ESSAYS ON CUSTOMER ENGAGEMENT STRATEGIES AND TACTICS IN BUSINESS AND CONSUMER MARKETS

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aus

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To Luise, Nikolas & Romi,

to my parents,

and to those who accompanied me in my discovery of marketing science.

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1 Introduction

In the last decade, customer engagement has become a key topic for both practitioners and researchers (Forbes 2015; Kumar et al. 2010; Pansari and Kumar 2017; Vivek, Beatty, and Morgan 2012). A recent study by McKinsey & Company, for example, shows that 69% of CEOs consider customer engagement a top strategic priority for their business (McKinsey 2014). On the other hand, only 25% of CMOs state that they have a comprehensive understanding of the phenomenon customer engagement (CMO Council 2014). This is particularly critical because customer engagement has a considerable effect on profits (Kumar and Pansari 2016).

Thus, it is not surprising that customer engagement also remains a "hot topic" in academia and one of the top MSI research priorities (2010, 2014, 2016). Classically, customer engagement deals with customer behavior beyond purchase and thus non-monetary contributions by the customer (e.g., van Doorn et al. 2010), such as Word-of-Mouth (WOM), feedback and online reviews, or participation in the innovation process. However, customer engagement also pertains to mental engagement with a brand and thus focuses on experiences at specific touchpoints, such as the exposure to an advertising or the interaction with the firm's frontline employees (e.g., Brodie et al. 2011; Malthouse and Calder 2011). There is a general agreement that customer engagement is a multidimensional concept (Beckers, Risselada, and Verhoef 2014) comprising affective, attitudinal, and behavioral components. Thus, for the scope of this dissertation, it is defined as "the mechanics of a customer's value addition to the firm, either through direct or/and indirect contribution" (Pansari and Kumar 2017, p. 2).

While previous literature largely focused on the conceptualization of customer engagement (e.g., Brodie et al. 2011; van Doorn et al. 2010; Pansari and Kumar 2017), only a few studies have investigated how managers can actually stimulate and/or facilitate customer

engagement (e.g., Eisingerich et al. 2019; Godes and Mayzlin 2009; Harmeling et al. 2017). However, the latter is of high importance since only a few customers are truly engaged (Libai 2011) and it is often left to the firm to take the initiative to engage the customer (Vivek, Beatty, and Morgan 2012). Thus, marketers need to understand how to design and successfully implement customer engagement initiatives.

Accordingly, this dissertation investigates customer engagement strategies and tactics. While customer engagement strategy pertains to the overarching plan to leverage customer engagement to achieve the firm's goals, customer engagement tactics deal with single actions taken by the firm to facilitate customer engagement across the various touchpoints in the customer journey. Specifically, this dissertation includes three essays, each addressing distinct questions with respect to customer engagement over the customer journey. Table 1 presents an overview of the three essays including author and publication-status information.

Table 1: Overview of Dissertation Projects

Essay	Title	Author(s)	Status
I	From Customer to Partner Engagement – A Conceptualization and Typology of Engagement in B2B	Werner Reinartz and Manuel Berkmann	Published in *Customer Engagement Marketing* (eds. R. Palmatier, V. Kumar, and C. Harmeling)
II	Leveraging B2B Field Service Employees as a "Second" Sales Force	Manuel Berkmann, Maik Eisenbeiß, and Werner Reinartz	Under review (1st round): *Journal of Marketing*
III	Zapping in TV Advertising – The Role of (Non) Engaging Content	Manuel Berkmann, Maren Becker, and Werner Reinartz	Prepared to submit to: *Journal of Marketing Research*

Note: Being the lead author of essay II and III, Manuel Berkmann contributed significantly to each one of them (idea generation, conceptualization, data collection, analysis, and write-up). Also for essay I, Manuel Berkmann made a significant contribution, in particular in terms of literature analysis, conceptualization, and write-up.

The first essay is conceptual in nature and deals with a strategic analysis of customer engagement in business markets, whereas the second and third essay are empirical and

investigate two specific customer engagement tactics: the new role of field service employees as customer engagement facilitators in business-to-business (B2B) markets and the role of (non) engaging content in advertising in business-to-consumer (B2C) markets.

Specifically, the first essay of this dissertation titled "From Customer to Partner Engagement − A Conceptualization and Typology of Engagement in B2B", co-authored by Werner Reinartz and Manuel Berkmann, provides an analysis of the strategic relevance of customer engagement in business-to-business markets. It analyzes a number of specific properties of business markets (e.g. the derived character of demand or the formalization of exchange) and discusses their implications for the phenomenon of customer engagement. Furthermore, the authors argue that the concept of customer engagement should be extended to partner engagement in order to reflect the complexity and network character of value chains in business markets. Finally, the authors develop a typology of partner engagement behaviors in business markets covering all stages of the customer journey. Thus, this research paper provides a contribution to the marketing literature by conceptualizing the customer engagement phenomenon for the B2B context and analyzing the strategic implications for managers.

The second essay, titled "Leveraging B2B Field Service Employees as a 'Second' Sales Force" and co-authored by Manuel Berkmann, Maik Eisenbeiß, and Werner Reinartz, deals with technical field service employees that engage in selling activities in addition to their main service job. In this study, the authors investigate a recent development among industrial equipment manufacturers to employ the field service force for cross- and up-selling. Thus, they leverage the service touchpoints as opportunities to engage customers in the post-purchase phase. This represents a tactical activity to pro-actively manage the installed base and strengthen existing customer relationships. The authors employ a unique longitudinal dataset obtained from a major global industrial company, consisting of more than 140,000 customer visits of field service employees over a period of four years and more than 18,000 selling

activities initiated during the service visits. Drawing on the Motivation-Opportunity-Ability (MOA) framework, the authors identify a number of drivers for the industrial B2B context (e.g., success of the service job, technical competence of the field service employee, or customer openness) and investigate their impact on selling activity and selling success.

Finally, the third essay, titled "Zapping in TV Advertising – The Role of (Non) Engaging Content" and co-authored by Manuel Berkmann, Maren Becker, and Werner Reinartz, investigates how marketers can use executional content cues in their TV advertisings (e.g., informativeness, creativity, or branding) to engage consumers and mitigate zapping behavior. To this end, advertising content functions as a means to mentally transport the consumer into the narrative (Malthouse and Calder 2011; Wang and Calder 2006, 2009). The authors develop a conceptual framework linking multiple content factors to psychological responses and zapping behavior. They test this content-zapping relationship by drawing on a unique multi-source dataset of individual zapping behavior of more than 2,500 German television viewers combined with advertising data and content information for 1,315 spots representing 308 brands from 96 categories. Figure 1 provides an overview of the three research projects and structures them along the customer journey and level of managerial action. The next section summarizes motivation, research objectives, main results, and implications of each essay.

Figure 1: Conceptual Framework and Classification of Dissertation Projects

2 Summary of Dissertation Projects

2.1 Essay I: From Customer to Partner Engagement − A Conceptualization and Typology of Engagement in B2B

In the last decade, customer engagement has become a key topic for both practitioners and researchers. Reflecting the importance of customer engagement for managers, researchers have proposed several approaches to conceptualizing (e.g., Brodie et al. 2011; van Doorn et al. 2010) and measuring (e.g., Kumar and Pansari 2016; Vivek et al. 2014) customer engagement. Moreover, initial studies have used customer engagement to explain consumer behavior in empirical applications (e.g., Eisingerich et al. 2019; Eisingerich, Auh, and Merlo 2014; Verleye, Gemmel, and Rangarajan 2014). Yet, looking at the extant literature, it becomes apparent that the focus is almost exclusively on customer engagement in business-to-consumer (B2C) settings while business-to-business (B2B) settings have largely been neglected (Vivek, Dalela, and Beatty 2016). Thus, the question arises to what extent customer engagement matters in the B2B context and how B2B managers should deal with the new phenomenon.

Following the call for more B2B specific research (Lilien 2016), in the first essay, the authors aim at addressing the void in the engagement literature and focus on a conceptualization of engagement in the domain of B2B relationships. Specifically, the authors review specific properties of B2B markets (e.g., the derived character of demand, the multi-person nature of the buying process, the high degree of interaction, the formalization / rationality of exchange, or the small number of players in the market) and discuss their implications for engagement. One finding, for example, is that engagement in business markets needs to be assessed within a broader context of a firm's network considering both horizontal and vertical relationships. Another finding is that there are more "natural" opportunities in business markets to get engaged. Collectively, the implications of the properties indicate that there are specific aspects to the concept of engagement in business markets that warrant a dedicated investigation.

Based on the findings, the authors argue that the concept of customer engagement should be extended to *partner engagement* in order to reflect the complexity and network character of value chains in business markets. It is, thus, a generalization of the customer engagement concept that applies to both horizontal and vertical relationships as well as direct and indirect partners in the business network. Building on this conceptualization, the authors propose a novel definition of partner engagement as a partner's volitional behavior towards any other stakeholder in the value chain affecting the focal firm's business, including both direct (purchase related) but mainly indirect (referral, influence, knowledge) behaviors.

To provide guidance for B2B managers, the paper presents an overview of the most relevant partner engagement behaviors. For that, the authors develop a typology of B2B partner engagement that builds on two dimensions: The dimension assertiveness relates to a partner's focus on its own outcomes, while cooperativeness as the second dimension relates to the level to which the partner attempts to satisfy the other party's concerns. Using the typology, the authors classify the various types of B2B partner engagement as either "Disengagement", "Tactical Engagement", "Assertive Engagement", or "Strategic Engagement" and discuss the conditions and consequences of each engagement class. In addition to managerial implications, the paper also proposes avenues for future research on customer / partner engagement in B2B.

2.2 Essay II: Leveraging B2B Field Service Employees as a "Second" Sales Force

Field service employees play an important role in the customer management of industrial companies. In addition to their regular tasks of maintaining and repairing equipment, they assume many important functions (Rapp et al. 2015; Ulaga and Reinartz 2011): They are the supplier's face to the customer, act as problem solvers and relationship managers, collect valuable customer information and often identify important sales opportunities. As such, they are critical boundary spanners into the client firm. Recently, B2B managers have started to leverage these service touchpoints as additional opportunities to engage customers in the post-

purchase phase. This pertains to pro-active education, feedback seeking, or prevention (Challagalla, Venkatesh, and Kohli 2009) – but also to selling activities. However, field service employees face a number of challenges to successful selling. Most importantly, selling as a new tactical engagement activity may be at odds to the regular service job. Thus, it is of utmost importance for managers to understand how they can leverage field service employees effectively as a "second" sales force.

To address this question, the authors develop a comprehensive conceptual framework to explain field service employees' selling behavior. For that, they conduct a qualitative study consisting of multiple interviews with field service employees to identify relevant drivers of selling activity and selling success (e.g., success of the service job, technical competence of the field service employee, or customer openness) and structure them along the established Motivation-Opportunity-Ability (MOA) framework (e.g., Sabnis et al. 2013).

For the empirical analysis, the authors draw on a unique secondary dataset from a cooperating global industrial company that sells high-tech manufacturing equipment in combination with industrial services. This dataset consists of cross-sectional and longitudinal data from the field service organization covering more than 140,000 service visits of 420 field service employees over a period of four years (2012–2015) in combination with data on more than 18,000 selling activities initiated during the service visits. To assess the impact of the different MOA dimensions, the authors estimate two logit panel models with random effects – one to explain field service employees' selling activity (i.e., engagement-inducing behavior) and one to explain selling success (i.e., engagement success).

The results reveal several interesting findings, in particular that factors specific to the industrial service context are key antecedents to the field service employees' selling behavior. For example, the field service employee's success in restoring operability of equipment increases the likelihood of selling activity but decreases the chances of its success. Further,

generalists with broad technical competence (compared to specialists with deep technical competence) are more likely to engage in selling activities and more likely to convert these activities into sales. In addition, consistent with previous conceptual research (Challagalla, Venkatesh, and Kohli 2009), customer expertise is an important determinant of both selling activity and selling success. Results of a simulation demonstrate the revenue-generating potential of field service employees engaging in tactical selling: Selling activities increase the revenue per visit by 20% with significantly stronger lifts for specific constellations. The paper, thus, provides actionable insights for B2B managers how to leverage field service employees as a "second" sales force.

2.3 Essay III: Zapping in TV Advertising – The Role of (Non) Engaging Content

TV advertising remains a key pillar in the communication mix of many brands and constitutes an important touchpoint to foster consumer engagement with the brand. However, to be effective advertising needs exposure. Thus, one of the main reasons for low advertising effectiveness is the consumers' conscious avoidance of ads (Tellis 2004). When consumers avoid an ad by leaving the room or zapping, advertisers lose the ability to communicate their brand message and the investment is lost. It is, thus, crucial for advertisers to understand which factors influence the avoidance of advertising, i.e. zapping.

Specifically, the third essay focuses on the role of advertising content as the vehicle to engage consumers. That is, by creating engaging advertising content marketers may succeed in drawing consumers into the narrative (Malthouse and Calder 2011; Wang and Calder 2006, 2009) and thus mitigate zapping. The role of content thus far has only been investigated in lab studies. These studies found indicative evidence that content affects zapping. Although this stream of research has contributed a great deal of insight, there is still limited understanding of the boundary conditions and to what extent these findings also hold for zapping behavior outside of the lab, i.e., in the real world. Being the first to investigate the relationship between

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advertising content and zapping in the field, this study aims to provide marketing managers with actionable implications on how to create engaging content for their ads.

To do so, the authors develop a conceptual framework linking five important and frequently employed content factors (emotionality, informativeness, creativity, humor, and branding) to psychological responses and zapping behavior. They test the content-zapping relationship by drawing on a unique multi-source dataset from a German TV broadcaster. Specifically, this dataset comprises individual level viewing information for a panel of more than 2,500 individuals for one major entertainment format over a period of three months in 2016. The authors combine this data with content information for a total of 1,315 ads obtained via expert coding. In this procedure, five experts coded 20 executional content cues, which were subsequently condensed into six content factors using principal component analysis. To investigate the effect of the content factors on the zapping behavior, a binary logit model with brand and individual fixed effects is estimated.

Results show that ad content indeed influences zapping behavior in the field – even when controlling for a large number of context variables (e.g., position) and including brand and individual fixed effects. This implies that some – not all – content factors can be an effective tool to engage viewers and mitigate zapping. Specifically, the findings show that creativity and late brand timing in ads are associated with less zapping, whereas informativeness and a strong brand presence are associated with more zapping. Moreover, the authors show that the influence of content on zapping differs between more and less familiar brands as well as between search and experience categories. The paper, thus, provides managers with actionable findings that they can apply given their specific situation.

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ESSAY I: FROM CUSTOMER TO PARTNER ENGAGEMENT –

A CONCEPTUALIZATION AND TYPOLOGY OF ENGAGEMENT IN B2B

Authors: Werner Reinartz and Manuel Berkmann

ABSTRACT

This chapter focuses on engagement in business-to-business contexts. It analyzes a number of specific properties of business markets (e.g. the derived character of demand or formalization / rationality of exchange) and discusses their implications for the phenomenon of customer engagement. Furthermore, the authors argue that the concept of customer engagement should be extended to partner engagement in order to reflect the complexity and network character of value chains in business markets. Finally, the authors develop a typology of partner engagement behaviors in business markets and discuss differences with respect to the level of engagement (organizational vs. individual), underlying relational factors as well as special cases. Based on the analysis, the authors derive specific implications for B2B managers and provide avenues for future research in the domain of partner engagement.

Keywords: Partner engagement, business-to-business, typology, business value chain, vertical and horizontal collaboration, properties of B2B markets, assertiveness, cooperativeness

1   Introduction

In the last decade, customer engagement has become a key topic for both practitioners and researchers. For Forbes Insights, "engagement is everything" (2015, p. 3). The increasing importance in marketing practice gets support from a recent study by McKinsey & Company that shows that 69% of CEOs consider customer engagement a top strategic priority for their business (McKinsey 2014). On the other hand, only 25% of CMOs state that they have a comprehensive understanding of the phenomenon customer engagement (CMO Council 2014). Also in marketing research, engagement is regarded as a top priority as indicated by continued representation in the MSI Research Priorities (2010, 2014, 2016).

In fact, there has been considerable progress in conceptualizing and measuring customer engagement (Brodie et al. 2011; van Doorn et al. 2010; Hollebeek, Srivastava, and Chen 2016; Kumar and Pansari 2016; Pansari and Kumar 2017). While some studies define customer engagement as behavioral manifestations beyond purchase (van Doorn et al. 2010), others argue that customer engagement is rather a psychological state of mind (Brodie et al. 2011). There is a general agreement, however, that customer engagement is a multidimensional concept (Beckers, Risselada, and Verhoef 2014) which can be holistically defined as "the mechanics of a customer's value addition to the firm, either through direct or/and indirect contribution" (Pansari and Kumar 2017, p. 2). Yet, looking at the extant literature, it becomes apparent that the focus is almost exclusively on customer engagement in business-to-consumer (B2C) settings while business-to-business (B2B) settings have largely been neglected (Vivek, Dalela, and Beatty 2016).

This is surprising given the tremendous importance of customer engagement in B2B settings. The lead user concept introduced by von Hippel (1986) was one of the first descriptions of customer engagement and originates in B2B innovation research. It states that firms can improve their innovation efforts by involving selected customers whose "needs will become

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general in a marketplace months or years in the future" (von Hippel 1986, p. 791). This approach is still valuable to B2B firms today. The software company SAP, for example, has implemented the lead user idea in the form of a Co-Innovation Lab intended to continuously gather insights from key clients and partners in order to leverage their innovation potential. As another instrument to foster collaboration with and among the many different partners (e.g. users, developers, implementation partners, etc.) SAP hosts a Community Network with 2 million unique visitors a month (Carboni 2014).

In addition, two trends are expected to increase the relevance of engagement in business markets and thus warrant a thorough understanding of the phenomenon. First, the digitization provides opportunities for increasing interconnectedness among the players. As firms and their products and services become parts of broader systems ("Industry 4.0"), the need for system interoperability and collaboration increases (Porter and Heppelmann 2015). Second, we witness an ongoing de-verticalization of value chains. For example, in the automobile industry the value-added by OEMs like GM, Toyota or Volkswagen is projected to decrease from 44% in 1985 to 18% in 2015 (Statista 2016). The trend towards outsourcing and collaboration is also prevalent within the marketing function. Take for example the number and scope of players involved in digital marketing activities (internal marketing department, data provider, creative agency, publisher, ad networks, intermediaries for online shops, etc.), which has led to the creation of the role of lead agencies whose main responsibility is coordinating all players involved (Bauer et al. 2017). Both trends exemplify that firms no longer operate in environments with a limited number of partners. Rather, they are part of complex networks comprising suppliers, competitors, partners and customers. Thus, it is of utmost importance to understand how B2B players engage with each other in order to create value.

Despite the high relevance of engagement for business marketing practice, business marketing research on engagement in B2B is scarce. Except for the work of Vivek and

colleagues (2016), the conceptual literature on engagement has largely focused on consumer markets (Brodie et al. 2011; van Doorn et al. 2010). Following the call for more B2B specific research (Lilien 2016), we aim to address the void in the engagement literature and focus on a conceptualization of engagement in the domain of B2B relationships. Specifically, we seek to make the following contributions. First, we review specific properties of B2B markets and analyze their implications for engagement in business markets. Second, we suggest a broadening of perspective and an extended conceptualization of engagement in B2B. We propose to refer to this phenomenon as "partner engagement" instead of (just) "customer engagement". By taking a holistic view of the network a firm operates in, we seek to generalize recent initial work on B2B engagement by Vivek and colleagues (2016) and try to fully capture the complexity of B2B settings. Third, we develop a typology of partner engagement by adopting a framework from the organizational behavior literature. Fourth, based on the typology, we discuss different types of engagement with respect to the level of engagement (organizational vs. individual), underlying relational factors and special cases that help understand and manage partner engagement. Finally, we suggest several avenues for future research in the domain of partner engagement in B2B.

2   A B2B Perspective on Engagement

Customer engagement is regarded as the new frontier in the domain of customer management and relationship marketing (Verhoef, Reinartz, and Krafft 2010). Taking a historical perspective, Beckers, Risselada and Verhoef (2014) describe a three stage development: Until the 1990s, marketing was focused on discrete transactions and one-way communication from the firm to the customer, e.g. by mass media advertising and direct mailings. The era of relationship marketing that followed (early 1990s to 2005) emphasized the importance of (two-way) firm-customer interaction and a joint value creation process. The current era of engagement is marked by a more holistic perspective, in which the classical firm-

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customer dyad has been opened up and considers interactions with other stakeholders (e.g. other customers) as well.

Against this background it is notable that although relationship marketing originated in B2B marketing (e.g. Dwyer, Schurr, and Oh 1987), the literature on engagement today almost exclusively focuses on B2C settings. If we consider the almost similar economic weight of B2B and B2C transaction volumes in the global economy, one should expect similar levels of academic attention for engagement in both markets (Lilien 2016). Yet, there is a clear mismatch between the importance in practice and the representation in research. Is this due to the fact that there is no difference between B2B and B2C with respect to engagement? Or, alternatively, is engagement simply less relevant in B2B? On the contrary, we argue that the specific properties of B2B markets make the concept of engagement highly relevant and yield distinct implications for its understanding. Therefore, the next section is intended to establish an overall theoretical framework for engagement in B2B. For that, we discuss specific properties of B2B markets and derive implications for engagement in these markets.

2.1 Specific Properties of B2B Markets and Their Implications for Engagement

The key difference between business-to-business and business-to-consumer markets is the fact that in B2B settings organizations - and not the individual end consumer - act as decision makers and buyers. While many specific properties of B2B markets have been described in extant literature (e.g. Grewal and Lilien 2012; Lilien 2016), we will focus on five properties that are most relevant for the concept of engagement since they deal with relational aspects (Homburg, Kuester, and Krohmer 2013):

- The derived character of demand

- The multi-person nature of the buying process

- The high degree of interaction

- The formalization / rationality of exchange

- The small number of players in the market

First, the derived character of demand (Grewal et al. 2015) implies that compared to consumers B2B buyers (only) purchase products and services to satisfy the needs of their respective customers. Thus, the demand of downstream partners in the value chain ultimately drives the behavior of firms in business markets. This requires a broader focus than just the focal firm-customer dyad and often entails approaches for marketing to the customers' customers (Dahlquist and Griffith 2014; Homburg, Wilczek, and Hahn 2014). To add to the complexity, many firms collaborate with partners (e.g. consulting firms) or their own suppliers (e.g. special component manufacturers) in order to create value for their customers in a complex value chain system. This points to the importance of both a vertical and horizontal perspective and leads to the following implication for engagement in B2B[1].

Implication 1: Engagement in business markets needs to be assessed within a broader context of a firm's network considering both horizontal and vertical relationships.

The second important property of B2B is the multi-person nature of the buying process (Lilien and Wong 1984). While in consumer markets, the most complex setup for decision-making is a household, in B2B markets multiple functions and persons are involved in decision-making. The buying center concept, for example, describes five different roles (decision maker, gatekeeper, influencer, user, buyer) that should be considered when analyzing organizational decision making (Johnston and Bonoma 1981). Moreover, recent empirical research shows that relationship multiplexity is an important driver of firm performance. For example, multiple contacts at the individual level can help improve the value of supplier-customer relationships (Palmatier 2008). Thus, identifying those contacts within a partner's buying center that have a

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[1] One could argue that upstream and horizontal B2B relationships are also relevant for firms in B2C markets (e.g. banks, electronic equipment manufacturers, fashion). In that sense, firms marketing to the end consumer are a special case where there is only one stakeholder downstream. For the sake of consistency, however, we confine our analysis to the constellation when the direct customer of the focal firm is still an organization (see Figure 1).

high likelihood for positive engagement is very important (Adamson et al. 2015). At an organizational level, multiple ties (e.g. standard product/service supply, R&D alliances, marketing alliances, joint ventures, mutual equity investments, board overlock) have been shown to positively influence overall sales while reducing sales volatility (Tuli, Bharadwaj, and Kohli 2010). Hence, both forms of multiplexity create additional opportunities for engagement while making the analysis more complicated at the same time. This leads to the following implication.

Implication 2: Engagement in business markets should be analyzed taking a

multi-level perspective and distinguish between individual and organizational

level behavior.

Third, business market relationships often feature a high degree of interaction and integration of operating processes (Grewal and Lilien 2012). This goes along with an increased importance of personal selling and (long-term) relationships in general. The high degree of interaction is mainly due to the complexity and need for customization of many industrial products which leads to the strong presence of direct sales models in business markets (Anderson, Narus, and Narayandas 2009). Moreover, process integration is often the result of strong mutual interdependence and the insight that integration serves the interest of both parties (Tuli, Kohli, and Bharadwaj 2007).

Implication 3: In business markets, there are more "natural" opportunities to get

engaged in order to improve the organization's own and/or the partner's

situation.

Another important property of business markets is rationality and the high degree of formalization of exchange that comes with it. In contrast to consumer markets, impulse buying is rare and purchase decisions are usually the result of clearly defined processes that are based on criteria and organizational requirements (Grewal et al. 2015). This implies less emotional,

more rational benefit-oriented reasons for engagement (Vivek, Dalela, and Beatty 2016). Indeed, empirical research on community participation shows that – although personal motives such as experiential and symbolic benefits still play a role (Bruhn, Schnebelen, and Schäfer 2014) – B2B community participants use the community for problem solving rather than socializing (Bone et al. 2014).

> *Implication 4:* In business markets, there are different and additional types of
>
> engagement behaviors, which are more formally organized. The formalization
>
> can manifest itself in internal rules on how to interact with partners that are
>
> potentially hindering engagement on an individual level.

Finally, business-to-business markets usually comprise a smaller number of players for both supply and demand (Grewal and Lilien 2012). This can lead to competition among customers for a certain supplier or partner. For example, the concepts of preferred supplier (e.g. in automotive) or preferred partner (e.g. exclusivity agreements with retailers) both focus on getting exclusive access to an important market player instead of "sharing" with others (Kumar, Petersen, and Leone 2007). This also applies to the "resource" engagement which is limited for every market participant (van Doorn et al. 2010).

> *Implication 5:* The small(er) number of players in business markets potentially
>
> fuels competition for engagement.

The discussion above shows that there are specific aspects to the concept of engagement in business markets. The insights derived here will serve as a theoretical basis for the subsequent steps of conceptualizing and developing a typology of engagement in B2B.

2.2 From Customer Engagement to Partner Engagement

The implication from the first property suggests that engagement needs to be assessed within a broader context of a firm's network. Figure 1 illustrates a simplified example of a business network. With the focal firm at the center of the network, the figure shows that there

are numerous ties with partners both vertically and horizontally in the value chain. Downstream, firms often collaborate with their customers in order to better meet the needs of their customers' customers. The lead user approach (von Hippel 1986) that was introduced earlier is a good example for that. Similarly, the focal firm may turn upstream to collaborate with a supplier to improve its own offering. Finally, the lines from the focal firm to partners and competitors indicate that there are also relevant ties with other players on the same (horizontal) level of the value chain. In all situations, the behavior of the partner(s) is crucial for the success of the focal firm.
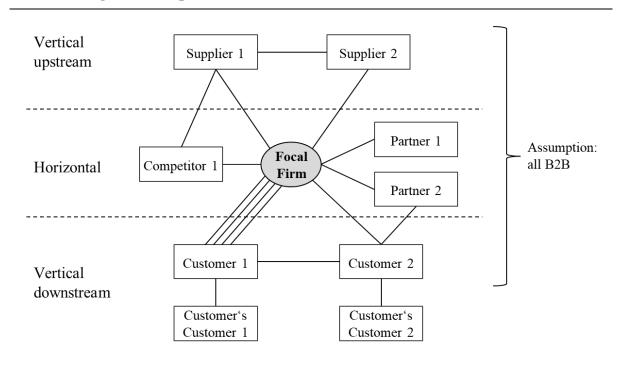
Figure 1: Graphical Illustration of a Network in Business Markets

Notes: Illustration adapted based on Wuyts et al. (2004)

While the vertical (channel) perspective is well understood, the horizontal collaboration with partners or competitors has received far less attention in the marketing literature (Rindfleisch and Moorman 2001). Yet, within the B2B network there is a host of specialized intermediaries that perform important functions for the value chain. These intermediaries may comprise financial partners (e.g. insurances, banks, brokers), advertising or promotion

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agencies, logistics specialists, sales and implementation support, IT vendors or market research firms (Palmatier, Stern, and El-Ansary 2015). The relationship between the focal firm and these partners are often complex and typically based on informal arrangements (Plouffe et al. 2016) in which both parties collaborate based on aligned interests (Tuli, Kohli, and Bharadwaj 2007). The B2B software and IT industry is a good example for that. Around major players like IBM, Oracle or SAP, an ecosystem of support firms has developed that assume different services like consulting, implementation, or software customization. For example, SAP relies heavily on partners to market their software applications to small and medium enterprises (SMEs). In this setup, the partners fulfill important functions like generating leads, providing advice to clients and implementing the software. As many partners are not bound by exclusivity arrangements, their influencing behavior towards potential clients constitute an important facet of engagement towards SAP.

Another aspect illustrated in Figure 1 is the multiplexity of ties between the focal firm and potential engagement partners (as indicated by multiple lines between the focal firm and customer 1). In the case of a mechanical engineering company selling milling equipment, like Sandvik Coromant for example, we find ties between a sales account executive and several contacts in the customer firm (e.g. operations engineer, plant manager, purchaser), but also between employees of the service field force and users of the equipment. Depending on the respective importance, there may also be relationships between top management representatives. The partner engagement can occur at different levels of formalization. For example, innovation co-development initiatives are usually contract-based (i.e. formalized) and can thus be considered organizational engagement while we may also observe personal engagement at the individual level, e.g. in the form of recommendations within the personal network that usually occur spontaneously and are unregulated.

The discussion of the structural framework shows that the context for engagement in business markets is complex. More stakeholders mean more opportunities for engagement. Thus, we posit that in business markets the concept of customer engagement should be extended to partner engagement in order to reflect the importance of many stakeholders and their behavior for the success of the focal firm. This is in line with prior research in business markets. For example, scholars of the IMP group established a network perspective for studying business markets (Håkansson 1982). Moreover, "partnering" is regarded as a viable and focused market strategy (Anderson, Narus, and Narayandas 2009). With this conceptualization we build on and extent recent work by Vivek, Dalela and Beatty (2016) who focused on dyadic relationships between the focal firm and its business clients. We aim at generalizing the concept of engagement and apply it to both horizontal and vertical relationships as well as direct and indirect partners in the business network. The extended perspective for engagement is also reflected in relationship management tools in practice. Similar to the customer focused approach in B2C which has led to a widespread adoption of CRM tools, the importance of managing all partners effectively in B2B is mirrored in partner relationship management tools offered by leading software companies such as Oracle or Salesforce.com. These tools facilitate managing relationships with both partners and customers (e.g. in indirect multi-stage distribution channels), for example with respect to certification and training, lead management or the coordination of marketing programs. These examples highlight the relevance of Partner Relationship Management (PRM) as an extension of Customer Relationship Management (CRM) in B2B.

Building on previous conceptualizations of (customer) engagement (van Doorn et al. 2010; Kumar et al. 2010; Pansari and Kumar 2017) and the discussion on business networks above, we consequently define partner engagement as a partner's volitional behavior towards any other stakeholder in the value chain affecting the focal firm's business, including both direct

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(purchase related) but mainly indirect (referral, influence, knowledge) behaviors. Please note that this definition focuses on actual behavior as opposed to psychological or attitudinal aspects (van Doorn 2011). This is appropriate in the business market context for two reasons: First, a partner's action is what makes the difference and has a real impact on the focal firm's business (Bolton 2011). Second, given the multi-person nature of B2B relationships and the higher degree of formalization, individual psychological states are less relevant as well as more difficult to measure and aggregate. Thus, behavior can be interpreted as the outcome of individual or group-based decision processes.

3   A Typology of B2B Partner Engagement

Many types of engagement behavior are not new to marketing research and practice, yet so far they have been investigated separately. Only recently, scholars have started to considers these behaviors as part of the overarching phenomenon of customer engagement (Verhoef, Reinartz, and Krafft 2010). Table 1 provides an overview of the many types of engagement classified into four different groups with regard to their value contribution to the firm, as suggested by Kumar et al. (2010). Engagement types more prevalent or specific to business market contexts are marked with an asterisk. The classification by Kumar et al. (2010) is a valuable first step for understanding different engagement types. Yet, the classification remains descriptive in nature and merely focuses on the value contribution to the firm. Therefore, we propose a typology that can help structure the various types of B2B partner engagement, analyze similarities and differences between them, and thus, gain important insights into the underlying mechanisms.

Table 1: Overview of Types of Engagement with Exemplary Articles for the B2B Context

Indirect value contribution			Direct value contribution
Referral / Reference	**Influence**	**Knowledge**	**Purchase**
"Relates to the acquisition of new customers through a firm initiated and incentivized formal referral program" (Kumar et al. 2010, p. 299)	*"Customers' influence on other acquired customers as well as on prospects"* (Kumar et al. 2010, p. 299)	*"Feedback provided to the firm for ideas for innovation and improvements, and contributing to knowledge development"* (Kumar et al. 2010, p. 299)	*"Repeat purchases or additional purchases through up-selling and cross-selling"* (Kumar et al. 2010, p. 299)
▪ Hada, Grewal, and Lilien (2014) ▪ Kumar, Petersen, and Leone (2013) ▪ Godes (2012)	*Word-of-mouth (WOM)* ▪ Libai et al. (2010) ▪ von Wangenheim and Bayón (2007) *C2C Support / Exchange* ▪ Chakravarty, Kumar, and Grewal (2014) ▪ Gruen, Osmonbekov, and Czaplewski (2007) *Community participation* ▪ Bone et al. (2014) ▪ Bruhn, Schnebelen, and Schäfer (2014) *Complaints* ▪ Haverila and Naumann (2011) ▪ Homburg and Fürst (2005)	*Co-Development** ▪ Chang and Taylor (2016) ▪ Homburg and Kuehnl (2014) ▪ Joshi and Sharma (2004) *Information sharing** ▪ Frazier et al. (2009) ▪ Fang (2008) *Feedback/Suggestions* ▪ n/a *Trainings** ▪ Ulaga and Reinartz (2011) *Joint marketing / sales activities** ▪ Dahlquist and Griffith (2014) ▪ Homburg, Wilczek, and Hahn (2014)	▪ Grewal et al. (2015) ▪ Lacoste (2012) ▪ Kumar et al. (2008)

Notes: * = Engagement types more prevalent or specific to business markets

3.1 Overview of the Typology

Three criteria guided the development of our typology. First, the typology should build on previous engagement research and has to be able to accommodate all the different types of engagement. Second, it should reflect the specific properties of B2B markets. Third, it should help uncover similarities and differences between the different types of engagement, in particular provide insights from a managerial point of view. Based on these criteria, we adopt a framework from the organizational behavior literature (Thomas 1976, 1992). Originally, it was applied to explain conflict resolution styles[2]. In this respect, Thomas' concept of conflict and the corresponding behavior can be interpreted as a form of (negative) engagement. However, the dimensions used in the framework are applicable to positive types of partner engagement as well.

Figure 2 shows the dimensions and resulting quadrants of the typology for partner engagement. The dimension a*ssertiveness* relates to a partner's focus on its *own* outcomes. For example, a partner may employ engagement behaviors to achieve its own goals such as increasing its own margins, securing channel access, or creating a distinct image (if necessary at the expense of other players in the network). *Cooperativeness* as the second dimension relates to the level to which the partner attempts to satisfy the *other party's* concerns (e.g. innovating the marketplace or increasing overall channel volume). The dimensions used in the typology fit the criteria outline above well. They are consistent with previous conceptual work on customer engagement highlighting the importance of customer goals (concern for oneself) and the purpose of engagement with respect to the focal firm (concern for the other) (van Doorn et al. 2010). Moreover, the dimensions are key parameters of B2B strategies (Anderson, Narus, and Narayandas 2009) and thus reflect the specific properties of B2B (e.g. the formalization of

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[2] The idea of the original work by Thomas (1976) was to develop a generic theory of conflict and conflict management and the social processes involved. With respect to the framework, Thomas described five conflict-handling modes (Avoiding, Accommodation, Compromise, Competition, Collaboration) using a two-dimensional taxonomy based on assertiveness and cooperativeness.

exchange). Compared to other potential dimensions that were initially considered (e.g. high vs. low, or positive vs. negative, or horizontal vs. vertical engagement), our typology also provides managerially relevant dimensions to uncover similarities and differences between the engagement types. It should be noted that in the context of partner engagement, this typology has to be analyzed from the perspective of the party that is exhibiting engagement behaviors. That is, we discuss a partner's engagement behavior and its underlying drivers in order to understand the implications for the success of the focal firm.
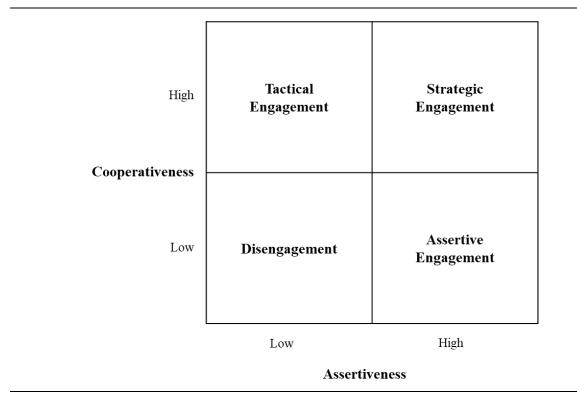
Figure 2: Typology of Partner Engagement

Crossing the two dimensions leads to four distinct types of partner engagement. If both assertiveness and cooperativeness are high, a partner is likely to show *strategic engagement* behavior. This could be, for example, the commitment of a supplier or customer to co-development activities with the focal firm. Similarly, a horizontal partner may be willing to offer trainings to the focal firm or have its employees participate in the focal firm's training program. Referring back to the SAP example above, this could mean that an implementation

partner is willing to invest resources by having its employees attend trainings of SAP in order to learn more about most recent product innovations and its value propositions.

If assertiveness is high but cooperativeness is low, a partner is likely to show behaviors that can have negative[3] effects on the focal firm. Examples for this group of *assertive engagement* are negative WOM, complaints or even lawsuits. This is in line with previous research emphasizing that engagement can have positive or negative valence (van Doorn et al. 2010).

If conversely, assertiveness is low and cooperativeness is high, we expect more *tactical engagement* behavior. Given the low own stakes, a partner may act in favor of the focal firm for different reasons: One motivation could be to give in to the demand of the focal firm in order to avoid open conflict (appeasement). On the other hand, tactical engagement behavior can be a means to make investments into a relationship at relatively low cost in order to generate goodwill at the focal firm.
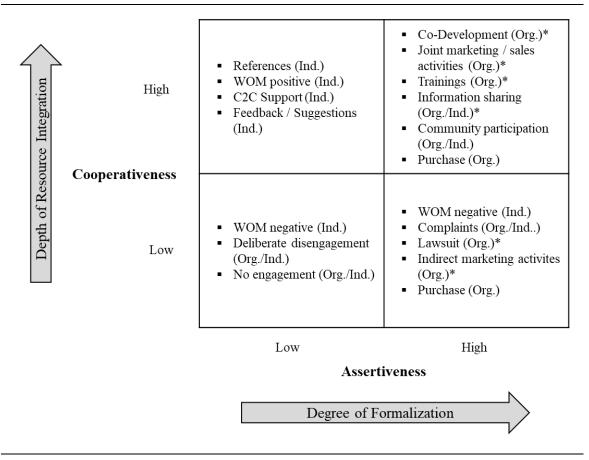
Finally, we label the scenario when both dimensions are low *disengagement*. In this case, a partner is likely to show low intensity to no engagement behavior at all. This comprises, for example, deliberate disengagement, which is likely to occur if a partner has already entered into a preferred partnership with a competitor of the focal firm. The disengagement quadrant is an important part to complete the "engagement picture". As discussed above, resources for engagement are limited, so it is neither possible nor meaningful to have high engagement with every partner. In fact, anecdotal evidence suggests that only a minority of customers or partners is actually highly engaged with 90% remaining rather passive (Libai 2011).

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[3] It should be noted that under the condition of high assertiveness and low cooperativeness, a partner's engagement can also have positive effects, e.g. by creating a pull effect in the value chain in the case of indirect marketing activities (Homburg, Wilczek, and Hahn 2014). However, engagement types with negative effects prevail (see Figure 3).

3.2 Insights from the Typology

In order to uncover similarities and differences among the types of partner engagement and generate deeper insights, we assigned the engagement types listed in Table 1 to the four quadrants of the typology. For each engagement type, the dimensions assertiveness and cooperativeness were rated in terms of high vs. low. If available, we used information from the respective paper itself (e.g. Bone et al. 2014); for the remainder, the assignment was done based on the judgment of the researchers. We will discuss ambiguous cases subsequently. Figure 3 shows an overview of the final typology. For example, we assigned co-development to the strategic engagement quadrant, as the majority of co-development activities require both a high level of assertiveness and a high level of cooperativeness. Given the enormous size of resource investments necessary to make a co-development work, both partners will only engage if they expect value from the cooperation (Hoyer et al. 2010). Similarly, both high assertiveness and high cooperativeness are important prerequisites for open sharing of strategic information (Frazier et al. 2009). Conversely, a partner may show a high level of cooperativeness when referring other clients or contacts to the focal firm or spreading positive WOM while his own outcomes are of minor importance (i.e. low assertiveness).

Obviously, for some types of engagement the position within the typology may vary depending on the specific business context. For example, the levels of concern for oneself and for the other party can differ for community participation (Bone et al. 2014). Similarly, a partner may generate positive WOM even if the concern for the impact on the focal firm is rather low (in this case, WOM may be triggered rather by the concern for a third party than by the concern for the party that is the object of WOM). From Figure 3, some interesting patterns emerge. We discuss these insights next.

Figure 3: Examples of Partner Engagement

		Low	High
Depth of Resource Integration ↑	High	▪ References (Ind.) ▪ WOM positive (Ind.) ▪ C2C Support (Ind.) ▪ Feedback / Suggestions (Ind.)	▪ Co-Development (Org.)* ▪ Joint marketing / sales activities (Org.)* ▪ Trainings (Org.)* ▪ Information sharing (Org./Ind.)* ▪ Community participation (Org./Ind.) ▪ Purchase (Org.)
	Low	▪ WOM negative (Ind.) ▪ Deliberate disengagement (Org./Ind.) ▪ No engagement (Org./Ind.)	▪ WOM negative (Ind.) ▪ Complaints (Org./Ind..) ▪ Lawsuit (Org.)* ▪ Indirect marketing activites (Org.)* ▪ Purchase (Org.)

Cooperativeness

Assertiveness

Degree of Formalization →

Notes: Ind. = Engagement at individual level; Org. = Engagement at organizational level;
* = Engagement types more prevalent or specific to business markets

Level of partner engagement behavior. The distribution of engagement behaviors in Figure 3 that occur at the individual level vs. those behaviors that usually occur at the organizational level shows that individual engagement behaviors dominate if assertiveness is low while organizational behaviors are important if assertiveness is high. Thus, the more important a certain behavior for the outcome of the partner the higher the degree of formalization (Homburg, Workman, and Jensen 2002; Pemer, Werr, and Bianchi 2014). If the engagement behavior takes place at the organizational level, it is reasonable to expect that internal rules and processes ensure that the behavior of several boundary spanning actors is well aligned and consistent. This does not necessarily hold for individual level engagement. Boundary spanning employees may influence others by sharing their own experiences and

evaluation with the focal firm outside of the own organization's influence (Wieseke et al. 2012). Thus, in a nutshell, high assertiveness usually translates into organizational level engagement behavior and increased formalization, while other engagement behaviors with low assertiveness are mainly driven by personal motives.

Depth of resource integration. It is interesting to note that among the types of partner engagement shown in Figure 3 some are mainly driven by one party while others require action of both sides. WOM and deliberate disengagement are examples for one-sided actions of the partner; that is, the behavior is under full discretion of the partner with no or little involvement of other parties. Other types of engagement such as co-development or joint marketing activities require cooperation between the partner and the focal firm. Thus, a partner may strive for strategic engagement, but it will only become reality if the focal firm shows similar intentions and the willingness to cooperate (Ulaga and Eggert 2006). As indicated by the vertical arrow in Figure 3, higher levels of cooperativeness require higher levels of resource integration. This is in line with recent research that links customer engagement to the service dominant logic and posits that resource integration is a foundational process for customer / partner engagement (Hollebeek, Srivastava, and Chen 2016). C2C support, for example, requires a stronger integration of (mainly operant) resources compared to disengagement while information sharing or mutual participation in trainings also goes along with deeper resource integration as compared to complaints or lawsuits. It should be noted that the depth of resource integration is not to be equated with the overall level of resource investments, as the latter is rather conditional on the level of assertiveness (i.e. the determination of a party to influence the outcome in its own favor). As a take-away, this implies that coordination is an important organizational capability (Teece, Pisano, and Shuen 2007) in order to extract value from a partner's tactical or strategic engagement.

Conditions for different partner engagement types. Several factors can help understand the conditions under which the different partner engagement behaviors are more or less likely to occur. These factors are all key concepts from the relationship marketing literature, in particular: trust, commitment and dependence (Palmatier, Dant, and Grewal 2007). They are considered important antecedents of engagement (van Doorn et al. 2010). Therefore, we briefly analyze the configurations of these factors for each of the four quadrants. In the case of *disengagement*, trust can be at any level (from low over medium to high), while commitment and dependence are at low levels. If we take the example of negative WOM: A partner may still have sufficient levels of trust into the integrity of the focal firm (Morgan and Hunt 1994), yet low commitment and low dependence create a situation in which nothing prevents the partner from spreading negative information about the focal firm. *Assertive engagement* is based on low levels of all three underlying factors. In particular, it requires either symmetric (i.e. mutual) dependence or even asymmetric dependence in favor of the partner (Scheer, Miao, and Palmatier 2014). *Tactical engagement*, in turn, is characterized by high levels of trust and low to medium levels of commitment which – in combination with the low concern for the own outcome – leads to a rather opportunistic utilization of this type of engagement. Moreover, it can occur at any level of dependence and can be characterized as "picking the low hanging fruit". *Strategic engagement*, finally, requires high levels for trust, commitment and dependence. Most notably, symmetric dependence is a necessary requirement to make this type of engagement a success for both parties (Tuli, Kohli, and Bharadwaj 2007; Vivek, Dalela, and Beatty 2016). Based on the reasoning above, we conclude that it is important for managers to consider the overall underlying relationship conditions in order to adequately judge a partner's engagement behavior.

Special case: Preferred or exclusive partnerships. As already discussed above, in certain situations B2B firms enter into preferred or exclusive arrangements with suppliers or partners

(Ulaga and Eggert 2006). For the parties within the arrangement this turns potential previous engagement into a formalized relationship. For players outside of the arrangement this may result in deliberate disengagement of the respective supplier or partner. These kinds of constellations can occur both up- or downstream as well as horizontally. Due to the strategic importance of the arrangements, they are usually formalized on an organizational level and governed by detailed contracts (Sieweke, Birkner, and Mohe 2012). In some industries, for example in the consulting industry, exclusivity arrangements severely reduce the market potential. Therefore, in order to avoid exclusivity arrangements (and thus forego other business opportunities), consulting firms often employ "chinese walls" (i.e. organizational, personal and IT-system related separation between teams working for competing clients) in combination with strict confidentiality rules for their employees.

Special case: Vertical marketing activities. In B2B markets, it is common that firms collaborate with other players in the value chain for their marketing or sales activities (Dahlquist and Griffith 2014; Wuyts et al. 2004). This is particularly relevant when marketing to indirect downstream customers. In a recent study, Homburg, Wilczek and Hahn (2014) discuss three different marketing approaches to indirect customers: direct customer downstream support, cooperative indirect customer marketing and independent indirect customer marketing. As illustrated in Figure 3, these vertical marketing activities can occur both under high as well as low cooperativeness. If we take, for example, a situation involving the focal firm, one of its suppliers and its customers (see Figure 1): Direct customer downstream support and cooperative indirect customer marketing can be considered as strategic engagement behavior of the focal firm's supplier (high assertiveness and high cooperativeness). If the supplier, however, engages in independent indirect marketing activities with the focal firm's customers, this can be classified as assertive engagement (high assertiveness but low cooperativeness towards the focal firm). The findings of Homburg and colleagues (2014) are in line with our reasoning for

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the underlying factor of dependence. In fact, they demonstrate that independent indirect marketing activities work best in the case of up- or downstream but not midstream locus of power, i.e. an asymmetric dependence in favor of the supplier or the customer.

Special case: "Vertical coopetition". Another interesting aspect illustrated in Figure 3 is the dual classification of purchases as both strategic and assertive engagement. Depending on the underlying factors, customers exhibit different levels of cooperativeness when purchasing goods or services from its suppliers. This phenomenon can often be observed in the behavior of large multinational key accounts towards their suppliers when there is an asymmetric distribution of power in favor of the key accounts (e.g. Nestlé in the CPG market or OEMs in the automotive industry). By employing both cooperation and competitive market based exchange (e.g. online auctions, tenders or competitive bidding) simultaneously these key accounts exhibit an engagement behavior coined as "vertical coopetition" (Lacoste 2012, p. 649). In summary, the discussion above shows that the typology is able to accommodate special cases of engagement as well. It further highlights the importance of considering the specific context in order to assign the behavior to the right quadrant and draw ensuing conclusions.

Importance of strategic engagement in B2B. Finally, it is interesting to examine the relative importance of each type of engagement. Overall, we find that strategic engagement is an extremely important type of engagement in B2B (Kumar and Pansari 2016). This is evident in the magnitude of different types assigned to the upper-right quadrant in Figure 3. This finding is corroborated by a recent meta-analysis on innovation effectiveness that shows, for example, that integrating customers or partners in new product development activities is more promising in B2B compared B2C contexts (Chang and Taylor 2016). Due to the specific properties of B2B (in particular formalization / rationality and high degree of interaction), we also posit that both assertiveness and cooperativeness can reach higher levels in B2B settings. Overall, we conclude that strategic engagement is of great importance in B2B. This is driven by aligned

interests and significant benefits for both parties, i.e. a win-win situation if the business environment for engagement is designed properly.

4   Discussion

4.1   Summary

Customer engagement is a key topic for both practitioners and researchers. A review of the literature, however, suggests that there is a dominant focus on customer engagement in B2C settings while the phenomenon has largely been neglected for B2B settings. Therefore, this chapter focuses on engagement in business-to-business contexts. First, we review specific properties of B2B markets and derive implications with respect to engagement. The insights show, for example, that engagement in business markets should be assessed within a broader context of a firm's network. Further, in business markets, engagement should be distinguished between individual and organizational behavior.   Second, we offer an extended conceptualization of engagement in B2B. Specifically, we propose that the concept of customer engagement should be extended to partner engagement in order to reflect the complexity and network character of value chains in business markets. Third, we develop a typology of partner engagement behaviors in business markets based on the dimension of assertiveness and cooperativeness. The typology helps to better understand similarities and differences between types of partner engagement. Finally, we derive insights from the typology. For example, our analysis indicates that high assertiveness of a partner usually translates into organizational engagement behavior (e.g. co-development activities) and increased formalization while other engagement behavior (e.g. referrals) are mainly driven by personal motives. Moreover, the insights show that it is important for managers to consider the overall underlying relationship conditions (i.e. trust, commitment, dependence) in order to understand its partners' engagement behavior. We also show that special cases (in particular exclusive partnerships, vertical marketing activities, and vertical coopetition) fit into the typology.

4.2 Managerial Implications

The findings of our research bear important implications for managers. Most importantly, the extended conceptualization of engagement suggests that B2B managers are well advised to broaden their focus and consider partner engagement in addition to customer engagement. This entails analyzing relevant stakeholders in the network with respect to positive and negative engagement behaviors and subsequently monitoring those systematically. The monitoring can be facilitated by using partner relationship management tools offered by many B2B software vendors (e.g Salesforce.com, Oracle, NetSuite, Relayware). From a managerial point of view, it is also important to acknowledge that certain types of engagement are often specific to certain departments (e.g. R&D, operations, marketing or sales). Thus, it requires centralized efforts to get an overview of the different engagement behaviors, but potentially a decentralized approach to deal with the different types of engagement.

Our typology of partner engagement provides managers with an actionable tool to understand and manage their partners' engagement. Based on the dimensions assertiveness and cooperativeness each type of (potential) engagement behavior can be classified. The classification yields important implications, for example with respect to the expected degree of formalization, the necessary depth of resource integration as well as the level (personal vs. organizational) of engagement. The typology, thus, can be used to devise partner engagement strategies.

In addition to that, the insights into the underlying factors of the typology provide proactive levers for managing partner engagement: First, gain power status in relationships to be able to counter assertive engagement strategies if necessary. Second, strengthen trust and commitment via relationship investments to build the foundation for strategic engagement of partners. Third, try to design business models and channel systems that align interests with partners to guard against opportunism and destructive engagement.

4.3 Avenues for Future Research

Our work follows the call of many scholars for more B2B specific research of marketing phenomena (Grewal et al. 2015; Lilien 2016; Vivek, Dalela, and Beatty 2016). We offer an initial conceptualization of engagement in B2B and develop a typology of partner engagement behaviors. Yet, we believe further research is needed to fully understand the nature, drivers and consequences of engagement in business markets.

First, given the inherent heterogeneity of the B2B domain (Lilien 2016), we need to better understand the heterogeneity of engagement within B2B. What are differences in engagement with regard to different industries (e.g. financial services, commodities, automotive, etc.), different product types (goods vs. hybrid offerings vs. services), different stages of the value chain or different environmental factors (e.g. technological dynamism, level of competition)?

Second, we believe investigating the "level" of engagement could be an exciting area for future research. How does engagement on an organization level (formalized) differ from personal level (informal) engagement? Under which conditions are those behaviors complements, substitutes or even countering each other? Which personal motives play a role for individual level engagement behavior?

Third, it could be interesting to contrast the effectiveness of engagement from different partners for the same type of engagement. For example, whose inputs are most effective for co-development of innovation (suppliers, customers, partners, other)? What are differences in the impact of positive or negative WOM from different partners?

Finally, B2B managers would greatly benefit from insights on how to manage engagement successfully. On the "providing side", this comprises a better understanding of a "culture of engagement", management of organizational engagement, regulation of engagement behavior of individual employees, and measurement of engagement effectiveness. On the "receiving side", it is about understanding how to create platforms or an environment for

partners to show positive engagement behavior, how to develop organizational capabilities to extract full value from a partner's engagement behavior and how protect the firm against assertive engagement of partners.

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ESSAY II: LEVERAGING B2B FIELD SERVICE EMPLOYEES AS A "SECOND" SALES FORCE

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ABSTRACT

As markets mature and competition increases, firms need to extract the full revenue-generating potential of the entire frontline. As a response, some B2B firms have begun to use their technical field service force for tactical selling activities. However, knowledge is scarce about whether and how firms can leverage their field service employees effectively as a "second" sales force. To address this gap, the authors employ a unique longitudinal dataset obtained from a major global industrial company, consisting of more than 140,000 customer visits of field service employees over a period of four years and more than 18,000 selling activities initiated during the service visits. Drawing on the Motivation-Opportunity-Ability (MOA) framework, the authors identify a number of drivers for the industrial B2B context (e.g., success of the service job, technical competence of the field service employee, or customer openness) and investigate their impact on selling activity and selling success. Results show diverging effects of the drivers for the two stages, thereby providing business-marketing managers with actionable insights on how to leverage their technical field force.

Keywords: Field service employees, business-to-business, service-sales ambidexterity, Motivation-Opportunity-Ability (MOA) framework, panel logit model

1   Introduction

Frontline employees—the sales force or service force—represent the core interface with the customer for most business-to-business (B2B) firms. Traditionally, firms have structured their organizational frontline in silos, with salespeople responsible for sales and service people responsible for service. However, to exploit the full revenue-generating potential of the entire frontline, firms have begun to add selling to the responsibilities of their field service employees[1]. At first sight, this strategy has a strong rationale. Unlike salespeople, field service employees work on-site during the deployment of equipment to perform technical maintenance and repair services. This allows them to collect valuable information about the client's processes. Thus, during the service visits there are natural occasions to identify sales opportunities and engage in selling activities.

However, field service employees face a number of challenges to successful selling. First, field service employees and salespeople differ substantially with regard to personality, role description, and skill set. Second, as selling in industrial service situations is highly context-specific (de Ruyter, Patterson, and Yu 2014), the field service employee needs to identify the "right" moment to engage in selling during the service visit. Third, as selling is usually a tactical add-on activity, the field service employee needs to carefully balance service and sales activities and handle the interdependencies between the two. Fourth, to engage in selling activities, field service employees need to embrace selling as part of their job, even though selling may feel at odds with their regular service job (Finkel 2015). Finally, to create value for both the customer and the supplier, the selling effort needs to translate into sales. For the customer, a field service employee's selling activity creates value if she/he identifies an equipment issue and offers a

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[1] Service should not be confused with service sales, i.e. salespeople that sell services. We distinguish between selling (acquiring new customers) and servicing (providing service/support to existing customers). In the remainder of this paper, the term "field service employees" refers to technical service personnel.

solution that improves the equipment's operability. For the supplier, using field service employees as an auxiliary sales force makes sense only if selling activities generate sales.

Indeed, industry reports show a mixed picture. While a study by McKinsey & Co. indicates that firms can increase revenues by up to 10% by leveraging their service force for up- and cross-selling (Eichfeld, Morse, and Scott 2006), other sources show that many firms fail to reap these benefits (Finkel 2015; Murcott 2007). Thus, it is of utmost importance for managers to understand how they can leverage field service employees effectively as a "second" sales force.

Despite the importance of these challenges, no study has investigated field service employees' selling behavior and its antecedents and consequences in the B2B context. Moreover, related studies in the B2C context have focused almost exclusively on motivational factors related to selling behavior by service employees (e.g., Gabler et al. 2017; Jasmand, Blazevic, and de Ruyter 2012; Yu, Patterson, and de Ruyter 2012). Yet, literature on the Motivation-Opportunity-Ability (MOA) framework suggests that opportunity and ability factors are important additional dimensions in order to explain B2B frontline employees' behavior (Nijssen, Guenzi, and van der Borgh 2017; Sabnis et al. 2013). Thus, identifying and incorporating those dimensions for non-sales people engaging in selling is essential. In addition, the relative importance of the different factors is unclear. Understanding the relative impact of the MOA dimensions on both selling activity and selling success would enable managers to implement concrete measures to strengthen the ambidexterity of their field service force. Guided by these issues, we consider the following three research questions:

(1) What motivational, opportunity, and ability factors are relevant to field service employees' selling behavior in a B2B context?

(2) Which of these factors drive field service employees' selling activity and selling success?

(3) Which MOA dimension (motivation, opportunity, or ability) has the greatest impact on field service employees' selling behavior and do the dimensions differ in their impact on selling activity and selling success?

To address these questions, we develop a comprehensive conceptual framework to explain field service employees' selling activity and selling success. We conduct a qualitative study consisting of multiple interviews with field service employees to identify relevant motivational, situational, and ability drivers of selling activity and selling success. We test our framework by drawing on a unique longitudinal dataset consisting of cross-sectional and longitudinal data from the field service organization of a major global industrial company. The dataset comprises longitudinal data on more than 140,000 service visits of 420 field service employees over a period of four years (2012–2015) in combination with longitudinal data on more than 18,000 selling activities initiated during the service visits.

This study makes several contributions to the literature. First, this study is the first to investigate the selling behavior of field service employees in an industrial B2B context. Using a qualitative approach, we develop a conceptual framework that identifies relevant drivers of field service employees' selling activity and selling success and structures them along the established MOA framework, resulting in new insights about drivers of selling performance in the industrial service context. Second, we add to the generalizability of the service–sales ambidexterity concept—a relatively new concept in the marketing literature focusing on mastery of seemingly conflicting tasks (Jasmand, Blazevic, and de Ruyter 2012), in this case tactical selling activities in addition to the main service job. While prior work focuses on conventional B2C services (e.g., banking, telecommunication, hospitality), we investigate field service employees' selling in a more complex industrial context that presents less standardized service incidents at the client site. Third, we offer a first assessment of service–sales ambidexterity based on observed behavior from field data, thereby extending previous studies

that relied on cross-sectional surveys of the service force (e.g., Gabler et al. 2017; Jasmand, Blazevic, and de Ruyter 2012; Yu, Patterson, and de Ruyter 2012). By taking a service visit perspective, we are able to capture important situational factors that may be critical to the success of cross-selling activities (de Ruyter, Patterson, and Yu 2014).

Our results show that factors specific to the industrial service context are key antecedents to field service employees' selling behavior. For example, the field service employee's success in restoring operability of equipment increases the likelihood of selling activity but decreases the chances of its success. Further, generalists with broad technical competence (compared to specialists with deep technical competence) are more likely to engage in selling activities and more likely to convert these activities into sales. In addition, consistent with previous conceptual research (Challagalla, Venkatesh, and Kohli 2009), customer expertise is an important determinant of both selling activity and selling success. Results of a simulation demonstrate the revenue-generating potential of field service employees engaging in tactical selling: selling activities increase the revenue per visit by 20% with significantly stronger lifts for specific constellations. We thus provide actionable insights how to leverage field service employees as a "second" sales force.

2 Conceptual Background

2.1 Previous Literature

Field service employees. Many firms employ a broad range of boundary spanners, each with different roles and responsibilities (e.g., product salespeople, inbound call-center agents, field service technicians). In this study, we focus on field service employees, who are important part of customer management, particularly in industrial B2B after-sales services (Homburg and Garbe 1999; Ulaga and Reinartz 2011). Field service employees' main tasks constitute installation of equipment, routine maintenance, emergency repair, and parts supply (Wilson, Boström, and Lundin 1999). These tasks require a dedicated technical background (e.g.,

electronics, mechanics, IT) and are usually performed at the client site during operation of the equipment. Sales representatives, on the other hand, have a clear commercial orientation and focus on selling equipment and services to their customers. Table 1 compares significant differences between the two groups of frontline employees with respect to personality and skill set as well as the customer contact situation. In light of these differences, the extent to which findings from the sales literature apply to service employees engaged in selling is unclear and warrants a dedicated investigation.

Table 1: Comparison of Field Service Employee and Sales Representative

	Field Service Employee	**Sales Representative**
Main orientation	Technical	Commercial
Function	Servicing existing customers	Acquiring new customers and expanding existing customer relationships
Client contact situation	Re-active, problem solving / trouble shooting, on-site during operations of equipment, tense atmosphere if operations are interrupted	Pro-active, remote or on-site (but usually in meeting rooms), more relaxed atmosphere
Skill set	Technical skills (electronics, mechanics, IT)	Commercial and inter-personal skills
Customer knowledge	Low	High
Technical knowledge	High	Low
Interpersonal skills	Medium	High
Focal object	Equipment (maintain or restore operability of equipment)	Customer (identify customer needs and sell solution)
Importance of selling activity	Add-on activity (if at all)	Main activity

While salespersons as boundary spanners have been subject to research for decades, the role and strategic significance of technical field service employees as boundary spanners has been largely neglected in extant research—a surprising oversight given the crucial role of field service employees in B2B customer management. In addition to their regular tasks of maintaining and repairing equipment, field service employees assume many important

functions. They are the supplier's face to the customer, act as problem solvers and relationship managers, collect valuable customer information, and often identify promising sales opportunities (Rapp et al. 2015; Ulaga and Reinartz 2011). As such, they are critical boundary spanners into the client firm. Moreover, field service employees are ideally suited for cross-selling spare parts or value-adding services during their on-site visits because of their recognized technical skills and direct insights into clients' processes. However, the limited research on field service employees' role (e.g., van Birgelen et al. 2002; Schepers et al. 2011) contains no study investigating field service employees' selling behavior and its antecedents and consequences.

Service–sales ambidexterity. The phenomenon of service–sales ambidexterity has recently attracted the attention of marketing scholars. The term ambidexterity was initially used in strategic management in order to describe a firm's ability to pursue the seemingly conflicting goals of exploitation and exploration (Raisch and Birkinshaw 2008). With the study by Jasmand, Blazevich, and de Ruyter (2012) the concept was introduced into the domain of service and sales management. A discussion of sales-service ambidexterity, i.e., the addition of service tasks to the responsibility of salespersons (e.g., Ahearne, Jelinek, and Jones 2007) is beyond the scope of this review. Instead, we focus on the emerging research on service-sales ambidexterity, which is more relevant for the context of this study. Service-sales ambidexterity refers to the mastering of seemingly conflicting tasks, in particular the field service employee's "engagement in both the customer service provision and cross-/up-selling during service encounters" (Jasmand, Blazevic, and de Ruyter 2012, p. 22). Table 2 summarizes the current literature. Following the MOA framework, we categorize the determinants of service–sales ambidexterity that were used in the literature into the dimensions motivation, opportunity, and ability.

Table 2: Summary of Related Literature and Contributions

	Independent Variables			Dependent Variables		Industry	Data Collection Method		Data Structure		Methodology
	Moti-vation	Oppor-tunity	Ability	Activity Measure	Success Measure		Survey	Field Data	Cross-Sectional	Longi-tudinal	
Jasmand et al. (2012)	✓			✓	✓	Services	✓		✓		SEM
Yu et al. (2012)	(✓)			✓	✓	Services	✓		✓		HLM
Schepers et al. (2011)	✓	✓		✓		Information technology	✓		✓		Multilevel regression
Rapp et al. (2015)	✓			✓	✓	Services	✓		✓		HLM
Ogilvie et al. (2017)	✓			✓	✓	Services	✓		✓		Polynomial regression
Gabler et al. (2017)	✓			✓	✓	Services	✓		✓		Polynomial regression
Patterson et al. (2014)	✓	✓			✓	Services	✓		✓		OLS
Yu et al. (2015)	✓			✓	✓	Services	✓		✓		HLM
Faia and Vieira (2017)	✓			✓	✓	Services	✓		✓		OLS
Günes et al. (2010)		✓			✓	Services		✓		✓	Random coefficient logit
This study	✓	✓	✓	✓	✓	B2B / Industrial		✓	✓	✓	Panel logit model

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Table 2 shows that most prior work has focused on motivational drivers of service–sales ambidexterity. For example, a customer service representative's locomotion orientation facilitates ambidextrous behavior (Jasmand, Blazevic, and de Ruyter 2012). Similarly, learning orientation has a positive effect on ambidextrous behavior while performance orientation has a negative or non-significant effect (Yu, Patterson, and de Ruyter 2015). Researchers have devoted significantly less attention to opportunity factors (e.g., Schepers et al. 2011) and no study yet has investigated concrete ability factors[2]. Given the importance of these factors for the context of this study, this gap in the literature is significant.

With regard to the study context and methodology, Table 2 shows that previous studies have almost exclusively been conducted in conventional B2C service environments like financial services or telecommunications call-center operations, using cross-sectional survey designs. Given the significant differences between B2B and B2C markets, transference of these studies' results to the B2B context requires caution. This restraint pertains particularly to the greater complexity and heterogeneity often encountered in business markets, such as technical complexity of products and services, large-unit transactions, importance of personal relationships, specialized roles of frontline employees, and complex buying processes (Grewal and Lilien 2012; Lilien 2016). Thus, investigating service–sales ambidexterity specifically for the industrial B2B context is warranted. Moreover, despite its merits a survey-based approach has several drawbacks, for example biases induced by social desirability and reliance on key informants. Most importantly, a survey cannot always capture situational factors that are crucial for understanding when and how field service employees can engage effectively in selling activities. Therefore, with the present study, we aim to add to the existing literature by taking a

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[2] Self-efficacy is often used as a proxy for one's perceived ability to master certain tasks (Krishnan, Netemeyer, and Boles 2002). However, the literature mainly regards self-efficacy as a motivational factor (e.g., Bandura and Locke 2003; Krishnan, Netemeyer, and Boles 2002; Schunk 1995). Thus, we classify these studies under the motivation dimension. To our knowledge, no research has investigated ability factors beyond self-efficacy or using objective instead of subjective proxies for ability.

more comprehensive conceptual approach to service–sales ambidexterity and testing the framework in an industrial business-to-business context using observed behavior from longitudinal field data of field service employees' service visits.

2.2 MOA Framework and Selling by Field Service Employees

In order to understand the selling behavior of field service employees, it is important to note that selling is an activity field service employees perform in addition to their main service job. In fact, successful service provision is the key priority, whereas selling is only a tactical activity. Consequently, the behavior and the outcome of the behavior must be distinguished (e.g., Jasmand, Blazevic, and de Ruyter 2012). The field service employee must be motivated to engage in selling, to identify promising opportunities during the service visit, and to pitch these to the customer (behavioral perspective). However, the selling activity must translate into actual sales, with the customer placing an order (outcome perspective). We therefore include two dependent variables in our conceptual framework: selling activity and selling success (Figure 1). Selling activity is defined as the extent to which a field service employee engages in selling in addition to the main service job by identifying sales opportunities and pitching them to the customer. Selling success in turn is the customer's decision to purchase after the selling activity of the field service employee. Notably, the field service employee takes the decision for the first step, whereas the customer takes the second step.

To identify determinants of field service employees' selling activity and selling success, we draw on the Motivation-Opportunity-Ability (MOA) framework. While the MOA framework was originally proposed in the advertising context (MacInnis, Moorman, and Jaworski 1991), it has been used to explicate other marketing phenomena, including salespeople's behavior (e.g., Sabnis et al. 2013). We propose that motivation, opportunity, and ability influence field service employees' selling activity and selling success.

Three considerations bolster the use of the MOA framework in the context of service–sales ambidexterity. First, the MOA framework can be applied to explain and predict behavior on both the organizational and individual level (Nijssen, Guenzi, and van der Borgh 2017). Second, it allows investigation of service–sales ambidexterity in a comprehensive manner. Specifically, it includes individual factors (motivation and ability) of the field service employee as well as external situational factors (opportunity) that are highly relevant to the decision to engage in service–sales ambidexterity (de Ruyter, Patterson, and Yu 2014). Finally, the MOA provides a general framework adaptable to a specific research context (Nijssen, Guenzi, and van der Borgh 2017; Sääksjärvi and Samiee 2011). Thus, it allows identification and incorporation of relevant factors in field service employees' selling activities during service visits.

We derive these MOA factors from a rigorous qualitative study supported by a literature review of related research. To ensure identification of factors specific to the industrial service context and consistent with our eventual sampling frame, we conducted exploratory interviews with 20 industrial field service employees from the cooperating company[3]. These semi-structured interviews lasted 28 minutes on average and covered the field service employees' general perception of the selling activity, their individual approach during service visits, and potential for future improvement. Following the MOA framework, we focused on motivational, opportunity, and ability factors. All interviews were recorded, transcribed verbatim, and subjected to a thematic content analysis using the established qualitative technique of open, axial, and selective coding (e.g., Corbin and Strauss 2008). This approach resulted in 16 factors, of which 11 were included in the conceptual framework[4].

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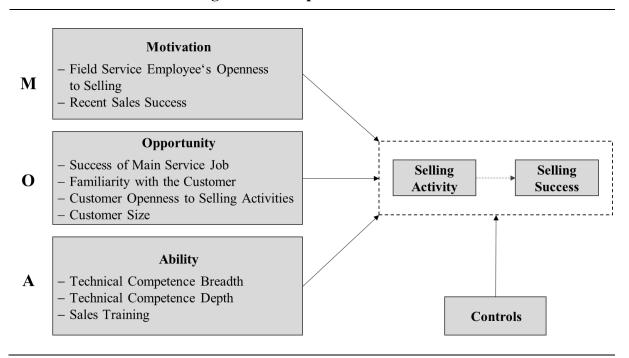
[3] We acknowledge that this might give rise to non-generalizability concerns. However, we employed this approach to ensure that we conducted interviews in a company that has already implemented selling by service employees. For details, please refer to the section "Research Setting" and Web Appendix W1.

[4] We excluded five factors for which we were not able to obtain data in our subsequent empirical study (e.g., details of the technician-customer interaction during the service visit). For details, see Web Appendix W1.

Table 3: Overview of MOA Drivers of Selling Activity and Selling Success

MOA Classification	Variable Name	Illustrative Interview Statement	Definition
Motivation	Field service employee's openness to selling	"In principle, the additional selling activities work well, make sense and are fine for me. It is good for the firm, it is good for the customer, and it is also good for me."	Degree to which the field service employee is willing to assume selling activities in addition to the main service job
	Recent sales success	"I earn about 200€ every 3 month, on the side, that is not too bad. A nice incentive, actually. If you realize 'yes it works' and you visit another client and he says 'your advice was great,' then you go for another sale, sure."	Motivating force triggered by the previous experience of achievement
Opportunity	Success of the main service job	"In our business, things get expensive quickly. Sometimes, when I fix an issue at a machine, I realize there are additional defects. This quickly leads to downtimes of more than a week…and of course the client is mad."	Degree to which the equipment is operational at the end of the service visit
	Familiarity with the customer	"When I know the client for a long time and tell him: 'This part is broken, we need to change it', then he believes me. Different story for a client that I do not know…then he is like 'says who exactly'?"	Degree to which a field service employee has built a relationship with the customer through past visits
	Customer openness to selling activities	"Recently, I customer told me he had a colleague visiting earlier…and he said like 'great guy, great work…that was a super great tip… I'll do it again next year, for sure.'"	Degree to which the customer is receptive to selling activities of field service employees
	Customer size	"When you speak directly to the owner who has 3-4 machines, that is totally different from large clients that have an entire production line. […] Tips are much better received by larger companies with their own maintenance crew."	Overall size of its production and the size of the installed equipment base
Ability	Technical competence	"We have different product lines from different business units and plants…if I visit the customer and he also has a machine from a different business unit, I do not know anything or at least only little about it."	Degree to which the field service employee has a broad (deep) competence with respect to servicing different product lines or multiple subfields of engineering
	Sales training	"I remember, we had a sales training once. Many things were obvious for me, but there were many good points, how to sell the product…pro and con arguments, this is what we learned."	Dedicated training for field service employees to improve their selling-related skills through instruction in the product portfolio and basic selling techniques

To ensure the validity of our MOA framework, we presented our results to the firm's management, who confirmed the list of identified factors. In a last step, we compared the identified factors to the business-to-business, services, and sales literature and concluded that our factors represent important facets of field service employees' selling activities in general. A detailed description of the coding and the qualitative analysis that led to the identified MOA factors is available in section W1 in the Web Appendix. Table 3 provides an overview of the MOA factors considered in this study. Figure 1 displays the conceptual framework. In the following, we introduce the MOA factors included in our framework and provide hypotheses for their effect on selling activity and selling success.

Figure 1: Conceptual Framework

2.3 Motivation

Motivation is a key factor in the behavior and performance of frontline employees (Jasmand, Blazevic, and de Ruyter 2012; Sabnis et al. 2013; Schepers et al. 2011). It refers to the desire and willingness to engage in a behavior (MacInnis, Moorman, and Jaworski 1991).

In our study, we focus on two motivational drivers that emerged from the qualitative study: field service employees' openness to selling and their recent sales success.

Field service employee's openness to selling. Openness to selling represents an individual attitude of the respective field service employee toward extra-role tasks. Previous ambidexterity research has revealed great heterogeneity among service employees with respect to the general acceptance of tasks beyond the regular job description (Yu, Patterson, and de Ruyter 2012). We define field service employee's openness to selling as the degree to which the employee is willing to assume selling activities in addition to the main service job.

A high openness to selling may be related to the field service employee's felt ownership toward the customer's processes. Thus, engaging in selling activities for preventive maintenance purposes can be understood as a sign that the technician cares for the customers and the "well-being" of their equipment. This view was strongly supported during our interviews: "My job is to make sure the machine is maintained properly. […] This also means pointing out critical issues, to simply guarantee the quality of the machine" (Interview 7). Recent research shows that so-called customer stewardship control is an important antecedent of extra-role behavior (Schepers et al. 2012). Further, field service employees who are open to the selling activity appear to perceive less role conflict and role ambiguity (Schepers et al. 2011) between their traditional service job and additional sales activity, which is likely to increase ambidextrous behavior like selling: "I always say, we as technicians, we are kind of little salespeople since we work at the clients' site and directly speak to them" (Interview 9). Overall, we posit that general openness to selling is likely to lead to a greater likelihood of engaging in selling activities. Thus, we propose the following hypothesis:

H1a: Field service employees' openness to selling has a positive effect on the likelihood of selling activity.

Similarly, the field service employee's openness to selling is important for the success of the selling activities. Recent research shows that openness is associated with individual learning orientation, which is considered a key success factor in complex selling situations (Ulaga and Loveland 2014). In our interviews, field service employees who indicated a general openness toward the selling activity repeatedly mentioned that they develop their own heuristics for what works and what does not. For example, "This measuring device that we have in our portfolio...basically sells itself. Every client orders it…. I recommend [it] to every client that wants to maintain the equipment on his own" (Interview 20). Thus, field service employees with an openness to selling are more likely to reflect on their selling activities and learn from previous experiences. This learning orientation is conducive to the success of service–sales ambidexterity (Yu, Patterson, and de Ruyter 2015). Consequently:

H$_{1b}$: Field service employees' openness to selling has a positive effect on the likelihood of selling success.

Recent sales success. Another factor that acts a motivational force is the success of a previous selling activity. We define recent sales success as a motivating force triggered by the previous experience of achievement. That is, the experience of previous success should have a positive impact on the field service employee's selling activity. First, recent experiences of success can lead to elevated mood, which serves as a catalyst for subsequent behavior. Support comes from attribution-expectancy theory (Teas and McElroy 1986), which links past performance to effort intentions in future situations. Specifically, previous success is associated with attributions to both effort and ability as well as the intentions to continue with the successful strategy (Dixon, Spiro, and Jamil 2001). Second, a recent success is likely to reassure the field service employee that the selling tactic works and is advantageous for the customer, the firm, and the employee. As one field service employees noted during the interview, "Generating leads is not an easy task, but it works…you see you close a couple of leads

successfully, earn some bucks. That is pretty nice for everyone" (Interview 13). On the basis of this reasoning, we hypothesize:

H2a: Recent sales success has a positive effect on the likelihood of selling activity.

Recent sales success also influences the likelihood of success of subsequent selling activities. Most importantly, recent success is likely to increase the field service employee's task-specific self-esteem, which is positively associated with performance (Bagozzi 1978). The effect on task-specific self-esteem also emerged in our interviews as important for field service employees, especially as selling is not their main task: "If you realize 'yes it works' and you visit another client who says 'your advice was great,' then you go for another sale, sure" (Interview 13). Moreover, recent research has investigated the idea of sales momentum and finds that positive momentum indeed increases performance of subsequent selling activities (Ahearne et al. 2017). Thus, we also expect a positive effect on selling success.

H2b: Recent sales success has a positive effect on the likelihood of selling success.

2.4   Opportunity

Any potential selling activity depends strongly on the circumstances. By incorporating opportunity factors, we are able to capture the "extent to which a situation or context is conduce to enable action" (Schmitz 2013, p. 58; Rothschild 1999; Siemsen, Roth, and Balasubramanian 2008). Previous literature shows that a situation-driven approach is important in both service and sales (Homburg, Wieseke, and Bornemann 2009; de Ruyter, Patterson, and Yu 2014; Schmitz, Lee, and Lilien 2014). Drawing on the results of the qualitative study, we focus on two factors describing the service situation—success of the main service job and familiarity with the customer—and two customer factors—customer openness and customer size[5].

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[5] In the MOA context, opportunity can have a positive and a negative connotation (Schmitz 2013). While the positive perspective is expressed in the availability of conducive context (e.g., Gruen, Osmonbekov, and Czaplewski 2007), the negative perspective pertains to situational elements that complicate and impede the action (Siemsen, Roth, and Balasubramanian 2008; MacInnis, Moorman, and Jaworski 1991). Our conceptualization captures both aspects: Familiarity and customer openness represent the positive view of opportunity while success of the main service job (or its absence) represents both the positive or negative perspective in one variable.

Success of the main service job. We define success of the main service job as the degree to which the equipment is operational at the end of the service visit. Availability of the equipment is critical to operational excellence in the industrial B2B context, primarily because a supplier's products are part of the customer's production and consequently customers are sensitive to costs associated with downtime (Wilson, Boström, and Lundin 1999). As one field service employee noted during our interviews, "In our business, things get expensive quickly. Sometimes, when I fix an issue at a machine, I realize there are additional defects. This quickly leads to downtimes of more than a week…and of course, the client is mad" (Interview 13). Thus, a key objective of every service visit is to restore operational readiness of the equipment irrespective of whether the visit was for routine maintenance or for an emergency (Wilson, Boström, and Lundin 1999).

The success of the main service job should influence the likelihood of both the selling activity and selling success. With regard to the former, we posit that the outcome of the service job is an important determinant of the atmosphere of the service visit. If the field service employee fails to solve the problem at hand a tense atmosphere may result, lessening the likelihood the employee will engage in selling actitities for another issue. With restoration of operational readiness, however, the field service employee has fulfilled his/her main task and delivered service to the promised level, creating a more relaxed atmosphere favorable for engaging in selling activity. As one interviewee put it, "When I have finished my task, I normally do some test runs because I never leave the client before the machine produces parts again. Then I have at least one hour… That is the time that I use to finish my service reports and also slip in my selling" (Interview 16). Thus, we hypothesize:

H3: The success of the main service job has a positive effect on the likelihood of selling activity.

A successful service job may also influence the chances of selling success. The field service employee has proved his/her technical expertise, which makes the advice more credible and thus may increase the chances of selling success. Failure to restore operability of the equipment may lessen customers' receptivity to selling attempts and thus decrease chances of selling success: "If the machine is still not up and running, then sometimes the customer is about to explode. When I start selling in this situation, then you hear something like: 'Are you crazy now, make sure you get the thing to work'" (Interview 1). These arguments suggest a positive effect. On the other hand, some customers might be purely focused on operativeness and be uninterested in any additional improvement: "I just had the case…a client really only wanted to have the bare minimum done. Even though I really urged him to fix the issue properly, he said like 'the machine is back up and running, let us keep it working for now'" (Interview 9). This view suggests a negative effect. Given these opposing theoretical arguments, we do not formulate a hypothesis and leave the answer to the empirics.

Familiarity with the customer. Another important facet of the situation is the field service employee's familiarity with the customer where the visit takes place. Importantly, unlike salespeople, who usually work alone in their sales territory, field service employees are often assigned to their service jobs on the basis of skills and availability. Still, they operate in a predefined territory to minimize travel and ensure fast response times. Thus, we expect heterogeneity in the degree to which field service employees have worked for the same customer in the past. We therefore define familiarity with the customer as the degree to which a field service employee has built a relationship with the customer through past visits.

We expect familiarity to be a positive antecedent to both selling activity and selling success. First, during previous visits, field service employees have built a relationship with the customer personnel and have become acquainted with the overall customer situation. In such a familiar environment, a field service employee is more likely to identify a sales opportunity and

pitch it to the customer. Second, customers develop trust in the specific field service employee, which is primarily based on the technical service but can also pertain to selling activities: "Clients that you visit often, that are satisfied with your work…of course they trust you more" (Interview 20). Finally, familiarity is also likely to positively affect the probability that a customer accepts an offer: "When I have known the client for a long time and tell him: 'This part is broken, we need to change it,' then he believes me. Different story for a client that I do not know…then he is like 'says who exactly?'" (Interview 16). In sum, we expect a positive effect of familiarity on both selling activity and selling success.

H4a: Familiarity with the customer has a positive effect on the likelihood of selling activity.

H4b: Familiarity with the customer has a positive effect on the likelihood of selling success.

Customer openness to selling activities. In B2B markets, products are often technologically complex and use cases vary significantly from customer to customer. Thus, customer factors are crucial for understanding the success of selling activity and selling success. One of these factors is the general customer openness to the selling activities of field service employees. Recent literature has highlighted the importance of customer adaptiveness (Tuli, Kohli, and Bharadwaj 2007) and customer role readiness (Verleye, Gemmel, and Rangarajan 2014). This openness toward the supplier's activities is often a result of positive previous experiences (Challagalla, Venkatesh, and Kohli 2009). Thus, we define customer openness as the degree to which the customer is receptive to selling activities of field service employees, which is shaped by a learning process over time. We argue that customer openness is conducive for both the field service employee's selling activities and their success. First, open customers are generally more receptive to advice from technicians and welcome a detailed quote: "My customers are much more sensitive to that now...they are ordering more maintenance now or

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making sure the equipment is serviced regularly" (Interview 10). Previous research confirms these arguments, showing that customer appreciation is a pivotal factor for the service employees' extra-role behavior (Schepers et al. 2011). Second, open customers are more likely to accept the offer since they have learned to appreciate the value of the field service employee's advice. As one interviewee put it, "Recently, a customer told me he had a colleague visiting earlier…and he said like 'great guy, great work…that was a super great tip…. I'll do it again next year, for sure'" (Interview 13). Thus, we suggest that customer openness is conducive for both selling activity and success:

H5a: Customer openness has a positive effect on the likelihood of selling activity.

H5b: Customer openness has a positive effect on the likelihood of selling success.

Customer size. Another important customer characteristic in our context is the customer's size in terms of production and the installed equipment base. We argue that customer size is an important situational determinant of both selling activity and selling success. Our interviews revealed a strong correlation between customer size and customer expertise as well as the importance customers attach to regular maintenance of their equipment. Specifically, the interviewees pointed out that larger customers employ their own well trained maintenance crews. In fact, for some larger customers regular service is mandatory to meet standards of industry certification. These customers therefore put a greater focus on regular maintenance of their equipment ("Especially the big companies, like automotive manufacturers...buy only where the corresponding suppliers are certified…because they need to adhere to certain standards. For them it is clear that the machines are serviced regularly", Interview 11). Consequently, regular maintenance from the customer side decreases the likelihood that a field service employee will find technical issues and thus engage in selling activities. Formally:

H6a: Customer size has a negative effect on the likelihood of selling activity.

In terms of selling success, however, greater expertise on the client side can also have a positive effect. One interviewee noted that customer expertise makes convincing customers easier: "Our advice is much better received by larger companies with their own maintenance crew, as the topic of maintenance is much more present and I talk about technical things eye to eye" (Interview 6). Moreover, a recent study suggests that larger customers with higher usage intensity are more "prone to incur greater losses in the event of a product malfunction or failure than light users" (Challagalla, Venkatesh, and Kohli 2009, p. 77). Therefore, they should be more likely to follow pro-active advice by field service employees. On the basis of these reasons, we hypothesize for customer size:

H6b: Customer size has a positive effect on the likelihood of selling success.

2.5 Ability

In line with previous MOA research, we define ability as the "set of skills and proficiencies needed to achieve a goal" (Sabnis et al. 2013, p. 56). For field service employees engaging in selling behavior, two skill sets are relevant: technical service skills and selling skills. Therefore, we include both technical competence (service skills) and participation in a dedicated sales training (selling skill) in our model and, thus, focus on concrete ability factors that a firm can influence via employee recruiting and training and development.

Technical competence. Technical competence is the key skill of a field service employee that greatly exceeds the technical skills of a salesperson. In this study, we differentiate between the breadth and depth of technical competence. We define technical competence breadth as the degree to which the field service employee has broad competence with respect to servicing different product lines or covering multiple subfields of engineering. We define technical competence depth as the degree to which the field service employee has deep knowledge of a specific product line or subfield of engineering. The distinction allows us to capture different skill profiles of field service employees (generalist vs. specialist) and understand which type of

employee is more suited to engage in selling activities (Challagalla, Venkatesh, and Kohli 2009).

With regard to technical competence breadth, we expect a positive impact on both selling activity and selling success. First, field service employees with broad technical competence are more likely to detect cross-selling opportunities, particularly where a customer has several machines from the same supplier. In this case, the field service employee can also keep an eye on equipment that she/he is not servicing during the current service visit: "When we are on site...and we realize something…, for example the machine next to us is not operational or extremely loud. Then you can say 'man, let us take a look together, something is wrong there… I guess it needs a new actuator'" (Interview 2). Second, machine operators may approach field service employees for help during service visits. Field service employees with broad technical competence are more likely to be able to help the customer and demonstrate their expertise, increasing the likelihood of selling success: "I always go to the machine with the operator and ask him 'show me precisely where the problem is or what you are interested in'…and then I can give him pros and cons from a technician's perspective in a personal way…that is much more effective than on the phone" (Interview 18). Thus, we hypothesize for technical competence breadth:

H7a: Technical competence breadth has a positive effect on the likelihood of selling activity.

H7b: Technical competence breadth has a positive effect on the likelihood of selling success.

With respect to technical competence depth of the field service employees, we expect a differential effect. On the one hand, field service employees with a deep technical competence have a comparably narrower focus for their service visits, leading to fewer openings to identify sales opportunities among the customer's equipment: "We have different product lines from

different business units and plants…if I visit a customer and he also has a machine from a different business unit, I do not know anything or at least only a little about it" (Interview 17). On the other hand, field service employees with very deep technical knowledge are able to distinguish seriously needed from nice-to-have repairs, and because of their technical reputation are likely to make a more credible pitch. Thus, we expect that specialized field service employees will generate fewer but more successful leads:

H8a: Technical competence depth has a negative effect on the likelihood of selling activity.

H8b: Technical competence depth has a positive effect on the likelihood of selling success.

Sales training. Training is a standard tool for developing employees' skills and abilities (Farrell and Hakstian 2001). In this study, sales training refers to a dedicated training for field service employees to improve their selling-related skills through instruction in the product portfolio and basic selling techniques. As such, training empowers field service employees and is positively related to service–sales ambidexterity (Yu, Patterson, and de Ruyter 2012). Moreover, the sales literature shows that training aimed at improving a salesperson's product knowledge and selling/negotiation skills is positively related to future performance (Kumar, Sunder, and Leone 2014). Field service employees with knowledge of the product portfolio have the overview and confidence necessary for customer contact situations. Several interviewees mentioned this, as the following example shows: "It would be helpful to get a training here. We have so many things like maintenance contracts…. I do not really know when I can sell these kinds of services. If I knew more about it, I could address it with my clients" (Interview 20). Moreover, improved selling skills help field service employees to make a more compelling case for buying the additional product or service. Employees with sales training experience underlined this benefit: "A couple of years ago, I participated in a training by a

salesperson. He taught us how to talk to the customer. I mean, we are technicians, not salespeople. These trainings can help a lot...learning how to present things from a customer's perspective" (Interview 13). Thus, in essence, we expect a positive effect of training on both selling activity and selling success, leading to the following hypotheses:

H9a: Training has a positive effect on the likelihood of selling activity.

H9b: Training has a positive effect on the likelihood of selling success.

3 Data and Methodology

3.1 Research Setting

For this study, we cooperated with a major global industrial company that sells high-tech manufacturing equipment in combination with industrial services. This offers an ideal product/service setting and access to a unique dataset consisting of cross-sectional and longitudinal data from their field service organization. The cooperating company is a major player in its industry (~7,500 employees; ~€2.7bn revenue) and active in more than 70 countries. Still, it is a representative example of the many companies selling engineered industrial products (Wilson, Boström, and Lundin 1999): It combines a niche focus with an international presence and emphasizes value-adding services with more than 25% top-line contributions. The company serves a wide range of customers from small businesses to large global players, with key customers coming from the automotive, medical engineering, machine tools, and industrial equipment industries. List prices of the equipment range between €100k and €2m, the charge for an average service visit is between €500 and €2,000, and the revenues from field service employees' selling activities generally range from €1,000 to €5,000, contributing significantly to the success of the after-sales business. We believe this context is representative of many industrial settings and thus results are generalizable to other industries such as printing and large office equipment, household appliances, or B2B machinery manufacturing in general.

3.2   The Service and Selling Process

Field service employees visit customers on site for maintenance, repair, or overhaul services. During those service visits, they often become aware of additional issues (e.g., parts need to be replaced, the machine setup is suboptimal indicating improper handling of users, indicators for imminent break down are present). Field service employees are encouraged to point out such issues to the customer staff and offer a solution, thus engaging in selling activity. Proposed solutions range from simple spare parts to more complex components that are critical for the operability of the equipment as well as value-added services such as full-service contracts or remote monitoring. In our study, however, we cannot distinguish the type of product or service offered. The decision to engage in selling activities lies with the field service employee. While management's directives clearly emphasize the priority of outstanding service quality, field service employees are encouraged to engage in selling activities when appropriate. Thus, selling is regarded as a tactic to leverage employees' presence, improve customer operations, and strengthen existing customer relationships. As an incentive, field service employees receive a commission for every successful sale.[6] Further, the company uses an IT-based tool to facilitate selling by field service employees. As part of the regular service report, employees can enter the proposed solution into a database that is accessible from the employee's mobile service device. Each entry triggers a process in the back-office that generates a quote that is sent to the customer. After the customer decides, the "lead" entry in the database is closed via an interface with the ERP system, and in the event of a sale, the field service employee receives a commission.[7] On average one field service employee makes about

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[6] Spare parts required for the specific task of the current service visit are not considered as selling activity.

[7] The process does not involve interaction with the a product sales manager, primarily because the sales manager is responsible for selling the equipment but not spare parts and services. These after-sales services are provided by a separate organizational entity. The rare cases when the selling activity of the field service employee concerns new equipment are handled outside of the standard process. Thus, the selling activity we investigate is limited to cross-selling spare parts and services. Further, no conflict exists between salespeople and field service employees about potential remuneration as the product sales managers are remunerated solely based on sales of new equipment, whereas field service employees are remunerated based on the volume of generated after-sales business.

87 service visits per year with an average duration of 10 hours. The ratio of selling activities to service visits is about 12.5%, indicating selling activities during every eighth service visit. The ratio of success is about 40%. However, it should be noted that there is a fairly large amount of variance among the field service employees.

3.3 Data Collection and Variable Operationalization

We obtained a unique set of secondary data from the cooperating company. The dataset comprises longitudinal data on 150,750 service visits of 456 field service employees over a period of four years (2012–2015) for one of their key markets in combination with longitudinal data on selling activities during the service visits ("lead database"). The service visit database contains information on the time of the visit, the reason for the visit, the status of the equipment before and after the visit (operational vs. not operational), and whether the visit was covered by a warranty. The lead database contains 26,011 entries of selling activities that we matched to the respective service visits. Thus, the level of analysis for this study is the service visit.

Preliminary examination of the data revealed a few field service employees with a distinctive history of extremely long visits (up to 900 hours) and a strong concentration of visits at a specific customer. Additionally, the data included observations for employees who worked only part-time as field service employees and spent the rest of their time in the back office. Following a case-by-case discussion with the cooperating company's data manager, we decided to eliminate these observations since they were governed by a different data-generating process.[8] Thus, our final sample contains 145,553 service visits of 420 field service employees who engaged in a total of 24,783 entries of selling activities.

We further enrich the dataset with information on field service employees' technical

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[8] For example, discussions revealed that most outlier observations came from a small team of field service employees that worked on "special" cases. The data manager of the cooperating company recommended separating these observations since the visits were not comparable to the majority of "standard" visits. A post-hoc analysis of our model for the sample including the eliminated observations showed that the overall results did not change.

competence, obtained from internal records of skill certificates for each employee. We integrate information on participation of field service employees in a dedicated product and sales training, which allows us to analyze a quasi-experimental setup. The training sessions were offered in 2013 and 2014. In total, there were eight training sessions for 82 field service employees in different regions. A one-day training provided the employees with a comprehensive overview of products and services available for their selling activities as well as an introduction to the particular selling tool. The training also included an introduction of basic selling techniques.[9]

We describe the operationalization of the variables next, focusing on the MOA variables. We provide a detailed overview of all variables in Web Appendix W2. Table 4 provides descriptive statistics for the focal variables.

Dependent variables. We use two dependent variables to measure the selling behavior of field service employees. The first dependent variable, selling activity (*SELLING$_{it}$*), is a binary variable indicating whether a field service employee i at the service visit t engaged in selling activity. The second dependent variable, selling succ*ess* (*SUCCESS$_{it}$*), is also operationalized as a binary variable indicating whether—given a selling activity at service visit t—the selling activity was successful. Thus, we observe selling success only if the field service employee engaged in a selling activity.[10]

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[9] The training intervention may give rise to endogeneity concerns. We address this topic as part of the robustness checks in the results section.

[10] We use a binary operationalization for both stages. That is, we analyze whether a field service employee engages in selling activity given a service visit and not how many different products/services are recommended ("entries" in the database). This approach is consistent with the challenge of service–sales ambidexterity described in the literature—that is, convincing service employees to embrace selling at all. The distribution of the number of items per selling activity is highly skewed, with 76% of cases taking the value of one. We control for the number of items (NOITEMS$_{it}$) per selling activity on the second stage when modeling selling success.

Table 4: Descriptive Statistics

Variables	1	2	3	4	5	6	7	8	9	10	11
1. Selling activity	1.000										
2. Selling success	NA	1.000									
3. Field service employee's openness to selling	.224	.071	1.000								
4. Recent sales success	.128	.088	.475	1.000							
5. Success of the main service job	.017	-.076	.006	.008	1.000						
6. Familiarity with the customer	-.004	.115	.045	.038	.030	1.000					
7. Customer openness to selling activities	.082	.169[+]	.188	.146	.007	.237	1.000				
8. Customer size	-.001	.090	.000	.005	.001	.250	.315	1.000			
9. Technical competence breadth	.086	.054	.215	.142	.029	-.055	.056	-.022	1.000		
10. Technical competence depth	.041	.002	.187	.086	-.012	-.021	.048	-.025	.417	1.000	
11. Sales training	.020	.011	.072	.046	.013	-.019	.110	-.013	.015	.003	1.000
N	145,533	18,196	145,533	145,533	145,533	145,533	145,533	145,533	145,533	145,533	145,533
Min	0	0	0	0	0	0	0	0	1	1	0
Max	1	1	49	1	1	775.25	72	1	14	9.2	1
Mean	.13	.41	4.80	.27	.92	14.16	1.38	.23	5.85	3.63	.13
SD	.33	.49	5.34	.44	.28	39.43	3.58	.42	3.58	2.00	.33

Notes: [+] Correlation coefficient of stage 2 with corresponding operationalization of the customer openness variable; Correlation coefficients shown are Spearman for metrics variables and Cramer's V for binary variables; N = 145,553 (all correlations larger than |.010| are significant for $p < .05$); N = 18,196 for correlation coefficients with Selling success (all correlations larger than |.014| are significant for $p < .05$).

Motivation factors. We measure the field service employee's openness to selling ($FSEOPEN_{it}$) as the number of selling activities in the preceding quarter. In addition, we operationalize recent sales success ($RECSUCCESS_{it}$) as a binary variable indicating whether a previous selling activity was successfully closed during the 30-day period preceding the current service visit. This event is triggered by the client's decision about the quote and thus is not influenced by the field service employee. The field service employee is notified of status changes of his selling activities and can access all his entries in the lead database.

Opportunity factors. We measure success of the main service job ($SERVSUCCESS_{it}$) using a dummy variable indicating whether the equipment is operational at time of departure. The familiarity with the customer ($FAMILIARITY_{it}$) is measured as the sum across the number of hours spent with the respective customer in the past 360 days using a rolling window approach. We measure customer openness to field service employees' selling activity ($CUSTOPEN_{it}$) as the total number of successful selling activities by all technicians for the respective customer. The operationalization differs slightly between the stages. When modeling selling activity at stage 1, we employ the number of successful selling activities prior to the current service visit. When modeling selling success at stage 2, we employ the number of successful selling activities prior to the time of the customer decision (i.e., when the entry was closed). For customer size ($CUSTSIZE_{it}$), we draw on the cooperating company's internal segmentation system. This A/B/C/D segmentation is based on a scoring approach comprising several factors (e.g., total items of equipment from the supplier) and thus measures customer size from the supplier's perspective. We use a dummy variable for customer size, which takes the value of one for A customers and zero otherwise.

Ability factors. For the competence variables, we draw on the cooperating company's internal records of skill certificates for each field service employee. From these certificates, we compute the variable technical competence breadth ($TECHCOMPBR_i$) as the number of product

lines that a field service employee can service. In addition, we compute the variable technical competence depth (*TECHCOMPDE$_i$*) as the average number of certificates within one product line (Prabhu, Chandy, and Ellis 2005). The variable sales training (*TRAINING$_{it}$*) is an indicator for participation in a dedicated product and sales training for field service employees. It is operationalized as a dummy variable that takes the value of one if the field service employee has participated in such a training prior to the current service visit and zero otherwise.

3.4 Model Specification and Estimation

To model the impact of the MOA factors on selling activity and selling success, we specify the following mixed binary logit models. P_{it}^{SELL} measures the probability that field service employee i during service visit t engages in selling activity and P_{it}^{SUCC} measures the probability that the selling activity of field service employee i during service visit t is successful.

(1) $P_{it}^{SELL} = P(SELLING_{it}=1 \mid x) = \frac{1}{1+e^{-z_{it}}}$

With $z_{it} = \alpha_i + \beta_1 FSEOPEN_{it} + \beta_2 RECSUCCESS_{it}$

$+ \beta_3 SERVSUCCESS_{it} + \beta_4 FAMILIARITY_{it} + \beta_5 CUSTOPEN_{it} + \beta_6 CUSTSIZE_{it}$

$+ \beta_7 TECHCOMPBR_i + \beta_8 TECHCOMPDE_i + \beta_9 TRAINING_{it}$

$+ \sum_{j=10}^{14} \beta_j CTRL_{it}^{SELL} + \varepsilon_{it}^{SELL}$

where $\alpha_i = \alpha_0 + \mu_i$ *and* $\mu_i \sim N(0, \sigma_\mu^2)$.

(2) $P_{it}^{SUCC} = P(SUCCESS_{it}=1 \mid x) = \frac{1}{1+e^{-z_{it}}}$

With $z_{it} = \alpha_i + \beta_1 FSEOPEN_{it} + \beta_2 RECSUCCESS_{it}$

$+ \beta_3 SERVSUCCESS_{it} + \beta_4 FAMILIARITY_{it} + \beta_5 CUSTOPEN_{it} + \beta_6 CUSTSIZE_{it}$

$+ \beta_7 TECHCOMPBR_i + \beta_8 TECHCOMPDE_i + \beta_9 TRAINING_{it}$

$+ \sum_{j=10}^{16} \beta_j CTRL_{it}^{SUCC} + \varepsilon_{it}^{SUCC}$

where $\alpha_i = \alpha_0 + \mu_i$ *and* $\mu_i \sim N(0, \sigma_\mu^2)$.

To facilitate reading, we suppress the indices for the MOA components in stage 1 and stage 2. In both equations, we specify a field employee-specific constant α_i, which allows us to control for unobservable characteristics of the respective field service employee. We capture the influence of these unobservables in the random term μ_i that is assumed to be normally distributed with zero mean and standard deviation σ_μ^2. In addition to this random intercept, we include an idiosyncratic error component for stage 1 and for stage 2. The model components include the MOA variables of interest as well as a vector of control variables. The β parameters are to be estimated. We estimate the models with maximum likelihood. The likelihood function is conditioned on the unobserved common effects that must be integrated out to obtain the unconditional likelihood function that can be maximized. The integration takes place via Laplace quadrature approximation. We use the R package glmmML (Broström 2019) for estimation.

We acknowledge there might be a sample selection effect from stage 1 (selling activity) to stage 2 (selling success) and correlated errors across the stages. However, owing to the large number of observations (i.e., service visits) per unit (i.e., field service employee), common approaches of joint estimation fail because of numerical issues.[11] Therefore, we model the two stages separately and compare the results to several alternative model specifications. We find no substantial differences between the models.

4   Results

We present the results of the model estimation in Table 5. In the first column, we report the effects of the independent variables on selling activity (stage 1) and in the second column, we report effects on selling success (stage 2). In both models, the random error term for the field service employees is highly significant, indicating strong differences between the field

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[11] We have on average about 340 observations per field service employee. The log likelihood must be computed by computing the product of the T probabilities for the given individual. Thus, terms in the log likelihood become extremely small, which causes the model to fail.

service employees. The integration of random effects is further corroborated by a highly significant likelihood ratio (LR) test ($p < .001$) in both models, indicating that the random model provides a better model fit than a pooled model. The predictive performance of the model is good. We split the sample into estimation and holdout samples. We use a random draw of 10% of the observations per stage for holdout prediction while estimating the models with the remaining observations. Classification accuracy is 87.5% (estimation) and 87.8% (holdout) for selling activity on stage 1 and 69.1% (estimation) and 69.7% (holdout) for selling success on stage 2. Together, these results indicate acceptable predictive validity of our model (Spann, Fischer, and Tellis 2015).

Table 5: Results

	Stage 1: Selling Activity			Stage 2: Selling Success		
	Hypothesis	**Estimate**	**SE**	**Hypothesis**	**Estimate**	**SE**
Intercept		-3.195***	(.110)		-.209	(.108)
Standard deviation of intercept		0.777***	(.033)		.425***	(.028)
Motivation						
Field service employee's openness to selling	+	.043***	(.002)	+	.007*	(.003)
Recent sales success	+	.115***	(.020)	-	.004	(.039)
Opportunity						
Success of the main service job	+	.159***	(.034)	+/-	-.570***	(.067)
Familiarity with the customer	+	-.000	(.000)	+	.000	(.000)
Customer openness to selling activities	+	.018***	(.002)	+	.038***	(.004)
Customer size	-	-.188***	(.023)	+	.114**	(.044)
Ability						
Technical competence breadth	+	.076***	(.013)	+	.040***	(.010)
Technical competence depth	-	.031	(.025)	+	-.011	(.018)
Sales training	+	.409***	(.044)	+	-.061	(.068)
Controls						
Duration of visit		.020***	(.000)		.012***	(.001)
Equipment warranty		-1.164***	(.025)		-.606***	(.057)
Machine status at arrival		.098***	(.018)		.041	(.035)
Joiner		-.029	(.125)		-.159	(.105)
Leaver		-.391*	(.172)		.229	(.170)
Number of proposed items		-	-		.318***	(.023)
Lead time		-	-		-.010***	(.000)
log likelihood		-47,650			-10,775	
N		145,553			18,196	

Notes: Standard errors are in parentheses. *$p < .05$, **$p < .01$, ***$p < .001$ (two-sided).
Expected sign in hypotheses: "+" = positive effect on DV; "-" = negative effect;
"+/-" = no directional hypothesis, positive or negative effect possible.

4.1 Effects of MOA Factors

Motivation. In line with H_{1a} and H_{1b}, we find a positive effect of the field service employee's openness to selling on selling activity (H_{1a}: $\beta_1 = .043$, $p < .001$) and a weaker but still positive effect on selling success (H_{1b}: $\beta_1 = .007$, $p < .05$). In contrast, recent sales success increases the likelihood to engage in selling activity (H_{2a}: $\beta_2 = .115$, $p < .001$) but has an insignificant effect on selling success (H_{2b}: $\beta_2 = .004$, n.s.). Thus, we find partial support for H_{2a} and H_{2b}. The results suggest that a recent success creates some momentum in that the field service employee is motivated to engage in further selling activity. However, the positive effect does not lead to a higher likelihood of success of these selling activities.

Opportunity. We argued that the success of the main service job is an important determinant of both selling activity and selling success, as it captures the extent to which the field service employee fulfills his/her role and provides the context for the selling activity. Indeed, we find a positive effect on selling activity (H_{3a}: $\beta_3 = .159$, $p < .001$) and a negative effect on selling success (H_{3b}: $\beta_3 = -.570$, $p < .001$), confirming H_{3a} and H_{3b}. We did not find a significant effect for familiarity on either selling activity (H_{4a}: $\beta_4 = -.000$, n.s.) or selling success (H_{4b}: $\beta_4 = .000$, n.s.). Thus, we reject H_{4a} and H_{4b} and conclude that relational aspects seem to have no significant influence on the selling behavior of field service employees. In contrast, the results suggest that customer factors play an important role with diverging effects on both stages. While we find that, as expected, the customer's openness to selling activities has a positive effect on both the likelihood for selling activity (H_{5a}: $\beta_5 = .018$, $p < .001$) and the likelihood of selling success (H_{5b}: $\beta_5 = .038$, $p < .001$), customer size exerts a differential impact for both stages. Specifically, the likelihood for engaging in selling activities decreases for visits at large clients (H_{6a}: $\beta_6 = -.188$, $p < .001$). However, if a field service employee has engaged in selling activities, the odds of selling success are higher at larger clients (H_{6b}: $\beta_6 = .114$, $p < .001$). Thus, we can confirm H_{6a} and H_{6b}.

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Ability. Among the ability factors, we find support for H$_{7a}$ (β_7 = .076, p < .001) and H$_{7b}$ (β_7 = .038, p < .001), suggesting that technical competence breadth has a positive effect on both selling activity and selling success. That is, field service employee generalists with broad technical competence detect more selling opportunities and convert them more successfully. For field service employees specialists with deep technical competence, we find no significant effects (H$_{8a}$: β_8 = .031, n.s.; H$_{8b}$: β_8 = -.011, n.s.). Thus, we reject H$_{8a}$ and H$_{8b}$. Finally, consistent with H$_{9a}$, we find a strong positive effect of training and selling activity (H$_{9a}$: β_9 = .409, p < .001), but a non-significant effect on selling success (H$_{9b}$: β_9 = -.061, n.s.) suggesting that sales training seems to increase the number of selling activities but not their quality.

Controls. With respect to the control variables, longer service visits increase both the likelihood of selling activity (β_{10} = .020, p < .001) and the likelihood of selling success (β_{10} = .012, p < .001). We find a strong negative effect of equipment warranty on both selling activity (β_{11} = -1.164, p < .001) and selling success (β_{11} = -.606, p < .001), which suggests that if service visits are covered by a warranty, the likelihood for selling activities and their success decreases compared to the default situation in which the customer pays for the service visit. In addition, we included the machine status at arrival (operating vs. not operating), capturing the severity of the situation, and find a positive effect on selling activity (β_{12} = .098, p < .001) but a null effect for selling success (β_{12} = .041, n.s.). In combination with the effect for success of main service visit, this result indicates that field service employees tend to engage in more selling if the situation at the client is more relaxed, without interrupted operations at arrival and departure. We find no significant differences for field service employees who joined during our observation period (stage 1: β_{13} = -.029, n.s.; stage 2: β_{13} = -.159, n.s.) and a negative effect on selling activity for field service employees who left their job during the observation period (β_{14} = -.391, p < .05; the effect on selling success is non-significant: β_{14} = .229, n.s.). Finally, we find significant effects for the control variables that are specific to stage 2. The number of

items proposed as part of the selling activity has a positive effect on the likelihood of success (β_{15} = .318, p < .001), whereas the likelihood of success decreases as time elapses between the service visit and the decision of the client (β_{16} = -.010, p < .001).

4.2 Robustness Checks

We performed several additional analyses to check whether our estimation results are robust. Specifically, we tested for a sample selection between stage 1 and stage 2, for the endogeneity of training participation, and for sensitivity to operationalization of the variables.

Sample selection. To test whether a sample selection effect affects our results for stage 2 (selling success), we consider multiple alternative model specifications (Table W3a in section W3 of the Web Appendix). First, we estimate a bivariate probit model with sample selection but without random effects for field service employees. Thus, we pool our dataset across field service employees, which facilitates computation but does no longer account for the nested structure of the observations. The results do not differ substantially from the separate models with random effects. Second, to reduce the computational challenge of too many observations per unit (Greene 2012), we randomly select 50 observations per field service employee and estimate a bivariate probit model with random effects and sample selection for this subsample. Again, the results for stage 2 do not change substantially. Finally, we estimate a model with a carry-over factor from stage 1 to stage 2. For that, we compute the ratio of the number of selling activities to the number of service visits in the time window 30 days prior to the current service visit of the respective field service employee capturing the person-specific propensity to engage in selling activity prior to the current visit. When including this carry-over factor in the model for stage 2, we find a non-significant effect and do not observe any substantial change for the variables of interest. Together, these results suggest that independent modeling of the two stages does not lead to a substantial change in the results for stage 2, and therefore we are confident that our results do not suffer from any systematic bias.

Endogeneity of training participation. Participation in sales training is potentially endogenous (e.g., selection owing to weak performance). We therefore estimated the likelihood of training participation on the basis of a number of potential drivers (e.g., selling activity in the previous year). The results (Table W4a in section W4 of the Web Appendix) show that the main driver of training participation is the proximity of the field service employee's territory to the training location. Thus, selection for training is based on the region of the field service employees. The management of the cooperating firm confirmed this finding. We also used a propensity score matching approach and again found no substantial differences in the estimated results (Tables W4b and W4c in section W4 of the Web Appendix). In sum, these results suggest that endogeneity is not very likely.

Variable operationalization. Finally, we tested different operationalizations for several variables, such as different window sizes for Field Service Employee's Openness to Selling, Recent Sales Success and Familiarity as well as different options for transforming categorical into dummy variables (e.g. Customer Size). The results are robust to those variations in operationalization (see Table W3b in section W3 of the Web Appendix).

5   Discussion

Despite the widespread adoption of servitization strategies of many B2B companies—that is, the shift from products to services and/or solutions (Mathieu 2001; Tuli, Kohli, and Bharadwaj 2007; Ulaga and Reinartz 2011; Worm et al. 2017)— extant research has largely neglected the role of B2B field service employees. While salespersons' role as boundary spanners has been studied for decades, we know only little about the role and strategic significance of technical field service employees as boundary spanners. We address this void in the literature and investigate the role of field service employees as a "second" sales force. We adapt the Motivation-Opportunity-Ability (MOA) framework to the industrial service context and test it using a large-scale dataset from a global industrial company. The results have

both managerial and theoretical implications for how B2B managers can leverage field service employees as a "second" sales force.

5.1 Managerial Implications

Our results are useful for B2B managers contemplating leveraging their field service employees as an ancillary sales force. First, our study provides insights into whether and how to design this shift toward a more ambidextrous frontline. We study the case of a major global industrial company that sells high-tech manufacturing equipment in combination with industrial services, whose situation is representative for many B2B contexts. The cooperating company employs a process in which field service employees identify selling opportunities during their service visits and engage in selling activities for spare parts and services. By leveraging the on-site presence of field service employees, these tactical selling activities contribute about 5% to the company's top line. This contribution is substantial given that the main focus of the field service employees is maintaining and repairing equipment.

Second, findings for the motivation dimension of our MOA framework show that field service employee's openness to selling and a recent sales success both have a positive effect on selling activity. Thus, managers are advised to establish a culture among their service force that promotes openness to new activities and pro-active service behavior. Managers from the cooperating company stressed that this attitude can be achieved by having the field service employee take (psychological) ownership for the operability of the equipment. In addition, managers should design the support system to make recent successes salient, for example by highlighting recent closures in a dashboard after login or via congratulation emails.

Third, our results indicate that opportunity factors are important. For example, if the main service job is successful, field service employees are much more likely to engage in selling activity. However, successful completion of the service also decreases the chances of success of the selling activity. Managers can use these insights to make their field service employees

aware of and sensitive to choosing situations appropriate for selling activity. By leveraging recent technologies, managers could also provide field service employees with a recommendation system that indicates which products/services sell well in a given situation.

Fourth, the results on technical competence suggest that broad technical competence of the field service employee increases both the chances for engaging in selling activities and the chances for selling success, whereas deep technical competence has no influence on either concern. This insight is important, because it suggests that generalists with broad technical competence have an ideal skillset to be leveraged as add-on salesforce, whereas specialists with deep technical competence might be better left focus on their technical job.

Finally, our results indicate that sales-oriented training can be useful to field service employees in taking the first steps in selling activities. Thus, it is advisable to have new starters and insecure field service employees participate in such a training. Further trainings may be used to increase the quality of the selling approach and help improve conversion rates. Notably, all of our results provide managers with actionable insights that can be applied relatively quickly, for example as part of the firm's recruiting and employee development activities (e.g., technical qualification for the field service force).

To illustrate the managerial value of our results, we ran a simulation. For that, we computed the change in the likelihood of selling activity and selling success. This simulation allows us to compare the estimated parameters to each other and evaluate the economic magnitude of their impact. We focus on MOA variables with significant estimates. As a baseline, we define a scenario in which all variables are set to their sample mean. We then simulate the impact of a change in the variable of interest by increasing metric variables by 100% or setting a dummy variable from 0 to 1. The simulated values are all within the sample range of the respective variables. Figures 2 and 3 show the results of the simulation for selling activity and selling success respectively.

Figure 2: Magnitude of Impact of MOA Variables on Likelihood of Selling Activity

		0%	5%	10%	15%	20%	25%	30%
Base scenario				12.5%				
Motivation								
Field service employee's openness to selling	[Increase 100%]			12.5%	14.9%			
Recent sales success	[Dummy 0 → 1]			12.2%	13.5%			
Opportunity								
Success of the main service job	[Dummy 0 → 1]			11.0%	12.7%			
Familiarity with the customer	[Increase 100%]	*Not significant*						
Customer openness to selling activities	[Increase 100%]			12.5%	12.8%			
Customer size	[Increase 100%]			13.0% 11.0%				
Ability								
Technical competence – Breadth	[Increase 100%]			12.5%		18.3%		
Technical competence – Depth	[Increase 100%]	*Not significant*						
Sales training	[Dummy 0 → 1]			12.0%		17.0%		

Notes: The analysis simulates the likelihood of selling activity if the focal variable increases by 100% (for metric variables) or changes from 0 to 1 (for dummy variables) indicated by the grey shaded bars. The base scenario is the sample average for the likelihood of engaging in selling activity (mean value for all variables).

We find the strongest positive effects for technical competence breadth and training. For example, our simulation shows that the likelihood of engaging in selling activity during a service visit increases from 12.5% to 18.2% if we move from a field service employee with an average to someone with high technical competence breadth. In addition, the likelihood of selling success increases from 40.7% to 47.1%. Similarly, participating in sales training increases the likelihood of selling activity from 12.0% to 17.0% (we do not simulate the impact for selling success, as the parameter estimated for stage 2 is not significant).

We also find configurations that have a significant negative impact on both selling activity and selling success. Most importantly, the success of the main service job reduces the likelihood of selling success from 53.8% to 39.7%. Thus, the positive effect from stage 1 is offset by the strong effect on stage 2. However, even for that "adverse" scenario, the resulting probability of

selling success is still fairly high (almost 40%) and close to the base scenario. We also find a negative impact for customer size on selling activity (-2.0%), which is offset by a positive impact on selling success (+ 2.8%)

Figure 3: Magnitude of Impact of MOA Variables on Likelihood of Selling Success.

		0%	10%	20%	30%	40%	50%	60%
Base scenario						40.7%		
Motivation								
Field service employee's openness to selling	[Increase 100%]					40.7%	42.0%	
Recent sales success	[Dummy 0 → 1]	*Not significant*						
Opportunity								
Success of the main service job	[Dummy 0 → 1]			13.0%	39.7%		53.8%	
Familiarity with the customer	[Increase 100%]	*Not significant*						
Customer openness to selling activities	[Increase 100%]					40.7%	42.9%	
Customer size	[Increase 100%]					40.0%	42.8%	
Ability								
Technical competence – Breadth	[Increase 100%]					40.7%	47.1%	
Technical competence – Depth	[Increase 100%]	*Not significant*						
Sales training	[Dummy 0 → 1]	*Not significant*						

Notes: The analysis simulates the likelihood of selling success if the focal variable increases by 100% (for metric variables) or changes from 0 to 1 (for dummy variables) indicated by the grey shaded bars. The base scenario is the sample average for the likelihood of selling success (mean value for all variables).

What do these findings mean for the resulting revenue and thus the contribution of the selling activity by field service employees to the top line? To answer this question, we multiply the probabilities for the two stages to get the probability of success per visit. Multiplying this result with the average revenue generated through the selling activities provides the average revenue contribution of the field service employee's selling activity. For confidentiality reasons, we show only relative effects. Thus, Figure 4 displays the incremental revenue per visit generated by selling activities compared to the average revenue the company earns through service fees per visit. On average, selling activities increase the revenue per visit by 20%, with

significantly stronger lifts for visits of field service employees with high technical competence and after sales trainings. In sum, this simulation underlines the revenue-generating potential of leveraging field service employees for tactical selling.
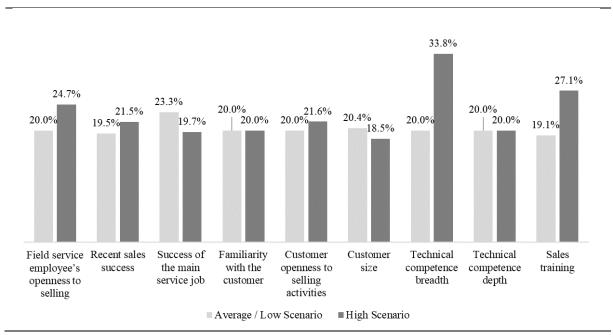
Figure 4: Incremental Revenue per Visit through Selling Activity
(in % of Service Fees)

5.2   Theoretical Implications

Our study makes several contributions to the marketing literature. First, research has largely neglected the role of field service employees despite its importance in many B2B firms. We thus contribute to the literature by investigating their potential additional role as tactical add-on salesforce. We therefore answer a recent call for research on understanding the various facets of organizational frontlines (Singh et al. 2017). While prior studies focused on service–sales ambidexterity in B2C services, we investigate selling by field service employees in the context of more complex industrial solutions, where the selling takes place in person at the client site as opposed to own facilities (e.g., in banking) or remotely (e.g., in call centers). We argue that achieving service–sales ambidexterity is more challenging in the industrial B2B context than in a conventional B2C service context, such as banking, where both sales and service have traditionally been part of the responsibilities of most relationship managers. A

comparison of descriptives from our sample to those of other studies supports this view. Previous studies in the context of a call center for a telco company (Jasmand, Blazevic, and de Ruyter 2012) or retail banking (Yu, Patterson, and de Ruyter 2012) report means for ambidextrous behavior that are close to six on a seven-point scale, indicating a high overall level of ambidexterity. In our sample, field service employees engage in selling activities in only 12.5% of their service visits, indicating a lower overall level.

Second, we investigate the service–sales ambidexterity concept in a comprehensive manner. Previous research has investigated selected drivers of service–sales ambidexterity, such as motivational factors (e.g., Jasmand, Blazevic, and de Ruyter 2012) or the overall service/sales climate (e.g., Ogilvie et al. 2017). We develop a more comprehensive conceptual framework that adapts the well established MOA framework to the B2B service context and derive relevant drivers through a rigorous qualitative study. Similar to a previous application of the MOA framework in the sales context (Sabnis et al. 2013), we demonstrate its utility in the industrial service context.

Our results show that the MOA factors are specific to the industrial service context (e.g., field service employees' technical competence) and that considering only factors identified in the sales literature is inadequate. Thus, building on the established MOA framework, we theorize and find evidence for new critical success factors of service–sales ambidexterity in the industrial B2B context. For example, our results indicate that factors related to the state of the equipment, such as operability at the end of the service visit or the existence of a warranty, strongly influence field service employees' selling activities. Moreover, we find that a broad technical competence of the field service employees is critical to success of their selling activities. Finally, customers' technical expertise and openness to the selling activities significantly influence the success of selling activities. Previous literature for both service and selling has not considered these factors.

Importantly, we also find that some conventional sales instruments seem to be effective. Our results indicate that providing field service employees with sales training helps them assume their role as an auxiliary sales force as it strongly increases their propensity to engage in selling activities. However, training does not substantially improve the success of the selling activities.[12] Overall, our findings show that within the MOA framework, opportunity and ability factors have the strongest impact on field service employees' selling behavior. Thus, future research should consider these factors, which are very specific to the technical service context, in addition to motivational factors that predominated in previous studies.

Finally, to implement and test the MOA framework in the context of field service employees' selling behavior, we employ a novel approach by using longitudinal field data from a cooperating company. To our knowledge, this study is the first to assess service–sales ambidexterity based on observed behavior of B2B field service employees during customer visits. We thus study the phenomenon on a micro level (Rouziès et al. 2009), whereas previous studies have typically relied on cross-sectional surveys among the service force. By taking a service-visit perspective, we capture situational factors that have long been suggested as essential to the success of cross-selling activities (de Ruyter, Patterson, and Yu 2014), allowing us to control for important differences of the individual service visit. Data of this nature are difficult to obtain, especially on a large scale. However, as the results show, they help to get a more comprehensive picture of the drivers of selling activity and selling success of field service employees.

5.3 Limitations and Future Research

Our study is not without limitations, which may serve as directions for future research. First, we conduct a single-company study. While we argue that the cooperating industrial

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[12] It should be cautioned, however, that this finding holds for the specific training (one-day training with focus on product portfolio and basic selling techniques) at the cooperating company.

equipment manufacturer is representative of many industrial companies, future research is needed to corroborate our findings and investigate potential differences arising from industry characteristics. Second, we rely on secondary data obtained from the cooperating company. While we see clear benefits in analyzing the phenomenon of service–sales ambidexterity by drawing on "objective" data, a better understanding of the underlying mechanisms might emerge from an approach combining secondary data with survey information obtained from field service employees or customers. Third, we cannot fully rule out endogeneity for the training treatment. Although our analysis suggests that selection for training is not based on performance, future research could employ a fully randomized experimental design and potentially also test the effect of different types of training. Fourth, owing to non-variance in our dataset, we were not able to investigate the effect of financial incentives. An interesting question, however, is how financial incentives work in the case of field service employees engaging in selling behavior and whether results differ from those reported in the established sales literature. Finally, future work could take a broader perspective and study the collaboration of field service employees and salespeople in up- and cross-selling.

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APPENDIX ESSAY II

In this Appendix, we provide details on the procedure and findings of the qualitative study (A) and an overview (incl. descriptive statistics) of all variables (B). We also provide details about the robustness checks (C) and address the potential endogeneity of training participation (D).

Appendix A: Qualitative Study

We conducted a qualitative study in order to generate relevant drivers of field service employee's selling behavior. For that we conducted interviews with 20 field service employees from the cooperating company selected by the management to represent a broad sample of their service force (e.g. with respect to region, job experience, technical competence, etc.). Table W1a provides an overview of the interviews. We acknowledge that this approach might give rise to non-generalizability concerns. However, we employed this approach in order to ensure that we conduct interviews in a company that has already implemented selling by service employees. Given that many industrial companies still operate in the classical sales and service silos, there is not a big range of companies to sample from. In order to ensure generalizability, we used the MOA framework as a guiding structure for the interviews and compared the identified factors to the existing literature. Based on this, we are confident that these variables apply to the context of field service employees' selling activities in general.

The interviews were semi-structured lasting 28 minutes on average and covered the field service employees' general perception of the selling activity, their individual approach during service visits and potentials for future improvement. Consistent with our objective to fill the MOA framework, we put a specific focus on motivation, opportunity and ability factors. All interviews were recorded, transcribed verbatim, and subjected to a thematic content analysis using the established qualitative technique of open, axial and selective coding (e.g. Corbin and Strauss 2008). The open coding yielded 507 coded statements (see columns A in Table A2 and Table A3 for a selection of statements). After that, we conducted axial coding and aggregated similar codes leading to 41 facets of selling activity and related other factors (see columns B in Table A2 and Table A3). We then compared those facets to concepts from the existing service and sales literature (see columns C) and performed selective coding which help us deduce 16

key factors of field service employees' selling behavior (see columns D in Table A2 and Table A3).

We assessed this list of factors against several criteria, namely: frequency (how frequently and consistently was the factor mentioned during the interviews?), actionability (is the factor relevant from a managerial perspective?), measurability (is the factor measurable in a field study?), and obtainability (is the factor obtainable from co-operating firms?). This resulted in 8 factors that make up our final MOA framework and an additional 3 factors that were considered as controls. Table A2 provides an overview of the factors of the MOA framework while the remaining factors are shown in Table A3.

Table A1: Overview of Qualitative Interviews

Interview Number	Region	Name	Duration
I1	A	*n/a*	31:53:00
I2	A	*n/a*	26:26:00
I3	B	*n/a*	31:23:00
I4	C	*n/a*	34:55:00
I5	C	*n/a*	24:04:00
I6	D	*n/a*	34:22:00
I7	D	*n/a*	35:55:00
I8	D	*n/a*	23:04:00
I9	D	*n/a*	27:44:00
I10	E	*n/a*	32:20:00
I11	E	*n/a*	26:54:00
I12	E	*n/a*	25:06:00
I13	F	*n/a*	38:52:00
I14	F	*n/a*	22:10:00
I15	F	*n/a*	25:33:00
I16	G	*n/a*	28:14:00
I17	G	*n/a*	15:31:00
I18	G	*n/a*	24:07:00
I19	G	*n/a*	21:53:00
I20	G	*n/a*	26:02:00

Table A2: Derivation of Drivers of Selling Activity and Selling Success

Interview Statement (A)	Generic Term (B)	Related Concepts from Literature (C)	Variable Name (D)	MOA Classification (E)
I always say, we as technicians, we are kind of little salespeople since we work at the client's site and directly speak to him. (I9)	Role as add-on salesforce	n/a		
In principle, the additional selling activities work well, make sense and are fine for me. It is good for the firm, it is good for the customer, and it is also good for me. (I16)	General attitude towards selling activity	* Openness (Ulaga and Loveland 2014)	Field service employee's openness to selling	M
Generating leads is not an easy task, but it works...you see you close a couple of leads successfully, earn some bugs. That is pretty nice for everyone. (I13)	Experience of success	* Experience and attribution of success/failure (Dixon, Spiro, and Jamil 2001; Teas and McElroy 1986)	Recent sales success	M
I earn about 200€ every 3 month, on the side, that is not too bad. A nice incentive, actually. If you realize "yes it works" and you visit another client and he says "your advice was great", then you go for another sale, sure. (I13)	Motivation by previous success	* Sales momentum (Ahearne et al. 2017)		
In our business, things get expensive quickly. Sometimes, when I fix an issue at a machine, I realize there are additional defects. This quickly leads to downtimes of more than a week...and of course the client is mad. (I13)	Equipment downtime	Operational environment (Aarikka-Stenroos and Jaakkola 2012)	Success of the main service job	O
I just had the case...a client really only wanted to have the bare minimum done. Even though I really urged him to fix the issue properly, he said like "the machine is back up and running, let us keep it working for now". (I9)	Restoration of operational readiness	n/a		
Clients that you visit often, that are satisfied with your work...of course they trust you more. Then, they say like "okay, if you say that, we do it, you know your stuff". (I20)	Trust in advice	Trust (Ahearne, Jelinek, and Jones 2007; Fang et al. 2008)		
When I know the client for a long time and tell him: "This part is broken, we need to change it", then he believes me. Different story for a client that I do not know...then he is like "says who exactly"? (I16)	Personal relationship with customer	* Customer-salesperson relationship (Reynolds and Beatty 1999)	Familiarity with the customer	O
If you know the client well, that is definitely an easier game. You always have to prove yourself a little bit, with your work. (I20)	Building reputation	* Salesperson familiarity (Rowe, Seevers, and Zemanek 2014)		

Table A2: (continued)

Quote	Concept	Reference	
Some customer are really open to that… they train their employees on a regular basis anyway…and there are other who say "I don't need that, the machine has to run, everything else doesn't matter" …you see there are big, big differences. (I16)	Differences among customers	External environment (Verbeke, Dietz, and Verwaal 2011)	
Especially the big companies, like automotive manufacturer…buy only where the corresponding suppliers are certified…because they need to adhere to certain standards. For them it is clear, that the machines are serviced regularly. (I11)	External certifications for larger customers	n/a	Customer size O
Tips are much better received by larger companies with their own maintenance crew, as the topic of maintenance is much more present and I talk about technical things at eye level. (I6)	Customer maintenance focus and expertise	Customer operational counselling (Tuli, Kohli, and Bharadwaj 2007)	
For some things, you just need to pitch it right to the customer…and of course, the technical understanding of the customer is important, too. (I2)	Customer technical insight	* Specialized customer personnel (Schmitz, Lee, and Lilien 2014)	
My customers are much more sensitive to that now…they are ordering more maintenance now or making sure the equipment is serviced regularly. (I10)	Customer learning / adaptiveness	Customer adaptiveness (Tuli, Kohli, and Bharadwaj 2007)	
Recently, I customer told me he had a colleague visiting earlier…and he said like "great guy, great work…that was a super great tip… I'll do it again next year, for sure". (I13)	Customers' past experience with technician selling activity	Customer role readiness (Verleye, Gemmel, and Rangarajan 2014)	Customer openness to selling activities O
It also depends a lot how co-operative the foreman is. Some really value it, they bring it up themselves and ask what can be improved. (I5)	Customer openness	Customer openness to experience (Challagalla, Venkatesh, and Kohli 2009)	

(continued

Table A2: (continued)

	Broad skillset	* Product / technical knowledge (Homburg and Jensen 2007; Mariadoss et al. 2014)	
My advantage is…I have a good package…that I do mechanics and electronics, that is definitely an asset. (I13)	Broad skillset	* Product / technical knowledge (Homburg and Jensen 2007; Mariadoss et al. 2014)	
I always go to the machine with the operator and ask him "show me precisely where the problem is or what you are interested in"…and then I can give him pros and cons from a technician's perspective. (I18)	Technical expertise / perspective	Specialized knowledge and skills (Aarikka-Stenroos and Jaakkola 2012)	
In the field of drilling, I work across almost all machines series…so I do not have just three that I service, for me it is rather 15. (I18)	Broad coverage of product lines	* Technical skills (Wachner, Plouffe, and Grégoire 2009)	A
We have different product lines from different business units and plants…if I visit the customer and he also has a machine from a different business unit, I do not know anything or at least only little about it. (I17)	Product line specific knowledge	Specialized knowledge and skills (Aarikka-Stenroos and Jaakkola 2012)	
There was a one-day workshop…the responsible manager introduced us to the idea and processes of the sales support system. That was very interesting. (I18)	Training for sales support system	* User training for sales force automation systems (Ahearne, Jelinek, and Rapp 2005)	
I remember, we had a sales training once. Many things were obvious for me, but there were many good points, how to sell the product…pro and con arguments, this is what we learned. (I11)	Sales training	Cross-training (Aksin and Harker 1999)	A
It would be helpful to get a training here. We have so many things like maintenance contracts…I do not really know when I can sell these kind of services. If I knew more about it, I could address it with my clients. (I20)	Training for service portfolio	* Task-related / product knowledge training (Kumar, Sunder, and Leone 2014)	

Group labels: Technical competence (rows 1–4); Training (rows 5–7).

Notes: Sources / interview numbers of each statement are in parentheses in column (A). * in column (C) indicates concepts from the sales literature.

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Table A3: Overview of Drivers <u>Not</u> Considered in MOA Framework

Interview Statement (A)	Generic Term (B)	Related Concepts from Literature (C)	Variable Name (D)	MOA Classification (E)	Reason for not Including in MOA Framework (F)
If the lead volume is small, say 200€ to 250€...I get a couple of bugs. That's nice, but after tax it is almost nothing. (I16)	Commission level	* Sales compensation plans (Kishore et al. 2013)			
Let me put it this way: I don't do it for the money. I would also do it if they gave me nothing for that. (I7)	Low-powered incentives	* Incentive rate / ratio of variable to fixed pay (Lo, Ghosh, and Lafontaine 2011; Rouziès et al. 2009)	Financial incentive	M	No variance in dataset
In my case...I get my commission share, so I try to sell everything to everybody. (I11)	Financial incentive	* Compensation-based control (Schmitz, Lee, and Lilien 2014)			
I make a decision for myself...also without considering specifications of the management. (I10)	Management specifications	* Leadership behavior (Schmitz, Lee, and Lilien 2014)	Leadership	M	Mentioned only by few interviewees, no data available
I've already discussed this with my manager...but I simply define my job in a different way...I am a service technician, not a salesman. (I17)	Supervisor feedback	Managerial recognition (Rapp et al. 2015) * Supervisor support (Hohenberg and Homburg 2016)			
Sometimes I tell older colleagues that are not so much into it: „hey, put in that lead...it is good for you, for everybody". (I13)	Internal propagation of selling activity	* Teamwork orientation (Ulaga and Loveland 2014) * Collaboration (Plouffe et al. 2016)	Internal collaboration	O	Mentioned only by few interviewees, no data available
The first thing we should change is to copy the technician who generated the lead, if we email the offer to the client. (I11)	Open communication with back-office	Hybrid offering deployment capability (Ulaga and Reinartz 2011) Cross-functional collaboration (Ellinger 2000)			
Generating a sale from the lead works well for multi-day visits. If we get out the offer the first day and the technician is still on site anyway, then they have it done on top. (I4)	Multi-day service visits	n/a	Duration	O	Mentioned only by few interviewees, included as control variable
For short visits or troubleshooting, you are pretty focused on the job itself...there are just less opportunities for leads. (I15)	Short service visit	n/a			

(continued)

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Table A3: (continued)

Statement (A)	Concept	Source (C)		Grouped concept	Notes
I always say, „hey let's take a look together"…then I explain it to him and in 99% he says "sure, we should do this", we should send an offer. (I19)	Technical argumentation	* Technical selling skills (Wachner, Plouffe, and Grégoire 2009)		Technician-customer interaction	No data available (would require observational data)
When I find things that should be fixed, I bring the client in and show it to him…so he can see for himself that something's wrong. (I20)	Demonstration	Interpersonal skills (Homburg and Jensen 2007; Wachner, Plouffe, and Grégoire 2009)	O		
I then tell the customer that he should calculate what such a machine costs per hour and how much time will be saved if he directly knows what to do, for example by booking a training for the machine operators. (I11)	Customer-oriented argumentation	* Customer-oriented selling (Saxe and Weitz 1982)			
The tool itself is pretty straightforward and easy to handle… many things are already given…you can easily select the products and just add a couple of details. (9)	Ease of use	* Perceived Ease-of-use (Avlonitis and Panagopoulos 2005)		Access to information	Mentioned only by few interviewees, no data available
I do not have access…don't know whether the parts are in stock, that makes it cumbersome. (I14)	Access to information	* Sales technology accessing (Hunter and Perreault 2007)	O		
As far as I know, warranty cases are excluded. So when I exchange a part for a machine under warranty, I cannot turn that into a lead. (I2)	Warranty cases	n/a		Equipment warranty	Mentioned only by few interviewees, included as control variable
When a client purchases a new machine, it usually comes with a warranty, so it takes 2–3 years until there is anything we can do. (I17)	Warranty period	n/a	O		
In many cases, as a technician, you are not very welcome. When a machine breaks down for the first time, that's okay. But after a second or third time…"this crappy thing is down again"…then it is not the right time to start cross-selling. (I6)	Critical service situation	Critical service encounters (Bitner, Booms, and Mohr 1994)		Machine status at arrival	Mentioned only by few interviewees, included as control variable
Sometimes, when a machine is down…and the entire situation is quite tense…maybe the customer also has time pressure…then I would probably not point out another minor issue, but just ignore it. (I2)	Tense atmosphere	Operational environment (Aarikka-Stenroos and Jaakkola 2012)	O		

Notes: Sources / interview numbers of each statement are in parentheses in column (A). * in column (C) indicates concepts from the sales literature.

Appendix B: Overview of All Variables

Table B1: Operationalization of Control Variables

Variable Name	Description	Operationalization	Mean	SD
Duration	Indicates the length of the respective service visit	Number of hours spent for the service visit (based on service report)	10.33	12.65
Warranty	Indicates whether the visit was paid by the customer or covered by a warranty	0 = paid; 1 = warranty	.28	.45
Machine status at arrival	Indicates whether the machine was operational or not operational at the beginning of the service visit	0 = not operational; 1 = operational	.53	.50
Joiner	Indicates whether a field service employee joined during the observation period	0 = other; 1 = joiner	.07	.25
Leaver	Indicates whether a field service employee left the job during the observation period	0 = other; 1 = leaver	.04	.20
Lead time	Indicates the length of the decision process for the quote	Time in days between the selling activity took place and the decision of the customer (from ERP database)	71.27	86.10
Number of items	Indicates the number of products/services that the field service employee recommended	Number of items recorded for a given selling activity (based on "lead" database entry)	1.36	.85

Table B2: Descriptive Statistics, All Variables

Variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1.Selling Activity	1.000																		
2.Selling Success	NA	1.000																	
3.FSE's openness to selling	.224	.071	1.000																
4.Recent sales success	.128	.088	.475	1.000															
5.Success of the main service job	.017	-.076	.006	.008	1.000														
6.Familiarity with the customer	-.004	.115	.045	.038	.030	1.000													
7.Customer openness to selling activities	.082	.169	.188	.146	.007	.237	1.000												
8.Customer size	-.001	.090	.000	.005	.001	.250	.315	1.000											
9.Technical competence breadth	.086	.054	.215	.142	.029	-.055	.056	-.022	1.000										
10.Technical competence depth	.041	.002	.187	.086	-.012	-.021	.048	-.025	.417	1.000									
11.Sales training	.020	.011	.072	.046	.013	-.019	.110	-.013	.015	.003	1.000								
12.Duration of visit	.119	.110	-.009	.004	.073	.109	.103	.144	.007	-.112	-.007	1.000							
13.Equipment warranty	-.135	-.117	-.061	-.040	.073	.025	-.096	.017	-.042	-.031	-.003	-.032	1.000						
14.Machine status at arrival	.006	-.013	-.014	-.001	.246	.051	.003	-.005	-.034	-.044	-.005	-.067	.101	1.000					
15.Joiner	.005	.004	-.025	-.010	.016	-.041	.107	.021	-.141	-.158	.166	.036	.029	.026	1.000				
16.Leaver	-.033	-.014	-.122	-.068	-.004	.004	-.086	.003	-.246	-.270	-.036	.009	.002	.009	-.054	1.000			
17.Customer openness to selling activities[+]	NA	.238	.126	.126	.000	.368	.911	.374	.042	.018	.072	.224	-.108	.030	.087	-.051	1.000		
18.Number of proposed items[+]	NA	.134	.075	.023	.019	.051	.057	.065	-.018	-.036	.000	.188	-.029	.017	.016	-.004	.185	1.000	
19.Lead time[+]	NA	-.364	-.126	-.135	.063	-.118	-.213	-.046	.022	.048	-.065	-.011	.066	.010	-.034	.065	-.160	.056	1.000
N	145,553	18,196	145,553	145,553	145,553	145,553	145,553	145,553	145,553	145,553	145,553	145,553	145,553	145,553	145,553	145,553	18,196	18,196	18,196
Min	0	0	0	0	0	0	0	0	1	1	0	.25	0	0	0	0	0	1	0
Max	1	1	49	1	1	775.25	72	1	14	9.2	1	199.75	1	1	1	1	75	17	510
Mean	.13	.41	4.80	.27	.92	14.16	1.38	.23	5.85	3.63	.13	10.33	.28	.53	.07	.04	2.47	1.36	71.27
SD	.33	.49	5.34	.44	.28	39.43	3.58	.42	3.58	2.00	.33	12.65	.45	.50	.25	.20	5.16	.85	86.10

Notes: Correlation coefficients shown are Spearman for metrics variables and Cramer's V for binary variables; N= 145,553 (all correlations larger than |.010| are significant for $p < .05$); N = 18,196 for correlation coefficients with Selling Success and with variables 17, 18, 19 (variables specific to stage 2 marked with [+]) (all correlations larger than |.014| are significant for $p < .05$)

Appendix C: Robustness Checks

We performed several additional analyses to check whether our estimation results are robust. Tables C1 and C2 give a detailed overview about the results of our robustness checks. In order to test whether a potential sample selection effect affects our results for stage 2 (selling success), we consider multiple alternative model specifications:

(a) First, we estimate a bivariate probit model with sample selection but without random effects for field service employees. Thus, we pool the observation of all field service employees. → see model (I) in Table C1

(b) We randomly select 50 observations per field service employee and estimate a bivariate probit model with random effects and sample selection for this subsample. We chose this approach in order to overcome the computational challenges arising from too many observations per unit (Greene 2012). → see model (II) in Table C1

(c) Third, we estimate a model with a carry-over factor from stage 1 to stage 2. For that, we compute the ratio of the number of selling activities to the number of service visits in the time window 30 days prior to the current service visit of the respective field service employee. By that, we capture the person specific propensity to engage in selling activity prior to the current visit. → see model (III) in Table C1

We also tested different operationalizations for several variables, specifically:

– Field service employee's openness to selling: Number of selling activities in preceding year (rolling window) instead of previous quarter

– Recent sales success: Binary variable indicating whether a previous selling activity was successfully closed during the 14-day (instead of 30-day) period preceding the current service visit

- Familiarity with the customer: Number of visits at the respective customer (instead of hours) in the past 360 days based on a rolling window approach

- Customer openness to selling activities: Total number of selling activities (both successful and unsuccessful as opposed to only successful in the main model) by all technicians for the respective customer

- Customer size: Dummy variable which takes the value of 1 for the customer segments A and B (instead of only A) and zero otherwise

- Technical competence depth: Maximum (instead of average) number of certificates within one product line

→ see Table C2

Table C1: Alternative Model Specifications

	(I) Bivariate Probit Model with Sample Selection and without Random Effects		(II) Bivariate Probit Model with Sample Selection and Random Effects (for Reduced Sample)		(III) Logit Models with Random Effects and Carry-Over Factor	
	Stage 1 Selling Activity	Stage 2 Selling Success	Stage 1 Selling Activity	Stage 2 Selling Success	Stage 1 Selling Activity	Stage 2 Selling Success
Intercept	-1.740*** (.021)	-1.995*** (.027)	-3.637*** (.449)	-.016 (.136)	-3.195*** (.110)	-.208 (.108)
Standard deviation of intercept	-	-	1.832*** -	0.561*** -	0.777*** (.033)	.425*** (.028)
Motivation						
FSE's openness to selling	.050*** (.001)	.038*** (.001)	4.275*** (.939)	.007 (.004)	.043*** (.002)	.007 (.004)
Recent sales success	.113*** (.010)	.138*** (.013)	-.829 (.633)	.132* (.057)	.115*** (.020)	.005 (.038)
Opportunity						
Success of the main service job	.095*** (.018)	-.072** (.022)	1.291** (.427)	-.445*** (.121)	.159*** (.034)	-.570*** (.067)
Familiarity with the customer	-.000 (.000)	-.000 (.000)	.029*** (.003)	-.000 (.001)	-.000 (.000)	.000 (.000)
Customer openness to selling	.014*** (.001)	.019*** (.001)	.021 (.013)	.015** (.005)	.018*** (.002)	.038*** (.004)
Customer size	-.104*** (.012)	-.040** (.015)	.213 (.111)	.108 (.069)	-.188*** (.023)	.114** (.044)
Ability						
Technical competence breadth	.019*** (.001)	.026*** (.002)	.336*** (.029)	.021* (.008)	.076*** (.013)	.040*** (.010)
Technical competence depth	-.002 (.003)	-.005 (.003)	.279*** (.043)	-.004 (.016)	.031 (.025)	-.011 (.018)
Sales training	.015 (.013)	-.014 (.017)	.772*** (.166)	-.072 (.078)	.409*** (.044)	-.061 (.068)
Controls						
Duration of visit	.013*** (.000)	.014*** (.000)	.014*** (.003)	.007*** (.001)	.020*** (.000)	.012*** (.001)
Equipment warranty	-.555*** (.012)	-.625*** (.018)	-.703*** (.126)	-.420*** (.089)	-1.164*** (.025)	-.606*** (.057)
Machine status at arrival	.070*** (.009)	.059*** (.012)	.184 (.108)	-.022*** (.059)	.098*** (.018)	.041 (.035)
Joiner	.037* (.019)	.008 (.025)	.062 (.153)	-.196* (.077)	-.029 (.125)	-.159 (.105)
Leaver	-.090** (.028)	-.003 (.040)	-.459** (.172)	.148 (.138)	-.391* (.172)	.229 (.170)
Number of proposed items	-	.061*** (.005)	-	.144*** (.029)	-	.318*** (.023)
Lead time	-	-.003*** (.000)	-	-.005*** (.000)	-	-.010*** (.000)
Carry-over factor	-	-	-	-	-	-.011 (.106)
log likelihood		-59,951		-1,880	-47,650	-10,775
N	145,553	18,196 (selected)	20,030	2,605 (selected)	145,553	18,196

Notes: Standard errors are in parentheses. *p < .05, **p < .01, ***p < .001 (two-sided)

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Table C2: Alternative Variable Operationalizations

	Stage 1 Selling Activity		Stage 2 Selling Success	
Intercept	-3.070***	(.100)	-.340	(.101)
Standard deviation of intercept	.761***	(.033)	.420***	(.027)
Motivation				
Field service employee's openness to selling[A]	.015***	(.001)	.002	(.001)
Recent sales success[A]	.072***	(.022)	.092*	(.041)
Opportunity				
Success of the main service job	.164***	(.034)	-.583***	(.067)
Familiarity with the customer[A]	-.003	(.003)	.027***	(.006)
Customer openness to selling activities[A]	.006***	(.001)	.005**	(.002)
Customer size[A]	-.160***	(.018)	.241***	(.036)
Ability				
Technical competence breadth	.085***	(.015)	.045***	(.011)
Technical competence depth[A]	-.004	(.008)	-.004	(.006)
Sales training	.320***	(.018)	-.056	(.068)
Controls				
Duration of visit	.020***	(.001)	.011***	(.001)
Equipment warranty	-1.162***	(.025)	-.637***	(.057)
Machine status at arrival	.098***	(.018)	.044	(.035)
Joiner	.019	(.123)	-.110	(.104)
Leaver	-.420*	(.166)	.224	(.168)
Number of proposed items	-	-	.326***	(.023)
Lead time	-	-	-.010***	(.000)
log likelihood	-47,675		-10,790	
N	145,553		18,196	

Notes: Standard errors are in parentheses. *$p < .05$, **$p < .01$, ***$p < .001$ (two-sided)

Variables with alternative operationalization are marked with A:

- Field service employee's openness to selling: Number of selling activities in preceding year (rolling window) instead of previous quarter
- Recent sales success: Binary variable indicating whether a previous selling activity was successfully closed during the 14-day (instead of 30-day) period preceding the current service visit
- Familiarity with the customer: Number of visits at the respective customer (instead of hours) in the past 360 days based on a rolling window approach
- Customer openness to selling activities: Total number of selling activities (both successful and unsuccessful as opposed to only successful in the main mode) by all technicians for the respective customer
- Customer size: Dummy variable which takes the value of 1 for the customer segments A and B (instead of only A) and zero otherwise
- Technical competence depth: Maximum (instead of average) number of certificates within one product line.

Appendix D: Endogeneity of Training Participation

There is the possibility that participation in the sales trainings is endogenous (e.g. selection due to weak performance). In order to address this, we estimated the likelihood of training participation based on a number of potential drivers (e.g. selling activity in the previous year). The trainings were offered in 2013 and 2014. In total, there were eight trainings for 82 field service employees in different regions of the country in scope.

We estimate the likelihood to participate in any of the offered trainings except for the case that a field service has already participated in a training. If this is the case, we remove the subsequent potential training dates (which however does not change the results). Then we compute the potential drivers, e.g. the number of customer visits prior to the given training opportunity (based on a rolling-window approach). The variable "Match between Field Service Employee's Territory and the Training Location" is a dummy variable taking the value of 1 if the trainings takes place in "home" region of the respective field service employee and 0 otherwise. Job experience is measured as the time since the very first service visit.

Table D1: Modelling Training Participation

	Likelihood of Training Participation	
Intercept	-3.103***	(.338)
Technical Competence Breadth	-.008	(.039)
Technical Competence Depth	.074	(.068)
Number of Customer Visits (last 360 days)	-.002	(.003)
Number of Selling Activities (last 360 days)	-.009	(.009)
Match between FSE Region and Training	2.878***	(.261)
Job Experience	-.003***	(.001)
log likelihood	-276	
N	2,790	

Notes: Standard errors are in parentheses.
*p < .05, **p < .01, ***p < .001 (two-sided)

For the propensity score matching, we follow the approach described in Garnefeld et al. (2013). We used observations from the year 2012 (i.e. before the training treatments in 2013 and 2014) as a base to find matching pairs of field service employees based on the relevant drivers. We obtained these drivers from modelling the likelihood of training participation only based on year 2012 (the results are consistent with the rolling window approach shown in Table D1). Then, we ran the propensity score matching based on the drivers and training participation as the separating factor. We used the nearest neighbor matching method implemented in the Matchit package in R. We were able to find a matching twin for all field service employees that participated in the trainings. The improvement in group means is shown in Table D2. We then used the matched sample to estimate the main model (see Table D3).

Table D2: Propensity Score Matching, Group Means Before and After Matching

Before Matching			After Matching		
Control Group (N = 346)	Treatment Group (N = 84)	Matching Variable (2012)	Control Group (N = 84)	Treatment Group (N = 84)	Percentage Reduction in Bias
.182	0.252	Distance	0.252	0.252	.99
4.922	5.310	Technical Competence Breadth	5.393	5.310	.78
2.863	3.225	Technical Competence Depth	3.305	3.225	.78
86.653	71.845	Number of Customer Visits	75.607	71.845	.75
9.772	7.321	Number of Selling Activities	7.476	7.321	.94
.266	0.548	New Joiner	0.536	0.548	.96
.856	0.726	Dummy for Missing Value (0)	0.691	0.726	.72
.145	0.274	Dummy for Missing Values (1)	0.310	0.274	.72

Notes: We calculated the percentage reduction in bias using the following formula (Rosenbaum and Rubin 1985):

$$PRB = 1 - \left| \frac{\overline{X}_i^A - \overline{X}_j^A}{\overline{X}_i^B - \overline{X}_j^B} \right|$$

where PRB = percentage reduction in bias,
$\overline{X}_i^A$ = the mean for the treatment group after matching,
$\overline{X}_j^A$ = the mean for the nontreatment group after matching,
$\overline{X}_i^B$ = the mean for the treatment group before matching, and
$\overline{X}_j^B$ = the mean for the nontreatment group before matching

Table D3: Propensity Score Matching, Results for Matched Sample

	Stage 1 Selling Activity		Stage 2 Selling Success	
Intercept	-3.390***	(.188)	-.119	(.186)
Standard deviation of intercept	.738***	(.049)	.458***	(.046)
Motivation				
Field service employee's openness to selling	.036***	(.003)	-.003	(.004)
Recent sales success	.160***	(.032)	.021	(.061)
Opportunity				
Success of the main service job	.121*	(.054)	-.431***	(.107)
Familiarity with the customer	-.000	(.000)	.000	(.000)
Customer openness to selling activities	.018***	(.003)	.040***	(.006)
Customer size	-.163***	(.036)	.106	(.070)
Ability				
Technical competence breadth	.105***	(.020)	.044***	(.016)
Technical competence depth	.012	(.036)	-.033	(.028)
Sales training	.441***	(.045)	-.014	(.075)
Controls				
Duration of visit	.016***	(.001)	.012***	(.002)
Equipment warranty	-1.200***	(.041)	-.633***	(.094)
Machine status at arrival	.094***	(.029)	.010	(.056)
Joiner	.200	(.157)	-.169	(.137)
Leaver	.274	(.326)	.740*	(.301)
Number of proposed items	-	-	.226***	(.029)
Lead time	-	-	-.011***	(.001)
log likelihood	-18,815		-4,271	
N	57,322		7,266	

Notes: Standard errors are in parentheses.

*$p < .05$, **$p < .01$, ***$p < .001$ (two-sided)

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ESSAY III: ZAPPING IN TV ADVERTISING – THE ROLE OF (NON) ENGAGING CONTENT

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ABSTRACT

Advertising avoidance ("zapping") represents a major problem for both advertisers and broadcasters. The current study investigates how marketers can use executional content cues in their TV advertisings (e.g., informativeness, creativity, or branding) to engage the viewer and mitigate zapping behavior. The authors develop a conceptual framework linking multiple content factors to psychological responses which in turn affect zapping behavior. They test the content-zapping relationship by drawing on a unique multi-source dataset of individual zapping behavior of more than 2,500 German television viewers combined with advertising data and content information for 1,315 spots representing 308 brands from 96 categories, thus representing the first large scale field study in this domain. Importantly, the results show that ad content indeed influences real-world zapping behavior. For example, creativity and late brand timing in ads are associated with less zapping, whereas informativeness and a strong brand presence are associated with more zapping. Moreover, the authors find that the influence of content differs between more and less familiar brands as well as between search and experience categories. The paper provides actionable implications for managers.

Keywords: TV advertising, advertising avoidance, zapping, advertising content, expert coding, principal component analysis, logit model with multiple fixed effects

1   Introduction

Advertising helps to build brands and generate sales. However, to be effective advertising needs exposure. One of the main reasons for low advertising effectiveness is consumers' conscious avoidance of ads (Tellis 2004). Ad avoidance is particularly problematic for video advertisements. While print and display ads only require a few seconds of attention to convey their message, video ads often require consumers to watch the entire ad. When consumers avoid an ad by leaving the room or zapping, advertisers lose the ability to communicate their brand message and the investment is lost. Zapping – defined as the act of changing channels during a commercial break (Wilbur 2016) – is not only a problem for advertisers, but also for broadcasters, as the reach of the entire ad break (and thus the attractiveness of the channel for advertisers) decreases. Therefore, it is crucial for advertisers and broadcasters to understand which factors influence the avoidance of advertising, i.e., zapping.

Previous literature has identified several factors that influence zapping. Specifically, they find that household characteristics such as the viewers' demographics and their previous TV viewing behavior affect zapping (e.g., Deng and Mela 2018; Siddarth and Chattopadhyay 1998; Teixeira, Picard, and el Kaliouby 2014; Wilbur 2016; Zigmond et al. 2009). Also, context characteristics such as program genre, length of the commercial break or the position within the commercial break show an effect (e.g., Danaher 1995; Deng and Mela 2018; van Meurs 1998; Siddarth and Chattopadhyay 1998). These studies provide valuable insights into the occurrence of zapping. However, managers have limited control, if any, over these factors. In contrast, one factor that managers can indeed control is the advertisings' content. We define advertising content as the executional cues that managers use to convey the ad message and engage the viewers (for example artistic value, humorousness, warmth, action, suspense, etc.). In fact, it is the content of the ads that engages, entertains, or bores the viewer and thus drives zapping behavior.

The role of ad content thus far has only been investigated in lab studies. These studies found first indications that content does affect zapping. For instance, they show that entertaining ads reduce, whereas a strong brand presence increases zapping (Teixeira, Wedel, and Pieters 2010; Woltman Elpers, Wedel, and Pieters 2003). Although this stream of research has contributed a certain degree of insight, it is unclear to what extent these findings also hold in practice. In fact, there is a lack of large-scale analyses using data of actual behavior to validate findings from laboratory studies in the field as evident in Siddarth and Chattopadhyay's (1998) call for more research on the effect of qualitative content variables in the field. Moreover, while previous studies on content in TV advertising (e.g., Becker, Wiegand, and Reinartz 2019; Chandy et al. 2001) suggest that the impact of content depends on the type of brand and category, there is still a limited understanding of the boundary conditions for the effect of content on zapping. Guided by these issues, we focus on the following research questions:

(1) Does advertising content affect zapping behavior in the field? If yes, which content factors drive/mitigate the viewers' zapping behavior?

(2) Do these effects depend on the type of brand or category; specifically, do they differ for high vs. low familiar brands and search vs. experience categories?

To address these questions, we draw on a unique multi-source dataset from a German TV broadcaster. This dataset comprises individual level viewing information for a panel of more than 2,500 individuals for one major entertainment format over a period of three months in 2016. We combine this data with content information on the 1,315 ads that aired during the focal show. Using an expert coding procedure (Chandy et al. 2001), we coded 20 executional content cues for each ad, which we subsequently condensed into six content factors applying principal component analysis.

Building on this unique and comprehensive dataset, we contribute to the literature in the following important ways: First, we examine real-world zapping behavior and demonstrate that

– after controlling for many other relevant drivers – content indeed influences zapping. We find that some content factors are associated with less zapping (e.g., creativity or late brand timing), while others are associated with increased zapping (e.g., informativeness or high brand presence). Second, we show that the influence of content on zapping depends on brand and category characteristics. Specifically, we find that the effects differ significantly between brands with low versus high familiarity and search versus experience goods. As a result, we provide managers with actionable findings that they can apply given their specific situation.

2 Literature Review

Ad avoidance is a major problem for the advertising industry. During a commercial break, consumers can avoid ads by leaving the room, using a second screen, or zapping away. In the case of the latter, consumers actively decide against watching the ad (Danaher 1995; Gustafson and Siddarth 2007). There are different reasons why consumers zap: they may be curious about the content of another channel, want to watch another show in the meantime, or simply dislike the specific ad (Wilbur 2008). Previous literature shows that during a commercial break up to 30% of the viewers zap away (e.g., Schweidel and Kent 2010; Steinberg and Hampp 2007), resulting in a considerable loss in exposure for the advertising brands.

Several studies have thus investigated which factors drive consumers' zapping behavior (refer to Table 1 for an overview). Most of these studies (e.g., Danaher 1995; Deng and Mela 2018; van Meurs 1998) focused on the effect of household characteristics (e.g., household size, age, or previous zapping behavior) and context characteristics (e.g., program genre, ad position within the commercial break). Others examined factors pertaining to brand or category characteristics (e.g., brand attitude or category involvement) of the advertised brand (e.g., Teixeira, Picard, and el Kaliouby 2014). While findings related to household, context, and brand characteristics provide valuable insights into the occurrence of zapping, managers have little control over these factors. In contrast, content is the only lever that managers fully control.

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Thus, to increase the effectiveness of their ads, they need insights how content affects zapping.

This is why we focus on the role of content in this study. Several lab studies suggest that content affects zapping (see Table 2). They show, for example, that brand presence increases zapping (Teixeira, Wedel, and Pieters 2010), whereas entertaining content decreases it (Teixeira, Picard, and el Kaliouby 2014; Woltman Elpers, Wedel, and Pieters 2003). However, it is unclear to what extent these and other findings can be transferred to the actual behavior of consumers when watching TV. First, laboratory studies force viewers to process ads actively, whereas in the real market environment they generally process ads passively (Tellis 2004). Given that attention is a prerequisite for zapping, it could be that lab studies overstate the effect for (non-engaging) content that fails to grab consumers' attention. Second, lab studies mostly focus on a few selected content cues and cannot account for moderation effects (due to the limited sample size). Thus, these studies require validation in the field by investigating actual zapping behavior for a large number of actually broadcasted ads from multiple categories[1].

One related study is that of Wilbur (2016), which analyses the effect of different objects in the ad (e.g., a pet or a phone) on zapping using an algorithmic classifier. This study is one of the few attempts to study the effect of content on actual zapping behavior. However, it focuses on single objects ("what is displayed") rather than generalizable content cues ("how is the ad is executed") and does not consider moderating effects. Another notable study is that of Siddarth and Chattopadhyay (1998), who – based on 16 ads – find initial evidence that integrating a brand-differentiating message affects zapping. The novelty of our study, however, is that we focus on several actionable content cues in a broad range of real TV ads and investigate their effect on zapping while considering brand and category characteristics as important boundary conditions.

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[1] Some previous studies in the field suggest that brand and ad content characteristics do not have a substantial influence on zapping (Danaher 1995; Deng and Mela 2018; van Meurs 1998). It should be noted, however, that none of these studies had a particular focus on ad content and thus not a suitable dataset to investigate its impact.

Table 1: Overview of Related Literature on Zapping

Drivers of Zapping	Effect	Selected Studies
Consumer / Household Characteristics		
Age	Inconclusive	Danaher (1995); Teixeira, Wedel, and el Kaliouby (2014); Teixeira, Wedel, and Pieters (2010, 2012)
Gender (Male = 1)	+[2]	Danaher (1995); Teixeira, Wedel, and el Kaliouby (2014); Teixeira, Wedel, and Pieters (2010, 2012)
Household Size	+	Danaher (1995)
Income	+	Danaher (1995)
Previous Zapping Behavior	Inconclusive	Siddarth and Chattopadhyay (1998); Woltman Elpers, Wedel, and Pieters (2003)
Prior Ad Exposure	+[3]	Danaher (1995); Deng and Mela (2018); Siddarth and Chattopadhyay (1998); Teixeira, Picard, and el Kaliouby (2014); Woltman Elpers, Wedel, and Pieters (2003); Wilbur (2016)
Purchase History	-	Siddarth and Chattopadhyay (1998); Tuchman, Nair, and Gardete (2018)
Household Heterogeneity[1]	Yes	Deng and Mela (2018); Gustavsson and Siddarth (2007); Tuchman, Nair, and Gardete (2018)
Context Characteristics		
Network (Heterogeneity)[1]	Yes	Deng and Mela (2018); Schweidel, Foutz, and Tanner (2014); Wilbur (2016)
Program Genre (Heterogeneity)[1]	Yes	Danaher (1995); Deng and Mela (2018); Schweidel, Foutz, and Tanner (2014); Schweidel and Kent (2010); van Meurs (1998); Wilbur (2016)
Timing of the Ad Break (Heterogeneity)[1]	Yes	Schweidel, Foutz, and Tanner (2014); Siddarth and Chattopadhyay (1998); van Meurs (1998); Wilbur (2016)
Attractiveness of Other Channels	+	Van Meurs (1998)
Number of Ads in the Break	Inconclusive	Danaher (1995); van Meurs (1998)
Position of Ad within the Break	+	Deng and Mela (2018); Schweidel, Foutz, and Tanner (2014)
Brand / Category Characteristics		
Brand Familiarity	Inconclusive	Teixeira, Wedel, and Pieters (2010, 2012)
Brand Attitude	-	Teixeira, Picard, and el Kaliouby (2014)
Category Heterogeneity[1]	Yes	Deng and Mela (2018); Teixeira, Picard, and el Kaliouby (2014); Wilbur (2016)
Category Involvement	-	Teixeira, Wedel, and el Kaliouby (2014)
Ad Characteristics		
Content		➢ *See Detailed Overview in Table 2*
Length	Inconclusive	Danaher (1995); Schweidel, Foutz, and Tanner (2014); Siddarth and Chattopadhyay (1998); Teixeira, Picard, and el Kaliouby (2014); Teixeira, Wedel, and Pieters (2012);

Notes.: [1] Studies either contained fixed effects or multiple dummies indicating significant differences; [2] Majority of studies with a positive effect;
[3] Majority of studies with a positive effect, only Siddarth and Chattopadhyay (1998) with a J-shaped effect.

Table 2: Overview of Studies on Ad Content and Zapping

Study	Ad Content Cues						Method				
	Infor-mation	Emotions	Humor	Creativity	Brand Presence	Other	Lab	Field	Sample	Moderator Analysis	Content Assessment
Olney, Holbrook, and Batra (1991)	+	−		U[1]			✓		146 ads 102 individuals	No	Expert coding
Woltman Elpers, Wedel, and Pieters (2003)	+			−[1]		Entertainment (−)[3]	✓		45 ads 190 individuals	No	Expert coding
Teixeira, Wedel, and Pieters (2010)				U	+[2]		✓		31 ads 1,998 individuals	No	Video software
Teixeira, Wedel, and Pieters (2012)				U	+[2]	Surprise (−)[3] Joy (−)[3]	✓		28 ads 58 individuals	No	Facial recognition
Teixeira, Picard, and el Kaliouby (2014)	−			n.s.	n.s.[4]	Entertainment (−)[3]	✓		82 ads 178 individuals	No	Facial recognition & expert coding
Siddarth and Chattopadhyay (1998)						Brand differentiating message (−)		✓	40 ads[5] 350 households	No	Expert coding
Wilbur (2016)						22 objects (e.g., pets, toys)		✓	1,000 ads No of individuals not disclosed	No	Algorithmic classifier
This study	✓	✓	✓	✓	✓		✓		571 ads 2,517 individuals	Yes	Expert coding

Notes: Signs indicate the effect on zapping: + Positive effect; − Negative effect, ∪ curvi-linear (U-shaped) effect; n.s. = not significant; [1] Measuring uniqueness/originality which is a sub-dimension of creativity (Smith et al. 2007); [2] Multiple measures for brand presence that consistently indicate a positive effect; [3] We classify these measures as "Other" because they do not capture the content cues of the ad but rather the viewers' affective response (joy, surprise, and entertainment), measured via facial recognition or survey. These are distinct from its cause. In fact, they are the reaction to the ad stimulus, e.g., creativity or humor (Teixeira, Picard, and el Kaliouby 2014; Teixeira, Wedel, and Pieters 2012) ; [4] Measuring brand timing via expert coding; [5] Content cues only available for a subset of 16 ads via expert coding.

3 Conceptual Framework

3.1 Content Drivers of Zapping

We propose a conceptual framework for the content drivers of viewers' zapping behavior (see Figure 1). This framework is grounded in previous literature on advertising content and insights from exploratory interviews with consumers.

The left-hand side of Figure 1 displays five broad dimensions of advertising content that are considered important factors for advertising effectiveness in both research and practice (Chandy et al. 2001; MacInnis, Rao, and Weiss 2002). Specifically, we investigate *emotionality* and *informativeness,* as previous research has identified these factors as the two main routes to influence consumer behavior (Teixeira, Picard, and el Kaliouby 2014). We further consider two often used and sometimes controversially discussed content dimensions in advertising, namely *creativity* and *humor* (Smith et al. 2007; Woltman Elpers, Mukherjee, and Hoyer 2004). Finally, we integrate *branding* as the decisive dimension that makes an ad an ad. Integrating branding cues in the ad connects the creative and its message to the brand and thus distinguishes an ad from a short movie (Tellis et al. 2019).

We aim to understand whether and how those content dimensions drive consumers' zapping behavior (see right-hand side of Figure 1) where zapping is the act of changing channels during a commercial break (Wilbur 2016). We posit that zapping is an immediate behavioral response of the viewer to the ad exposure. To explain this response, we draw on different psychological responses as a theoretical mechanism although we do not measure them (as indicated by the dotted lines in Figure 1) (Tellis et al. 2019). Thus, we delineate two aspects of advertising: the executional content cues used to design the creative (e.g., emotional cues, informational cues, artistic and further design elements, etc.) and the psychological response they evoke among viewers (e.g., feeling entertained, bored, overwhelmed, or skeptical, etc.)[2].

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[2] We derive these responses from the literature and our interviews and distinguish affective and cognitive types.

Figure 1: Conceptual Framework

Advertising Content

- Emotionality
- Informativeness
- Creativity
- Humor
- Branding

Brand Familiarity

Category Type

Viewer Psychological Response

Affective
- Touched
- Surprised
- Overwhelmed
- Annoyed

Cognitive
- Entertained
- Interested vs. bored
- Confused
- Skeptical

Viewer Behavioral Response

Zapping

Controls

Notes: We obtained data from three different sources: Rounded rectangles indicate content factors collected from expert coding; rectangles indicate moderators collected from a consumer survey; circles indicate zapping data and control variables obtained from secondary viewing and advertising data of AGF and Nielsen. The elements in the dotted rectangle indicate potential psychological responses of viewers to ads (which we use for our theoretical reasoning but do not measure directly in this study).

Consistent with our objective to derive actionable implications for managers and advertisers, we focus on the former in our empirical analysis. Thus, we aim to provide managers with guidance on how to use advertising content to engage consumers. Notably, previous research has shown that ad content exerts direct effects on zapping and thus explains it reasonably well "beyond the mediating role of emotions and attitudinal components" (Olney, Holbrook, and Batra 1991, p. 449). We discuss the ad content dimensions and how they engage viewers next[3].

Emotionality. The first ad content dimension that is extensively used in advertising is emotionality. Managers integrate emotional appeals in ads to engage consumers and stimulate positive feelings. To create emotionality, advertisers make use of specific advertising cues such as music, warmth, love, likeability of the characters, or drama and – in the advertising context

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[3] We highlight the psychological responses in *italics* throughout this manuscript.

to a lesser extent – sadness, fear, anger (Tellis et al. 2019). In our sample, the ad of Depot, a retailer for home accessories, is a good example of emotionality in ads (see Appendix A). The ad shows how two adult children surprise their parents with a refurbished garden during wintertime prepared for a peaceful family get together. The ad clearly shows how moved the parents are by this surprise.

In general, marketers use emotionality in ads as they hope that the positive feelings they evoke will transfer to the brand and ultimately lead to a positive brand evaluation (Belch and Belch 2015). Prior research has shown that emotional appeals have an indirect influence on purchase intention through attitude towards the ad or ad attractiveness (Pham, Geuens, and De Pelsmacker 2013; Teixeira, Picard, and el Kaliouby 2014). Zapping, in turn, can be understood as an immediate measure of the viewer's attitude towards the ad (Siddarth and Chattopadhyay 1998; Teixeira, Picard, and el Kaliouby 2014).

Emotionality in ads triggers psychological responses among viewers that are of interest with regard to zapping. In particular, if an ad features cues associated with warmth and love, this is likely to make viewers feel *moved and touched*. These emotions require less cognitive effort from the viewer (Tellis 2004) and thus keep him/her in a rather passive state. As consumers mainly watch TV for entertainment and relaxation (Wilbur 2016), emotional ads are less likely to trigger an action by the viewer and, thus, associated with less zapping. This view is consistent with findings in lab studies. For example, Olney, Holbrook, and Batra (1991) find that commercials featuring emotional cues and feelings are less likely to be zapped compared to commercials that feature factual information. Thus, we expect a negative effect of emotionality in ads on the zapping behavior of viewers, i.e., the higher the emotionality of an ad the lower the zapping of viewers.

Informativeness. The second ad content dimension we investigate is informativeness. Brand managers often aim to persuade consumers by incorporating informational cues such as

evidence of favorable product/service attributes or prices into the ad. A good example of this dimension is the electronics retail brand Media Markt. The ad provides information on various attributes and prices of products sold at the retailer (see Appendix A). Informational cues should convince consumers of the superiority of the brands over their competitors and thereby increase consumers' interest in the ad and the offering (Belch and Belch 2015).

Previous laboratory studies leave unclear whether informative cues influence zapping. On the one hand, Teixeira, Picard, and el Kaliouby (2014) find a negative, albeit marginal, effect of informational cues on zapping. These cues may increase the relevance of ads (Goodrich, Schiller, and Galletta 2015) and help consumers to evaluate the offer (Liaukonyte, Teixeira, and Wilbur 2015). On the other hand, two earlier studies (Olney, Holbrook, and Batra 1991; Woltman Elpers, Wedel, and Pieters 2003) find a positive effect of informational cues on zapping. They argue that informational cues are often perceived as *dry and boring*, especially if the consumer is not interested in the advertised category (Tellis et al. 2019). They might also *overwhelm* consumers, who watch TV to relax because they require cognitive efforts (Tellis 2004). Furthermore, informational ads are also more likely to stimulate counterarguments and trigger *skepticism* (Tellis 2004). Given that consumers do not primarily watch TV to gather product information, we expect informational cues to have a positive impact on zapping.

Creativity. The third ad content dimension we study is creativity. Creativity is often considered the key to success in advertising and many practitioners firmly believe that it is essential for advertising to be effective (Nyilasy and Reid 2009). Moreover, it is one of the major success criteria for many advertising agencies as evident in the magnitude of creativity awards, e.g., the Cannes Lions (Adweek 2019). Creativity refers to "the extent to which an ad contains brand or execution elements that are different, novel, unusual, original, unique, etc." (Smith et al. 2007, p. 820). Thus, it is a holistic concept featuring several elements. For example, the level of originality captures the extent to which an ad is different from other ads and contains

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unique ideas. Moreover, it combines verbal and visual aspects to create artistic value and features unusual connections and suspense (Yang and Smith 2009). Creativity is well illustrated by a Google ad in our sample (see Appendix A). In this ad, the Google search box gradually transforms into an upright rectangular shape that turns out to be the new Google phone. During this process, the white box "hides" the object of attention of various scenes from daily life. Thus, the ad combines originality, suspense, and strong visuals.

Managers value creativity in ads due to its ability to break through the advertising clutter and to enhance ad effectiveness (e.g., Pieters, Warlop, and Wedel 2002; Smith et al. 2007). Specifically, studies find that creative ads can draw attention to both the ad and the brand (Pieters, Warlop, and Wedel 2002), increase viewers' motivation to process the ad (Smith et al. 2007), and reduce viewers' resistance to persuasion (Yang and Smith 2009).

Concerning the impact on zapping, there are three potential psychological mechanisms at work. First, creativity can trigger feelings of *surprise* due to its unusual connection of aspects and suspense in the storyline. In a lab study, Teixeira, Wedel, and Pieters (2012) show that surprise has a direct reducing effect on zapping. Second, creativity can evoke *feelings of interest* for the ad and through its artistic nature *entertain* the audience. This is likely to retain viewers, as they want to watch the ad until the end. Indeed, Olney, Holbrook, and Batra (1991) show in their lab study that there is a mediated effect of uniqueness via interest on zapping. Third and in contrast to the previous arguments, creativity may also have a disadvantageous effect on zapping if the ad puts forward too many different ideas or connects them in an unrealistic way (Smith et al. 2007). Similarly, colorful and fast-paced visual elements may lead to overload (Baack, Wilson, and Till 2008) and thus make the viewer *feel overwhelmed* and trigger channel switching (Teixeira, Wedel, and Pieters 2010, 2012). Notwithstanding this last argument, we expect the engaging and entertaining nature of creativity to prevail. In line with the majority of previous studies, we expect a negative effect of creativity on zapping.

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Humor. Humor is the fourth important dimension of advertising content. Although it is considered a popular cue to evoke emotions (Tellis 2004), it is distinct from emotionality as an ad content dimension. Moreover, it shares some overlap with creativity, but it is usually treated as a stand-alone construct in advertising research (Eisend 2009). Humor can be defined as "painless incongruity […] between two elements that the communicator brings together" (Tellis 2004, p. 173). Incongruity arises from a difference between what is displayed in the ad and the viewers' general expected beliefs, attitudes, and/or behaviors (Woltman Elpers, Mukherjee, and Hoyer 2004). Depending on the form of incongruity, humor can come as parody, satire, self-deprecation, or pun. A good example is an ad of Volkswagen showing horses that are "laughing" at a man trying to park a car with a horse trailer. Here, parody arises from incongruity between the normal and the new context (see Appendix A).

Advertisers use humor to put the audience in a good mood and to reduce their resistance to persuasion to facilitate a transfer of positive emotions from the ad to the brand (Teixeira and Stipp 2013; Eisend 2011; Janiszewski and Warlop 1993). Moreover, a meta-analysis shows that humor is positively associated with attention to the ad, attitude towards both the ad, and purchase intention, but negatively associated with credibility (Eisend 2009). In the context of online video ads, a recent study shows that ads rated as humorous can achieve both high persuasiveness and reach (Tucker 2015).

Humor in advertising can trigger both affective and cognitive psychological responses among viewers. Previous research has established that humor generates feelings of *surprise* (Alden, Mukherjee, and Hoyer 2000; Woltman Elpers, Mukherjee, and Hoyer 2004) and *entertainment* (Teixeira and Stipp 2013), which both have been associated with reduced zapping behavior (Teixeira, Wedel, and Pieters 2012; Woltman Elpers, Wedel, and Pieters 2003). One drawback of humor, however, is that it requires some time to unfold, i.e., develop the incongruity between two elements (Woltman Elpers, Mukherjee, and Hoyer 2004). During

this time, the ad may appear *confusing* to the viewer and thus induce a desire for avoidance. Moreover, even if the incongruity is eventually resolved, humor may be perceived as stale or phony, which reduces credibility (Eisend 2009) and as a consequence may trigger a zap. Thus, there are contradicting mechanisms for the impact of humor on zapping and we refrain from stating a directional expectation.

Branding. The final ad content dimension we study is branding. The integration of different branding cues such as brand name, logo, jingle or slogan is arguably one of the most important aspects of advertising. By definition, all ads integrate branding cues to some extent (Tellis et al. 2019). How prominently they are featured, however, varies greatly across ads and is an on-going issue between brand managers and advertising agencies. Gordon Euchler, Head of Planning at BBDO, explains that while brand managers argue for a strong brand presence, agencies prefer a low brand presence. In our sample, the Coca Cola ad offers an excellent example of a strong brand presence. Each frame in the ad displays either the product or the logo (see Appendix A).

Ads that feature branding cues prominently increase the probability that consumers recognize the advertising brand. If consumers fail to register the brand or - even worse - incorrectly attribute the ad to a competing brand, advertisers waste their investments without any return. Given that around half of the consumers fail to correctly identify the brand name after watching an ad, marketing managers believe that strongly featuring the brand is crucial (Franzen 1994; Rossiter and Bellman 2005). Baker, Honea, and Russel (2004) also suggest that the brand should be included early in the ad because it facilitates consumers' ability to associate the brand with the ad's content. Furthermore, previous literature also showed that featuring brands prominently in ads not only enhances brand recall (Stewart and Furse 1986) but also sales (Bruce, Becker, and Reinartz 2019).

Concerning zapping, branding cues might trigger two (adverse) psychological responses. First, a strong brand presence might *annoy* consumers and thus reduce the ad's likeability. Aaker and Bruzzone (1985) show that salient branding cues decrease the ad's "soft-sell" character and instead increase its less favorable "hard-sell" character. In line with this argumentation, Tellis et al. (2019) show that salient and early branding also reduces the chance that consumers share an ad online. Second, strong brand presence might *evoke ad skepticism* (Dix and Phau 2017). Strong salience of the brand elements might trigger counter-arguments if consumers sense the ad tries to influence their thinking and behavior. In fact, Teixeira, Wedel, and Pieters (2010) analyze the effect of several branding cues on advertising avoidance in a lab experiment and find that brand salience increases avoidance. However, in a real-world setting consumers are not actively paying attention to the ad and might thus not even notice the branding cues. Thus, one could also argue that branding does not bother consumers enough to initiate a zap. Nevertheless, given the arguments above and previous findings we expect that featuring branding cues prominently has a positive effect on zapping.

3.2 Brand and Category Contingencies

Previous literature suggests that the effect of ad content depends on the type of brand or category. For example, Chandy et al. (2001) show that emotional content is more effective for established brands, whereas informational content is more effective for new brands. Becker, Wiegand, and Reinartz (2019) further show that the effect of authentic advertising depends on brand size and consumption purpose. In our study, we investigate whether brand familiarity and the type of category moderate the effect of content on zapping.

Consumers have different levels of knowledge for familiar vs. unfamiliar brands and may, therefore, process their ads differently (Chandy et al. 2001). For example, informational cues might be less relevant for familiar than unfamiliar brands, since consumers have already established a clear brand image in their minds (Kent and Allen 1994). Furthermore, previous

literature found that consumers are more likely to pay attention to ads of familiar brands (Alba, Hutchinson, and Lynch 1991; Campbell and Keller 2003). Since zapping is an active response to an ad, attention is a necessary antecedent of zapping. Thus, to avoid zapping familiar brands may choose to *entertain* consumers with an emotional and creative story. Also, content that requires cognitive effort such as humor and creativity might be *overwhelming* for unfamiliar brands when consumers need more cognitive resources to process the information provided by the ad. We thus expect brand familiarity to moderate the effect of content on zapping.

The second moderating factor we investigate is the influence of search vs. experience goods. Consumers can evaluate the quality of search goods (e.g., electronics) before consumption, while they can evaluate the quality of experience goods (e.g., restaurants) only after consumption (Nelson 1970). Thus, informational cues should be more relevant for search goods for which the ad can help consumers evaluate the offering and thus reduce purchase risks (Franke, Huhmann, and Mothersbaugh 2004). Furthermore, consumers might rely more on brand names to evaluate the performance of experience goods. Consequently, consumers might be *less annoyed* and thus less likely to zap when ads for experience goods strongly feature the brand. Also, because the evaluation of experience goods relies on subjective feelings a lighter persuasion through humor and emotions might fit better. Thus, consumers might be less likely to zap emotional or humorous content for experience goods (Spotts, Weinberger, and Parsons 1997). Given these arguments, we expect the category type to moderate the relationship between content and consumers' zapping behavior.

4 Data

To investigate the drivers of zapping behavior, we draw on a unique multi-source dataset that combines (1) actual TV viewing information from set-top boxes, (2) demographic information about the individuals from a household panel, (3) advertising scheduling information from The Nielsen Company, (4) information on the advertising content from expert

coding, and (5) brand and category information from a consumer survey and expert coding. We describe the different sources and provide information on the variables next.

4.1 TV Viewing and Advertising Data

We obtained TV viewing data from *Arbeitsgemeinschaft Videoforschung* (AGF), a consortium of all major German broadcasters to measure television-viewing behavior. The data comes from a panel of more than 5,000 representative households in German and tracks moment-by-moment TV viewing behavior of its members using set-top boxes. Specifically, we obtained 5-second-by-5-second TV viewing information for the 2016 season of "The Voice of Germany", a popular casting show that is broadcasted during prime-time on a major German network. The focus on one specific format is beneficial for the purpose of this study, i.e., understanding the impact of content on zapping behavior: First, as previous research shows that zapping differs between programming environments (e.g., van Meurs 1998; Schweidel and Kent 2010), we hold this factor constant thus reducing potential interfering sources of heterogeneity. Second, we keep the number of ads that need to be analyzed concerning their content on a manageable level. Third, the specific format provides an attractive environment for advertisers as it features a large number of viewers (absolute), high ratings/market share (relative) and a broad audience of viewers (scope). The dataset covers 17 broadcasting dates from October to December 2016 with an average duration of 2 hours and 15 minutes.
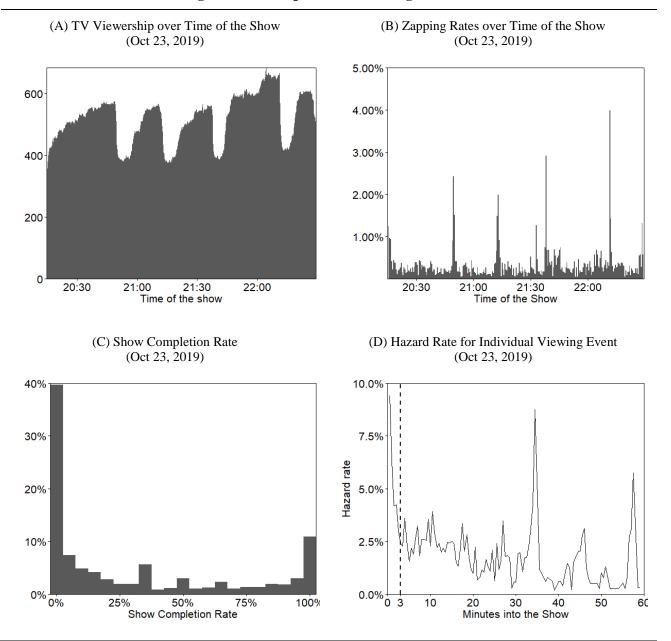
We match the TV viewing data with information about ad scheduling from Nielsen for the given dates. For each advertisement, the data reports the precise airtime, length of the spot, information on the brand and the related product category as well as an ID for the exact creative that was aired. We can thus infer advertising viewing and potential zapping by measuring whether the individual viewer was watching the channel at the given time or not.

We define a zap as the occurrence of channel switching during a specific ad after a continued duration of watching the program or ad break. For that, we adopt Wilbur's (2016)

measure of the Passive/Active Zap (PAZ) and focus on the first zap after watching the show for a minimum of 3 min prior to the ad break. The structure of our data (see Figure 2) resembles those of previous studies in the TV viewing context (e.g., Deng and Mela 2018; Wilbur 2016)[4]. Please refer to Appendix B for details on the PAZ procedure.

To arrive at the final sample, we conducted several further steps. First, we aggregated the 5-second-by-5-second intervals at the spot level to reduce redundant information at the spot level. Thus, similar to previous research (Siddarth and Chattopadhyay 1998) our unit of analysis is the individual-spot observation. Second, we removed all observations from individuals younger than 14 years. By that, we ensure the results are based on the addressable target consumers. This is also in line with the core target group definition of the broadcasting network (14-49 years). Third, we had to deal with observations from multiple individuals from the same household. To avoid double-counting a zap if several members of the same household were logged in on the same TV device, we randomly selected one individual per household and ad break. To account for group watching, we computed a dummy variable for these cases. These adjustments resulted in a final sample of 395,175 observations from 2,517 individuals covering 76 ad breaks with 1,315 spots. We compared our sample to the overall panel and concluded that it is representative of the overall German TV viewership (see Table B1 in Appendix B for the composition of the samples).

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[4] Readers may wonder why the indicated average zapping rates are rather low. Here, it should be noted that this rate indicates the zapping rate *per* spot. It is in line with the magnitude of zapping in previous studies in the field (Schweidel, Foutz, and Tanner 2014; Siddarth and Chattopadhyay 1998). Further, as shown by Siddarth and Chattopadhyay (1998), a low average zapping rate per spot can still have a tremendous impact on the ads that follow in the same pod (see Panel A of Figure 2). Because TV advertising is expensive the absolute dollar value of customers that are lost for the broadcaster and the brands is significant despite the comparably low probability of zapping an individual ad (Gustafson and Siddarth 2007).

Figure 2: Descriptive TV Viewing Patterns

(A) TV Viewership over Time of the Show
(Oct 23, 2019)

(B) Zapping Rates over Time of the Show
(Oct 23, 2019)

(C) Show Completion Rate
(Oct 23, 2019)

(D) Hazard Rate for Individual Viewing Event
(Oct 23, 2019)

4.2   Ad Content Coding

Variable operationalization. To operationalize the five ad content dimensions and to provide actionable advice for managers, we reviewed the literature and identified the most relevant variables for each content dimension. In line with our conceptualization, we focused our search on constructs that describe executional elements of the spot rather than the psychological responses of the viewer. To ensure we do not miss any key variable, we also

conducted a series of 12 qualitative interviews with consumers and completed our list of variables. Due to resource constraints, we had to confine the list of scales to a reasonable amount. Thus, if the literature suggested multiple aspects for one dimension (e.g., creativity), we selected those that were most salient during the interviews. This process yielded 20 scales for the different content cues that we used to code the content of the video ads. We adopted established scales from the advertising content literature where possible. A summary can be found in Table 3. All scales were measured using 7-point Likert scales.

Coding procedure. Consistent with previous studies on video advertising content (Becker, Wiegand, and Reinartz 2019; Chandy et al. 2001; Tellis et al. 2019), we employed a sample of five independent expert coders to evaluate the content cues of the 571 unique creatives in our sample[5] (for details on the procedure, please refer to Appendix C). We assessed inter-coder reliability using the intraclass correlation coefficient (ICC). The ICCs ranged between 0.71 and 0.90 indicating a good to excellent reliability for the different measures (Koo and Li 2016), especially given the fact that all characteristics were rated on a continuous scale. We excluded three variables (Believability, Brand Integraleness, and Comprehension) from further analysis as the ICCs were below the acceptable threshold[6]. We also tested for construct validity using Cronbach's Alpha and found all constructs to work as intended with all alphas exceeding 0.90. In the last step, we computed the mean across all five coders to determine the value for each content cue.

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[5] Overall, the dataset covers 1,315 spots in 76 ad breaks. Each spot can be identified by a specific "motive code". In an initial step, two research assistants reviewed all spots and identified 571 unique creatives, which form the basis for the content analysis.

[6] The low consistency between coders most likely comes from the fact that all three variables have a certain subjective component. Thus, we conclude that these variables are less suitable for objective measurement approaches.

Table 3: Operationalization of Ad Content Variables

Variable	Operationalization	Inter-coder Reliability	Cronbach's Alpha	Source
Artistic Value	The ad: - was visually/verbally distinctive. - made ideas come to life graphically/verbally - was artistically produced	.81	.93	Smith et al. (2007)
Believability	The information in the ad was: - Not at all / highly believable - Not at all / highly trustworthy - Not at all / absolutely true	0.25	.97	Gurhan-Canli and Maheswaran (2000)
Brand Duration	Duration of how long the brand is shown in the ad (in seconds)	n/a[1]	n/a[2]	Teixeira, Wedels, and Pieters (2010)
Brand Frequency	Count of number of times the brand is mentioned or shown in the ad	n/a[1]	n/a[2]	Teixeira, Wedels, and Pieters (2010)
Brand Integrale-ness	How integral was the brand to the narrative?	.23	n/a[2]	Akpinar and Berger (2017)
Brand Prominence	Please indicate how prominent the brand was in the ad.	.90	n/a[2]	Tellis et al. (2019)
Brand Recognition	Time until the coder was able to recognize the advertised brand (in seconds)	.85	n/a[2]	
Brand Timing	Time after how many seconds the brand was mentioned or shown for the first time (in seconds)	.84	n/a[2]	Tellis et al. (2019)
Category Recognition	Time until the coder was able to recognize the category of the advertised brand (in seconds)	.78	n/a[2]	
Compre-hension	The ad was: - difficult / not difficult to understand - confusing / straightforward - complicated / not complicated	.17	.98	Phillips (2000)
Humorous-ness	The ad I saw was: - humorous - funny - amusing	.86	.97	Chatto-padhyay and Basu (1990)

(continued)

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Likeability of the Character / Spokes-person	The main actor(s) / spokesperson(s) in the ad were: - likeable/unlikeable - friendly/unfriendly - agreeable/disagreeable	.71	.97	Forehand and Deshpandé (2003)
Originality	The ad is: - different from other ads - surprising - original - not ordinary	.84	.97	Pieters, Warlop, and Wedel (2002)
Rational appeal	The ad: - was informative - was factual - provides relevant information about the product and/or the product usage	.87	.96	Hirschman (1986); Cox and Cox (2001)
Repetition	To what extent did the ad repeat certain aspects (e.g., slogan, catch-line, jingle)	.73	n/a[2]	
Silliness	The ad was: - silly - ridiculous - based on flat jokes	.80	.95	
Suspense	Please indicate to what extent you agree with the following statements: - When watching the ad, it was uncertain how the story of the ad would end. - The story of the ad revealed itself at the end. - The story of the ad makes the viewer curious about the ending.	.90	.96	
Verbal Complexity	Please indicate how verbally complex the ad was.	.88	n/a[2]	
Visual Complexity	Please indicate how complex the visual creation of the ad was.	.90	n/a[2]	
Warmth	Please describe to what extent the following emotions describe the ad: - warmhearted - emotional - moving	.87	.94	Aaker and Williams (1998)

Notes: [1] No inter-coder reliability measure available as this variable was measured by one research assistant only. One of the authors conducted checks for a random sample of spots and found no differences. [2] No measure for Cronbach's Alpha available as this variable was measured with a single item scale.

Table 4: Results Principal Component Analysis

Rated Content Cues	Content Factors					
	Emotio-nality	Informa-tiveness	Creativity	Humor	Brand Presence	Brand Timing
Likeability of Character / Spokesperson	.90					
Warmth	.82					
Verbal Complexity		.87				
Rational appeal		.79				
Visual Complexity			.93			
Artistic Value			.92			
Originality			.72	.46		
Suspense			.62			
Humorousness				.92		
Silliness				.91		
Brand Frequency					.80	
Brand Duration					.70	
Repetition					.65	
Brand Prominence					.60	-.44
Brand Recognition						.94
Brand Timing						.94
Category Recognition						.92

Notes: Rotated Varimax Solution of Principal Component Analysis. All loadings < .40 suppressed. The first column shows the names of the original rated variables. The first row of the table shows the names corresponding to the six identified components.

Principal component analysis. To assess to what extent the selected variables represent the ad content dimensions from our conceptual framework, we use a principal component analysis (Tellis et al. 2019). For that, we treat the executional content cues as formative indicators of the content factors. Based on the Eigenwert criterion, we identify a six-factor solution explaining 80.5% of the variance. Table 4 shows the rotated factor matrix. Notably, humor turns out to be a distinct factor from both emotionality and creativity, thereby confirming our conceptualization. Interestingly, branding is represented by two distinct factors with the first representing the overall level of brand presence in the ad and the second focusing on the early vs. late timing of the brand elements. Based on the results, we label the six content factors as "emotionality", "informativeness", "creativity", "humor", "brand presence", and "brand timing". We use the derived factor scores for our subsequent empirical analysis (Olney,

Holbrook, and Batra 1991). Table 5 shows descriptive statistics for the content factors while the full distributions are detailed in Appendix D.

4.3 Further Variables and Descriptive Statistics

Moderator variables. In our second research question, we ask whether the impact of the content factors depends on brand or category characteristics. Consequently, we developed measures to investigate potential moderating effects. To capture differences in brand familiarity among the 308 brands in our sample, we surveyed 2,983 participants representative of the German population. In that survey, each brand was evaluated by at least 30 respondents. We adopted the scale proposed by Zhou, Yang, and Hui (2010) and measured it on a 5-point Likert scale. For the moderation analysis, we employed a median split (median = 3.1). The second moderating factor was obtained by having two research assistants classify the 96 categories (e.g., cars, clothing, coffee, online retailers, credit cards, travel agencies) in our dataset as (1) search good, (2) experience good, or (3) credence good. The inter-coder agreement percentage was 78%; discrepancies were resolved by discussion. For the moderator analysis, we use a split into search vs. experience goods[7].

Table 5: Descriptive Statistics and Correlations of Content Factors

	Content Factors					
	Emotio-nality	**Informa-tiveness**	**Creativity**	**Humor**	**Brand Presence**	**Brand Timing**
Mean	-.08	.01	-.04	.02	.02	-.04
Maximum	3.96	3.69	3.39	4.19	4.10	10.50
Minimum	-2.72	-2.62	-2.32	-1.28	-2.38	-1.31
SD	1.00	.98	.96	.98	.95	.84
Observations	395,175	395,175	395,175	395,175	395,175	395,175
Emotion	1.00	-.01	.03	.05	-.01	-.14
Information		1.00	-.04	.02	.13	.21
Creativity			1.00	-.20	-.02	-.19
Humor				1.00	.05	.00
Brand presence					1	.02
Brand timing						1

[7] Of the 96 categories, only two were classified as credence goods (i.e. pharmacy chain and OTC drugs). For the sake of simplicity, we subsume credence goods under the group of experience goods as they share important features, e.g., pre-purchase uncertainty.

Control variables. Previous research has identified several variables that might influence zapping. We include the majority of these variables as controls. The variables are computed based on the information provided in the TV viewing data or the advertising scheduling data respectively. Specifically, we included context variables such as the position within the ad break, spot length, type of ad, or attractiveness of competing channels (Danaher 1995; Deng and Mela 2018; van Meurs 1998). When analyzing the effect of content it is paramount to account for position effects[8] in order to disentangle ad-break-induced zapping from content-induced zapping (see Panel A in Figure 2). Thus, we include a dummy indicating the first three positions of each ad break[9]. Further, we account for the fact that viewers tend to zap less towards the end of a break (in order not to miss the re-start of the show) by including a dummy for the last three positions per break. In addition, we include the length of each spot and a dummy variable for the type of ad indicating whether the ad was part of a product/sales campaign or a brand/image campaign. The variable attractiveness of competing channels captures the overall quality of the programming on other channels as measured by their weighted ratings. We also include two proxies for the previous exposure to each creative: For that, we measure the total ad spend for the creative in 2016 (outside of the focal show) to capture overall ad familiarity (e.g., Teixeira, Wedel, and Pieters 2012) and complement this with a measure capturing the individual exposure to the creative within the focal show for each viewer (Siddarth and Chattopadhyay 1998). Besides, the previous zapping variable captures the viewer's past zapping habits (Siddarth and Chattopadhyay 1998). Finally, we include a dummy to account for multi-person watching within the same household. Please refer to Appendix D for details on all variables including descriptive statistics.

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[8] There is a possibility that advertisers strategically select certain a position within the ad break. To assess this, we analyzed the distribution of positions per brand. The result shows a random pattern for all but three brands that only book advertising space for the first position (see Table D4 in Appendix D). The broadcaster also confirmed this finding. Despite the option to book certain positions, the majority of ads are randomly allocated within one break as part of the broadcaster's scheduling.

[9] This is based on an inspection of the patterns within the ad breaks. We test the sensitivity in a robustness check.

5   Model Specification and Estimation

To investigate the effect of the six content factors on the zapping behavior of viewers, we estimate a binary logit model with brand and individual fixed effects. This approach is well documented (e.g., Deng and Mela 2018; Siddarth and Chattopadhyay 1998) and fits the structure of our data well. As the variation of content in our data is at the spot level, the unit of analysis is the individual-spot level[10]. We specify our model as follows:

$$(1) \qquad P_{ibt} = P(Zap_{ibt}=1 \,/\, x) = \frac{1}{1+e^{-z_{ibt}}}$$

$$with \quad z_{ibt} = \alpha_i + \gamma_b + \beta_1 \times Emotion_{ibt} + \beta_2 \times Information_{ibt} + \beta_3 \times Creativity_{ibt}$$
$$+ \beta_4 \times Humor_{ibt} + \beta_5 \times Brand\ presence_{ibt} + \beta_6 \times Brand\ Timing_{ibt}$$
$$+ \sum_{j=7}^{16} \beta_j \times CTRL_{ibt} + \varepsilon_{ibt}$$

$i = 1, 2, …, I$ (number of individuals);
$b = 1, 2, …, B$ (number of brands);
$t = 1, 2, …, T$ (number of spots)

where P_{ibt} measures the probability that individual i zaps spot t of brand b. The parameters α_i, γ_b, and β_j are to be estimated. The coefficients β_{1-6} represent the effects for the content factors of interest, while β_{7-16} are the parameter estimates for the vector of control variables $CTRL_{ibt.}$

To assess whether our model faces multi-collinearity problems, we estimate a linear model and compute variance-inflation-factors, out of which none reaches the critical threshold (see Table D5 in Appendix D). Together with the moderate magnitude of the bivariate correlations (see Table D2 in Appendix D), this suggests that multi-collinearity is not an issue[11].

Zapping behavior may be driven by individual differences (e.g., the general attitude towards advertising) of the viewers as well as brand or category factors. We control for these

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[10] A more granular investigation of moment-to-moment content and zapping behavior (as done in several lab studies) is beyond the scope of this study, as this would have led to an explosion in coding effort. Thus, even though we could use viewing / zapping information on the level of 5-second intervals, we model the probability of zapping at the spot level to avoid an inflation of zeros for our dependent variable. Moreover, Siddarth and Chattopadhyay (1998) show that the time to zap decision only adds limited value beyond the zap occurrence.

[11] Also recall that we applied principal component analysis to extract the ad content factors. The Varimax rotation ensures that the identified content factors are more or less orthogonal.

factors by including individual (α_i) and brand[12] (γ_b) fixed effects (Tuchman, Nair, and Gardete 2018). One important side effect of this, however, is that by including fixed effects in the model all units for which there is no variance in the dependent variable get eliminated during estimation. This means, for example, that a viewer that never zaps over the period of 76 ad breaks is not considered in the estimation of the model. Effectively, this is similar to the latent class approach of Siddarth and Chattopadhyay (1998) who show that one segment of viewers representing 67% of the households is "generally unresponsive in their zap decision" (p. 132).

The effect of the content factors on zapping may also be biased by endogeneity. Endogeneity may ensue as a consequence of reverse causality, i.e., zapping driving the selection of content of the ads. This, however, is not very likely in our case given the short time horizon of the observation period (3 months) in comparison to the elaborate and time-consuming development process of video advertising campaigns. This view was supported in interviews with several managers of advertising agencies that stressed that they test their creative ideas based on liking but do not interfere anymore once the ads are scheduled. In support of this argument, we also checked the age of the creatives and found that the majority was broadcasted for the first time within the preceding two months (80% percentile = 59 days).

A second source of endogeneity might be related to omitted variables. Specifically, managers or advertisers may exhibit strategic behavior by learning from previous campaigns and proactively adjusting the content of the ads to reduce zapping behavior. Although this would mean that we should not find any variance in different spots for the same brand (which we find is not true), we cannot fully rule out strategic behavior. However, by including the brand fixed effects, we take effective steps to mitigate endogeneity concerns. As shown by Germann, Ebbes, and Grewal (2015) the fixed effects approach provides an effective solution

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[12] In our dataset, each brand is only represented in one product category. Thus, we only specify a brand fixed effect.

against endeidy when the time dimension is short. Thus, we conclude that endogeneity does not pose a serious threat to the precision of our estimates.

We estimate the models with unconditional maximum likelihood. For that, we use the estimator implemented in the R package Alpaca (Stammann and Czarnowske 2018). This package employs a pseudo-demeaning in combination with analytical bias correction to accommodate high-dimensional fixed effects in large datasets (Stammann, Heiß, and McFadden 2016). For the moderating effects, we employ a split-sample approach based on the median (for brand familiarity) and categorical value (for category type) respectively.

6   Results and Discussion

We present the results of the model estimation in Table 6. The overall model fit is acceptable as indicated by a pseudo-R-square of 17.8%. It is in line with previous research in the advertising domain using binary outcome variables (e.g., Goldfarb and Tucker 2011). Our first important finding is that ad content influences zapping behavior beyond a large number of control variables. However, we only find effects for some content factors. We discuss the results for the content factors, control variables, and moderating conditions next.

6.1   Content Drivers of Zapping

Contrary to the negative prediction, emotionality has no significant effect on zapping ($\beta_1 = -.043$, n.s.). This finding contrasts with previous laboratory results (Olney, Holbrook, and Batra 1991), where feeling appeals had a positive effect on viewing time, i.e. a negative effect on zapping. A possible reason for this could be that content with low arousal emotions does not evoke the necessary attention that either drives zapping or engages the consumer.

The results provide support for our expectation that informativeness increases zapping ($\beta_2 = .161$, $p < .01$). Our findings thus shed light on inconclusive findings in previous lab studies. While some studies found a negative effect of informativeness on zapping (Teixeira, Picard, and el Kaliouby 2014), others found a positive effect (Olney, Holbrook, and Batra 1991;

Woltman Elpers, Wedel, and Pieters 2003). One reason for the positive effect of zapping could be that consumers find informative ads *dry and boring* rather than a source of relevant information (Goodrich, Schiller, and Galletta 2015). Recall that informativeness is driven by rational appeals and verbal complexity (see Table 4). Thus, they often contain a lot and fast-paced talking which may *overwhelm* the viewer and in turn trigger zapping.

Table 6: Results

	Estimated Effect on Zapping	
Content Factors		
Emotionality	-.043	(.054)
Informativeness	.161**	(.057)
Creativity	-.187**	(.067)
Humor	-.005	(.038)
Brand presence	.148**	(.049)
Brand timing	-.166***	(.039)
Controls		
First three positions in ad break	.967***	(.098)
Last three positions in ad break	-1.120***	(.288)
Spot length	.045***	(.006)
Type of ad	-.232*	(.100)
Attractiveness of competing channels	-.067	(.279)
Total ad spend	-.023	(.024)
Exposure to creative	.079	(.052)
Exposure to creative ^{2}	-.005	(.006)
Previous zapping	.092***	(.012)
Multi-person watching	-.227***	(.078)
Individual fixed effects	✓	
Brand fixed effects	✓	
R^2	.178	
log likelihood	-12,596	
N (observations)	237,851	

Notes: Standard errors are in parentheses. N (brands) = 268; N (individuals) = 1,275.
✓ indicates that these fixed effects are included in the model.
*$p < .05$, **$p < .01$, ***$p < .001$.

We find a negative and significant effect for creativity ($\beta_3 = -.187$, $p < .01$) implying that ads rated high on creativity are associated with less zapping. Thus, this supports our theoretical argument that creative ads featuring visually appealing and artistic images are successful in engaging the viewer. The finding is in line with a recent study investigating dual-screen usage. Liaukonyte, Teixeira, and Wilbur (2015) propose that visual pleasing content leads to less

online activity because creative stimuli arrest consumers' attention and discourage them from disengaging with the commercial. Artistic value and visual complexity, two of the cues that drive creativity (see Table 4), thus seem to reduce zapping behavior. In addition to the artistic cues, a suspenseful storyline also contributes to creativity. To illustrate the effect of suspense, consider the example of two ads (see Appendix A): In the first ad, Google shows the transformation of a rectangular leaving the viewer *curious* about the ending of the ad. In contrast to that, the second ad by Rügenwalder introduces a vegetarian sausage with a rather predictable ending. Furthermore, creative ads might simply be more *entertaining*. To test this assumption, we retrospectively coded how entertaining the ad was and correlated this with our ad content dimensions. In fact, we find the by far strongest correlation with creativity ($\rho = .74$, p < .001).[13] Together, these results suggest that creativity can help advertisers prevent viewers from zapping, thus confirming the widespread opinion in practice.

The results provide no support that humor affects zapping ($\beta_4 = -.005$, n.s.). There might be several reasons for this null effect: First, few ads in our dataset are perceived as very humorous. The low variance of this variable may cause the insignificant effect. Second, previous research already states that "while some ads are spectacularly successful at raising a laugh, others may fail to do so" (Woltman Elpers, Mukherjee, and Hoyer 2004, p. 592). Thus, the reason for the insignificant effect may lie in the extreme discrepancy between the type of humor an ad tries to attempt and the level of amusement actually evoked among the viewers. This points to heterogeneity as a critical factor for the effectiveness of humor. Third, given that silliness is also driving humor (see Table 4), it could be that some of the humorous ads are perceived as stale and silly and thus *annoy* the viewer. As a consequence, positive and negative

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[13] Previous studies (e.g., Teixeira, Wedel, and Pieters 2012) suggest that the effect of creativity might be curvilinear. We do not find such an effect.

effects might cancel each other out. Hence, the challenge for marketers is to create ads that are perceived as funny by the majority of the viewer without appearing silly.[14]

Finally, brand presence has a positive effect on zapping (β_5 = .148, p < .01) while brand timing has a significant negative effect (β_6 = -.166, p < .001). This finding supports our theoretical argument that salient branding cues reinforce the "hard-sell" character of advertising and triggers *annoyance* among viewers resulting in ad avoidance. Our findings further suggest that managers can prevent zapping to a certain extent by showing the brand late during the ad. Conversely, it also means that showing the brand early in the ad induces zapping behavior. This finding is contrary to the "rule" of Baker, Honea, and Russel (2004) who propose that showing the brand early helps connect the ad's message to the brand.

6.2   Control Variables

We divide the control variables into three groups: ad-context factors, previous exposure to the ad, and individual context factors. Concerning the first group, we find that the position of the ad within the ad break has a strong effect on zapping. Our results show that the first three positions in the ad break are associated with significantly more zapping (β_7 = .967, p < .001) while the last three positions are associated with significantly less zapping (b = -1.120, p < .001). Thus, in contrast to a recent field study by Deng and Mela (2018) but in line with Schweidel, Foutz, and Tanner (2014), we find that the first positions increase zapping. This is most likely because we account for the first real commercial and disregard trailers preceding the ad block[15]. By including another dummy for the last three positions, we further account for the dynamics of zapping within the ad break. The ads run in the context of an entertainment format where ad breaks are usually placed at tension peaks of the show (Danaher 1995). Thus,

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[14] Berlyne (1972) and Teixeira and Stipp (2013) suggest that humor has a U-shaped effect on zapping arguing that medium levels of humor generate most pleasure by striking the optimal level of arousal. However, we do find support for this in our dataset.

[15] Deng and Mela (2018) argue that it takes the viewer some time to initiate an avoidance action. In our case, this time is covered by trailers, which usually run for 10 seconds.

people do not zap towards the end of the break, as they do not want to miss the re-start of the show (Wilbur 2016). Taken together, our results suggest that it is vital to account for the position in the ad break, especially in field studies, to disentangle ad break effects from ad content effects. We further find that spot length ($\beta_9 = .045$, $p < .001$) and type of ad ($\beta_{10} = -.232$, $p < .05$) have significant effects on zapping while the attractiveness of the competing channels does not influence the zapping behavior ($\beta_{11} = -.067$, n.s.).

We find no significant effects of the exposure variables. Neither total ad spend ($\beta_{12} = -.023$, n.s.) nor the individual exposure to the same creative within our sample (linear term: $\beta_{13} = .079$, n.s.; quadratic term: $\beta_{14} = -.005$, n.s.) show significant estimates. These results contradict previous findings by Siddarth and Chattopadhyay (1998) who find a J-shaped exposure effect. This difference, however, can be explained by the shorter time frame of our study. While our data covers commercials over a period of 3 months, they analyzed the exposure to commercials over two years. Thus, our maximum number of exposures is significantly lower than their range of exposures. Moreover, by including individual fixed effects we control for exposures outside of the context of our show, which provides another explanation for finding a non-significant effect.

Finally, we find significant effects for the individual context factors. The more frequently a viewer zapped previous commercials, the higher the likelihood the viewer zaps also the current commercial ($\beta_{15} = .092$, $p < .001$). This is in line with previous research showing that it is important to control for differences between viewers beyond the fixed effects included in our model (Siddarth and Chattopadhyay 1998; Woltman Elpers, Wedel, and Pieters 2003). In addition, we find that watching in a group is associated with less zapping ($\beta_{16} = -.227$, $p < .001$). This is consistent with a previous study (van Meurs 1998) and indicates that people watching in a group may choose to engage in a conversation instead of switching channels. Therefore, it is also important to control for this context effect.

6.3 Moderation Effects

Thus far, we have discussed findings aggregated across all brands and product categories. Now, we investigate whether the effect of content varies with brand familiarity and category type (search vs. experience goods). Table 7 summarizes the results of the moderation analysis. We use a split-sample approach and thus conduct the two analyses separately. By that, we can test the moderation while including brand fixed effects at the same time[16]. Another advantage of using a split-sample approach is that we allow each beta to vary and thus obtain specific results for the respective subsample.

Table 7: Results, Moderation

	Brand Familiarity				Category Type			
	Low		High		Search Good		Experience Good	
Content Factors								
Emotionality	.095	(.133)	-.055	(.062)	-.085	(.078)	-.045	(.085)
Informativeness	.027	(.144)	.152*	(.066)	.116	(.092)	.204**	(.078)
Creativity	-.079	(.175)	-.156*	(.078)	-.103	(.115)	-.260**	(.096)
Humor	-.202**	(.079)	.021	(.051)	-.122*	(.062)	.078	(.052)
Brand presence	.296*	(.145)	.124*	(.055)	.086	(.084)	.203**	(.064)
Brand timing	-.243	(.172)	-.098*	(.046)	-.173**	(.057)	-.120	(.105)
Controls	✓		✓		✓		✓	
Individual fixed effects	✓		✓		✓		✓	
Brand fixed effects	✓		✓		✓		✓	
R^2	.197		.178		.182		.190	
log likelihood	-5,650		-6,069		-4,245		-7,496	
N (observations)	83,921		89,387		57,648		117,188	
N (brands)	168		100		107		162	
N (individuals)	805		865		688		958	

Notes: Standard errors are in parentheses. ✓ indicates that these variables / fixed effects are included in the model. For the sake of brevity, we report the estimates for the control variables in Table E1 in Appendix E. *p < .05, **p < .01, ***p < .001

Moderating effects of brand familiarity. Overall, we find that the impact of several content factors depends on brand familiarity. For emotionality, we find no differences in the effect between more and less familiar brands. Thus, in line with the overall sample, we find that emotionality is neither associated with more nor with less zapping.

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[16] As noted, it is important to include brand fixed effects to control for potential endogeneity concerns. We thus, report split sample results here. In a robustness check, we also estimated a model with interaction terms but without brand fixed effects and find similar effects.

Interestingly, we find differences in the effect of informativeness. While the effect is not significant for less familiar brands ($\beta_2^{\text{low BF}}$ = .027, n.s.), we find a positive and significant effect for high familiar brands ($\beta_2^{\text{high BF}}$ = .152, p < .05). In line with our expectation, this implies that providing information is less critical for unfamiliar brands, whereas for well-known brands consumers disapprove of too much information. Most likely because for the latter they already have a clear brand image in their minds (Kent and Allen 1994) and thus perceive additional information to be *dry and boring*.

We also find diverging effects for creativity. Although both estimates have positive signs, the effect of creativity is only significant for familiar brands ($\beta_3^{\text{high BF}}$ = -.156, p < .05). Thus, consistent with our expectation, using visually complex and artistic elements in combination with suspense seems to work for familiar brands. Consider the example of the Google ad again: Here the informed viewer can identify the ad as a Google ad early on – yet, the creativity of the spot *engages* and *entertains* the viewer making it worthwhile watching the spot until the end.

The interaction between brand familiarity and humor offers further interesting insights. While we find no measurable effect in the aggregated model, the results for the interaction models show a negative and significant effect for less familiar brands ($\beta_4^{\text{low BF}}$ = -.202, p < .01). Thus, humor appears to be effective in generating feelings of *surprise* and *entertainment* and thus engage viewers, in particular for less familiar brands. Indeed, previous research suggests that if unfamiliar brands manage to create an ad that appears novel and interesting (e.g., through humor) consumers engage in more extensive processing (Campbell and Keller 2003) - and thus refrain from zapping.

Finally, the results for branding are relatively consistent across brands. For both high and low familiar brands, excessive branding is associated with more zapping ($\beta_5^{\text{low BF}}$ = .296, p < .05; $\beta_5^{\text{high BF}}$ = .124, p < .05). For familiar brands, there is an attenuating effect of showing

the brand late in the spot ($\beta_6^{\text{high BF}}$ = -.098, p < .05). The effect for less familiar brands is also negative but not significant ($\beta_6^{\text{low BF}}$ = -.243, n.s.).

Moderating effects of category type. Consistent with our expectations, we also find diverging effects for search and experience goods. While we find no significant effects for emotionality (β_1^{Search} = -.085, n.s.; $\beta_1^{\text{Experience}}$ = -.045, n.s.), the results for informativeness are interesting. The insignificant effect for search goods (β_2^{Search} = .116, n.s.) indicates that for these kinds of products providing a lot of information does not induce zapping. This could be because informational cues are indeed more relevant for search goods as they help consumers evaluate the offering and reduce purchase risks (Franke, Huhmann, and Mothersbaugh 2004). Another explanation could be that consumers have a greater tolerance for information in ads for search goods. In contrast to that, we find a strong positive effect of informativeness for experience goods ($\beta_2^{\text{Experience}}$ = .204, p < .01) suggesting that including a great number of informational cues is not a viable strategy for managers of experience goods.

We find an attenuating effect of creativity for experience goods ($\beta_3^{\text{Experience}}$ = -.260, p < .01). Thus, using artistic and unique elements seems to be a good fit with the experiential character of the offering (e.g., movies, computer games, and many other services) resulting in less zapping. We do not find a similar effect for search goods.

In addition, we find a surprising effect for humor. Contrary to our expectations, the effect is non-significant for experience goods ($\beta_4^{\text{Experience}}$ = .078, n.s.), but negative and significant for search goods (β_4^{Search} = -.122, p < .05). This might be explained by previous studies that show that humor can be used to support the message of a brand and increase ad effectiveness for functional products (e.g. auto tires, insurance, appliances), which overlap strongly with the search good category (Eisend 2009; Spotts, Weinberger, and Parsons 1997).

Finally, the results for branding also provide interesting insights. In contrast to the overall effect in the aggregate model, the effect of brand presence for search goods is not significant

(β_5^{Search} =.086, n.s.) indicating that brand presence is not associated with more zapping. Thus, similar to the result for informativeness, branding does not "hurt" in ads for search goods. Moreover, the effect for brand timing is negative and significant (β_6^{Search} = -.173, p < .01). For experience goods, the results show a different picture. Here, brand presence has a positive effect on zapping (β_5^{Search} = .203, p < .01) without any attenuating effect of showing the brand late in the spot (β_6^{Search} = -.120, n.s.).

6.4   Robustness Checks

To investigate whether our findings are robust to different model specifications, variable operationalization, and conceptualization, we conduct a number of additional analyses. First, we check whether our findings are sensitive to model specifications. For that, we estimate a model with brand fixed effects only, one with individual fixed effects only, and one without any fixed effects, thus pooling our observations across all brands and individuals. We find similar results across all models (detailed in Table E2 in Appendix E). Further, we aggregated all individual observations at the spot level and modeled the number of zaps per spot by using a Poisson specification. Again, we find very similar effects to the disaggregated model (see Table E2 in Appendix E). Thus, we conclude that our findings are robust. Moreover, it shows that content has a significant influence on zapping independent of whether we control for the nested structure of observations or not.

Second, we investigate whether our results are driven by specific ads, in particular, those that are very similar to the surrounding programming. Despite its role as a prime environment for a broad range of brands, "The Voice of Germany" also attracts many ads promoting entertainment services (e.g., artists' new albums, movies, concerts). Thus, we eliminate all ads related to entertainment and estimate the main model for the reduced sample. Results show similar effects for both content factors and control variables (see column (I) in Table E3 in Appendix E).

Third, to assess potential strategic position selection by certain brands, we re-estimated the model without the three brands that show signs of strategic position selection (see Table D4 in Appendix D) and find similar results. This indicates that strategic position selection is not a threat to the validity of our results (see column (II) in Table E3 in Appendix E).

Fourth, we estimate the main model using alternative operationalizations of the control variables. Using these alternative measures yields similar results (see Table E4 in Appendix E). Surprisingly but consistent with Schweidel and colleagues (2014), we find that several ads from the same category in the same break are associated with less zapping.

Finally, we test the validity of our conceptualization. For that, we had three research assistants dummy code the spots in our sample for another set of concrete content cues (e.g., plot type, celebrities, music, and special occasion). We find that these factors are antecedents to the ad content factors but do not directly influence zapping (see Table E5 and Table E6 in Appendix E for details). Together, these findings support the conceptualization of advertising content and its impact on zapping.

7   Implications

Ad avoidance is problematic with video advertisements both on TV and online. When consumers avoid an ad by zapping or skipping, advertisers lose the ability to communicate their brand message and the investment is lost. Moreover, zapping in the TV context is also highly critical for broadcasters, as it impairs the attractiveness of the channel for advertisers. Advertisers and broadcasters must, therefore, understand which factors influence the avoidance of advertising, i.e. zapping. Surprisingly, extant literature has mainly focused on context factors (e.g., factors pertaining to the ad break environment and viewership) over which advertisers have at best limited control. This study is the first to investigate the role of advertising content in the field thereby complementing existing lab studies. Based on a conceptual framework, we link five important advertising content dimensions (emotionality, informativeness, creativity,

humor, branding) to zapping and investigate the effects using real-world ads and real-world zapping behavior. For that, we collected data on individual-level TV viewing and zapping behavior for more than 2,500 individuals and combine it with information about the content of 571 unique ads obtained from expert coders. The results of our study have important managerial and theoretical implications, which we discuss next.

7.1 Managerial Implications

Does advertising content affect zapping behavior in the field? Our results demonstrate that content matters. Beyond established effects on recall and brand sales, we show that the ad's content has a significant effect on consumers' zapping behavior. Our results disconfirm the view that zapping is a random and unconscious behavior (Danaher 1995; van Meurs 1998) but show that zapping is a reaction to the content (Siddarth and Chattopadhyay 1998). Thus, zapping is an immediate indicator of ad (dis)liking and managers should care about it. Broadcasters should have an interest, as a better understanding of the effects of content can help them retain viewership. Advertisers should have an interest, too, as the "right" content makes ads more effective. To get better insights into the effectiveness of TV ads, managers may want to request more detailed information about zapping behavior for their campaigns. Thus far, broadcasters routinely report viewership metrics at 5 min intervals or ad break level only. By getting more detailed information, managers will be able to compare the effectiveness of their TV ads to similarly granular information from online video ads (e.g., on Youtube or Facebook).

Which content factors drive / mitigate the viewers' zapping behavior? Do these effects depend on the type of brand or category? Our research provides five concrete implications for brand managers and advertisers, which we summarize in Table 8. First, contrary to popular belief, emotionality does not prevent zapping (Tellis 2004). However, it does not hurt either. Thus, managers may use warmth and likeable characters if they fit the brand message, but not at any cost. The creative focus should rather be allocated to other content factors.

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Table 8: Summary of Results and Managerial Implications

Effect on Zapping	Unfamiliar Brands		Highly Familiar Brands		Search Category		Experience Category		Overall Implications for Content Factor
	Effect	Implications	Effect	Implications	Effect	Implications	Effect	Implications	
Emotionality									• Utilize emotional cues if suitable for brand message • Leverage special occasions and music to create emotionality
Informativeness			↑	• Refrain from using informational cues to prevent boredom for viewers			↑	• Emphasize experiential aspects instead of "dry" informative cues	• Avoid too many informational cues • Reduce verbal complexity
Creativity			↓	• Use creative ads to entertain viewers • Make use of creative elements to strengthen the brand			↓	• Use creative elements (e.g. visual and artistic) to transport the benefits of the product/service	• Use creativity to engage viewer • Use visually appealing design, originality, and suspense to make ad stand out
Humor	↓	• Use humor to entertain viewer and draw attention to your brand			↓	• Use humor to draw attention to your brand • Connect humor to the brand message			• Use humor selectively • Make sure the level of humor is appropriate for the brand/context
Brand presence	↑	• Refrain from excessive branding to avoid annoying viewers	↑	• Refrain from excessive branding to avoid annoying viewers			↑	• Refrain your excessive branding to not interfere with the experiential focus of the ad	• Refrain from excessive branding
Brand timing			↓	• Show the brand late in the ad to create a strong ad finish	↓	• Show the brand late in the ad to connect message to the brand			• Show the brand late to avoid "hard-sell" impression of the ad
Brand / Category Specific Implications	• Utilize relative flexibility in content (e.g., informativeness) • Use humor, but brand sparsely		• Brand familiarity narrows flexibility in content (e.g. informativeness) • Use creative elements and show the brand late to "close" the story		• Providing information is acceptable • Use humor to add some "lightness" to the ad • Use branding sparsely		• Use creativity to present the product/service in an interesting way • Refrain from impairing the experiential nature of the ad with information and branding cues			

Notes: The table provides an overview of the effects of the different content factors (first column) on zapping for the different brand and category constellations (columns 2-5); ↑ indicates a positive effect (i.e., more of the content factor is associated with more zapping); ↓ indicates a negative effect; blank cells indicate a null effect.

Second, managers should refrain from including too much information in their ads. Even though informational cues drive zapping, 42 % of the ads in our sample still score high on informativeness (rated informativeness $\geq$ 4). Thus, we advise managers to rethink their communication strategy and to use the strength of TV to surprise and entertain consumers, while leaving information to other advertising channels such as print (Clow and Baack 2007). If managers, nevertheless feel the need to provide informative content they should make sure that it is relevant. For example, we show that informativeness does not hurt for unfamiliar brands or search goods. Thus, managers should use copy tests to evaluate the content and only keep informative cues when they are perceived as relevant and valuable.
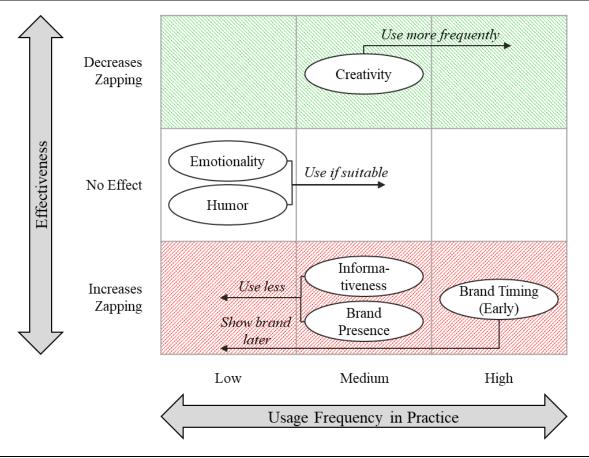
Third, creativity pays off. Our results underscore that the plethora of creativity awards in the advertising industry is justified because creative ads can engage consumers and reduce their zapping behavior. Surprisingly, however, only the minority of ads in our sample (35%) are creative (rated creativity $\geq$ 4), with an even smaller number of ads featuring very creative elements (only 11% rated with a creativity level $\geq$ 5 on a 7-point scale). This suggests that marketers are underutilizing the power of creativity to improve the reach of their ads. Hence, from an engagement and exposure point of view, brand managers are advised to invest in creative agencies. This holds in particular for familiar brands and experience goods. Familiar brands should use creativity to entertain viewers and reduce zapping thereby using the exposure to further strengthen their brand image. Similarly, experience goods should use creative cues (e.g. visual and artistic style) to get the product/service experience across.

Fourth, generally managers do not use humor often (only 6% of ads were rated $\geq$ 4 on humor). Also, unfamiliar brands and search goods do not use humor more often than other groups – but they should! Our results show that for these brand and products, humor can help engage the consumer and reduce zapping. One reason why managers hesitate to use humor might be that everyone interprets humor differently and that some customers may even find

humor offensive. Nevertheless, based on our results managers should not be deterred by this and dare to use humor if it fits the brand message, in particular for less familiar brands and search goods.

Finally, our study also informs brand managers and advertising agencies about the usage of branding cues in TV ads. As pointed out by Gordon Euchler, Head of Planning at BBDO, brand managers often argue for a strong brand presence whereas agencies prefer a low brand presence. Our results suggest that agencies are right in this case – at least when it comes to optimizing reach and minimizing ad avoidance. Across all contexts (except for search goods) our results suggest that excessive branding increases zapping. Moreover, showing the brand early in the spot also increases zapping for familiar brands and search goods whereas showing the brand late in the spot attenuates zapping in these cases. However, almost 75% of the ads in our sample show the brand within the first 5 seconds of the ad. Thus, our results suggest that – contrary to what managers do at the moment – it is better to brand sparsely and place the brand at the end of the spot. Figure 3 provides an overview of the implications by contrasting the content factors based on usage frequency in practice and their impact on zapping.

We want to caution that managers should be aware of certain trade-offs when it comes to advertising content. Making the brand very salient in TV ads annoys viewers and induces ad avoidance. Yet, previous research also shows that heavy branding has a positive effect on downstream metrics, in particular brand recall (Stewart and Furse 1986) and sales (Bruce, Becker, and Reinartz 2019). Similarly, other content factors reduce zapping, but in turn do not translate 1:1 into sales. For example, Teixeira, Picard, and el Kaliouby (2014) find that entertainment has a positive effect on ad interest but a curvilinear (inverted U-shaped) effect on purchase intent because too entertaining ads distract from the brand message. Thus, brand managers should decide on the content strategy of their ads depending on the overall strategic objective of the campaign. If the goal is to build the brand and create a positive brand image,

managers are advised to use creative ads that entertain and stimulate the consumer and show the brand late (Teixeira, Picard, and el Kaliouby 2014). This decreases the likelihood of zapping and ensures effective communication of the brand message. If the goal, however, is to increase sales, managers should rather opt for the "hard-sell" approach by providing relevant information and by branding strongly. Although this might trigger a zap, the activation makes the ad and the brand salient in the consumer's mind leading to positive downstream effects.

Figure 3: Implication Matrix

Notes: Effectiveness based on main model results; Usage frequency based on the representation in our dataset: Low < 20%, 20% < Medium < 60%, and High > 60%. We consider a content factor to be used if the average value of the underlying content cues per spot is larger than the scale mean, e.g., ≥ 4 for creativity.

Lastly, our study also holds important implications for broadcasters seeking to maximize the reach of their ad breaks and thus the attractiveness of their platform. Instead of analyzing the audience for the entire ad break, broadcasters should look into the dynamics of zapping *within* the ad break. By identifying ads that are associated with more ad avoidance broadcasters

can consider different pod placements for them. For example, they could place creative ads at the beginning of the ad break to minimize audience loss – and place "hard-sell" ads with heavy information and branding cues towards the end of the ad break when viewers tend to zap less. To achieve this, broadcasters may consider offering better deals to brands that place ads with zapping-reducing content.

7.2 Theoretical Implications

The significant findings for our content factors are noteworthy. They show that content indeed affects real-world zapping behavior – even after controlling for household and brand fixed effects and several important control variables[17]. This is not for granted as previous field studies (e.g., Danaher 1995; van Meurs 1998) suggested that brand and ad content factors do not have any influence on zapping behavior. In fact, in those studies, it was argued that zapping is purely driven by context factors, i.e., in what environment or to whom the ad is shown (Deng and Mela 2018). Our study is the first to investigate brand and content factors in detail and on a large scale using actual zapping behavior from set-top boxes in combination with expert coding of a large amount of executional content cues. With this precise instrument, we are able to discover significant content effects. Our study, thus, shows that content is an important element when modeling ad avoidance behavior and researchers should account for it accordingly. It further provides external validity to findings of previous lab studies that have assessed the (non-) effectiveness of different content cues for mitigating ad avoidance (e.g., Olney, Holbrook, and Batra 1991; Teixeira, Picard, and el Kaliouby 2014; Woltman Elpers, Wedel, and Pieters 2003).

Yet, our research also shows that it is important to investigate the effect of content on zapping in the field in addition to pre-dominant lab studies. This becomes obvious when we

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[17] We include brand and individual fixed effects as an effective way to control for potential endogeneity (Germann, Ebbes, and Grewal 2015). Yet, the findings do not depend on this specification, as we find similar results without fixed effects.

compare two aspects: First, in the field, we observe zapping rates in the range of 1-3% per spot. Overall, this may cumulate to a dip in reach of the entire commercial break of about 5% (Danaher 1995) to 30% (this study). Thus, zapping continues to be a major challenge for broadcasters and brands. In lab studies, however, the artificial environment leads to a severe overstatement of zapping incidents: Woltman Elpers et al. (2003) report zapping rates per spot between 30% and 82% while Teixeira et al. (2012) report an average zapping rate of 48%. This may overestimate the effects of content factors. Second, context matters a lot. In our study, for example, we find a strong and persistent positive effect of the position on zapping behavior (which is in line with the idea that many viewers automatically zap at the beginning of an ad break). These factors cannot be investigated in a lab setting. Woltman Elpers et al. (2003) for example find no position effect in their study. Moreover, in contrast to lab studies using field data allows researchers to investigate important moderating brand and category effects.

Interestingly, we find similar patterns for the effect of content on zapping as a previous study that investigated the effect of content on sharing in social networks (Tellis et al. 2019). For example, the results of both studies imply that using informational cues is not helpful for most brands as it triggers zapping and reduces the odds of going viral. Similarly, excessive branding in ads is detrimental both in terms of zapping and sharing in social media. These consistent results imply that managers should also consider the effects of the content of their ads across channels. For example, it is common to complement TV campaigns with online media coverage – paid, earned, and owned media. Many brands provide additional creative ad material on their own Youtube channels to stimulate and facilitate social sharing of these ads. Thus, managers can leverage similar creative content in different channels to create synergies. A deeper investigation of the cross-channel consistency of content effects is an exciting area for future research.

7.3 Limitations and Future Research

From a conceptual and a managerial point of view it is important to distinguish between the objective measurement of the ad's content and the subjective perceptions (affective and cognitive) of viewers. We used objective coding for the content to provide managers with actionable insights from real-worlds ads and associated zapping behavior. Yet, this approach is limited with respect to explaining the process of how the different content factors influence zapping. Future research is needed to find a way to combine field data with psychological process insights.

We investigate the phenomenon of ad avoidance in the context of TV ads. Thus, our results are limited to this context. It would be interesting, however, to understand to what extent these effects also hold for online video context (e.g., Youtube). Here, often users have the option to skip an ad either immediately or after a couple of seconds. Also, in this domain, existing research has predominantly been conducted in labs. Thus, future research should investigate the impact of content factors on the skipping behavior of online video (pre-roll) ads in the field.

Lastly, future research is needed to understand how broadcasters can optimally design the ad break as a whole. While we control for position effects, future research might focus on optimizing the sequence of different ad contents. Related to this, subsequent studies might also want to quantify the dollar value of ad-reducing content and assess the viability of position pricing to optimize the ad break.

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APPENDIX ESSAY III

In this Appendix, we provide illustrative examples of TV spots for the different content factors (A). We also provide details on the viewing data and the Passive-Active Zap approach (B) as well as on the content coding procedure (C). Further, the Appendix includes a detailed overview of the variables with operationalization of the control variables and descriptive statistics for all variables (D). Finally, we detail the procedure and the results of the robustness checks (E).

Appendix A: Illustrative TV Spots for Content Factors

Figure A1: Illustrative TV Spot for Emotionality

Figure A2: Illustrative TV Spot for Informativeness

Figure A3: Illustrative TV Spot for Creativity (Low)

Figure A4: Illustrative TV Spot for Creativity (High)
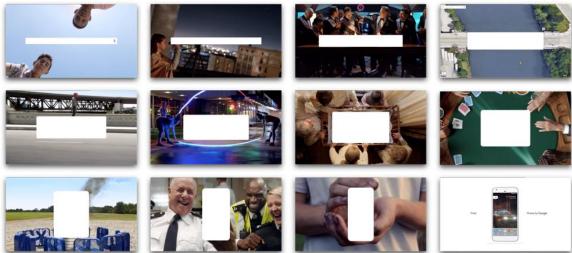
Figure A5: Illustrative TV Spot for Humor

Figure A6: Illustrative TV Spot for Branding

Appendix B: Viewing Data and Passive/Active Zap (PAZ)

We observe the viewing behavior for each individual in the panel on a 5-second-by-5-second level. Thus, for each interval of 5 seconds, we know whether the respective viewer has turned on the channel of interest. If a viewer tunes in or out during the interval, the system records the exact number of seconds that the user was active during the interval (e.g., 3 out of 5 seconds). Thus, even though our data is at the 5-second level, we can infer the exact second, in which a viewer has zapped away. We define a zap as the occurrence of channel switching during a specific ad after a continued duration of watching the program or ad break. For that, we adopt Wilbur's (2016) measure of the Passive/Active Zap (PAZ). The measure treats watching television as a rather passive activity and zapping as an act of active avoidance. The first zap that occurs after a period of continued watching is considered the beginning of the active state (Wilbur 2016). Thus, we focus on the first zap and require each viewer to have watched the program for at least 3 min before the start of the commercial break in order to be considered in our sample. By that, we filter out noise that is induced by viewers tuning in and out shortly before or after the start of the commercial break, which is unlikely to be related to advertising content but rather to the commercial break itself (Wilbur 2016). The 3 min check is performed for each of the 76 ad break, so that an individual may be part of the dataset for one ad break (i.e., no zap in the 3 min before that ad break) but not for others (i.e., zap in the 3 min before the ad break).

The focus on the first zap effectively means that we do not allow viewers to "come back" during one single ad break. Thus, if a viewer (that was considered in the sample for the given ad break based on the 3 min condition) zaps, we record this first zap and remove this viewer for the remainder of the ad break. This is for two reasons: First, the number of additional zaps after an initial zap is relatively low (<10%). Second and more importantly, any subsequent zap is likely to be driven by the fact that a viewer returns to his preferred channel, checking whether

the show has resumed and zapping again after realizing that it is still commercial break (Wilbur 2016). This procedure is consistent with our objective to identify content drivers of zapping.

To determine the length of the passive condition window, we analyzed the show sampling behavior in our dataset. Consistent with previous studies (Deng and Mela 2018; Wilbur 2016) we find that in our dataset the hazard rate of people switching the channel decreases drastically within the first 3 min and remains relatively stable afterwards (see Figure 2, Panel D in the manuscript for an example from Oct 23, 2016). Imposing the 3 min condition reduces our sample size by 5% on average. We tested further possible conditions and found no major sensitivities. In fact, it seems that the loyalty of viewers is comparably high, which may be due to the entertainment format (Schweidel, Foutz, and Tanner 2014).

The final sample comprises 2,517 individuals, which is approximately one quarter of the overall panel size (see Table B1 for an overview of the sample demographics). This underlines the broad appeal of the focal show.

Table B1: Sample Demographics

	Study Sample	Panel
Number of Participants	2,517	11,835
Sex		
Male	41%	48%
Female	59%	52%
Age		
< 18	15%	16%
18-29	11%	10%
30-39	15%	10%
40-49	22%	14%
50-59	21%	18%
60-69	11%	16%
> 69	5%	16%
Household Income (in €)		
< 1000	8%	9%
1000 - 2000	26%	27%
2000 - 3000	28%	28%
3000 - 4000	21%	19%
4000 - 5000	9%	9%
> 5000	8%	8%
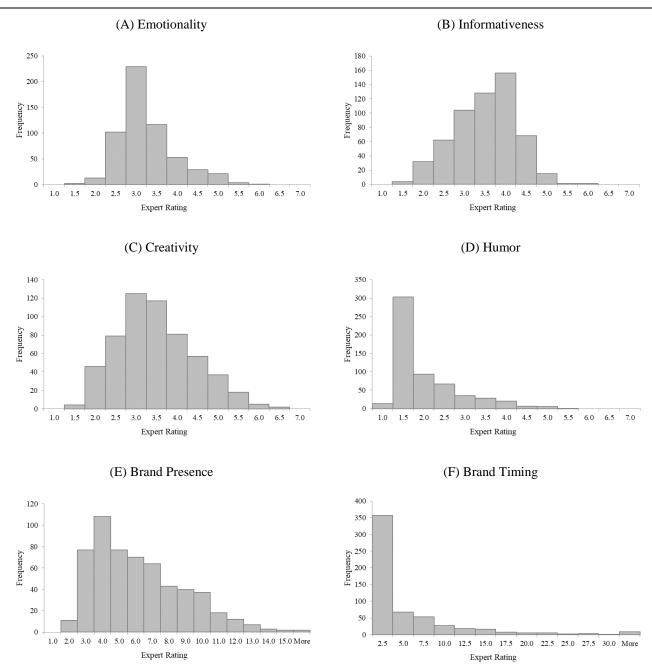
Appendix C: Content Coding

The dataset covers 1,315 spot in 76 ad breaks. Each spot can be identified by a specific "motive code". In an initial step, two research assistants reviewed all spots and identified 571 unique creatives, which form the basis for the content analysis. Consistent with previous studies on video advertising content (Becker, Wiegand, and Reinartz 2019; Chandy et al. 2001; Tellis et al. 2019), we employed a sample of independent experts to evaluate the content cues of the 571 unique creatives in our sample. This procedure ensures the content is evaluated as objectively as possible in order to provide applicable insights for managers and advertisers. The experts that evaluated all executional content cues were five graduate students from a large German university.

Before they started the coding, all experts participated in a one-day training session. During this training, we introduced the coding instructions and explained and discussed all variables based on test video ads that were not part of our dataset. After that, the experts received a set of 20 training ads (again unrelated to our sample) to code at home. We reviewed coding consistency and clarified discrepancies regarding clarity of instructions and understanding of the variables during a second training day.

After this training phase, we provided each expert with the coding instructions and the set of 571 ads for them to code at home at their own pace over a period of 3 months. They were instructed to base their evaluation solely on the information provided in the ads. We also asked them to rate no more than 25 ads per day and to take a break after five ads in a row to avoid fatigue. In order to avoid any order bias, the sequence of the ads was randomized for each expert. On average, the experts needed 5 minutes per ad. Their coding efficiency improved with the number of commercials coded.

Figure D1: Distribution of Content Factors

(A) Emotionality

(B) Informativeness

(C) Creativity

(D) Humor

(E) Brand Presence

(F) Brand Timing

Notes: Distributions of each content factor calculated as the average of the underlying content cues. We chose to display these as an indicator for the level in each content factor as opposed to the distribution of the factor scores because these also include cross-loadings from other content cues. In fact, the distributions of the factor scores show very similar patterns.

Table D1: Operationalization of Control Variables

Variable Name	Description	Operationalization	Mean	SD
First three positions in ad break	Indicates whether the ad was among the first three in the ad break (also including trailers or sponsoring which are not part of the dataset).	1 = first three positions; 0 = other.	.05	.22
Last three positions in ad break	Indicates whether the ad was among the last three in the ad break (also including trailers or sponsoring which are not part of the dataset)	1 = last three positions; 0 = other.	.02	.13
Spot length	Indicates how long the ad is.	Duration of the ad in seconds.	20.58	8.47
Type of ad	Indicates whether the ad was part of a product/sales campaign or a brand/image campaign.	1 = product/sales; 0 = brand/image.	.63	.48
Attractiveness of competing channels	Indicates the attractiveness of the programming on the seven major national channels.	Sum of the ratings of the programming on competing channels at the time of the ad, weighted by accessibility of the program (low, medium, high).	.44	.09
Total ad spend	Indicates the total expenditures for the creative as a proxy for exposure to the ad outside of the focal show.	Log of the expenditures for the creative in 2016 minus the expenditures for airings during the focal show.	6.13	1.70
Exposure to creative	Indicates the degree to which the individual viewer has been exposed to the same creative over the course of the focal show.	Number of previous exposures to the same creative for the given individual during the focal show.	1.64	1.36
Previous zapping	Indicates the extent to which the individual has been actively zapping during previous ad breaks.	Number of zaps (within our sample) prior to the current ad.	0.41	1.21
Multi-person watching	Indicates whether the individual watches the show jointly with other persons from the same household.	1 = multi-person watching; 0 = single-person watching.	0.47	0.50

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Table D2: Correlation Table and Descriptive Statistics for All Variables

Variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1.Zap	1.00																	
2.Emotionality	.01	1.00																
3.Informativeness	.00	-.01	1.00															
4.Creativity	.01	.03	-.04	1.00														
5.Humor	.00	.05	.02	-.20	1.00													
6.Brand presence	.01	-.01	.13	-.02	.05	1.00												
7.Brand timing	.00	-.14	.21	-.19	.00	.02	1.00											
8.First three positions in ad break	.04	.06	-.13	-.16	.00	-.03	-.09	1.00										
9.Last three positions in ad break	-.01	-.02	-.01	-.01	-.01	.01	.04	-.03	1.00									
10.Spot length	.03	.27	.11	.50	.06	.20	.17	-.15	-.01	1.00								
11.Type of ad	-.02	-.28	.50	-.31	.01	.11	.09	-.10	.03	-.27	1.00							
12.Attractiveness of competing channels	.00	-.03	.00	.03	-.02	-.04	.01	.02	.00	.01	-.01	1.00						
13.Total ad spend	.01	.07	.10	.19	.14	.22	.07	-.08	.02	.33	-.07	.02	1.00					
14.Exposure to creative	-.01	-.09	.00	-.06	.05	-.02	-.01	.08	.00	-.08	.04	.01	.18	1.00				
15.Previous zapping	.06	-.01	-.01	.01	-.02	-.01	-.01	.02	.01	.00	.00	.12	.00	-.03	1.00			
16.Multi-person watching	-.02	.00	.00	.00	-.01	.00	.00	.00	.00	.00	.00	-.02	-.01	.02	-.08	1.00		
17.Brand Familiarity	.01	.10	-.01	.12	.05	.01	.16	-.10	.06	.32	-.04	.01	.19	-.04	-.01	-.01	1.00	
18.Search (1) vs. Experience (0) Good	.00	-.10	-.09	.11	-.06	-.12	.09	-.10	.02	.14	-.08	.01	-.19	-.02	-.01	.00	.06	1.00
Min	0	-2.72	-2.62	-2.32	-1.28	-2.38	-1.31	0	0	5	0	.27	0	1	0	0	1	0
Max	1	3.96	3.69	3.39	4.19	4.10	10.50	1	1	89	1	.67	8.60	17	39	1	4.66	1
Mean	.01	-.08	.01	-.04	.02	.02	-.04	.05	.02	20.58	.63	.44	6.13	1.64	.41	.47	3.02	.39
SD	.08	1.00	.98	.96	.98	.95	.84	.22	.13	8.47	.48	.09	1.70	1.36	1.21	.50	.89	.49

Notes: Correlation coefficients shown are Spearman; N= 395,175 (all correlations larger than |.01| are significant for p < .001);

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Table D3: Correlation Matrix for All Content Elements

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1.Creativity	1.00															
2.Emotionality	.00	1.00														
3.Humor	.00	.00	1.00													
4.Informativeness	.00	.00	.00	1.00												
5.Brand presence	.00	.00	.00	.00	1.00											
6.Brand Timing	.00	.00	.00	.00	.00	1.00										
7.Argument	-.43	-.29	-.28	.21	.08	-.10	1.00									
8.Demonstration	.03	.02	-.05	.07	.01	.05	-.28	1.00								
9.Story	.25	.20	.08	.02	-.06	-.08	-.53	-.21	1.00							
10.Drama	.23	.12	.29	-.33	-.03	.18	-.42	-.17	-.32	1.00						
11.Special occasion	-.04	.19	-.05	-.02	.04	.07	.04	-.05	-.03	.02	1.00					
12.Celebrity	.29	-.05	-.10	-.02	-.14	-.08	-.13	.14	.07	-.02	-.01	1.00				
13.Music integration	.13	.07	-.05	.07	.04	-.01	-.01	-.15	.10	.02	.03	.04	1.00			
14.Music type	-.17	-.12	.05	.21	-.08	.01	.15	.01	-.10	-.07	-.05	-.11	NaN	1.00		
15.Music dominance	.33	.03	.00	-.40	.04	.09	-.25	.00	.03	.27	-.02	.11	NaN	-.47	1.00	
16.Jingle	.04	.04	.09	.00	.01	-.04	-.05	-.11	.05	.09	-.06	-.06	-.01	.01	-.02	1.00

Notes: N=571 unique spots. NaN due to missing values (if no music present), in these cases correlation with "Music type" and "Music dominance" based on N=541 (all correlations larger than |.08| are significant for p < .05).

Table D4: Ad Position Choice Across Brands

Brand	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	Total
DR.OETKER	6	7	3	3	2	1	2	2	1	1	3	1	4	3		2	2								43
FITBIT	6	1	1	1	3		3	1	1		3	1	2	2	2	2									29
AMAZON		1	3	1	4	3	3	1	2		1	3		4	1										27
JOCHEN SCHWEIZER		2	3	2	3	1	1	1	1	3	1	2		1	2	4	1								27
MEDIA MARKT			1	1	1	1		2	3	1	2	2	1	1	2	1		1	1	1					22
MERCEDES		1		1							1		1	2	3	5	5	2	1						22
PARSHIP	21																								21
SATURN	1	1	1		5	2		1		1	1	1	2		1	1	1	1							20
POSTER XXL						2	3	4	2	5	4														20
L'OREAL PARIS	3			1	1	1		4	2		1	1	1		1	1		1		1	1				20
1+1		1	3		3		1		2			3	2	3		1			1						20
CHECK24	2	13	1										2						1						19
TELEKOM	1	2	2	1	1	2		1				1	2		1		2	1							17
LIDL	1	1	1		1	2	1	1	1	2		1	2	3											17
SKY			1		3	2	1	1		1	2	2	1	1	1										16
NESPRESSO			2	2	2		1				1	1		2	1			1		1	1				15
VERIVOX						1			2	1	5	2	3					1							15
SAMSUNG	1		1	1	2	1					1		1	2	2	1	1								14
COCA-COLA		1		1	1	1		2		1	1	1		3	1			1							14
NESCAFE	5	3		1							2								2		1				14
APPLE	1	1	2			2			2	2				1	1	1									13
O2			1	4	1	3		1				1	1				1								13
MOBILCOM-DEBITEL	2			2	2	1					1			1	3					1					13
ALWAYS			2	1		1	1	1	1		2	1	1		1				1						13
RENAULT		2		2		1	2				1		1	1	2										12
PHILIPS								3	2	1	5				1										12
ROLLER		1		1	2	1			2	3					1				1						12
MYDAYS						1	1	1	1	1	1			1		3		1			1				12
OTTO			1				1		1	1			1	3	2	1	1								12
CONGSTAR	1	3						2	1			2		1		1									11
PAMPERS			1		1		1		1	2	1	1	1	2											11
GARNIER				1	2	1			1						2		2		1						10
DALLMAYR		2				1			1				1		3		1	1							10
BÄRENMARKE									1	2		1		1	1	1	1						1		9
EDEKA			1	1					1		2	1					1		2						9
HEAD+SHOULDERS			1	1	1	1	1	1		1				1	1										9
GILLETTE		1		1		1					1	1	2					2							9
TCHIBO			3	1					2				2				1								9
COMMERZBANK			1					2	2	1	1							1		1					9
ORAL-B			1		1		1		2		1		1	1		1									9
HERTA			1		1	1	1		1		1		1		1										8
SPECIAL.T			1		1		2					1	1		1								1		8
AMORELIE						1	1	1	2	1	1		1												8
MC DONALD'S				1			1		1			1		2		1	1								8
WICK			1	1					1				2	1			1						1		8

(continued)

Table D4: (continued)

Brand	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	Total
ALDI		1			1	1					2	1	1			7
HIDROFUGAL	4	3														7
BAUHAUS		1	1	1	1	2				1						7
BRUNO BANANI			1		1			2	1		1		1			7
ZTE			1	1		1	1	1	1	1						7
FUERST VON METTERNICH		3			1			1		1		1				7
ABOUT YOU				1		1	1	2		1						6
JEAN PAUL GAULTIER			1	1		1			1	1			1			6
PANTENE PRO-V		1	1		1						1	2				6
FORD		1	1				1		1	1	1					6
MELITTA	2				2		1			1						6
BRAUN			1	1		1		2	1							6
LANCOME		2	1		1				1				1			6
PURINA				1	1				2		1	1				6
HUGO BOSS			2	1							1		1		1	6
PACO RABANNE			2	1		1					1		1			6
AKTION MENSCH			2			1	1	1		1						6
ALLIED						2	1		1		1			1		6
ZALANDO	1	2				1	1							1		6
KINDER	1			1			1		1	1				1		6

Notes: Each cell contains the number of times the respective brand was allocated to the position within the ad break. Brand with presumed strategic position choice are marked in grey. Only brands that aired more than five spots during the focal show are displayed here.

Table D5: Variance Inflation Factors

	VIF
Content Factors	
Emotionality	1.34
Informativeness	1.48
Creativity	1.65
Humor	1.11
Brand presence	1.20
Brand timing	1.50
Controls	
First three positions in ad break	1.10
Last three positions in ad break	1.01
Spot length	2.44
Type of ad	1.81
Attractiveness of competing channels	1.02
Total ad spend	1.13
Exposure to creative	6.22
Exposure to creative ^{2}	6.14
Previous zapping	1.02
Multi-person watching	1.01

Appendix E: Model Specification and Robustness Checks

Table E1 details the results of the moderator analysis. In addition, we performed several additional analyses to check whether our estimation results are robust. *First*, we check whether our findings are sensitive to *model specifications*. For that, we consider several alternative model specifications:

- A model with brand fixed effects only → see model (I) in Table E2

- A model with individual fixed effects only → see model (II) in Table E2

- A model without any fixed effects (thus pooling the observations across all brands and individuals) → see model (III) in Table E2

- An aggregate model of the number of zaps per spot using a Poisson specification → see Table E3

Second and third, we investigate whether our *results are driven by specific ads or specific brands respectively*. For that, we identify the specific ads and remove them from the dataset before estimated the main model. Specifically, we look at two potential confounding aspects:

- Ads that are very similar to the surrounding programming, i.e., ads promoting entertainment services (e.g., artists' new albums, movies, concerts). We eliminate all ads related to entertainment and estimate the main model for the reduced sample. → see model (I) in Table E4

- Ads belonging to brands with a presumed strategic position choice, as identified in Table D4. We remove the three brands (Parship, Check24, and Hidrofugal) and re-estimated the model. → see model (II) in Table E4

Fourth, we estimate the main model using *alternative operationalizations* of the control variables. → see Table E5

- For the position variables, we employ dummy variables indicating the very first and very last spot in the commercial break (instead of first three and last three).

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- For exposure to the creative, we count the number of previous exposures to the same creative for the given individual on the same day (instead of all dates in our sample).

- In addition, we include a measure for category clutter as suggested by Schweidel, Foutz, and Tanner (2014). For that, we compute the number of exposures to ads from the same category within the same ad break.

- For previous zapping, we use a dummy indicating whether the individual zapped during the previous ad break (instead of a counter across all ad breaks).

Finally, we test the *validity of our conceptualization*. For that, we had three research assistants dummy code the spots in our sample for another set of concrete advertising cues (e.g., plot type, celebrities, music, special occasion). Similar to Tellis et al. (2019), we wanted to understand how these elements are related to the content factors. We trained coders in the same manner as for the main study and assessed reliability using Krippendorf's Alpha (Krippendorff 2004). All variables reached satisfying levels of reliability; disagreements were solved by discussion. The results displayed in → Table E7 show interesting patterns. Most importantly, we find that using celebrities is positively associated with creativity of the ads but negatively with emotionality and informativeness. Moreover, verbal music enhances emotionality of the ads. Similarly, dominant music is positively related to creativity but negatively related to humor. We also find a positive correlation between featuring special occasions and emotionality. Several emotional spots related to Christmas (recall our sample period is October to December 2016) can explain this finding. To test the conceptual validity of our framework, we estimated an alternative model that contains the aforementioned additional content cues as explanatory variables of zapping → see Table E6. We find that none of the additional content cues except for special occasion has a significant effect on zapping. Together, these findings support our conceptualization of advertising content and its impact on zapping.

Table E1: Results Moderation Analysis (Details)

	Brand Familiarity		Category Type	
	Low	**High**	**Search Good**	**Experience Good**
Content Factors				
Emotionality	.095 (.133)	-.055 (.062)	-.085 (.078)	-.045 (.085)
Informativeness	.027 (.144)	.152* (.066)	.116 (.092)	.204** (.078)
Creativity	-.079 (.175)	-.156* (.078)	-.103 (.115)	-.260** (.096)
Humor	-.202** (.079)	.021 (.051)	-.122* (.062)	.078 (.052)
Brand presence	.296* (.145)	.124* (.055)	.086 (.084)	.203** (.064)
Brand timing	-.243 (.172)	-.098* (.046)	-.173** (.057)	-.120 (.105)
Controls				
First three ads in ad break	1.401*** (.171)	.873*** (.132)	1.059*** (.208)	1.080*** (.116)
Last three ads in ad break	-1.938*** (.385)	-1.120*** (.291)	-.968* (.402)	-1.351** (.421)
Spot length	.072*** (.016)	.036*** (.007)	.042*** (.010)	.048*** (.015)
Type of ad	-.201 (.187)	-.162 (.124)	-.539*** (.161)	-.090 (.136)
Attractiveness of competing channels	-.471 (.450)	.445 (.376)	.375 (.483)	-.254 (.353)
Total ad spend	-.038 (.041)	-.055 (.032)	-.022 (.039)	-.048 (.032)
Exposure to creative	.161 (.079)	.016 (.072)	.104 (.087)	.085 (.067)
Exposure to creative ^{2}	-.016 (.010)	.005 (.008)	-.004 (.010)	-.008 (.008)
Previous zapping	.076*** (.016)	.114*** (.018)	.074*** (.021)	.107*** (.015)
Multi-person watching	-.109 (.116)	-.323** (.107)	-.239 (.130)	-.221* (.099)
Individual fixed effects	✓	✓	✓	✓
Brand fixed effects	✓	✓	✓	✓
R^2	.197	.178	.182	.190
log likelihood	-5,650	-6,069	-4,245	-7,496
N (observations)	83,921	89,387	57,648	117,188
N (brands)	168	100	107	162
N (individuals)	805	865	688	958

Notes: Standard errors are in parentheses. ✓ indicates that these variables / fixed effects are included in the model.
*p < .05, **p < .01, ***p < .001

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Table E2: Results Alternative Model Specifications

	(I) GLM w/ Brand Fixed Effects		(II) GLM w/ Individual Fixed Effects		(III) GLM w/o Fixed Effects	
Intercept	-	-	-	-	-5.370***	(.148)
Content Factors						
Emotionality	-.037	(.051)	-.055*	(.022)	-.080***	(.022)
Informativeness	.173**	(.035)	.047*	(.024)	.062**	(.023)
Creativity	-.217***	(.064)	-.054*	(.027)	-.078**	(.026)
Humor	-.006	(.035)	-.031	(.021)	-.020	(.020)
Brand presence	.133**	(.047)	.031	(.022)	.027	(.021)
Brand timing	-.157***	(.038)	-.129***	(.024)	-.138***	(.023)
Controls						
First three ads in ad break	1.255***	(.089)	.998***	(.063)	1.448***	(.057)
Last three ads in ad break	-1.324***	(.287)	-.908***	(.261)	-1.015***	(.260)
Spot length	.043***	(.006)	.049***	(.003)	.047***	(.003)
Type of ad	-.224*	(.095)	-.205***	(.053)	-.232***	(.052)
Attractiveness of competing channels	-.306	(.245)	-.282	(.251)	-.530*	(.214)
Total ad spend	-.018	(.022)	-.011	(.012)	-.000	(.012)
Exposure to creative	-.315***	(.045)	.084	(.049)	-.251***	(.043)
Exposure to creative ^{2}	.016**	(.005)	.006	(-.900)	.013*	(.005)
Previous zapping	.169***	(.006)	.096***	(.012)	.167***	(.006)
Multi-person watching	-.297***	(.040)	-.217***	(.078)	-.298***	(.039)
Individual fixed effects	-		✓		-	
Brand fixed effects	✓		-		-	
R^2	.067		.160		.047	
log likelihood	-15,554		-12,950		-15,976	
N (observations)	381,733		246,153		395,175	
N (brand)	268		308		308	
N (individuals)	2,517		1,275		2,517	

Notes: Standard errors are in parentheses.
*p < .05, **p < .01, ***p < .001

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Table E3: Results Aggregated Sample

	Poisson GLM	
Intercept	-.117	(.138)
Content Factors		
Emotionality	-.061**	(.021)
Informativeness	.054*	(.023)
Creativity	-.054*	(.026)
Humor	-.017	(.020)
Brand presence	.048*	(.021)
Brand timing	-.136***	(.022)
Controls		
First three positions in ad break	1.474***	(.056)
Last three positions in ad break	-1.035***	(.259)
Spot length	.047***	(.003)
Type of ad	-.200***	(.052)
Attractiveness of competing channels	-.308	(.209)
Total ad spend	-.006	(.011)
R^2	.264	
log likelihood	-1,360	
N	1,315	

Notes: Standard errors are in parentheses.
*p < .05, **p < .01, ***p < .001

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Table E4: Results for Specific Subsamples

	(I) Model w/o Show Format Related Ads		(II) Model w/o Three Brands with Strategic Position Choice	
Content Factors				
Emotionality	-.049	(.054)	-.052	(.054)
Informativeness	.163**	(.059)	.188**	(.058)
Creativity	-.163***	(.069)	-.183***	(.068)
Humor	.001	(.038)	-.019	(.046)
Brand presence	.138**	(.050)	.150**	(.050)
Brand timing	-.156***	(.040)	-.151***	(.040)
Controls				
First three ads in ad break	.952***	(.100)	.970***	(.102)
Last three ads in ad break	-1.176***	(.288)	-1.177***	(.288)
Spot length	.043***	(.006)	.044***	(.006)
Type of ad	-.245*	(.106)	-.225*	(.100)
Attractiveness of competing channels	.074	(.286)	.205	(.290)
Total ad spend	-.032	(.024)	-.024	(.024)
Exposure to creative	.072	(.053)	.063	(.052)
Exposure to creative ^{2}	-.005	(.006)	-.002	(.006)
Previous zapping	.094***	(.013)	.085***	(.013)
Multi-person watching	-.205**	(.079)	-.253**	(.081)
Individual fixed effects	✓		✓	
Brand fixed effects	✓		✓	
R^2	.185		.198	
log likelihood	-11,988		-11,578	
N (observations)	220,180		221,790	
N (brand)	245		265	
N (individuals)	1,248		1,208	

Notes: Standard errors are in parentheses.

*p < .05, **p < .01, ***p < .001

Table E5: Results Alternative Variable Operationalizations

	Estimated Effect on Zapping	
Content Factors		
Emotionality	-.081	(.054)
Informativeness	.161**	(.057)
Creativity	-.189**	(.068)
Humor	-.003	(.038)
Brand presence	.147**	(.050)
Brand timing	-.165***	(.039)
Controls		
First ad in ad break[A]	.671***	(.083)
Last ad in ad break[A]	-.230***	(.117)
Spot length	.045***	(.006)
Type of ad	-.271**	(.099)
Attractiveness of competing channels	.489	(.277)
Total ad spend	-.038	(.024)
Exposure to creative (per day) [A]	.056	(.086)
Exposure to ads from same category (per break) [A]	-.332***	(.058)
Zap during previous ad break[A]	.413***	(.063)
Multi-person watching	-.228**	(.078)
Individual fixed effects	✓	
Brand fixed effects	✓	
R²	.178	
log likelihood	12,601	
N	237,851	

Notes: Standard errors are in parentheses. N (brands) = 268; N (individuals) = 1,275.
[A] indicates alternative variable operationalization:

- Position variables: Dummy for first/last position in the ad break, without considering sponsoring/trailer (instead of first/last three ads).
- Exposure to creative (per day): Number of previous exposures to the same creative for the given individual on the same day (instead of all dates in our sample)
- Exposure to ads from same category (per break): Number of exposures to ads from the same category within the same ad break (as an additional measure for clutter)
- Zap during previous ad break: Dummy variable indicating whether the individual zapped during the previous ad break (instead of counter across all ad breaks).

*p < .05, **p < .01, ***p < .001

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Table E6: Results Alternative Content Cues

	Estimated Effect on Zapping	
Content Factors		
Emotionality	-.019	(.057)
Informativeness	.149*	(.058)
Creativity	-.192**	(.069)
Humor	-.018	(.041)
Brand presence	.139 **	(.050)
Brand timing	-.170***	(.041)
Additional Content Factors		
Music integration	.004	(.265)
Celebrity	.260	(.146)
Jingle	.445	(.234)
Drama	-.042	(.128)
Story	-.041	(.106)
Special occasion	-.221*	(.107)
Controls		
First three positions in ad break	.964***	(.100)
Last three positions in ad break	-1.168***	(.288)
Spot length	.046***	(.006)
Type of ad	-.251*	(.100)
Attractiveness of competing channels	-.002	(.281)
Total ad spend	-.019	(.024)
Exposure to creative	.080	(.052)
Exposure to creative [2]	-.005	(.006)
Previous zapping	.092***	(.012)
Multi-person watching	-.229***	(.078)
Individual fixed effects	✓	
Brand fixed effects	✓	
R^2	.178	
log likelihood	-12,591	
N	237,873	

Notes: Standard errors are in parentheses. N (brands) = 268; N (individuals) = 1,275.
*p < .05, **p < .01, ***p < .001

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Table E7: Drivers of Content Factors

Content Cues	Creativity		Emotionality		Humor		Informativeness	
	Mean	p-value	Mean	p-value	Mean	p-value	Mean	p-value
Demonstration	.572	.000***	.501	.001***	.113	.425	.201	.177
Story	.741	.000***	.717	.000***	-.116	.217	.540	.000***
Drama	.723	.000***	.670	.000***	-.660	.000***	-.974	.000***
Celebrity	.575	.000***	-.238	.029*	.021	.840	-.243	.027*
Music Type[1]	.013	.882	-.241	.013*	.101	.272	.112	.247
Music Dominance	.456	.000***	-.190	.061	-.642	.000***	-.160	.117
Special Occasion	-.067	.557	.671	.000***	-.036	.765	-.147	.245
Jingle	.108	.344	.068	.588	.113	.349	.101	.424

Notes: N = 541 unique spots. [1] Dummy coding: 1=Instrumental, 0=Verbal; Category "Argument" serves as baseline for "Demonstration", "Story", and "Drama" dummies. *p < .05, **p < .01, ***p < .001.

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