Technische Universität München
TUM School of Management
Lehrstuhl für Strategie und Organisation

Online Employer Reviews: Text-Mining Analyses of Contents, Effects, and Employer Responsiveness

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Vollständiger Abdruck der von der Fakultät für Wirtschaftswissenschaften der Technischen Universität München zur Erlangung des akademischen Grades eines Doktors der Wirtschaftswissenschaften (Dr. rer. pol.) genehmigten Dissertation.

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Die Dissertation wurde am 08.03.2021 bei der Technischen Universität München eingereicht und durch die TUM School of Management am 23.08.2021 angenommen.

Acknowledgments

I wish to thank all the wonderful people who have supported, inspired, and encouraged me throughout writing this dissertation. First, I would like to thank my supporters and co-authors. Prof. Dr. Isabell M. Welpe, thank you for always believing in me and my capabilities, encouraging and supporting me to pursue even my most ambitious goals, and providing me with the conditions I needed to write this dissertation. Prof. Dr. Andranik Tumasjan, thank you for your excellent supervision and for being there for me when I truly needed you. Prof. Dr. Filip Lievens, thank you for your wise advice and ideas that took my work to the next level. Prof. Dr. Nicola Breugst, thank you for reviewing this thesis as the second examiner. Prof. Dr. Alwine Mohnen, thank you for chairing the examination board. Marvin Schuth, Nicholas Folger, David Jung, and Eileen Einwächter, thank you for supporting me in developing the content dictionary and topic model presented in this dissertation. Finally, I would like to thank the people at Kununu for their continued support of my research on employer review data.

Furthermore, I would like to thank all my colleagues at the Chair for Strategy and Organization. I refrain from naming anyone specifically here, as you all have made the last few years a very memorable and fruitful experience for me, and I am grateful to have become true friends with several of you. Finally, I would like to express my deepest gratitude to my friends and family. I am incredibly privileged to have you in my life. Without you, I would certainly have lost the will to finish this dissertation along the way. I especially want to thank my parents, Monika and Emil, and my brother Daniel (with family) for their love and encouragement throughout this journey. Finally, I want to thank my heart Marina for giving me strength and comfort whenever I need it.

Munich, January 2021

Abstract

Today, the employer image of firms is co-created by employers along with current and former employees publishing reviews on employer review websites. Although these employer reviews attract broad interest and shape public opinion about organizations as employers, employer image research has failed to develop a profound understanding of the online employer review phenomenon. Consequently, knowledge of employer reviews generated by current and former employees is severely limited. Specifically, little is known about the nature of third-party employer (TPE) images held by former/current employees and how companies should deal with these workplace judgments that are outside their direct control. This dissertation addresses this void in the literature in three essays.

Essay I presents a systematic, multidisciplinary literature review, reporting the information extractable from employer reviews, text-mining techniques to extract information from the textual contents of employer reviews, research topics addressable with employer review data, and the data sources used. Based on a systematic analysis of 28 peer-reviewed journal articles, Essay I shows that studies have extracted insider knowledge, information on employee satisfaction and changes in employee satisfaction, insights into workplace culture, and linguistic style from employer reviews. Four distinct text-mining techniques, topic modeling, dictionary-based text analysis, data-mining software, and individual word frequencies, are used. Studies have extracted information from employer reviews to predict firm performance, explore employee satisfaction factors, and analyze the linguistic style of employer reviews. Glassdoor is the primary data source used. Finally, Essay I identifies five promising avenues for further research.

Essay II integrates insights from new media reputation formation with the employer image literature and theorizes that personal (rather than impersonal), symbolic (rather than instrumental), and emotional (rather than cognitive) content determines TPE image valence.

An analysis of about half a million online employer reviews highlights an intriguing discrepancy. Although instrumental, impersonal, and cognitive content is more prevalent in TPE images presented on employer review websites, symbolic, personal, and emotional content dominates TPE image valence. Furthermore, these content characteristics matter for companies because they significantly affect whether companies are ranked among "best employers" by job-seekers through their link with companies' TPE image. Critically, Essay II challenges the prevailing perspective on employer image by showing that first-hand experiences, symbolic traits (anthropomorphism), and emotionality play a dominant role in forming TPE images.

Essay III builds on theoretical and empirical work that deals with the effects of felt accountability on individuals' efforts to justify judgments and theorizes that an employer's responsiveness to its reviewers serves as a mechanism of indirect control over employer reviews by creating an accountability-enhancing context. A topic model analysis of approximately half a million employer reviews confirms this theorizing. Responsive employers receive reviews with more diverse and extensive employer information than non-responsive employers. Responsiveness particularly promotes more diverse and extensive negative employer reviews and more diverse and extensive employer reviews of former employees. Essay III extends the theoretical perspectives, which have focused largely on the role of responding to negative third-party judgments as a means of threat management, and guides employers in dealing with third-party branding.

Deutsche Kurzfassung (German Abstract)

Das Arbeitgeberimage von Unternehmen wird heute sowohl von Arbeitgebern als auch von aktuellen und ehemaligen Mitarbeitern mitgestaltet, die Bewertungen auf Arbeitgeberbewertungsportalen veröffentlichen. Obwohl die daraus resultierenden Arbeitgeberbewertungen auf breites Interesse stoßen und die öffentliche Meinung über Unternehmen als Arbeitgeber prägen, hat es die Arbeitgeberimageforschung versäumt, ein tiefgreifendes Verständnis für das Phänomen der Online-Arbeitgeberbewertungen zu entwickeln. Folglich ist der Wissensstand über Arbeitgeberbewertungen, die von aktuellen und ehemaligen Mitarbeitern erstellt werden, stark eingeschränkt. Insbesondere ist wenig bekannt über die Merkmale dieser von ehemaligen und bestehenden Mitarbeitern gehaltenen Drittparteien-Arbeitgeberimages und wie Unternehmen mit diesen Arbeitsplatzurteilen außerhalb ihrer direkten Kontrolle umgehen sollten. Diese Dissertation adressiert diese Lücke in der Literatur in drei Essays.

Essay I präsentiert eine systematische, multidisziplinäre Literaturübersicht, in der die Informationen, die aus Arbeitgeberbewertungen extrahiert werden können, Text-Mining-Techniken zur Extraktion von Informationen aus den textlichen Inhalten von Arbeitgeberbewertungen, Forschungsthemen, die mit Daten aus Arbeitgeberbewertungen adressiert werden können, und die verwendeten Datenquellen vorgestellt werden. Basierend auf einer systematischen Analyse von 28 Zeitschriftenartikeln zeigt Essay I, dass Studien Insiderwissen, Informationen über Mitarbeiterzufriedenheit und Veränderungen in der Mitarbeiterzufriedenheit, Einblicke in die Arbeitsplatzkultur und den sprachlichen Stil aus Arbeitgeberbewertungen extrahieren. Dabei kommen vier verschiedene Text-Mining-Techniken zum Einsatz: Topic Modeling, wörterbuchbasierte Textanalyse, Data-Mining Software und individuelle Worthäufigkeiten. Die Studien extrahieren Informationen aus Arbeitgeberreviews um die Unternehmensleistung vorherzusagen, Faktoren der

Mitarbeiterzufriedenheit zu erforschen und den sprachlichen Stil von Arbeitgeberbewertungen aufzudecken. Glassdoor ist die primäre Datenquelle, die verwendet wird. Abschließend identifiziert Essay I fünf vielversprechende Wege für weitere Forschung.

Essay II integriert Erkenntnisse aus Forschungsbereichen, die sich mit der Reputationsbildung durch neue Medien beschäftigen, mit der Literatur zum Arbeitgeberimage und stellt die Theorie auf, dass persönliche (und nicht unpersönliche), symbolische (und nicht instrumentelle) und emotionale (und nicht kognitive) Inhalte die Valenz von Drittparteien-Arbeitgeberimages bestimmen. Eine Analyse von etwa einer halben Million Online-Arbeitgeberbewertungen zeigt eine verblüffende Diskrepanz auf. Obwohl instrumentelle, unpersönliche und kognitive Inhalte in den Drittparteien-Arbeitgeberimages auf Arbeitgeberbewertungsportalen häufiger vorkommen, dominieren symbolische, persönliche und emotionale Inhalte die Valenz der Drittparteien-Arbeitgeberimages. Darüber hinaus sind diese Inhaltsmerkmale für Unternehmen von Bedeutung, da sie durch ihre Verknüpfung mit dem Drittparteien-Arbeitgeberimage von Unternehmen einen signifikanten Einfluss darauf haben, ob Unternehmen von Arbeitssuchenden zu den „besten Arbeitgebern" gezählt werden. Essay II stellt die vorherrschende Perspektive auf das Arbeitgeberimage in Frage, indem es zeigt, dass Erfahrungen aus erster Hand, symbolische Eigenschaften (Anthropomorphismus) und Emotionalität eine dominante Rolle bei der Bildung von Drittparteien-Arbeitgeberimages spielen.

Essay III baut auf theoretischen und empirischen Arbeiten auf, die sich mit den Auswirkungen gefühlter Verantwortlichkeit auf die Bemühungen von Individuen, Urteile zu rechtfertigen, befassen, und stellt die Theorie auf, dass die Responsivität eines Arbeitgebers gegenüber seinen Reviewern als ein Mechanismus der indirekten Kontrolle über Arbeitgeber-Bewertungen dient, indem ein Verantwortlichkeit-fördernder Kontext geschaffen wird. Eine Topic Model-Analyse von etwa einer halben Million Arbeitgeberbewertungen bestätigt diese

Theorie. Responsive Arbeitgeber erhalten Bewertungen mit vielfältigeren und umfangreicheren Arbeitgeberinformationen als nicht-responsive Arbeitgeber. Responsivität fördert insbesondere vielfältigere und umfangreichere negative Arbeitgeberbewertungen und vielfältigere und umfangreichere Arbeitgeberbewertungen von ehemaligen Mitarbeitern. Essay III erweitert theoretische Perspektiven, die sich weitgehend auf die Rolle von Reaktionen auf negative Unternehmensbeurteilungen durch Dritte als Mittel des Bedrohungsmanagements konzentriert haben, und gibt Arbeitgebern einen Leitfaden für den Umgang mit der Arbeitgebermarkenbildung durch Dritte.

Table of Contents

List of Figures

List of Tables

List of Abbreviations

AJG	Academic Journal Guide
ACSI	American Customer Satisfaction Index
B2B	Business-to-Business
BPTW	Best Place to Work
CATA	Computer-Aided Text Analysis
CC	Cognitive Content
CI	Confidence Interval
CRSP	Center for Research and Security Prices
df	degrees of freedom
e.g.	exempli gratia
EC	Emotional Content
et al.	et alii
HLM	Hierarchical Linear Modeling
HR	Human Resources
i.e.	id est
IC	Impersonal Content
INC	Instrumental Content
JCR	Journal Citation Report
KLD	Kinder, Lydenberg, Domini
LDA	Latent Dirichlet Allocation
LIWC	Linguistic Inquiry and Word Count
LL	Log Likelihood
M	Mean
NMRF	New Media Reputation Formation
p.	page
PC	Personal Content
R&D	Research & Development
ROA	Return on Assets
SC	Symbolic Content
SD	Standard Deviation
SE	Standard Error
SLR	Systematic Literature Review
STM	Structural Topic Model
SVM	Support Vector Machines
TPE	Third-Party Employer
TÜV	Technischer Überwachungsverein
vs.	versus

1 Introduction[1]

1.1 Motivation and Research Questions

What individuals associate with an organization as a place of work is no longer defined and shaped exclusively by the company itself but also by third parties outside the company's control (Dineen, Van Hoye, Lievens, & Rosokha, 2019). Current and former employees co-create the image of employers on websites such as Glassdoor, Kununu and Indeed, regardless of possible contradictions with the employer's official representation. They do so by voluntarily and anonymously submitting online reviews of their employer based on pre-defined questionnaires that include both sections for quantitative assessments and open text responses. The resulting employer reviews attract broad interest and shape public opinion about companies as employers. Some sources indicate that more than one in three Internet users (36%) have read an online review on the employer review website Kununu (Brehme & Brandau, 2018) and that up to 52% of US job seekers read employer reviews before applying (Westfall, 2017). The traction of these websites is also reflected in the vast number of reviews they offer to their large user base. Glassdoor, for example, recorded 30 million unique visitors per month in 2016 (Adams, 2016) and reported a database of 55 million employer reviews, CEO approval ratings, salary reports, and other job insights in May 2020 (Glassdoor, 2020). Kununu reported over 4 million employer reviews for nearly one million companies at the same time (Kununu, 2020).

While research questions surrounding company-created employer images have been the subject of a multitude of studies across a variety of disciplines over the past two decades (Theurer, Tumasjan, Welpe, & Lievens, 2018), few theoretical and empirical studies have

[1] This chapter is partly based on and includes elements of Höllig (2021), Höllig and Tumasjan (2021), and Höllig, Tumasjan, and Lievens (under review).

focused on understanding these “communications, claims, or status-based classifications generated by parties outside of direct company control that shape, enhance, and differentiate organizations’ images as favorable or unfavorable employers” (Dineen et al., 2019, p. 176). Consequently, despite the widespread use of employer review websites (e.g., Brehme & Brandau, 2018; Westfall, 2017), our knowledge of employer reviews generated by current and former employees is severely limited. This is regrettable, as the emergence of employer reviews challenges theories about the conceptualization of employer images (see, e.g., Lievens & Slaughter, 2016) and requires companies to deal with the associated loss of control over their own images as employers (see Dineen et al., 2019). The pressing need to develop an understanding of the nature, actual impact and management of employer reviews is illustrated by several experimental studies that have consistently shown that employer reviews can shape the perceptions and decisions of potential employees (Carpentier & Van Hoye, 2020; Evertz, Kollitz, & Süβ, 2019; Könsgen, Schaarschmidt, Ivens, & Munzel, 2018; Melián-González & Bulchand-Gidumal, 2016; Stockman, Van Hoye, & da Motta Veiga, 2019).

Accordingly, this dissertation seeks to address this void in the literature and thus to further our understanding of the online employer review phenomenon in three essays. Essay I seeks to consolidate the current state of employer review data research. Employer reviews provide an unprecedented data source and thus novel research opportunities to gain insight into employee views and opinions that would be difficult to obtain utilizing other data sources, such as panel surveys (Stamolampros, Korfiatis, Chalvatzis, & Buhalis, 2019, 2020; Storer & Reich, 2019). Harnessing these opportunities requires that researchers identify research questions that are answerable with employer review data and the information that can be extracted from these reviews. However, the initial studies that may provide such insight are scattered across several disciplines and are therefore difficult to survey. Thus, Essay I seeks to consolidate the heterogeneous and fragmented field of employer review data research to provide a substantial foundation for further research. Therefore, Essay I seeks to answer this dissertation's first research question:

> ***Research Question 1:*** *What research topics have been covered so far using online employer review data, what information can be extracted from employer reviews, and how can that information be extracted?*

Second, Essays II and III seek to address two salient research gaps that emerge from the current state of research. To date, research on employer review data lacks theory-driven analysis of the textual content of online employer reviews. Critically, we do not know (a) what kind of content is used to co-create the image of employers via employer reviews and (b) whether this content impacts how favorably companies are seen as employers. As the third-party employer (TPE) images created by former and current employees through posting employer reviews might differ vastly from the prevailing view of employer image which is mostly based on the premise that employer image is under direct company control (Dineen et al., 2019), developing a better understanding of TPE images is crucial for further theory building. Otherwise, the conceptual clarity of future research in the employer image field might be diminished by drawing from an outdated view of employer image when exploring TPE images. At a practical level, this improved understanding might provide rigorous theoretical and empirical evidence to enable organizations to adapt their employer branding activities in the wake of third-party branding.

Although still in its infancy, the scientific interest in the TPE images disseminated through employer reviews has developed into at least two distinct research streams. First, several studies have used predominantly experimental designs to analyze the effect of employer reviews on prospective applicants' attitudes and intentions towards organizations as a place of work (Evertz et al., 2019; Könsgen et al., 2018; Melián-González & Bulchand-Gidumal, 2016; Stockman et al., 2019). These studies show that the valence of TPE images can have effects, but they neither specified nor examined the content of TPE images. Second, some studies have adopted explorative approaches to identify the content of employer reviews. More specifically, they have employed data-mining software such as IBM Watson (Dabirian, Kietzmann, & Diba, 2017; Dabirian, Paschen, & Kietzmann, 2019) and Leximancer (Ross, Intindola, & Boje, 2017) to identify content categories in employer reviews of selected companies. Other studies have applied topic modeling (Y. Jung & Suh, 2019; Stamolampros et al., 2019, 2020), an unsupervised machine learning algorithm designed to reveal the hidden semantic structure and thus topics of a collection of documents (Guo, Vargo, Pan, Ding, & Ishwar, 2016). Finally, studies have also applied computer-aided text analysis (CATA; Duncan, Chohan, & Ferreira, 2019; Pitt, Botha, Ferreira, & Kietzmann, 2018; Pitt, Plangger, Botha, Kietzmann, & Pitt, 2019; Robertson, Ferguson, Eriksson, & Näppä, 2019) but have done so exploratively, using pre-defined content dictionaries, rather than in a focused, i.e., theory-driven analysis of reviews' textual content. Thus, while the second stream of research delves into the content of TPE images, researchers have unfortunately explored content only in an exploratory manner with selected samples and have neither adopted a theory-driven approach nor explored the impact of the extracted content categories, e.g., on the perceptions of job-seekers.

To address this shortcoming in the literature, Essay II integrates these two research strands and draws from recent theories on the formation of organizational reputation in the social media era (e.g., Etter, Ravasi, & Colleoni, 2019; Mena, Rintamaki, Fleming, & Spicer, 2016; Ravasi, Rindova, Etter, & Cornelissen, 2018; Rindova, Martins, Srinivas, & Chandler, 2018; Schrempf-Stirling, Palazzo, & Phillips, 2016) to establish a theoretical understanding of the conceptualization of TPE images created through employer reviews. Furthermore, Essay II evaluates the relevance of TPE images to the perceptions of job seekers. Thus, Essay II seeks to answer this dissertation's second research question:

> ***Research Question 2:*** *What content shapes the TPE image presented by former and current employees through their employer reviews, and how does this TPE image affect the perceptions of job seekers?*

Current employer review research provides limited insight not only into the content of employer reviews but also into how employers should deal with these third-party judgments of them. Following Dineen et al. (2019), companies may proactively take measures to influence third-party sources of employment information such as employer review websites. Correspondingly, a growing number of studies have explored how organizations may proactively manage social evaluations such as employer reviews (George, Dahlander, Graffin, & Sim, 2016). One of these measures, advocated by thought leaders such as the Society for Human Resource Management, is for employers to carefully monitor and respond to employer reviews (e.g., Bates, 2016; Grensing-Pophal, 2019; Lewis, 2019; Maurer, 2017). A response is a free-text comment that is displayed publicly under the corresponding review, and an employer's response count is often displayed prominently by employer review websites. However, while this approach is widely advocated (e.g., Bates, 2016; Grensing-Pophal, 2019; Lewis, 2019; Maurer, 2017), we lack an understanding of the consequences of responding to employer reviews. The prevailing theoretical perspectives focus largely on the reactions of companies to negative third-party judgments (e.g., Dineen et al., 2019; Etter et al., 2019; George et al., 2016; Ki & Nekmat, 2014; Pfarrer, Decelles, Smith, & Taylor, 2008; Ravasi et al., 2018; T. Wang, Wezel, & Forgues, 2016) and thus neglect the possibility that responding to employer reviews may provide value beyond the lens of threat management. This possibility is also suggested by recent empirical work in the marketing domain showing that customers review responsive hotels differently than non-responsive hotels (e.g., Chevalier, Dover, & Mayzlin, 2018; Proserpio & Zervas, 2017; Y. Wang & Chaudhry, 2018). Consequently, the few studies concerned with how companies can deal with employer reviews explore the role of responses to negative employer reviews (Carpentier & Van Hoye, 2020; Könsgen et al., 2018).

Against this backdrop, Essay III seeks to advance our understanding of the consequences of responding to employer reviews and thus to provide guidance on how employers should deal with the loss of control associated with employer reviews (see Dineen et al., 2019). To do so, it draws from the model of social judgment and choice (originally called the "social contingency model"; Hall, Frink, & Buckley, 2017; Tetlock, 1985, 1992), which recognizes accountability as the fundamental social contingency that steers individuals' actions given their desire to preserve their self-image, to theorize about the consequences of an employer becoming responsive to its current and former employees posting employer reviews. Essay III then explores the theorized differences between the content of reviews posted about responsive and non-responsive employers. Thus, Essay III seeks to answer this dissertation's third research question:

> ***Research Question 3:*** *What are the consequences of employers becoming responsive on an employer website to the content of the employer reviews posted about them?*

In summary, three research questions are addressed in three separate essays to provide comprehensive insight into the employer review phenomenon. Essay I presents a systematic literature review (SLR) of the current state of research on employer review data. Essay II presents a theory-driven analysis of employer reviews' textual content to establish a theoretical understanding of the nature of the TPE images presented through employer reviews. Furthermore, Essay II explores employer reviews' relevance to the perceptions of job seekers. Finally, Essay III presents an analysis of the consequences of responding to employer reviews. All three essays are embedded in the employer image literature. Furthermore, they draw from two main theoretical approaches: Essay II draws from recent theories on the formation of organizational reputation in the social media era, especially Etter et al.'s (2019) recent new media reputation formation (NMRF) framework. Essay III draws from accountability theory, which asserts that individuals act differently when they expect that their actions will be evaluated and subsequently rewarded/sanctioned by a salient audience (for a comprehensive review of accountability theory, see Hall et al., 2017; Lerner & Tetlock, 1999). The theoretical background of this dissertation is introduced in more detail in the following section.

1.2 Theoretical Background

1.2.1 (Third-Party) Employer Image

When companies face the challenge of attracting, recruiting and retaining highly qualified employees, employer image management, termed external employer branding in human resources (HR) practice, is vital and thus widely practiced (Dineen et al., 2019; Lievens & Slaughter, 2016). Employer image can be defined "as an amalgamation of transient mental representations of specific aspects of a company as an employer as held by individual constituents. Important elements in this definition include that an image (a) is held by individuals (versus the general public), (b) might fluctuate (versus being relatively stable), (c) targets specific aspects (versus an overall impression), and (d) is cognitive in nature" (Lievens & Slaughter, 2016, p. 406). Past research has focused mainly on how companies can brand themselves as attractive employers (Dineen et al., 2019). In other words, they have focused on branding that is directly controlled by the company (e.g., Theurer et al., 2018). This company-controlled branding enables companies to present a thoroughly constructed self-image to potential applicants, employees and the wider public. However, in the era of social media, the employer image is not defined, shaped and controlled exclusively by the company itself but is also co-created by current and former employees and other external stakeholders (Etter et al., 2019; Lievens & Slaughter, 2016). In this vein, Dineen et al. (2019) formally define TPE branding "as communications, claims, or status-based classifications generated by parties outside of direct company control that shape, enhance, and differentiate organizations' images as favorable or unfavorable employers” (p. 176). Examples include best place to work (BPTW)-type certifications (see Dineen & Allen, 2016), word-of-mouth exchanges in face-to-face communication (see, e.g., Van Hoye & Lievens, 2007), and employer reviews.

Employer reviews, such as those from Glassdoor, an employer review website that had collected approximately 55 million employer reviews and other employer information by 2020 (Glassdoor, 2020), typically include quantitative ratings on five-point Likert scales and open text comments on the employer. A prominent characteristic of any employer review is the overall rating, which indicates reviewers’ judgment of the employer and thus whether they present their employer with a more positive or negative TPE image. Thus, a one-point rating indicates a very negative judgment (and thus a very negative TPE image), while a five-point rating indicates a very positive judgment (and thus a very positive TPE image). The open text comments often respond to a predefined questionnaire. For example, the employer review website Kununu asks reviewers to answer questions about several specific aspects of their employer and about their employer’s pros, cons, and opportunities for improvement.

While employer image research on online employer reviews is still in its infancy, it has developed into at least two distinct research streams. First, several studies have used predominantly experimental designs to analyze the effect of employer reviews and the effects of employers’ responses to employer reviews on prospective applicants’ attitudes and intentions towards organizations as a place of work (Carpentier & Van Hoye, 2020; Evertz et al., 2019; Könsgen et al., 2018; Melián-González & Bulchand-Gidumal, 2016; Stockman et al., 2019). Second, researchers have adopted explorative approaches to analyze the content and thus to identify, e.g., employer image attributes mentioned in employer reviews. For instance, studies have employed data-mining software such as IBM Watson (Dabirian et al., 2017, 2019) and Leximancer (Ross et al., 2017) to identify content categories in employer reviews of selected companies. To date, these two strands of research have evolved separately, and no efforts have been made to integrate them. The first research stream consists of only experimental studies but lacks exploration of the content of employer reviews. The second stream has explored the content of employer reviews, but researchers have unfortunately done so only exploratively, using selected samples (up to 6,336 employer reviews) and have lacked theory-driven analysis of this content. Another key limitation is that the effects of the extracted content categories on job seeker's perceptions and intentions have not been examined. Furthermore, both research streams offer little understanding of how employers should deal with employer reviews and the associated loss of control, as employers cannot directly control such reviews disseminated about them (exceptions are Carpentier & Van Hoye, 2020; Könsgen et al., 2018).

Given these shortcomings of the current state of research on employer reviews, this dissertation seeks to further our understanding of the online employer review phenomenon. In a broader sense, it seeks to develop rigorous theoretical and empirical evidence to advance theory building on TPE images and to support organizations in adapting their branding activities in the wake of third-party branding.

1.2.2 Social Media and the Formation of Organizational Reputation

To address shortcomings in the current state of research on employer reviews, Essay II's theory-driven analysis of employer reviews' textual content draws upon recent theories on the formation of organizational reputation (e.g., Etter et al., 2019; Mena et al., 2016; Ravasi et al., 2018; Rindova et al., 2018; Schrempf-Stirling et al., 2016). These theories also focus on the role of social media, such as blogs, discussion forums, social networks and review websites, in the formation of organizational reputation (Etter et al., 2019). In particular, Etter et al.'s (2019) recent NMRF framework posits that social media have fundamentally changed how opinions on the quality, competence, or character of organizations are generated and spread. In the context of employer branding, social media enable third parties to co-create an organization's image as an employer (Dineen et al., 2019) and thus to shape the content about employers to which the public is exposed. However, the information about organizations disseminated via social media likely differs from analytical and relatively neutral reviews, e.g., by journalists (Etter et al., 2019) or company-issued information (Dineen et al., 2019).

With regard to Essay II, Etter et al.'s NMRF framework (2019) suggests that information about organizations disseminated by social media users, such as online reviewers, displays three distinct features. First, Etter et al. (2019) suggest that much of the information about organizations produced on social media is based on personal experience, such as a customer's first-hand experience with a product ("such as shock at a cell phone catching fire"; Etter et al., 2019, p. 37). In this vein, social media can be considered large-scale word-of-mouth media (Mangold & Faulds, 2009) that enable users to publish first-hand experiences on a variety of topics (Etter et al., 2019). Second, Etter et al. (2019) suggest that social media allow users to create and express individual, social and organizational identities by emphasizing the characteristics of organizations that are in line with or conflict with their own values and beliefs (Marwick & Boyd, 2011; Papacharissi, 2013). In other words, social media users express themselves by selecting what they discuss (or do not discuss; Papacharissi, 2013) in order to satisfy their inherent motives, for example, to connect with others (Berger, 2014; Hollenbaugh, 2010). Third, Etter et al. (2019) suggest that users of social media experience fewer constraints in terms of format and style than, for example, journalists due to the latter's professional norms. As a result, social media users produce original creative content, e.g., through the combination of different formats such as text, graphics, audio, video, and animation (M. H. Jackson, 2009). Moreover, with regard to style, social media users increasingly produce emotionally charged content (Etter et al., 2019). As emotions influence the way in which "information is gathered, stored, recalled, and used to make particular attributions or judgments" (Nabi, 2003, p. 227), emotionally charged content is more likely than non-emotionally charged content to be shared and disseminated (Berger & Milkman, 2012).

1.2.3 Accountability Theory

To address shortcomings in the current state of research on employer reviews, Essay III's analysis of the consequences of employers' responsiveness to employer reviews draws from accountability theory (for a comprehensive review of accountability theory, see Hall et al., 2017; Lerner & Tetlock, 1999). Felt accountability is defined as the "perceived expectation that one's decisions or actions will be evaluated by a salient audience and that rewards or sanctions are believed to be contingent on this expected evaluation" (Hall & Ferris, 2011, p. 134). According to Tetlock (1985, 1992), accountability is a powerful individual determinant of human social behavior. If individuals do not feel accountable, they can act with complete disregard for the consequences of their behavior (Mitchell, Hopper, Daniels, Falvy, & Ferris, 1998). However, when individuals feel accountable, they will expect to have to explain their actions when they are evaluated by others. Moreover, they will expect negative (positive) consequences when they are unable (able) to sufficiently explain their actions (Lerner & Tetlock, 1999). At the same time, accountability affects not only the actions of individuals but also their cognitive processing (Hall et al., 2017). In particular, accountability influences what and how individuals think (Frink et al., 2008). Thus, prior to individuals' actions, accountability causes them to become aware of their cognitive processing in their selection and analysis of reasons, to consider a wider range of reasons, to think more deeply about their actual reasons, and to envisage plausible counterarguments for their intended actions (Lerner & Tetlock, 1999).

With regard to Essay III, accountability theory suggests that feeling accountable governs individuals' effort to justify judgments, as they seek to increase the likelihood that they will be viewed positively by their audience. Specifically, accountable (vs. non-accountable) individuals exert cognitive effort to understand the subject being judged (De Dreu, Beersma, Stroebe, & Euwema, 2006) and to differentiate and aggregate a variety of arguments that support or even contradict their judgment (M. C. Green, Visser, & Tetlock, 2000; see also Lee, Herr, Kardes, & Kim, 1999). Individuals do so by engaging in a more complex and extensive information search process (Dalla Via, Perego, & van Rinsum, 2019; Huneke, Cole, & Levin, 2004) and in a more careful and thorough analysis of judgment-relevant information (Dalla Via et al., 2019; Hattrup & Ford, 1995; Siegel-Jacobs & Yates, 1996; Thompson, Roman, Moskowitz, Chaiken, & Bargh, 1994). Consequently, studies that analyze the content of justifications written by accountable individuals have found that accountability encourages the provision of longer, more information-rich, and more linguistically complex written justifications for judgments (e.g., DeZoort, Harrison, & Taylor, 2006; Gordon & Stuecher, 1992; Koonce, Anderson, & Marchant, 1995; Levi & Tetlock, 1980).

1.3 Methodology

Different methods were applied in the three essays of this dissertation to answer the previously mentioned research questions. More specifically, a method was adapted to each specific essay's research question as well as to the essay's target audience. Essay I presents a SLR following the recommendations of Briner and Denyer (2012). First, the research object was defined. Second, the literature databases as well as the search terms relevant to the SLR were defined. Third, publications from the previously defined databases were retrieved and merged. Fourth, the identified publications were screened, and inclusion and exclusion criteria were applied. Finally, the literature review, i.e., the full-text analysis of the remaining publications, was performed, and the results were synthesized into distinct concepts following the suggestions of Webster and Watson (2002). 647 articles were identified in seven databases. After removing duplicates, 549 articles were analyzed for content eligibility and the 63 remaining articles were analyzed for qualitative eligibility. Nine articles were identified by performing forward and backward searches. Finally, the dataset used in the first essay comprised 28 peer-reviewed full-text articles published from 2014 to 2020 across nine disciplines. Subsequently, the identified literature was coded into three key concepts and 13 sub-concepts.

Essays II and III present text mining-based analyses of employer review data. Text mining can be defined as “the discovery and extraction of interesting, non-trivial knowledge from free or unstructured text” (Kao & Poteet, 2007, p. 1). The employer reviews used for both essays were published between May 2007 and June 2018 on Kununu, the most popular review site in German-speaking areas (Könsgen et al., 2018). Since its launch in 2007, Kununu has invited current and former employees to anonymously submit reviews about their employer. The reviews include both quantitative ratings, which are summarized in an overall rating (from 1.00 to 5.00 stars), and open text comments. Text comments may include various aspects of the employer, such as company culture, work-life balance, and work environment, as well as comments on the perceived pros, cons and opportunities for improvement of the employer. Reviewed employers are given the option to respond directly to the reviews. If they choose to do so, their response is shown publicly under the corresponding review.

Kununu is committed to ensuring the authenticity of the posted reviews. Hence, users must register with a valid email address and agree to comply with Kununu’s review guidelines; for example, no personal information may be published (Kununu, 2019a). Kununu monitors adherence to these guidelines through technical security measures and a community management team. In general, no reviews are deleted or changed as long as they comply with the review guidelines (Kununu, 2019b). Against this backdrop, Kununu is certified by an independent auditing institute for its protection of user data and anonymity (TÜV Saarland, 2019).

The employer reviews used for the analyses in Essays II and III were collected from Kununu using a self-designed web crawler written in the Python programming language.[2] The open-source web crawling framework Scrapy, which allows "for crawling web sites and extracting structured data which can be used for a wide range of useful applications, like data mining, information processing or historical archival" (Scrapy, 2020), was used. Employer reviews were collected over the course of two weeks in August 2018, and about half a million employer reviews were collected. In detail, all online reviews of German employers that had received at least two reviews by July 2018 were collected. Thus, Austrian, Swiss, US-American and other employers were excluded to ensure the homogeneity of the review texts (e.g., regarding dialects or country-specific terminology). Furthermore, for Essay II, the employer review dataset was merged on a company level with Universum's "Most Attractive Employers 2019" ranking for Germany. Universum ranks Germany's most attractive employers based on a survey of 46,904 students (Universum, 2019b).

Since Essays II and III are both based on the same employer review dataset, this dissertation closely followed the recommendations of Kirkman and Chen (2011) on publishing multiple papers using the same dataset. In this vein, a uniqueness analysis was conducted; i.e., the research questions, theories used, variables included, and theoretical and managerial implications were compared across the two essays. Since the research question addressed, the theoretical explanations for phenomena, the variables, and the theoretical and managerial implications are substantially distinct, it was deemed appropriate to use the same dataset in both essays. The overlap of variables between the two essays was minimal, particularly because the text-mining technique used to process the reviews' textual content

[2] In 2016/2017, Kununu provided several test datasets in a fruitful collaboration between the TUM Chair for Strategy and Organization and Kununu, which allowed first analyses and the development of a data-driven understanding of Kununu's employer reviews. Since these test datasets faced various limitations, the employer reviews were finally crawled.

was adapted to the research design required for each essay. In Essay II, CATA, i.e., dictionary-based text analysis, is utilized to process the review's textual content, while Essay III utilizes topic modeling, more precisely latent dirichlet allocation (LDA). According to Guo et al. (2016), who empirically compared both text analysis methods, LDA-based text analysis yields more nuanced details, while dictionary-based text analysis allows a more focused and thus theory-driven approach. Since Essay II involves a focused analysis of the reviews' textual content based on pre-defined theoretical assumptions derived from recent theories on the formation of organizational reputation in the social media era, dictionary-based text analysis was determined to be the appropriate text analysis technique. On the other hand, since Essay III requires a nuanced analysis of the reviews' textual content to measure the diversity and extensiveness of the information, LDA-based text analysis was determined to be the appropriate text-mining technique.

In more detail, in Essay II, CATA allowed the identification of the (co-)occurrence of textual content characteristics in online employer reviews. More specifically, the reviews' textual content was processed through Linguistic Inquiry and Word Count (LIWC) software. LIWC estimates the presence (i.e., percentage) of grammatical and psychological categories in text by matching the words with predefined content dictionaries (Pennebaker, Boyd, Jordan, & Blackburn, 2015; Pennebaker, Mehl, & Niederhoffer, 2003; Tausczik & Pennebaker, 2010). Categories (i.e., lists of words) measured with content dictionaries are built under the assumption that their underlying artifacts share the same meaning. In this vein, LIWC includes an empirically validated dictionary to measure the beliefs, fears, thought patterns, social relationships, and personalities of individuals (Pennebaker et al., 2015) and has been used in a plethora of studies, for example, to analyze the prevalence of function words in job interviews (Moore, Lee, Kim, & Cable, 2017), positive emotions in negotiations (Wilson, DeRue, Matta, Howe, & Conlon, 2016) and negative emotions in customer–salesperson interactions (King, Shapiro, Hebl, Singletary, & Turner, 2006). For Essay II, the most recent German adaptation of the LIWC dictionary DE-LIWC2015, which holds 18,711 words, word stems, and emoticons in 80 categories (Meier et al., 2018), was utilized. Furthermore, a novel dictionary that can be used with LIWC was developed. Such dictionaries have been used to investigate constructs such as “market orientation” (Zachary, McKenny, Short, & Payne, 2011), “organizational psychological capital” (McKenny, Short, & Payne, 2012) and “entrepreneurial orientation” (Short, Broberg, Cogliser, & Brigham, 2010). The development followed the recommendations of Short et al. (2010). In this vein, to establish content validity, i.e., the extent to which a measure captures all the features of a particular construct (Nunnally & Bernstein, 1993), the dictionary was constructed first deductively from theory and then inductively from the employer review dataset; finally, the two results were merged. More specifically, for the deductive step, 21 studies that identify one or several employer image attributes were collected, the attributes were coded into higher-order attributes, and a word list was generated for each attribute. The word lists resulting from the deductive step were subsequently validated by three raters. For the inductive step, the 2,000 most commonly used words from the review corpus were identified and automatically and manually revised. The words were subsequently assigned to either none, one or a multiple of the previously identified attributes by the three raters. In the final step, the deductive and inductive lists were merged, duplicates were deleted, and the lists were revised for LIWC. The final word (stem) list for each attribute was then rated by two raters. The final dictionary consists of 938 words and word stems in 17 categories (i.e., employer image attributes).

In Essay III, topic modeling, more specifically LDA, as described in Blei, Ng, and Jordan (2003) and Pritchard, Stephens, and Donnelly (2000), using collapsed Gibbs sampling (Griffiths & Steyvers, 2004), allowed the estimation of information diversity (i.e., the diversity of employer information presented in a review) and information extensiveness (i.e., the extensiveness of employer information presented in a review). Topic models have been applied in many contexts, such as the analysis of consumer ads (Gong, Abhishek, & Li, 2018), blog content (Vir Singh, Sahoo, & Mukhopadhyay, 2014), and hotel reviews (Hu, Zhang, Gao, & Bose, 2019). Estimating the topic model included summarizing all individual comments given by a reviewer to a specific employer into one comprehensive review. Furthermore, compound words (e.g., “work-life balance”) were built, and the data were standardized (including stop-words removal, lower text conversion, rare-term removal, and stemming; Blei & Lafferty, 2009; Blei et al., 2003). Building on a model log-likelihood analysis (Griffiths & Steyvers, 2004) and a qualitative examination for a varying number of topics (2-120), a 70-topic model that revealed clearly interpretable topics was deemed appropriate. Three human resource management scholars labeled each topic based on its top 15 highly associated terms and 40 highly associated reviews.

Aside from the text-mining techniques employed, the two essays also vary with respect to the econometric methods used. In Essay II, the approach of Luo and Azen (2013) was followed to explore the nature of the TPE image presented by current and former employees when posting employer reviews. In this vein, first, because the employer review data are nested, hierarchical linear modeling (HLM; see, e.g. Hofmann, Griffin, & Gavin, 2000; Raudenbush & Bryk, 2002) was applied. Ignoring the nested structure of the data may result in biased estimates of the standard errors of the regression coefficients (e.g., Moerbeek, 2004). Therefore, in particular, a cross-classified random-effects model was fitted, as employer reviews (Level 1) are nested within employers and quarters at the same time (Level 2), whereas employers and quarters are not nested within but crossed with each other. Subsequently, dominance analysis was applied to determine the importance of the predictors in the identified model. Dominance analysis is one of the most frequently applied methods for determining the relative importance of predictors in the organizational sciences (Braun, Converse, & Oswald, 2019). The method can be applied in a variety of settings, including multiple regression (Azen & Budescu, 2003), logistic regression (Azen & Traxel, 2009), and HLM (Luo & Azen, 2013). According to Luo and Azen (2013), the dominance analysis method allows the evaluation of the relative contribution of individual predictors in a chosen set to the explained variance of the overall model. Predictors with larger (vs. smaller) contributions are considered more important. In addition to HLM and dominance analysis, Essay II also employs a mediation analysis under the counterfactual framework (Imai, Keele, & Tingley, 2010; Imai, Keele, & Yamamoto, 2010) to assess the indirect (through TPE image valence) relationship between reviews' content characteristics and an employer being ranked as a "best employer" (as indicated by best employer surveys; e.g., Universum, 2019c, 2019a). Following this approach, indirect, direct, and total effects were estimated within the counterfactual framework by fitting two random-effects models where employers (Level 1) were nested within industries (Level 2).

In Essay III, a difference-in-differences analysis was applied across multiple treatment groups and multiple time periods. Difference-in-differences has been applied in a plethora of contexts, including estimating HIV incidence rates induced by platform implementation (Greenwood & Agarwal, 2016), user behavior induced by mobile application adoption (J. Jung, Bapna, Ramaprasad, & Umyarov, 2019), and consumer sales induced by selective promotions (Rietveld, Schilling, & Bellavitis, 2019). Difference-in-differences designs attempt to identify causal relationships by mimicking an experimental design in observational data (Angrist & Pischke, 2008). In this vein, Essay III employed fixed-effects models, which are often considered the "gold standard" when estimating within-firm relationships (Bliese, Schepker, Essman, & Ployhart, 2020), to model the consequences of an employer's responsiveness to its reviews in a difference-in-differences framework. For this model to be valid, responsiveness must resemble an exogenous event. With this in mind, in Essay III, models were also controlled for systematic differences between responsive and non-responsive employers in a supplementary analysis.

In summary, several research methods were applied to answer the research questions of this dissertation. A strong focus was placed on extracting information from the employer reviews' textual content using two distinct text-mining techniques.

1.4 Structure, Contributions, and Main Results

Following this introductory first chapter, as the main part of this dissertation, chapters two through four present the three independent essays. Each essay focuses on one of the research questions described above. Therefore, each essay contains a separate introduction, theoretical background, hypothesis development (if applicable), methodology, results, and discussion section. Finally, the fifth chapter presents a discussion of the overall findings and contributions of this dissertation, provides implications for theory and practice, and highlights directions for future research. In the remainder of this chapter, a brief summary of the findings and contributions of each essay is provided.

Essay I presents a multidisciplinary literature review that structures current research from nine disciplines into three major concepts (research topics, text-mining techniques, and data sources) and identifies five avenues for future research with regard to utilizing employer review data. The presented analysis of 28 peer-reviewed journal articles shows that studies have extracted insider knowledge, information on employee satisfaction and changes in employee satisfaction, insights into workplace culture, and linguistic style from employer reviews. These studies have aimed to predict firm performance, explore employee satisfaction factors, and analyze the linguistic style of employer reviews. Glassdoor is the primary data source used. Furthermore, four distinct text-mining techniques (topic modeling, dictionary-based text analysis, data-mining software, and individual word frequencies) are used to extract information from the reviews' textual content. Essay I contributes to the exploitation of research opportunities based on employer review data by presenting a structured overview of the information that can be extracted from employer review data, how such information can be extracted, and the research topics that can be addressed thereby in a comprehensive employer review data research framework.

Essay II presents, based on a dominance analysis of approximately half a million online employer reviews, that personal (rather than impersonal), symbolic (rather than instrumental), and emotional (rather than cognitive) content determines TPE image valence. Furthermore, Essay II demonstrates that these content characteristics matter because they determine companies' TPE image, which in turn is linked to whether companies are ranked among "best employers" by job seekers. Essay II advances employer image theory by demonstrating how TPE images are formed in the minds of former/current employees who post employer reviews. Critically, Essay II challenges the prevailing perspective on employer image by showing that first-hand experiences, symbolic traits (anthropomorphism), and emotionality play a dominant role in forming TPE images.

Essay III demonstrates that employers, by becoming responsive to reviews on employer review websites, as indicated by their very first response, may create accountability-enhancing contextual conditions for reviewers (i.e., former or current employees). This feeling of accountability is reflected in reviewers' efforts to justify their review and thus in responsive employers receiving reviews that present more diverse and extensive employer information than those for non-responsive employers. Responsiveness particularly promotes more diverse and extensive negative reviews and more diverse and extensive reviews by former employees. Essay III extends the theoretical perspectives, which have largely focused on the role of responding to negative third-party judgments (see Dineen et al., 2019; Etter et al., 2019; George et al., 2016; Pfarrer et al., 2008; Ravasi et al., 2018; T. Wang et al., 2016), and provides employers with guidance on how to deal with TPE branding.

Although millions of employer reviews are currently available on the Internet, research in this area is still in its infancy. This dissertation as a whole makes at least two important contributions to advancing the understanding of the online employer review phenomenon in research and practice. First, it contributes substantially to understanding the nature of TPE images and thus the content of employer reviews. Second, it highlights the relevance of employer reviews to employer image management and offers valuable advice for companies in dealing with employer reviews.

2 Essay I: Online Employer Reviews as a Data Source: A Systematic Literature Review[3]

Currently, employer reviews are available in large volumes and from various providers. For instance, the employer review website Glassdoor reported a database of 55 million employer reviews, CEO approval ratings, salary reports, and other job insights in May 2020 (Glassdoor, 2020). The emergence of online employer reviews, as a unique type of user-generated content, is likely to provide new research opportunities beyond the work undertaken so far concerning online reviews by customers of products or services (Stamolampros et al., 2020). Harnessing these opportunities requires that researchers identify the research topics addressable with employer review data and the information that can be extracted from these reviews' content. However, the initial studies that may provide such insight have been scattered across several disciplines and are thus challenging to survey.

Therefore, to facilitate the exploitation of online employer reviews, I conduct a systematic literature review (SLR) of the research that has so far been done utilizing employer review data and structure it into distinct concepts (see Webster & Watson, 2002). I pursue three research objectives: first, to identify the research topics addressable using employer review data; second, to reveal the information extractable from employer reviews as well as how to do so; and finally, to identify relevant research gaps to stimulate future research using employer review data.

2.1 Theoretical Background

For this study, I define online employer reviews as employee-generated employer evaluations or judgments posted on third-party websites (adapted from Mudambi & Schuff, 2010). Employer review content reflects the selected beliefs that current and former

[3] This chapter is partly based on and includes elements of Höllig (2021).

employees hold about their employer (adapted from Cable & Turban, 2001). Employees develop these beliefs through various experiences with their employer (see, e.g., Lievens & Slaughter, 2016). For instance, current and former employees may form such beliefs by personally and thus first-hand experiencing an organization's employment practices (see Dineen et al., 2019).

To capture these experience-based beliefs, existing and former employees who opt to post reviews about their employer are typically guided by predefined questionnaires that comprise quantitative ratings on five-point Likert scales as well as open-ended text comments about the employer. For instance, the employer review website Kununu prompts reviewers to rate and comment on several individual aspects, such as company culture, and answer three brief questions on their employer's pros, cons, and opportunities for improvement. Aside from inviting employees instead of customers to generate content, employer review websites operate comparably to product or service review websites such as Amazon, TripAdvisor, or Yelp. To date, the emergence of product and service reviews has produced an extensive body of research (see, e.g., N. Huang, Hong, & Burtch, 2017). However, as employer review content and thus the rich information extractable from employer reviews likely differs substantially from the information obtainable from product and service reviews (see Stamolampros et al., 2020), employer reviews have opened a rich and novel field of research. Specifically, employer reviews likely provide vast potential for insight into current and former employees' experience-based beliefs about their employer and their decision to present those beliefs to the wider public.

2.2 Methodology

I conducted my SLR following the suggestions of Briner and Denyer (2012). First, I clearly defined my research objective. Second, I defined the literature databases as well as the search terms relevant to my review. Third, I retrieved publications from the previously defined databases and merged the results. Fourth, I scrutinized the identified publications and applied inclusion and exclusion criteria. Finally, I performed my review, i.e., conducted a full-text analysis with the remaining publications and synthesized my results into distinct concepts (see Webster & Watson, 2002).

My literature review had the following objective: to identify studies that use online employer reviews as a data source to reveal the information obtained, the way the information was obtained, the research topics covered, and the data sources used. Thus, I sought to identify only studies that used, for instance, Glassdoor's employer reviews, but not other job information offered by employer review websites such as salary reports or interview experience reports.

To identify the overall body of research, I did not limit my review to a single discipline. Rather, I searched publication databases covering a multitude of disciplines: Scopus, EBSCOhost, ScienceDirect, ProQuest, Web of Science, ACM Digital Library, AIS eLibrary, and Google Scholar. To search those databases, I defined the following search string and adapted it to the syntax of each publication database:

("employer reviews" OR "online employer reviews" OR "online employee reviews" OR "employer review data" OR "employee review data" OR "glassdoor reviews") OR ("employee reviews AND "review data")

I used the search string for all fields (including title, abstract, keywords, and full text). However, I limited the database searches to full-text articles written in English. Furthermore, to ensure consistency throughout my search phase and the associated repeated database searches, I considered only publications issued or in press before 1 January 2020. My search process yielded 53 results for Scopus, 49 results for EBSCOhost (academic journals, journals, and conference materials), 72 results for ScienceDirect, three results for ProQuest, nine results for Web of Science, five results for ACM Digital Library, 12 results for AIS eLibrary, and

454 results for Google Scholar. In summary, my database search yielded 657 results. After duplicate entries were eliminated based on the publication titles, 569 publications remained.

Next, I screened titles, abstracts, keywords, and, if necessary, each publication’s full text. Following my literature review objective, I retained only publications that utilize actual online employer reviews as a data source. After this screening, 63 publications remained: eight conference proceedings, three dissertations, 29 working papers (e.g., published on SSRN), and 23 journal articles. To guarantee each publication’s quality, I discarded those not included in the Academic Journal Guide (AJG) 2018 by the Association of Business Schools or the Journal Citation Report (JCR) 2018 by Thomson Reuters. Then, 19 peer-reviewed journal articles remained. Subsequently, to exhaust the relevant literature, I followed the citation trials that led to other articles. More specifically, I conducted forward and backward searches to identify publications that might have been missed with my search strategy. The forward and backward searches yielded another nine peer-reviewed journal articles relevant to my review. Figure 2-1 provides an overview of my search process.

My review set comprises 28 peer-reviewed journal articles published between 2015 and 2020. The articles were published in journals with a JCR 2018 Journal Impact Factor between 0.876 and 9.360. I also coded the journal disciplines using the categories indicated by AJG and JCR. My review set covers nine disciplines, although most articles were published in the management, finance and accounting, and marketing fields. For an overview of years and disciplines, refer to Figure 2-2.

The full-text analysis of the articles in my review set indicated that none of the articles that were divided into multiple studies (Canning et al., 2020; Könsgen et al., 2018; Wolter, Bock, Mackey, Xu, & Smith, 2019) utilized employer reviews in more than one study. However, I noted that two articles did not make a distinction between individual studies but still presented several conceptually distinct analyses (M. Huang, Li, Meschke, & Guthrie, 2015; Stamolampros et al., 2019). Therefore, I counted them as containing more than one concept when synthesizing the results of my full-text analysis into distinct concepts (see Webster & Watson, 2002). However, I did not count determinant analyses (T. C. Green, Huang, Wen, & Zhou, 2019; Hales, Moon, & Swenson, 2018) as separate studies, as they were not within the actual scope of the articles and thus may not have been subject to the same rigor as the articles' main analyses.

Figure 2-1

Search process

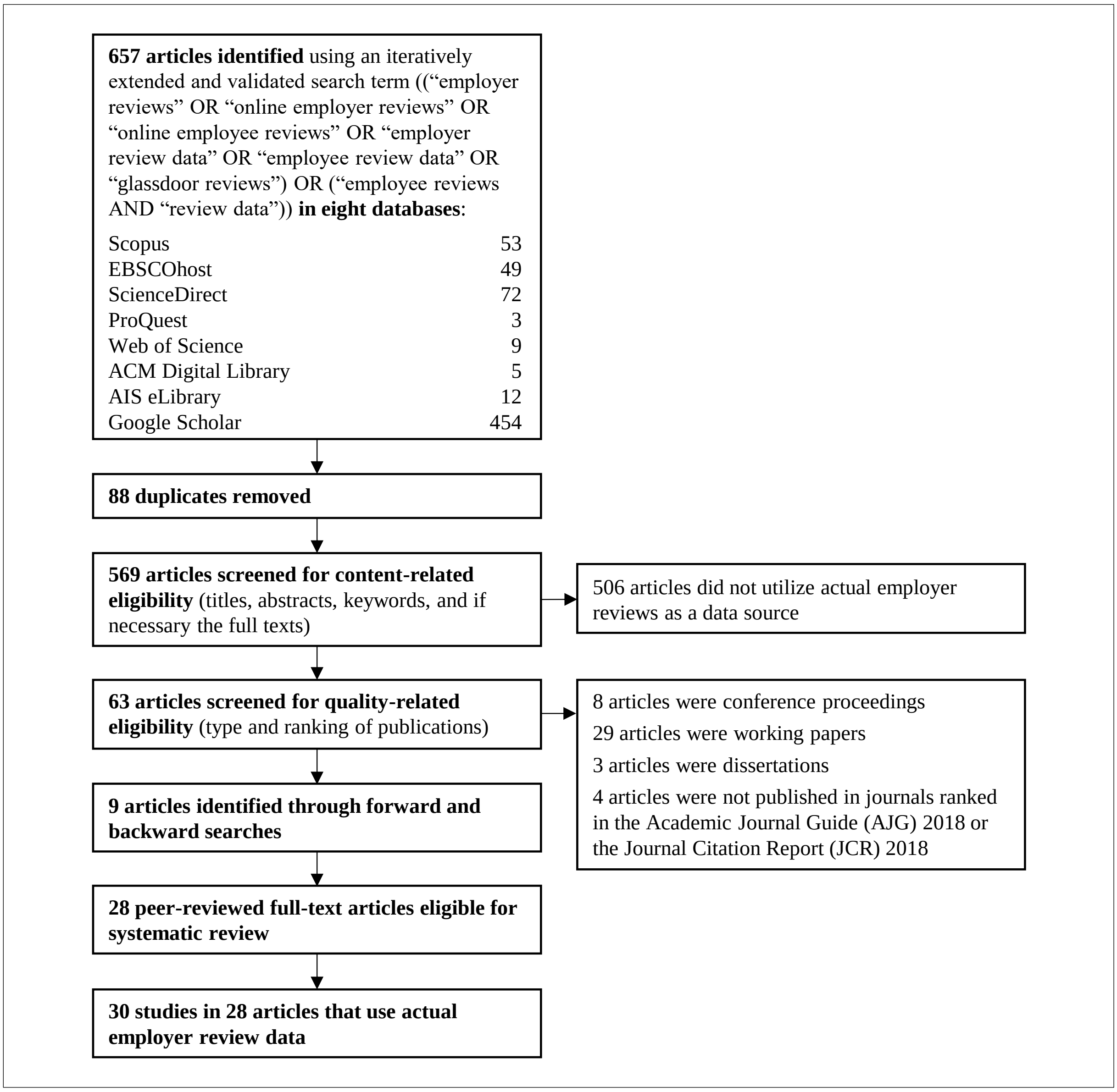
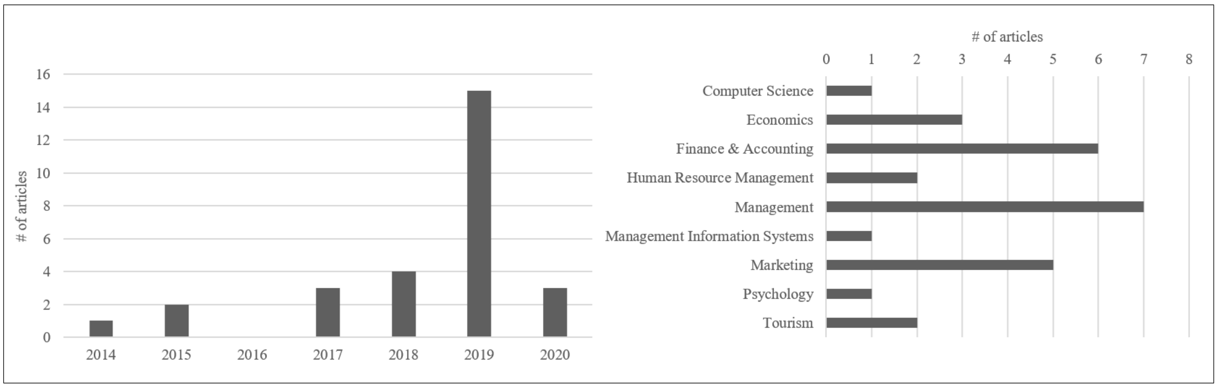


Figure 2-2

Years and disciplines covered with the SLR



2.3 Results

Table 2-1 provides an overview of the concepts and their frequencies resulting from the analysis of the 28 peer-reviewed articles in my review set. I present my findings in more detail below.

2.4 Research Topics

2.4.1 Predict Firm Performance

Ten studies used information derived from online employer reviews to predict firm performance. Three different types of information can be obtained from employer reviews to estimate firm performance. First, employer reviews provide *information about employee satisfaction and changes in employee satisfaction*. Against this backdrop, employee satisfaction was positively correlated with firm performance with respect to return on assets (ROA; M. Huang et al., 2015; Melián-González, Bulchand-Gidumal, & González López-Valcárcel, 2015; Stamolampros et al., 2019; Symitsi, Stamolampros, & Daskalakis, 2018), Tobin’s Q (M. Huang et al., 2015; Symitsi et al., 2018), operating margin (Melián-González et al., 2015), and revenue per employee (Melián-González et al., 2015). Furthermore, changes in employee satisfaction (i.e., employee satisfaction trajectories) of employees with customer contact correlated positively with customer satisfaction (Wolter et al., 2019). Moreover, quarterly changes in the employee satisfaction of current (vs. former) employees and

Table 2-1

Frequencies of SLR concepts

Concept	Frequency	Percent
Research topic		
Predict firm performance	10	33.33%
Explore factors of employee satisfaction	14	46.67%
Analyze the linguistic style of employer reviews	3	10.00%
Other	3	10.00%
	n = 30	100.00%
Text-mining techniques		
Topic modeling	4	25.00%
Dictionary-based text analysis	5	31.25%
Data-mining software	4	25.00%
Individual word frequencies	2	12.50%
Other	1	6.25%
	n = 16	100.00%
Data sources		
Glassdoor	24	85.71%
Indeed	2	7.14%
Jobplanet	1	3.57%
Kununu	1	3.57%
	n = 28	100.00%

employees working in headquarters states predicted stock returns one-quarter ahead (T. C. Green et al., 2019).

Although Green et al. (2019) used information on employee satisfaction from employer reviews, their findings touched on the second type of information that can be obtained from employer reviews to estimate firm performance: *insider knowledge*. For instance, Glassdoor's employer reviews include a survey of employees' opinions on their employer's six-month business outlook (positive, neutral, or negative). Specifically, employees are prompted with the following question: "In the next six months do you think your company will perform better, worse, or remain the same?" (Hales et al., 2018, p. 92). This business outlook indicator was shown to predict future operating performance as indicated by ROA and various other performance components (sales growth, cost of goods sold, R&D expenditure, and inventory turnover; K. Huang, Li, & Markov, 2020). Estimating functional performance indicators on the basis of the business outlook was more effective if the responses were provided by employees from the same functional area (e.g., sales employees' outlook predicting sales growth; K. Huang et al., 2020). Furthermore, business outlook was associated with a wide range of indicators for future corporate disclosures, including key income statement information, transitory reporting items (e.g., restructuring charges), earnings surprises, and management forecast news (Hales et al., 2018).

The third type of information that can be obtained from employer reviews to estimate firm performance is *insights into workplace culture*. Corritore et al. (2020) used employer reviews to capture two distinct types of cultural heterogeneity, namely, interpersonal and intrapersonal heterogeneity. Interpersonal heterogeneity describes the "misalignment in cultural perceptions among the individuals who make up the organization" (Corritore et al., 2020, p. 8). Intrapersonal heterogeneity describes "the breadth of cultural beliefs to which those individuals subscribe" (Corritore et al., 2020, p. 8). While interpersonal heterogeneity was negatively related to ROA as a proxy for a firm's capacity for efficient execution, intrapersonal heterogeneity was positively related to Tobin's Q and patent output as a proxy for a firm's capacity for recombinant innovation and creativity (Corritore et al., 2020). Finally, Au et al. (2019) used employer reviews to gain information about the extent of companies' employee flexibility, defined as "employees' ability to react and respond to unexpected changes in the firm's environment" (p. 1). Employee flexibility was positively associated with stock returns for firms exposed to external risk (Au et al., 2019).

2.4.2 Explore Factors of Employee Satisfaction

Rather than utilizing employee satisfaction information derived from employer reviews as an independent variable, 14 studies used this information as a dependent variable and explored employee satisfaction factors. Of these studies, six explored the role of factors derived from non-employer review data in employee satisfaction. In this context, four distinct types of information from external data sources were utilized to estimate employee satisfaction. First, some studies estimated employee satisfaction based on organizations' *structure*. Companies with demographically diverse boards were more likely to implement progressive management programs that were well received by employees (Creek, Kuhn, & Sahaym, 2019). Moreover, employees of family firms reported higher satisfaction in their employer reviews (also concerning individual aspects such as work-life balance) than employees of non-family firms (M. Huang et al., 2015). Second, two studies estimated employee satisfaction based on organizations' *workplace culture*. Companies that emphasize (vs. do not emphasize) adaptability (e.g., act quickly, seize opportunities) in their culture received higher overall satisfaction ratings in their employer reviews (O'Reilly, Caldwell, Chatman, & Doerr, 2014). Furthermore, Fortune 500 companies that maintain a growth (vs. fixed) mindset received higher culture and value ratings in their employer reviews (Canning et al., 2020). Third, one study estimated employee satisfaction based on organizations' *financials*. Employees in financially constrained (vs. unconstrained) companies reported lower satisfaction ratings (as indicated by overall ratings and individual ratings of work-life balance, senior management, and career opportunities; Jing, Keasey, Lim, & Xu, 2019). Finally, one study estimated employee satisfaction based on *policies* in a difference-in-differences setting (Storer & Reich, 2019). In detail, a state-level minimum wage increase positively affected newly hired employees' satisfaction but negatively affected the satisfaction of senior and high-ranking (i.e., department managers) employees (Storer & Reich, 2019).

Moreover, eight studies explored the role of factors derived from employer review data on employee satisfaction. In this vein, studies in this group utilized variables derived from reviews' (textual) content, including pro and con comments, as well as individual ratings and information on the tenure of the reviewing employees (former vs. current employee). I provide an overview of the text-mining techniques used to extract information from the employer reviews' textual content in the next section. Moro et al. (2020) demonstrated the most important satisfaction factors for IT employees based on a support vector machine

(SVM) model. Furthermore, Jung and Suh (2019) identified 30 topics (i.e., job satisfaction factors), such as “organizational culture”, via topic modeling. Subsequently, the authors demonstrated that the sentiment and importance of these job satisfaction factors differ between industries, companies, years, and current and former employees (Y. Jung & Suh, 2019). Finally, the authors identified the most important factors for the reviews’ overall quantitative ratings in a dominance and correspondence analysis (Y. Jung & Suh, 2019).

Stamolampros et al. (2019) employed several analyses to explore employee satisfaction factors in tourism and hospitality firms. In detail, the authors examined the influence of individual ratings on the reviews’ overall rating (Stamolampros et al., 2019). In accordance with the findings of Jung and Suh (2019), senior leadership was among the most important factors. However, while Jung and Suh (2019) identified compensation and benefits as the second most important factor, compensation and benefits were least important for the overall rating in the analysis of Stamolampros et al. (2019). Stamolampros et al. (2019) further demonstrated that employees who choose to leave a firm are likely to be most dissatisfied, that male employees are more satisfied than female employees, and that companies with higher revenue also achieve higher employee satisfaction. Furthermore, the authors showed that an employee’s likelihood of leaving a company is affected by culture values, senior leadership, and career opportunities. Finally, the authors also explored the textual content of their employer review dataset via topic modeling and identified 20 job satisfaction/dissatisfaction factors that differ in their prevalence according to the overall rating (Stamolampros et al., 2019). Correspondingly, Stamolampros et al. (2020) also identified employee satisfaction factors in the tourism and hospitality industry using topic modeling. The authors identified ten factors and demonstrated that the prevalence of these factors varies across sub-industries (Stamolampros et al., 2020).

Finally, one study took another approach and explored neither reviews' textual content nor overall ratings but instead used employees' indication of whether they would recommend their employer through their Glassdoor reviews (yes vs. no). In this vein, Saini and Jawahar (2019) showed a positive impact of reviews' individual ratings as well as Universum's Top 100 employer ranking on employees' recommendations. Furthermore, by examining the interaction with employees' characteristics, the authors showed, for instance, that work-life balance is more important for part-time employees than for full-time employees (Saini & Jawahar, 2019).

Three studies compared satisfaction factors at the company level instead of at the review level. In this vein, qualitative differences were found in exploratively derived topics, i.e., company-provided benefits and governance structures, between the reviews of companies appearing in Fortune's Best Companies 2014 ranking and 24/7 Wall St.'s 2014 Worst Places to Work ranking (Ross et al., 2017). Furthermore, the prevalence of exploratively derived employer branding value propositions differed between reviews for best and worst places to work (according to Glassdoor rankings) and between reviews from former and current employees (Dabirian et al., 2017, 2019).

2.4.3 Analyze the Linguistic Style of Employer Reviews

Three studies analyzed the linguistic style of employer reviews. Significant differences were found in word choice and verbal tone between the highest- and lowest-rated reviews (i.e., one-star vs. five-star reviews) as well as between the reviews for companies that are ranked best and worst in a B2B ranking from Brandwatch, which lists the top 200 B2B brands on social media (Pitt et al., 2018, 2019). More specifically, five-star reviews (vs. one-star reviews) displayed more optimism, embellishment, variety, complexity, commonality, analytical thinking, authenticity, and emotional tone and contained fewer words but displayed less activity, certainty, realism, insistence, and clout (Duncan et al., 2019; 2019).

Furthermore, reviews for top-ranked (vs. low-ranked) employers displayed more optimism, embellishment, variety, and complexity but less activity, certainty, and realism (Pitt et al., 2019).

2.4.4 Other

Finally, three studies utilized employer review data that were not categorizable into previously defined concepts. First, Könsgen et al. (2018) analyzed the within-company deviation of overall ratings and sentiment in a preliminary study. The authors showed that reviews for the same company are rather discrepant and examined the effects of this discrepancy in a subsequent online experiment (Könsgen et al., 2018). Second, M. Huang et al. (2017) predicted auditing outcomes (audit fees, issuance of modified going concern opinions, and audit report lag) using employer reviews' satisfaction rating (i.e., overall rating). The authors showed that lower ratings increase audit fees, audit report lag length, and firms' likelihood of receiving modified going concern opinions (M. Huang et al., 2017). Third, Robertson et al. (2019) compared brand personality perceptions between reviews of high- and low-ranked firms according to Brandwatch's B2B ranking and between high-and low-rated reviews according to reviews' overall rating. The authors demonstrated that top-ranked (vs. low-ranked) employers are perceived as less exciting, rugged, and sincere. Furthermore, high-rated (vs. low-rated) (one-star vs. five-star) reviews displayed more competence, excitement, sincerity, and sophistication but less ruggedness (Robertson et al., 2019).

2.5 Text-Mining Techniques

2.5.1 Topic Modeling

The 16 studies utilizing the textual content of employer reviews applied four distinct approaches to extracting information. First, four studies utilized topic modeling to discover the hidden structure, i.e., topics in employer reviews' textual content. More specifically, Corritore et al. (2020) and Jung and Suh (2019) used latent dirichlet allocation (LDA). LDA assumes that documents are composed of probabilistically distributed topics, which in turn are composed of probabilistically distributed words (Blei et al., 2003). Although both studies utilized the same topic model algorithm, each took a different approach regarding preprocessing of the initial text corpus. Jung and Suh (2019), before taking further measures such as extracting bigrams, discarded non-noun words as identified by preliminary part-of-speech tagging. Corritore et al. (2020), again before taking additional steps such as trimming nonsense terms, discarded sentences that did not contain the word “culture” or a close synonym. These decisions were based on the results that were to be achieved through the application of LDA. Jung and Suh (2019) aimed to identify interpretable and thus coherent job satisfaction factors expressed in employer reviews’ textual content. Accordingly, the authors estimated a topic model with 65 topics and clustered them into 30 factors (Y. Jung & Suh, 2019). Corritore et al. (2020), on the other hand, used the topic model to develop a measure of interpersonal and intrapersonal heterogeneity based on topic distribution between and within reviews. Therefore, the authors created a 500-topic model to estimate conceptually distinct topics (Corritore et al., 2020). Another class of topic models was utilized by Stamolampros et al. (2019, 2020): the structural topic model (STM; Roberts, Stewart, & Airoldi, 2016). STMs allow document-level covariates, i.e., review metadata such as reviewers’ status (current vs. former), position, department, or industry, to be accounted for when estimating topics. Thus, STMs relax the restrictive assumption that topics are equally reflected in all documents, i.e., reviews (Stamolampros et al., 2019, 2020). Stamolampros et al. (2019, 2020) considered only reviews from tourism and hospitality firms and opted to estimate coherent and interpretable topics to discover the relevant job factors for staff in these firms. Stamolampros et al. (2020) presented a 10-topic model, and Stamolampros et al. (2019) divided the textual content into positive and negative feedback and presented a 20-topic model.

2.5.2 Dictionary-Based Text Analysis

Second, five studies utilized dictionary-based text analysis to extract information from the reviews' textual content. More specifically, three studies applied DICTION (Pitt et al., 2018, 2019; Robertson et al., 2019). DICTION is a text analysis program developed by communication researchers to identify text dimensions based on word frequency (Short & Palmer, 2008). In other words, documents are analyzed by counting words assigned to specific dimensions in the document according to predefined or user-defined content dictionaries, and the count is then divided by the total number of words in the document. Pitt et al. (2018) utilized DICTION's predefined content dictionary and extracted five dimensions from employer reviews that are fundamental to any document: certainty, optimism, activity, realism, and commonality. Pitt et al. (2019) extracted these five dimensions and four further dimensions: insistence, embellishment, variety, and complexity. In comparison, Robertson et al. (2019) utilized DICTION's capability to estimate the word frequencies of dimensions in user-defined content dictionaries and extracted Aaker's (1997) five dimensions of brand personality: sincerity, excitement, competence, sophistication, and ruggedness. Duncan et al. (2019) used another widely used text analysis program, LIWC (Linguistic Inquiry and Word Count; Tausczik & Pennebaker, 2010), to determine the word frequency counts of various dimensions based on predefined or user-defined content dictionaries. More specifically, the authors focused on LIWC's predefined dictionary and extracted four dimensions from employer reviews: analytical thinking, clout, authenticity, and emotional tone (Duncan et al., 2019). Finally, using no specific text analysis program, Au et al. (2019) used a dictionary-based method to measure employee flexibility in employer reviews' textual content. Specifically, they developed a word list associated with employee flexibility from the literature and extended it using WordNet's thesaurus. Subsequently, the authors calculated a flexibility ratio for each review by counting the total number of words associated with employee flexibility and dividing it by the total number of words per review (Au et al., 2019).

2.5.3 Data-Mining Software

Third, four studies used data-mining software to extract information from reviews' textual content. Dabirian et al. (2017, 2019) used IBM Watson. According to Dabirian et al. (2017), Watson analyzes content on "(1) parts of speech, including the nouns, verbs, and adjectives that employees used; (2) sequences of words in a sentence and phrase constituents; and (3) sentiment, separating positive and negative expression and phrases" (p. 4). Subsequently, the authors coded the IBM Watson outputs (i.e., expressions and phrases) into content dimensions informed by the literature (Dabirian et al., 2017). More specifically, Dabirian et al. (2017) coded the output into seven employer value propositions: social value, interest value, application value, development value, economic value, management value, and work-life balance. Using the same technique, Dabirian et al. (2019) added an eighth dimension: brand image. Könsgen et al. (2018) also used IBM technology, AlchemyAPI, to identify the sentiment (from -1 (negative) to +1 (positive)) as well as the length in characters of the textual content of their employer review data. Finally, Ross et al. (2017) utilized Leximancer, a text analysis software that creates concept maps (e.g., from word frequencies and common occurrences of words) that allow visual exploration of key concepts and relations in text documents.

2.5.4 Individual Word Frequencies

Fourth, two studies extracted individual word frequencies per employer review and determined their relevance by correlating them with a secondary variable. Storer and Reich (2019) identified the words in their employer reviews' pros and cons sections that become more common after a minimum wage increase. Moro et al. (2020) extracted the ten most frequent nouns in their employer reviews' pros, cons, and management advice sections and examined their relevance to the reviews' overall ratings using an SVM model.

2.5.5 Other

Finally, one study considered the length (i.e., number of words) difference between comments in the pros and cons sections as an alternative text-based measure of employee satisfaction (T. C. Green et al., 2019). Green et al. (2019) argued that employees who are satisfied with their employer tend to use more words in the pro section and fewer words in the con section of their reviews.

2.6 Data Sources

2.6.1 Glassdoor

Of the SLR studies, 24 used Glassdoor as a data source. Apart from review metadata, i.e., the review date and the name of the reviewed company, Glassdoor reviews comprise the reviewer's status (current vs. former employee), location, type (e.g., full-time, part-time), job title, and tenure. The reviews' main source of information is an overall rating of the employer measured on a one-item five-point scale, often used as a proxy for employee satisfaction (e.g., M. Huang et al., 2015), and individual ratings, each measured on a one-item five-point scale, for work-life balance, culture and values, career opportunities, compensation and benefits, and senior management. Moreover, the reviews comprise a business outlook indicator based on whether employees perceive their employer's business outlook as positive, neutral, or negative; a recommendation indicator (yes, no); and a CEO approval indicator (positive, neutral, negative). The textual content is divided into "Pros", "Cons" and "Advice to Management" sections.

2.6.2 Indeed

Two studies used Indeed as a data source (Au et al., 2019; Ross et al., 2017). Indeed reviews comprise the following in addition to the review date and name of the reviewed employer: reviewer's job title, location, individual ratings measured on a one-item five-point scale (work-life balance, compensation benefits, job satisfaction, management, and job culture), an overall rating as the mean of these individual scales, and a free-text comment as well as comments for pros and cons (Au et al., 2019). Thus, the information provided in Indeed reviews is quite comparable to Glassdoor review information.

2.6.3 Jobplanet

One study used Jobplanet as a data source (Y. Jung & Suh, 2019). According to Jung & Suh (2019), Jobplanet is one of the most popular review sites in South Korea. It delivers the same information as Glassdoor, including an outlook indicator as well as the same individual ratings (Y. Jung & Suh, 2019).

2.6.4 Kununu

One study used Kununu as a data source. Kununu is one of the most popular review sites in German-speaking areas (Könsgen et al., 2018). Könsgen et al. (2018) used Kununu reviews' textual content and overall rating (1 to 5 stars) for their preliminary study, i.e., Study 1. However, the authors gave no further insight into the information provided via Kununu's reviews except that the reviews comprise a title, a text and a rating.

2.6.5 Sample and Matching

The studies in my review set used 1,185 (Ross et al., 2017) to 1,245,000 (Au et al., 2019) unique employer reviews for their analyses. The majority used Compustat data or CRSP data to enrich their review dataset with additional variables. Moreover, the studies used data from SmartMoney.com, Thomson-Reuters I/B/E/S First Call, Thomson Reuters Eikon, Thomson Reuters Datastream Infobase, Thomson Reuters Institutional (13f) Holdings, Execucomp, and BoardEx as well as Satisfaction Index (ACSI), and Kinder, Lydenberg, Domini Research & Analytics (KLD) Social Ratings. Studies that predicted employee satisfaction also combined employer review data with data retrieved not from a dedicated database but from a content analysis of mission statements from Fortune 500 companies' websites (Canning et al., 2020), a survey of firms headquartered in the US and Ireland

(O'Reilly et al., 2014), and state-level information on minimum wage increase (Storer & Reich, 2019).

2.7 Discussion

My SLR revealed 28 high-quality peer-reviewed journal articles from a multitude of disciplines that utilize employer review data. My review indicates that online employer reviews are a fast-growing topic in academia. I structured the current research to allow further exploitation of this source of data.

My analysis revealed three major research topics. First, some studies extract information from employer review data to predict firm performance. Specifically, these studies obtain information about employee satisfaction and changes in employee satisfaction, insider knowledge, and insights into workplace culture from employer review data. They use this information to predict, e.g., ROA, Tobin's Q, or patent output. Second, some studies explore factors of employee satisfaction. Specifically, they explore the role of employee satisfaction factors derived from non-employer review data, i.e., information on organizations' structure, workplace culture, and financials as well as policies. Furthermore, some studies explore the role of factors derived from employer review data, especially reviews' textual content. Finally, some studies analyze the linguistic style of employer reviews. More specifically, these studies compare the linguistic styles of content for the best and worst companies.

Studies across all research topics utilized various text-mining techniques to quantify the textual content of reviews. I identified four groups of techniques used so far: topic modeling, dictionary-based text analysis using programs such as DICTION, data mining using software such as IBM Watson, and extracting individual word frequencies. Regarding data sources, I found that Glassdoor data are primarily used and are often merged with Compustat and/or CRSP data. I aggregated my findings into a comprehensive research framework (see Figure 2-3).

2.7.1 Avenues for Future Research

Based on my SLR, I envision five major research topics to focus on in the next years. First, I see further research opportunities in predicting firm performance from information gained from employer reviews' textual content. Only two studies identified with my SLR predicted firm performance based on insight gained into workplace culture from employer reviews' textual content (Au et al., 2019; Corritore et al., 2020). However, constructs developed for computer-aided text analysis, such as organizational psychological capital, which is defined as an "organization's level of positive psychological resources: hope, optimism, resilience, and confidence" (McKenny et al., 2012, p. 157), offer great potential for predicting firm performance by gaining novel insight into workplace cultures from employer review data.

Second, extending my first point, I see great value for academics and practitioners alike in a theory-driven discovery of employer reviews' textual content. My SLR indicates that there is a lack of theory-driven analysis of the textual content of online employer reviews. Instead, explorative approaches such as topic modeling or other data-mining software are used to quantify the textual content (e.g., Y. Jung & Suh, 2019). Furthermore, in terms of dictionary-based approaches, dictionaries developed for other contexts were used and thus also represent an explorative approach. While explorative analyses provide great value for understanding online employer reviews' textual content, the systematic development of dedicated content dictionaries would extend our understanding of online employer reviews derived from theory (Short et al., 2010). For instance, the organizational reputation literature provides several suggestions about the type of textual content that should manifest in online employer reviews (see Etter et al., 2019).

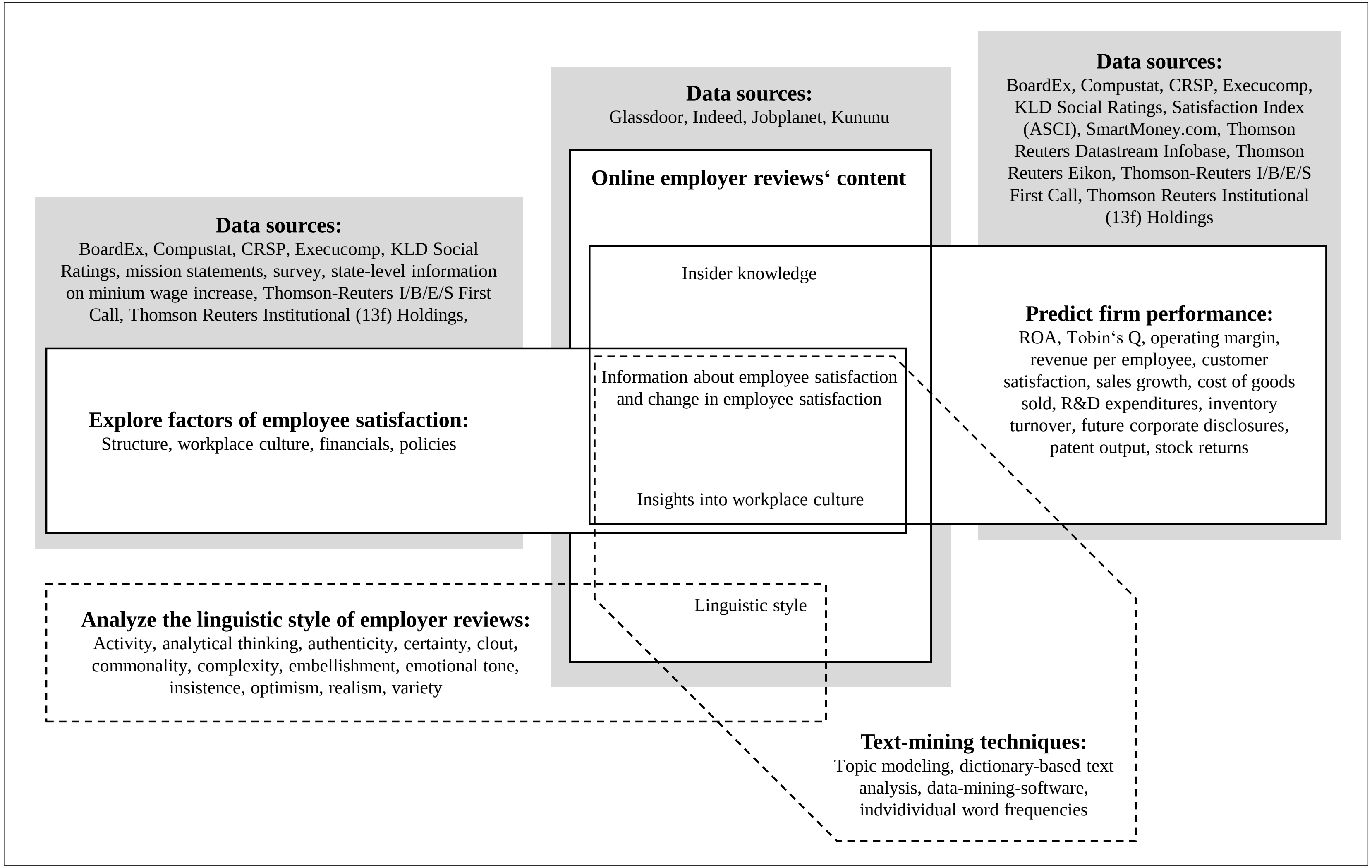
Third, I see further research opportunities in predicting firm performance with regard to recruiting outcomes. My SLR shows that studies focus mainly on financial indicators of firm performance, such as Tobin's Q, ROA, and revenue per employee. However, given that experimental studies consistently show that employer reviews can affect job seekers' attitudes and intentions (Evertz et al., 2019; Könsgen et al., 2018; Melián-González & Bulchand-Gidumal, 2016; Stockman et al., 2019), studying the impact of employer reviews on recruiting indicators, such as the quantity and quality of applications, is particularly vital.

Fourth, I see that further research is necessary to compare employer reviews with traditional survey instruments. Several authors in my SLR argued that online reviews offer value beyond traditional surveys (Y. Jung & Suh, 2019; Stamolampros et al., 2019, 2020). However, given the potential impact of self-selection on online employer review data, employer review content should be compared with the results of randomized employee (satisfaction) surveys. Although evidence for the generalizability of employer review data at the firm level is also provided by the ability to predict firm performance, a comparison with traditional survey instruments would bring some certainty.

Fifth, further research should explore the determinants of employer reviews. The SLR studies give only limited insight into what determines the content of employer reviews. Employer review websites typically do not disclose the identity of reviewers within profile information because they opt to offer employees the opportunity to freely judge their employers without fear of legal consequences or other forms of retaliation (A. E. Jackson, 2016). Thus, employer review websites differ to some extent in context from product or service review websites. However, such differences serve as a significant distinction between contexts when assessing, e.g., the impact of management responses (Chen, Gu, Ye, & Zhu, 2018). Therefore, future research should investigate whether our knowledge of product and service review determinants can be transferred to employer reviews.

Figure 2-3

Employer review data research framework



2.7.2 Limitations

My literature review is not without limitations. First, I restricted it to studies that utilize actual employer review data in their analyses. Thus, I exclude studies that investigate the perception of employer reviews, e.g., in regard to organizational attraction (Evertz et al., 2019). However, understanding perceptions of employer reviews is an important component in the general understanding of employer reviews. I thus encourage a systematic review of this research stream.

Second, I restricted my review to studies that are listed in the AJG or JCR. In this way, I avoided the difficult task of assessing publication quality and instead relied on an external quality indicator. However, at the same time, I excluded a large number of currently circulating working papers that might provide interesting insight into current research trajectories.

2.7.3 Conclusion

Online employer reviews represent a unique type of user-generated content, reflecting current and former employees' experience-based beliefs about their employer, that offers a wide range of research opportunities. However, the research is currently scattered across several disciplines and is therefore difficult to survey. Therefore, my study, which provides a synthesis of the current research and identifies unmet research needs, seeks to aid researchers interested in using employer review data to leverage research opportunities arising from employer review content.

3 Essay II: Employer Images in the Wild: Toward a Better Understanding of Third-Party Employer Images on Employer Review Websites[4]

Employer review websites (e.g., Glassdoor, Indeed, Kununu, Jobplanet, Kanzhun) where employees anonymously post quantitative and open text evaluations about employers are thriving. For example, in 2019, Glassdoor contained nearly 50 million items of employer-related information (e.g., reviews, salary reports) on more than 900,000 companies in 190 countries (Lewis, 2019). Other surveys indicate that more than one in three German Internet users (36%) have already read an online review on Kununu (Brehme & Brandau, 2018) and that up to 52% of U.S. job-seekers read employer reviews before applying (Westfall, 2017).

This emergence of employer review websites and social media in general have led to a revolution in the recruitment landscape. In the past, job-seekers developed their image of an employer (i.e., the totality of the attributes that they associate with an organization as a place to work; Lievens & Slaughter, 2016; Theurer et al., 2018) mostly on the basis of company-controlled image information. Now, employer review websites that operate outside of company control also inform them and, thus, constitute third-party employer (TPE) branding. TPE branding refers to "communications, claims, or status-based classifications generated by parties outside of direct company control that shape, enhance, and differentiate organizations' images as favorable or unfavorable employers" (Dineen et al., 2019, p. 176).

Despite the widespread role of employer reviews in TPE branding, we do not have answers to many pressing questions. Critically, we do not know (a) what kind of content is used to co-create the image of employers via employer reviews and (b) whether this content

[4] This chapter is partly based on and includes elements of Höllig, Tumasjan, and Lievens (under review). Therefore, the plural instead of the singular is used throughout this chapter. Author contributions are summerized in Appendix C.

impacts how favorably companies are seen as employers. However, establishing a better understanding of the TPE image created by current and former employees through employer reviews is crucial for further theory building. This is the case, because TPE image may substantially differ from our prevailing conceptualizations of employer image which is mostly based on the premise that employer image is under direct company control (Dineen et al., 2019). In the wake of increasing TPE branding proliferated by employer review websites, it is thus crucial to update and complement our prevailing employer image conceptualizations because, ultimately, the image that job-seekers hold about employers determines companies' recruitment success and image management activities (Cable & Turban, 2001).

Our study aims to shed light on the nature and effects of TPE images on the basis of information presented on employer review websites[5]. Drawing on the new media reputation formation (NMRF) framework (see Etter et al., 2019), we theorize and empirically show that a) personal rather than impersonal, b) symbolic rather than instrumental, and c) emotional rather than cognitive content dominate[6] in determining whether a more positive or more negative TPE image (i.e., TPE image valence, as indicated by reviews' overall quantitative rating) is presented in employer reviews. To test these propositions, we rely on computer-aided text analysis (CATA) and analyze approximately half a million employer reviews submitted to Kununu (i.e., Europe's largest employer review website). Furthermore, we demonstrate that these theory-grounded content features actually matter by linking them to

[5] More than 20 years ago, Cable and Turban's (2001) seminal chapter called for more research to better understand employer image (i.e., what features do job-seekers associate with an organization) because it is vital for a company's recruitment success. Interestingly, employer reviews enable to "peak" into the minds of former and current employees and thus serve as written transcriptions of which features they associate with the organization as a place to work.

[6] We use the term "dominate" throughout the paper in reference to the terminology of the statistical method used to test our hypotheses; namely dominance analysis (e.g., Luo & Azen, 2013). In a regression model, one predictor dominates another predictor if it accounts for a higher proportion of the explained variance in the dependent variable. Thus, in our case, one content category dominates another content category when it plays a greater role in predicting the valence of the TPE images presented through employer reviews.

companies' TPE image and, through that, to the probability of a company being ranked as a "best employer" by job-seekers.

The contributions of our study are fourfold. First, we integrate the NMRF framework (see Etter et al., 2019) into the employer image domain to refresh the prevailing employer image perspective stemming from a pre-TPE branding era. Accordingly, our study updates existing employer image conceptualizations (see Lievens & Slaughter, 2016): Whereas the prevailing view posited that job-seekers' employer image was derived mostly from messages by organizational agents (e.g., recruiters), the new co-created perspective gives more voice to bottom-up input from organizational members such as current and former employees. As a result, we posit that the content used for describing a company as a place to work will be conceptually different.

Second and relatedly, we show that symbolic trait attributions (e.g., "this organization is sincere") have particular importance in the formation of TPE image. This highlights that anthropomorphism not only plays a role in organizational identity (Ashforth, Schinoff, & Brickson, 2020) but also in the formation of TPE image. Hence, our study also extends previous work showing that symbolic employer attributes are especially relevant among organizational insiders (i.e., employees; see Lievens, Van Hoye, & Anseel, 2007).

Third, we extend the theoretical perspectives of employer images being primarily cognitively driven (Collins & Kanar, 2013; see also Lievens & Slaughter, 2016) by adding that emotional processing is ultimately more relevant to TPE images. Thus, our study posits that employer image research has so far underestimated the role of emotionality in the formation of images. Furthermore, as emotions possess persuasive power to influence the formation and change of individuals' attitudes on a variety of topics (Van Kleef, Van Den Berg, & Heerdink, 2015), our study also suggests that the emotionality of employer information, as an effectiveness-enhancing characteristic, needs to be integrated into theory in employer image management research.

Fourth, we integrate two strands of prior employer review research that so far have evolved separately. One strand is devoted to the experimental investigation of the effects of employer reviews (e.g., Evertz et al., 2019), whereas the other relates to the exploration of the content of actual employer reviews (e.g., Dabirian et al., 2019). Our study integrates these two research streams by establishing a conceptual understanding of TPE images presented through employer reviews and linking these TPE images to an important recruitment-related outcome, namely external "best employer" rankings by job-seekers.

3.1 Theory and Hypotheses

3.1.1 Company-Controlled Employer Images

Given the value of employer image for a company's recruitment success, employer image research and management have sparked considerable interest among both practitioners and academics (Dineen et al., 2019; Lievens & Slaughter, 2016; Theurer et al., 2018). In a review of almost two decades of employer image research, Lievens and Slaughter (2016) distinguished an organization's employer image from related constructs (i.e., identity, familiarity, and reputation) and defined it "as an amalgamation of transient mental representations of specific aspects of a company as an employer as held by individual constituents [job-seekers]" (p. 409). Whereas one automatically and holistically perceives an employer as having or not having an attractive image, Lievens and Slaughter (2016) posited that the more elementalistic associations (i.e., the different attributes) that make up this general image are complex and require cognitive processing (see also Collins & Kanar, 2013).

Apart from the cognitive processing of these various employer-related associations, another characteristic of prevailing employer image conceptualizations is that the associated employer image attributes can be categorized using the instrumental-symbolic framework

(Lievens & Slaughter, 2016; Theurer et al., 2018). This framework categorizes the attributes that individuals associate with employers into instrumental or symbolic ones. Instrumental attributes refer to the objective, physical and tangible attributes of a job or an organization (Lievens, 2007). Examples of instrumental attributes are pay, location and career opportunities (Lievens, 2007; Lievens & Highhouse, 2003; Van Hoye, Bas, Cromheecke, & Lievens, 2012). Conversely, symbolic attributes refer to the subjective, abstract and intangible attributes of a job or an organization (Lievens & Highhouse, 2003). Thus, symbolic attributes describe a job or an organization in terms of the traits that are assigned to the job or organization (Lievens, 2007; Lievens & Highhouse, 2003; Van Hoye et al., 2012). Symbolic attributes include innovativeness, prestige, or sincerity (see, e.g., Lievens, 2007; Lievens & Highhouse, 2003), and are closely related to Slaughter et al.'s (2004) concept of organizational personality, which is defined as "the set of human personality characteristics perceived to be associated with an organization" (p. 86). Given that symbolic attributes assign human characteristics to organizations, they are also an example of anthropomorphizing organizations (Ashforth et al., 2020).

Current employer image research (Lievens & Slaughter, 2016) also aimed at understanding the process of how job-seekers arrive at a multitude of complex employer-related associations. Early theory posited that "any information source, ranging from company's brand advertisement to friends' word-of-mouth, has the potential to affect job seekers' employer knowledge" (Cable & Turban, 2001, p. 132). Since then, empirical findings have supported that various experiences, including recruitment ads (e.g., Walker & Hinojosa, 2013), recruiters (e.g., Dineen, Ash, & Noe, 2002), and word-of-mouth (e.g., Van Hoye & Lievens, 2009) foster employer image perceptions.

In sum, the prevailing conceptualization of employer image seems to have several key features. First, the diverse attributes (either instrumental or symbolic) associated with employer image require cognitive processing. Second, both instrumental and symbolic attributes play a role in one's overall perception of a company's employer image. Third, any experience may affect job-seekers' employer image perceptions. Although word-of-mouth has been given a place among these experiences, past research has focused mainly on company-controlled employer image communication (Dineen et al., 2019), which allows companies to present a carefully constructed image to job-seekers and the wider public. Therefore, as shown in Figure 3-1, prior research posited that the employer image held by job-seekers mainly stemmed from company-controlled employer image management (see the grey column). This *company-controlled employer image* reflects the totality of image-related attributes espoused by company agents (e.g., recruiters) and communicated via recruitment ads, company websites, media, etc.

3.1.2 Third-Party Employer (TPE) Images on Employer Review Websites

In recent years, due to the rapid rise of social media, a company's employer image is no longer exclusively defined, shaped, and controlled by the company itself but is also co-created by third parties outside of direct company control, including current employees, former employees, and customers (Etter et al., 2019; Lievens & Slaughter, 2016). As shown in Figure 3-1, this gave rise to the *TPE image*, which reflects the totality of image-related attributes that parties outside of direct company control associate with the organization as a place to work and communicate to organizational outsiders (such as job-seekers). A popular example for the communication of such TPE images are employer reviews provided through social media sites such as employer review websites (Dineen et al., 2019). Given that the prevailing employer image conceptualization dates from an era in which TPE branding did not exist, it did not factor in elements specific to TPE images. Hence, we risk adopting an outdated perspective on employer image.

Figure 3-1

Differences between company-controlled and third-party employer image

Employer image held by job-seekers
(i.e., totality of attributes associated with an organization as a place of work)

stems from

	Company-controlled employer image	**Third-party employer (TPE) image**
Definition	Totality of attributes that organizational agents associate with an organization as a place of work.	Totality of attributes that parties outside of direct company control associate with an organization as a place of work.
Examples	Image-related content presented on company websites, recruitment ads, brochures, media communications, etc.	Image-related content presented on employer review websites such as Glassdoor, Indeed, Kununu, etc.
Constituents	Organizational agents (e.g., recruiters)	Organizational members (i.e., former/current employees)
Information source	Predominantly based on more generalized experiences and facts; espoused	Predominantly based on personal (first-hand) experiences (see Hypothesis 1); enacted
Image attributes	Comprises both instrumental and symbolic attributes	Predominantly comprises symbolic employer attributes (see Hypothesis 2)
Processing	Predominantly cognitively-loaded	Predominantly emotionally-charged (see Hypothesis 3)

Although still in its infancy, the scientific interest in the TPE images disseminated through employer reviews has developed into at least two distinct research streams. First, several studies have used predominantly experimental designs to analyze whether employer reviews can have an effect on job-seekers' attitudes and intentions towards organizations as a place of work (Evertz et al., 2019; Könsgen et al., 2018; Melián-González & Bulchand-Gidumal, 2016; Stockman et al., 2019). Second, researchers have adopted exploratory approaches and used, for example, data-mining software such as IBM Watson (Dabirian et al., 2017, 2019) or Leximancer (Ross et al., 2017) to identify content categories in employer reviews of selected companies.

To date, these two strands of research have evolved separately and no efforts have been made to integrate them. The first research stream consists of experimental studies that show that the valence of TPE images *can* have effects (on job-seekers' attitudes and intentions). These studies have neither specified the content of TPE images, nor examined this content's relevance for the valence of TPE images. Although the second stream of research has delved into the content of TPE images, researchers in this stream have applied CATA only in an exploratory approach to selected samples (up to 6,336 employer reviews) and have not examined the effectiveness of the extracted content categories for predicting recruitment outcomes. Our study integrates these two research strands. To do so, we theorize about the content reflected in employer reviews, the relevance of this content in determining whether these content features bring about more positive or negative TPE images (i.e., TPE image valence), and the influence of such TPE images on companies being ranked among "best employers" by job-seekers.

3.1.3 Content and Valence of TPE Images

To theorize on the content and valence of the TPE images presented through employer reviews, it is useful to integrate recent insights on the formation of organizational reputation in the wake of social media (e.g., Etter et al., 2019; Mena et al., 2016; Ravasi et al., 2018; Rindova et al., 2018; Schrempf-Stirling et al., 2016) into the employer image literature. These theories focus not only on the role of information cues disseminated by organizational agents themselves, or by traditional news media (e.g., journalists) but also on the role of information cues disseminated through social media, such as blogs, discussion forums, social networks, and review websites (Etter et al., 2019). In particular, Etter et al.'s (2019) new media reputation formation (NMRF) framework posits that social media have fundamentally changed the way opinions on the quality, competence, and character of organizations are generated and spread. Social media enable third parties to co-create an organization's image as an employer (Dineen et al., 2019), thereby shaping the content about employers to which the public is exposed.

The NMRF framework's central premise is that the information about organizations disseminated via social media is likely to differ conceptually from that in analytical and relatively neutral reviews, e.g., by journalists (Etter et al., 2019) and from company-controlled information (Dineen et al., 2019). Specifically, information about organizations disseminated by social media users differs in terms of a) the *sources* of information, b) the *motives* for providing it, and c) the format and style *constraints* on producing and disseminating it (Etter et al., 2019). We use these three axioms of the NMRF framework to guide our theorizing on the content and valence of TPE images disseminated on employer review websites.

First, we hypothesize first-hand experiences and thus personal content (e.g., "I was offered numerous development opportunities") instead of impersonal content (e.g., "There are numerous opportunities for development") to be of particular importance for the TPE image presented by former and current employees through online reviews. Two reasons concerning the *sources* of information shared via social media can be derived from the NMRF framework to ground this hypothesis. First, employer review websites can be considered systematic, large-scale word-of-mouth media (Mangold & Faulds, 2009) that enable third-parties (current/former employees) to publish their first-hand experiences on a variety of workplace topics. In other words, employer review websites are explicitly dedicated to providing TPE information largely based on personal experiences (Dabirian et al., 2017; Dineen & Allen, 2013; Dineen et al., 2019) rather than serving as outlets for impersonal, report-like employer image information. Current/former employees that post employer reviews might even reason that it makes less sense to include such impersonal, report-like information because it can be found elsewhere in company-controlled employer image communication. Correspondingly, Dineen et al. (2019) considered online employer reviews one of the “personal sources” (p. 193) that provide employer information. Second, unlike official sources or journalists, online reviews are not restricted by professional standards (Etter et al., 2019) that mandate objective, unbiased, factual, and balanced reporting (e.g., Hanitzsch et al., 2011). Thus, online employer reviews should be based on employer information that third parties have readily available to them (i.e., their personal experiences) instead of on additional triangulating information needed to publish more objective reports.

When individuals share their personal experiences rather than objective unbiased information, their linguistic style reflects this choice (Parhankangas & Renko, 2017; Toma & D’Angelo, 2015). More specifically, a focus of attention on oneself when sharing personal experiences manifests in personal content via the increased use of first-person singular pronouns (e.g., “I”, “me”, “my”; see Davis & Brock, 1975; Rude, Gortner, & Pennebaker, 2004). In contrast, a focus of attention on persons and situations separated from oneself manifests in impersonal content via the increased use of third-person and impersonal pronouns (e.g., “it”, “he”, “she”; see Gunsch, Brownlow, Haynes, & Mabe, 2000; Pennebaker, 2011; Perdue, Dovidio, Gurtman, & Tyler, 1990). Thus:

Hypothesis 1. *TPE image valence is dominated by the use of personal (instead of impersonal) content in employer reviews.*

As noted above, employer image attributes can be categorized using the instrumental-symbolic framework (Lievens & Highhouse, 2003). Although both of these attribute categories play a role in the prevailing conceptualization of employer image (Lievens & Slaughter, 2016), we hypothesize symbolic employer image attributes to be of particular importance for the TPE image presented by former and current employees through online reviews. As one reason, the NMRF framework posits that social media allow users to create and express individual, social, and organizational identities by emphasizing characteristics of organizations that are in line with (or contrary to) their own values and beliefs (Marwick & Boyd, 2011; Papacharissi, 2013). In other words, social media users express themselves by selecting what they discuss (or do not discuss; Papacharissi, 2013) to satisfy their inherent *motives* (Berger, 2014; Hollenbaugh, 2010). Critically, unlike instrumental attributes, symbolic attributes are tied to individuals' concern for social identity and self-expression (Highhouse, Thornbury, & Little, 2007). Accordingly, TPE images may especially be dominated by symbolic content (e.g., "This is a caring organization") that allow the reviewers (former/current employees) to self-express (Berger, 2014; Hollenbaugh, 2010). As another reason, using symbolic content in employer reviews anthropomorphizes the organization. In this vein, Ashforth et al. (2020) posit that attributing human qualities to an organization ("the who") is a default schema that organizational members adopt when describing an organization to others because it is "far more poignant and animating" than referring to structural, objective company factors ("the what"; p. 30). Thus:

Hypothesis 2. *TPE image valence is dominated by the use of symbolic (instead of instrumental) content in employer reviews.*

As mentioned, prevailing conceptualizations of employer image focus on cognitive processing (Lievens & Slaughter, 2016). We challenge this aspect in the context of TPE image because we expect emotional (rather than cognitive) content to be of particular importance for the TPE image presented by former and current employees through online reviews. Emotional content refers to the expression of emotions in text via words such as "happy", "cried", and "hurt" (see Bantum & Owen, 2009). This contrasts with cognitive content (i.e., the expression of words that indicate cognitive processing such as actively thinking about a situation, e.g. "think", "because", and "know"; see Barclay & Skarlicki, 2009). Three rationales underlie our expectation of emotional content being especially salient for the TPE image presented. First, company reviews of third-parties such as current or past employees are bound to fewer format and style *constraints* than the image-related content generated by organizational agents (e.g., recruiters). Importantly, Etter et al. (2019) specified that social media messages present more emotionally charged content because they are not bound to the professional standards of press messages. Second, posting reviews of products, services, and by extension companies is typically motivated by strong emotions (Berger, 2014). Hence, these emotions, such as anger, manifest in the content of resulting online reviews (e.g., Toubiana & Zietsma, 2017). Third, emotions influence the way in which "information is gathered, stored, recalled, and used to make particular attributions or judgments" (Nabi, 2003, p. 227). That is, emotionally charged content is more likely than non-emotionally charged content to be shared and disseminated (Berger & Milkman, 2012). As submitters might understand the "power of emotions" and thus anticipate emotionally-charged content to be perceived as more salient and visible, employer reviews might be more emotionally charged. Thus, we propose the following hypothesis:

> ***Hypothesis 3.*** *TPE image valence is dominated by the use of emotional (instead of cognitive) content in employer reviews.*

In sum, drawing on the NMRF framework we posit that the nature of TPE images (exhibited by current/former employees) on employer review websites is dominated by personal (rather than impersonal), symbolic (rather than instrumental) and emotional (rather than cognitive) content. Importantly, TPE images thus challenge the prevailing employer image conceptualization (see Lievens & Slaughter, 2016; see Figure 3-1).

3.1.4 TPE Images and Being Considered as a Favorable Employer by Job-Seekers

A further critical test of our propositions is whether the content and valence of TPE images presented via employer reviews affect a company being considered a favorable employer by job-seekers. Therefore, it is important to know whether the review content characteristics determine not only TPE image valence (i.e., the quantitative overall review rating) but, in turn, are also associated with a company being ranked as a "best employer" (as indicated by best employer surveys among job-seekers; e.g., Universum, 2019c).

There are several reasons why a company's TPE image as reflected in employer reviews might influence the perceptions of company outsiders (e.g., job-seekers) who take note of it. These reasons directly flow from our hypotheses. First, as presented in Hypothesis 1, TPE images presented through employer reviews reveal first-hand experiences with the company as an employer (see Theurer et al., 2018). So, if employer reviews provide distinct knowledge that is observable only first-hand by employees, and not, for example by customers (Bowen & Ostroff, 2004), then the content might be seen as more genuine. Second, in line with Hypothesis 2, the use of symbolic, anthropomorphized content in TPE images might resonate well with job-seekers that read the reviews because anthropomorphizing the organization "provides a frame for predicting the behavior of the organization (i.e., "because the organization is like a person, it should act like a person")" (Ashforth et al., 2020, p. 38-39). This increased predictability of who the organization is, helps to reduce uncertainty and employer knowledge gaps among (prospective) job-seekers. Third, as already mentioned in Hypothesis 3, employer information provided by third parties is more emotionally charged and is therefore likely to exert a more persuasive influence on individuals' attitudes and judgments (see Nabi, 2003). In sum, we conclude that through their link with TPE image valence, employer review content characteristics (i.e., personal/impersonal, symbolic/instrumental, and emotional/cognitive content) influence whether companies are seen as favorable employers by job-seekers, i.e., companies being ranked as a "best employer". Thus:

Hypothesis 4. *There is an indirect (through TPE image valence) relationship between content characteristics (personal/impersonal, symbolic/instrumental, and emotional/cognitive content) and being ranked as "best employer" by job-seekers.*

3.1.5 TPE Images' Consensus

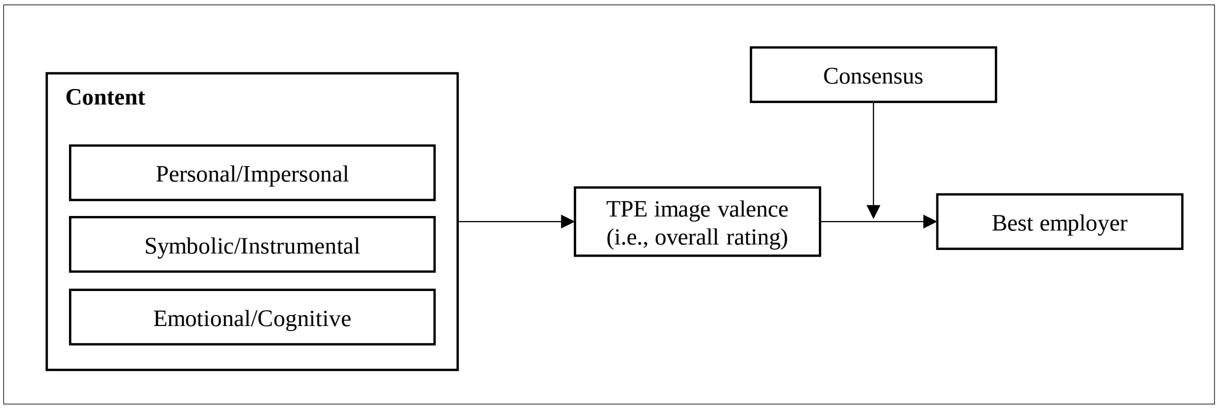
Finally, one crucial element for the impact of the TPE images on employer rankings is whether the TPE images produced and shared by third parties are in consensus. In the employer review context, consensus relates to whether multiple reviews present a similar positive (or negative) TPE image of the employer. Consensus permits the uniform interpretation of messages and increases the credibility of individual messages because it allows triangulation with other messages (Dineen et al., 2019). In product reviews, for example, higher consensus increased the influence of reviews on purchasing decisions (Yao, Fang, Dineen, & Yao, 2009). Likewise, experimental employer review research found that higher consensus among employer reviews can increase job pursuit intentions (Könsgen et al., 2018). Accordingly, we expect an employer's TPE image on employer websites to have a stronger impact on whether a company is being ranked as a "best employer" if the TPE image is consistent (i.e., employer reviews are in agreement concerning TPE image valence). Thus:

Hypothesis 5. *Consensus moderates the relationship between TPE image valence and being ranked as a "best employer", such that the relationship is stronger when consensus is relatively high.*

In summary, our research model is shown in Figure 3-2. We do not make claims about causality, because job-seekers in a best employer survey may also factor in many other cues to decide whether a company is a "best employer". Nonetheless, our model provides a strong test of our hypotheses because it links descriptive (content characteristics) and evaluative information on a TPE website such as Kununu (provided by former and current employees) to an external best employer survey (completed by company outsiders, namely job-seekers).

Figure 3-2

Research model



3.2 Method

3.2.1 Research Context

To test our hypotheses, we analyzed approximately half a million employer reviews published between May 2007 and June 2018 on Kununu, the largest European employer review website. Since its launch in 2007, Kununu invites current and former employees to anonymously submit reviews about their employer. The reviews include both open text comments and quantitative ratings which are summarized in an average overall rating (from 1.00 to 5.00 stars). Text comments may comprise various aspects of the employer, such as company culture, work-life balance, and work environment, as well as comments on the perceived pros, cons, and opportunities for improvement.

Kununu is committed to ensuring the authenticity of posted reviews. Hence, users must register with a valid email address and agree to comply with Kununu's review guidelines; for example, no personal information may be published (Kununu, 2019a). Kununu monitors adherence to these guidelines through technical security measures and a community management team. In general, no reviews are deleted or changed as long as they comply with the review guidelines (Kununu, 2019b). Kununu is also certified by an independent auditing institute for its protection of user data and anonymity (TÜV Saarland, 2019).

3.2.2 Data

Our sample comprised 623,555 online employer reviews submitted by current and former employees of German-based employers between May 2007 and June 2018. In detail, our sample included all online reviews of German employers that had received at least two reviews by July 2018. We excluded Austrian, Swiss, US-American and other employers to ensure the homogeneity of the review texts (e.g., regarding dialects or country-specific terminology). We conducted review-level analyses using only employer reviews that (a) included text comments (430,365 of 623,555) and (b) did not consist solely of, for example, single characters or erroneous terms (429,219 of 430,365), because no word could be matched to the DE-LIWC2015 dictionary (Meier et al., 2018; see below). In summary, we conducted review-level analyses with 429,219 reviews of 21,414 German employers posted over 45 quarters. Furthermore, we conducted employer-level analyses with 12,951 German employers in 43 industries. For this purpose, we calculated the averages of our review-level measures at the employer level and added three further employer-level measures (see below). For the employer-level analyses, we used all reviews for employers that had received at least ten reviews by July 2018 (564,478 of 623,555).[7]

3.2.3 Review-Level Measures

CATA allows us to identify the (co-)occurrence of content characteristics in our extensive dataset of online employer reviews. More specifically, we measure the extent of personal/impersonal, symbolic/instrumental, and emotional/cognitive content in online employer reviews through Linguistic Inquiry and Word Count (LIWC) software. LIWC

[7] While our analyses at the review-level used only reviews with (meaningful) text to reduce the noise in the data (429,219), we ran our analyses at the employer-level using all the reviews in our data set (623,555). This is because potential employees may consider all employer reviews of the employer when deciding whether a company is a “best employer”. As a result, even reviews that have no text and that therefore display a 0% prevalence of content characteristics might shape an employer’s aggregate presence on a review website. The only restriction made was that we included only employers with at least ten reviews to ensure robustness.

estimates the presence (i.e., percentage) of grammatical and psychological categories in text by matching the words with predefined content dictionaries (Pennebaker et al., 2015, 2003; Tausczik & Pennebaker, 2010). Categories (i.e., lists of words) measured with content dictionaries are built on the basis of the assumption that their underlying artifacts share the same meaning. In this vein, LIWC includes an empirically validated dictionary to measure individuals' beliefs, fears, thought patterns, social relationships, and personalities (Pennebaker et al., 2015).

In our study, we utilized the most recent German adaptation of the LIWC dictionary (DE-LIWC2015), which contains 18,711 words, word stems, and emoticons in 80 categories (Meier et al., 2018). Furthermore, as elaborated below, we developed and utilized a custom dictionary, which holds 938 words, and word stems in 17 categories, as a supplement to LIWC. We assessed the following categories to capture the content of employer reviews:

Personal/Impersonal content. We measured the presence of personal/impersonal content in online employer reviews using DE-LIWC2015's capability to measure the extent of personal and impersonal pronouns in text. Thus, we measured whether employees wrote their reviews in a personal style on the basis of the extent of their use of first-person singular pronouns (e.g., "I", "me", "my"; DE-LIWC2015's "1st person singular" category). Furthermore, we measured whether employees wrote their reviews in an impersonal style on the basis of the extent of using third-person singular and plural pronouns (e.g., "she", "him", "they"; DE-LIWC2015's "3rd person" category) as well as impersonal pronouns (e.g., "it", "it's", "those"; DE-LIWC2015's "Impersonal pronouns" category). As DE-LIWC2015 offers no predefined category that measures the extent of third-person singular/plural pronouns and impersonal pronouns simultaneously, we created a new category combining separate DE-LIWC2015 categories without duplicates (only two words occurred in both categories: "dessen" [whose] and "einem" [an]).

Symbolic/Instrumental content. We measured the presence of symbolic/instrumental employer image attributes in online employer reviews by developing a novel dictionary that can be used alongside LIWC. We followed the recommendations of Short et al. (2010) in constructing our dictionary to capture symbolic and instrumental employer image attributes in online employer reviews. To establish content validity (i.e., the extent to which a measure captures all features of a particular construct; Nunnally & Bernstein, 1994), we constructed our dictionary via a combined approach. More specifically, we created our dictionary first deductively on the basis of theory, and then inductively on the basis of the online reviews in our dataset; finally we merged the two results.

For the deductive step, starting from Keller's (1993) and Aaker's (1997) brand attributes and Lievens and Highhouse's (2003) adaptation to the employer image literature, we collected 21 studies that identified one or several employer brand attributes in the context of the instrumental-symbolic framework or a comparable framework. We collected these studies until saturation was reached (until adding attributes mentioned within these studies no longer provided novel attributes). We coded the attributes retrieved into seven symbolic attributes (i.e., LIWC sub-categories), namely competence, corporate social responsibility, innovativeness, prestige, ruggedness, sincerity, and sophistication, and 10 instrumental attributes, namely benefits, challenging work, compensation, development & career opportunities, flexible working hours, job security, leader behavior, location, organizational & team climate, and travel opportunities. We refer to Table 3-1 for an overview of the resulting 17 attributes, their definitions, an example from Kununu, and the attributes in the literature that were considered in coding the attributes. On the basis of the definitions, we created an initial word list for each attribute using relevant keywords from collected studies. We translated these keywords forward and backward from English to German. If no or only a few keywords could be found for an attribute, we created initial word lists based solely on the

Table 3-1

Definitions, example reviews, and related attributes in literature for the employer image attributes in the LIWC dictionary

Employer image attribute	Definition	Example review	Related attributes in literature
Symbolic attributes			
Competence	It is discussed whether the employer is perceived as capable, experienced, and reliable.	“Reliable. Trustworthy. Confident. Fast-paced & authentic.” (40%)	Competence (Aaker, 1997; Davies, Chun, da Silva, & Roper, 2004; Lievens, 2007; Lievens & Highhouse, 2003; Lievens, Van Hoye, & Schreurs, 2005; Van Hoye et al., 2012), prestige (Otto, Chater, & Stott, 2011), style/thrift (Slaughter et al., 2004)
Corporate social responsibility	It is discussed whether the employer is perceived as a good corporate citizen e.g., the social community and natural environment benefit from its actions.	“regional commitment; social and community engagement; social employer” (62.50%)	Application (Berthon, Ewing, & Hah, 2005), trustworthiness (Kausel & Slaughter, 2011; Slaughter et al., 2004), community relations/environment (K. B. Backhaus, Stone, & Heiner, 2002), corporate social responsibility (Biswas & Suar, 2016), employer information (Cable & Turban, 2001), honesty (Otto et al., 2011), stakeholder benefits (Ambler & Barrow, 1996; Dowling, 1994)
Innovativeness	It is discussed whether the employer is perceived as young, exciting, and up-to-date.	“modern, young and innovative company.” (60%)	Enterprise (Davies et al., 2004), excitement (Aaker, 1997; Lievens, 2007; Lievens et al., 2005), innovation (Otto et al., 2011), innovativeness (Kausel & Slaughter, 2011; Lievens & Highhouse, 2003; Slaughter et al., 2004; Van Hoye et al., 2012), interest (Berthon et al., 2005)
Prestige	It is discussed whether the employer is perceived as reputable, e.g., whether employees working for the employer enjoy social approval.	“Market leader, well-known and serious.” (50%)	Company reputation (Collins & Stevens, 2002), development value (Berthon et al., 2005), dominance (Kausel & Slaughter, 2011), prestige (Biswas & Suar, 2016; Lievens, 2007; Lievens & Highhouse, 2003; Lievens et al., 2005; Otto et al., 2011; Van Hoye et al., 2012), prestige/reputation (Uggerslev, Fassina, & Kraichy, 2012), respectability (Highhouse, Zickar, Thorsteinson, Stierwalt, & Slaughter, 1999), stakeholder benefits (Ambler & Barrow, 1996; Dowling, 1994), style/thrift (Slaughter et al., 2004)
Ruggedness	It is discussed whether the employer is perceived as tough, strong, and dominant.	“Powerful brand - Powerful people - Powerful products” (50%)	Dominance (Slaughter et al., 2004), machismo (Davies et al., 2004), power (Otto et al., 2011), ruggedness (Aaker, 1997; Lievens, 2007; Lievens et al., 2005), ruthlessness (Davies et al., 2004)

Table 3-1 (continued)

Sincerity	It is discussed whether the employer is perceived as trustworthy, down-to-earth, and kind.	"Serious, reliable, kind, helpful" (75%)	Agreeableness (Davies et al., 2004), trustworthiness (Kausel & Slaughter, 2011; Slaughter et al., 2004), cheerfulness (Lievens, 2007; Lievens et al., 2005), honesty (Otto et al., 2011), sincerity (Aaker, 1997; Lievens & Highhouse, 2003; Lievens et al., 2007, 2005; Van Hoye et al., 2012)
Sophistication	It is discussed whether the employer is perceived as chic, glamorous, and exclusive.	"chic premises - good working conditions, calm working atmosphere due to transparent structures, everyone knows their fields and duties" (6.67%)	Chic (Davies et al., 2004), prestige (Lievens & Highhouse, 2003; Otto et al., 2011), sophistication (Aaker, 1997), style/thrift (Slaughter et al., 2004)
Instrumental attributes			
Benefits	Benefits that are not directly related to the amount of work accomplished, such as insurance, pension plans, and amenities like free coffee are discussed.	"free parking, great subsidized canteen, nice working atmosphere" (57.14%)	Benefits (Collins & Stevens, 2002; Lievens & Highhouse, 2003; Uggerslev et al., 2012), pay and benefits (Lievens, 2007; Lievens et al., 2005)
Challenging work	It is discussed whether the tasks are interesting, varied, in line with the employee's skills, and therefore rewarding.	"Challenging tasks, great responsibility, exciting projects" (83.33%)	Autonomy/challenge (Uggerslev et al., 2012), challenging and interesting work (Cable & Judge, 1996; Cable & Turban, 2003; Turban, Forret, & Hendrickson, 1998), interesting work (Collins & Stevens, 2002), job information (Cable & Turban, 2001), task demands (Highhouse et al., 1999; Lievens & Highhouse, 2003; Van Hoye et al., 2012), task diversity (Lievens, 2007; Lievens et al., 2005), work variety (Highhouse et al., 1999)

Table 3-1 (continued)

Compensation	Benefits that directly correspond to the number of accomplished working hours or work results (salary, commission), as well as allowances and bonuses, are discussed	"The financial compensation is below average." (60%)	Compensation/pay/salary (Uggerslev et al., 2012), economic (Berthon et al., 2005), equity in reward administration (Biswas & Suar, 2016), excellent prospects for high future earnings (Cable & Judge, 1996; Cable & Turban, 2003; Turban et al., 1998), job information (Cable & Turban, 2001), pay (Highhouse et al., 1999; Lievens & Highhouse, 2003), pay and benefits (Lievens, 2007; Lievens et al., 2005), pay/security (Van Hoye et al., 2012), salary/wage (Collins & Stevens, 2002)
Development & career opportunities	Training, opportunities for career progression, and space for personal growth are discussed.	"Frequent trainings, advanced trainings and seminars" (60%)	Advancement (Highhouse et al., 1999; Lievens, 2007; Lievens & Highhouse, 2003; Lievens et al., 2005; Van Hoye et al., 2012), advancement opportunities (Collins & Stevens, 2002), advancement/promotions (Uggerslev et al., 2012), availability of excellent training program (Collins & Stevens, 2002), development (Berthon et al., 2005; Uggerslev et al., 2012), economic (Berthon et al., 2005), educational opportunities (Lievens, 2007; Lievens et al., 2005), job information (Cable & Turban, 2001), opportunity for advancement/new learning experiences (Cable & Judge, 1996; Cable & Turban, 2003; Turban et al., 1998), opportunity to learn new skills (Collins & Stevens, 2002)
Flexible working hours	It is discussed whether working hours can be organized autonomously, including possibilities to work from home (home office).	"Home office, flexible arrangement of working hours, part-time work," (83.33%)	Work hours (Highhouse et al., 1999), flexible working hours (Lievens & Highhouse, 2003), flextime/work-life balance (Uggerslev et al., 2012), working conditions (Van Hoye et al., 2012)
Job security	Job security is discussed with regard to whether the employment relationship reliably lasts at least the agreed time and cannot be easily terminated by the employer.	"Secure job and secure salary" (60%)	Economic (Berthon et al., 2005), job security (Collins & Stevens, 2002; Lievens, 2007; Lievens et al., 2005; Uggerslev et al., 2012)

Table 3-1 (continued)

Leader behavior	Managers and supervisors are discussed, e.g., whether they treat their subordinates with respect and empathy, whether they convey the company's vision and whether they are perceived as trustworthy and supportive.	"Appreciative supervisors, fair goal agreements" (75%)	Leadership of top management (Biswas & Suar, 2016), supervisor/management (Uggerslev et al., 2012)
Location	The geographical location of the workplace is discussed, e.g., whether it is convenient and easily accessible.	"Very interesting tasks. Accessible via public transport." (42.86%)	Employer information (Cable & Turban, 2001), location (Collins & Stevens, 2002; Highhouse et al., 1999; Lievens & Highhouse, 2003; Uggerslev et al., 2012)
Organizational & team climate	The working environment is discussed, e.g., whether it is collaborative, whether it offers a beneficial group dynamic between colleagues, and whether social and team-building activities are offered.	"Nice colleagues, pleasant working atmosphere, open communication, good relations" (88.89%)	Employee relations (K. B. Backhaus et al., 2002), social (Berthon et al., 2005), people information (Cable & Turban, 2001), high employee morale (Cable & Judge, 1996; Cable & Turban, 2003; Turban et al., 1998), good corporate culture (Collins & Stevens, 2002), coworkers (Highhouse et al., 1999; Uggerslev et al., 2012), social/team activities (Lievens, 2007; Lievens et al., 2005), employee relations/treatment/teamwork/social activities (Uggerslev et al., 2012)
Travel opportunities	Possibilities for working abroad or for traveling are discussed.	"Team cohesion, working atmosphere, international work, travel activities" (40%)	Travel opportunities (Lievens, 2007; Lievens et al., 2005), travel (Uggerslev et al., 2012)

Notes: Review examples were drawn from the Kununu dataset and translated from German to English using DeepL (https://www.deepl.com/). The percentage of words that fit the corresponding attribute in the German comment is noted in the brackets.

definition of the attribute. To capture each attribute sufficiently with its associated words, we extended the initial list of keywords with synonyms and collocations by using several synonym finders (e.g., https://www.openthesaurus.de). The word lists resulting from the deductive step were subsequently validated by three raters (the first author and two student researchers) who rated the fit of each word with its supposed attribute on a scale of one to five (one indicated a very good fit (e.g., synonym) and five a very poor fit) after a brief introduction of each attribute based on its definition. The rating process resulted in an average interrater reliability of 71.27% between the three raters (Holsti, 1969). Words with an average rating below 2.5 were removed from the word list of that attribute.

For the inductive step, we drew the 2,000 most commonly used words from our sample, removed stop words such as pronouns and articles using the programming language Python, and manually revised the remaining words to remove, for example, duplicates that occurred in both singular and plural forms. Accordingly, 729 words remained and were subsequently assigned to either none, one or multiple of the previously identified 17 attributes by three raters (the first author and two student researchers) after a brief introduction of each attribute on the basis of its definition and Kununu examples. The rating process resulted in an average interrater reliability of 75.45% between the three raters (Holsti, 1969). Word assignments for which the raters did not agree during the rating process were subsequently discussed and assigned if consensus was reached and not assigned otherwise. All words that could not be assigned to any attribute were then reviewed to determine whether they could be used to construct a new attribute. However, no new attribute was identified. In addition, all words that fell into more than three attributes were removed to ensure and improve dimensionality (e.g., “aktivitäten” [activities]).

Ultimately, we merged the deductive and inductive lists and deleted duplicates. To avoid redundancy, we further built word stems by replacing suffixes of words from the same word family with an asterisk, but only if their meaning remained the same when suffixes were added again. LIWC can then capture any word that matches the word stem (e.g., hungr* matches hungry, hungrier, hungriest; Pennebaker et al., 2015). The final word (stem) list for each attribute was then rated by two raters (the first author and one associated researcher in the human resource management field who had never seen the dictionary before) after a brief introduction of each attribute on the basis of its definition. The rating process resulted in an interrater reliability of 86.62% between the two raters (Holsti, 1969). The individual interrater reliability for each attribute ranged from 75.56% to 100.00%. All words that the raters did not initially agree on were briefly discussed and eventually removed from the dictionary. This process was also guided by examining reviews that had the highest presence of words and word stems associated with each of the individual attributes in our dictionary (we examined the top 30 reviews per attribute, thus 510 reviews in total). We discovered that three words belonging to the sophistication attribute were not used as expected and did not reflect the attribute's definition, thus leading to a majority of false positives in these reviews. So, we removed these words ("erstklassig" (first-class), "exzellent" (excellent), and "klasse" (class)). The final dictionary consisted of 938 words and word stems in 17 categories.

In sum, following an approach similar to how sub-categories and main-categories are defined in LIWC's default dictionary (Pennebaker et al., 2015), we developed a new directory that created a symbolic (instrumental) content variable containing all words and word stems in each individual symbolic (instrumental) attribute's word list (without duplicates). We refer to Table 3-2 for example words of each category and the number of words and word stems.

Emotional/Cognitive content. We measured the presence of emotional/cognitive content in online employer reviews using DE-LIWC2015's "affective processes" and "cognitive processes" categories. Words in the affective processes category included "happy",

Table 3-2

Categories and sub-categories in the employer image attributes dictionary

Employer image attribute	Example words (in German)	#words
Instrumental attributes	elterngeld, arbeitsabläufe, branchendurchschnitt*	628
Benefits	elterngeld, altersvorsorge, kostenlos*	79
Challenging work	arbeitsabläufe, aufgabenspektrum, eigeninitiative	76
Compensation	branchendurchschnitt*, einkommen, entlohnung	59
Development & career opportunities	aufstiegschancen, berufsbegleitend*, fortbildung*	62
Flexible working hours	arbeitszeit*, familienfreundlich*, homeoffice	73
Job security	abgebaut, befrist*, fristlos*	57
Leader behavior	feedbackgespräche, honoriert*, personalführung	77
Location	bahnhof*, parkplätze, lage	49
Organizational & team climate	kameradschaft*, mitarbeiterbeziehung*, arbeitsumfeld	95
Travel opportunities	betriebsreise*, flug*, reise*	20
Symbolic attributes	erfahr*, ethi*, kreatives	328
Competence	erfahr*, kompeten*, konsistent*	56
Corporate social responsibility	ethi*, geimeinnütz*, nachhaltig*	54
Innovativeness	kreatives, zukunft*, innov*	53
Prestige	berühmt*, geschätzt*, populär*	35
Ruggedness	domin*, rücksichtslos*, taff*	36
Sincerity	angenehm*, aufrichtig*, authentisch*	71
Sophistication	elegan*, exklusiv*, gehoben*	35

Notes: "#words" refers to the number of different words and word stems that make up the dictionary category. Words may occur in more than one category

"nice", and "hate", and thus represented the degree to which employees expressed both positive and negative emotions through their employer reviews. Words in the cognitive processes category included "cause", "think", and "know", and thus represented the depth and complexity of thinking when employees evaluated their employers through their reviews.

TPE image valence. We measured whether a more positive or negative TPE image was presented with an employer review (i.e., the TPE image's valence) using the review's overall rating. An employer review's overall rating, commonly expressed on a five-point scale, represents its key quantitative feature. For example, Glassdoor awards its "Best Places to Work Awards" based on companies' average overall rating (Glassdoor, 2019). Kununu's employer reviews prominently display an overall star rating (from 1.0 to 5.0 stars). Kununu's overall rating is calculated as the average of star ratings (from 1.0 to 5.0 stars) across 13 dimensions of the employer (including corporate culture, management support, teamwork);

the internal consistency (Cronbach's α) of these dimension ratings was .97. Employer reviews with an overall rating of one star (as opposed to an overall rating of five stars) reflect a very negative (as opposed to a very positive) TPE image.

3.2.4 Employer-Level Measures

Best employer. We aggregated our review dataset at the employer level and matched it with Universum's best employer survey 2019 in Germany (Universum, 2019c) to measure whether an employer is ranked as a "best employer". Given that organizational outsiders, namely job-seekers instead of employees complete this survey, reliance on this "best employer" ranking provides a strong test of our hypotheses. Once a year, Universum surveys students in Germany and over 50 other countries and, among other questions, asks them to select up to five companies they would most like to work for. Students can select companies from a predefined list but may also enter companies in a free-text form. The absolute number of entries then results in a ranking of the best employers per field of study. The survey for the 2019 ranking was carried out between October 2018 and April 2019 (Universum, 2019c). Therefore, it did not overlap with the period in which we extracted employer review information from Kununu. Universum surveyed 46,904 students and published the best employers in seven fields, ranking 75 to 100 employers per field: business, engineering, IT, natural science, humanities/social sciences/education, law, and health/medicine (Universum, 2019c). In total, 321 unique employers were ranked as best employers because several were ranked in more than one field. Of these, we were able to match 281 employers to our employer review dataset. The resulting variable was dummy coded 1 for an employer ranked as a "best employer", and 0 otherwise.

Consensus. Consensus refers to "agreement across message senders (either within or across sources)" (Dineen et al., 2019, p. 189). We measured consensus on TPE image valence of an employer represented by the employer reviews using the standard deviation of the employer's overall rating (as a within-group dispersion measure; see Roberson, Sturman, & Simons, 2007). A high standard deviation indicates a TPE image valence with low consensus.

Number of reviews. We recorded the number of reviews per employer when we aggregated our review dataset at the employer level. The number of reviews is a count variable and serves both as a potential confounder, since the number of reviews of an employer may influence how potential employees perceive this employer, and as a proxy for the size of an employer (larger employers, with more employees, may receive more reviews). We log-transformed the number of reviews before modeling.

3.2.5 Review-Level Analyses

Our review-level analysis sought to better understand the underlying features of TPE images through scrutinizing online employer reviews. More specifically, we aimed at assessing the relative importance of content characteristics (i.e., personal/impersonal, symbolic/instrumental, and emotional/cognitive) for the nature of the TPE image exhibited by current and former employees through their reviews. First, given the nested nature of our dataset, we applied hierarchical linear modeling (HLM; see, e.g., Hofmann et al., 2000; Raudenbush & Bryk, 2002) to model the influence of personal/impersonal, symbolic/instrumental, and emotional/cognitive content on TPE image valence. Second, we applied the dominance analysis (e.g., Luo & Azen, 2013) method to determine the importance of the predictors in the identified model.

HLM. The data in our study were nested. Ignoring this nested structure when regressing content characteristics on TPE image valence may result in biased estimates of the standard errors of the regression coefficients (e.g., Moerbeek, 2004). Therefore, we fitted a cross-classified random-effects model in which employer reviews that comprised content characteristics and ratings (Level 1) were nested within employers and quarters at the same time (Level 2), whereas employers and quarters were not nested within but crossed with each other. To estimate the effects on TPE image valence, we used full maximum likelihood estimation. This also allowed us to conduct deviance tests to assess improvements in model fit due to the addition of predictors (Raudenbush & Bryk, 2002). In detail, we modeled our dependent variable via the following equation:

$$
\begin{aligned}
&TPE\ image\ valence_{ijk} \\
&\qquad = \gamma_0 + \beta_1 Personal\ content_{ijk} + \beta_2 Impersonal\ content_{ijk} \\
&\qquad + \beta_3 Symbolic\ content_{ijk} + \beta_4 Instrumental\ content_{ijk} \\
&\qquad + \beta_5 Emotional\ content_{ijk} + \beta_6 Cognitive\ content_{ijk} + u_{0j} + v_{0k} + e_{ijk}
\end{aligned}
\tag{1}
$$

Index *i* denotes reviews, *j* denotes employers, and *k* denotes quarters. Thus, review *i*'s rating is modeled as a function of personal/impersonal, symbolic/instrumental, and emotional/cognitive content within each employer *j* and quarter *k*. γ_0 is the general intercept, u_{0j} is the random effect of employer *j*, v_{0k} is the random effect of quarter *k*, and e_{ijk} is the random error. We are interested in $\beta_{1 \ldots 6}$, the Level 1 fixed effects, as they represent the impact of review content characteristics on TPE image valence.

Dominance analysis. Building upon the estimation of the effects of our predictors, we sought to compare the relative importance of each predictor to test our hypotheses. Dominance analysis is one of the methods most frequently applied in the organizational sciences for determining the relative importance of predictors (Braun et al., 2019). To determine which predictor contributes a larger proportion, we compared the predictors' contributions to the explained variance of every possible subset model (which comprises subsets of the predictors). Dominance analysis permits the investigation of three levels of dominance: complete, conditional, and general. The strictest form of dominance (i.e., complete dominance) implies that the additional contribution of one predictor (e.g., personal, symbolic, and emotional content) to the explained variance of every possible subset model is greater than that of another predictor (e.g., impersonal, instrumental, and cognitive content).

We measured the explanatory power of our models and thus of our predictors using the approach proposed by Snijders and Bosker (1994). Snijders and Bosker's (1994) approach determines a two-level HLM model's Level 1 variance (R_1^2) as the proportional reduction of the error in predicting Level 1 outcomes.

3.2.6 Employer-Level Analyses

Our employer-level analyses sought to assess the indirect (through TPE image valence) relationship between content characteristics (i.e., personal/impersonal, symbolic/instrumental, and emotional/cognitive content) and an employer being ranked as a "best employer" (see Hypothesis 4). Therefore, we employed a mediation analysis under the counterfactual framework (Imai, Keele, & Tingley, 2010; Imai, Keele, & Yamamoto, 2010). Following the counterfactual perspective, we considered the change in our dependent variable, an employer's probability of being ranked as a "best employer", that would occur if the mediator, an employer's TPE image valence (i.e., a company's overall rating on Kununu), while maintaining treatment status, could be changed from the value it would take under the control condition (0% prevalence of a content characteristic) to the value it would take under the treatment condition (10% prevalence of a content characteristic). This change is our value of interest. It represents the indirect effect of the intervention (0% prevalence of a content characteristics vs. 10% prevalence of a content characteristic) on the outcome (being ranked as a "best employer") exerted through the mediator (TPE image valence). Furthermore, the mediation analysis under the counterfactual framework also allowed us to estimate a direct effect (i.e., the remaining effect of the intervention on the outcome that is not exerted through the mediator) and a total effect (i.e., the sum of the indirect and direct effects).

To estimate the indirect, direct, and total effects, we fitted two random-effects models where employers (Level 1) were nested within industries (Level 2).[8] First, we modeled our outcome variable, being ranked as a "best employer", in a logistic regression model. Second, we modeled our mediator variable, TPE image valence, in a linear regression model. Finally, we estimated the indirect, direct, and total effects through 2000 bootstrapped quasi-Bayesian Monte Carlo simulations (see Imai, Keele, & Tingley, 2010). In detail, we modeled our outcome variable via the following equation:

$$\begin{aligned} &Best\ employer_{jl} \\ &\quad = \gamma_0 + \beta_1 Personal\ content_{jl} + \beta_2 Impersonal\ content_{jl} \\ &\quad + \beta_3 Symbolic\ content_{jl} + \beta_4 Instrumental\ content_{jl} \\ &\quad + \beta_5 Emotional\ content_{jl} + \beta_6 Cognitive\ content_{jl} \\ &\quad + \beta_7 TPE\ image\ valence_{jl} + \beta_8 log(Number\ of\ reviews)_{jl} + u_{0l} + e_{jl} \end{aligned} \tag{2}$$

Moreover, we modeled our mediator variable via the following equation:

$$\begin{aligned} &TPE\ image\ valence_{jl} \\ &\quad = \gamma_0 + \beta_1 Personal\ content_{jl} + \beta_2 Impersonal\ content_{jl} \\ &\quad + \beta_3 Symbolic\ content_{jl} + \beta_4 Instrumental\ content_{jl} \\ &\quad + \beta_5 Emotional\ content_{jl} + \beta_6 Cognitive\ content_{jl} \\ &\quad + \beta_7 log(Number\ of\ reviews)_{jl} + u_{0l} + e_{jl} \end{aligned} \tag{3}$$

The index *j* denotes employers, and *l* denotes industries. γ_0 is the general intercept, u_{0l} is the random effect of industry *l*, and e_{jl} is the random error.

We further aimed at assessing whether the relationship between a company's TPE image and the company being ranked as a "best employer" is moderated by the consensus of

[8] Nesting employers within industries (i.e., estimating a more complex three-level HLM) does not affect the results of our review-level analyses. The results are available upon request.

the company's TPE image. Our variables of TPE image valence (i.e., a company's overall rating on Kununu) and consensus (i.e., the standard deviation of a company's overall rating on Kununu) were statistically interdependent (r = -.539, p < .001; see Table 3-4). So, their joint effects on our outcome variable, being ranked as a "best employer", do not necessarily take the form of a simple linear relation but may result from one or both variables having a nonlinear relationship with our outcome variable (see Lindell & Brandt, 2000). To account for variable interdependence, we added squared terms of TPE image valence and consensus to our models (see Cole, Bedeian, Hirschfeld, & Vogel, 2011). In detail, we modeled our outcome variable using the following equation:

$$\begin{aligned} Best\ employer_{jl} &= \gamma_0 + \beta_1 TPE\ image\ valence_{jl} + \beta_2 Consensus_{jl} \\ &+ \beta_3 (TPE\ image\ valence)^2_{jl} + \beta_4 (Consensus)^2_{jl} \\ &+ \beta_5 (TPE\ image\ valence_{jl} * Consensus_{jl}) \\ &+ \beta_6 log(Number\ of\ reviews)_{jl} + u_{0l} + e_{jl} \end{aligned} \tag{4}$$

The index *j* denotes employers, and *l* denotes industries. γ_0 is the general intercept, u_{0l} is the random effect of industry *l, and* e_{jl} is the random error.

3.3 Results

3.3.1 Descriptive Statistics

Means, standard deviations, and correlations among all review-level variables are presented in Table 3-3, whereas means, standard deviations, and correlations among all employer-level variables are presented in Table 3-4. As shown in Table 3-3, employer reviews in our dataset incorporated on average less personal content (0.96%) than impersonal content (5.88%), less symbolic content (4.59%) than instrumental content (16.35%), and less emotional content (10.35%) than cognitive content (19.13%).

Table 3-3

Means, standard deviations, and correlations among review-level variables

		M	*SD*	1	2	3	4	5	6
1	Personal content	0.96	2.52						
2	Impersonal content	5.88	6.29	0.019***					
3	Symbolic content	4.59	6.91	-0.079***	-0.171***				
4	Instrumental content	16.35	14.71	-0.157***	-0.295***	0.301***			
5	Emotional content	10.35	9.09	-0.045***	-0.157***	0.206***	0.333***		
6	Cognitive content	19.13	10.45	0.053***	0.263***	0.008***	-0.172***	-0.023***	
7	TPE image valence (i.e., overall rating)	3.46	1.23	0.117***	-0.110***	0.212***	0.194***	0.166***	-0.070***

Notes: N = 429,219 reviews of 21,414 employers over 45 quarters. All variables represent percentages (0.00 – 100.00), except for TPE image valence which is rated on a 5-point scale.
*$p < .05$; **$p < .01$; ***$p < .001$

3.3.2 Dominance Analysis

Hypotheses 1-3 propose that personal, symbolic, and emotional content will play a dominant role in determining the TPE image presented in employer reviews. Therefore, as the first step, we fitted a cross-classified random-effects model with personal/impersonal, symbolic/instrumental, and emotional/cognitive content as predictors and with overall rating, as a measure of the TPE image valence (from positive to negative) presented by an employer review, as the outcome variable. Our model decreased the deviance by 36394.40 compared to a null model (i.e., a model without any predictors), indicating a better fit than that of the null model ($p < .001$). As shown in Table 3-5, personal content (0.068, $p < .001$) was positively associated with TPE image valence, whereas impersonal content (-0.003, $p < .001$) was negatively associated with TPE image valence. In terms of the magnitude of the effect, employer reviews that featured 10% personal content were rated 0.68 stars higher than reviews that featured 0% personal content. 0.68 stars represents 19.65% of the average TPE image valence of all employer reviews in our sample (M = 3.46). Furthermore, symbolic (0.023, $p < .001$) and instrumental content (0.009, $p < .001$) were also positively associated with TPE image valence. Employer reviews that featured 10% symbolic content were rated

Table 3-4

Means, standard deviations, and correlations among employer-level variables

		M	*SD*	1	2	3	4	5	6	7	8	9
1	Personal content	0.65	0.62									
2	Impersonal content	4.11	1.64	0.269***								
3	Symbolic content	3.27	1.66	0.047***	-0.027***							
4	Instrumental content	11.35	3.89	-0.044***	-0.038***	0.501***						
5	Emotional content	7.17	2.26	0.171***	0.218***	0.455***	0.582***					
6	Cognitive content	13.34	3.51	0.289***	0.632***	0.206***	0.206***	0.440***				
7	TPE image valence	3.45	0.67	0.109***	-0.196***	0.436***	0.328***	0.236***	-0.103***			
8	Best employer	0.02	0.14	-0.030***	-0.062***	-0.029***	0.001	-0.023***	-0.055***	0.021***		
9	Consensus	1.05	0.30	0.057***	0.194***	-0.232***	-0.211***	-0.063***	0.146***	-0.539***	-0.009	
10	Number of reviews	43.59	93.74	0.011	-0.036***	-0.038***	-0.021***	-0.030***	-0.045***	0.023***	0.417***	0.024***

Notes: N = 12,951 employers in 41 industries.
*p < .05; **p < .01; ***p < .001

0.23 stars higher than reviews that featured 0% symbolic content, representing 6.65% of the average TPE image valence. Finally, while emotional content (0.011, $p < .001$) was positively associated with TPE image valence, cognitive content (-0.005, $p < .001$) was negatively associated with it. Employer reviews that featured 10% emotional content were rated 0.11 stars higher than reviews featuring 0% emotional content, representing 3.18% of the average TPE image valence.

After fitting the model, as the second step, we conducted a dominance analysis to compare the relative importance of the model's Level 1 predictors (i.e., review content characteristics) in explaining the variance in its Level 1 outcome variable (i.e., TPE image valence). Our results show that an additional 9.90% of the total Level 1 variance (R_1^2) in reviews' ratings (compared to the null model) can be explained through the content characteristics measured with LIWC, namely personal/impersonal, symbolic/instrumental, and emotional/cognitive content (see Table 3-6).

Table 3-5

HLM of content characteristics on TPE image valence

	TPE image valence		
Predictor	Estimate	*SE*	*t*
	Regression coefficients (fixed part)		
(Intercept)	2.948	0.0328	89.76***
Personal content	0.068	0.0007	102.57***
Impersonal content	-0.003	0.0003	-11.76***
Symbolic content	0.023	0.0003	90.01***
Instrumental content	0.009	0.0001	67.42***
Emotional content	0.011	0.0002	59.98***
Cognitive content	-0.005	0.0002	-30.71***
	Variance components (random part)		
Employer	0.342	0.5850	
Quarter	0.045	0.2123	
Residual	1.077	1.0378	
	Model summary		
Deviance (-2LL)	1283612.10		
Decrease in deviance, *df* (6)	36394.40***		

Notes: N = 429,219 reviews of 21,414 employers over 45 quarters. Decrease in deviance indicates model fit increase by comparing the model to a null model (i.e., a model that included no predictors).
**p* < .05; ***p* < .01; ****p* < .001

Table 3-6

Dominance analysis of content characteristics on TPE image valence

		Additional contribution of:					
Subset model	R_1^2	PC	IC	SC	INC	EC	CC
k = 0 average	0.0000	0.0124	0.0110	0.0469	0.0392	0.0292	0.0047
Personal content (PC)	0.0116		0.0113	0.0512	0.0475	0.0312	0.0055
Impersonal content (IC)	0.0102	0.0127		0.0406	0.0305	0.0246	0.0018
Symbolic content (SC)	0.0461	0.0167	0.0047		0.0193	0.0166	0.0050
Instrumental content (INC)	0.0384	0.0207	0.0023	0.0270		0.0123	0.0012
Emotional content (EC)	0.0285	0.0143	0.0063	0.0343	0.0223		0.0042
Cognitive content (CC)	0.0039	0.0132	0.0081	0.0472	0.0358	0.0288	
k = 1 average		0.0155	0.0065	0.0400	0.0311	0.0227	0.0036
PC, IC	0.0229			0.0446	0.0381	0.0263	0.0023
PC, SC	0.0628		0.0047		0.0250	0.0177	0.0060
PC, INC	0.0591		0.0018	0.0287		0.0122	0.0015
PC, EC	0.0428		0.0063	0.0377	0.0285		0.0050
PC, CC	0.0171		0.0081	0.0517	0.0435	0.0307	
IC, SC	0.0508	0.0166			0.0157	0.0147	0.0029
IC, INC	0.0407	0.0202		0.0257		0.0117	0.0006
IC, EC	0.0348	0.0144		0.0308	0.0177		0.0021
IC, CC	0.0120	0.0131		0.0417	0.0293	0.0248	
SC, INC	0.0654	0.0224	0.0011			0.0085	0.0021
SC, EC	0.0627	0.0178	0.0028		0.0112		0.0046
SC, CC	0.0511	0.0177	0.0026		0.0164	0.0162	
INC, EC	0.0508	0.0206	0.0017	0.0232			0.0016
INC, CC	0.0397	0.0209	0.0017	0.0279		0.0127	
EC, CC	0.0327	0.0151	0.0041	0.0346	0.0196		
k = 2 average		0.0179	0.0035	0.0347	0.0245	0.0176	0.0029
PC, IC, SC	0.0675				0.0211	0.0158	0.0037
PC, IC, INC	0.0609			0.0276		0.0117	0.0009
PC, IC, EC	0.0491			0.0341	0.0235		0.0027
PC, IC, CC	0.0251			0.0461	0.0367	0.0267	
PC, SC, INC	0.0878		0.0007			0.0083	0.0025
PC, SC, EC	0.0805		0.0027		0.0156		0.0056
PC, SC, CC	0.0688		0.0024		0.0216	0.0173	
PC, INC, EC	0.0713		0.0013	0.0248			0.0019
PC, INC, CC	0.0606		0.0012	0.0298		0.0126	
PC, EC, CC	0.0478		0.0040	0.0383	0.0254		
IC, SC, INC	0.0665	0.0221				0.0082	0.0015
IC, SC, EC	0.0655	0.0177			0.0092		0.0031
IC, SC, CC	0.0537	0.0175			0.0143	0.0149	
IC, INC, EC	0.0525	0.0201		0.0222			0.0010
IC, INC, CC	0.0414	0.0205		0.0267		0.0121	
IC, EC, CC	0.0368	0.0150		0.0318	0.0166		
SC, INC, EC	0.0739	0.0222	0.0008				0.0024
SC, INC, CC	0.0675	0.0228	0.0005			0.0088	

Table 3-6 (continued)

SC, EC, CC	0.0673	0.0188	0.0013		0.0090		
INC, EC, CC	0.0524	0.0208	0.0011	0.0240			
k = 3 average		0.0197	0.0016	0.0305	0.0193	0.0136	0.0025
PC, IC, SC, INC	0.0885					0.0080	0.0020
PC, IC, SC, EC	0.0832				0.0134		0.0039
PC, IC, SC, CC	0.0712				0.0194	0.0160	
PC, IC, INC, EC	0.0726			0.0240			0.0013
PC, IC, INC, CC	0.0618			0.0287		0.0121	
PC, IC, EC, CC	0.0518			0.0354	0.0221		
PC, SC, INC, EC	0.0961		0.0005				0.0028
PC, SC, INC, CC	0.0904		0.0002			0.0086	
PC, SC, EC, CC	0.0861		0.0011		0.0129		
PC, INC, EC, CC	0.0732		0.0007	0.0258			
IC, SC, INC, EC	0.0747	0.0219					0.0019
IC, SC, INC, CC	0.0680	0.0225				0.0086	
IC, SC, EC, CC	0.0686	0.0186			0.0080		
IC, INC, EC, CC	0.0534	0.0205		0.0232			
SC, INC, EC, CC	0.0764	0.0226	0.0003				
k = 4 average		0.0212	0.0005	0.0274	0.0151	0.0106	0.0024
PC, IC, SC, INC, EC	0.0966						0.0024
PC, IC, SC, INC, CC	0.0906					0.0085	
PC, IC, SC, EC, CC	0.0872				0.0118		
PC, IC, INC, EC, CC	0.0739			0.0251			
PC, SC, INC, EC, CC	0.0989		0.0001				
IC, SC, INC, EC, CC	0.0766	0.0224					
k = 5 average		0.0224	0.0001	0.0251	0.0118	0.0085	0.0024
PC, IC, SC, INC, EC, CC	0.0990						
Overall average		0.0182	0.0039	0.0341	0.0235	0.0170	0.0031

Notes: N = 429,219 reviews of 21,414 employers over 45 quarters. The column labeled R_1^2 represents the Level-1 variance component and thus represents the variance in TPE image valence explained by Level 1 variables for the model appearing in the corresponding row (i.e., predictive ability at Level 1). Columns represent the additional contributions to the explained Level-1 variance gained by adding the column variable to the row model.

Hypothesis 1 states that personal content rather than impersonal content will play a dominant role in determining TPE image valence. In terms of the relative importance of these six predictors, the dominance analysis revealed that personal content completely dominates impersonal content as the contribution of personal content is higher than the additional contribution of impersonal content for every subset model. Accordingly, the average additional contribution of personal content to the null model was 1.82%, and that of impersonal content was 0.39%, supporting Hypothesis 1. In line with Hypothesis 2, which posits that symbolic content rather than instrumental content will play a dominant role in determining TPE image valence, symbolic content completely dominates instrumental attributes. Specifically, the average additional contribution to the null model was greater for symbolic (3.41%) than for instrumental content (2.35%). Finally, in accordance with Hypothesis 3, which posits that emotional content rather than cognitive content will play a dominant role in determining the TPE image valence, emotional content completely dominates cognitive content. Emotional content added an average contribution of 1.70% to the null model, while cognitive content added 0.31%. In addition to testing our hypotheses, the dominance analysis showed that symbolic attributes completely dominated not only instrumental attributes but also every other predictor in our model. Thus, symbolic attributes had the most dominant role in determining TPE image valence.

3.3.3 Mediation Analysis

Hypothesis 4 states that there is an indirect (through TPE image valence) relationship between content characteristics (personal/impersonal, symbolic/instrumental, and emotional/cognitive content) and an employer being ranked as a "best employer" by job-seekers. To establish whether mediation was present, we examined the estimations of the indirect effects resulting from our mediation analysis under the counterfactual framework. Table 3-7 (line A) shows that compared to employers with a 0% prevalence of personal, symbolic, and instrumental content, employers with a 10% prevalence of personal content (0.011, p = .005), symbolic content (0.010, p = .009), instrumental content (0.001, p = .008), and emotional content (0.002, p = .014) in their employer reviews received a higher overall rating on Kununu, which in turn made them more likely to be ranked as a "best employer". Furthermore, compared to employers with 0% prevalence of impersonal and cognitive content, employers with a 10% prevalence of impersonal content (-0.003, p = .013), and cognitive content (-0.004, p = .008) in their employer reviews received a lower overall rating on Kununu, which in turn made them less likely to be ranked as a "best employer". As the dependent variable is binary, all estimated effects represent the increase or decrease in the probability that an employer is ranked as a "best employer". Total effects were significant only for personal content (-0.028, p = .008) and impersonal content (-0.046, p = .002). However, significant total effects do not have to be present to identify indirect effects (see Imai, Keele, & Tingley, 2010; Tingley, Yamamoto, Hirose, Keele, & Imai, 2014). Thus, supporting Hypothesis 4, our mediation analysis showed that content characteristics indirectly affect whether an employer is ranked as a "best employer" due to the content characteristic effects on TPE image valence, as indicated by overall rating.

Hypothesis 5 states that consensus moderates the relationship between TPE image valence and an employer being ranked as a "best employer" such that the relationship will be stronger when consensus is relatively high. Following the recommendations of Cole et al. (2011), we fitted four logistic random-effects models to explore Hypothesis 5. As shown in Table 3-8, Model 1 explored only the main effect of an employer's TPE image valence and indicated that TPE image valence was positively associated with the employer being ranked as a "best employer" (0.618, p < .001) when controlling for the logged number of reviews. In terms of log-likelihood, this means that, for example, the odds that an employer with a 4-star overall rating on Kununu will be ranked as a "best employer" is 1.86 times the odds of an employer with a 3-star overall rating. Model 2 explored the TPE image valence × consensus interaction and indicated that the interaction between TPE image valence and consensus was significant in estimating the employer being ranked (2.281, p < .001). However, after we included squared terms for both TPE image valence and consensus (Model 3), we found no significant interaction between TPE image valence and consensus (0.466, p = .777). Thus, although our results indicated a two-way interaction, this was a spurious by-product due to the interdependence of TPE image valence and consensus (see Cole et al., 2011). Therefore, Hypothesis 5 was not supported.

Table 3-7

Mediation analysis for effect of content characteristic through TPE image valence on being ranked as a "best employer"

Content characteristic	Indirect effects				Direct effects				Total effects			
	Estimate	95% CI lower	95% CI upper	*p*	Estimate	95% CI lower	95% CI upper	*p*	Estimate	95% CI lower	95% CI upper	*p*
Personal content	0.011	0.002	0.030	0.005	-0.039	-0.062	-0.020	0.003	-0.028	-0.042	-0.020	0.008
Impersonal content	-0.003	-0.006	0.000	0.013	-0.043	-0.078	-0.020	0.003	-0.046	-0.082	-0.020	0.002
Symbolic content	0.010	0.002	0.020	0.009	-0.022	-0.050	0.000	0.072	-0.012	-0.034	0.010	0.246
Instrumental content	0.001	0.000	0.000	0.008	0.005	-0.003	0.010	0.159	0.007	-0.001	0.010	0.095
Emotional content	0.002	0.000	0.000	0.014	0.002	-0.020	0.020	0.785	0.004	-0.017	0.020	0.659
Cognitive content	-0.004	-0.008	0.000	0.008	-0.008	-0.034	0.010	0.491	-0.012	-0.040	0.000	0.258

Notes: N = 12,951 employers in 43 industries. All models were controlled for the log-transformed number of reviews and for the remaining content characteristics.
CI = Confidence Interval.

Table 3-8

HLM of TPE image valence and consensus on being ranked as a "best employer"

	Model 1			Model 2			Model 3		
Predictor	Estimate	*SE*	*t*	Estimate	*SE*	*t*	Estimate	*SE*	*t*
				Regression coefficients (fixed part)					
(Intercept)	-14.713	0.7730	-19.02***	-4.772	1.4145	-3.37***	-33.922	11.2163	-3.02**
TPE image valence	0.618	0.1554	3.97***	-1.781	0.3817	-4.67***	12.132	4.2224	2.87**
Consensus				-9.397	1.4796	-6.35***	6.413	10.2418	0.63
TPE image valence squared							-1.816	0.4525	-4.01***
Consensus squared							-5.716	2.7105	-2.11*
log(Number of reviews)	2.033	0.0846	24.03***	2.043	0.0869	23.52***	1.948	0.0895	21.76***
TPE image valence × consensus				2.281	0.4354	5.24***	0.466	1.6381	0.28
				Variance components (random part)					
Industry	3.129	1.7690		3.126	1.7680		2.866	1.6930	
				Model summary					
Deviance (-2LL)	1500.49			1469.14			1423.74		
Decrease in deviance, *df* (6)	929.10***			960.44***			1005.85***		

Notes: N = 12,951 employers in 43 industries. Decrease in deviance indicates model fit increase by comparing the model to a null model (i.e., a model that included no predictors). The residual variance in logistic regression models is fixed to $\frac{\pi^2}{3}$ and thus not reported here.

*p < .05; **p < .01; ***p < .001

3.3.4 Additional Analyses

To complement our analysis of symbolic and instrumental attributes as main categories, we also analyzed the relative importance of individual attributes within these main categories. These additional analyses illuminate which instrumental and symbolic attributes are especially salient in determining TPE image valence. In the main category of instrumental attributes, dominance analysis showed that organizational and team climate completely dominated every other instrumental attribute. Challenging work completely dominated every other instrumental attribute with the exception of organizational and team climate. In the main category of symbolic attributes, sincerity completely dominated every other symbolic attribute. Innovativeness completely dominated every other symbolic attribute with the exception of sincerity.[9]

We also conducted two other analyses. First, we assessed possible differences between employer reviews of current and former employees because the former are still attached to the organization and might thus (even be coached to) write different (more positive) reviews. Our propositions about the content underlying TPE images on employer review websites assumed that information and experiences about organizations disseminated by either current or former employees are similar. However, it might not be the case that current or former employees are a homogeneous group of social media users. First, as reputation management and social media monitoring play an increasingly important role in organizational strategy (George et al., 2016; Ravasi et al., 2018), employer review websites have been criticized for being “gamed” by employers (Dineen et al., 2019). Specifically, Dineen et al. (2019) suggest that companies may sometimes encourage or even pressure their employees to post positive employer

[9] Tables with individual attributes’ correlations, HLM, and dominance analysis results are available upon request.

reviews. In fact, the Wall Street Journal identified more than 400 companies that received suspicious Glassdoor reviews in an analysis of millions of employer reviews (Winkler & Fuller, 2019). Second, reviews by current and former employees might also differ due to current employees' still being formally tied to the company. So, current employees may feel accountable for the TPE image presented by their review because they directly benefit from their company's success, whereas former employees are no longer attached to the company and thus do not have to post "the right things" (Dineen et al., 2019; see also Hall et al., 2017).

Hence, our additional analyses explored potential differences between current and former employees. First, in line with the above expectations, former (M = 2.76) and current employees (M = 3.81) differ significantly (p < .001) in terms of their TPE image valence. Second, and more importantly in terms of our propositions, we evaluated whether dominance analysis yielded different results for reviews disseminated by current versus former employees. We first fitted a cross-classified random effects model using solely reviews posted by current employees, and solely reviews posted by former employees. Both models significantly reduced deviation compared to a null model (p < .001). We then conducted a dominance analysis to compare the relative importance of the models' Level 1 predictors and determined the relative importance of each predictor. For current employees, personal content (1.32%) added more additional average contribution to the null model than impersonal content (0.10%), symbolic content (2.59%) added more additional average contribution to the null model than instrumental content (1.35%), and emotional content (1.35%) added more additional average contribution to the null model than cognitive content (0.12%). Regarding former employees, personal content (2.70%) added more additional average contribution to the null model than impersonal content (1.09%), symbolic content (3.84%) added more additional average contribution to the null model than instrumental content (2.05%), and emotional content (2.17%) added more additional average contribution to the null model than cognitive content (0.37%). In both groups, personal content completely dominated impersonal content, symbolic content completely dominated instrumental content, and emotional content completely dominated cognitive content. In summary, dominance analysis did not yield different results for current versus former employees. These results justify treating these two groups as homogeneous in our analysis.

Second, we evaluated whether common method variance might explain our results. In our main analysis, we explored the indirect (through TPE image valence) relationship between content characteristics (personal/impersonal, symbolic/instrumental, and emotional/cognitive content) and an employer being ranked as a "best employer" by job-seekers at the employer level of analysis. Since both content characteristics and TPE image valence, as indicated by overall rating, originate from a single data source (i.e., the reviews posted about the employer), problems of common method bias may arise for this part of our model (Podsakoff, Mackenzie, Lee, & Padsakoff, 2003). Therefore, as a robustness check, our third set of additional analyses used an approach similar to that of Van Hoye et al. (2012) and randomly split the reviews per employer into two groups. Next, we randomly selected half of the reviews for each employer and aggregated these reviews' content characteristics at the employer level. We then used the other half of the reviews to aggregate these reviews' overall ratings to the employer-level. The reviews, and thus the sources, forming employer-level content characteristics and TPE image valence differed. We then re-estimated the indirect effects in a mediation analysis under the counterfactual framework (N = 12,951). The results were consistent with the main analysis (details are available upon request). Compared to employers with a 0% prevalence of personal, symbolic, instrumental, and emotional content, employers with a 10% prevalence of personal (0.003, p = .011), symbolic (0.004, p = .015), instrumental (0.001, p = .012), and emotional content (0.001, p = .007) received higher overall ratings on Kununu, which in turn made them more likely to be ranked as a "best employer". Furthermore, compared to employers with a 0% prevalence of impersonal and cognitive content, employers with a 10% prevalence of impersonal (-0.002, p = .013) and cognitive content (-0.002, p = .019) received lower overall ratings on Kununu, which in turn made them less likely to be ranked as a "best employer". Thus, common method bias did not seem to threaten our results.

3.4 Discussion

3.4.1 Main Conclusions

To advance our understanding of the conceptualization of employer images, we theorized on and empirically investigated which content characteristics determine TPE image valence of online employer reviews. Our examination of approximately half a million online employer reviews from Europe's largest employer review website led to two main findings. First, we discovered that personal, emotional, and especially symbolic content determined TPE image valence. Both former and current employees tend to especially rely on symbolic image attributes (rather than instrumental attributes) because this allows them to express the core values of the organization and thereby at the same time also often either self-express or impress others (Highhouse et al., 2007). The reliance on personal and emotional content in employer reviews is in line with what readers expect from such websites (Dabirian et al., 2017; Dineen & Allen, 2013; Dineen et al., 2019) because online reviewers are not constrained by professional/journalist standards (Etter et al., 2019; Hanitzsch et al., 2011), and want to attract attention (Berger & Milkman, 2012).

Second, we presented unprecedented field-based evidence that TPE images matter for companies. We showed that employer review content characteristics do not only determine whether a company has a more positive or negative TPE image but that these characteristics are in turn also linked to whether companies are ranked as "best employers" by job-seekers in external surveys. This underscores the role that TPE image plays for recruitment in the social media era and thus the growing importance of TPE branding for organizations (besides the existing company-controlled employer branding). Today, a significant part of companies' employer image is shaped outside of their control and this TPE image also affects key outcomes of interest, such as being ranked as a “best employer”.

3.4.2 Implications for Theory

As a first theoretical contribution, we integrate the NMRF framework (Etter et al., 2019) into the employer image literature. Doing so is important to advance the employer image literature because existing conceptualizations of employer image were developed before the advent of social media and posited that the employer image held by job-seekers accrued mostly from recruitment messages from organizational agents (e.g., recruiters). Conversely, the new co-created perspective on employer image also incorporates bottom-up input from organizational members (current and former employees), as reflected in TPE branding. Juxtaposing the company-controlled and the TPE image (see Figure 3-1) should provide conceptual clarity in future employer image research and ensure it is up to speed with how images are created in the wake of social media.

We theorized and showed that the nature of TPE images differed from the prevailing employer image conceptualization that was adopted over the last two decades (see Lievens & Slaughter, 2016). This new perspective on employer image changes our thinking in this domain in at least four ways. First, symbolic trait attributions are much more important than instrumental attributions in the formation of TPE image, whereas this is not the case in prevailing employer image conceptualizations. The importance of symbolic traits for TPE image valence can be understood by self-expression/social identity motives (Highhouse et al., 2007) and by the power of anthropomorphism in terms of sensemaking and social connection (Ashforth et al., 2020). This highlights that anthropomorphism not only plays a role in organizational identity (Ashforth et al., 2020) but also in the formation of TPE images. The connection drawn by this study between the employer image and organizational identity literature is reasonable considering that the TPE images presented through employer reviews are shaped by organizational members (current and former employees), who are central to organizational identity. Accordingly, this study suggests that the symbolic attributes mentioned in employer reviews might resemble the core, distinctive, and reasonably enduring features of an organization.

As another novel insight, the co-created perspective challenges prevailing theoretical perspectives of employer images being primarily cognitively driven (Collins & Kanar, 2013; see also Lievens & Slaughter, 2016) by adding that emotional processing is ultimately more relevant for TPE images. This is the case because we discovered that TPE images are not formed solely through cognitive reflection on workplace experiences, but also factor in emotional processing. As our findings highlight the role of emotional processing in the formation of TPE images, they indicate that the TPE image shares this conceptual characteristic with reputation (which has a strong affective component; Ponzi, Fombrun, & Gardberg, 2011). As a related implication, our findings also suggest that theories on how companies may control their image and thus position themselves as attractive employers are incomplete (see Theurer et al., 2018). Thus far, we have largely ignored incorporating the role of emotionality into employer image management.

A third important insight relates to the marked discrepancy between the prevalence of content characteristics in employer reviews and their role in determining TPE image valence. When one reads employer reviews, one often gets the impression that people mostly “rant” about instrumental factors such as low pay, weak leaders, and low promotion opportunity and not so much about companies’ sincerity or innovativeness. The mean values in our study confirm the higher frequency of impersonal, instrumental, and cognitive content. However, importantly, the lower frequency of personal, symbolic, and emotional content determines TPE image valence. Apparently, there is some kind of “rarity effect” in employer reviews wherein less frequent characteristics seem to make the key difference as to whether a company will receive a high or low overall rating in employer reviews. This "rarity effect" speaks to the importance of differentiation and standing out in employer branding (K. Backhaus & Tikoo, 2004).

Fourth, we discovered that there is a hierarchy in the importance of content characteristics as determinants of TPE image valence. Among the three important content characteristics (personal, symbolic, and emotional), symbolic content emerged as the single most important content characteristic determining TPE image valence because it dominated personal and emotional content. In other words, describing companies in a trait-like manner and attributing human qualities to them in employer reviews has the most influence on the favorability of companies. Adding first-hand experiences and emotions then serve to support this key symbolic content because these elements might make the company story stick even more in the minds of the employer review writer and reader (Heath & Heath, 2007).

3.4.3 Implications for Practice

Our study has several implications for companies. First, our finding that an employer's TPE image presented through employer reviews is associated with key outcomes of interest, such as "best employer" rankings of job-seekers, should encourage firms to closely monitor employer review websites and act on the reviews (e.g., to counter what they perceive as to be incorrect information). In the light of our findings, companies should be especially wary of the symbolic, emotional, and personal contents because these are more impactful than instrumental, cognitive, and impersonal contents for their overall TPE image valence.

Second, building on this point, our work presents a systematic approach, CATA, to evaluate reviews' textual content. Through our novel content dictionary, companies may identify fine-grained employer image information from employer reviews to analyze their TPE image and the TPE images of competitors. Our dictionary can be applied to any amount of text or any number of reviews and allows these attributes to be evaluated in real-time.

Accordingly, companies can integrate our dictionary into a broad employer image "intelligence" approach and social media monitoring software to identify temporal or across-company trends.

3.4.4 Limitations

Our study is not without limitations. First, we analyzed a comprehensive data set of approximately half a million employer reviews, which corresponded to all employer reviews posted on Kununu, Europe's largest employer review website, between May 2007 and June 2018 for German employers with at least two reviews. Although this provided us with a comprehensive insight into reviews by employees from a wide range of positions, departments, and industries, our employer reviews were nevertheless limited to a single employer review website. As a result, our data did not allow us to draw conclusions across countries and cultures. Therefore, further studies should conduct cross-cultural analyses via other employer review websites, such as Glassdoor, Indeed, and Kanzhun.

Second, we used CATA on the basis of a predefined dictionary (DE-LIWC2015) and a purpose-built dictionary to analyze the content characteristics of employer reviews with regard to their relevance to the represented TPE image. Besides CATA, topic modeling (i.e., an unsupervised machine learning algorithm for finding groups of words like topics from a collection of documents) is another popular approach for analyzing texts. A comparative study of Guo et al. (2016) concluded that topic modeling reveals more differentiated content details, whereas CATA permits a more focused analysis of previously defined topics. As we intended to identify a priori, theoretically derived topics, CATA seemed best suited here.

Third, the content characteristics that we extracted explained only approximately 10% of the variance in the TPE image valence as rated by current and former employees through their reviews. Although it is quite remarkable that we can explain nearly one-tenth of the variance solely by quantifying the textual content of the employer reviews, this finding also suggests that a large part of the variance is explained by factors not covered in our study. Therefore, further research should determine what other determinants are relevant to the TPE images presented in employer reviews. For instance, product or service review research shows that management responses to reviews deserve attention (Proserpio & Zervas, 2017).

3.4.5 Directions for Future Research

Our study offers some intriguing avenues for future research. First, it calls for creating a more comprehensive understanding of the importance of the various experiences that may affect employees' employer image perceptions. This includes, for example, understanding how employer image management (e.g., identity building within an organization) shape the formation of the employer's TPE image. Relatedly, research should examine companies' efforts to "game" the employer review process and how job-seekers as readers of employer websites perceive these efforts of deceptive information dissemination. Our study merely touched upon this issue by finding no differences in review characteristics between former and current employees.

Second, our study calls for creating a better understanding of the role of emotions in the formation of employer images. More specifically, employer image research should explore whether not only the formation of TPE images, as a distinct conceptual image construct, but also the formation of employer images among job-seekers is emotionally motivated. In this regard, employer image research should investigate the effectiveness of emotional employer information for employers' self-branding. After all, emotions possess persuasive power to influence the formation of and changes in individuals' attitudes on a variety of topics (Van Kleef et al., 2015).

Third, our study calls for further investigation of the effects of different types of TPE branding on key recruitment and retention outcomes. Employer image research has so far neglected to investigate the role of TPE branding for outcomes such as turnover (a notable exception is the study of Dineen & Allen, 2016). Along these lines, employer image research would benefit from comparing the effectiveness of TPE branding vs. company-controlled employer branding. Relatedly, we need to investigate how job-seekers integrate the (often discrepant) information from these different sources.

3.4.6 Conclusion

The present study advances theory and empirical research on TPE images. As theorized, our results on the basis of approximately half a million employer reviews from Europe’s largest employer review website suggest that personal (rather than impersonal), symbolic (rather than instrumental), and emotional (rather than cognitive) content determines TPE image valence. Furthermore, we demonstrate that a better understanding of the nature of these TPE images is crucial, as companies’ TPE image is related to whether they are ranked among “best employers” by job-seekers. Critically, our study challenges the prevailing perspective on employer image by showing that first-hand experiences, symbolic traits (anthropomorphism), and emotionality play a dominant role in forming TPE images.

4 Essay III: Enhancing Accountability: An Analysis of the Consequences of Responding to Employer Reviews[10]

Employer reviews published by current and former employees on websites such as Glassdoor, Kununu, and Indeed attract broad interest and shape the opinions of millions of potential employees. Surveys suggest that 36% of Internet users have already read a review on Kununu (Brehme & Brandau, 2018), and 52% of job seekers in the US read reviews before applying (Westfall, 2017). Furthermore, experimental studies consistently demonstrate that employer reviews can shape potential employees' attitudes and intentions towards employers (Carpentier & Van Hoye, 2020; Evertz et al., 2019; Könsgen et al., 2018; Melián-González & Bulchand-Gidumal, 2016; Stockman et al., 2019). Against this backdrop, thought leaders such as the Society for Human Resource Management recommend that employers carefully monitor and respond to employer reviews (e.g., Bates, 2016; Grensing-Pophal, 2019; Lewis, 2019; Maurer, 2017), and a growing number of studies have explored how organizations may proactively manage third-party judgments such as employer reviews (George et al., 2016). A response is a free-text comment that is publicly displayed under the corresponding employer review (see Figure 4-1).

However, despite growing academic interest, our understanding of the consequences of responding to online employer reviews is severely limited. The prevailing theoretical perspectives largely focus on the reactions of companies to negative third-party judgments, such as sending repair signals to address potential reputational threats (see, e.g., Dineen et al., 2019; Etter et al., 2019; George et al., 2016; Ki & Nekmat, 2014; Pfarrer et al., 2008; Ravasi et al., 2018; T. Wang et al., 2016). Hence, there is a need to develop a theory-driven understanding of the consequences of employers responding to employer reviews beyond the

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[10] This chapter is partly based on and includes elements of Höllig and Tumasjan (2021). Therefore, the plural instead of the singular is used throughout this chapter. Author contributions are summerized in Appendix C.

lens of threat management. We explore these consequences by building on theoretical and empirical work that deals with the effects of felt accountability on individuals' efforts to justify judgments to hypothesize that responsive employers receive reviews that present more diverse and extensive employer information than non-responsive employers (for a comprehensive review of accountability theory, see Hall et al., 2017; Lerner & Tetlock, 1999). A text mining-based analysis of approximately half a million employer reviews posted on Europe's largest employer review website between May 2007 and June 2018 confirms our theorizing. Specifically, we apply topic modeling, a text-mining technique, to derive review-level measures for information diversity and extensiveness and subsequently explore the impact of an employer's responsiveness on these measures by applying a difference-in-differences design.

Our work makes three major contributions to the literature. First, we extend theoretical perspectives that emphasize the role of responses to third-party judgments for threat management (see Dineen et al., 2019; Etter et al., 2019; George et al., 2016; Pfarrer et al., 2008; Ravasi et al., 2018; T. Wang et al., 2016) by adding that employer responsiveness also plays a role of indirect control over such judgments by establishing an accountability-enhancing context. Critically, we show that responsiveness is particularly vital to exerting indirect control over negative third-party judgments and judgments of third parties detached from the organization. Second, we contribute to the employer image literature by exploring the impact of employer responses using actual employer review data rather than exploring perceptions and intentions in online experiments (see Carpentier & Van Hoye, 2020; Könsgen et al., 2018). In this vein, our study also addresses open calls for a more profound understanding of the information about employers disseminated online (Dineen et al., 2019; Lievens & Slaughter, 2016; Theurer et al., 2018). Third, we concurrently advance the emerging accountability literature that investigates the effects of felt accountability in a field setting (e.g., Mero, Guidice, & Werner, 2014).

4.1 Theoretical Framework and Hypotheses

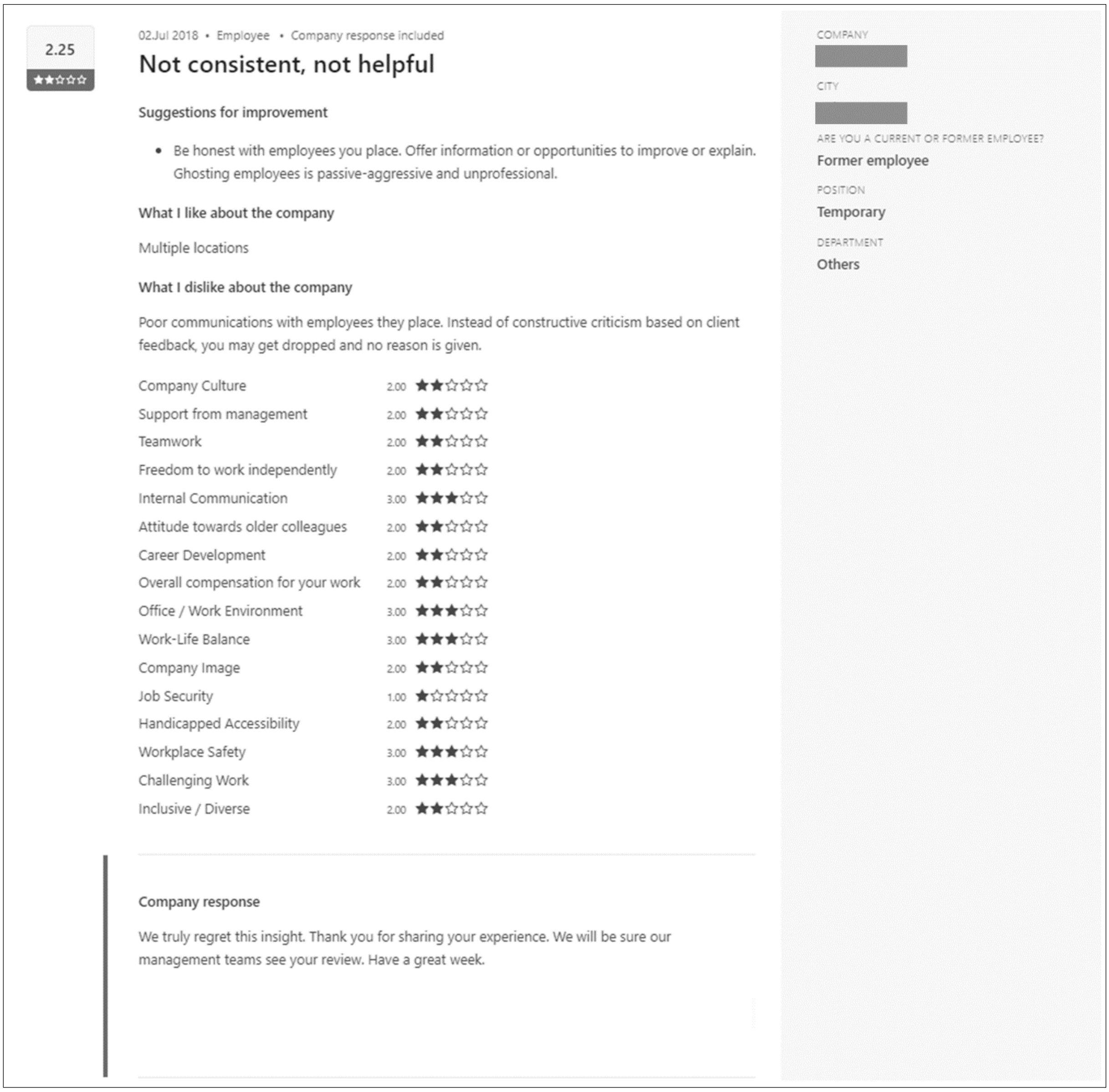
4.1.1 Employer Reviews in the Context of Employer Image Research

The employer image literature has so far focused on the information cues that organizations disseminate themselves to shape individuals' perceptions of the organization as a place to work (i.e., individual's employer image perceptions; see Lievens & Slaughter, 2016). More recent theories have also dealt with third-party employer (TPE) branding, which refers to "communications, claims, or status-based classifications generated by parties outside of direct company control that shape, enhance, and differentiate organizations' images as favorable or unfavorable employers" (Dineen et al., 2019, p. 176). A prominent example of the TPE images created and disseminated by parties outside direct company control are reviews posted by current and former employees on employer review websites. Employer reviews typically include quantitative ratings on five-point Likert scales and open text comments on the employer. A salient characteristic of any employer review is its overall rating, which indicates the reviewer's judgment and thus whether the review presents a more positive or negative TPE image (i.e., the valence of the TPE image). Experimental research shows that employer reviews, depending on the valence of the TPE image presented with the review, can positively or even negatively affect potential employees' attitudes and intentions towards organizations as a place of work (Carpentier & Van Hoye, 2020; Evertz et al., 2019; Könsgen et al., 2018; Melián-González & Bulchand-Gidumal, 2016; Stockman et al., 2019).

Despite the potential of employer reviews to attract or repel potential employees (Carpentier & Van Hoye, 2020; Evertz et al., 2019; Könsgen et al., 2018; Melián-González & Bulchand-Gidumal, 2016; Stockman et al., 2019), our understanding of how employers should deal with employer reviews is severely limited. Employers cannot directly control employer reviews (Dineen et al., 2019; Lievens & Slaughter, 2016). Unlike, for example, job advertisements (e.g., Walker & Hinojosa, 2013), companies cannot present thoroughly

Figure 4-1

Example of an employer review including an employer response on Kununu's US website



constructed employer information to potential applicants, employees, and the broader public via employer reviews. However, they can decide to respond or not respond to employer reviews (Dineen et al., 2019). In this context, the prevailing theoretical perspectives consider primarily the reaction of companies to negative third-party judgments that potentially threaten the companies' reputation (see, e.g., Dineen et al., 2019; Etter et al., 2019; George et al., 2016; Ki & Nekmat, 2014; Pfarrer et al., 2008; Ravasi et al., 2018; T. Wang et al., 2016). For instance, in their model of organizational reintegration, Pfarrer et al. (2008) stress the role of repair signals that companies may send to repair their reputation when it is threatened or damaged through third-party judgments. Consequently, the few studies concerned with how companies can deal with employer reviews explore the role of responses to negative employer reviews (Carpentier & Van Hoye, 2020; Könsgen et al., 2018).

Drawing from accountability theory (see Hall et al., 2017; Lerner & Tetlock, 1999) and recent empirical work in the marketing field showing that customers review responsive hotels differently than non-responsive hotels (e.g., Chevalier et al., 2018; Proserpio & Zervas, 2017; Y. Wang & Chaudhry, 2018), we note that the prevailing theoretical perspectives, which consider companies’ reactions to third-party judgments mainly from a threat management perspective (e.g., Pfarrer et al., 2008), seem insufficient to explain an employer’s responsiveness to employer reviews. Indeed, theoretical and empirical work on the influence of felt accountability on individuals’ efforts to justify their judgments suggests that the role of employer responses may extend beyond governing the influence of negative employer reviews on the perceptions of, for example, potential employees (see Carpentier & Van Hoye, 2020; Könsgen et al., 2018). Furthermore, we note that while the literature suggests that responding to employer reviews can be beneficial for companies (Carpentier & Van Hoye, 2020; Könsgen et al., 2018), the findings to date have been based on online experiments, and the literature does not provide any empirical evidence for the effects of employer responses in a field setting. Consequently, we seek to develop a theory-driven understanding of responding to employer reviews by facilitating an extensive dataset of actual employer reviews.

4.1.2 Employers’ Responsiveness and Reviewers’ Felt Accountability

As a central premise of this study, we argue that when employers become responsive on employer review websites, they establish an accountability-enhancing context and thus exert *indirect* control over the TPE images disseminated by third parties. Specifically, by becoming responsive, employers create the contextual conditions for current and former employees to feel accountable for the reviews they publish on employer review websites. Evidence that reviewers (i.e., current and former employees) feel accountable is demonstrated through their efforts to justify their judgment of their employer.

We build this premise on the model of social judgment and choice (originally called the "social contingency model"; Hall et al., 2017; Tetlock, 1985, 1992), which recognizes accountability as a fundamental force that guides individuals' behavior and decisions. Felt accountability is defined as the "perceived expectation that one's decisions or actions will be evaluated by a salient audience and that rewards or sanctions are believed to be contingent on this expected evaluation" (Hall & Ferris, 2011, p. 134). With that in mind, accountability guides the behavior and decisions of individuals in accountability-enhancing contexts, as individuals seek to maintain their public and private self-image (see also Schlenker, Weigold, & Doherty, 1991). Specifically, to maintain their image, individuals adapt their behavior or decisions when faced with accountability demands in such a manner as to be favorably perceived by the salient audience (Hall et al., 2017). For instance, to avoid appearing foolish or incompetent in front of the audience, individuals may perform a self-critical search for reasons to justify their actions (Lerner & Tetlock, 1999).

The model of social judgment and choice implies that felt accountability emerges from the subjective interpretation of deliberately controllable contextual factors (see also Tetlock, Vieider, Patil, & Grant, 2013). A context may enhance accountability when what people say or do (a) can be observed by a salient audience, (b) is identifiable or attributable to them, (c) requires justification, and (d) is evaluated by the salient audience with some implicit consequences (Lerner & Tetlock, 1999). Against this backdrop, we argue that an accountability-enhancing context emerges on employer review websites once employers become responsive. First, employer reviews can be observed by any visitor to an employer review website. Visitors may include other reviewers (see Godes & Silva, 2012), such as current and former employees as well as potential employees (see Evertz et al., 2019; Könsgen et al., 2018; Melián-González & Bulchand-Gidumal, 2016; Stockman et al., 2019). Second, reviews are attributable to individual reviewers, as each review is authored by a single unique reviewer, i.e., a unique current or former employee, rather than, for example, a group of several employees. Thus, although reviewers remain anonymous, their judgment of their employer can be attributed to them, evaluated, and followed by a consequence (see below). Accordingly, attributability in the employer review context is comparable to experimental designs in which accountability is enhanced by prompting anonymous participants to provide written justifications for their judgment along with an indication that their judgment will be evaluated (e.g., Dalla Via et al., 2019; Fennema & Perkins, 2008). Consistently, Sedikides et al (2002) disaggregate various facets of accountability-enhancing contexts in multiple experimental studies and demonstrate that while identifiability can further enhance felt accountability, contexts without identifiability also promote felt accountability. Third, a judgment of an employer requires justification. Employer review websites specifically prompt reviewers to provide open text comments and thus allow them to explain their judgment in detail. Finally, by publishing a first response, employers indicate that they are responsive. Responsiveness refers to the ability and willingness of an employer to evaluate employer reviews and respond to reviews based on this evaluation. Therefore, once their employer has become responsive, current and former employees notice their employer as part of the audience and may expect evaluation and consequences of their review. Positive consequences equal positive responses from the employer, for instance, acknowledging responses, in which the employer thanks employees for making the effort to provide reviews with detailed written justifications, or accommodating responses, in which the employer apologizes, takes responsibility, and identifies actions for improvement (see Carpentier & Van Hoye, 2020). Negative consequences equal negative responses from the employer, for instance, denying responses, in which the employer denies responsibility for the points raised in the review and offers counterevidence (see Carpentier & Van Hoye, 2020), or rejecting responses, in which the employer rejects the review because of its inadequate justification.

4.1.3 Felt Accountability and Review Justification

We expect that reviews of employers that have established an accountability-enhancing context through their responsiveness (see above) differ from reviews of non-responsive employers. Specifically, we hypothesize that the reviews of responsive employers present more diverse and extensive employer information than the reviews of non-responsive employers; information diversity, i.e., the variety of information, and information extensiveness, i.e., the quantity of information, are two key elements of individuals' information processing in judgment situations (see, e.g., Hwang & Lin, 1999; Iselin, 1988). We base our hypotheses on empirical accountability research that shows that accountable (vs. non-accountable) individuals, in an attempt to impress their audience, may exert cognitive effort to gather, analyze, and report diverse and extensive information to support their judgment (see, e.g., DeZoort et al., 2006; M. C. Green et al., 2000; Lerner & Tetlock, 1999; Levi & Tetlock, 1980; Tetlock, 1983; Tetlock, Skitka, & Boettger, 1989). Specifically, accountable (vs. non-accountable) individuals may exert cognitive effort to understand the subject under judgment (De Dreu et al., 2006) and to differentiate and aggregate a variety of arguments that support or even contradict their judgment (M. C. Green et al., 2000; see also Lee et al., 1999). Individuals may do so by engaging in a more complex and extensive information search process (Dalla Via et al., 2019; Huneke et al., 2004) and in a more careful and thorough analysis of judgment-relevant information (Dalla Via et al., 2019; Hattrup & Ford, 1995; Siegel-Jacobs & Yates, 1996; Thompson et al., 1994). Consequently, studies that analyze the content of written justifications of accountable individuals find that accountability encourages the provision of longer, more information-rich, and more linguistically complex written justifications (e.g., DeZoort et al., 2006; Gordon & Stuecher, 1992; Koonce et al., 1995; Levi & Tetlock, 1980). In the employer review context, current and former employees exert cognitive effort to analyze employer information that they have gathered through personal experience or stories from others to form their judgment of their employer (see Cable & Turban, 2001). Employees then use this employer information in their written justifications to present their judgment as usual or expected under the given circumstances (see, e.g., Shaw, Wild, & Colquitt, 2003). Specifically, employees may provide specific information about their employer to highlight the employer's shortcomings (e.g., "bad image, dissatisfied customers") or strengths (e.g., "timely pay") to ultimately justify the negative or positive judgment of their employer. The information available to substantiate a judgment of an employer spans a variety of topics. For instance, Jung and Suh (2019) identify 65 topics, such as "organizational culture", "work intensity and efficiency", and "reputation", in an exploratory analysis of 204,659 employer reviews on a Korean employer review website. Thus, we propose the following hypotheses:

Hypothesis 1. *An employer's responsiveness is positively associated with the employer information diversity in its reviews.*

Hypothesis 2. *An employer's responsiveness is positively associated with the employer information extensiveness in its reviews.*

Furthermore, we hypothesize that particularly the *negative* reviews of responsive employers present more diverse and extensive employer information than the negative reviews of non-responsive employers. We base our hypotheses on empirical accountability research that shows that individuals may follow coping strategies for dealing with accountability demands other than exerting cognitive effort (see, e.g., Tetlock et al., 1989). Cognitively demanding coping is more likely when the subject of judgment is personally relevant to the accountable individuals (see, e.g., Petty & Cacioppo, 1990), when the individuals are motivated to make an accurate judgment (Quinn & Schlenker, 2002), and when the audience is knowledgeable about the subject and has a legitimate right to inquire about the reasons for the judgment (Lerner & Tetlock, 1999). Critically, cognitively effortful coping is more likely when accountable individuals are unaware of the audience's views (e.g., Hall et al., 2017; Lerner & Tetlock, 1999; Tetlock et al., 1989). When individuals are aware of the audience's views, they may also choose the cognitively "lazy" strategy of simply adopting the views of their audience, thereby avoiding unnecessary cognitive effort and the risk of conflict (Lerner & Tetlock, 1999). However, individuals do not need to be explicitly informed about the audience's views since they can also deduce the audience's views from the available information (Tetlock et al., 1989; Weigold & Schlenker, 1991). Consequently, in a performance appraisal context, it is commonly assumed that positive ratings are less likely to cause conflict and thus are easier to justify than negative ratings (Mero, Guidice, & Brownlee, 2007) since appraisers deduce that those being appraised expect the highest possible rating (Harari & Rudolph, 2017). In light of these considerations, it is conceivable that employees can to some extent deduce that their employer expects particularly positive judgments, as employers likely want to be branded positively by third parties to support their recruiting efforts, which is also indicated in that employer review websites award employers with the highest overall ratings (e.g., Glassdoor's Best Places to Work Awards; Glassdoor, 2019). Accordingly, a review presenting a more negative TPE image provides a higher risk of conflict and is harder to justify as usual or expected under the given circumstances using employer information than a review presenting a more positive TPE image (see Mero et al., 2007). Thus, we propose the following hypotheses:

Hypothesis 3. *The responsiveness-diversity relationship is moderated by TPE image valence (i.e., overall rating) such that the relationship between responsiveness and information diversity is stronger for more negatively judged employer reviews.*

Hypothesis 4. *The responsiveness-extensiveness relationship is moderated by TPE image valence (i.e., overall rating) such that the relationship between responsiveness* *and information extensiveness is stronger for more negatively judged employer reviews.*

Accountability-enhancing contexts are not equally effective across individuals. Instead, the interpretation of these contexts may vary, and individuals may experience varying degrees of felt accountability in the same context (e.g., Frink & Klimoski, 1998; Tetlock, 1985, 1992). This perspective follows the model of social judgment and choice (Hall et al., 2017; Tetlock, 1985, 1992), which implies that while contextual factors enhancing accountability are intentionally controllable, individuals who perceive these contextual factors interpret and subsequently transform them into a subjective state of mind (see also Frink & Klimoski, 1998). In other words, a context shaped in such a way that individuals operating in that context feel accountable may induce a varying degree of felt accountability and therefore result in varying behavior (see also Mero et al., 2014). In the employer review context, current and former employees may vary in their subjective interpretation of the accountability-enhancing context created through employers' responsiveness. After all, current and former employees differ in their relationship to the employer. While current employees are attached to the company, former employees are detached (Dineen et al., 2019). According to Dineen et al. (2019), this implies that current employees (even if the information they disseminate is outside the direct control of the employer) may to some extent feel accountable for the employer information they share, as they may expect consequences for sharing certain information. For instance, current employees may feel an obligation to convey an employer image that is in line with that provided by the employer through its official information cues or to unnaturally bolster their employer's image. As a consequence of strengthening the employer image, employees then profit from the success of their employer, e.g., because the employer is able to recruit outstanding employees due to its excellent image. Former employees can freely disseminate information about their employer without feeling obliged to pass on “the right” information (Dineen et al., 2019). Therefore, we pose the following research question:

> ***Research Question:*** *Do responsiveness-diversity and responsiveness-extensiveness relationships differ between former and current employees?*

4.2 Methodology

4.2.1 Background

To test our hypotheses, we examined online employer reviews posted on Kununu, the largest employer review website in Europe. Since its launch in 2007, Kununu, including its US site launched in 2016, has collected over 4 million employer reviews worldwide (Kununu, 2020). Current and former employees voluntarily and anonymously submit reviews of their employer based on a predefined questionnaire that includes both sections for quantitative ratings (from 1.00 to 5.00 stars) and open-ended text comments on various employer aspects. The most salient quantitative metric is an overall rating in the range of 1.00 to 5.00 stars, which represents the average of all individually rated employer aspects. Finally, in addition to the open-ended comments on these individual aspects, employees have the opportunity to answer three brief questions regarding pros (“What do you like about the company?”), cons (“What do you dislike about the company?”) and suggestions for improvement (“What are your suggestions for improvement?”).[11] Kununu pays particular attention to the authenticity of reviews. Users must provide a valid e-mail address and comply with Kununu’s review guidelines. Kununu has technical security measures in place to enforce its review guidelines and employs a community management team that manually checks reviews. These guidelines include, for example, a prohibition on publishing personal data (Kununu, 2019a). As a general

[11] Kununu changed its review template in 2010, switching from one open-ended comment field to several open-ended comment fields for each rated aspect of the employer. Our main results are fundamentally the same when restricting our study period to January 2010-June 2018; these results are available upon request.

policy, Kununu does not delete or change reviews as long as they follow its review guidelines (Kununu, 2019b). Kununu's efforts to ensure the authenticity of its reviews are also reflected through the certification of its website for its protection of users' data and their anonymity by an independent auditing institute (TÜV Saarland, 2019).

Reviewed employers have the option of responding directly to the reviews. If they choose to do so, their response is shown publicly under the corresponding review (see Figure 4-1). The total number of reviews received, the average rating of all reviews, and the number of employer responses submitted are additionally prominently displayed on the employer's Kununu profile. Except for employer responses, Kununu offers no features, such as helpfulness votes, follower counts, or peer comments, that would allow for potential consequences of reviewers' judgment. To gain a better understanding of the consequences of the evaluation of a Kununu review by the employer, we coded the content of 100 randomly selected employer responses in terms of messages addressed to the employee. In nearly every instance (94%), the employer thanked the employee for posting a review on Kununu (e.g., "Dear ex-employee, thank you very much for your feedback on how you felt about your work at EMPLOYER"). Twenty percent of the responses explicitly expressed appreciation that the employee made the effort to provide detailed written justifications (e.g., "We are pleased that you have taken the time to evaluate EMPLOYER as an employer in such detail and thus contribute to our recommendation"). Seven percent of the responses included an apology for the shortcomings identified by the employee (e.g., "We are very sorry that you are clearly not satisfied with your job at this moment"). In 23% of the responses, the employer expressed a commitment to improve and to follow the employee's suggestions for improvement (e.g., "This will improve in the medium term. We will – in order to create room quickly – move one team to a rented property"). In 13% of the cases, the employer rejected the employee's criticism as unjustified (e.g., "Unfortunately, we cannot comment on the issues you have raised without further explanation from you"). In 36% of the responses, the employer invited the employee to participate in a follow-up dialogue, e.g., via e-mail or in a personal meeting (e.g., “Providing excellent and fair employee support is very important to us – in this respect we take your criticism very seriously. I would like to invite you to contact me so that we can arrange an appointment. Of course, I will, if you wish, treat your concern confidentially”). Content coding of 100 randomly selected employer responses illustrated that employers provide responses tailored to their reviews. This finding reassured us that the employers' responses indeed represent a consequence of their evaluation of the reviews.[12]

4.2.2 Measures

We created the following variables for our study from the review content.

First dependent variable: Information diversity. Information diversity is the topic entropy *T* of review *i* for employer *j* in quarter *k*. To build this measure, we estimated a total of 70 topics by applying topic modeling, a text-mining technique. More specifically, we applied latent dirichlet allocation (LDA) as described in Blei, Ng, and Jordan (2003) and Pritchard, Stephens, and Donnelly (2000) using collapsed Gibbs sampling (Griffiths & Steyvers, 2004). To estimate our topic model, we first summarized all individual comments made by a reviewer about a specific employer in one comprehensive review. To further reduce computational complexity, we standardized the data. Specifically, we removed stop words such as pronouns and articles as well as corpus-specific stop words such as “employer”, converted the text to lowercase, removed punctuation and very rare terms (words appearing in <0.1% of documents), and decreased word variability by reducing words to their stems (Blei & Lafferty, 2009; Blei et al., 2003). As LDA follows a bag-of-words approach that disregards sentence structure and syntax, we identified frequently occurring bigrams and trigrams in the documents. Bigrams and trigrams represent words that form a compound and

[12] The example responses were translated from German to English via DeepL (https://deepl.com/translator).

together provide a defined meaning such as “work-life balance” (trigram) or “home office” (bigram). If these separate words were not systematically replaced by the appropriate corresponding single term, LDA would incorrectly ignore their close connection. After preprocessing, our corpus held 2,873 unique terms in 424,564 reviews. We estimated the LDA model with a varying number of topics (2-120). The algorithm outputs topic loadings (i.e., the per document distribution across the number of topics) and a list of terms most closely associated with each topic. To date, no commonly accepted rule exists for analytically determining the number of “optimal” topics for a given corpus (Schmiedel, Müller, & vom Brocke, 2018). Therefore, we first used model log-likelihood (Griffiths & Steyvers, 2004) to guide the selection of the optimal number of topics for our corpus. Although the model fit improved monotonically as the number of topics increased, the gains from adding more topics diminished at approximately 60 topics. Second, as recommended by Schmiedel et al. (2018), we qualitatively examined terms and reviews that are strongly associated with each topic in our various models to interpret the meaning identified with each topic. We used the top 15 terms most strongly associated with each topic. Furthermore, we extracted 40 strongly associated reviews (highest topic loadings) for each topic to further guide our labeling process. We found that our small topic models (2–65 topics) merged similar topics and did not clearly differentiate between the themes. This finding is also in accordance with our examination of model log-likelihood. Furthermore, larger topic models (> 85 topics) showed duplicate topics that differed mostly in style. Finally, after an initial labeling of the remaining topic models (70–85) by the first author, we selected the 70-topic model that revealed the clearly interpretable topics. Next, two associated researchers in the human resource management field individually reviewed each of the 70 topics to independently assign an initial descriptive label to each topic. The labeling process resulted in high intercoder agreement of 80.5% between the two researchers and the first author (Holsti, 1969), indicating a consensus for most topics among the raters. After a series of discussions among the raters, we relabeled the remaining topics. The second round was also guided by a visualization of topics using LDAvis, a web-based interactive visualization[13] (Sievert & Shirley, 2014). The labeling affects only the qualitative terminology and represents a validation of the quality of our resulting topic model. The labels do not affect the actual quantitative measurement of topic probabilities described below, which was used to compute the information diversity variable to test our hypotheses. See Table 4-1 for an overview of the topic labels, an example review that loads highly on the respective topic, and the top 15 highest-loading terms (unigrams, bigrams, trigrams) per topic. The terms were stemmed as part of preprocessing to homogenize the term space.

The resulting topic model assumes that each review in our dataset covers a mixture of topics and thus is characterized by a distribution of topic probabilities *p(topic|review).* For instance, if our review dataset were to address only two topics, overtime and leadership, each review would cover these two topics with given probabilities. An overtime-focused review might then have the probabilities *p(overtime|review)* = 80% and *p(leadership|review)* = 20%. We use Shannon entropy (Shannon, 1948), a measure for dispersion of a probability distribution, to estimate the topic entropy T of each review. In our case, for each review i, the topic entropy T is formally defined as

$$T = -\sum_{t=1}^{70} p_{it} * log\,(p_{it}), \qquad with \sum_{t=1}^{70} p_{it} = 1 \tag{1}$$

[13] LDAvis plots topics in a two-dimensional field. Topics are represented by circles that are proportional in size to the frequency of each topic's terms (unigrams, bigrams, trigrams) over the entire text corpus. Proximity is based on similarity of term distributions; thus, overlapping circles represent topics with similar terms (see Sievert & Shirley, 2014).

High values denote high information diversity (i.e., a diverse set of employer information is presented to justify the review), and low values denote low information diversity (i.e., a narrow set of employer information is presented to justify the review).

Second dependent variable: Information extensiveness. Information extensiveness is the number of employer information words of review *i* for employer *j* in quarter *k*. To build this measure, we counted the number of words per review after preprocessing (i.e., after removing stop words, etc.) the corpus to 2,873 unique terms. Thus, high values denote high information extensiveness (i.e., extensive employer information is presented to justify the review), while low values denote low information extensiveness (i.e., limited employer information is presented to justify the review).

Table 4-1

Topics, example reviews and highest-loading terms

#	Topic	Example review	Top 10 terms (in German)
1	Topic indeterminate		aufgab selt grundsaetz einzeln fuehrt person information teil positiv regel
2	Overtime	Overtime can be compensated by taking time off or payment.	ueberstund gehalt arbeitszeit erwartet freizeit ausgleich vorhand druck stund mehrarbeit
3	Social exchange	Regular lunches, also across teams. Cool team events like summer party, North Sea getaway, soccer tournament...Snack&Hear on Friday.	regelmaess team gemeinsam meeting aktuell event projekt off them veranstalt
4	Topic indeterminate		manag leut jahr job mensch management erfahr team richtig hotel
5	Topic indeterminate		leut chef halt echt richtig bekommt alt geld jahr job
6	Company development	EMPLOYER is continually developing on the advertising market and is growing in the right direction.	jahr wachstum veraender positiv stark aktuell bereich stetig verbessert entwickl
7	Topic indeterminate		imag puenktlich gehaelt entscheid urlaub lob arbeitszeit geschaetzt weiterbild meeting
8	Equal opportunities	Everyone has the same opportunities and possibilities to achieve something, regardless of origin, gender, position, religion, etc.	alt geschlecht roll unterschied gross leistung egal spielt mensch erfahr
9	Sales	Sell, sell, sell anything else doesn't count in that place.	kund vertrieb produkt aussendien verkauf provision umsatz zahl markt jahr

Table 4-1 (continued)

10	International orientation	Global enterprise with high ambitions.	international deutschland deutsch produkt standort konz gross management global weltweit
11	Understaffing	Constant overloading of employees due to understaffing.	personal staendig leitung aufgab druck qualitaet stell stress bereich schaff
12	Personnel service provider	Quick response to questions. Very competent employees/contacts. No 0/8/15 interviews. You'll be taken care of, even if you are rejected.	kund freundlich frag einsatz schnell kontakt ansprechpartn erreichbar betreu kompetent
13	Hire and fire	Canceled during the trial period without direct statement of reasons.	monat tag kuendig woch gespraech frag gekuendigt person bekommt stell
14	Recommendation	Very good reputation. I am proud to work here and I recommend the employer unconditionally.	ruf urlaub arbeitszeit betriebsklima empfehl weiterbild gehalt sozial stolz famili
15	Training	Very good in-house seminars and training courses for the qualification of employees.	intern schulung weiterbild extern angebot int seminar ext bereich fortbild
16	Competence	Managers should not be selected exclusively on the basis of professional competence, many things can fail because of social incompetence.	fuehrungskraeft kompetenz sozial fuehrung fachlich fuehrungskraft kompetent fuehrungseb qualifiziert fuehr
16	Competence	Managers should not be selected exclusively on the basis of professional competence, many things can fail because of social incompetence.	fuehrungskraeft kompetenz sozial fuehrung fachlich fuehrungskraft kompetent fuehrungseb qualifiziert fuehr
17	Personnel restructuring	Massive downsizing over the next few years. The good employees leave EMPLOYER in droves.	jahr alt frueh geschaeftsfuehr mittlerweil lang langjaehr verlass vorstand imag
18	Conditionality	This depends very much on each colleague.	stark bereich abhaeng fuehrungskraeft unterschied haengt fuehrungskraft gross teil grundsaetz
19	Sense of belonging	Working at EMPLOYER feels a bit like being part of a big family. I am proud and grateful to belong!	mensch tag gross jahr famili erfahr gefuehl spass richtig leb
20	Work hours	Core-hours are from 9 - 3 o'clock. You can't leave the building until 3 o'clock. But you can also start at 6 o'clock like I do. They insist on adhering to core working hours.	tag uhr arbeitszeit woch stund urlaub frueh wochen paus laeng
21	Intra and interdepartmental interactions	The solidarity in the individual departments is great. But also in the whole organization the colleagues are always there for you.	abteil kommunikation einzeln unterschied abteilungsleit gross zusammenhalt aufgab bereich stark
22	Fair remuneration	Fairer treatment and fairer payment!!!	bezahl fair umgang arbeitsklima gehalt angemess kommunikation flexibl_arbeitszeit work gerecht
23	Structural rigidity	Cumbersome workflows, all processes should be optimized.	prozess struktur lang intern starr kommunikation veraltet hierarchi ablaeuf buerokrati

Table 4-1 (continued)

24	Recognition	Performance is rewarded both in monetary terms and through recognition.	leistung gefoerdert belohnt einsatz engagement honoriert anerkenn sozial gefordert chanc
25	Feedback culture	The working atmosphere is low in hierarchy, very appreciative and professional. The open-door policy promotes open exchange. Feedback is always given constructively.	off feedback individuell regelmaess team fair konstruktiv austausch gefoerdert ehrlich
26	Gender equality	There are more women than men in management positions.	frau maenn fuehrungsposition position aelt jahr gehalt weiterbild weiblich aelt_kolleg
27	Air conditioning	No air conditioning, up to 36 degrees in summer.	somm klimaanlag heiss wint vorhand warm kalt bueros raeum fenst
28	Transparent decision-making	They do not make clear and comprehensible decisions. Everybody's next to themselves. Right doesn't know what left does.	entscheid getroff nachvollziehbar kommunikation wichtig information treff kommuniziert lang transparenz
29	Trustworthiness	Commitments, promises must be made in writing, otherwise they will not be kept.	eingehalt versprech versproch kommunikation vorhand absprach gehalt zusag einhalt aussag
30	Communication gap	Internal communication should be improved.	kommunikation verbessert verbess team abteil zusammenarbeit intern_kommunikation bereich zusammenhalt einzeln
31	Research & Development	EMPLOYER offers many exciting opportunities and projects due to its expertise in mechanics, electronics and software, especially in product development, connectivity technology and software development.	projekt entwickl bereich interessant technisch produkt kund them technologi softwar
32	Topic indeterminate		kommunikation positiv punkt gehalt ordnung absolut negativ bereich gross imag
33	Follow-up mentality	They should listen more to employees & accept improvement suggestions or work them out together.	wuensch kritik meinung ernst verbesserungsvorschlaeg vorschlaeg laesst kommunikation eingegang lob
34	Criticism of management	It gets better from middle management upwards. Lower management is awful.	management eben kommunikation fuehrung manag strategi produkt entscheid vorhand polit
35	Salary comparison	The salaries are very good in comparison within the industry. Compared to other industries rather low. The welfare benefits are very good.	gehalt gehaelt gering niedrig weiterbild sozialleist branch durchschnitt vorhand hoeh
36	Employer review vocabulary	All in all, a good employer. Some people seem to use this platform to let off frustration (over their own failure?). Can‘t relate to some of the reviews here.	bewert positiv negativ meinung punkt kommentar jahr erfahr imag kununu
37	Worksite	Open-plan office is something one has to like, height-adjustable desks, ergonomic workstations.	bueros buero gross grossraumbuero schreibtisch hom_offic alt grossraumbueros arbeitsplaetz aufgab

Table 4-1 (continued)

38	Time flexibility	Excellent flextime arrengements! I was able to keep all important private appointments without any problems.	urlaub arbeitszeit aufgab kurzfrist privat flexibel termin problem jederzeit absprach
39	Bonus payments	Vacation bonus, Christmas bonus, profit sharing.	urlaub gehalt weihnachtsgeld jahr urlaubsgeld leistung ueberstund tag sozialleist weihnacht
40	Topic indeterminate		leut lieb geld richtig bekommt falsch egal meinung schoen wort
41	Perks	Free drinks and fruit.	kaffe kostenlos obst getraenk wass kantin frisch ess schoen buero
42	Abusive environment	Complete control and monitoring of employees.	druck staendig angst mobbing verhalt kontroll herrscht kuendig tagesordn geschaeftsfuehr
43	Work-family balance	Thanks to flexible working hours, home office and great colleagues, it is possible for me to balance work and family.	hom_offic flexibl_arbeitszeit arbeitszeit famili kind flexibl beruf flexibilitaet flexibel gleitzeit
44	Corporate Social Responsibility	Social responsibility for employees and the local community.	sozial engagement bank angebot unterstuetz bereich engagiert unterstuetzt weiterbild sozialleist
45	Consulting	Up to the Managing Consultant everything is fine, then there is a bottleneck into the Partner area, which is not very permeable.	projekt kund berat partn abhaeng interessant intern stark gehalt jahr
46	Internship	Working students and interns are 100% involved into the development process.	praktikant aufgab praktikum team student werkstudent projekt einblick frag bekommt
47	Problem-solving	In case of problems and concerns, a solution is always sought together with the employer and usually a solution is always found!	problem loesung off gemeinsam off_ohr versucht probl gesucht team gefund
48	Fixed-term contracts	There are only fixed-term contracts.	ausbild jahr angestellt befristet chanc azubis vertraeg stell gehalt uebernomm
49	Long-term strategy	No long-term corporate strategy, employees are “burned”!	strategi langfrist nachhalt staerk ziel umsetz entwickl konsequent vision fuehrung
50	Great job	It’s everything just right... that’s what a perfect employer looks like!	team spass chef job absolut klass passt echt tag zufried
51	Creativity	Plenty of freedom to contribute and implement your own ideas and suggestions.	ide einbring off umgesetzt vorschlaeg umsetz gefoerdert einzubring team kreativ
52	Employee and co-worker treatment	Respectful and friendly interaction between employees.	umgang off fair respektvoll freundlich miteinand kollegial untereinand ehrlich umgang_miteinand
53	Mutual support	Great team! Employees support each other, you are in good hands.	team off frag off_ohr jederzeit fuehlt freundlich spass unterstuetz tag
54	Location	At the moment still good accessibility to public transport.	standort oeffent kantin lag schoen zentral dien muench parkplaetz bueros
55	Money vocabulary	15€ per hour.	geld stund monat tag eur gehalt bekommt bezahlt bezahl lohn

Table 4-1 (continued)

56	Leadership	Authoritarian leadership style	kommunikation wertschaetz fehlend fuehrung vorhand mangelnd fuehrungsstil mangelhaft struktur fuehrungseb
57	Topic indeterminate		teamleit team gehalt druck bekommt tag callcent job staendig call_cent
58	Goal setting	The targets are set in an unrealistic manner - and as a result hardly any timetable is kept.	ziel erreich realist druck erreicht unrealist gesetzt vorgab aufgab zahl
59	Autonomy	Employees are given a great deal of freedom and responsibility.	verantwort aufgab uebernehm gross vertrau freiheit eigenverantwort team breit uebertrag
60	Modernness	State-of-the-art technology. The offices and furniture could be more up to date.	modern technik stand bueros schoen mod arbeitsplaetz ausstatt neu raeum
61	Start-up atmosphere	A great team and exciting tasks. (Still) a pronounced startup mentality.	team dynam zusammenhalt spass atmospha start event stark flach_hierarchi motiviert
62	Retail	There are many stores and therefore good job vacancies.	filial kund druck tag personal staendig verkauf stund lad filialleit
63	Creative agency	Great small agency, with regular working hours, great colleagues, relaxed deadlines, very good project management and nice clients.	team agentur projekt kund branch spannend gross schoen buero nett
64	Humanity	Treat employees as people and not as numbers or cost factors.	mensch angestellt vorhand behandelt verhalt umgang absolut menschlich geschaeftsfuehr zaehlt
65	Industry	Elect a works council, pay tariff wages, family-friendly shift system in production.	produktion betriebsrat betrieb bezahl tarif arbeitnehm maschin leiharbeit schicht taetig
66	Hierarchy	Flat hierarchy, short decision-making processes.	kurz flach schnell weg entscheidungsweg flach_hierarchi lang hierachi hierarchi kommunikationsweg
67	Job security	Secure job; timely payment of salary.	arbeitsplatz sich puenktlich bezahl arbeitszeit gehalt lohn nachteil gehaltszahl betriebsklima
68	Nice people	The colleagues are all helpful and friendly.	nett freundlich angenehm hilfsbereit arbeitsklima atmospha nett_kolleg arbeitsatmospha kompetent chef
69	Task variety	Interesting, versatile and challenging tasks.	interessant aufgab abwechslungsreich projekt spannend taetig vielfaelt anspruchsvoll arbeitsklima international
70	Organizational culture	You can’t get more participation rights than here. A lot of emphasis is put on the company culture, the employees and the well-being of the employees are at highest priority. GREAT!	wert off gelebt wertschaetz ehrlich gelegt gross vertrau umgang legt

Notes: Example reviews were translated from German to English via DeepL (https://deepl.com/translator).

In Table 4-2, we illustrate the information diversity and extensiveness of four sample reviews. These examples demonstrate that reviews with comparable information extensiveness (i.e., employer information word count) may address a vastly different number of topics, even if they use several of Kununu's individual comment fields. For instance, one example review presented in Table 4-2, although the reviewer used several individual comment fields, concerns mostly leadership. Nonetheless, as expected, we found a positive correlation between the number of comment fields used by reviewers and information diversity ($r = .465$, $p < .001$).

Independent variable: Responsiveness. Responsiveness is our central variable of interest and represents the difference estimator in our difference-in-differences analysis. It reflects whether an employer indicated its responsiveness with a first response to an online employer review. Review i for employer j in quarter k is dummy coded 1 if the review was posted after employer j had posted its first response to a review and 0 otherwise.[14]

First moderating variable: TPE image valence. TPE image valence describes whether review i for employer j in quarter k presents a more positive or negative TPE image. TPE image valence thus represents whether an employee judged the employer as positive, mediocre, or even negative (the higher the score, the more positive the judgment). TPE image valence is measured using the reviews' overall rating (from 1.0 to 5.0 stars).

Second moderating variable: Employment status. Employment status describes whether review i for employer j in quarter k was posted by a current or former employee. It is dummy coded 1 for reviews of former employees and 0 otherwise.

[14] Kununu discloses only the month of an employer's response, not the exact date. Therefore, we have modeled responsiveness at the month level to address this drawback of our dataset. For instance, if an employer responded to its first review in January 2017, responsiveness is dummy coded 1 for reviews of this employer posted after 31 January 2017 and 0 otherwise. The results for modeling responsiveness at the quarter level are fundamentally the same as the results reported in this article. The results are available upon request.

Table 4-2

Information extensiveness and diversity of four example reviews

Review	Extensiveness	Diversity
Pro: Timely payment **Contra:** Poor image, unhappy customers	5	4.682
Pro: Very open and friendly environment; very nice collegial atmosphere	5	1.902
Work atmosphere: Very crisp and jagged working style. High frequency and totally understaffed. **Teamwork:** With extremely stressful days, the team spirit is very important. **Career/Development:** After 2 years the opportunity to become a Senior Consultant exists. Excellent courses in CITY as well as an EMPLOYER degree. **Suggestions for improvement:** Great on-boarding and great seminars but bad off-boarding. Reduce employee fluctuation through more personal contact with employees. Do not look for faults but offer employees the opportunity to develop. Trust-based working hours should be respected on both sides. **Pro:** Interesting work, excellent introduction, structured way of working. I am grateful to EMPLOYER for everything I have learnt and only in retrospect did the meaning of many things become clear. But I also know what I don't want to do and will do better. **Contra:** Not enough internal staff, a lot of pressure from above for the Branch Managers, very controlled and bad cutting of employees. Sickness rates are extremely important. EMPLOYER is a hard employer and you have to like it and fit to the structure, otherwise it won't work.	53	5.334
Managerial behavior: Unfortunately, managers are often not well selected or trained. It is easy to get praised if you butter up the right people. **Teamwork:** When leadership is poor, the peasants unite and form a team. This could also be achieved with a good leadership style, but unfortunately this is not encouraged. **Communication:** One must not know or even question anything. Just turn off your brain and follow the lead. The company may break down, but maybe that's intended. **Equality:** Not unless the immediate supervisor is supportive. Unfortunately not due to qualification. **Career/Development:** When you're an executive, there are several opportunities. Coaching is unfortunately used to control the ordinary employee. **Overall compensation:** A joke and with many pitfalls when it comes to the variable salary. **Environmental/Social awareness:** Not present **Work-life balance:** Sickness is not acceptable. And overtime hours are regular and already accounted for with the low salary. **Image:** Unfortunately, bad. But it was great once. I proudly named my employer. Now I am ashamed. **Suggestions for improvement:** New leadership. **Pro:** The steady, punctual salary **Contra:** The unqualified managers	52	3.970

Notes: Reviews were translated from German to English via DeepL (https://deepl.com/translator). Information diversity and extensiveness are based on the German review. Titles in bold are not part of the review, but refer to Kununu's individual comment columns.

Covariates. To mitigate concerns that review *i*'s information diversity and extensiveness are contingent on factors other than employer *j*'s responsiveness, we included review-level control variables in our models. More specifically, we included the employee's position (employee vs. C-suite/leadership) and department (e.g., finance, IT, legal/tax). Furthermore, we accounted for all unobserved time-invariant employer-level control variables (e.g., industry, size, location) and for time effects affecting all employers (e.g., financial crises, seasonal effects) by including employer and time (quarterly) fixed effects in our models (see below).

4.2.3 Data

Our sample included online reviews submitted by current and former employees to Kununu between May 2007 and June 2018. More specifically, our sample comprised all online reviews of German-based employers (i.e., excluding Austrian, Swiss, US or other employers) that had received at least two online reviews by July 2018. We omitted non-German employers to ensure the homogeneity of the review texts (e.g., with regard to dialects or country-specific terminology). While information extensiveness could be calculated for reviews not containing any text comments (i.e., reviews with no text are not extensive), our information diversity measure could be calculated only for reviews containing text (i.e., reviews with no text are not narrow). Therefore, we considered only employer reviews that included meaningful text comments, i.e., text comments that did not consist solely of erroneous terms or stop words (424,564 of 623,555), which also allowed us to log-transform our information extensiveness variable for efficient estimation.[15] To further homogenize our dataset, we omitted reviews by interns, working students, freelancers, and temporary workers

[15] The results for modeling information extensiveness also using reviews without text (i.e., reviews with an information extensiveness of zero) in a Poisson regression model are fundamentally the same as the results reported in this article. The results are available upon request.

Table 4-3

Means, standard deviations, and correlations of the study variables

		M	*SD*	1	2	3	4	5
1	Information diversity	4.19	0.64					
2	Information extensiveness	33.39	43.90	0.421***				
3	log(Information extensiveness)	2.84	1.20	0.613***	0.793***			
4	TPE image valence	3.49	1.19	-0.040***	-0.158***	-0.191***		
5	Employment status (former employee)	0.27	0.44	0.052***	0.110***	0.136***	-0.417***	
6	Responsiveness	0.23	0.42	0.013***	0.032***	0.020***	0.056***	-0.036***

Notes: N = 298,269 reviews of 21,099 employers over 45 quarters.
*p < .05; **p < .01; ***p < .001

and reviews with no indication of the reviewer's position (298,269 of 424,564), as these employees' reviews may display a significantly different extent and diversity of employer information than reviews by regular current and former employees – for instance, a freelancer may get to know an employer only within a single project assignment. In summary, our main analyses were based on 298,269 reviews of 21,099 German employers (of which 3,700 became responsive at some point in our study period) over 45 quarters. Means, standard deviations, and correlations among all variables are reported in Table 4-3.

4.2.4 Estimation

To test our hypotheses, we applied a difference-in-differences analysis. More specifically, we fitted fixed-effects models, which are often considered the "gold standard" when estimating within-company relationships (Bliese et al., 2020), to model the effects of responsiveness on information diversity and extensiveness. To test our hypotheses, we used the following formulas:

$$Information\ diversity_{ijk} = \beta_0 Position_{ijk} + \beta_1 Department_{ijk} + \beta_2 Responsiveness_{ijk} + u_j + v_k + e_{ijk} \tag{2}$$

$$log(Information\ extensiveness)_{ijk} = \beta_0 Position_{ijk} + \beta_1 Department_{ijk} + \beta_2 Responsiveness_{ijk} + u_j + v_k + e_{ijk} \quad (3)$$

$$Information\ diversity_{ijk} = \beta_0 Position_{ijk} + \beta_1 Department_{ijk} + \beta_2 Responsiveness_{ijk} + \beta_3 TPE\ image\ valence_{ijk} + \beta_4 Employment\ status_{ijk} + \beta_5 \left(Responsiveness_{ijk} * TPE\ image\ valence_{ijk}\right) + u_j + v_k + e_{ijk} \quad (4)$$

$$log(Information\ extensiveness)_{ijk} = \beta_0 Position_{ijk} + \beta_1 Department_{ijk} + \beta_2 Responsiveness_{ijk} + \beta_3 TPE\ image\ valence_{ijk} + \beta_4 Employment\ status_{ijk} + \beta_5 \left(Responsiveness_{ijk} * TPE\ image\ valence_{ijk}\right) + u_j + v_k + e_{ijk} \quad (5)$$

$$Information\ diversity_{ijk} = \beta_0 Position_{ijk} + \beta_1 Department_{ijk} + \beta_2 Responsiveness_{ijk} + \beta_3 TPE\ image\ valence_{ijk} + \beta_4 Employment\ status_{ijk} + \beta_5 \left(Responsiveness_{ijk} * Employment\ status_{ijk}\right) + u_j + v_k + e_{ijk} \quad (6)$$

$$log(Information\ extensiveness)_{ijk} = \beta_0 Position_{ijk} + \beta_1 Department_{ijk} + \beta_2 Responsiveness_{ijk} + \beta_3 TPE\ image\ valence_{ijk} + \beta_4 Employment\ status_{ijk} + \beta_5 \left(Responsiveness_{ijk} * Employment\ status_{ijk}\right) + u_j + v_k + e_{ijk} \quad (7)$$

Index *i* denotes reviews, *j* denotes employers, *k* denotes quarters, u_j denotes employer fixed effects, v_k represents time (quarterly) fixed effects, and e_{ijk} is the remainder stochastic disturbance term. The fixed effects control for time-invariant differences in our dependent variables due to unobserved factors that differ across employers (e.g., size, industry, location), while time effects control for common time shocks affecting all employers (e.g., financial crises, seasonal effects). Furthermore, we adopted cluster-robust standard errors at the employer level to account for autocorrelation in the data across employers and over time (Bertrand, Duflo, & Mullainathan, 2004). Review *i*'s information diversity and extensiveness are modeled as functions of responsiveness within each employer *j* and quarter *k*. In equations 2-3, we are interested in β_2, as it represents the effect of responsiveness on information diversity and information extensiveness. In other words, β_2 signifies the difference between the information diversity and extensiveness of reviews of responsive and unresponsive employers. In equations 4-7, we are interested in β_5, as it represents the effect of responsiveness on information diversity and extensiveness depending on employment status and TPE image valence.

4.3 Results

Initially, we fitted fixed-effects models to explore the effects of responsiveness on reviews' information diversity and log-transformed information extensiveness. Model 1 includes the covariates, and Model 2 includes the main effect of responsiveness. As shown in Table 4-4 (Model 2), our first hypothesis, which states that responsiveness is positively associated with information diversity, was supported (0.012, $p = .033$). To examine the effect size, we calculated Cohen's *d*. To do so, we divided the coefficient of responsiveness (0.012) by the standard deviation of information diversity of all employer reviews in our sample ($SD = 0.64$). Cohen's *d* indicated a minor effect size ($d = 0.019$) for the association of responsiveness and information diversity. As shown in Table 4-5 (Model 2), our second hypothesis, which states that responsiveness is positively associated with information extensiveness, was also supported (0.053, $p < .001$). As information extensiveness was log-transformed before estimation, we were able to calculate the percentage change in information extensiveness due to responsiveness. The findings indicated that responsive employers

Table 4-4

OLS results for the effects of responsiveness on information diversity

	Model 1	Model 2	Model 3	Model 4	Model 5
Position (C-suite/leadership)	-0.045***	-0.045***	-0.039***	-0.039***	-0.039***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Department (administration)	0.030***	0.030***	0.034***	0.034***	0.034***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Department (design)	0.022	0.022	0.024	0.024*	0.024*
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Department (distribution/sales)	0.025***	0.025***	0.026***	0.026***	0.026***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Department (executive leadership)	-0.031*	-0.031*	-0.026	-0.026	-0.026
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
Department (finance)	0.010	0.010	0.011	0.011	0.011
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Department (human resources/recruiting)	0.031***	0.031***	0.039***	0.039***	0.039***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Department (IT)	0.031***	0.031***	0.032***	0.032***	0.032***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Department (legal/tax)	0.002	0.002	0.004	0.004	0.005
	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)
Department (logistics/materials management)	-0.010	-0.010	-0.014	-0.014	-0.014
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Department (marketing/product management)	0.046***	0.046***	0.050***	0.050***	0.050***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Department (medical)	0.070***	0.070***	0.074***	0.074***	0.074***
	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)
Department (others)	0.054***	0.054***	0.054***	0.054***	0.054***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Department (PR/communication)	0.040**	0.040**	0.044***	0.044***	0.044***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Department (production)	0.015	0.015	0.013	0.013	0.013
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Department (purchasing)	0.017	0.017	0.017	0.017	0.017
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Department (research/development)	0.049***	0.049***	0.051***	0.051***	0.051***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Responsiveness		0.012*	0.012*	0.044***	0.006
		(0.006)	(0.006)	(0.011)	(0.006)
TPE image valence			-0.015***	-0.013***	-0.015***
			(0.001)	(0.002)	(0.001)
Employment status (former employee)			0.034***	0.034***	0.028***
			(0.003)	(0.003)	(0.003)

Table 4-4 (continued)

Responsiveness × TPE image valence				-0.009^{**}	
				(0.003)	
Responsiveness × employment status (former employee)					0.025^{***}
					(0.007)
Employer fixed effects	Yes	Yes	Yes	Yes	Yes
Quarter fixed effects	Yes	Yes	Yes	Yes	Yes
R^2	0.121	0.121	0.122	0.122	0.123
Adjusted R^2	0.054	0.054	0.055	0.055	0.055

Notes: N = 298,269 reviews of 21,099 employers over 45 quarters. Cluster-robust standard errors (in parentheses). Reference category for position is "employee". Reference category for department is "not specified". Reference category for employment status is "current employee".
*p < .05; **p < .01; ***p < .001

Table 4-5

OLS results for the effects of responsiveness on log(information extensiveness)

	Model 1	Model 2	Model 3	Model 4	Model 5
Position (C-suite/leadership)	-0.154^{***}	-0.154^{***}	-0.099^{***}	-0.098^{***}	-0.098^{***}
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Department (administration)	0.027^{*}	0.027^{*}	0.058^{***}	0.059^{***}	0.059^{***}
	(0.014)	(0.014)	(0.013)	(0.013)	(0.013)
Department (design)	-0.007	-0.007	0.013	0.013	0.013
	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)
Department (distribution/sales)	0.050^{***}	0.049^{***}	0.064^{***}	0.065^{***}	0.065^{***}
	(0.014)	(0.014)	(0.013)	(0.013)	(0.013)
Department (executive leadership)	-0.107^{***}	-0.107^{***}	-0.060^{*}	-0.060^{*}	-0.059^{*}
	(0.028)	(0.028)	(0.027)	(0.027)	(0.027)
Department (finance)	-0.048^{*}	-0.048^{*}	-0.031	-0.030	-0.029
	(0.022)	(0.022)	(0.022)	(0.021)	(0.022)
Department (human resources/recruiting)	-0.002	-0.001	0.071^{***}	0.072^{***}	0.073^{***}
	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)
Department (IT)	0.047^{***}	0.046^{***}	0.061^{***}	0.062^{***}	0.062^{***}
	(0.014)	(0.014)	(0.013)	(0.013)	(0.013)
Department (legal/tax)	-0.012	-0.012	0.015	0.016	0.016
	(0.031)	(0.031)	(0.030)	(0.030)	(0.030)
Department (logistics/materials management)	0.020	0.019	-0.005	-0.004	-0.004
	(0.024)	(0.024)	(0.023)	(0.023)	(0.023)
Department (marketing/product management)	0.060^{***}	0.060^{***}	0.103^{***}	0.103^{***}	0.104^{***}
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
Department (medical)	0.084^{*}	0.085^{*}	0.119^{**}	0.120^{**}	0.120^{**}
	(0.039)	(0.039)	(0.038)	(0.038)	(0.038)

Table 4-5 (continued)

Department (others)	0.131***	0.131***	0.131***	0.132***	0.132***
	(0.012)	(0.012)	(0.011)	(0.011)	(0.011)
Department (PR/communication)	0.044	0.043	0.091***	0.091***	0.091***
	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)
Department (production)	0.069***	0.068***	0.047**	0.048**	0.048**
	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)
Department (purchasing)	-0.014	-0.014	-0.007	-0.006	-0.005
	(0.025)	(0.025)	(0.024)	(0.024)	(0.024)
Department (research/development)	0.114***	0.113***	0.139***	0.140***	0.141***
	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)
Responsiveness		0.053***	0.055***	0.220***	0.029*
		(0.012)	(0.012)	(0.024)	(0.012)
TPE image valence			-0.169***	-0.157***	-0.168***
			(0.003)	(0.003)	(0.003)
Employment status (former employee)			0.115***	0.116***	0.091***
			(0.006)	(0.006)	(0.007)
Responsiveness × TPE image valence				-0.046***	
				(0.006)	
Responsiveness × employment status (former employee)					0.108***
					(0.014)
Employer fixed effects	Yes	Yes	Yes	Yes	Yes
Quarter fixed effects	Yes	Yes	Yes	Yes	Yes
R^2	0.187	0.187	0.212	0.213	0.212
Adjusted R^2	0.125	0.125	0.152	0.152	0.152

Notes: N = 298,269 reviews of 21,099 employers over 45 quarters. Cluster-robust standard errors (in parentheses). Reference category for position is "employee". Reference category for department is "not specified". Reference category for employment status is "current employee".
*p < .05; **p < .01; ***p < .001

received reviews that presented 5.44% more extensive employer information than reviews received by non-responsive employers.

Next, we fitted fixed-effects models to explore the effects of responsiveness moderated by TPE image valence. Model 3 includes the main effect of our moderators, and Model 4 includes the interaction term of responsiveness and TPE image valence. As shown in Table 4-4 (Model 4), our third hypothesis, which states that the relationship between responsiveness and information diversity is moderated by TPE image valence, was supported (-0.009, p = .002). Furthermore, as shown in Table 4-5 (Model 4), our fourth hypothesis, which states that the relationship between responsiveness and information extensiveness is moderated by TPE image valence, was supported (-0.046, $p < .001$). To fully explore the interaction of responsiveness and TPE image valence, we examined the marginal effect of responsiveness on information diversity and extensiveness across different TPE image valence levels. An effective way to examine these effects is to plot their slope and confidence intervals (Brambor, Clark, & Golder, 2006). The solid sloping line in Figure 4-2 plots the marginal effect of responsiveness contingent on TPE image valence, while the shaded bands represent the 95% confidence interval. Thus, Figure 4-2 (left side) suggests that the positive effect of responsiveness on information diversity is stronger with lower TPE image valence (0.035 for one-star reviews). Cohen's *d* indicated a marginal effect size (d = 0.055) for the association of responsiveness and information diversity for one-star reviews. Apparently, the marginal effects plot also suggests that the effect of responsiveness becomes negative for five-star reviews. However, the marginal effects are not distinguishable from zero ($p > .05$) for TPE image valence above 3.7. Furthermore, Figure 4-2 (right side) suggests that the effect of responsiveness on information extensiveness is stronger with lower TPE image valence (0.174 for one-star reviews; marginal effects are not distinguishable from zero ($p > .05$) for TPE image valence above 4.2). Thus, responsive employers received one-star reviews that presented 19.01% more extensive employer information than one-star reviews received by non-responsive employers.

Finally, we fitted fixed-effects models to explore the effects of responsiveness moderated by employment status (i.e., former vs. current employees). Model 3 includes the main effect of our moderators, and Model 5 includes the interaction term of responsiveness and employment status. As shown in Table 4-4 (Model 5), we found a significant interaction of responsiveness and employment status in estimating information diversity (0.025, $p < .001$). Furthermore, as demonstrated in Table 4-5 (Model 5), we also found a significant

Figure 4-2

Marginal effect of responsiveness conditional on TPE image valence

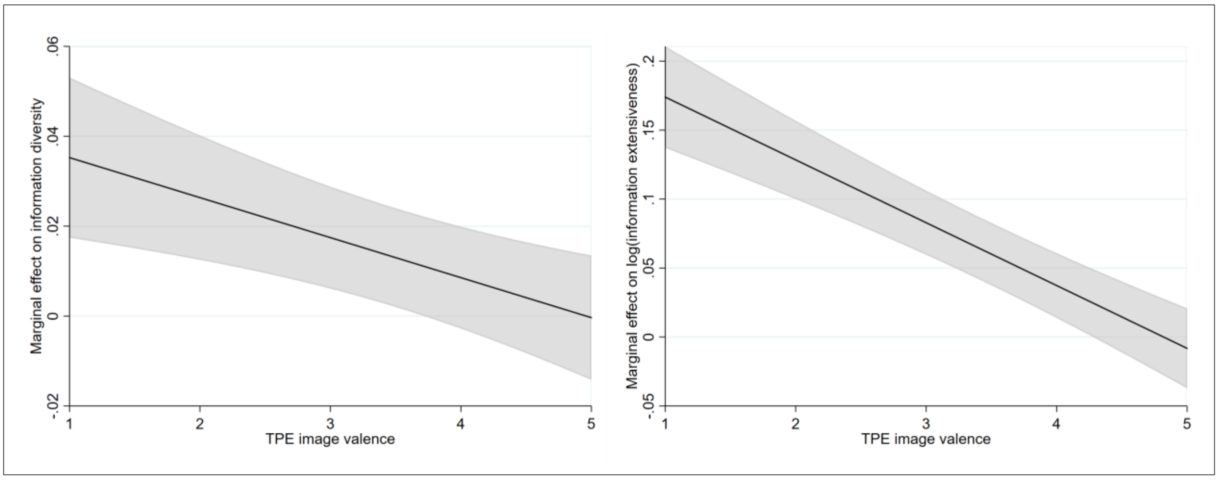
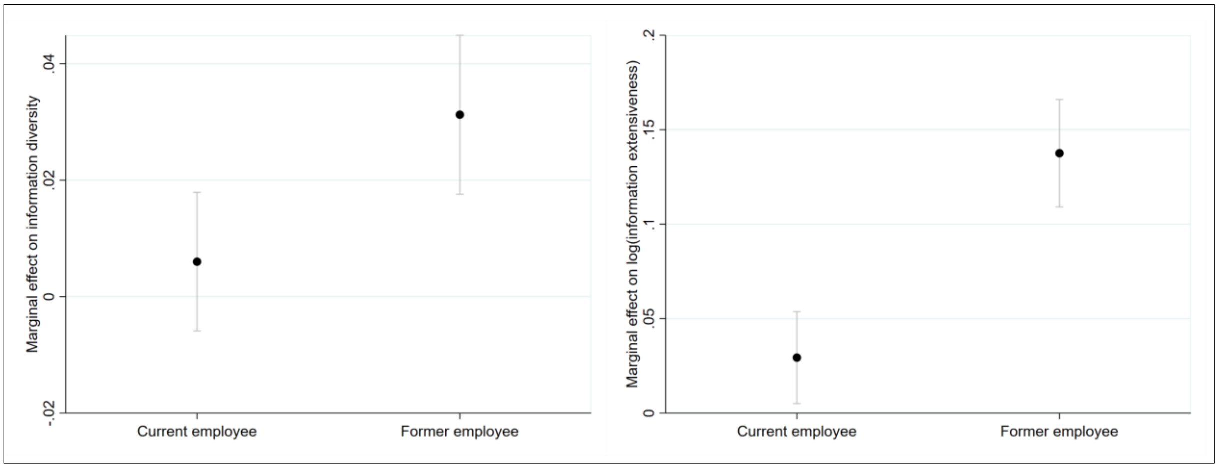


Figure 4-3

Marginal effect of responsiveness conditional on employment status



interaction of responsiveness and employment status in estimating log-transformed information extensiveness (0.108, $p < .001$). Figure 4-3 (left side) suggests that the positive effect of responsiveness on information diversity is stronger for former employees (0.031 for former employees vs. 0.006 for current employees; marginal effect for current employees was not distinguishable from zero ($p > .05$)). Cohen's d indicated a marginal effect size (d = 0.048) for the association of responsiveness and information diversity for former employees. Moreover, Figure 4-3 (right side) suggests that the effect of responsiveness on information extensiveness is also stronger for former employees (0.138 for former employees vs. 0.029 for current employees). Thus, responsive employers received reviews from former employees that presented 14.80% more extensive employer information than reviews from former employees received by non-responsive employers.

In summary, our difference-in-differences analysis demonstrated that responsive employers received reviews presenting more diverse and extensive employer information than reviews received by non-responsive employers. Furthermore, responsive employers received negative reviews presenting diverse and extensive employer information rather than positive reviews. Finally, responsive employers received reviews presenting diverse and extensive employer information by former employees rather than by current employees. Examination of the effect sizes revealed that responsiveness had a minor effect on information diversity, while the effect on information extensiveness was substantial (up to 19.01%). Although the effect on information diversity was not large by conventional standards (i.e., Cohen's *d* below 0.20), we considered it important because it was caused by a minimal intervention, i.e., only by an employer's first response to its reviews (see Cortina & Landis, 2008).

4.3.1 Supplementary Analyses

Endogeneity. Difference-in-differences designs attempt to identify causal relationships by mimicking an experimental design in observational data (Angrist & Pischke, 2008). In our case, we attempt to model the differences between reviews for responsive and non-responsive (i.e., treated and untreated) employers. For this model to be valid, responsiveness must resemble an exogenous event. However, since employers self-select for responding, unobserved time-variant differences between treated and untreated employers may be the reason why employers start responding. For instance, an employer might decide to become responsive because the employer information presented in its reviews becomes more diverse and extensive over time. To control for such unobserved heterogeneity in time trends between

Table 4-6

Time trend controlled effects of responsiveness on information diversity

	Model 1	Model 2	Model 3	Model 4	Model 5
Position (C-suite/leadership)	-0.045***	-0.045***	-0.039***	-0.039***	-0.039***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Department (administration)	0.030***	0.030***	0.033***	0.034***	0.034***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Department (design)	0.022	0.022	0.024	0.024	0.024
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Department (distribution/sales)	0.025***	0.025***	0.025***	0.026***	0.026***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Department (executive leadership)	-0.031*	-0.031*	-0.026	-0.026	-0.026
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
Department (finance)	0.010	0.010	0.010	0.011	0.011
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Department (human resources/recruiting)	0.031***	0.031***	0.039***	0.039***	0.039***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Department (IT)	0.031***	0.031***	0.032***	0.032***	0.032***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Department (legal/tax)	0.001	0.001	0.003	0.004	0.004
	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)
Department (logistics/materials management)	-0.010	-0.010	-0.014	-0.014	-0.014
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Department (marketing/product management)	0.046***	0.046***	0.050***	0.050***	0.050***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Department (medical)	0.070***	0.071***	0.074***	0.074***	0.074***
	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)
Department (others)	0.054***	0.054***	0.054***	0.054***	0.054***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Department (PR/communication)	0.040**	0.040**	0.044***	0.044***	0.044***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Department (production)	0.015	0.015	0.012	0.012	0.013
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Department (purchasing)	0.017	0.017	0.017	0.017	0.017
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Department (research/development)	0.049***	0.049***	0.051***	0.051***	0.051***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Responsiveness		0.016*	0.017*	0.048***	0.011
		(0.007)	(0.007)	(0.012)	(0.007)
TPE image valence			-0.015***	-0.013***	-0.015***
			(0.001)	(0.002)	(0.001)
Employment status (former employee)			0.034***	0.034***	0.028***
			(0.003)	(0.003)	(0.003)

Table 4-6 (continued)

Responsiveness × TPE image valence				-0.009**	
				(0.003)	
Responsiveness × employment status (former employee)					0.025***
					(0.007)
Employer fixed effects	Yes	Yes	Yes	Yes	Yes
Quarter fixed effects	Yes	Yes	Yes	Yes	Yes
Treatment-specific linear trend	Yes	Yes	Yes	Yes	Yes
Treatment-specific quadratic trend	Yes	Yes	Yes	Yes	Yes
R^2	0.121	0.121	0.123	0.123	0.123
Adjusted R^2	0.054	0.054	0.055	0.055	0.055

Notes: N = 298,269 reviews of 21,099 employers over 45 quarters. Cluster-robust standard errors (in parentheses). Reference category for position is “employee”. Reference category for department is “not specified”. Reference category for employment status is “current employee”.
*p < .05; **p < .01; ***p < .001

Table 4-7

Time trend controlled effects of responsiveness on log(information extensiveness)

	Model 1	Model 2	Model 3	Model 4	Model 5
Position (C-suite/leadership)	-0.154***	-0.154***	-0.099***	-0.098***	-0.098***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Department (administration)	0.027	0.027	0.058***	0.058***	0.059***
	(0.014)	(0.014)	(0.013)	(0.013)	(0.013)
Department (design)	-0.007	-0.007	0.013	0.013	0.013
	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)
Department (distribution/sales)	0.049***	0.049***	0.064***	0.064***	0.065***
	(0.014)	(0.014)	(0.013)	(0.013)	(0.013)
Department (executive leadership)	-0.107***	-0.107***	-0.060*	-0.060*	-0.059*
	(0.028)	(0.028)	(0.027)	(0.027)	(0.027)
Department (finance)	-0.049*	-0.049*	-0.031	-0.030	-0.030
	(0.022)	(0.022)	(0.022)	(0.021)	(0.022)
Department (human resources/recruiting)	-0.002	-0.002	0.071***	0.071***	0.072***
	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)
Department (IT)	0.046***	0.046***	0.060***	0.061***	0.062***
	(0.014)	(0.014)	(0.013)	(0.013)	(0.014)
Department (legal/tax)	-0.013	-0.013	0.013	0.014	0.015
	(0.031)	(0.031)	(0.030)	(0.030)	(0.030)
Department (logistics/materials management)	0.019	0.019	-0.006	-0.005	-0.005
	(0.024)	(0.024)	(0.023)	(0.023)	(0.023)
Department (marketing/product management)	0.059***	0.059***	0.102***	0.103***	0.103***
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)

Table 4-7 (continued)

Department (medical)	0.085^{*}	0.087^{*}	0.121^{**}	0.122^{**}	0.122^{**}
	(0.039)	(0.039)	(0.038)	(0.038)	(0.038)
Department (others)	0.131^{***}	0.130^{***}	0.131^{***}	0.132^{***}	0.132^{***}
	(0.012)	(0.012)	(0.011)	(0.011)	(0.011)
Department (PR/communication)	0.043	0.043	0.090^{***}	0.091^{***}	0.091^{***}
	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)
Department (production)	0.068^{***}	0.068^{***}	0.047^{**}	0.047^{**}	0.048^{**}
	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)
Department (purchasing)	-0.014	-0.014	-0.007	-0.006	-0.005
	(0.025)	(0.025)	(0.024)	(0.024)	(0.024)
Department (research/development)	0.113^{***}	0.113^{***}	0.139^{***}	0.140^{***}	0.140^{***}
	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)
Responsiveness		0.079^{***}	0.083^{***}	0.245^{***}	0.058^{***}
		(0.016)	(0.015)	(0.026)	(0.016)
TPE image valence			-0.169^{***}	-0.157^{***}	-0.168^{***}
			(0.003)	(0.003)	(0.003)
Employment status (former employee)			0.115^{***}	0.116^{***}	0.091^{***}
			(0.006)	(0.006)	(0.007)
Responsiveness × TPE image valence				-0.045^{***}	
				(0.006)	
Responsiveness × employment status (former employee)					0.107^{***}
					(0.014)
Employer fixed effects	Yes	Yes	Yes	Yes	Yes
Quarter fixed effects	Yes	Yes	Yes	Yes	Yes
Treatment-specific linear trend	Yes	Yes	Yes	Yes	Yes
Treatment-specific quadratic trend	Yes	Yes	Yes	Yes	Yes
R^2	0.187	0.187	0.212	0.213	0.213
Adjusted R^2	0.125	0.125	0.152	0.152	0.152

Notes: N = 298,269 reviews of 21,099 employers over 45 quarters. Cluster-robust standard errors (in parentheses). Reference category for position is "employee". Reference category for department is "not specified". Reference category for employment status is "current employee".
$^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$

responsive and non-responsive (i.e., treated and untreated) employers, we included treatment-specific linear and quadratic time trends in our models (see, e.g., Besley & Burgess, 2004). In other words, we controlled our models for a linear and a quadratic quarterly trend interaction with a treatment group dummy, coded 1 for employers that became responsive sometime during our study period and 0 otherwise. The inclusion of such time trends reflects a rigorous approach to controlling for systematic differences between treatment and control groups, but doing so may capture valid variance in the effects of the treatment (Wolfers, 2006). Despite this possibility, the effects found in our main analysis were robust to the inclusion of treatment-specific linear and quadratic time trends (see Tables 4-6 and Tables 4-7). Responsiveness was positively associated with information diversity (0.016, $p = .018$) and log-transformed information extensiveness (0.079, $p < .001$). Furthermore, the association between information diversity and responsiveness was moderated by TPE image valence (-0.009, $p = .002$) and employment status (0.025, $p < .001$). Finally, the association between log-transformed information extensiveness and responsiveness was moderated by TPE image valence (-0.045, $p < .001$) and employment status (0.107, $p < .001$).

Falsification tests. To rule out spurious correlations, we conducted several falsification tests (see Table 4-8). More specifically, as there is no theoretical rationale for why an employer's responsiveness should be associated with the occurrence of common words, numbers, or types of punctuation in its reviews, we would not expect to observe a significant effect on these measures (see N. Huang et al., 2017). We used Linguistic Inquiry and Word Count (LIWC) software to estimate the prevalence of grammatical and psychological categories in text by matching the words with predefined content dictionaries (Pennebaker et al., 2015). More specifically, we used LIWC's German-adaptation DE-LIWC2015 (Meier et al., 2018) to measure the prevalence of common verbs (e.g., "eat", "come", "carry"; 5405 words in total), numbers (e.g., "second", "thousand"; 92 words in total), and articles (e.g., "a", "an", "the"; 22 words in total) in our reviews. High values denote a high proportion of common verbs, numbers, and articles, while low values denote a low proportion. We found no significant effects of responsiveness on common verbs (0.055, $p = .410$), numbers (0.026, $p = .108$), or articles (0.073, $p = .135$). We also explored an alternative proxy for assessing the effects of responsiveness beyond information diversity and extensiveness. Specifically, we used LIWC (Meier et al., 2018; Pennebaker et al., 2015) to measure the prevalence of cognitive content (e.g., "cause", "ought", "known"; 3711 words in total) in employer reviews. Cognitive content reflects the depth and complexity of thinking (Tausczik & Pennebaker, 2010). As accountability influences what individuals think and, beyond that, cognitive processing, i.e., how individuals think (Frink et al., 2008), we expected that if responsiveness enhances accountability, this should be reflected in a heightened presence of cognitive content. We found a significant effect of responsiveness on cognitive content (0.172, p = .024).

Table 4-8

OLS results for the effects of responsiveness on LIWC variables

	Dependent variable			
	Verbs	Numbers	Articles	Cognitive content
Position (C-Suite / Leadership)	-1.130***	-0.122***	-0.081*	0.064
	(0.046)	(0.011)	(0.033)	(0.054)
Department (Administration)	0.116	-0.016	0.334***	0.160
	(0.073)	(0.017)	(0.054)	(0.083)
Department (Design)	-0.349*	-0.003	0.172	-0.135
	(0.159)	(0.032)	(0.117)	(0.182)
Department (Distribution / sales)	0.027	0.083***	0.411***	0.152*
	(0.064)	(0.014)	(0.045)	(0.069)
Department (Executive leadership)	-0.677***	0.109*	0.510***	-0.266
	(0.186)	(0.044)	(0.153)	(0.234)
Department (Finance)	-0.237*	0.004	0.096	-0.213
	(0.115)	(0.024)	(0.082)	(0.131)
Department (Human resources / recruiting)	-0.361***	-0.094***	0.315***	-0.213
	(0.101)	(0.019)	(0.079)	(0.117)
Department (IT)	0.013	0.050**	0.371***	0.339***
	(0.065)	(0.016)	(0.051)	(0.076)
Department (Legal / tax)	-0.099	-0.086	0.339*	-0.389
	(0.228)	(0.046)	(0.170)	(0.252)
Department (Logistics / materials management)	0.670***	0.197***	0.455***	0.156
	(0.128)	(0.034)	(0.097)	(0.135)
Department (Marketing / product management)	-0.599***	-0.044*	0.243***	0.070
	(0.083)	(0.017)	(0.064)	(0.101)
Department (Medical)	0.299	0.104	0.753***	-0.372
	(0.289)	(0.068)	(0.213)	(0.335)
Department (Others)	0.507***	0.072***	0.507***	0.488***
	(0.056)	(0.013)	(0.043)	(0.064)
Department (PR / communication)	-0.481**	-0.019	0.232*	-0.096
	(0.153)	(0.034)	(0.113)	(0.174)

Table 4-8 (continued)

Department (Production)	0.583***	0.185***	0.601***	0.269**
	(0.088)	(0.023)	(0.070)	(0.103)
Department (Purchasing)	-0.196	0.096**	0.212	-0.016
	(0.152)	(0.036)	(0.115)	(0.179)
Department (Research / development)	-0.339***	0.020	0.267***	0.451***
	(0.094)	(0.019)	(0.069)	(0.114)
Responsiveness	0.055	0.026	0.073	0.172*
	(0.067)	(0.016)	(0.049)	(0.076)
Employer fixed effects	Yes	Yes	Yes	Yes
Quarter fixed effects	Yes	Yes	Yes	Yes
R^2	0.120	0.085	0.088	0.088
Adjusted R^2	0.053	0.015	0.019	0.019

Notes: N = 298,269 reviews of 21,099 employers over 45 quarters. Cluster-robust standard errors (in parentheses). Reference category for position is “employee”. Reference category for department is “not specified”. Reference category for employment status is “current employee”.
*p < .05; **p < .01; ***p < .001

4.4 Discussion

We theorized that by becoming responsive on an employer review website, employers create an accountability-enhancing context for reviewers (i.e., their current and former employees). Evidence that reviewers (i.e., current and former employees) feel accountable is demonstrated through their efforts to justify their reviews. A difference-in-differences analysis confirms our theorizing: Responsive employers received reviews presenting more diverse and extensive employer information than reviews received by non-responsive employers. In particular, responsiveness promoted more diverse and extensive employer information in negative reviews and more diverse and extensive employer information in reviews by former employees. Statistically accounting for systematic differences between responsive and non-responsive employers reinforced our theory’s logic that indeed, an employer’s responsiveness caused information diversity and extensiveness in reviews and not vice versa. Furthermore, assessing the association between responsiveness and words that indicate cognitive processing supported our theoretical rationale that reviewers indeed cope with the accountability-enhancing context in a cognitively effortful manner.

4.4.1 Implications for Research and Practice

Our study makes three major contributions to the literature. First, it extends the prevailing theoretical perspectives that consider company reactions mainly through the lens of threat management (see, e.g., Dineen et al., 2019; Etter et al., 2019; George et al., 2016; Ki & Nekmat, 2014; Pfarrer et al., 2008; Ravasi et al., 2018; T. Wang et al., 2016). While companies' reactions to negative third-party judgments may serve as a valuable means of repairing a damaged reputation (e.g., Pfarrer et al., 2008), our findings suggest that employers' responses on an employer review website serve a purpose beyond threat management. In detail, an employer's responsiveness establishes an accountability-enhancing context and thus indirectly exerts control over employer reviews. Exerting such *indirect* control and thus promoting reviews with diverse and extensive employer information may benefit employers. For instance, providing potential employees with diverse and extensive information through justified reviews may improve the quality of an organization's applicant pool, as it allows job seekers to make more informed decisions about where to apply (see Dineen & Noe, 2009) and may reduce information ambiguity about the organization as a place of work (see Van Hoye, 2014). Thus, reviews that present diverse and extensive employer information may help employers "achieve their goal of better fitting job applicants" (Dineen et al., 2019, p. 212).

Second, while only experimental studies have previously demonstrated that responses to employer reviews can be impactful (Carpentier & Van Hoye, 2020; Könsgen et al., 2018), we demonstrate the impact of responsiveness in an analysis of approximately half a million actual employer reviews. With this in mind, we not only complement studies that have experimentally explored the effects of employer responses (Carpentier & Van Hoye, 2020; Könsgen et al., 2018) but also integrate these studies with another research stream that has rather recently begun to explore the textual content of actual employer reviews (e.g., Dabirian et al., 2017; Y. Jung & Suh, 2019; Stamolampros et al., 2020) but largely neglected to explore the determinants of reviews' textual content.

Third, we build on the model of social judgment and choice (Hall et al., 2017; Tetlock, 1985, 1992) to theorize about the effects of an employer's responsiveness. Therefore, we not only draw from accountability theory to provide a promising foundation for extending theories on the effects of companies' reactions to third-party judgments (e.g., Pfarrer et al., 2008) but also concurrently add to the accountability literature. More specifically, since accountability has been investigated primarily in laboratory studies that may not reflect its true nature (Hall et al., 2017; see also Mero et al., 2014), we make an empirical contribution by exploring the effects of felt accountability in a field setting. Furthermore, by exploring the difference between current and former employees, we introduce organizational attachment as a valid moderator of felt accountability effects. In our study, responsiveness had a stronger effect on former employees than on current employees. One possible explanation is that current employees already feel some degree of accountability for their judgment of their employer and therefore react less than former employees to the accountability demands imposed by their employer's responsiveness. Another explanation is that former employees may cite any employer-relevant topic in their reviews to justify their judgment when feeling accountable without risking contradicting the employer's official information cues and therefore react more than current employees to the accountability demands imposed by their former employer's responsiveness.

Our work also has practical implications. More specifically, it empirically explores the feasibility of recommendations to carefully monitor and respond to reviews on employer review websites, such as the recommendations from the Society for Human Resource Management (e.g., Bates, 2016; Grensing-Pophal, 2019; Lewis, 2019; Maurer, 2017). Based on the findings of our study, recommendations to respond to employer reviews seem valid, at least for promoting justified reviews. By ensuring that reviews are justified, employers may utilize employer review websites as a valuable means, e.g., of receiving feedback on their work environment (see employee voice literature; Dyne, Ang, & Botero, 2003) and providing an authentic employer image (see, e.g., Reis, Braga, & Trullen, 2017).

4.4.2 Limitations and Future Research

Our work is subject to several limitations that offer rich opportunities for future research. First, the reviews examined in our study are obtained from a single employer review website. Therefore, while our analysis allows for a comparison of the information diversity and extensiveness of reviews of responsive and non-responsive employers, our design does not permit us to determine whether the observed effects are caused by changes in the behavior of the reviewers or by self-selection. Although reviewers might start to justify their reviews with more diverse and extensive employer information due to the responsiveness of the employer (behavioral change), reviewers who are unable to justify reviews in this way might also refrain from publishing reviews after an employer has responded (self-selection). If self-selection is present, our results may be additionally attributed to other tactics that individuals pursue to cope with accountability demands: procrastination and escape (see M. C. Green et al., 2000). Further uncovering the causal relationship between responsiveness and the information diversity and extensiveness of employer reviews therefore presents a fruitful avenue for future work.

Second, we do not consider differences in employer response strategies such as style. Exploring response styles is a wide-open field for further research since it is quite conceivable that effective strategies for responding to customers are not equally useful for employees (see, e.g., Sparks & Bradley, 2017). For example, while a simple apology may be enough to recover a customer relationship, it is unlikely to be sufficient to recover a damaged employee relationship. Therefore, we encourage content analysis of employer responses and further experimental research to determine the effectiveness of different response strategies; see Carpentier and Van Hoye (2020) and Könsgen et al. (2018) as a starting point of this research avenue.

Finally, although employer review websites provide a rich and novel data source, they also have limitations. For example, we do not know the individual characteristics of reviewers (e.g., age and gender). In addition, unobservable factors may determine the content of online reviews on these websites. For example, organizations may proactively encourage satisfied employees to submit a review or, in the worst case, may even submit fake reviews to boost their employer image on these websites.

4.4.3 Conclusion

In conclusion, our work theoretically explores and empirically identifies the effects of an employer's responsiveness on the diversity and extensiveness of the employer information presented in its reviews on an employer review website. Critically, our study extends the prevailing theoretical perspectives that emphasize responding from a threat management perspective (see, e.g., Dineen et al., 2019; Etter et al., 2019; George et al., 2016; Ki & Nekmat, 2014; Pfarrer et al., 2008; Ravasi et al., 2018; T. Wang et al., 2016) and establishes that employer responsiveness also plays a role in *indirect* control over third-party judgments. Both academics (e.g., Dineen et al., 2019) and practitioners (e.g., Bates, 2016; Grensing-Pophal, 2019; Lewis, 2019; Maurer, 2017) have discussed how employers should deal with online employer reviews, and studies such as ours are critical to answering this question.

5 Overall Conclusion[16]

5.5 Summary of Main Findings and Contributions

This dissertation furthers our understanding of the online employer review phenomenon in three essays. Essay I presents a multidisciplinary SLR that structures the current research from nine disciplines into three major concepts and identifies five avenues for future research with regard to utilizing employer review data. Three major research topics emerged. First, studies extract information from employer review data to predict firm performance. In detail, these studies gain information about employee satisfaction and changes in employee satisfaction, insider knowledge, and insights into workplace culture from employer review data. They use this information to predict, e.g., ROA, Tobin's Q, or patent output. Second, studies explore factors of employee satisfaction. Specifically, these studies explore the role of employee satisfaction factors derived from non-employer review data, i.e., information on organizations' structure, workplace culture, and financials as well as policies. Furthermore, studies explore the role of factors derived from employer review data, especially reviews' textual content. Finally, studies analyze the linguistic style of employer reviews. More specifically, they compare the linguistic styles of the best and worst companies. Studies across all research topics utilize a variety of text-mining techniques to quantify the textual content of reviews. Four groups of techniques utilized in the existing research were identified: topic modeling, dictionary-based text analysis using programs such as DICTION, data mining using software such as IBM Watson, and extracting individual word frequencies. In regard to the data sources currently employed in the existing research, Glassdoor data are primarily used and often merged with Compustat and/or CRSP data. Considering its findings, Essay I contributes to harnessing research opportunities based on employer review data that go

[16] This chapter is partly based on and includes elements of Höllig (2021), Höllig and Tumasjan (2021), and Höllig, Tumasjan, and Lievens (under review).

beyond the work undertaken so far concerning online reviews by customers of products or services (see Stamolampros et al., 2020). Critically, Essay I demonstrates vast research opportunities in predicting firm performance from information gained from employer reviews' textual content, in a theory-driven discovery of employer reviews' textual content, in predicting firm performance with regard to recruiting outcomes, in comparing employer reviews with traditional survey instruments, and in exploring the determinants of employer reviews.

Essay II presents, based on a dominance analysis of approximately half a million online employer reviews, that personal (rather than impersonal), symbolic (rather than instrumental), and emotional (rather than cognitive) content determines TPE image valence. Furthermore, Essay II demonstrates that these theory-grounded content features actually matter by linking them to companies' TPE image and, through that, to the probability of a company being ranked as a "best employer" among job-seekers (as indicated by Universum's best employer survey; e.g., Universum, 2019c, 2019a). The findings of Essay II contribute to our understanding of the nature of third-party reviews, grounded in theory, which is crucial for advancing theory building on TPE branding. In detail, Essay II integrates the NMRF framework (Etter et al., 2019) into the employer image literature to establish a new co-created perspective on employer image that also incorporates bottom-up input from organizational members (current and former employees), as reflected in TPE branding. This new perspective on employer image changes our thinking in this domain in at least four ways. First, Essay II challenges the implicit assumption of the equal importance of employer image attributes across contexts made in prior theoretical perspectives (Lievens & Slaughter, 2016; Theurer et al., 2018) and shifts the theoretical focus towards a context-dependent understanding of employer image attributes. Second, Essay II extends the theoretical perspectives of employer images being primarily cognitively driven (Collins & Kanar, 2013; see also Lievens & Slaughter, 2016) by adding that emotional processing is ultimately more relevant than cognitive processing to TPE images. Third, Essay II highlights a discrepancy between the prevalence of content characteristics in employer reviews and their role in determining TPE image valence. Apparently, there is some kind of "rarity effect" in employer reviews wherein less frequent characteristics seem to make the key difference as to whether a company will receive a high or low overall rating in employer reviews. This "rarity effect" speaks to the importance of differentiation and standing out in employer branding (K. Backhaus & Tikoo, 2004). Fourth, Essay II discovered a hierarchy in the importance of content characteristics as determinants of TPE image valence. Among the three important content characteristics (personal, symbolic, and emotional), symbolic content emerged as the single most important content characteristic determining TPE image valence because it dominated personal and emotional content. Furthermore, Essay II integrates two strands of research that so far have evolved separately: one is devoted to the experimental investigation of the effects of employer reviews (e.g., Evertz et al., 2019), and the other relates to the exploration of the content of actual employer reviews (e.g., Dabirian et al., 2019). Finally, Essay II makes a methodological contribution by developing a CATA approach to assess and quantify the voluminous content of employer review data.

Essay III presents, based on a difference-in-differences analysis of approximately half a million online employer reviews, that responsive employers receive reviews presenting more diverse and extensive employer information than those received by non-responsive employers. Responsiveness particularly promotes more diverse and extensive negative reviews and more diverse and extensive reviews of former employees. The findings of Essay III extend theoretical perspectives that emphasize the role of responses to third-party judgments for threat management (see Dineen et al., 2019; Etter et al., 2019; George et al., 2016; Pfarrer et al., 2008; Ravasi et al., 2018; T. Wang et al., 2016) by adding that employer responsiveness also plays a role of *indirect* control over such judgments by employees through establishing an accountability-enhancing context. Furthermore, Essay III complements previous studies that have experimentally explored the effects of employer responses (Carpentier & Van Hoye, 2020; Könsgen et al., 2018) and thus integrates these studies with another research stream that has recently begun to explore the textual content of actual employer reviews (e.g., Dabirian et al., 2017; Y. Jung & Suh, 2019; Stamolampros et al., 2020). Finally, Essay III concurrently advances the emerging accountability literature that investigates the effects of felt accountability in a field setting (e.g., Mero et al., 2014).

5.6 Implications for Practice

In addition to structuring and advancing the current state of research on the employer review phenomenon, this dissertation has implications for practice. First, it finds support that online employer reviews are associated with the perceptions of potential employees. Thus, employers should closely monitor employer review websites and be especially wary of emotional, symbolic, and personal information because these are more impactful than cognitive, instrumental and impersonal information for the valence of the TPE image presented through reviews. If necessary, employers should take action and, for instance, scrutinize negative reviews and use their textual content to better understand the personal and emotionally processed workplace experiences that resulted in the review ratings.

Second, with regard to taking action, this dissertation finds support that one of the actions an employer may take, which is widely recommended, e.g., by the Society for Human Resource Management (e.g., Bates, 2016; Grensing-Pophal, 2019; Lewis, 2019; Maurer, 2017), seems to be a valid approach for gaining *indirect* control over reviews posted by current and former employees. More specifically, becoming responsive on an employer review website seems to be a valid way to promote justified reviews. By ensuring that reviews are justified, employers may utilize employer review websites as a valuable means, e.g., of receiving feedback on their work environment (see employee voice literature; Dyne et al., 2003) and providing an authentic employer image (see, e.g., Reis et al., 2017).

Third, with regard to closely monitoring employer reviews, this dissertation presents two systematic approaches to evaluating employer reviews' textual content: CATA and topic modeling. Through the novel CATA dictionary developed for this dissertation, companies may identify fine-grained employer image attributes in their review texts and consequently evaluate the relevance of these attributes for the TPE image produced via these reviews. Given the vast volume of currently available employer review data (Lewis, 2019) and the fact that the development of special-purpose content dictionaries is often challenging (Krippendorff, 2012), the provision of a rigorously developed content dictionary is of great value to the field. The content dictionary can be applied to any amount of text or any number of reviews and allows these attributes to be evaluated in real time. Accordingly, companies may also integrate the content dictionary into social media monitoring software that allows the identification of temporal or across-company trends and alerts users to deviations from these trends. Moreover, the topic model estimated within this dissertation further allows for an explorative understanding of the various topics discussed in employer reviews and their prevalence in reviews of employees from different departments and positions and with different employment statuses. In this vein, Appendix A presents ten learnings for (HR) managers based on the topic model developed within this dissertation.

5.7 Directions for Future Research

This dissertation structures and advances the current state of research on the employer review phenomenon. While several directions for future research have been mentioned throughout this dissertation, it identifies five major themes for future research.

First, this dissertation identifies vast research opportunities for a theory-driven exploration of the textual contents of employer reviews to derive employer-level constructs such as cultural heterogeneity (Corritore et al., 2020) and their relevance to various employer-level performance measures, especially recruiting performance measures. While such theory-driven exploration of reviews' textual contents may challenge researchers to develop special-purpose content dictionaries for CATA (Krippendorff, 2012), researchers may also rely on already available content dictionaries, such as dictionaries that allow the measurement of organizational psychological capital, which is defined as an "organization's level of positive psychological resources: hope, optimism, resilience, and confidence" (McKenny et al., 2012, p. 157).

Second, this dissertation identifies a great research need to clarify the role of emotions in the formation of TPE images. While employer image research has so far emphasized cognitive processing in employer image formation, research seems to have underestimated the role of emotional processing. Future research should therefore address what emotions are involved in the formation of TPE images and at what formation stages. For example, the role of anger or frustration should be clarified in the formation of TPE images (see, e.g., Toubiana & Zietsma, 2017).

Third, with regard to the formation of TPE images, this dissertation identifies a need to explore the specific personal experiences that trigger current or former employees to publish TPE images about their employer, e.g., through employer reviews. An understanding of what personal experiences trigger the dissemination of positive TPE images would certainly benefit employers in their efforts to facilitate such experiences. Related to this research need is the role and impact of the proactive encouragement of employees, e.g., via e-mail, to disseminate employer reviews.

Fourth, this dissertation identifies further research needed to understand the effects of employer reviews on recruiting outcomes in comparison with other TPE image sources, such as BPTW certifications (see Dineen & Allen, 2016), and with company-controlled employer image sources. In particular, the interplay between company-controlled information cues and third-party cues is an open field for future research. Dineen et al. (2019) suggest that when multiple sources triangulate the characterization of an employer's practices, the credibility of any specific message increases. Thus, theoretical frameworks, such as information-integration theory, which explains how an individual's attitude is formed from integrating different pieces of information (Carroll & Anderson, 1982), may have great value in pursuing this research avenue.

Finally, this dissertation identifies the research needed for further exploration and understanding of the effects of different employer response styles. It is quite conceivable that strategies that are effective in responding to customers are not equally useful in responding to employees (see, e.g., Sparks & Bradley, 2017). For example, while a simple apology may be enough to recover a customer relationship, it is unlikely to be sufficient to recover a damaged employee relationship. The studies of Carpentier and Van Hoye (2020) and Könsgen et al. (2018) serve as a starting point for this research direction.

6 Concluding Remarks

In summary, this dissertation presents a systematic overview of the current state of research on the employer review phenomenon and expands on it in a theory-driven econometric and text mining-based analysis of approximately half a million employer reviews. While the findings demonstrate a variety of theoretical and practical implications related to the employer review phenomenon, several questions remain unanswered. Therefore, this dissertation intends not only to complement the current research but also to inspire further research on the employer review phenomenon.

7 References

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8 Appendix

Appendix A: 10 Learnings for (HR) Managers from Topic Modeling Employer Reviews

Employer reviews provide unparalleled insight into what matters for current and former employees across a wide range of departments and positions. However, given the vast data available, manually exploring what employees discuss about their employer and their job, both positively and negatively, is hardly feasible. I approached this limitation in a supplementary analysis by combining the topic model developed for Essay III (see Table 4-1) with manual clustering to derive further learnings for practitioners using my extensive employer review dataset.

First, I merged the topics into higher-level dimensions and thus summarized the topic probabilities per review for topics in the same dimension (see Essay III for an explanation of topic probabilities). In total, I found, labelled, and defined 17 dimensions out of 50 topics (see Table 8-1), such as attentiveness, flexibility, and workspace. Some topics were not manually coded into higher-level dimensions, e.g., employer review vocabulary or industry specifics. Second, I applied a thresholding procedure (see, e.g., Ramirez, Brena, Magatti, & Stella, 2012) and moved from a probabilistic distribution of dimensions for each review (i.e., a fuzzy clustering of reviews) to assigning a fixed set of content dimensions per review (i.e., a hard clustering of reviews). I set a probability threshold of 10% (i.e., a review must have at least a 10% probability for a dimension), thus allowing for the possibility that a single review addresses more than one dimension. This also implies that I disregarded dimensions below the 10% threshold for each review. Applying a 10% threshold resulted in the assignment of two dimensions per review on average, with a maximum of seven dimensions per review. Some of the reviews remained without any assigned dimension (4.92%). Third, I created a median split from reviews' overall ratings (median = 3.91 stars) to form two categories: negative vs. positive employer reviews (see, e.g., Srinivasan, Haunschild, & Grewal, 2007).

Based on hard clustering of 424,564 employer reviews (i.e., employer reviews that did not consist solely of erroneous terms or stop words) according to their content dimensions, overall ratings (negative vs. positive), reviewers' employment status (current vs. former employee), reviewers' position (e.g., C-suite/leadership), and reviewers' departments (e.g., IT), I derived 10 learnings for (HR) managers (see Table 8-2).

Table 8-1

Dimensions, their definitions, and associated topics

Dimension	Definition	Topics
Attentiveness	Employees discuss the attentiveness given to them, e.g., whether suggestions for improvement are taken into account and whether mutual support is provided.	- Mutual support - Feedback culture - Follow-up mentality - Problem-solving
Corporate social responsibility	Employees discuss whether their company is a good corporate citizen, e.g., is environmental-friendly	- Corporate social responsibility
Equality	Employees discuss equal opportunities in their company, e.g., whether there are also female managers.	- Equal opportunities - Gender equality
Flexibility	Employees discuss flexibility, e.g., whether flextime or home office is offered.	- Time flexibility - Work-family-balance
Job security	Employees discuss job security in their organization, e.g., whether there have been restructuring procedures or whether fixed-term contracts are commonly offered.	- Fixed-term contracts - Hire and fire - Job security - Personnel restructuring
Leader behavior	Employees discuss their direct and indirect superiors, e.g., concerning their competence and decision transparency.	- Competence - Criticism of management - Leadership - Transparent decision-making
Location and travel	Employees discuss location-related characteristics of their company, e.g., whether locations are easily reachable by public transport.	- International orientation - Location
Organizational climate	Employees discuss the organizational climate in their organization, e.g., concerning humanity, culture, treatment.	- Abusive environment - Humanity - Employee and co-worker treatment - Organizational culture - Nice people - Sense of belonging
Organizational strategy	Employees discuss their company's strategy, e.g., whether it is long-term oriented and whether the company is growing.	- Company development - Long-term strategy
Organizational structure	Employees discuss the organizational structure in their company, e.g., whether hierarchies are flat or whether rigid processes exist.	- Hierarchy - Start-up atmosphere - Structural rigidity

Table 8-1 (continued)

Pay and benefits	Employees discuss their pay and benefits, e.g., concerning fairness and comparability.	- Bonus payments - Fair remuneration - Money vocabulary - Perks
Social interactions	Employees discuss social interactions in their organization, e.g., interactions between departments.	- Communication gap - Intra and interdepartmental interactions - Social exchange
Training	Employees discuss training opportunities in their company.	- Training
Trust	Employees discuss the trustworthiness in their organization, e.g., whether supervisors keep their word.	- Trustworthiness
Work tasks	Employees discuss the work assigned to them, e.g., concerning variety, self-determination in execution, objectives, and acknowledgement.	- Autonomy - Creativity - Goal setting - Task variety - Recognition
Workload	Employees discuss their workload, e.g., concerning regular weekly working hours and whether overtime is remunerated.	- Overtime - Understaffing - Work hours
Workspace	Employees discuss their workplace, e.g., concerning equipment and modernity.	- Air conditioning - Modernness - Worksite

Table 8-2

10 learnings for (HR) managers

#	Learning
1	**Organizational climate** is the most frequently discussed dimension. In detail, 33.90% of all reviews deal with this dimension, whereby it is overall more prevalent in positive (18.48%) than in negative (15.42%) reviews. While negative reviewers complain about harassment, positive reviewers mention the kindness of their colleagues and a sense of belonging. Organizational climate is also the most frequently discussed dimension in negative reviews by former employees (25.56%). Thus, considering its prevalence, managers should place great emphasis on creating a positive climate. This is also supported, by studies that show, for example, that organizational climate has a significant impact on an organizations' performance (Luthans, Norman, Avolio, & Avey, 2008), and that single toxic employees may de-energize whole work teams (Gallo, 2016).
2	**Pay and benefits**, the second most frequently discussed dimension (24.07%), tends to be negatively discussed (13.77% negative reviews vs. 10.30% positive reviews). Positive reviews praise fair payment, bonus payments, or benefits such as free drinks. Negative reviews, on the other hand, complain about below-average or disproportionate salaries. The gap between negative and positive reviews is more evident when examining reviews by former employees. 19.83% negative reviews and only 5.34% positive reviews by former employees discuss pay and benefits. In this vein, pay and benefits seem to concern employees rather when they are perceived as too low instead of when they are perceived as fair; and low payments may be a major driver for employees leaving a company. Against this backdrop, managers should ensure that pay is perceived as fair and competitive, otherwise, they may run the risk of losing their employees (see also Lum, Kervin, Clark, Reid, & Sirola, 1998).

Table 8-2 (continued)

3	**Work tasks** is the third most frequently discussed dimension. In detail, employees discuss work tasks in 22.15% of all reviews, including both, positive (14.58%), and negative (7.57%) reviews. Positive reviews deal with varied tasks, freedom and personal responsibility, negative reviews discuss one-sided activities that are strongly controlled and rarely rewarded. Besides social factors like organizational climate, attentiveness or leader behavior, the actual content of work is thus clearly in focus of employee's discussions. Noticeably, the dimension is almost twice as often mentioned in positive reviews as in negative reviews. The discrepancy of prevalence in negative and positive reviews is more pronounced when examining reviews from C-suite/leadership employees. 18.87% C-suite/leadership employees mention work tasks in positive reviews, and only 6.79% in negative reviews. However, in departments, where work tasks are likely to be more repetitive and one-sided, prevalence of the work task dimension is almost evenly distributed over positive and negative reviews. For instance, in production departments, 9.38% positive reviews and 8.31% of negative reviews mention work tasks. Given the prevalence of this dimension in negative reviews of these employee groups, managers should explore how work tasks can be transformed or framed in such a way that they are perceived positively (see Yoon, Whillans, & O'Brien, 2019).
4	**Leader behavior**, the fourth most frequently discussed dimension (16.67%), is rather mentioned in negative reviews (11.48%) than in positive reviews (5.19%). This applies both, for current employees, mentioning leadership behavior in 6.67% positive and 8.27% negative reviews, and for former employees, mentioning leadership behavior in 2.73% positive and 18.45% negative reviews. Positive reviews mention, e.g., decision-transparency, whereas negative reviews mention lack of communication, transparency, and immoral behavior of supervisors. Thus, although current employees tend to review more positively overall (see #10), they mention leadership behavior rather in negative than in positive reviews. And, for former employees, leader behavior is the third most frequently discussed dimension in negative reviews. With this in mind, positive leader behavior seems less noticeable than negative leader behavior, and negative leader behavior may drive employees to leave the company. Managers should therefore try to understand how detrimental leader behavior may develop and how to avoid it (see also Carucci, 2018).
5	**Corporate social responsibility (CSR)** is discussed in 2.62% of reviews across all departments and positions, by former and current employees, in positive as well as negative reviews. More specifically, CSR is more often discussed in positive reviews (1.73%) than in negative reviews (0.89%), and current employees (3.17%) discuss CSR more often than former employees (1.72%). Therefore, the absence of CSR measures seems not necessarily to attract negative attention, but the implementation and communication of these measures appear to contribute positively to the overall work experience of individual employees.
6	**Trust**, albeit seldom mentioned (4.19%), is more frequently mentioned in negative reviews (2.75%) than in positive reviews (1.43%). The gap between negative and positive reviews is more pronounced when examining reviews of former employees, mentioning trust in 4.95% negative reviews, but only in 0.08% positive reviews. In positive reviews, employees acknowledge that promises are always kept, while in negative reviews they acknowledge that promises should always be recorded, otherwise they will easily be broken. Thus, trust among employees as well as among superiors seems to represent a matter of course for employees and is thus rarely referred to positively. Breaches of trust, on the other hand, are certainly noted, concern employees in all positions and departments, and may also drive employee turnover (see also Clinton & Guest, 2014).

Table 8-2 (continued)

7	**Flexibility** is the thirteenth-most frequently discussed dimension (6.23%). Flexibility is more frequently mentioned by employees in white-collar departments such as human resources/recruiting (10.07%), legal/tax (9.15%), and finance (8.96%), than in blue-collar departments such as logistics/materials management (4.79%), or production (5.01%). When considering its overall prevalence, albeit often seen as a workplace necessity today (e.g., Dean & Auerbach, 2018), flexibility seems to play a minor role in comparison with other dimensions when employees evaluate their workplace.
8	**Workload**, the eighth-most discussed dimension across all departments and positions (10.95%), is mentioned more frequently in negative reviews (7.26%) than in positive reviews (3.69%). This gap is more prevalent when comparing negative reviews (11.68%) and positive reviews (2.13%) of former employees, and minor when comparing negative reviews (4.94%) and positive reviews (4.47%) of current employees. Positive reviews, for example, deal with the fact that working hours are adhered to or overtime can be compensated, negative reviews complain about a lack of personnel or that one must always be reachable. Accordingly, employees seem to perceive a high workload as negative, while they take a balanced or low workload for granted, which they do not need to mention very positively. Considering the differences between current and former employees, negative perceptions of workload may serve as a major driver for employees leaving a company (see also Bowling, Alarcon, Bragg, & Hartman, 2015).
9	Each **department** is dealing with the dimensions to different extents. For example, **CSR** is more frequently discussed by executive leadership employees (4.95%) than by logistics/materials management employees (1.72%), **job security** more frequently by production employees (19.01%) than by executive leadership employees (10.92%), **location & travel** more frequently by executive leadership employees (8.61%) than by legal/tax employees (5.45%) or **organizational strategy** more frequently by executive leadership employees (14.90%) than by design employees (5.92%). Accordingly, what matters for employees, does widely differ between departments. Therefore, instead of opting for one-size-fits-all approaches, managers should opt for individual solutions fitting the needs of their employees, e.g., based on the examination of online employer reviews or employee surveys (see also Morrel-Samuels, 2002).
10	Reviews of **current and former employees** differ substantially, as former employees mention every individual dimension more frequently in negative reviews than in positive reviews, while current employees mention every individual dimension except **job security**, **leader behavior,** and **workload** more frequently in positive reviews than in negative reviews. Against this backdrop, managers should consider motivating current employees to submit reviews (see also Klein, Marinescu, Chamberlain, & Smart, 2018) to, e.g., balance reviews of former employees with counterstatements. Besides, managers should carefully monitor the reviews of former employees, as they may allow direct insight into causes for these employees to leave. For instance, the three most frequently negatively mentioned dimensions by former employees across departments and positions are **organizational climate** (25.55%), **pay and benefits** (19.83%), and **leader behavior** (18.45%).

Appendix B: References for the Essays in this Dissertation

Essay I (Chapter 2)

Höllig, C. E. (2021). Online employer reviews as a data source: A systematic literature review. *Proceedings of the 54th Hawaii International Conference on System Sciences (HICSS)*, 4341–4350. Nominated for a best paper award. https://doi.org/10125/71144

Essay II (Chapter 3)

Höllig, C. E., Tumasjan, A., Lievens, F. (under review). Employer images in the wild: Toward a better understanding of third-party employer images on employer review websites. *Manuscript submitted for publication at the Academy of Management Journal.*

Essay III (Chapter 4)

Höllig, C. E., Tumasjan, A. (2021). Enhancing accountability: An analysis of the consequences of responding to employer reviews. *Working Paper.*

Appendix C: Author Contributions to the Essays in this Dissertation

Essay II (Chapter 3)

Christoph Höllig developed the research question and research design under the supervision of Andranik Tumasjan. He collected the data by himself and supervised two (former) students and one associated researcher in the Human Resource Management field of the TUM School of Management who helped in the coding of the employer image attributes dictionary. Christoph Höllig was responsible for the data analysis. The article was written in an iterative cooperative process, in which Christoph Höllig wrote the first draft of a full paper, which was further developed together with Andranik Tumasjan and Filip Lievens.

Christoph Höllig (lead author)

Prof. Dr. Andranik Tumasjan (co-author)

Prof. Dr. Filip Lievens (co-author)

Essay III (Chapter 4)

Christoph Höllig developed the research question and research design. He collected the data by himself and supervised two associated researchers in the Human Resource Management field of the TUM School of Management who helped in the coding of the topic model. Christoph Höllig was responsible for the data analysis. The article was written in an iterative cooperative process, in which Christoph Höllig wrote the first draft of a full paper, which was further developed with Andranik Tumasjan.

Christoph Höllig (lead author)

Prof. Dr. Andranik Tumasjan (co-author)