CREATING BUSINESS VALUE THROUGH SOCIAL MEDIA: AN INVESTIGATION OF THE DYNAMIC RELATIONSHIP BETWEEN SOCIAL MEDIA, BRAND EQUITY AND FIRM RISK

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CREATING BUSINESS VALUE THROUGH SOCIAL MEDIA:
AN INVESTIGATION OF THE DYNAMIC RELATIONSHIP
BETWEEN SOCIAL MEDIA, BRAND EQUITY AND FIRM RISK

Research in Progress

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Abstract

In recent years social media has become one of the most important marketing channels for companies, attracting significant attention of consumers, marketers and thus researchers. Previous research mainly focused on exploring the short-term effect of social media on shareholder value and the customer decision journey. This study tries to provide a holistic, short- and long-term view on how social media can create business value through its direct influence on distinct brand equity dimensions as well as firm risk. We furthermore investigate how distinct types of social media activity affects retail and professional investors differently. This study is based on a unique dataset consisting of daily social media data from four social media platforms, brand equity, stock price and credit risk data of 38 companies for 6 years. We investigate the dynamic relationship between the variables leveraging vector autoregression models. Preliminary results support our hypotheses that social media activity can create brand equity and reduce firm risk as measured in credit risk and idiosyncratic risk.

Keywords: Social media, user generated content, firm generated content, brand equity, firm risk, credit risk, idiosyncratic risk.
1 Introduction

Online advertising has become the most important channel for marketers in recent years with around 40% (~USD 227bn) of total advertising spending being allocated to it in 2018 (recode, 2018). Within online advertising, social media is turning into one of the strongest drivers with expected growth of approximately 21% in 2018 with a total of approximately USD 58 bn. On the other hand, the business value of social media advertising is being disputed by practitioners as it is difficult to measure (Hoffman and Fodor, 2010). Accordingly, researchers are turning their focus on exploring the effects of social media on business value as well as the underlying drivers.

Previous studies suggest that social media is transforming the way companies interact with their customers and investors as communication evolves from being one-way to multi-directional (Berthon, Pitt and Campbell, 2008; Mangold and Faulds, 2009; Rybalko and Seltzer, 2010). At the same time, researchers argue that social media has a significant effect on equity prices. Most of the research was focused on two underlying relationships: firstly, the role of social media in spreading (investment) information related to companies and thus measuring the consumers’ and investors’ general sentiment and its impact on the value of the company (Das and Chen, 2007; Bollen and Mao, 2011; Mao, Counts and Bollen, 2011; Chen, De, Hu and Hwang, 2014; Colicev, Malshe, Pauwels and O’Connor, 2018); secondly, social media as a communication channel between customers as well as between customers and companies (Dawar and Pillutla, 2000; L. F. Lee, Hutton and Shu, 2015; Borah and Tellis, 2016; Hsu and Lawrence, 2016; Colicev et al., 2018). However, little research investigated how social media can be proactively used to create long term value for businesses and thus reduce the firm’s risk. Our paper follows the established research on the relationship between brand equity and firm risk (Rego, Billett and Morgan, 2009), and connects it to more recent research that investigates the effect of social media on equity prices and volatility (Das and Chen, 2007; Bollen and Mao, 2011; Mao et al., 2011) as well as on the customer decision journey and shareholder value (Colicev et al., 2018).

In our paper we follow the research calls to increase the scope of analysis on the interaction between social media and brand equity to all leading social media platforms (Erdogmus and Ciccek, 2012; Labrecque, 2014; Schivinski and Dabrowski, 2014) as well as to analyse the dynamics of social media activity and brand equity on the daily level (Hsu and Lawrence, 2016). We add to the growing research of the effects of social media on distinct brand in the context of the brand equity theory (Aaker, 1991; Keller, 1993) and market-based assets (Srivastava, Shervani and Fahey, 1998; Rust, Lemon and Zeithaml, 2004) by linking social media interaction to the drivers of brand equity. We furthermore expand the research on the interaction of social media with brand equity as well as firm risk (Hsu and Lawrence, 2016; Colicev et al., 2018). To our best knowledge, this paper is the first to investigate the interdependencies of social media activity, brand equity and different measures for firm risk. Furthermore, we investigate how different types of social media affect retail and professional investors differently. We base our analysis on a unique dataset of high frequency data of all main social media platforms on a long-term horizon facilitating a unique data-set spanning 6 years and over 40.000 observations from 38 companies.

2 Conceptual Framework

2.1 Social Media

Marketing literature generally distinguishes two different types of social media content: firm-generated content (FGC) and user-generated content (UGC) (Chevalier and Mayzlin, 2006; Stephen and Galak, 2012; Bruhn et al., 2013; Srinivasan, Rutz and Pauwels, 2015; Kumar et al., 2016; Colicev et al., 2018). FGC is created by agents of the company and usually published via their own social media page or account. Generally, FGC is often used by companies as a marketing channel (Hutter, Hautz, Dennhardt
and Füller, 2013) and CRM-tool (Luo, Zhang and Duan, 2013; Trainor, Rapp and Agnihotri, 2013) to improve customer relationship. It is commonly measured through number of posts, whether text, videos or pictures, via the respective social media medium (Hsu and Lawrence, 2016; Kumar et al., 2016; Colicev et al., 2018). Secondly, user generated content (UGC) describes the social media activity of customers in the context of the firm's brand, e.g., by posting own content or interacting with the FGC. Given that UGC is a network based, distributed and non-linear phenomenon (Brodie, Ilic, Juric and Hollebeek, 2013), multiple measures are regularly being used to capture the effect. This includes among others valence, or sentiment, of user content (Tirunillai and Tellis, 2012; Hsu and Lawrence, 2016; Colicev et al., 2018), user likes (Srinivasan et al., 2015) or user comment/posts (Stephen and Galak, 2012; Goh, Heng and Lin, 2013).

2.2 Brand Equity

Consumer-based brand equity (CBBE) is regularly being used to measure the value of a brand from a customer-perspective, taking into consideration their views and feelings towards the brand (Keller, 1993). In marketing literature, he underlining effects for creation of CBBE is commonly based on cognitive psychology and network memory models (Aaker, 1991; Keller, 1993). When consumers experience a brand, characteristics of the brand and associated product attributes are stored in the memory. The stronger the experience with that specific brand, the more likely the memory is being activated when external triggers occur, e.g., when further information on the brand is provided, or in the process of a purchase decision (Keller, 1993). When the consumer is familiar with a brand and holds some favourable, strong, and unique brand associations in memory, consumer-based brand equity is created (Keller, 1993).

Brand equity can be measured through customer perceptions of the respective brands along the four dimensions of brand equity: awareness, perceived quality, associations, and loyalty (Aaker and Express, 1996). Brand communication can create brand equity when it yields a more favourable response to the observed product as opposed to an equal unbranded product (Yoo, Donthu and Lee, 2000). Furthermore, different kind of brand communication has diverging effects on the respective dimensions of brand equity (Yoo et al., 2000; Bruhn et al., 2013). For each dimension of brand equity, Aaker (1996) defined multiple measures. We select one measure for each dimension, namely brand awareness (for the brand equity dimension of awareness), perceived quality (perceived quality), perceived value (associations), customer satisfaction (loyalty).

We propose that being subjected to FGC, e.g., posts on Facebook, increases the awareness of the brand. As being exposed to anything related to the brand creates/reinforces an experience and/or memory, the consumer is more aware towards the brand (Keller, 1993; Mitra and Lynch, Jr., 1995; Hutter et al., 2013; Colicev et al., 2018).

H1.1: Increased FGC leads to higher brand awareness

Marketing literature has established that valence of UGC is very effective in conveying the quality assessment of a brand (or specific product) to other consumers, as it carries the opinion of the user (Goh et al., 2013). Accordingly, positive/negative UGC is known to influence the purchase decision of consumers, as it affects the perceived quality of other users positively/negatively (Dellarocas, 2006; Dimoka, Hong and Pavlou, 2012; Colicev et al., 2018).

H1.2: Brand equity dimension of perceived quality is influenced by (a) positive and (b) negative valence

Following a purchase, consumers tend to assess their actual product experience compared to the pre-purchase expectation. Literature suggests that they tend to look for consonant information from other consumers to reduce post-purchase cognitive dissonance (Adams, 1961). Accordingly, user post valence would influence customer satisfaction post-purchase (Colicev et al., 2018). Furthermore, companies

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1 We ignore the 5th dimension of Aaker's framework as it is market- and not customer-based.
leverage FGC to provide customer support, e.g., through answering questions or providing ad-hoc help in case of dissatisfaction. Thus, FGC should positively influence customer satisfaction (Gu and Ye, 2014; Ma, Sun and Kekre, 2015; Colicev et al., 2018).

**H1.3: Both UGC and FGC influence the brand equity dimension of customer satisfaction**

Companies use social media as marketing channel and try to shape the brand image or personality (Bruhn et al., 2013). Accordingly, we expect that FGC positively influences the brand equity dimension of association.

**H1.4: FGC influences the brand equity dimension of association**

### 2.3 Firm Risk

The effect of social media on capital market performance of companies is commonly attributed to its influence on investor sentiment and/or to its capability of conveying new information regarding the respective company (Antweiler and Frank, 2004; Das and Chen, 2007; Tetlock, 2007; Bollen and Mao, 2011; Mao et al., 2011; Chen et al., 2014).

Sentiment is related to psychological biases like overconfidence (Kahneman and Riepe, 1998; B. M. Barber and Odean, 2001) and limited attention in investors (Brad M. Barber, Odean and Zhu, 2009). These effects can deviate the asset prices from their fundamental value (Baker and Wurgler, 2007) and increase market volatility (Brown, 1999; B. M. Barber and Odean, 2001; W. Y. Lee, Jiang and Indro, 2002; Tetlock, 2007).

Literature suggests that retail investors are more strongly affected by market sentiment than professional ones (De Long, Shleifer, Summers and Waldmann, 1990; Brad M. Barber et al., 2009; Da et al., 2014). Accordingly, the sentiment adherent to social media interaction would influence retail investors stronger than professional ones. On the other hand, professional investors observe social media of companies to extract new information and include these in their investment decision (Antweiler and Frank, 2004; Tirunillai and Tellis, 2012; Luo, Zhang, et al., 2013). Accordingly, we expect that social media activity which conveys no information or mostly sentiment (e.g., FGC, UGC Interaction) to affect retail investors stronger than professional ones. Conversely, social media activity that conveys new information (e.g., positive/negative reviews or user posts) would affect professional investors more than retail ones.

Most studies focused on the effects of both social media and brand equity on stock market development and thus implicitly on both retail and professional investors. The market for credit default swaps (CDS) consists almost entirely of professional investors (Avellaneda and Cont, 2010). We will analyse the effect of social media on firm risk on these two markets to highlight differences in the degree of relevant market information UGC and FGC contain.

**H2.1: Social media interaction that contains new information regarding brands, i.e., user post valence, has more effect on professional investors, i.e., the CDS market**

**H2.2. Social media interaction that contains little new information and mostly sentiment, i.e., FGC and user interaction, has more effect on retail investors, i.e., the stock market**

Strong brand equity mitigates the negative effect of social media on stock prices in the case of product recalls (Hsu and Lawrence, 2016). Moreover, social media can be used to improve consumers’ perception of a brand/company and thus build consumer-based brand equity (Erdoğmuş and Çiček, 2012; Kim and Ko, 2012; Hutter et al., 2013; Schivinski and Dabrowski, 2014). Furthermore, Rego, Billett, and Morgan (2009) established, that consumer-based brand equity reduces firm risk. They argue that high brand equity leads to repeat-purchasing behaviour (Berthon, Hubert and Pitt, 1999; Keller, 2003) and lower consumer price sensitivity (Allenby and Rossi, 1991; Sivakumar and Raj, 1997; Ailawadi, Lehmann and Neslin, 2003), thus protecting cash-flows. Accordingly, Fornell, Morgeson, and Hult (2016) argue, that customer satisfaction, an element of brand equity, is positively linked to stock returns (Fornell et al., 2016). Higher awareness of a brand increases the probability that customers consider it
in their purchase decision and should thus increase profitability of that brand (Baldauf, Cravens and Binder, 2003; Hutter et al., 2013). Furthermore, strong brand-equity increases the awareness companies get, which in turn could lead to more demand from investors due to direct signalling, increasing the stock price (Singh, Faircloth and Nejadmalayeri, 2005; McAlister, Srinivasan and Kim, 2007). Perceived quality improves profitability, return on investment as well as stock performance of companies (Phillips, Chang and Buzzell, 1983; Jacobson and Aaker, 1987; Aaker and Jacobson, 1994). Perceived value is known to positively influence repurchases (Wu, Chen, Chen and Cheng, 2014) and should thus improve stock performance and reduce firm risk. Finally, Colicev et al. (2018) suggest that social media activity is able to influence the consumer in their customer decision journey and thus reduce idiosyncratic equity risk, but only find spurious evidence (Colicev et al., 2018).

**H3:** Increases in brand equity reduces firm risk

**H3.1:** Increased awareness reduces firm risk

**H3.2:** Increased perceived quality reduces firm risk

**H3.3:** Increased association with a brand (as measured in perceived value) reduces firm risk

**H3.4:** Increased customer satisfaction reduces firm risk

### 3 Data and Methodology

#### 3.1 Data

To examine the effect of social media on brand equity and firm risk we combine a wide range of data sets from different sources. To be able to observe the direct impact of social media interactions on brand equity and firm risk we chose a dataset of daily observations. Additionally, we chose a comparatively long timeframe of 6 years to allow analysis of long-term effects and derive generalisable conclusions.

We collect social media data for companies that are constituents in the S&P500 from a social media analytics company, allowing us to examine social media data across all four major social media platforms (Facebook, twitter, Youtube, Instagram). This data includes a wide range of metrics for both FGC and UGC. For FGC we collect the companies' posts for each social media platform respectively and use this to create a one-dimensional component leveraging principal component analysis. UGC is measured through the valence on user posts, the number of user posts and the number of fan/follower. We measure valence by assessing the amount of positive and negative words in each user post on Facebook on a brand's page and tag the post as positive/negative depending on whether more positive or more negative words are mentioned in it. We create a common variable for UGC interaction across all platforms by applying principal component analysis based on the number of followers, likes, and retweets.

We measure brand equity and its dimensions through the YouGov Brand Index provided by YouGov which has been successfully utilized by several researchers (Grundy and Moxon, 2013; Luo, Raithel and Wiles, 2013; Axjonow, Ernstberger and Pott, 2018; Colicev et al., 2018). YouGov leverages online panels to survey 5,000 randomly selected consumers each day for their opinion of brands covered. The sample is weighted by age, gender, race, education, income and region. It provides daily data for an aggregate measure of the brand equity, the BrandIndex, as well as indices for the different dimensions of brand equity discussed earlier, i.e., brand awareness, perceived quality, association (measured through perceived value), and customer satisfaction.

Next, we collect CDS pricing data from ThomsonReuters. Credit default swaps are financial instruments that allow debt investors to insure themselves against the bankruptcy of the debtor. They pay a yearly fee on the face value of the bond to a counterparty and receive the face value of that bond from the counterparty in case the bond issuer defaults. CDS are the most common credit derivatives and used to measure the credit risk of the bond issuer (Avellaneda and Cont, 2010) and thus are an accurate measure
for expected cash-flow stability or firm risk. CDS are priced as basis points (bps) over the respective face value of the CDS and commonly have a maturity of five years.

Furthermore, we collect stock data from Chicago’s Center for Research in Security Prices (CRSP) as well as common factors from Wharton Research Data Service to calculate the idiosyncratic equity risk for each company. To calculate the idiosyncratic risk of a company’s stock, we follow a common approach in the finance literature, Carhart’s four-factor model (Carhart, 1997). Firstly, we define a company’s return with:

$$ER_{it} = \alpha_{i,t} + \beta_{i,t} MR_t + s_{i,t} SMB_t + h_{i,t} HML_t + m_{i,t} MOM_t + \epsilon_{i,t} \sim N(0, \delta_{i,t})$$

Where $ER_{it}$ is the excess return of firm i in time t of the risk-free rate, $\alpha_{i,t}$ is the intercept, $MR_t$ is the excess return of an adequate market proxy over the risk-free rate, $SMB_i$ is the factor for company size, $HML_t$ is the premium for book-to-market factor, $MOM_t$ is the momentum-factor and $\epsilon_{i,t}$ is the error term. The idiosyncratic risk will be calculated as the variance of the error terms $\delta_{i,t}$.

Finally, we collect data for the control variables commonly used in the marketing literature, namely advertising spending, sales, and market value (Tirunillai and Tellis, 2012) through Compustat. The final dataset consists of 38 companies with a total size of 44,475 daily observations.

### 3.2 Methodology

We apply the persistence-modelling framework and adopt vector autoregressive (VAR) models to capture the long-term effect of social media activities on brand equity as well as firm risk. VAR models have been applied regularly in the marketing and finance literature due to several advantages over alternative models (Dekimpe and Hanssens, 1995; Pauwels, Silva-Risso, Srinivasan and Hanssens, 2004; Luo, 2009; Huang, Liu, Rhee and Zhang, 2010; Tirunillai and Tellis, 2012; Colicev et al., 2018). Firstly, VAR models allow to directly observe the immediate and lagged-term effects of our variables different, i.e., social media metrics on marketing-related variables as well as firm risk measures (Tirunillai and Tellis, 2012; Colicev et al., 2018). Thirdly, the models allow us to investigate the effects of the endogenous variables on each other. Furthermore, VAR models can estimate the long-term effect of unexpected shocks to one of the variables, e.g., UGC, on the other endogenous variables (Pesaran and Shin, 1998; Pauwels et al., 2004). Finally, it allows to control for non-stationarity, serial correlation and reverse causality (Luo, 2009; Tirunillai and Tellis, 2012).

We implement our research model through a panel VAR analysis (Abrego and Love, 2016) which has been regularly applied in the marketing, finance and econometrics literature (Hollifield, Neklyudov and Spatt, 2017; Lundgren and Zhou, 2017; Colicev et al., 2018). We specify our k-variate panel VAR model of order p as follows:

$$Y_t = Y_{it-1}A_1 + Y_{it-2}A_2 + \ldots + Y_{it-p+1}A_{p-1} + Y_{it-p}A_p + X_{it}B + u_{it} + e_{it}$$

Where $i \in (1,2,\ldots,N)$ are the panels, $t \in (1,2,\ldots,T_i)$ are the time periods, $Y_{it}$ is a ($lxk$) vector of the endogenous variables, $A_1, A_2, \ldots, A_{p-1}, A_p$ are the ($k \times k$) coefficients matrices, $X_{it}$ is the ($lxk$) vector of control variables, $B$ the ($k \times k$) matrix of its coefficients, $u_{it}$ and $e_{it}$ vectors of dependent variable-specific fixed effects and idiosyncratic errors. We assume that $E[e_{it}] = 0, E[e'_{it}, e_{is}] = 0, e_{it} \sim N(0, \Sigma)$ and $E[e'_{it}, e_{is}] = 0$ for all $t \neq s$.

We use Helmert transformation, or forward orthogonal deviation (FOD), to overcome the challenge that the fixed effects are correlated with the regressors, as the lagged dependent variables are used as independent variables in VAR models. FOD transforms the data by removing the mean of all future observations and thus allows the lagged variables to be independent (Arellano and Bover, 1995; Abrego and Love, 2016; Lundgren and Zhou, 2017). We test for non-stationarity of the variables, given that the existence of non-stationarity could lead to spurious regression which in turn would render the calculated coefficients inefficient and significance tests invalid (Granger and Newbold, 1974). Variables enter the
system in first differences if they are non-stationary and in levels if they are stationary. Finally, we use the Bayesian information criterion to choose the order of the panel VAR.

Furthermore, we test our research model for Granger causality, a method to explore whether a relationship between two variables is not only based on correlation, but also causality, to substantiate our findings. Granger causality investigates the feedback mechanisms between the two variables and tests whether a variable can predict the other beyond its own history (Granger, 1969).

4 Preliminary Results

The preliminary results confirm our hypothesis that social media has a strong influence on the dimensions of brand equity (BE) as well as firm risk. Furthermore, data suggests that social media affects professional and retail investors differently. Table 1 provides the results of the panel VAR. Given that the results are preliminary, the data needs to be interpreted cautiously.

<table>
<thead>
<tr>
<th></th>
<th>Awareness</th>
<th>Association</th>
<th>Perc. Quality</th>
<th>Satisfaction</th>
<th>Idiosync. risk</th>
<th>Credit Risk</th>
</tr>
</thead>
<tbody>
<tr>
<td>UGC Pos. valence</td>
<td>0.004 **</td>
<td>-0.001 n/s</td>
<td>0.053 ***</td>
<td>-0.002 n/s</td>
<td>0.000 n/s</td>
<td>0.002 ***</td>
</tr>
<tr>
<td></td>
<td>0.030</td>
<td>0.922</td>
<td>0.000</td>
<td>0.786</td>
<td>0.372</td>
<td>0.000</td>
</tr>
<tr>
<td>Neg. valence</td>
<td>-0.002 n/s</td>
<td>0.008 n/s</td>
<td>-0.038 ***</td>
<td>0.017 **</td>
<td>0.000 n/s</td>
<td>0.002 ***</td>
</tr>
<tr>
<td></td>
<td>0.384</td>
<td>0.295</td>
<td>0.000</td>
<td>0.022</td>
<td>0.645</td>
<td>0.000</td>
</tr>
<tr>
<td>Interaction</td>
<td>-86.406 ***</td>
<td>10.128 ***</td>
<td>8.397 ***</td>
<td>-33.015 ***</td>
<td>-0.005 ***</td>
<td>0.370 ***</td>
</tr>
<tr>
<td></td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>FGC Activity</td>
<td>4.514 ***</td>
<td>-29.535 ***</td>
<td>-28.254 ***</td>
<td>-28.506 ***</td>
<td>0.002 ***</td>
<td>0.045 *</td>
</tr>
<tr>
<td></td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.053</td>
</tr>
<tr>
<td>BE Satisfaction</td>
<td>-0.001 n/s</td>
<td>-0.005 n/s</td>
<td>-0.015 *</td>
<td>-0.015 *</td>
<td>0.000 n/s</td>
<td>0.000 n/s</td>
</tr>
<tr>
<td></td>
<td>0.454</td>
<td>0.602</td>
<td>0.087 -</td>
<td>0.089</td>
<td>0.887</td>
<td>0.899</td>
</tr>
<tr>
<td>Perc. Qual</td>
<td>-0.003 n/s</td>
<td>0.010 n/s</td>
<td>-</td>
<td>-0.015 *</td>
<td>0.000 n/s</td>
<td>0.000 n/s</td>
</tr>
<tr>
<td></td>
<td>0.169</td>
<td>0.371</td>
<td>0.087</td>
<td>0.089</td>
<td>0.693</td>
<td>0.545</td>
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<tr>
<td>Association</td>
<td>0.002 n/s</td>
<td>-</td>
<td>0.027 ***</td>
<td>0.007 n/s</td>
<td>0.000 n/s</td>
<td>0.000 n/s</td>
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<tr>
<td></td>
<td>0.280</td>
<td>-</td>
<td>0.001</td>
<td>0.337</td>
<td>0.367</td>
<td>0.481</td>
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<tr>
<td>Awareness²</td>
<td>-</td>
<td>0.033 n/s</td>
<td>-0.203 ***</td>
<td>-0.032 *</td>
<td>0.000 n/s</td>
<td>0.005 ***</td>
</tr>
<tr>
<td></td>
<td>-</td>
<td>0.193</td>
<td>0.000</td>
<td>0.092</td>
<td>0.783</td>
<td>0.001</td>
</tr>
</tbody>
</table>

*Table 1.* VAR results of initial analysis. *** is significant at the 0.01, ** at the 0.05 and * at the 0.1 level. No. of observations: 44.475; no. of companies: 38. Results for control variables not shown but are included.

We test our model for stability which is a precondition to use the results in further analysis. A VAR model is stable if the eigenvalues are strictly less than 1 (Hamilton, 1994). This is the case for our model which thus satisfies the stability condition.

² Due to a data error, the index for awareness could not be used. In the preliminary analysis awareness is approximated with the index for attention. The final analysis will include the index for awareness.
The preliminary results seem to confirm that FGC affects brand awareness (H1.1) and brand association (H1.4). The negative sign for FGC on brand association might imply, that intense marketing efforts via social media might have an adverse effect or that companies with low brand association try to increase FGC to improve association. Positive and negative valence influences perceived quality and the coefficients have the expected sign (H1.2). We can only find partial evidence that both UGC and FGC influence satisfaction, as positive valence is not significant (H1.3).

Furthermore, the preliminary results indicate that professional investors seem to focus on UGC to find new information regarding a brand as indicated by the significance of UGC for credit risk (2.1). On the other hand, retail investors seem to focus more on FGC and UGC interaction when considering their investments (2.2).

Finally, the effect of brand equity on risk (H.3) seems to be mostly insignificant, contradictory to other studies (Rego et al., 2009).

A VAR-Granger causality Wald test confirms granger-causality for the results discussed above. Given that the analysis is not final, the results need to be interpreted cautiously. There are several areas that require further investigation. Firstly, the lack of relevance of brand equity for firm risk is unexpected and contradictory to results of other studies. Secondly, further robustness checks need to be applied to check the validity of the results. Due to lack of space additional results for granger causality, impulse-response-functions, and results for the stability conditions are excluded.

5 Preliminary Conclusions

In this paper we aim to explore the relationship between social media, brand equity and firm risk. The results will to help evaluate the relevance of social media as a marketing channel, and as a driver of business value through affecting firm risk. Accordingly, the results are of importance for practitioners as they would provide guidance for future resource allocation in the marketing mix as well as in measuring the effectiveness of their marketing efforts. Furthermore, the results can help expand the theoretical discussion around the information-content of social media activity and the effect on capital markets.

The preliminary results indicate that social media creates brand equity as well as affects company risk. Furthermore, due to differing amounts of market-relevant information, different types of social media interaction seem to have contrasting effects on the stock market and the market for credit risk. The results indicate that social media might thus affect professional and retail investors differently.

Further analysis is needed to confirm the preliminary conclusions and expand the theoretical implications.
Reference

Journal of Marketing Research (Vol. 31). Retrieved from https://theharrispoll.com/wp-
Journal.
of Abnormal and Social Psychology, 62(1), 74–78.
Brands.” Marketing Science, 10(3), 185–204.
Disclosure on Corporate Reputation: A Non-professional Stakeholder Perspective.” Journal of 
Business Ethics, 151(2), 429–450.
Perspectives, 21(2), 129–151.
management: Evidence from organizations in the value chain.” Journal of Product & Brand 
Management, 12(4), 220–236.
Barber, B. M. and T. Odean. (2001). “Boys will be Boys: Gender, Overconfidence, and Common Stock 
547–569.
Brand Hurt or Help Rival Brands? Journal of Marketing Research (Vol. 53).
82–89.
social media replacing traditional media in terms of brand equity creation?”
57–82.


