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IS IT WORTH IT? DISMANTLING THE PROCESS OF SOCIAL MEDIA RELATED SALES PERFORMANCE

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Research Paper

Abstract

Social media platforms present unique possibilities for companies to interact with their customers and take up a key role in building relationships. A substantial body of research has demonstrated the impact of social media regarding, for example, brand awareness and corporate reputation. However, little is known concerning the financial Return on Investment from social media engagement and specific strategies to leverage it. To this end, the study draws on relationship marketing theory to develop and operationalise a research model, which understands objective firm performance in terms of sales as a result of relationship antecedents (i.e., corporate investment and dyadic similarity) mediated through the customer-perceived relationship strength. To test the assumed research model, we collect and analyse a dataset of over 1.5 million Twitter messages revolving around ten car manufacturers and measure the impact on new car registration volumes. The results of this study suggest that companies can increase their sales volume through greater relationship investment (i.e., by providing interest group-specific information) and by adopting a social media strategy that promotes the users' relationship satisfaction (i.e., raises the share of voice within user messages).

Keywords: Social Media Engagement, Objective Firm Performance, Sales, Relationship Marketing, Twitter.

1 Introduction

Social media platforms have become an established channel for companies to engage with users (Burton and Soboleva, 2011), draw conclusions about their opinions (Bulearca and Bulearca, 2010), and increase brand awareness (Jansen et al., 2009). Accordingly, most companies operate social media accounts to exchange information with their customers (Wagner, 2014). However, research has just begun to investigate the Return on Investment (ROI) that companies can derive from social media (Hoffman and Fodor, 2010). Regarding the appropriate measures for ROI, on the one hand, some researchers argue that social media does not revolve around sales but rather around building a community and fostering communication. Therefore, appropriate measures for social media investments would be platform-based and platform-specific attributes (e.g., attention, interaction, share of voice) (Fisher, 2009). On the other hand, 56% of practitioners reported that the biggest issue of social marketing was to relate social media activities to business outcomes (Etlinger et al., 2012) and that – as social media mature – bottom-line objective financial outcomes become essential (Kane et al., 2014b).

In recent years, research has begun to relate social media metrics to the objective firm performance. The majority of findings suggest a positive relation between a company's equity value and its social media engagement, for example, in terms of advertising campaigns or message numbers (Chung et al., 2014; Tirunillai and Tellis, 2012). Other studies have found corporate social media engagement to positively affect sales figures and profits (e.g., Goh et al., 2013; Ramkumar et al., 2013). While the existent research provides an encouraging starting point regarding the efficacy of social media engagement on the objective firm performance, current studies are limited in different regards. The related studies only consider single marketing campaigns or launches of social media accounts instead of the regular engagement behaviour (Kumar et al., 2013; Ramkumar et al., 2013; Tirunillai and Tellis, 2012), focus on ambiguous stock market measures instead of the more direct sales numbers (Chung et al., 2014; Hitt et al., 2015), are restricted to single company cases instead of more generalizable effects of multiple companies (Goh et al., 2013), or disregard company engagement efforts altogether (Seebach et al., 2011; Skodda and Benthaus, 2015). Moreover, the studies differ regarding their theoretical foundation or do not refer to a general theoretical framework at all. Consequently, researchers use the same measures (e.g., sentiment) for different constructs (e.g., word of mouth, valence of user-generated content) or operationalise the same constructs (e.g., communication intensity) through different measures (e.g., weighed number and valence of all past interactions, number of messages and comments). Furthermore, these constructs are used arbitrarily in the studies' research models (e.g., word of mouth as a predictor, mediator or outcome variable).

Accordingly, calls for research are surfacing, because the process of social media related objective firm performance is insufficiently understood up to date (Aral et al., 2013; Laroche et al., 2013) and research offers only little advice for firms on how to strategically use social media (Chung et al., 2014). Besides, currently it remains unclear how the firms' strategic use of online user communities can translate into business value (Dong and Wu, 2015). To address these aforementioned limitations, we refer to the established relationship marketing theory to comprehensively synthesise related research on business value creation through social media and operationalise constructs to test a theory-driven research model. In a nutshell, relationship marketing encompasses all corporate endeavours to build and maintain relationships with their customers (Morgan and Hunt, 1994). We regard relationship marketing to be an appropriate theoretical basis, because of its coherence with social media's core ability to facilitate interactions and deepen connections between firms and users (Ramkumar et al., 2013). In reference to relationship marketing, we assess the objective firm performance through its sales numbers (Palmatier et al., 2006). This is especially relevant for the context of business value of IT. In this regard, we concur with recent research that does not measure value in terms of the amount companies invest in IT but by considering the process of how companies can derive business value from social media (Dong and Wu, 2015). Overall, in this study we investigate *how corporate- and user-based social media attributes translate into objective firm performance*.

To address this research question, we collected and analysed a sample of more than 1.5 million Twitter messages from and about ten car companies as well as their respective new vehicle registration volumes from January 2014 to September 2015. Thereby, we expand the existent research perspective to the simultaneous consideration of customer- and corporation-based estimates, as well as their dyadic relationship strength to predict objective financial outcomes.

The remainder of this paper is organized as follows. First, we introduce relationship marketing theory and derive the study's underlying research model. Afterwards, we integrate existent social media findings in the assumed process of translating relational antecedents and mediators into objective financial outcomes based on theory. Here we also develop the study's respective hypotheses, which we test empirically in the subsequent chapter. Lastly, we discuss the study's findings with reference to the literature in the light of the relevant limitations and outline future research directions.

2 Theoretical Background

In this study, we focus on the process of social media based factors that enhance objective firm performance, which is currently only insufficiently understood and, thus, is of particular interest to social media research (Aral et al., 2013; Laroche et al., 2013). We transfer the established relationship marketing concept to the context of social media in order to comprehensively integrate existent social media research, derive meaningful constructs, and gain an understanding of their interdependencies. Considering the relationship building nature of social media, relationship marketing seems to be an appropriate theoretical foundation since it is understood as "*activities directed towards establishing, developing, and maintaining successful relational exchanges*" (Morgan and Hunt, 1994, pp. 22). We conceptually follow the framework of factors influencing the effectiveness of relationship marketing from Palmatier et al. (2006), which provides an extensive overview of key constructs and their relations. It distinguishes between relational antecedents, customer-focused mediators, and seller-focused outcomes (see figure 1) which are described in further detail below. It needs to be noted that the following literature overview and integration of previous findings follows the understanding of the aforementioned model. We apply the definitions and classifications of constructs from relationship marketing, which sometimes diverge from the terminology or model specification in the referenced studies. The currently inconsistent use of concepts within the social media literature demonstrates the importance of introducing a common theoretical framework for understanding relationship building and relational outcomes in social media.

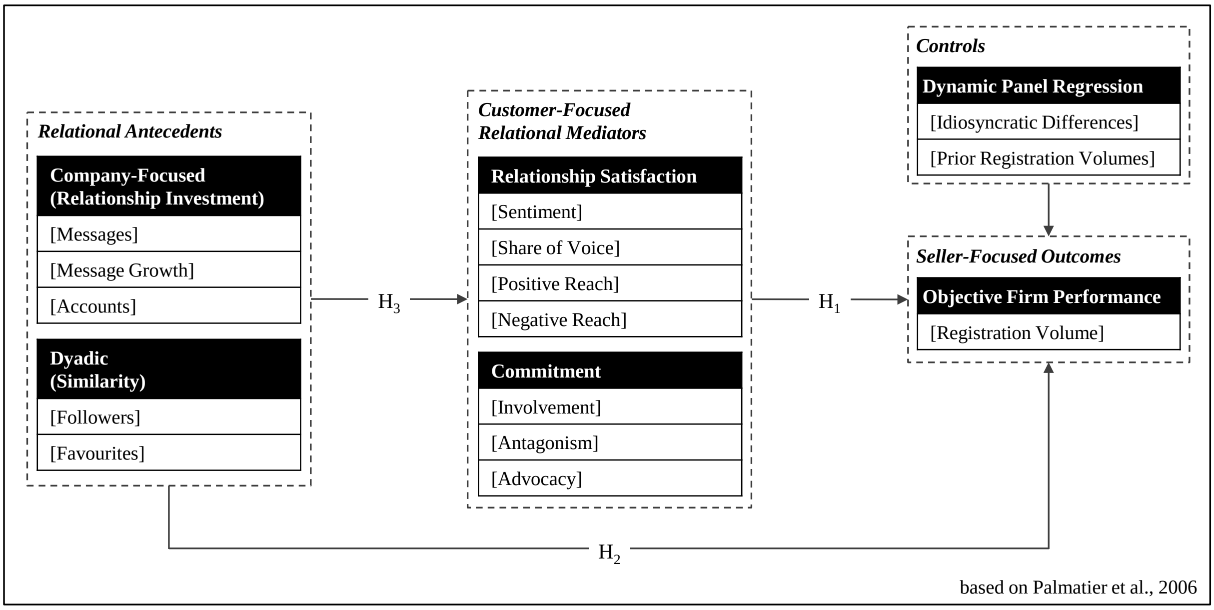

Figure 1. Research model for the mediator analysis of social media activities on objective firm performance.

2.1 Objective firm performance

Business value of the substantial research efforts regarding relationship marketing have produced several different relational outcome measures for success. Instead of customer-focused (i.e., expectation of continuity, word of mouth, and customer loyalty) or dyadic outcomes (i.e., cooperation), in this study we assess seller-focused outcomes (i.e., objective firm performance) which are arguably the ultimate success measure (Kane et al., 2014b). Objective firm performance is understood as the "*actual seller performance enhancements including sales […]*" and has been found to be affected among others by relationship investment, relationship satisfaction, and commitment (Palmatier et al., 2006, pp. 139). It needs to be noted, however, that while these relationship characteristics have a significant impact on financial performance measures like sales, their impact on dyadic and customer-focused outcomes is stronger (Palmatier et al., 2006). This indicates that even though financial ROI measures are ultimately decisive for companies, the actual benefits of relationship marketing and social media management might be more appropriately measured in other relationship oriented outcomes (Hoffman and Fodor, 2010).

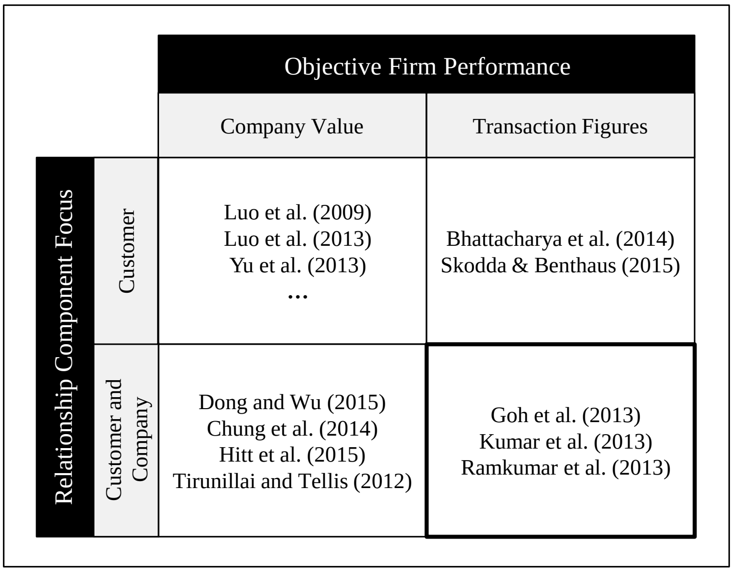

Figure 2. Overview of related social media research on objective firm performance.

The existent research on the relation between social media and objective firm performance can be classified based on the two commonly measured types of outcomes: company value and transaction figures (see figure 2). The highlighted quadrant constitutes the research focus of this study. The majority of the respective research measures the effects on firm equity value (e.g., Tobin's q, abnormal returns, stock prices) especially under consideration of user-generated content. As indicated through "…" in figure 2, a substantial body of research exists for the relationship between customer characteristics on social media and company value commonly assessed through equity prices (Risius et al., 2015). This line of research generally establishes a positive relationship between user sentiment and objective firm performance across different types of content (i.e., consumer ratings, forum postings, blogs, and microblogging messages) (Luo et al., 2013; Yu et al., 2013) with a particularly strong effect of negative sentiment (Luo, 2007; Luo, 2009; Risius et al., 2015; Tirunillai and Tellis, 2012) and user engagement (i.e., postings, comments, likes) (Chung et al., 2014). While equity value is a strong objective indicator of firm performance, it is affected by a variety of alternative factors like other unrelated corporate events (e.g., sales numbers, chairman changes) or industry developments (e.g., market growth, national economic rates) (Palmatier et al., 2006). Considering that a company's sales precede its equity value and following the law of parsimony, sales figures are more meaningful regarding the objective firm performance in this case. Accordingly, social media researchers increasingly associate a firm's online activities with sales figures. These findings demonstrate the respective predictive power of online search behaviour (Seebach et al., 2011), user sentiment (Bhattacharya et al., 2014; Skodda and Benthaus, 2015), active corporate social media engagement (Goh et al., 2013; Ramkumar et al., 2013) and marketing campaigns (Kumar et al., 2013). Considering the theoretical deliberations in combination with this initial empirical evidence for the validity of sales as a objective firm performance outcome (Palmatier et al., 2006), we regard a sales approximation to be a viable objective success measure for corporate social media activities.

2.2 Relationship components affecting objective firm performance

From a relationship marketing perspective, the strength of a relational bond between companies and customers is the key asset for deriving financial value from relational antecedents. A substantial body of research has identified different congeneric facets of these *customer-focused relational mediators* such as commitment and relationship satisfaction, which affect corporate performance. Considering that there is not one single best mediator to comprehensively capture the bonding between company and customer, we consider multiple aspects of the relational bond to account for synergistic mediator effects (Palmatier et al., 2006). Commitment describes the enduring (affective, behavioural, obligated, or normative) desire to maintain a valued relationship. It has been shown to have an especially strong impact on customer loyalty (Morgan and Hunt, 1994). Relationship satisfaction represents the customer's affective or emotional attitude toward a relationship and has been found to be an even stronger predictor of objective performance than commitment (Palmatier et al., 2006).

As shown earlier, the most information systems research relating social media metrics to actual firm performance has addressed these customer-focused perceptions of a brand. Researchers have been able to explain company performance by analysing user-generated content from social media. In general, this research has shown that a positive valuation of the companies from the customers translates into an improved firm performance. The relationship satisfaction has been measured in different ways such as user ratings of a company's products or the sentiment expressed in messages about a company across different platforms (i.e., blogs, microblogs, e-commerce websites, and forums). The social media enabled relationship strength has even stronger explanatory power of company performance than alternative behavioural metrics online (e.g., Google searches) or offline (e.g., conventional media) (Luo et al., 2013; Yu et al., 2013). These findings pertain across industries as well as specifically in the automotive sector (Seebach et al., 2011; Skodda and Benthaus, 2015). More detailed assessments of user-firm relationships have shown that especially a deterioration of the relationship affects corporate success (Luo, 2009; Risius et al., 2015). Recent findings indicate that it is not solely the publicly expressed affection for a company but its conformity with the privately held sentiment that explains purchase behaviour (Bhattacharya et al., 2014). Moreover, Chung et al. (2014) found positive effects of user commitment in terms of active consumer engagement on the objective firm performance. Considering the apparent theoretical and empirical insights, we propose:

H_1: *The stronger the relational bonding between users and companies, the better the companies' sales performance.*

Regarding the *relational antecedents*, researchers have investigated the effects of different relationship marketing endeavours. Among the company-focused relationship marketing strategies, relationship investment has been found to have the strongest direct impact on sales performance. It is defined through the amount of resources (e.g., time, effort, or personnel) spent on building stronger relationships with customers. Additionally, to extend the study's theoretical perspective beyond the common singular consideration of customer- or company-focused characteristics, we also include dyadic antecedents. By considering measures for the dyadic exchange quality, we acknowledge that both sides are actively involved in the relationship building and that its success is also a matter of the mutual perceptions. Thus, we assess similarity of users and companies, which is broadly understood as the degree of commonality in appearance and values between parties (Palmatier et al., 2006).

Recently, information systems research has begun to investigate the role of relational antecedents in form of corporate efforts on social media platforms. The findings generally show that increased corporate engagement in social media and a firm's capability to implement user-generated innovation recommendations improves its financial value (Dong and Wu, 2015; Hitt et al., 2015). This active engagement can encompass relational investments that range from launching a social media presence

(Ramkumar et al., 2013), over dedicating marketers to engage in brand related conversations (Goh et al., 2013), up to launching targeted social media campaigns (Kumar et al., 2013). Empirical findings suggest that increased relationship investment also translates into an improved sales performance on a more regular basis. For example, the investment of additional resources by facilitating access to information through sending more messages (Ramkumar et al., 2013), messaging more frequently, and enriching posts with different media types increases seller-focused outcomes (Chung et al., 2014). Respectively, open display of similarity with a brand by becoming a follower has been found to cause a feeling of connectedness and increases the profitability of a company (Ramkumar et al., 2013). Thus, we hypothesize:

H_2: *The stronger the relational antecedents, the better the companies' sales performance.*

While the specific type of relational bonding variable usually differs across studies, relationship marketing literature consistently assumes a *mediating model* for the impact of relational antecedents on objective performance. It is, for example, assumed that relationship investments cause expectations of reciprocity, which strengthens a relationship and positively affects relational mediators (Wulf et al., 2001). Furthermore, similarity can positively affect relational mediators by indicating that an exchange partner will support the counterpart's attainment of aspired goals. Accordingly, relationship investment and similarity have been found to be strongly related to relational mediators (Morgan and Hunt, 1994). While the effect of relationship investment on objective performance is only partially explained through relational mediators, similarity is strongly associated with commitment. The latter can be explained through the fact that similarity is a proxy for group-membership and that individuals strive to build strong relationships with "in-group" members (Palmatier et al., 2006).

Only a small share of information systems research has considered mediating effects on the firm sales performance. These findings, however, support the assumption of a mediating role of user-focused characteristics for the efficacy of corporate endeavours on its profits. Kumar et al. (2013) and Wulf et al. (2001) found customer based relationship satisfaction and its spread through the network to explain the efficacy of a higher relationship investment in form of a social media campaign. Also, increased offline investments in terms of advertising campaigns translate into improved relationship satisfaction on social media platforms (i.e., share of voice and sentiment), which account for abnormal returns on the stock market (Tirunillai and Tellis, 2012). Similarly, commitment in terms of user engagement behaviour has been found to mediate the effects of regular relationship investment on corporate equity values (Chung et al., 2014). We therefore assume:

Hypothesis 3: The effects of relational antecedents on the companies' sales performance are mediated by the strength of the relational bonding between users and companies.

3 Empirical Study

In order to examine the effects of social media on business outcomes and how companies can extract value from social media, we analysed the B2C relationship on Twitter and the respective seller performance in terms of new car registrations. Out of the different social media platforms worth analysing regarding our research question, we selected Twitter, which has been shown to be a viable solution for e-commerce activities by enabling organizations to successfully communicate with customers (Burton and Soboleva, 2011) and draw conclusions about users' opinions (Bulearca and Bulearca, 2010).

3.1 Case description and data collection

The study's method of data collection, processing, and analysis was based on the related multi-step process of knowledge discovery in databases developed by Fayyad et al. (1996).

In the first step, we *selected the sample* of car manufacturers whose social media enabled relationship marketing we wanted to analyse. Since the German automobile market is the only leading automotive market to offer comparable and reliable vehicle registration data to the public, we focused our analysis on the respective market. Thus, we obtained the monthly brand-new vehicle registration volumes from the German Federal Motor Transportation Authority. From the different possible manufacturers, we selected ten companies with the highest registration volume and the most unambiguous names. Thereby, we ensured to only consider popular brands with sufficient public interest to trigger an adequate number of social media messages with a reasonably low amount of data noise. These companies account for almost 80% of the overall new vehicle registrations during our analysis period.

The second step of *data collection* was conducted through a certified social media provider in order to collect messages in German from the microblogging platform. We identified keywords comprising the various spellings of the company names and their accounts to gather tweets from and about the selected companies. Each tweet that contained one of the keywords was considered for further analysis (keyword sample). The Twitter "firehose" data access from the professional social media data provider enabled us to collect all of the messages containing one of the keywords. The full data access ensures the elimination of common biases from the download rate restrictions of the public API access (e.g., underrepresentation of retweets or temporary interruptions) and provides additional meta-information on the account sending a message (e.g., number of followers and favourites). The keyword sample also prevents distortions from the less resource intensive tracking of hashtagged tweets (Bruns and Stieglitz, 2013). Overall, we collected 2,159,506 tweets that address or are sent from one of the selected ten companies during the period of January 2014 to September 2015.

The third step of *cleaning and pre-processing* of the tweets followed an objective set of rules to remove data noise from unrelated messages for the subsequent analysis. We first removed messages from noisy and spamming users before removing unrelated messages. In combination with the filters used for the data collection, we intend to improve data quality through the manual processing (Stieglitz et al., 2014). Initially, we manually screened the user tweets for usernames which were collected because they included one of the keywords but did not actually contain any information regarding the target (e.g., Max_Volkswagen_). In this way, tweets from and towards these 4,000 users with confounded names were removed from the sample. Subsequently, to exclude spamming users we considered the individual share of followers and tweets as an exclusion criterion. Following a rule of thumb, we deleted all tweets sent from users with zero followers and more than 50 messages as well as messages from users with fewer than 100 followers and a tweets-to-followers-ratio of 1,000 or higher. In the last cleaning step, we computed a word cloud based on the tweet content and screened the data for messages, which were unrelated to the company for other reasons (e.g., containing the name of a company sponsored sports arena) and consequently excluded tweets based on the 133 accordingly identified terms. In essence, we deleted 26% noisy tweets, which results in the final dataset of 36,320 tweets from company accounts and 1,593,978 user-generated messages.

3.2 Method and measures

In the following step, we transformed our dataset into the different antecedent, mediator, and outcome variables. To measure the *objective performance of a company*, in line with previous studies we used the monthly new vehicle registration volumes as a proxy for car sales (Requena-Silvente and Walker, 2007; Seebach et al., 2011). Next, we assessed relational antecedents through relationship investment and the dyadic relationship. To measure a company's *relationship investment*, we considered immediately manageable features of the company's social media presence in form of message (*Messages*) and account numbers (*Accounts*). Thereby, we assume that sending messages more frequently and actively managing multiple interest-group specific accounts represents a larger corporate relationship investment of time, effort, and resources. Thus, we computed the sum of messages sent from any corporate account and the number of accounts involved in sending these messages over the course of one month. To account for information overload issues, we also included the natural logarithm of message numbers since we expect that for each additional message sent to one's network, there will be a diminishing appreciation for the information of that message. The *similarity* between brands and users was approximated through the number of followers (*Followers*) and favourites (*Favourites*) of the aforementioned active company accounts. The number of followers is assumed to indicate the level of connectedness between a company and the users who voluntarily demonstrate their affinity toward the company (Clark and Melancon, 2013). We consider Twitter account favourites to be structurally comparable to Facebook 'Likes' (which have received more research attention) in the sense that they predominantly express a positive association with a party and indicate a similarity of interests (Kosinski et al., 2013). Customer-focused relational mediators were assessed through relationship satisfaction and commitment from the users. The common underlying measure of these metrics was the sentiment expressed in the user-generated messages. The message sentiment was identified by applying the German dictionary of the SentiStrength tool (Thelwall et al., 2012). SentiStrength is specialized in analysing microblogs and is considered the most elaborate approach for the analysis of Twitter sentiment (Nielsen, 2011; Ribeiro et al., 2015). Considering the dependency on pre-defined word lists, we adapted the dictionary to the specific automotive context by including relevant terms and removing ambiguous words (Ribeiro et al., 2015). SentiStrength follows a two-step approach: it first determines the presence of an emotion based on the underlying lexicon and then classifies the emotional strength (Liu, 2010; Wilson et al., 2005). Apart from the sentiment lexicon, the algorithm also considers some other lists of words or word groups. So-called booster words like "very" and "may" lead to an increase or decrease in strength of a following emotion word and negations cause an inverting of the scores. Under consideration of all these aspects, SentiStrength assigns a sentiment score between negative five to plus five for each message based on the strength of the emotion (Thelwall et al., 2012). To approximate *relationship satisfaction*, we computed the monthly average sentiment score of all messages towards a company (*Sentiment*) and counted the total number of user-generated messages (S*hare of Voice*). These are among the most frequently used estimates in social media analytics for the perception of brands (Liu, 2010). Moreover, we considered the spread of the positive (*Positive_Reach*) or negative (*Negative_Reach*) relationship satisfaction based on the number of followers a respective message potentially reached. These operationalisations are related to the conceptual relationship satisfaction measure of 'customer influence effect' from Kumar et al. (2013) to account for the respective impact strength. Lastly, we measured user commitment to the company by counting the number of messages per unique user (*Involvement*). We assume that the more messages a user sends about a company, the more he or she is involved with a brand. Thus, this measure captures the behavioural commitment of a user to a company (Palmatier et al., 2006). Additionally, to also assess the affective dimension of commitment, we differentiate between the number of positive (*Advocacy*) and negative messages (*Antagonism*) from unique users. Again, assuming that the more positive or negative messages someone sends, the stronger is one's outspoken support or resentment for a company.

Lastly, we considered the impact of the above mentioned variables with a five-month lag. The lag seemed reasonable with respect to the order lead time, the consumer decision process duration, and previous empirical findings regarding the delay. Order lead time is understood as the point of time from receiving the customer order to delivering the product to the customer (Gunasekaran et al., 2001). In the case of car manufacturers, it is affected by different factors like the production location, number of individual specifications, model type, and manufacturer. While the manufacturers themselves do not openly report this duration, newspapers approximate a delay of up to 3 months for the models in our data sample. Moreover, a car can be considered a high-involvement process since it is rather expensive and an infrequent purchase. This increases the complexity and duration of the purchase decision to reduce financial and psychological risks (e.g., social requirements, information overload) (Mullins et al., 2012). Thus, a car purchase decision has to be made under careful consideration of various aspects and with certain personal strain (e.g., investing time) (Baumgartner, 2002). Therefore, we consider a lag of five months between the antecedent and mediator variables and new vehicle registration to be reasonable. Similar lags have been empirically identified in related studies (Seebach et al., 2011; Skodda and Benthaus, 2015).

3.3 Empirical analysis and results

To test our hypotheses, we conducted three separate five-months lagged linear dynamic panel regressions with robust standard errors (Arellano and Bover, 1995; Blundell and Bond, 1998) and a canonical correlation between predictor and mediator variables to consider respective interdependencies principally guided by the classical mediator analysis approach (Baron and Kenny, 1986) (see table 1). By following the recommendation of Aral et al. (2013) to adopt a panel model, we address common identification concerns regarding correlated unobservables, endogeneity, and simultaneity when assessing firm performance. This approach enabled us to control for (1) any invariant a-priori idiosyncratic differences among the companies and (2) for the explanatory power of preceding monthly vehicle registration volumes in addition to the consideration of the focal effects of relational antecedents and relationship mediators (Wooldridge, 2012).

A comprehensive analysis of the respective idiosyncratic error distributions revealed no violation at higher order ($z_1 = .73$; $z_2 = 1.62$; $z_3 = 1.29$; $p > .1$) and, thus, showed no sign of autocorrelation or misspecification of the model (Arellano and Bond, 1991). Also, all regression analyses (Wald-$\chi^2_{(10)} = 4827.79$, $R^2 = .9005$, $p < .001$; Wald-$\chi^2_{(12)} = 26470.57$, $R^2 = .9573$, $p < .001$; Wald-$\chi^2_{(11)} = 4513.59$, $R^2 = .8688$, $p < .001$) and the canonical regression ($F_{35,\ 1399.03} = 15.2166$, $\Lambda_1 = .257443$, $RC_1 = 0.8190$, $p < .001$) were highly significant.

The second panel regression (*Model*$_2$) reveals that the relational bond between users and companies on social media can predict car registrations five months in advance (*hypothesis 1*). The results show that relationship satisfaction and commitment variables in terms of the company's share of voice among the users ($b_{SoV} = 0.33$), an increased involvement ($b_{Inv} = 1154.96$) especially in form of advocates ($b_{Adv} = 1592.63$), and the reach of positive messages ($b_{Pos} = 1430.5$) affect sales in the automotive industry. The other user-focused mediator variables like the message sentiment ($b_{Sent} = -2026.68$), the amount of antagonism ($b_{Ant} = -424.73$), and the share of negative followers remain insignificant ($b_{Neg} = 1261.86$). These findings, however, do not necessarily mean that the message sentiment does not have an impact on sales in general. They rather show more precisely that an outspoken support community which reaches a large follower base can encourage prospects to purchase a vehicle, while brand antagonists cannot deter generally interested customers and, thus, cannot reduce sales figures.

The results regarding *hypothesis 2* generally show that not only user-focused metrics but also corporate and dyadic relational endeavours affect a company's respective firm performance (*Model*$_1$). Out of the different facets considered in this study, we find that the number of accounts a company operates ($b_{Acc} = 522.19$) and the number of followers these accounts have ($b_{Fol} = 0.0003$) positively affect car sales. The number of messages a company sends, however, negatively influences registration numbers ($b_{Msg} = -4.6$) with a descriptively diminishing negative effect as the message numbers decrease ($b_{l\_Msg} = -468.03$). This seems to be a counterintuitive finding at first sight. Related research, however, has produced seemingly ambiguous findings regarding the effect of corporate message numbers. When launching a corporate social media presence, more messages have been found to improve sales performance (Ramkumar et al., 2013). On a more regular engagement basis, as it is the case here, message number effects have been found to be insignificant (Chung et al., 2014) or mediated by the addressed target (Goh et al., 2013). The latter means that company messages have only been found to increase firm profits if they are targeted to individual users but not when they address the general crowd. Overall, relating our findings to the literature indicates that it is not necessarily expedient to send large amounts of messages, but that it is advisable to occasionally send fewer messages to a targeted community through specialized company accounts. Reconsidering the interplay of our measures, a more individualized communication in form of singular messages from interest group specific accounts would represent an incremental effort – and thus relationship investment – compared to an undirected broadcasting approach. These findings, therefore, are generally in support of our *hypothesis 2*.

Objective Firm Performance		**Model$_1$** b	(SE)	**Model$_2$** b	(SE)	**Model$_3$** b	(SE)	**Canonical Corr.** B	(SE)
Controls	Constant	416.14	(462.87)	-3375.83*	(1336.47)	1453.71*	(638.04)	---	
	Lag$_{t-1}$	.62**	(.05)	.48***	(.05)	.57***	(.05)	---	
	Lag$_{t-2}$	-.28*	(.13)	-.13*	(.06)	-.28*	(.12)	---	
	Lag$_{t-3}$	.61***	(.09)	.46***	(.06)	.56***	(.1)	---	
	Lag$_{t-4}$	-.18†	(.11)	.02	(.12)	-.19†	(.11)	---	
	Lag$_{t-5}$	.08	(.1)	.03	(.04)	.02	(.09)	---	
Relational Antecedents									
Company-Focused	Messages	-4.6*	(2.22)	---		-3.033†	(1.78)	-.0013***	(.0003)
	ln_Messages	-468.03	(298.29)	---		-616.25	(388.11)	.2161***	(.0319)
	Accounts	522.19*	(263.77)	---		413.73	(252.79)	.111***	(.0155)
Dyadic	Followers	.3**	(.1)	---		.2	(.1)	.0001***	(.00003)
	Favourites	-.014	(.01)	---		-.0144†	(.008)	-.000002	(.000002)
Customer-Focused Relational Mediators									
Relationship Satisfaction	Sentiment	---		-2026.68	(2194.29)	---		.09	(.51)
	Share of Voice	---		.33*	(.14)	.66**		(.22)	.0002***
	Positive_Reach	---		1430.5*	(697.62)	---		.4	(.32)
	Negative_Reach	---		1261.86	(944.59)	---		-.16	(.48)
Commitment	Involvement	---		1154.96†	(658.2)	---		-.06	(.17)
	Antagonism	---		-424.73	(279.8)	---		.19	(.17)
	Advocacy	---		1592.63*	(788.9)	---		-.12	(.2)
Model Test Specifications									
Observations		274		389		274		---	
Instruments		193		204		194		---	
Groups		25		25		25		---	
Test statistic		4827.79***		26470.57***		4513.59***		.257443***	

Test statistic. Wald-χ^2 for the regression analyses, Wilks-Λ for the canonical regression
Statistics. Robust standard errors displayed in parentheses behind unstandardized coefficients for the regression analyses; standard errors displayed in parentheses behind canonical regression coefficients; follower numbers in thousands
p-values. *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$ significant; † $p < 0.1$ tendential significance

Table 1. Results of the analysis of social media metrics on objective firm performance.

Before conducting the third regression analysis that assesses mediating effects (*hypothesis 3*), we computed a canonical correlation between the assumed predictor and mediator variables to identify key mediator variables (*Canonical Correlation*). The first significant canonical correlation equation reveals a particularly strong connection between the previously as influential identified relational antecedents (i.e., messages, accounts, and followers) and the user share of voice (B_{Msg} = -0.0013, B_{Acc} = 0.111, B_{Fol} = 0.0000001, B_{SoV} = 0.0002). Thus, to test the mediating effects of *hypothesis 3*, we included user share of voice as a mediator variable in the third regression (*$Model_3$*). The analysis generally supports the hypothesis that customer-based relationship bonds mediate effects of relational antecedents on sales performance. Share of voice fully mediates the effects of the company account number (b_{Acc} = 413.73) and followers (b_{Fol} = 0.0002), while it partially mediates the influence of company messages (b_{Msg} = -3.033). These results are congruent to the findings from relationship marketing, that relationship investment is only partially mediated through relationship bonds (Palmatier et al., 2006). This indicates that by operating multiple accounts, providing targeted information, and inspiring users to follow the accounts, companies can increase their share of voice among users and ultimately increase the number of sold cars. On a final note, in the mediation regression, the number of account favourites becomes marginally significant, which indicates that user share of voice serves as a suppressor for irrelevant variance in the share of voice variable. As this is neither to be expected from a theoretical perspective, nor is it a common effect, future research will need to identify whether this finding is systematic or incidental.

4 Discussion and Conclusion

The goal of this study was to investigate the impact of corporate engagement efforts (i.e., relationship investment), customer-conceived relationship bonding (i.e., relationship satisfaction and commitment), and shared relationship perceptions (i.e., similarity) on the objective corporate performance theory-driven by relationship marketing. We synthesise related social media research based on the framework of factors influencing the effectiveness of relationship marketing from Palmatier et al. (2006). Resting upon these insights, we operationalise the respective constructs in a dataset of approximately 1.3 million Twitter messages to analyse their interrelations and effects on the objective performance of ten car manufacturers in a mediator model.

Generally, our results support the assumed model of strong relational antecedents translating into increased sales numbers mediated through the customer-focused relationship strength. Specifically, we find that an increased corporate relationship investment in form of targeted communication from interest-group specific accounts translates into higher sales numbers. Also, the commonly neglected dyadic relational antecedents, which are measured by follower numbers, translate into an improved sales performance. The regression coefficient seems relatively small (b_{Fol} = 0.0003), which indicates that approximately for every additional 3,333 followers reached by a company, one additional car is sold. In a simplified calculation, considering the average price of 28,330 EUR (approximately 37,679 USD) of a newly registered car in the considered market during the analysis period (Statista, 2014), this would represent an average gross value of 8.50 EUR (approximately 11.30 USD) for every follower in our study setup. In this regard, the study provides insights regarding the financial return of social media investments, which supports decision-makers to make an educated decision when discussing the allocation of generally restricted financial resources to different campaigns (e.g., television, marketing events). It also enables to estimate the pay-off from a social media campaign that is, for example, targeted at increasing follower numbers.

Regarding the customer-focused relationship strength, we find only positive effects for commitment and relationship satisfaction on the company performance. Apart from a large share of voice, especially measures related to a positive sentiment are able to predict car sales. Specifically, a large spread of positive messages and a strongly involved community of advocates translate into higher sales numbers. The insignificant effect of message sentiment can be explained through findings from Bhattacharya et al. (2014). They explain the occasionally positive or insignificant effects of sentiment through the (lacking) fit of privately held and publicly displayed sentiment. Considering that we only measure the publicly stated sentiment and that cars serve as status symbols, our results could be influenced by self-presentation tendencies which might prompt users to display an attitude to their network that differs from their private opinion or actually intended behaviour.

Lastly, we are able to explain the way in which relational antecedents translate into sales performance through the mediator analysis. Here we find that especially a company's share of voice among users explains the trajectory between antecedents and the objective performance. However, customer-focused measures only partially mediate the efficacy of relationship investment. This finding is in accordance with existent research in the marketing literature (Palmatier et al., 2006). This shows that there must be alternative, mediated ways in which relationship investment increases firm performance (e.g., reciprocity).

As further elaborated in the limitations, we can only assume the direction of effects to be as hypothesized based on findings from related literature. Although the empirical findings are in timely sequential order, this does not necessarily also imply a respective causal relation between measures.

4.1 Implications for theory and practice

Through the theory-driven approach of relating social media activities to the actual firm performance, this study offers substantial contributions for theory and practice. Generally, we provide insights into how the strategic use of social media technology can translate into IT business value (Aral et al., 2013; Dong and Wu, 2015).

First, we overcome current shortcomings of existing research by expanding the research perspective beyond the singular consideration of customer- or company-based metrics. The study shows the necessity for a comprehensive consideration of the value chain (including mediator and dyadic variables) when assessing the efficacy of corporate social media engagement strategies. Based on the apparent findings, to increase the social media financial ROI our recommendations for social media managers in the German automotive industry on Twitter are as follows:

- Social media managers should focus on increasing the company's share of voice among the users in order to leverage the financial return of the corporate relationship investment and their follower base. Related research has shown that this can be achieved, for example, through aligned online (Kumar et al., 2013) or offline advertisement campaigns (Tirunillai and Tellis, 2012).
- Firms benefit from a far reach of positive messages about the brand made by supportive users. Thus, we recommend concentrating social media activities on building user advocates and encouraging them to spread positive messages about the company. This can be achieved, for example, by sharing targeted interest group-specific information (Benthaus et al., 2015).

Second, the study addresses apparent gaps of prior studies which were limited to singular marketing campaigns or initial launches of social media accounts (Kumar et al., 2013; Ramkumar et al., 2013; Tirunillai and Tellis, 2012), used confounded outcome measures (Chung et al., 2014), considered only single company cases (Goh et al., 2013), or neglected corporate behaviour in general (e.g., Bhattacharya et al., 2014). Instead, to the best of our knowledge, this study is the first to comprehensively investigate the process of effects of the regular social media engagement, from multiple companies, on more specific sales figures.

Third, we address the lacking common theoretical foundation across social media studies. By applying relationship marketing theory, we were able to integrate different studies and their diverging measure operationalisations into theory-derived constructs. While we consider relationship marketing to provide a comprehensive and appropriate theoretical foundation for social media phenomena, others might find different theory approaches more suitable. In any case, the apparent arbitrariness of construct specification (e.g., word of mouth as outcome, mediator, or antecedent variable) and measurement (e.g., word of mouth through “stickiness”, sentiment, or message numbers) needs to be overcome to make findings comparable and generalizable. In this regard, this study shows relationship marketing theory to be one suitable approach.

4.2 Limitations and future research

Apart from the unique contributions of this study, some limitations need to be considered, which also provide a foundation for future research. Generally, the data we collected to conduct our empirical analysis limits the generalizability of the findings. In this sense, we have limiting factors regarding the industry (i.e., automotive sector), the culture (i.e., German or western cultural context), and the social media platform (i.e., microblogging or Twitter in particular). Thus, in future research we intend to expand the analysis to other markets and social media technologies, which have been found to functionally differ (Kane et al., 2014a). Also, considering that corporate social media efforts have a stronger impact on tech- and social media-prone customers, this sample selection bias might have caused an overestimation of our effects (Kumar et al., 2015). Other limitations arise from methodological aspects. Regarding the statistical analysis, the canonical regression between relational antecedents and customer-focused relational mediator variables revealed three significant canonical regressions, which indicates different underlying latent variables. Thus, we recommend considering different blocks of variables through factor analysis or SEM to sophisticatedly assess mutual interdependencies and the respective effects on firm performance. Regarding the sentiment analysis, SentiStrength is not capable to consider irony. So far, however, research is just beginning to develop sentiment tools capable of identifying irony (Bosco et al., 2013). Therefore, this is currently an inherent problem with sentiment analyses, which we could not overcome. However, we do not see a reason why the share of irony should vary within our data sample and, therefore, how it would systematically bias our findings.

Furthermore, even though we find a predictive relation with a sound theoretical foundation, empirically we measure correlations instead of causality. This issue of exogenity was particularly emphasized by Aral et al. (2013) in the context of social media performance measures, who argue that it can only be overcome by experimental setups. Therefore, other explanations for the relation of the mediator variables and firm performance need to be considered. For example, people who just ordered a car might send positive messages of pleasant anticipation about the car or express loyalty by following the manufacturer’s account to remove cognitive dissonance and justify the expenditure (Festinger, 1962). In this case, the five months delayed vehicle registration would explain the increase in positive messages and in followers five months earlier. It seems reasonable to assume that some form of respective reciprocal relationship between registration numbers and some of the predictive variables exists, while it is rather unlikely to be the case for all variables (e.g., number of accounts and company messages). Regarding future research, we recommend the consideration of other variables that might either explain the impact of company messages (e.g., reciprocity) or are described by relationship marketing such as communication, interaction frequency, and conflict. Especially the latter seems to be important in the light of the current engine manipulations and the proven strong effect on firm performance (Palmatier et al., 2006). Apart from the aforementioned experimental setup, a latent semantic analysis in combination with the sentiment could help to gain further insights regarding the impact of different topics and further support the assumed causality.

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