Customer Attitude from Social Media, Customer Satisfaction Index, and Firm Value

Social media has emerged as a key source of understanding customer satisfaction, which is used by investors in their investment decision. Nonetheless, whether and how social media metrics on customer attitude toward the company has not been thoroughly examined. This study develops a new index of customer satisfaction by using sentiment and content analyses of customer-generated social media content. Across multiple social media platforms, we found that positive testimonials (i.e., “Likes” from Facebook) and positive blogs have statistically positive associations with customer satisfaction, while customer complaints (from Facebook), negative blogs, and negative tweets are negatively associated with it by using a semiparametric model. Furthermore, we found that the proposed customer satisfaction index based on social media metrics is positively and statistically associated with firm’s market performance. In addition, we suggest that the new social media metrics about customer attitude toward the company would strongly complement existing customer satisfaction index such as ACSI.

1. Introduction

Customer satisfaction is one of the most important intangible assets of a firm that affects its market value (Fornell et al. 2016). Prior research suggests has high customer satisfaction leads to greater return on investment and cash flows (Aksoy et al. 2008; Anderson et al. 2004; Fornell et al. 2006; Gruca and Rego 2005; Tuli and Bharadwaj 2009) as satisfied customers are more likely to be loyal, thereby protecting market share, lowering price elasticity as well as selling/marketing costs (Anderson et al. 1994). To the extent that potential investors believe that customer satisfaction have positive impacts on future cash flows of a firm, they will seek and utilize information regarding customer satisfaction of firms to make investment decisions. In fact, research has shown that customer satisfaction does matter to investors who take satisfaction information into account while making their investment decisions (Anderson and Mansi 2009; Fornell et al. 2016; Luo et al. 2014). While it is difficult and costly to reliably assess customer satisfaction for a large number of firms on a regular basis, investors may use the American Customer Satisfaction Index (ACSI), which is the leading measure of customer satisfaction in the U.S., to obtain information about relative customer satisfaction of the three hundred largest companies in the U.S. consumer market (Fornell et al. 2006).[1] Specifically, it was found that higher ACSI leads to abnormal stock returns of approximately 10% per annum (Fornell et al. 2016). To leverage these insights, an exchange-traded fund has been recently created that uses ACSI to target companies with high customer satisfaction as a way to build stock portfolios that deliver long-term investment growth.

While ACSI has been a major source of obtaining customer satisfaction information, social media and online data collection has emerged as an important additional (potential) source of information about customer perceptions and opinions about firms. Further, with the advancement in information technology and big data analytics, investors have access to massive amounts of rich, real-time data about customers. Unlike ACSI data where customers respond to survey questions, online social media platforms allow investors to constantly and passively observe the customers' attitude toward the company and product (i.e., posting positive/negative messages and/or liking content on a firm's social media page, etc.) and infer the future impact of those actions on customer satisfaction as well as cash flows.

A few studies (Chen et al. 2011; Luo and Zhang 2013; Luo et al. 2013; Tirunillai and Tellis 2012) have shown that consumer generated content on consumer or third-party owned platforms (for e.g., blogs or review sites such as Amazon and Yelp) does affect the firms' market value. However, research that examines whether social media indicators of customer's attitudes,

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[1] ACSI provides annual customer satisfaction by gathering data from survey of about 70,000 households and utilizing a proprietary econometric model to calculate a customer satisfaction score. It has been shown that the information about customer satisfaction as released through ACSI does influence stock returns, thereby suggesting that investors utilize information contained in ACSI to determine the value of stock.

reactions, sentiments, or feelings toward the company are considered reliable by potential investors and if they also affect the firm's market value is lacking. Therefore, we investigate how these proxies of customer attitude toward the company from social media relate to customer satisfaction index such as ACSI and the impact of these social media metrics on the firm's market value. In this paper, we argue that (a significant number of) investors observe the customer attitude-related metrics on social media platform and use them as one of the factors in making their investment decision. Therefore, these social media metrics on customer attitude would complement existing customer satisfaction index such ACSI.

Consumer attitude toward the company can be measured in terms volume and valence of the content that consumers generate (i.e., Facebook posts and comments, Blogs, or Tweets) and their engagement with content created by the firm (i.e., liking). High volume of customer-generated content on the company may indicate that the (current and potential) consumers of the firm are highly involved and committed to the brand/product. Previous research has shown that individuals who actively participate in a community are; (1) more likely to engage with the focal brand/product in both offline and online communities (Algesheimer et al. 2005), (2) more committed to the brand (Jang et al. 2008), and (3) more likely to have greater expenditure on firm's products (Balasubramanian and Mahajan 2001; Manchanda et al. 2015).

While the volume of consumer-generated content may be an indicator of consumers' attitude toward the company, their active involvement and interest in the focal brand/firm, and the valence of the content is an important signal of the customer satisfaction. Research examining the relationship between consumer satisfaction and firm value suggests that customer satisfaction leads to sales and can be an economic asset (Anderson et al. 2004; Fornell et al. 2006; Gruca and Rego 2005) which is expected to influence firm value with high return and low risk (Fornell et al. 2006). In the social media context, the valence of consumer-generated content can reveal the quality of the focal firm's product/service and therefore can predict the current and future economic health of the firm. Specifically, consumer comments exhibiting positive sentiment on social media reflect positive word-of-mouth (WOM) from satisfied customers, which are expected to influence firm value. Unlike the customer satisfaction measured explicitly via surveys (like ACSI), a metric tracking the valence of consumer-generated content in social media serves as a passive observational measure from which the customer satisfaction can be inferred. Using advanced machine learning and big data analytic techniques, it is possible for investors, especially large/institutional investors to mine the consumer-generated content on social media to identify the content as having either positive or negative sentiment towards the company/brand. A greater positive sentiment would suggest that customers are satisfied and are sharing positive endorsement of the focal product/firm.

Negative sentiment, on the other hand, would be indicative of issues with the product failure and/or lapses in the service quality being raised by unsatisfied consumers. Though such an inference about the level of customer satisfaction based on sentiment analysis of the consumer-generated content may be noisier than a survey based satisfaction measure, this metric has the potential to provide real-time data on customer sentiment about the brand/firm (at low cost), which is impossible with the annual ACSI customer surveys that investors may rely on to make their investment decision. Prior research has shown that investors use ACSI customer satisfaction index for making investment decision. However, it is not clear if investors are also using data generated by indicators of customer attitude toward the company in social media to inform their investment decisions. To the extent that potential investors rely on the valence of the consumer-generated content as a signal of the product/service of the focal firm and use it as a proxy of customer satisfaction, the valence of customer attitude toward the company from social media would be positively associated with the market value of the firm.

In this study, we develop a new customer satisfaction index by using several indicators of customer's attitude toward the company from social media content, based on the detailed sentiment and content analyses. From a semi-parametric model of customer satisfaction index based on the Generalized Additive Model (GAM), we found that both positive and negative social media metrics about customer's attitude are significantly associated to customer satisfaction index. Importantly, we found that the new customer satisfaction index based on social media is significantly associated with an increase in the firm's market performance. Further, we suggest that social media metrics about customer satisfaction can serve as an important complement to existing customer satisfaction index such as ACSI.

2. Data and Empirical Settings

We randomly chose 63 South Korean firms out of top 100 firms in terms of the total market value, sales, and net income as sample firms. We then acquired three different social media data across Facebook, Blog, and Twitter. First, we acquired the Facebook business page dataset of our sample firms. The dataset was collected by developing a custom-designed Apache Hadoop/Hive-based crawler on a distributed computing platform. These customized agents, running in parallel on thirty Linux x86 servers, queried the Facebook API in order to acquire the specific post and comment information on each firm's Facebook page. As a result, all available data through the Facebook graph API for each firm was collected. To extract customers' attitude toward the focal company including their reactions, sentiment, and feeling, we employed text mining techniques. Specifically, by focusing on customers' posts and comments, we followed the sophisticated content categorization framework for customer posts on Facebook business pages which has been development by Yang et al. (2014): *positive testimonial*, *quality complaint, money complaint, social complaint, customer question, customer suggestion, and irrelevant message*. We first employed 'keyword search'-based classification. We randomly selected set of 1,500 customer posts and 3,500 customer comments. Then three RAs independently read the content and constructed a corpus for each category. We worked with RAs through several iterations to get the saturated corpus by adding keywords for unclassified contents. We then leveraged a qualitative approach along with keyword search approach to increase the accuracy of classification.[2] Overall, 48.65% of customer posts and comments are related to positive testimonial and appreciation and 8.26% of customer engagement represents their complaints. Based on this, we used the volume of customer complaints and positive testimonials. In addition, we measured customers' positive expression by the number of customers' "Likes" on a firm's posts in week *t*.

Second, based on the "firm key words," for the focal firm, four research assistants independently searched and carefully read all blogs from Google Blogs, and tweets from Twitter. Then they identified and counted overall positive, neutral, and negative sentiment *blogs* and *tweets* for the focal firm in week *t*.[3] As an index of customer satisfaction, we use the National Customer Satisfaction Index (NCSI). NCSI was developed by the National Quality Research Center of South Korea that is under the supervision of the University of Michigan, and it is based

[2] Specifically, after applying keyword search to entire customer posts/comments, 28,511 out of 43,976 customer posts and 849,515 out of 1,385,984 customer comments were classified. For the remaining content (i.e., 15,465 customer posts and 536,469 customer comments), ten undergraduate students were recruited and each student classified 55,193 customer posts/comments. Given that we did not pay attention to differences across types of complaint (quality, money, social complaint), each student focused to distinguish between positive testimonial and complaints by utilizing sentiment score from the previous sentiment analysis, and classified 99.3% of customer posts and comments.

[3] We utilized the search functions of Google Blogs website to find contents of the focal firms. In case of Twitter, it provides the advanced search functions to search positive Tweets or negative Tweets, so we used this advanced search function. The overall inter-rater reliability for the coding of conventional news, blogs, and Tweets was 0.98, suggesting a high level of agreement. For the remaining 2% where RAs did not reach an agreement, we labeled them as neutral.

on the ACSI measurement methodology and model that conducts measurement for announcement since 1994.

3. Developing a New Index of Customer Satisfaction

Given that our data allows us to have several indicators of customer's attitudes toward the company, reactions, sentiments, and feelings across multiple sources of social media (i.e., Facebook business page, Blogs, and Twitter), we can build a new index of customer satisfaction based on social media content. First, Let CS_{ijt} denotes the satisfaction of customer *j* on firm *i* at week *t*. We then calculated the customer satisfaction score of firm *i* at week *t*, CS_{it}, as $1/N \cdot \sum_{j}^{N} CS_{ijt}$, where *N* is the actual number of customers on firm *j* at week *t*. CS_{it} is approximately observed from NCSI as annual NCSI can be interpolated. We employed several interpolation schemes such as linear, cubic spline, nearest neighbor (Lancaster and Salkauskas 1986; Press et al. 2007) to generate the values of NCSI for each observed week. Given that three different interpolation approaches generate consistent estimations and linear interpolation had better model fit, we present result with liner interpolation later. Second, customer satisfaction, CS_{it}, can be determined by positive customer experiences, $PosiCE_{it}$, such as customer loyalty and usage behavior as well as negative customer experiences, $NegaCE_{it}$, such as customer complaints (Bolton 1998; Fornell 1992). Therefore, customer satisfaction, CS_{it}, is an unknown function of $PosiCE_{it}$ and $NegaCE_{it}$,

$$H(CS_{it}) = f\,(PosiCE_{it}, NegaCE_{it}) \tag{1}$$

We do not observe every positive/negative customer experiences across multiple contexts. Instead, by focusing on the sentiment of customer-generated content is social media, we approximate the RHS of Equation (1) as,

$$H(CS_{it}) \approx f\,(PosiCE_{it} \text{ from social media, } NegaCE_{it} \text{ from social media})$$

where, we use several social media metrics which can capture $PosiCE_{it}$ and $NegaCE_{it}$. In our data, we can use the volume of customer positive testimonials and Likes (from Facebook business pages), positive blogs, and positive tweets to capture $PosiCE_{it}$. Also, we can use the volume of customer complaints (from Facebook business pages), negative blogs, and negative tweets to capture $NegaCE_{it}$. However, since we cannot know the functional form of those variables, we approximate the function semi-parametrically. Among several semiparametric regression models (e.g., fractional polynomials, splines, generalized additive models), we approximate the function $H(.)$ by using Generalized Additive Model (GAM) (Hastie and Tibshirani 1990). The GAM is a generalized linear model with additive predictors consisting of smoothed covariates and provides increased flexibility in approximating the unknown function, $H(.)$.

The GAM fits the following flexible relationship between a set of covariates X and dependent variable Y, $\pi(\mathrm{H}(Y|X_1, X_2, \ldots, X_q)) = \alpha + g_1(X_1) + g_2(X_2) + \ldots + g_q(X_q)$ where π is a link function and $g_1, g_2, \ldots, g_q$ are nonparametric smoothing functions. Now, we model customer satisfaction score of firm i at week t,

$$s[\log(CS_{it} + 1)] = \omega 1_i + \Sigma g_{1r}(\textit{Facebook metrics};\ \omega_r)$$
$$+ \Sigma g_{2m}(\textit{Blog metrics};\ \omega_m) + \Sigma g_{3n}(\textit{Tweets metrics};\ \omega_n)$$

where $s \equiv f^{-1}(.)$ is the identity (Gaussian) link function, $\omega 1_i$ is an intercept term unique to each firm, i, and g_1, g_2, g_3 are cubic spline smoothing functions depending on the equivalent degrees of freedom for each predictor. We use the *gam* procedure (by Royston and Ambler) in the STATA software to estimate the GAM model and estimate our GAM model in a hierarchical manner. We first estimate our model with Facebook metrics only (see Model 1 of Table 1). We then estimate our model with Facebook and Blogs metrics (see Model 2) and Facebook, Blogs, and Tweets metrics (see Model 3). Given that Model 3 had better model fit (i.e., lower Deviance and higher total gain), we use all metrics from multiple sources of social media to estimate new customer satisfaction index. In the results of GAM model, we found that customer positive testimonials, "Likes", and positive blogs are positively and statistically associated with customer satisfaction, while customer complaints, negative blogs, and negative tweets are negatively associated with it. Then we got the fitted estimate of customer satisfaction score of firm *i* at week *t*, $\hat{\theta}_{it} = f\,(Facebook, Blogs, Tweets; \hat{\omega}.)$.

Table 1. Semiparametric Regression between NCSI and Social Media Metrics

Model	*(1)*	*(2)*	*(3)*
Source	*Facebook*	*Facebook + Blog*	*Facebook + Blog + Tweet*
Customer Complaints	-.0105553 (.0021775) $z = -4.848^{***}$	-.0096624 (.0021375) $z = -4.521^{***}$	-.0102323 (.0021142) $z = -4.840^{***}$
Customer Positive Testimonials	.0001607 (.000062) $z = 2.589^{***}$	.0001099 (.0000607) $z = 1.809^{***}$	.0001004 (.0000601) $z = 1.670^{***}$
Customer "Likes"	.0000109 (1.19e-06) $z = 9.157^{***}$	5.79e-06 (1.23e-06) $z = 4.722^{***}$	6.45e-06 (1.21e-06) $z = 5.309^{***}$
Positive Blogs		.0017787 (.0002102) $z = 8.461^{***}$	.001679 (.0002084) $z = 8.056^{***}$
Negative Blogs		-.0209967 (.0046691) $z = -4.497^{***}$	-.0209615 (.0046188) $z = -4.538^{***}$
Positive Tweets			.0004035 (.0006147) $z = 0.656$
Negative Tweets			-.0651804 (.0276873) $z = -2.354^{***}$
Observation	5,566	5,566	5,566
Deviance	12,419.7	11,806.3	11,539.0
Total gain (nonlinearity χ^2)	184.141	591.869	809.934
$\hat{\theta}_{it}$ *(mean, std)*	72.149 (0.288)	72.739 (0.432)	73.137 (0.464)

Notes. Significance: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.10$. We use the gam procedure (by Royston and Ambler) in the STATA software to estimate the GAM model. Robust standard errors are shown in parentheses.

Next, to examine whether the new index of customer satisfaction from social media is associated with firm's market performance (e.g., Fornell et al. 2006; Fornell et al. 2016), we use the following empirical model:

$$\text{Abnormal Returns}_{i,t} = \alpha_0 + \alpha_1 \text{ NEW CS Index}_{i,t} + \Sigma\, \gamma_k \text{ Firm's Activities outside of Social Media Dummies}_{i,t} + \Sigma\, \gamma_m \text{ Conventional Media Content}_{i,t} + \Sigma\, \gamma_j \text{ Firm Controls}_{j,t} + \Sigma\, \gamma_s \text{ Time Dummies}_s + \varphi_{i,t}. \tag{2}$$

Given that our focal new CS index captures customer satisfaction during a given week (from Saturday to Friday) and the abnormal returns are computed based on the closing stock price on Friday, new CS index precedes stock market reaction and therefore, we use contemporaneous values (*t*) for both independent and dependent variables. In order to mitigate the omitted variable bias and the resulting endogeneity concern, we include an extensive set of control variables that may be associated with firm's market performance.

We use abnormal returns that capture a firm's market performance beyond the firm's expected stock market returns. To estimate abnormal returns, we used the extended Fama-French model (Fama and French 1996). The Fama-French model has been recognized as a good proxy for stock market performance that considers market risk, firm size, as well as multiple value factors (Luo et al. 2013; Tirunillai and Tellis 2012). Specifically, we employed the following extended Fama-French model:

$$R_{it} - R_{ft} = \beta_{0i} + \beta_{1i}(R_{mt} - R_{ft}) + \beta_{2i}\, SMB_t + \beta_{3i}\, HML_t + \beta_{4i}\, MOM_t + \varepsilon_{it},$$

where R_{it} is the returns for firm *i* in week *t*; R_{ft} is the risk-free rate; R_{mt} is the average market returns; SMB_t is the small-minus-big capitalization factor; HML_t is the high-minus-low book-to-market equity factor; and MOM_t is the momentum factor in the given time period. We estimated the above equation for a rolling window of 30 trading days prior to the target day. Then, the

Abnormal Returns were then calculated as the difference between the actual returns and the expected returns.

Table 2. Firm Equity Value and New Index of Customer Satisfaction

Dependent Variable	*Abnormal Return*	*Abnormal Return*	*Abnormal Return*
Source	*Facebook*	*Facebook + Blog*	*Facebook + Blog + Tweet*
New CS Index based on Social Media Metrics	**0.013*** (0.007)**	**0.016*** (0.005)**	**0.024*** (0.005)**
New Product/Service Introduction	-0.002 (0.004)	-0.002 (0.004)	-0.002 (0.004)
Mergers and Acquisitions	-0.002 (0.006)	-0.002 (0.006)	-0.002 (0.006)
Advertising outside of Social Media	0.001 (0.004)	0.001 (0.004)	0.001 (0.004)
Competitive News/Buzz within Industry	-0.004 (0.006)	-0.004 (0.006)	-0.004 (0.006)
Positive Conventional News	0.002*** (0.001)	0.002*** (0.001)	0.002*** (0.001)
Negative Conventional News	-0.002** (0.001)	-0.002** (0.001)	-0.003** (0.001)
Firm Control Variables (Financial)	-included-	-included-	-included-
Time Dummies	-included-	-included-	-included-
Observation	5,566	5,566	5,566
R^2	0.202	0.206	0.210

Notes. Significance: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.10$. Models are reported using fixed-effects (FE). Models include firm's financial control variables (i.e., Total asset, R&D intensity, Advertising intensity, Operating margin, Leverage, Liquidity, and HHI), week dummies, but are not reported for brevity. Huber-White robust standard errors are shown in parentheses and clustered at the sector level.

We next control for a firm's activities outside of social media. Three research assistants independently identified a firm's activities outside of social media and classified these activities into four weekly dummy variables after reading major newspaper and magazine articles from the LexisNexis database (inter-rater reliability = 0.94): new product/service introduction, M&As, launching a new advertising campaign, and competitive news/buzz within industry. We also control for conventional news media (e.g., Yu et al. 2013) by searching and carefully reading every conventional news articles from Google News. In addition, we control for a number of financial variables that can affect firm performance. To control for growth opportunities available to a firm, we include *R&D Intensity*. In addition, we control for *Total Assets*, *Advertising Intensity*, *Operating Margin*, *Leverage*, and *Liquidity*. Finally, week dummies were included in our model to control for week-specific common shocks. We estimated Equation (2) by using a fixed-effects model based on a Hausman test.

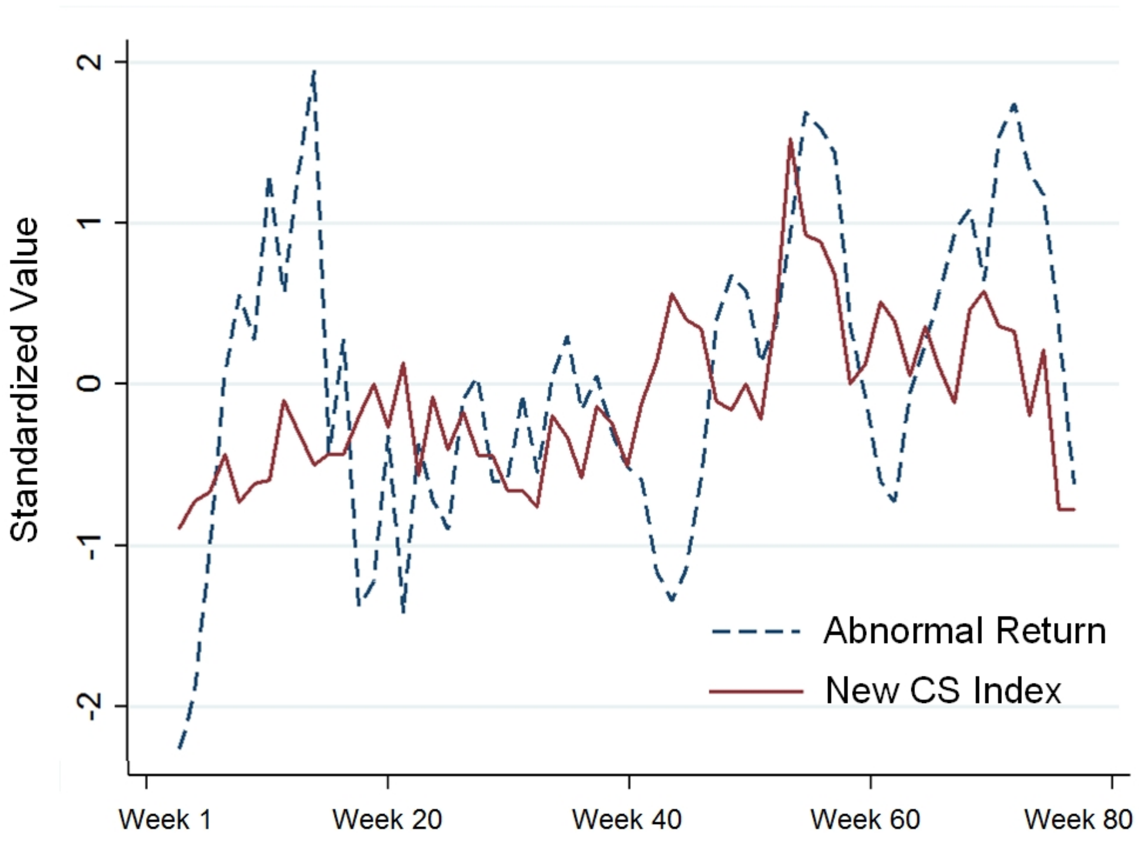

Figure 1. Firm Equity Value and New CS Index (for Samsung Electronics, Ltd.)

As shown in Table 2, new customer satisfaction index is positively and statistically associated with firm's market performance. In terms of economic significance, we found that new customer satisfaction index based on all kinds of social media (i.e., Facebook, blog, and Twitter) had a bigger magnitude of the estimated coefficient. Our results of estimating the fixed-effect model indicate that holding all other independent variables constant, an additional score of new CS index is associated with 0.024% increase in abnormal return. We checked that the magnitude and the sign of these elasticities are similar to various alternative specification such as random-effect and population-averaged model. As depicted in Figure 1, we look at the patterns of both abnormal return and new CS index for a representative sample firm, Samsung Electronics, Ltd. This plot gives us some insight into the co-occurring relationship between abnormal return and new CS index from social media (correlation between these two variables for the focal firm: $\rho = 0.33$).

4. Comparison with the Customer Satisfaction Index

We now take a different approach by comparing the social media metric of customer attitude with NCSI. We chose the quarterly level of analysis for this analysis. Using principal component analysis (PCA), we extracted two factors from social media metrics identified above. As shown in Table 3, the pattern of factor loadings supports the existence of two dimensions corresponding to positive feature and negative feature. Unlike semiparametric model, for each dimension of social media metric (positive and negative feature), we take a weighted average of the measurement items (weighted by their loadings in the underlying principal components) as the single-item measure. Then subtracting the single-item measure of positive feature to that of negative feature yields the overall score of customer attitude toward the company. The mean value of this customer attitude is 5.702 (std: 1.034). We used the linear-interpolated NCSI for each quarter. Then we standardized both the social media metrics of customer attitude and NCSI to allow a direct comparison of economic and statistical significance.

Table 3. Measurement of Proxies of Customer Attitude toward the company

Positive feature	*Mean*	*Std*	*Loading*	*1*	*2*	*3*	*4*	*5*	*6*
1. Customers' Testimonial	1498.8	4838.4	0.290						
2. Customers' Likes	188282.5	202307.6	0.375	0.32					
3. Positive Blogs	735.5	1175.6	0.318	0.14	0.38				
4. Positive Tweets	121.1	513.9	0.017	0.24	0.29	0.16			
Negative feature									
5. Customers' Complaints	29.4	102.3	0.477	-0.06	-0.03	-0.05	-0.04		
6. Negative Blogs	22.8	40.6	0.359	-0.19	-0.16	0.14	0.01	0.24	
7. Negative Tweets	20.1	11.2	0.164	-0.05	-0.03	-0.06	0.17	0.05	0.03

Notes. Average Variance Extracted (AVE): Positive (0.83), Negative feature (0.78), Cronbach's Alpha: Positive (0.81), Negative feature (0.69). We take the natural logarithm of variables to control their skewedness and the different absolute frequency.

We re-estimate Equation (2) with Tobin's *q* as an alternative measure of firm value by employing different specifications. Because Tobin's *q* has the advantage of capturing both short-term performance and long-term prospects based on the market value, it has been widely used in prior literature (e.g., Anderson et al. 2004; Bardhan et al. 2013). We calculated Tobin's *q* for our sample firms on a quarterly basis during our sample period. Table 4 presents the relationship between social media metric of customer attitude, customer satisfaction index, and firm value measured by Tobin's *q*. Across different specifications, we found that both key independent variables are positively and statistically associated with firm value, but the social media metric of customer attitude toward the company had a better statistical significance than NCSI. In terms of economic significance, the results indicate that the magnitude of estimated coefficient of customer attitude from social media is bigger than that of NCSI. Therefore, we suggest that the social media metric of customer attitude can complement existing customer satisfaction index.

Table 4. Firm Market Value and Customer Satisfaction Indexes

Dependent Variable	*Tobin's q*	*Tobin's q*	*Tobin's q*
Specification	*FE*	*FGLS*	*System GMM*
New CS Index from Social Media	**0.040***** **(0.012)**	**0.031***** **(0.004)**	**0.039***** **(0.018)**
National Customer Satisfaction Index (NCSI)	**0.029**** **(0.013)**	**0.010*** **(0.005)**	**0.025**** **(0.019)**
New Product/Service Introduction	0.006 (0.006)	0.001 (0.002)	0.007 (0.006)
Mergers and Acquisitions	-0.001 (0.008)	0.002 (0.002)	0.002 (0.011)
Advertising outside of Social Media	0.007* (0.005)	0.001 (0.002)	0.002 (0.006)
Competitive News/Buzz within Industry	0.011 (0.009)	0.004 (0.002)	0.012 (0.020)
Positive Conventional News	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)
Negative Conventional News	-0.002* (0.001)	-0.001* (0.001)	-0.002 (0.001)
Total Assets	0.167** (0.081)	0.046*** (0.009)	0.076 (0.249)
R&D Intensity	0.040** (0.019)	0.006 (0.010)	0.013 (0.013)
Advertising Intensity	0.098 (0.134)	0.056 (0.066)	0.034 (0.246)
Operating Margin	0.006*** (0.001)	0.006*** (0.001)	0.006*** (0.001)
Leverage	-0.003* (0.001)	-0.001 (0.001)	-0.002 (0.001)
Liquidity	-0.011 (0.003)	-0.028*** (0.005)	-0.014 (0.047)
HHI	-0.553 (0.373)	-0.041 (0.140)	-0.219 (0.613)
Time Dummies	-included-	-included-	-included-
Observation	632	632	632
Model fit	R^2 = 0.150	Wald χ^2 = 10192.81	Wald χ^2 = 4902.36

Notes. Significance: ***p < 0.01; **p < 0.05; *p < 0.10. Models are reported using fixed-effects (FE), feasible generalized least squares (FGLS), and system GMM estimation with differences in variables, respectively. Models include quarter dummies and sector dummies (except FE model), but are not reported for brevity. Huber-White robust standard errors are shown in parentheses and clustered at the sector.

5. Implications and Future Work

In this paper, we have developed a new index of customer satisfaction by using social media metrics of customer attitude toward the company, based on the sentiment and content analyses of customer-generated social media content. Across multiple social media platforms, by using a semiparametric model, we found that customer positive testimonials, "Likes" (from Facebook), and positive blogs are positively and statistically associated with customer satisfaction, while customer complaints (from Facebook), negative blogs, and negative tweets are negatively associated with it. Further, we found that new customer satisfaction index based on social media metrics is positively and statistically associated with firm's market performance. In addition, we found some clues that social media metrics about customer attitude toward the company would complement existing customer satisfaction index such as ACSI.

Our results suggest that investor can gauge up-to-date indicator of customer attitude toward the company in addition to the annual customer satisfaction index such as ACSI (e.g., Anderson et al. 2004; Fornell et al. 2016). This results can offer the future research. Although we employed three major social media platforms (Facebook, Blog, and Twitter), replications of this study by using additional sources of social media are need to enhance the generalizability of the results. Also, our results call for future research to develop theoretical model to explain how social media metrics of customer attitude toward the company complement the existing customer satisfaction.

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