (unequal variances), p-value = 0.0298, N = 16 companies), consumables (unpaired t-test (equal variances), p-value < 0.0173, N = 13 companies) and technology industry (unpaired t-test (equal variances), p-value = 0.505, N = 8 companies), and also for all industries combined (unpaired t-test (unequal variances), p-value < 0.001, N = 103 companies).

How can these results be explained? In the light of employees' possible concerns regarding anonymity, it seems plausible that employees who provide a more negative review of their company on *Glassdoor* are less likely to specify a clear company location compared to employees who provide a more positive review. Consequently, the results shown in Figure 2 can be explained by the fact that the average review scores included for *Glassdoor* are based on a subset of comparatively good reviews, whereas for *Kununu,* the whole range of reviews is included. This explanation is also supported if one compares *Glassdoor's* average review scores for reviews with and without an indicated company location. For reviews in German language with an indicated company location, the mean of the average review score is 3.84 whereas for reviews in German language without an indicated company location, the mean is 3.78. However, a comparison of these values from *Glassdoor* is problematic since the reviews with an indicated company location belong to the set of all reviews in German language.

Self-Selection and Time of Posting a Review

The provision of a company review on an ERP is voluntary. The reviews submitted are not random samples of the workforce and are therefore subject to a self-selection bias. Employees only write a review if the benefit they feel from doing so outweighs the effort involved in writing it. For reviews on online marketplaces, various authors (Marinescu et al., 2021; Luca & Zervas, 2016; Masterov et al., 2015; Hu et al., 2009) point out that the majority of reviews is written by users who made a particularly positive or negative product-related experience. Very positive reviews are usually observed more frequently than very negative reviews. People are open to sharing information on the internet, especially in states of arousal (Berger & Milkman, 2012; Berger, 2011). Therefore, for ERPs, one might assume that at least some employees feel the need to share their work-related experiences and opinions online, especially at times when work-related experiences take on an above-average positive or negative form.

If this assumption is applicable to a fraction of employees, this would imply that employees with moderate work-related experiences are under-represented on ERPs compared to their actual distribution in a company's workforce. However, for

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Glassdoor, Marinescu et al. (2021) find that the distribution of reviews is relatively balanced.

Users of online marketplaces are usually asked to provide a review in a message (e.g., by E-mail or messenger services such as WhatsApp) immediately after completing a transaction. The evaluation is thus made at a time when users are likely to remember the transaction relatively well. In contrast, on ERPs, it is much more difficult to make a statement about at which point of time in their career, employees decide to rate their company.

Imagine, for example, an employee after a job change who was far less satisfied with her former affiliated company than with her current company. After two months this employee rates her current company on an ERP benevolently and positively. After a further six months, the employee has settled into the environment of the new company and now views her job far less euphorically than in the first months. This process is known as hedonic adaption (or hedonic treadmill) (see e.g., Frederick & Loewenstein, 1999). It describes the phenomenon that after a positive or negative evaluated life change, the satisfaction level of a person will approach its original level after a relatively short time. In the example above, the employee's level of satisfaction, which has now fallen again, would not be reflected in her original review.

Based on the reviews on ERPs, no statement can be made about the degree of self-selection. Further, without a detailed qualitative analysis of single reviews, it is not possible to determine in which emotional state the reviewer was or how long she had been working for the evaluated company when she wrote the review. However, *Kununu's* filter functions allow aggregated review scores to be generated for both current and former employees. In order to get an approximate idea of whether the time of posting a review has a relevant impact on the average reviews, the average review scores of both current and former employees are compared below.

Over all companies, the average review scores for current employees (mean = 3.71, sd = 0.25) are significantly better (unpaired t-test (unequal variances), p-value < 0.001, N = 111 companies) than for former employees (mean = 3.33, sd = 0.43). This result is robust to all industry classifications in the data set (unpaired t-tests, all p-values < 0.1). This result is, however, not entirely surprising since it can be assumed that many former employees have left a company precisely because of dissatisfaction and therefore rate this company worse than current employees.

However, the results illustrate that a comparison of the aggregate ERP reviews of companies can be problematic if the percentage share of former employees' reviews among all reviews differs between these companies. For example, depending on the company, the percentage share of former employees' reviews among all reviews in

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the automotive industry ranges from 16.29 to 40.04 % (mean = 25.52 %, sd = 7.12 %, N=16 companies).

Employee's Awareness of their Impact on a Company's Reputation

Employees who rate a company on an ERP influence the reputation of that company. The company reviews on ERPs are read both by job-seekers and the current employees of a company. Studies (Wayne & Casper, 2012; Chapman et al., 2005) indicate that a good reputation increases the attractiveness of a company for job-seekers. A good reputation of a company attracts a higher number of job-seekers compared to companies with a lower reputation (Turban & Cable, 2003). In addition, a higher reputation attracts job-seekers with higher abilities (Bidwell et al., 2015). Current employees are also influenced by the reputation of their affiliated company. Their own engagement is positively influenced by the company's reputation (Shirin & Kleyn, 2017; Men, 2012) and they are more likely to remain in their company through well-established HRM practices (App et al., 2012). Arnold and Staffelbach (2012) show that employees who trust their employer and who have a high level of perceived employability show lower levels of job insecurities after a company restructuring.

When providing a company review on an ERP it is likely that at least a fraction of employees has an interest in maintaining the already good reputation or increasing the reputation of their affiliated company. Since co-workers with high abilities who fit well into the company can help to maintain and further improve a company's good reputation, the current employees of a company may benefit from their company recruiting the best possible applicants for vacant positions. In order to attract applicants, it is advantageous for companies to have a good reputation on an ERP. For these reasons, current employees have strong incentives to influence the reputation of their company in the most positive way. Helm (2011) examines which factors influence employees' awareness of their impact on a company's reputation. Her findings show that especially the pride employees feel for being affiliated with a company has a positive effect.

Considering the entire workforce of a company, it is unclear to what extent individual employees or employees in different positions are aware of their impact on the company's reputation. However, media reports on companies focus particularly often on the management personalities of companies. In addition, various studies (Conte, 2018; Love et al., 2017) examine the influence that executives (especially CEOs) have on the reputation of companies. It is therefore likely that employees in executive positions are particularly aware of their influence on a company's reputation. We would therefore expect the average reviews of executives to be better than those of non-executives.

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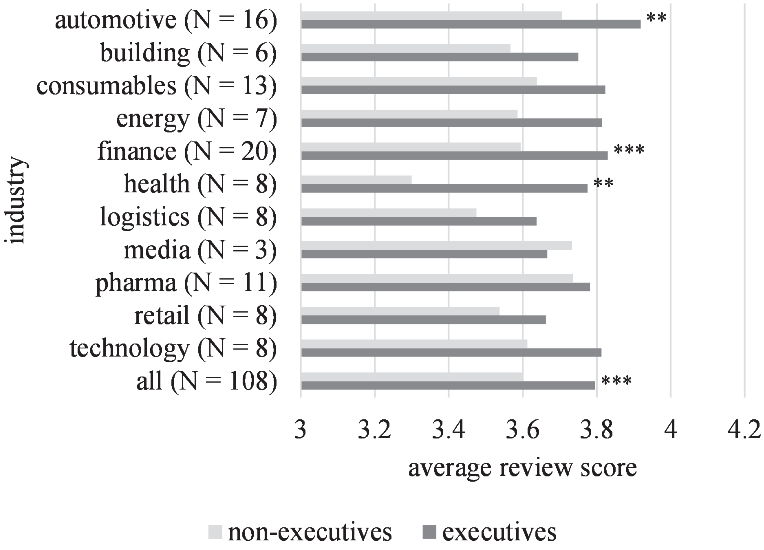
Figure 3. Mean review scores of non-executives and executives on Kununu ordered by industry.



Notes: Unpaired t-tests (unequal variances) for the following industries: automotive, building, logistics, all. Unpaired t-tests (equal variances) for the following industries: consumables, energy, finance, health, media, pharma, retail, technology. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure 3 shows the average review scores for the reviews of non-executives and executives on *Kununu*. The average review scores of executives are better than those of non-executives in each industry, except for the media industry for which only three companies are included in the data set. Significant differences can be observed for the automotive, finance, and health industry as well as for all industries combined. Regarding these results, it must be emphasized that based on the data it cannot be distinguished whether executives provide better average reviews because they have a stronger awareness of their impact on a company's reputation or whether they actually perceive their job as better because of e.g., above-average salaries and/or their prominent position within the company. Nevertheless, these results clearly show that the average reviews of employees in different positions can differ significantly. Consequently, these results further demonstrate that a comparison of the aggregate review scores of companies can be problematic if the percentage share of reviews from executives among all reviews deviates between these companies.

Socially Influenced Preferences

In their product- or service-related preferences, individuals are often influenced by the existing preferences of other people (Cialdini & Goldstein, 2004). A devia-

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tion of one's own preferences from other people's preferences can cause a state of cognitive imbalance. According to balance theory (Heider, 1946), people tend to adjust their attitudes towards the evaluated circumstances or objects or adjust their attitudes towards others in order to achieve a more balanced state of mind.

For the submission of employer reviews, it seems reasonable to assume that employees do not exclusively consider their own work-related opinions, but are influenced by the existing reviews of their current or former colleagues. The extent to which an employee's own opinion is influenced by existing reviews may also depend on the degree of sympathy an employee has with her current or former colleagues. Izuma and Adolphs (2013) have experimentally demonstrated that students improved their original rating of a t-shirt after they were told that their fellow students who were perceived as sympathetic rated the t-shirt better than themselves. At the same time, students downgraded their original rating of a t-shirt after learning that those sex offenders who were perceived as unsympathetic had rated t-shirts similarly well. Concerning how long people maintain this change of attitudes, there is conflicting evidence. While Izuma and Adolphs (2013) observed that preferences were still socially influenced after 4 months, Huang et al. (2014) found that such an effect was only noticeable for a few days before the subjects returned to their original preferences.

For the reviews on online marketplaces like *Amazon* or *eBay*, it can be assumed that social conformity pressure is only of extremely minor importance since the individual reviews come from people who are usually not connected to each other in any way. Reviews on ERPs are submitted anonymously, but compared to online marketplaces the social distance is much smaller. It certainly seems plausible that employees, especially based on job characteristics (e.g., position, department) included in single reviews, identify themselves with the persons who wrote existing reviews and therefore unconsciously give a better or worse review than they would have done without this priming.

However, based on the data collected for this paper, no evidence can be obtained as to whether and to what extent socially influenced preferences affect employee reviews on ERPs.

Regression Analysis

The fourth section showed that for *Kununu* 88 and *Glassdoor* 79 of the 114 companies in the data set are marked as active employers on the respective ERP. In the following, a regression analysis is used for both ERPs to test whether the average review scores of companies that are marked as active employers differ from the average review scores of companies that are not marked as active employers. For *Kununu*, it is further investigated whether the share of former employees' reviews and the share of executives' reviews still have an influence on the average review scores when including relevant control variables in the regression.

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Table 2: OLS Regression of Average Review Scores on ERP Characteristics, Company Characteristics, and Clustered Industries.

	Kununu			Glassdoor		
	(1)	(2)	(3)	(4)	(5)	(6)
Active Employer	0.07	0.09	0.14**	0.03	-0.03	-0.04
	(0.06)	(0.07)	(0.07)	(0.12)	(0.13)	(0.14)
Months since First Review	0.01***	0.01***	0.00*	0.00	0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Reviews from Former Employees (%)		-0.01*	-0.01***		data not available	
		(0.00)	(0.00)			
Reviews from Executives (%)		-0.01	-0.01*		data not available	
		(0.00)	(0.00)			
Employees (in 1000)		0.00	-0.00		-0.00	-0.00
		(0.00)	(0.00)		(0.00)	(0.00)
DAX			0.06			0.20*
			(0.05)			(0.10)
Automotive			0.08			0.12
			(0.09)			(0.21)
Retail			-0.08			-0.04
			(0.16)			(0.24)
Energy			-0.08			-0.33
			(0.13)			(0.25)
Pharma			0.06			-0.04
			(0.11)			(0.24)
Building			-0.11			-0.21
			(0.10)			(0.27)
Technology			-0.08			0.15
			(0.12)			(0.24)
Consumables			-0.01			0.25
			(0.13)			(0.22)
Logistics			-0.20			-0.24
			(0.11)			(0.25)
Finance			-0.13			-0.16
			(0.08)			(0.20)
Health			-0.34**			-0.80**
			(0.15)			(0.54)
Constant	2.79***	3.13***	3.47***	3.64***	3.63***	4.09***
	(0.21)	(0.29)	(0.40)	(0.30)	(0.35)	(0.37)
N	113	97	97	103	89	89
R^2	0.08	0.15	0.33	0.01	0.01	0.27

Note: The numbers (1) to (6) refer to different regression models. In all models the dependent variable is the average review score. The independent variables in models (1) and (4) refer directly to ERP characteristics of the companies. Where possible, models (2) and (5) additionally take into account further ERP characteristics as well as the number of employees (in 1000) for each company. Models (3) and (6) further take into account whether a company has been

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listed in the German stock index DAX since 2007 and whether a company is classified in the respective clustered industry. Robust standard errors in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

In the OLS regression models in Table 2, the average review score on *Kununu* is the dependent variable in models 1–3 while the average review score on *Glassdoor* represents the dependent variable in models 4–6. The upper four independent variables relate to the ERPs directly. The variable *active employer* is a dummy variable that takes a value of 1 if a company is marked as an active employer on the respective ERP. The variable *months since first review* counts the number of months since the first review on each ERP. *Reviews from former employees (%)* contains the percentage share of reviews from former employees among all reviews. Likewise, *reviews from executives (%)* contains the percentage share of reviews from executives among all reviews. A further control variable is *employees (in 1000)* which is an average of the average number of employees in the years 2016 and 2014. The remaining control variables refer to company characteristics and are dummy variables taking a value of 1 if a company has been listed in the German stock index *DAX* since 2007 or is classified in the respective clustered industry.

For *Kununu*, no robust effect of an active profile can be observed. Only in model 3, an active profile positively affects (p-value < 0.05) the average review score of a company. For *Glassdoor,* no effect of an active profile can be observed in any model. It has to be noted that there is no data available on how long a company has had an active employer profile. Therefore, based on the results from Table 2, no conclusive statement can be made as to whether an active employer profile has an effect on average review scores. The variable *months since first review* has a positive effect for *Kununu* in all models, but not in any of the models for *Glassdoor*. For *Kununu*, a significantly negative effect can be observed for the percentage share of reviews from former employees. This result implies that a 10 % increase in the percentage share of reviews from former employees on average leads to a reduction of the average review score by 0.1 stars. The variable *reviews from executives (%)* has a significantly negative effect in model 3 but not in model 2. This result differs from the result in Figure 3, where the average review scores of executives were significantly better than the average review scores of non-executives. However, the negative coefficient of *reviews from executives (%)* is significant only at the 10 % level and the regression in Table 2 contains a number of control variables that are not included in Figure 3. Therefore, we refrain from a further interpretation of this result. Additionally, for *Kununu* and *Glassdoor*, negative effects (p-value < 0.05) for the industry *health* can be observed.

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Suggestions for Informative ERP Designs

How to Address Possible Bias Factors

The results from the previous section have shown that the perceived level of anonymity can affect a review's informativeness. It was highlighted that the concrete design of an ERP has an influence on the average review scores. It seems reasonable that *Glassdoor* aims to motivate as many employees as possible to provide a review by offering a voluntary option to indicate a company's location. Especially for international companies, it is often unclear to ERP users to which location or geographical area a review refers. In the case of small companies, the possibility to deliberately avoid specifying the company's location appears reasonable as it guarantees the anonymity of the reviewer. However, for the reviews of larger companies, it is quite questionable what benefit individual reviews have if it is unclear whether these reviews relate to locations in e.g., Portugal, Brazil or Germany.

ERP operators have to weigh up how they can persuade employees to provide informative reviews whilst accounting for their concerns regarding anonymity. To address this issue, ERPs could oblige employees to indicate a company location when providing the review, but give them an option not to publish the company location publicly with their review. In this way, the review scores and further related values of such a review could at least be included in the aggregated scores of a specific company location.

Employees from smaller companies might fear that they could easily be identified by their bosses or colleagues through their ERP review. To address such concerns, ERPs could give these employees the option to only include their review in the aggregated score of their company and not as a separately visible review. It is further conceivable that such reviews could be disclosed as visible reviews only after at least a certain number of reviews have been provided for the respective company since an individual assignment to reviews would then be less likely.

The next suggestions refer to self-selection and the time of posting a review. Self-selection of particular groups of employees could mainly be reduced if companies would actively encourage their whole workforce to provide reviews on ERPs. ERPs could focus their marketing efforts particularly on those groups of employees who are currently underrepresented on the respective ERP. Regarding the time of posting a review, it has been shown that the reviews of current and former employees differ. In order to allow a better comparison between companies, ERPs could set their filter defaults in such a way that initially only the average review scores of current employees are displayed. The possibility that a fraction of reviews has been written in aroused states could be reduced by asking employees of ERPs to verify or renew their submitted reviews regularly. Reviews that are regularly verified or updated by the same employee could be flagged as highly informative by ERPs. By re-examining her first review, an employee might register if she had written

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her first review with too much euphoria or anger and accordingly correct the first review if necessary. The ERP could then calculate an average review score from the individual reviews of an employee in order to prevent the reviews from counting more than once.

A useful suggestion regarding the possible biasing impact of an employees' awareness of her impact on a company's reputation is more complicated. Without the use of time-consuming questionnaires (e.g., in Helm, 2011) it is impossible to determine an employees' awareness of her impact on a company's reputation and even with a detailed questionnaire, a socially desirable response behavior cannot be ruled out. However, on the profile pages of individual companies, ERPs could highlight which percentage shares of the reviews were provided by which groups of employees. ERPs could further indicate when average review scores differ particularly strong between different groups of employees (or between different locations of the same company).

An additional suggestion refers to the socially influenced preferences of employees. ERPs could increase the informativeness of reviews by trying to prevent possible priming through already existing reviews. *Glassdoors'* "Give to get" policy partly helps to reduce a possible priming effect as employees have only limited access to content when they visit *Glassdoor* for the first time. Nevertheless, it would make sense for ERPs to consider a design in which users when opening a company's ERP site are asked whether they just want to inform themselves or if they want to rate their company first. In the second case, users could be reminded that in order to capture unbiased opinions, it would be useful for them to write a review before reading any of the other existing reviews.

Further Suggestions

To ensure the best possible matching process between employees and companies via ERPs, it would be beneficial to employees if they could individually weight which attributes are particularly important to them in the search process for a suitable company. Suitable companies could then be presented in a ranking based on the individual weightings and the already submitted reviews.

A company's average review score displayed by ERPs is based on all reviews submitted since the existence of a company's site on the ERP. If a user now compares the average review scores of different companies on an ERP, the average review scores are the result of reviews that have not been written within the same time frame. By using the filter function of *Kununu*, it is possible to display a company's average review score of the past month, the past 6 months, and the past 12 months. Here, it is suggested that ERPs could display the average review score of the last 12 or 24 months by default. Job-seekers would benefit from this by being able to compare companies' current working conditions with each other without having to set a filter first. Such a design feature would also strengthen the incentive for companies

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to improve their employer quality. First, companies could not rely on good reviews older than 12 or 24 months. Second, implemented quality improvements by companies would also become visible more quickly since poor reviews older than 12 or 24 months would no longer be included in the average review score.

Especially for larger companies where employees may not have to be very concerned about maintaining their anonymity, it would be reasonable to specify demographic variables when submitting a review on an ERP. Drabe et al. (2015) show that job satisfaction varies between different age groups and that different age groups attach importance to different factors with regard to their job satisfaction. Therefore it would be useful if, for example, an older employee could specify on an ERP via a filter that she only wants to see reviews of employees older than 45 years.

ERPs could additionally enable registered users to mark reviews from other users as helpful. In this way, ERP users who have posted a review would be informed whether their review was perceived as helpful which could motivate them to provide more (informative) reviews in the future.

Further, it would be useful if current and former employees could voluntarily state in their reviews how long they have been working or have worked for the rated company and how many companies they have worked for previously. Based on this information, ERPs could present details about how long former employees have worked for that company on average and thereby provide ERP users with an indication of a company's employee turnover rate. Additionally, former employees could be asked on a voluntary basis about the reasons why they left a company.

Conclusion, Limitations, and Suggested Research Agenda

This article examined specific design features of ERPs in detail. By consulting the relevant literature, it was shown that the rating environment of ERPs differs substantially from the well-studied rating environments of online marketplaces. Possible bias factors such as the perceived level of anonymity and the timing of review provision resulting from the special rating environment of ERPs were discussed. Whenever possible, it was empirically demonstrated that these factors can have an influence on aggregated review scores. Suggestions on how to address the problems connected with these bias factors were presented. Additionally, further suggestions for more informative ERP designs were outlined.

This paper has a number of limitations. At the level of the individual reviews, there was no control on when these reviews were provided. In particular, the results from the comparison of the average review scores of *Kununu* and *Glassdoor* should be treated with caution as *Kununu* has been active in Germany for a much longer time. To perform the regression analysis with as many reviews as possible, the average review scores based on the complete review period were chosen as the dependent variable. The dependent variable was recorded at a fixed date in April

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2020, whereas the independent variable *employees (in 1000)* refers to dates several years earlier. In addition, whether the companies were marked as active employers on the respective ERP was also recorded on a fixed date. Therefore, no statement can be made as to when this activity started or whether inactive companies were active on the respective ERP in the past. The data set contains ERP values and company key figures for 114 large companies that are active in Germany. Therefore, it is unclear whether the differences between the average review scores on *Kununu* and *Glassdoor* and between the different subgroups on *Kununu* also apply to smaller companies and/or companies outside Germany.

ERPs and the information provided on them offer numerous perspectives for future research. Similar to the study by Marinescu et al. (2021), the effects of implemented design changes on ERPs could be examined more closely. Since the (attempted) posting of counterfeit reviews can be observed on many platforms (Luca & Zervas, 2016; Mayzlin et al., 2014), related to ERPs this issue also presents a promising field of research. Since laboratory experiments allow to control for a wide range of confounds (see e.g., Cloos et al., 2021; Weimann & Brosig-Koch, 2019), they could be used to investigate in detail the extent to which factors such as socially influenced preferences influence the evaluation of one's own employer.

The information provided on ERPs could also be used to extend existing research on corporate social responsibility (see e.g., Fietze et al., 2019; Henry & Möllering, 2019; Uzhegova et al., 2019). At the level of individual companies, future studies could examine whether the existing level of corporate social responsibility, or whether and how newly implemented corporate social responsibility initiatives have an effect on a company's reviews. Furthermore, the question of how platform users interpret the ratings of ERPs compared to the ratings on online marketplaces would offer an important and interesting field of research that has not been investigated yet.

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Appendix

A1: Industry Classification of the Companies in the Data Set

Automotive / Supplier / Mechanical Engineering (N = 16): Volkswagen AG, Daimler AG, BMW AG, Robert Bosch GmbH, INA-Holding Schaeffler GmbH & Co. KG, ZF Friedrichshafen AG, Ford-Group Germany, Opel Automobile GmbH, MAHLE GmbH, Freudenberg & Co. KG, Continental AG, Liebherr-International-Gruppe Deutschland, ABB-Gruppe Deutschland, Hella KGaA Hueck & Co., Krones AG, Voith GmbH

Retail (N = 9): Rewe-Gruppe, Edeka-AG, Aldi-Süd, METRO AG, Otto Group, dm-drogerie markt, Tchibo, Lidl, Kaufland

Energy / Water- / Waste Management (N = 8): EWE AG, Stadtwerke München GmbH, RWE AG, E.ON SE, Vattenfall-Gruppe Deutschland, EnBW Energie

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Baden-Württemberg AG, Rethmann SE & Co. KG (Remondis), Stadtwerke Köln GmbH

Pharma / Chemistry (N = 13): Bayer AG, BASF SE, Fresenius SE & Co. KGaA, Evonik Industries AG, C. H. Boehringer Sohn AG & Co. KG, MERCK KGaA, LANXESS AG, Roche-Gruppe Deutschland, Sanofi-Gruppe Deutschland, Wacker Chemie AG, B. Braun Melsungen AG, Lyondellbasell-Gruppe Deutschland, Bilfinger SE

Building- / Raw Materials / Steel (N = 7): Adolf Würth GmbH & Co. KG, thyssenkrupp AG, Salzgitter AG, STRABAG Gruppe Deutschland, Saint-Gobain-Gruppe Deutschland, VINCI-Gruppe Deutschland, K+S AG

Technology / Telecommunications (N = 8): Linde AG, SAP SE, Siemens AG, Deutsche Telekom AG, IBM-Gruppe Deutschland, Carl Zeiss AG, United Internet AG (1&1), HP-Gruppe Deutschland

Consumables (N = 14): BP-Gruppe Deutschland, Henkel AG & Co. KGaA, Dr. August Oetker KG, Shell-Gruppe Deutschland, BSH Hausgeräte GmbH, Tchibo GmbH, Beiersdorf AG, Procter & Gamble-Gruppe Deutschland, Nestlé-Gruppe Deutschland, INGKA-Gruppe Deutschland (IKEA), Miele & Cie. KG, Philip Morris International-Gruppe Deutschland, TOTAL-Gruppe Deutschland, H & M Hennes & Mauritz-Gruppe Deutschland

Health / Other Services (N = 10): Asklepios Kliniken GmbH, Sana Kliniken AG, Adecco-Gruppe Deutschland, AVECO Holding AG (WISAG), DEKRA SE, Vivantes – Netzwerk für Gesundheit GmbH, DFS Deutsche Flugsicherung GmbH, Rhön-Klinikum AG, Charité Universitätsmedizin Berlin KöR, Kühne + Nagel-Gruppe Deutschland

Logistics / Defence / Transportation (N = 7): Deutsche Bahn AG, Deutsche Post DHL, Deutsche Lufthansa AG, Airbus-Gruppe Deutschland, Fraport AG, Rheinmetall AG, Rolls-Royce-Gruppe Deutschland,

Finance / Consulting / Insurance / Investment (N = 21): Commerzbank AG, Allianz SE, Deutsche Bank AG, Münchener Rückversicherungsgesellschaft AG, Deutsche Börse AG, KPMG AG, Norddeutsche Landesbank Girozentrale, Landesbank Baden-Württemberg, Bayerische Landesbank, HDI Haftpflichtverband der Deutschen Industrie V.a.G., Ernst & Young-Gruppe Deutschland, KfW Bankengruppe, HGV Hamburger Gesellschaft für Vermögens- und Beteiligungsmanagement mbH, UniCredit-Gruppe Deutschland (HypoVereinsbank), DZ Bank AG, PricewaterhouseCoopers AG, AXA-Gruppe Deutschland, HUK-COBURG, Debeka-Gruppe, Signal-Iduna Gruppe, Vonovia SE

Media (N = 3): Bertelsmann SE & Co. KGaA, Axel Springer SE, ProSiebenSat.1 Media SE

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