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Can customer sentiment impact firm value? An integrated text mining approach

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A R T I C L E I N F O

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A B S T R A C T

Developing measures to capture customer sentiment and securing a positive customer experience is a strategic necessity to improve firm profitability and shareholder value. The paper considers the relationship between customer satisfaction, earnings, and firm value as these drives change in stock prices, customer, and investor sentiment. The present study investigates the impact of customer sentiment polarity on stock prices based on Indian automobile sector databased such as the Indian Nifty Auto SNE (Maruti Suzuki, Tata Motors, and Eicher). A top-down approach is adopted to construct a financial proxy-based sentiment index completed with sentiment extracted from automobile news and customer reviews. The paper uses a text mining approach to holistically measure customer sentiment's impact on investor sentiment and stock prices. The study was initially performed at the overall individual stock from the Nifty Auto NSE but focused on the top three passenger vehicle manufacturing companies i.e., Maruti Suzuki, Tata Motors, and Eicher. It was found that the sentiment index was augmented with news and customer reviews allows predicting more accurately NIFTY AUTO stock price movements. This implies that customer sentiment is a major driver of investor sentiment which in turn impacts the stock market and the firm value. Thus, the present study is an integrated approach to holistically measure customer sentiment's impact on investor sentiment and stock prices.

1. Introduction

Firms engage in ongoing efforts to retain existing customers while continually taking steps to attract new customers (Beaujean et al., 2006). To improve purchasing retention rates, firms focus on gaining customer loyalty (Fraering and Minor, 2013) while improving the customer satisfaction index. Hence, customer loyalty is fostered over time by managing 'personalized co-created experiences to the customer's best satisfaction' (Crosby and Johnson, 2007), where the customer experience is a journey along the strategic value chain management process for creating 'holistic customer value, achieving differentiation and sustainable competitive advantage' (Verhoef et al., 2009).

Both customer loyalty and experience have an impact on customer 'sentiment' which represents expectations of a stock's risk-return profile that are not justified by available information. Components of irrationality coexist independently at the aggregated customer and investor levels. Customer sentiment influences a firm's brand image and its sales (Karim, 2011). Customer opinions impact a firm's turnover, which in turn influence its earnings potential, growth rate, market capitalization, and stock returns. Moreover, changes in customer sentiment can directly impact investor sentiment, and these beliefs often impact stock returns (Baker and Wurgler, 2006; Merrin et al., 2013). Customer sentiment analysis assesses opinions on each of a product's attributes and brings a firm closer to its present or potential customers by capturing customer needs and their 360° feedback to shape its products, marketing solutions, and after-sales deliverables (Liu et al., 2019). Better service to customers with cost-effective pro-active measures helps to develop business and increase earnings, thereby improving asset returns (Bird et al., 2001). Magids et al. (2015) proposed that a company's gains increase when it connects with customers' emotions. They

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mentioned several essential factors that influence customers, including the product's uniqueness, its ability to provide confidence in the future, and the satisfaction gained due to a sense of wellbeing, thrill, or a feeling of security and success in possessing it.

Customer sentiment is captured during pre- and post-consumption, and measuring it requires data on customer views, expert reviews, news, company announcements, and all other complementary information (Pai and Liu, 2018). In a nutshell, customer sentiment is a mixed bag of customers' satisfaction index, i.e., positive polarity, coexisting with opposing polarity, and neutral feelings. Customer satisfaction is a measure of how services/products of a firm meet or surpass customer expectations, whereas customer sentiment is an emotional response towards a brand/service or product that may develop even without consuming the product (De Smedt and Daelemans, 2012; Michelle, 2019). Customer satisfaction is a post-consumption reaction and self-generated experience (Xun Xu, 2021); it is "specifically based on product usage or service experience, and therefore represents a narrower slice of the customer's experience" (Mittal and Frennea, 2010). In other words, customer sentiment is an emotional response due to human biases; however, customer satisfaction represents a concrete reaction that is largely independent of bias, only after undergoing or sharing the product's consumption experience. Giese and Cote (2000) defined customer satisfaction as a consumer's response with a particular focus that occurs at a particular time after making a choice or post-consumption. According to Anderson and Fornell (2000), customer satisfaction has three antecedents: perceived quality, perceived value, and customer expectations. Customer satisfaction, i.e., the positive quotient of customer sentiment index, is a market-based asset that is earned by a firm with the support of other cost and profit centers like R&D, production, HR, and finance (Hanssens et al., 2009). Fornell et al. (2009) verified that customer satisfaction has the potential to positively impact firm returns by shaping investors' expectations about future cash flows. Market researchers have applied various models using American Customer Satisfaction Index (ASCI) data to affirm that customer satisfaction impacts firm capitalization in the form of mispricing its stocks (Fornell et al., 2006, 2009; Aksoy et al., 2008; Ittner et al., 2009; Jacobson and Mizik, 2009; Ivanov et al., 2013; Capuano et al.,2021).

Analysts have introduced various models for the measurement of satisfaction/dissatisfaction (Fernandes and Santos, 2007). Customer reviews provide input for measuring customer satisfaction; however, analysts must be able to distinguish deceptive opinions from genuine customer feelings (Farhadloo et al., 2016). One model analyses the gap between customers' expectations and their perceived experience of performance of a service or a product. Cronin and Taylor (1992) propose the 'confirmation/disconfirmation' theory of combining the 'gap' described by customer satisfaction (1991) as two different measures (perception and expectation of performance) into a single measurement of performance according to expectation.

To understand the polarity, derived from customer sentiment (Campuano et al., 2021, Sengupta et al., 2021), we need to control its effects on financial indicators. Hence, in this paper, we develop a model for identifying such polarities. Consequently, this paper highlights the role of customer sentiment in building investor sentiment in the market. The paper's primary aim is to measure the impact of customer sentiment extracted from various sources on firm returns. To accomplish this objective, we examine three sources of customer opinions, namely change in brand image, customer pre-, and post-consumption reviews, and product reviews from experts, and we measure the incremental influence of each source on investor sentiment and company returns. We primarily focus on the auto industry due to such products' market pricing, customers' pride in possession, and the periodicity of its replacement/replenishment. However, the model is applicable across many industrial segments where customer reactions are available and measurable and where the impact of customer sentiment on investor behavior is measurable. We consider that industry and services sector segments like automobiles, airlines, consumer durables, banks, retail chains, telecom operators, hospitality industry, and medical care have visible customer vs. investor relations. Therefore, we discuss factors influencing customer sentiment in various sectors.

The conceptual framework attempted in the paper is at variance with related literature. While related literature has extensively covered the impact of investor sentiment on asset returns (e.g., Huerta-Sanchez and Escobari, 2018), we conduct an in-depth study of the combined influence of customer sentiment and satisfaction on stock returns. Moreover, we develop a holistic sentiment index from quantitative and textual datasets and study the value of customer satisfaction from a focussed perspective of a single industry. Other market researchers have used ACSI data to show that changes in national customer satisfaction indices impact stock returns (Fornell et al., 2006; O'Sullivan and McCallig, 2012). However, a national customer satisfaction index represents the aggregate satisfaction derived by all customer classes (i.e., consumers of all categories of goods and services rather than firm-specific customers) from all products whether imported or produced in the country. Furthermore, some firms dealing in the products may not be listed companies. It is essential to relate customer satisfaction value to the listed firm, and customer satisfaction from a product deriving from another firm is irrelevant to the firm under observation.

Finally, customer sentiment analysis is conducted deploying various statistical tools like search volume index (SVI), NLP, and machine learning, among others. Some studies have developed customer satisfaction indices using text analytics of tweets and presented them as customer sentiment indices (Wan and Gao, 2015; Pagolu et al., 2016; Al-Otaibi et al., 2018; Kumar et al., 2020; Biswas et al., 2021; Ulrike et al., 2011). For example, Anastasia and Budi (2016) compute a net sentiment score (NSS) comprised of positive and negative sentiments expressed on social media, which they call a satisfaction index. We extend such works by compiling an integrated sentiment index that incorporates data from customer and expert reviews as well as news and announcements that have a bearing on investor sentiment.

2. Literature review and hypothesis development

The automobile industry follows two basic product strategies: 1) a 'continuous spectrum' approach that focuses on the market as a whole, and 2) a targeted strategy that is tailored for multiple, discrete segments. On the one hand, automobile firms use the former to target existing customers by offering new models with a buyback option of their used vehicles or generate favorable stock market reactions with brand-enhancing measures such as announcements of environmental innovations like 'green vehicle' concepts (Ba, Lisic, Liu and Stallaert, 2013). On the other hand, an automobile firm's products are spread across customer segments, and consistency in its product strategy impacts its market performance. Auto sector companies attempt to discern customers' 'sweet-spots' and develop different vehicle models for various target groups, and the asset market reacts to customers' feedback on new vehicle models (Pauwels et al., 2018). By applying choice-based conjoint analysis, companies capture customers' perception of a product and remodel its features. The current COVID-19 pandemic is affecting automobile markets and production all over the globe (Baldwin and Tomiura, 2020). To maintain a stable price-earnings ratio (Anderson and Brooks, 2006), companies must focus on customer-centric strategies to ensure sales. The literature discussed in the below sections considers various scenarios that might impact customer sentiment and asset price throughout an automaker's life cycle, as illustrated in Fig. 1.

2.1. The spread of negative news resulting in product recall or reduced customer base

News stories and product reviews can be mined to find their implications on the investor sentiment of a firm (Ramaswami et al., 2009; Zhang et al., 2019; Xin et al., 2019; Choi et al., 2121). According to Fama

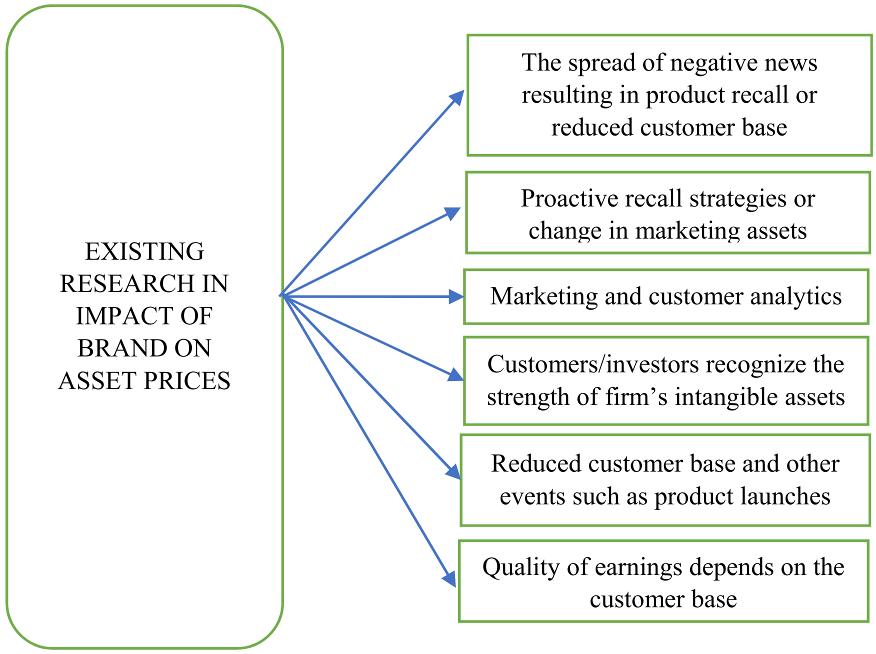

Fig. 1. Scenarios of ways customer sentiment can influence stock prices.

(1970), market reaction to information such as product announcements or news will result in immediate price adjustments, and any subsequent information, such as customer or expert reviews, will have less impact. However, any intense negative reviews will impact the market price in the long run. Moreover, whereas asset prices adjust relatively slowly to positive news of a brand or firm R&D activity, negative news spreads rapidly and quickly influences asset prices. Investors process the news and may adjust expectations for the sponsor's future cash flow, thereby impacting the share price (Mishra et al., 1997; Reiser, 2012). Tipton et al. (2009) found that misleading marketing methods can affect a firm's value when regulatory agencies intervene, and asset price sharply drops for firms facing product recalls, although it might recoup due to customer and investor confidence in the brand and the firm's follow-up actions. The findings illustrate that substantial brand equity protects firms from negative sentiment although competitors seize upon such opportunities (Rhee and Haunschild, 2006). Customer reviews directly impact investor sentiment. Negative reviews by customers and rating agencies affect asset prices and trade volume (Tirunillai and Tellis, 2012). Tirunillai and Tellis (2012) found that the risk of negative chatter peaks about four days from following an online posting. According to Manner (2017) and Yang et al. (2017), investors' attention to market predictions is represented by both direct and indirect proxies. Direct proxies are the search volume index (SVI), network broadcasting via Twitter, news, customer emotions, and the satisfaction index. Thus, product reviews on blogs and SVIs of firm products attract market attention.

2.2. Proactive recall strategies or change in marketing assets

Chen et al. (2009) found that initiating proactive recall strategies negatively reflects on firm value, as investors anticipate earnings surprises due to the lowering of analyst estimates as a pre-announcement adjustment. Srinivasan and Hanssens (2009) showed that investors' sentiment to changes in crucial marketing assets is reflected in their expectations of firm cash-flows and thereby impacts asset prices.

2.3. Marketing and customer analytics

Kumar and Shah (2009) found that if marketing techniques increase customer lifetime value (CLV), they have the potential to influence asset returns. Customer analytics can help choose techniques like CLV that use NPV of future cash-flows from the present and potential customers after adjusting for risk. In Germann et al. (2013) the paper discusses how the deployment of marketing analytics can improve firm value. Using 'upper echelons theory and the firm's resource-based view,' the paper surveys 212 senior executives of Fortune 1000 firms and found that marketing analytics is particularly beneficial to firms facing intense competition, with rapid customer preferences. In the context of increased media fragmentation, Sports sponsorship is considered an important tool for building brand equity and corporate image (Cornwell et al., 2001; Trappey et al., 2021) as it constitutes a vital part of the "marketing communication mix" (Tripodi, 2001).

2.4. Customers/Investors recognize the strength of a firm's intangible assets

The following five key areas exhibit the linkage of a customer sentiment or satisfaction index and strength of a firm's intangible assets: 1) analysts' views on a firm's intangible assets (Gu and Wang, 2005); 2) the main drivers of market value; 3) incorporating brand value in cash flows and a firm's economic value-added; 4) marketing strategies (including segmentation and product differentiation for securing brand loyalty and repeat orders), and 5) views of investors about a firm's intangible asset wealth. Thus, customer satisfaction (Fornell et al., 2006) is an essential asset that helps firms build investors' expectations for future cash flows and paves the way for improved asset returns (Hanssens 2009). Fornell et al. (2006) verified that investment in customer satisfaction produces high returns for low risk; whereas customer satisfaction as measured by the ACSI is significantly related to firm value, the stock market appears indifferent to news on ACSI. Probing further by constructing stock portfolios, they revealed that it is possible to outperform the market index by investing in firms rated high in the ACSI.

Aksoy et al. (2008) and O'Sullivan and Mc Calling (2012) examined the relationship between customer satisfaction, earnings, and firm value and used the Ohlson model to consider the impact of customer satisfaction on Tobin's q, a widely used marketing research measure, to assess firm performance. The authors reported that the impact of the

ACSI on firm value is significant over and above the impact of earnings. Chung et al. (2012) found that the predictability of stock returns due to investor sentiment appears more pronounced during periods of economic expansion than during recessions [although this finding was not acceptable to Garcia-Moya et al. (2013)]. During periods of economic expansion, a firm's value is negatively affected if its market share grows at a rate slower than the industry average, the best in the industry, or past growth rates. The fact that companies are now required to disclose non-financial information in their annual returns establishes the importance of marketing and customer satisfaction information for firm valuation (Storkenmaeir et al., 2012). Thus, a firm's financial disclosures include information on customer satisfaction to boost investor sentiment (Kimbrough, 2007; Luo et al., 2014; Eachempati et al., 2021; Gupta et al., 2021; Choi et al., 2020; Schmalz et al., 2021. However, Mizik and Jacobson (2007) suggested that financial accounting statements should also include asset values of customer satisfaction and brand equity rather than expressing them in profit statements. Higher customer satisfaction can assure consistent future cash flows leading to better asset returns with reduced volatility (Hanssens et al., 2009; Ramaswami et al., 2009).

2.5. Reduced customer base and other events such as product launches

Recent cases involving SNS firms such as Facebook and Twitter indicate that their share prices were affected due to a dip in their customer strength or customer sentiment even when the firms' financial results had improved (Matt, 2017). The strong form of efficient market hypothesis posits that markets react to leakage of product features before their launch by incorporating the expected value into the stock price (Fama, 1998). Volatility in asset price at the time of product launch is visible when the official news confirms the leaked news, and the reactions of investors with confirmation bias are delayed, thereby resulting in overreaction. The failure of a product launch in an Indian automobile company negatively affected its asset price (Matt, 2017).

2.6. Quality of earnings depends on the customer base

Firms with satisfied customers continue to grow; hence, the organizational growth rate is a strong indicator of customer satisfaction. Studies have identified longevity and revenue recurrence due to revenue (and customer) expansion rather than cost control (Jegadeesh and Livnat, 2006). However, Rajgopal et al. (2003) found that when analysts and investors find a considerable backlog of pending sales orders in a firm's financial statements, they tend to give more value resulting in 'a long(short) position in the lowest(highest) deciles of order backlog that generates significant abnormal returns'. Gu and Wang (2005) identified positive links between patent rights and projected earnings, although investors do not fully absorb asset prices due to certain biases. Some investors are concerned when a firm invests in massive advertisement campaigns, as they fear backlash and dividends' deferment due to such massive expenditure (Kothari, 2001). Fornell et al. (2006) found that the stock market did not adjust to the release of customer satisfaction data during the first 15 days; however, even when markets initially underreact, investors will engage if the data have any economic value, as it has the potential for exploitation in the future.

2.7. Limitations of existing studies

The limitations of the studies are:

Firstly, sentiment is not computed at different levels. For accomplishing the objective of validating customer sentiment impact on stock market, the study needs to measure the impact both at an individual firm level and then, at a market level.

Secondly, while the impact of customer sentiment has been studied, there is a need to demonstrate the incremental explanation power of customer sentiment on stock market. This would reaffirm the need for incorporating customer reviews to evaluate a firm's performance.

Thirdly, while customer sentiment is measured, the variation of sentiment over time is not validated in real-time for actual stock market events. This would corroborate the explanatory power of the index.

Fig. 2

To address the first research gap, a Bottom-up sentiment measurement approach is adopted. Initially, the sentiment is computed at an individual firm level and its impact on firm returns is evaluated. This is an initial screening mechanism to identify which firms of the sector have the most significant impact on sectoral returns. Subsequently, these firms are aggregated at a sectoral level and the sentiment is measured and impact is validated on sector-level returns.

To address the second research gap stated above, a sentiment index approach is adopted where three sentiment indices are constructed. The first one is a baseline sentiment index which only captures the impact of baseline financial indicators on the stock market. The second index is a news-integrated sentiment index that incrementally builds on the first one by incorporating market news sentiment to better explain the market performance. The third one is the customer reviews-induced sentiment index which further incrementally attempts to explain market performance with the incorporation of the customer and expert reviews sentiment.

Thirdly, an anecdotal validation of the customer sentiment index on real-time stock market events is illustrated in subSection 3.2.4. This validation aims to capture the co-movement of the sentiment indices with stock market events at the same point in time. This real-time validation helps in corroborating the performance of the index.

Thus, a real-time bottom-up sentiment index-driven model is formulated to validate the impact of customer sentiment on the stock market at the firm and sectoral levels. The rationale for adopting the hypotheses in the paper is explicated:

2.8. Hypotheses

We propose to test the following hypotheses in the paper, as illustrated in Fig. 3:

H_{1a}: Customer sentiment polarity developed from various product or customer-centric announcements from automobile firms and firm-specific news do not impact firm returns.

H_{1b}: Apart from industry news, customer and expert reviews do not incrementally impact NIFTY AUTO sectoral index returns.

To validate the hypotheses, we investigate both short- and long-term stock market responses to critical events such as a company's new product/model launch, a service provided to customers, or overall experience with a product in the Indian automobile sector. The sentiment index is a numerical guide for measuring investor or customer sentiment. We study the impact of customer sentiment on firm value, i.e. capitalization by using firm-level financial indicators apart from customers' reactions to company announcements and news to compute customer sentiment polarity (**H_{1a}**). We also study customer sentiment polarity at the industry level (**H_{1b}**) by using the following methodology to study the incremental impact of various sources of customer sentiment polarity on the investor sentiment index and in turn on Nifty Auto returns. In Section 3, we conduct two empirical studies of the Indian automobile sector at both the firm and market levels to validate both the hypotheses that customer sentiment impacts a firm's stock returns. The methodology to investigate the first hypothesis (H_{1a}) and results are illustrated in sub-Section 3.1 and the methodology for the second hypothesis (H_{1a}) and corresponding results are illustrated in sub-Section 3.2.

3. Impact of customer sentiment on automobile sector: an empirical study

As Brown and Cliff (2004) proposed, sentiment analysis may be conducted at a firm level and market level. Sentiment can be measured

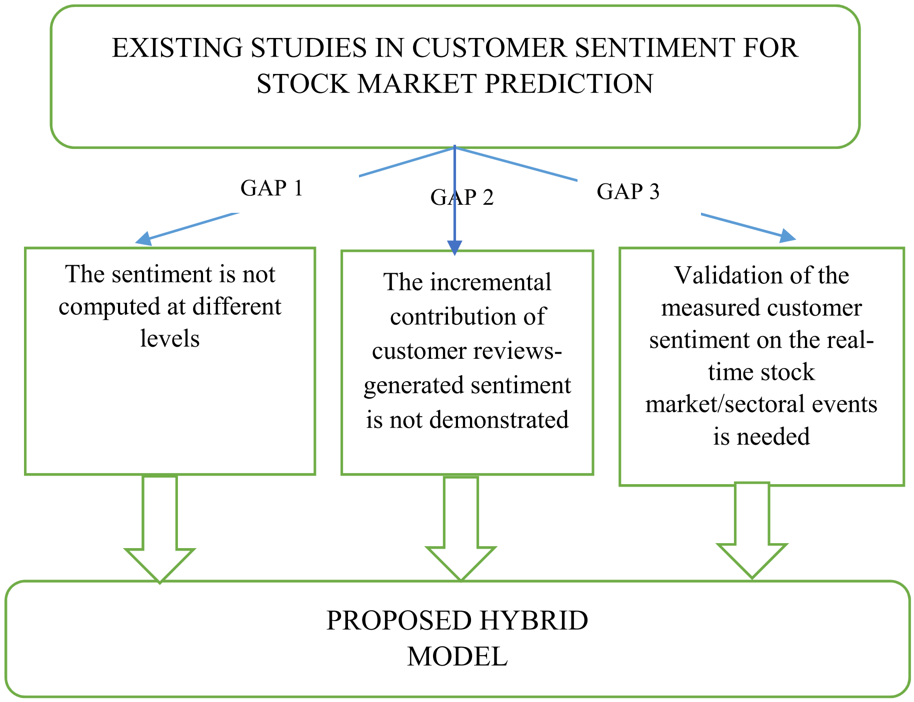

Fig. 2. Research Gap.

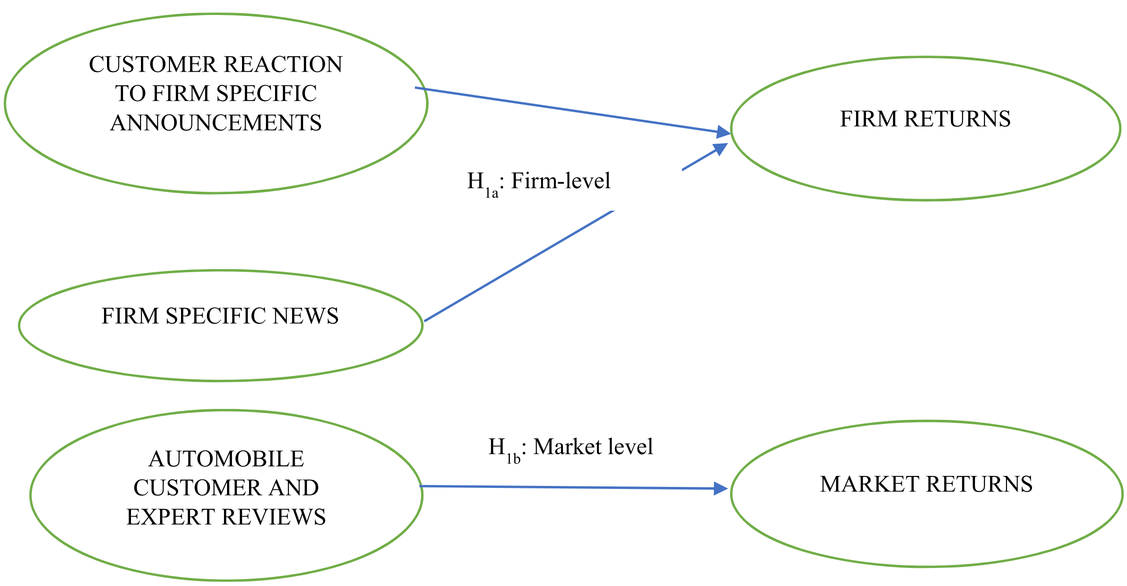

Fig. 3. Hypotheses.

either using a bottom-up approach or by a top-down approach. The bottom-up approach (Baker and Wurgler, 2006) involves measuring sentiment at an individual firm level and then aggregating the findings to a market level for more validation. The top-down approach conversely, generalizes the market sentiment and drills down to the individual firm level. Considering the impact of customer sentiment is to be evaluated at an automobile sector level, a bottom-up approach would be more appropriate. This is because analyzing sentiment granularly at a firm-level would initially provide an insight into which firms of the sector contribute to the overall sectoral sentiment. Based on this, the firms can be filtered out and the top firms with sentiment impact can be aggregated for the sectoral study level. This would enable a more accurate sentiment impact on the stock market. Therefore, the study initially is at the firm level and then investigates at a market level.

In Section 3.1, we examine the impact of customer sentiment on stock prices at the firm level from various perspectives. The study covers individual companies listed in the National Stock Exchange's (NSE) Nifty Auto Index that manufacture passenger vehicles, namely Maruti Suzuki and Tata Motors, which are the main constituents of the Nifty Auto Index with 40% and 7.5% weightage, respectively, as well as Eicher Motors, which manufactures motorcycles and commercial vehicles. We mine textual information from various product announcements or customer-centric announcements made by the above firms as well as firm-specific news, and then we extract the customer sentiment polarity from these sources using the N-Vivo tool. A least square regression model with firm-level financial indicators and sentiment polarity as regressors is implemented at an individual firm level and for the entire dataset. Notably, as demonstrated in Section 3.1.3, although we can

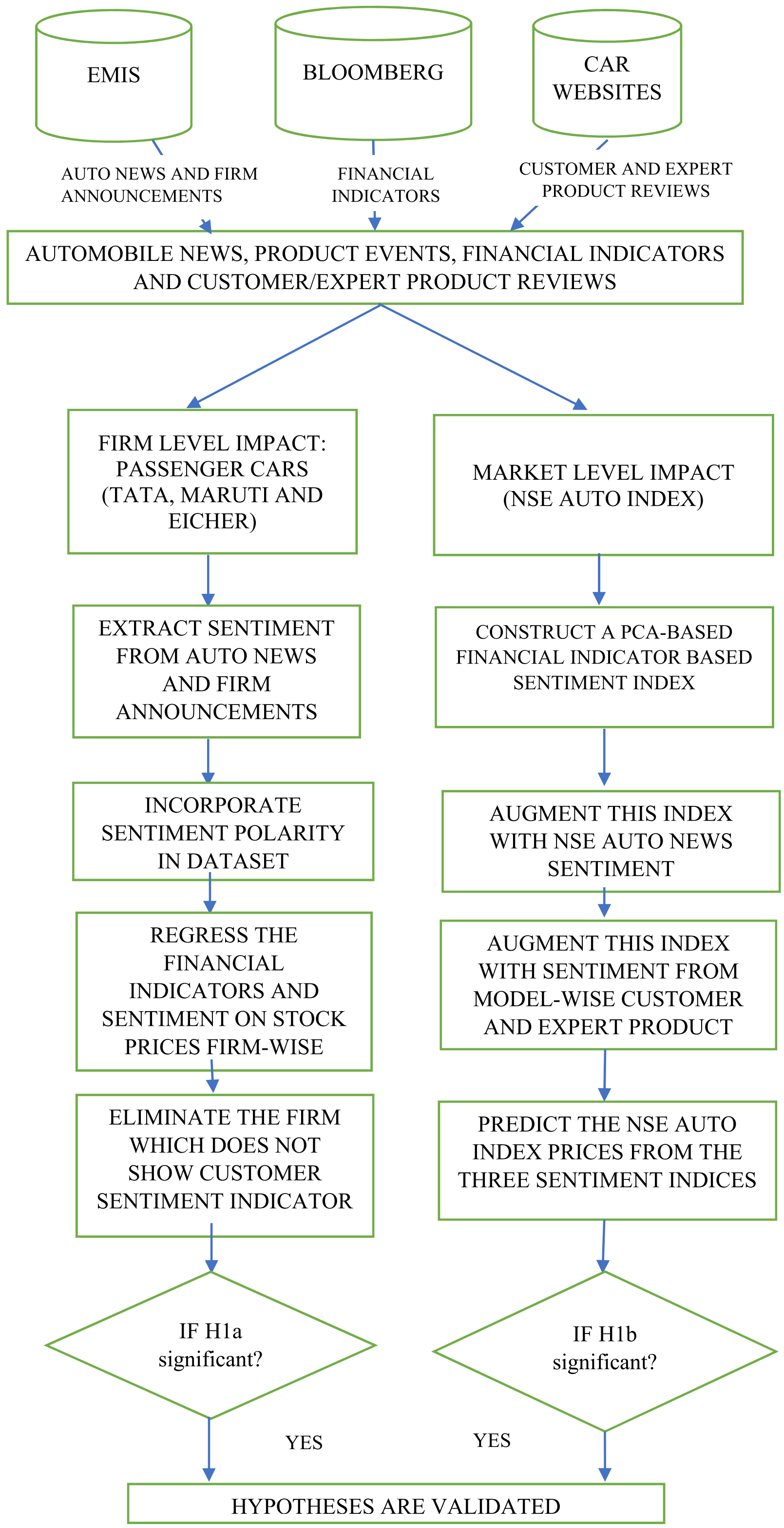

Fig. 4. Methodology for the studies.

observe the impact of the polarity of the customer sentiment in the case of Maruti Suzuki and Tata Motors, no such impact is noticed in the case of Eicher Motors, and therefore, this company is eliminated from further analysis.

Following the firm-level study, we present the study conducted at the market level in Section 3.2. We proceed in several steps to further understand the incremental impacts of customer satisfaction and sentiment derived from customer reviews and product reviews by experts on the stock market. First, to identify sentiment from financial indicators, we collect quantitative financial indicators for NSE's Auto and construct a Monthly Sentiment Index (MSI) using principal component analysis (PCA). Section 3.2.1 shows the methodology adopted for developing a

Composite Sentiment Index (CSI), which reflects the proxy sentiment of the financial indicators. The index was further augmented by extracting customer sentiment from analyses of news on and from the automobile sector to construct an Integrated Sentiment Index (ISI) in Section 3.2.2. In Section 3.2.3, we extract customer, influencer, and expert product reviews to investigate their incremental impacts on the NSE's (National Stock Exchange) Nifty Auto Index, and a sentiment score is computed and incorporated as a variable in the Enhanced Integrated Sentiment Index (EISI). We then implement three least square regression models to evaluate the incremental impacts of each explanatory variable. Following hypothesis validation in Section 3.2.4, the results are presented and discussed in Section 3.2.5. Fig. 3 illustrates the methodology undertaken for the study.

3.1. Firm-level impact of company announcements and product news

3.1.1. Dataset creation

The NSE Nifty Auto Index lists companies in the Indian automobile sector, among which three major passenger vehicle manufacturers are Tata Motors, Maruti Suzuki, and Eicher Motors. For the firm-level study, we do not consider expert or customer reviews but rather aggregate the reviews at the car model level, which are relevant to determine model performance but not to determine which firm has the most significant bearing on the Nifty Auto Index. However, sentiments gleaned from expert and customer product reviews are reported in firm news.

To perform the above-mentioned step, we extract 34,782 firm-level news and event reports dating from 2010 to 2018 from the Emerging Market Information Systems (EMIS) database on a time series basis using keywords related to the NSE Auto Index. The extracted news and events, which include reports of stock prices and industrial production, are analyzed as a proxy for measuring customer sentiment on the performance of the company's automobile models. Similarly, we use the Consumer Sentiment Index and its values from the Bombay Stock Exchange website. The impact of the overall consumer mood on the Indian economy may have a bearing on a firm's customer sentiment, and hence, we consider consumer sentiment as an additional factor (Fisher and Statman, 2000; Kelkar and Mokhade, 2016). Financial indicator data such as market capitalization, profit, leverage, and selling and administrative costs/sales ratio and respective company stock returns from the same period are taken from Bloomberg and aggregated yearly. We assemble the dataset for analysis by aggregating year-wise customer sentiment at the firm level. The dataset comprises 30 observations relevant to the three automakers, assuming that not all automakers are listed companies.

Fig. 4

3.1.2. Methodology

3.1.2.1. Extraction of customer sentiment. We use the open-source tool N-Vivo to extract customer sentiment and calculate its polarity by coding and analyzing specific automobile company-related keywords with a bearing on the Nifty Auto Index in news and event reports in the EMIS news database (Bazeley and Jackson, 2013). Initially, using the NVivo tool, we extract the raw automobile news from the emerging markets information system (EMIS) Database and clean the corpus for eliminating stop words, punctuation marks, adversative conjunctions, high and low intense words, and prepositions and for performing conversions from uppercase to lowercase and vice-versa. The software later eliminates the stale duplicate news (i.e., news containing the same headline and news body but at a different timestamp) and filters out only the unique sector-related news.

$$NORM\_VARIABLE_i = (VARIABLE_i - - MIN(VARIABLE_{1..k})) / ((MAX(VARIABLE_{1..k}) - VARIABLE_i), \quad (2)$$

Table 1
Variable Name, definitions, and data source.

Construct Name	Concept/Definition	Data Source
BSE Consumer Sentiment Index [BSE CSI_Normalized]	The benchmark was constructed by the Bombay Stock Exchange (BSE) to measure consumer expectations/ consumer sentiment.	BSE Website
Firm Size [MCAP]	The market capitalization of the firm	BSE Website
Leverage	The ratio of debt borrowed by the firm to the existing stocks held by the firm	CRSP (center for Research in Security Prices)
Profit	The ratio of income to stocks value	CRSP (center for Research in Security Prices)
Selling and General Administrative Expenses to Sales [SGA/Sales]	Selling and General Administrative Expenses to Sales	CRSP (center for Research in Security Prices)
Sentiment Polarity [Sentiment_Polarity]	The measure of sentiment direction (the extent to which positive or negative) extracted from news	EMIS(Emerging Markets Information System) and Bloomberg news

The sentiment polarity values are computed for the same period as financial proxy indicator data. We calculate the polarity as the ratio of net positive references to complete references and incorporate it as the variable SENTIMENT_POLARITY, which is used along with firm-specific financial indicators to compile the consolidated dataset of financial and sentiment-related data.

3.1.2.2. Variable operationalization and model. Following Luo and Tung (2007), the companies' annual stock returns are utilized as the dependent variable reflecting firm financial performance. Following Campbell et al. (2001), we calculate firm annual stock returns (FIR_RET) as the percent increase or decrease in the annual stock price of the three as firms represented by the formula:

$$FIR\_RET_{i,t} = \left(FIR_{i,t} - FIR_{i,t-1}\right) / FIR_{i,t-1}, \quad (1)$$

where $FIR_{i,t-1}$ is the annual stock price of the firm 'i' in period 't-1'. This calculated return for each company is the dependent variable $FIR\_RET_{i,t}$ for the proposed model.

Previous studies did not take into account the impact of company news and its impact on stock performance. We aggregate the computed sentiment polarity (from news taken from EMIS database users) by year to the firm level, and the resulting variable SENTIMENT_POLARITY is operationalized along with the financial indicators. Similarly, the BSE Consumer Sentiment Index data, which is available on a yearly time series basis, were normalized to a range of 0 to 1 using the min-max normalization method to normalize the variable with the formula:

where k is the total number of observations. The normalized values are incorporated into the Model as the BSECSI_NORMALIZED variable from 2010 to 2018.

Based on the above-cited studies (Campbell et al., 2001; Luo and Tung, 2007), we incorporate the fundamental financial indicators,

Table 2
Univariate summary statistics.

Summary Statistics	BSE CSI_Normalized	Firm Size MCAP	Leverage	Sentiment_Polarity	Profit	SGA Sales	Stock Returns
Mean	0.927879	334,652.1	0.172031	−0.112905	1.862172	0.011204	0.297389
Median	0.879097	307,632.1	0.027322	−0.099711	1.65782	0	0.225644
Maximum	1	788,718.2	0.651109	−0.012	4.403969	0.115096	1.776639
Minimum	0.867402	23,341	0	−0.170003	0.78036	0	-0.317693
Std. Dev.	0.065824	243,346.9	0.220504	0.049188	0.837586	0.024758	0.423234
Skewness	0.215871	0.346722	0.8799	0.477806	1.435881	3.176304	1.55324
Kurtosis	1.056213	1.95985	2.100113	2.779122	5.091926	13.05547	6.573672

namely MCAP (market capitalization of public company stock), profitability (the ratio of income to stocks value), leverage (the ratio of debt borrowed by the firm to the existing stocks held by the firm) and sales and general administrative (SGA) expenses as a ratio of sales, i.e., SGA/SALES. We aggregate all these variables on a yearly time series basis from 2010 to 2018.

Overall, the variables or constructs used, definitions, and data source are summarized in Table 1:

Table 2 presents the summary statistics for the variables considered for inclusion in the model

Least squares regression is applied to analyze the cause-effect relationship between the customer sentiment and financial indicator variables and the stock return performance (Table 3).

The proposed model for extracting customer sentiment and examining the impact on stock prices is illustrated in Fig. 5:

To construct the regression model, we first scrape firm-level announcements and automobile news posted on news databases like EMIS (Blodgett et al., 2015), and we use natural language processing to calculate the sentiment polarity by taking the net of positive and negative reviews to obtain the bullishness index for customer sentiment (Rao and Srivastava, 2012). The corresponding stock prices for the companies listed on the NSE are then regressed with the bullishness index to understand the extent to which customer sentiments influence stock price direction by examining the coefficient $\beta 1$ and the p-value:

$$\Delta StockPrice(t) = \beta 1 * Bullishness\ Index + \in \tag{3}$$

The customer sentiments are correlated with the investor sentiment index constructed using financial indicators to help understand the importance of customer sentiment and its relevance in the textual information for building a robust prediction model for stock price movement:

$$\begin{aligned} FIR\_RET_{i,t} = \ & \beta 0 + \beta 1 * SENTIMENT\_POLARITY_{i,t} + \beta 2 * BSECSI\_NORMALIZED_{i,t} \\ & + \beta 3 * MCAP_{i,t} + \beta 4 * Profitability_{i,t} + \beta 5 * Leverage_{i,t} + \beta 6 * SGA/Sales_{i,t}, \end{aligned} \tag{4}$$

where i designates firm and t represents the time point (year).

Similarly, to analyze the impact of customer sentiment on individual automobile firms at a more granular level, we filter the dataset firm-wise and formulate the regression model for each of the three firms. The results are provided below in Tables 4–6:

Table 3
Consolidated dataset regression results.

Variables	Coefficients	Standard Error	*t*	*p*
Intercept	4.92108531	1.368719047	3.595395	0.004204
SENTIMENT_POLARITY	1.70540487	1.929407921	0.883901	0.003956
BSECSI_NORMALIZED	-4.3307302	1.477142962	-2.93183	0.013646
Firm Size (MCAP)	-1.118E-07	4.73068E-07	-0.23639	0.817471
Profit	-0.0470323	0.106141625	-0.44311	0.666275
Leverage	-1.0154499	0.374719866	-2.70989	0.020295
SGA/Sales ratio	-2.5279323	3.102204735	-0.81488	0.432429

$R^2 = 0.66$.

3.1.3. Results and implications

As shown in Table 3, the results of the regression model run on the longitudinal panel consolidated dataset for all three firms from 2010 to 2018 indicate that the model can explain up to 66% of the stock returns. The SENTIMENT_POLARITY, BSECSI_NORMALIZED, and Leverage variables contribute the most to the stock return values. The regression model run on the longitudinal panel consolidated dataset for Tata Motors can explain up to 83% of the stock returns from 2010 to 2018 (Table 4). The p values for SENTIMENT_POLARITY, BSECSI_NORMALIZED, firm size (MCAP), SGA/Sales, and leverage indicate that all of these variables significantly influence the stock return values. The results of the regression model run on the longitudinal panel consolidated dataset for Maruti Suzuki indicate that the model can explain up to 76% of the stock returns (Table 6). In this case, all variables have a significant impact on the stock returns. In contrast to the other two cases, the results of the regression model run on the longitudinal panel consolidated dataset for Eicher Motors during the same period indicate that the variables can explain up to 25% of the stock returns (Table 5). However, in this case, none of the variables has a significant impact on the stock returns. The significant p values of the SENTIMENT_POLARITY variable for Maruti Suzuki and Tata Motors demonstrate that we can reject hypothesis H_{1a} in the case of these two companies. However, the insignificant p-value of this variable for Eicher Motors confirms the hypothesis H_{1a} for Eicher Motors. Eicher Motors is eliminated from further analysis.

3.2. Impact of product and customer reviews on the Nifty Auto Index: A sentiment index approach at the industry level

The following methodology is adopted to determine the incremental impact of customer sentiment drawn from customer reviews and expert reviews on various automobile models.

Firstly, we construct a composite sentiment index (CSI) using financial indicators that serve as a proxy for investor sentiment (3.2.1). To enhance the effectiveness of the CSI, we factor customer sentiment drawn from news on the NSE Auto Index from the EMIS and the NSE website to develop an Integrated Sentiment Index (ISI; Section 3.2.2). As the ISI can only explain 27.2% of the combined variance in the Index, we develop a more accurate index by factoring customer sentiment extracted from customer and expert reviews (Section 3.2.3). To validate the hypothesis of whether sentiment extracted from customer and expert reviews (influencer ratings/reviews) augments the ISI to better explain the market, we mine reviews from websites containing year-wise reviews for each car model (Section 3.2.3). Finally, Section 3.2.5 presents the results and implications of our analysis.

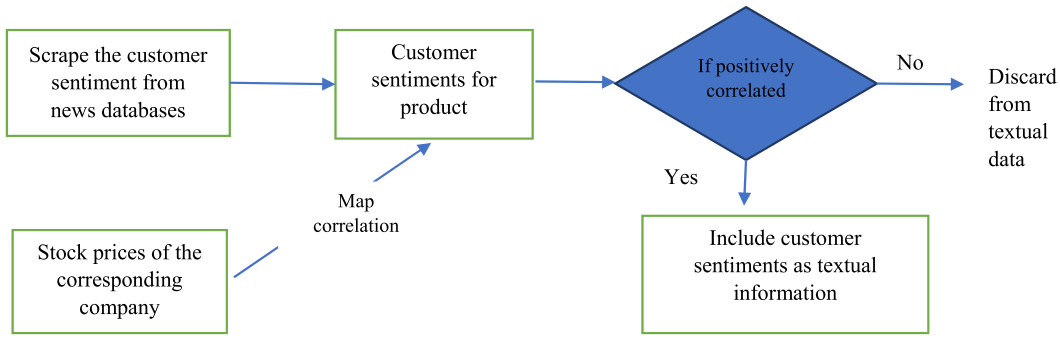

Fig. 5. Model for correlating customer sentiments with stock prices.

Table 4
Dataset regression model results for Tata Motors.

Variables	Coefficients	*p*
Intercept	3.305306	0.067345
SENTIMENT_POLARITY	-0.24594	0.008688
BSECSI_NORMALIZED	-2.56156	0.030101
Firm Size (MCAP)	-4.2E-07	0.048089
Profit	-0.06877	0.890862
Leverage	-0.06134	0.009553
SGA/Sales	-2.78073	0.006438

Adjusted $R^2 = 0.83$.

Table 5
Dataset regression model results for Eicher.

Variables	Coefficients	*p*
Intercept	4.163723	0.175839
SENTIMENT_POLARITY	-0.64594	0.868796
BSECSI_NORMALIZED	-2.08152	0.130101
Firm Size(MCAP)	-4.3E-07	0.548089
Profit	-0.07932	0.890862
Leverage	-0.05923	0.955352
SGA/Sales	3.75072	0.643842

adjusted $R^2 = 0.25$.

Table 6
Dataset regression model results for Maruti Suzuki.

Variables	Coefficients	*p*
Intercept	5.782345	0.085839
SENTIMENT_POLARITY	-0.34594	0.006879
BSECSI_NORMALIZED	-3.07156	0.000701
Firm Size (MCAP)	-5.4E-07	0.007476
Profit	-0.08477	0.000762
Leverage	-0.06134	0.000560
SGA/Sales	-2.78073	0.004782

Adjusted $R^2 = 0.76$.

Table 7
Composite financial-proxy based sentiment index.

Variable	PC1
ADVANCE_DECLINE_RATIO	-0.062
FOREIGN_INSTITUTIONAL_NET_FLOW	0.151
PB_RATIO	-0.509
PE_RATIO	-0.457
TRADE_VOLUME	0.55
TURNOVER	0.45

3.2.1. Construction of the composite sentiment index with financial proxy indicators

3.2.1.1. Methodology. We begin by constructing a composite sentiment index that incorporates financial indicators collected from the NSE website that serves as a proxy for investor sentiment (Baker et al., 2008): advance and decline ratio; turnover rate (number of shares traded out of the tradable shares in the NSE Auto Index); trading volume; price-earnings ratio; and inflows from foreign sources (foreign institutional investors). Then, we perform principal component analysis on the raw values using the SPSS statistical tool. We only consider eigenvalues that exceed 1. The results of the PCA show that the first component explains' 51% of the variance. The proxy financial indicators used to construct the Sentiment index are illustrated in Table 7 with respective factor loadings.

The SENT index/CSI is computed as a monthly sentiment index by substituting the respective month values for the above indicators to correlate with Nifty market movements from 2013 to 2018:

$$\begin{aligned} SENT &= -0.0162 * ADVANCE\_DECLINE\_RATIO + 0.15 * FII\_FLOW \\ &-0.509 * PB\_RATIO - 0.4578 * PE\_RATIO + 0.55 * TRADE\_VOLUME \\ &+0.45 * TURNOVER. \end{aligned} \tag{5}$$

3.2.1.2. Market implications of the composite sentiment index. Fig. 6 compares the direction of the monthly sentiment index with that of the NSE Nifty Auto Index for the years 2013–2018.

A gap in actual vs. predicted stock prices is evinced by a regression line plot of the CSI and NSE Auto index closing prices (Fig. 7).

Next, the monthly sentiment index computed from 2013 to 2018 is correlated with the corresponding changes in stock prices in the NSE Nifty Auto Index (Fig. 8). The correlation is found to be negative, thus proving that a sentiment index derived solely from financial proxy variables is not sufficient to explain stock price direction. Therefore, we also consider the sentiment of news events and customer reviews for index construction.

3.2.2. Construction of the integrated sentiment index

3.2.2.1. Methodology. Sentiment extraction from news related to the NSE Auto Index and calculation of sentiment polarity is conducted as illustrated above in Fig. 6. We perform sentiment analysis by applying a predefined machine learning and dictionary-based sentiment classification model and using the open-source N-Vivo tool to auto-code sentiments from the EMIS database according to four sentiment grades, namely very positive (+1), moderately positive (+0.5), moderate negative (-0.5), and very negative (-1).

The sentiment polarity values are computed for the same period as the financial proxy indicator data (2013–2018). The polarity is incorporated as the variable SENTIMENT_POLARITY along with the proxy financial indicators taken from Baker and Wurgler (2006) that are used

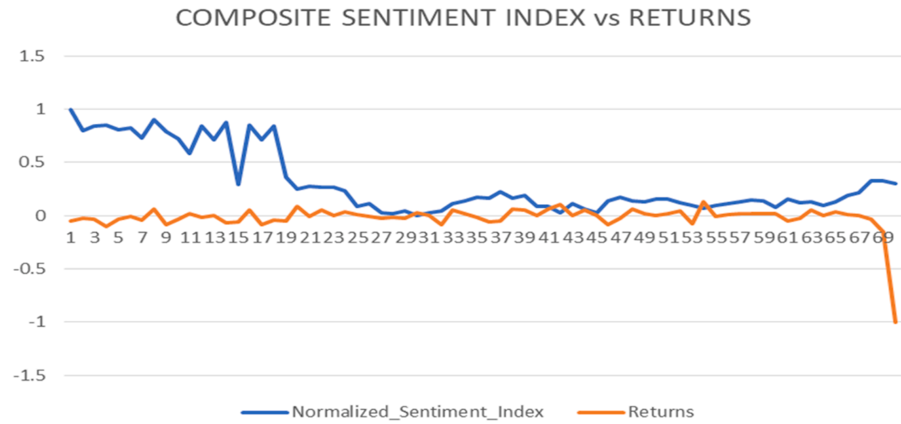

Fig. 6. Movement of the Composite Sentiment Index (2013 to 2018).

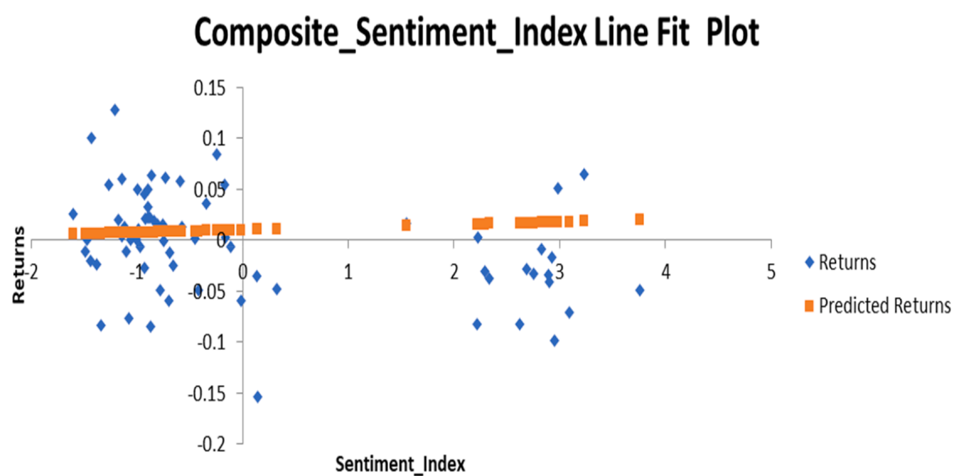

Fig. 7. Line fit plot for actual vs. predicted Nifty prices.

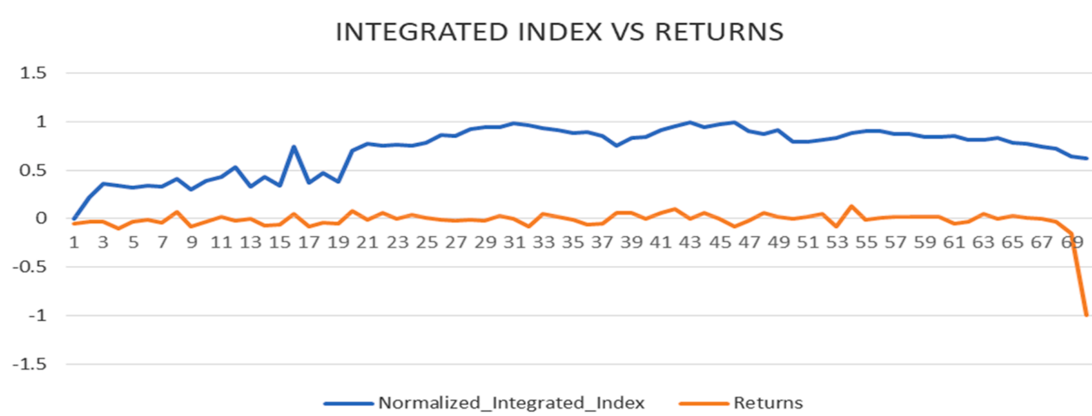

Fig. 8. Movement of the Integrated Sentiment Index and Nifty Auto Index returns (2013–2018).

to prepare the financial proxy-based CSI to construct an Integrated Sentiment Index. We perform principal component analysis on the integrated dataset, and the first principal component, which has an eigenvalue greater than 1, is taken to construct the sentiment index:

$$\sum Factor\ Loading_i * \frac{i}{Stdev_i}, \tag{6}$$

where i/Stdev$_i$ represents the normalized indicator value for a particular month and factor loading is obtained from principal components. We regress the ISI on the Nifty Auto Index prices to obtain predicted prices, as shown in formula 7:

$$\begin{aligned} INT\_SENT \; = \; & 0.059 * ADVANCE\_DECLINE\_RATIO - 0.087 * FII\_FLOW \\ & +0.51 * PB\_RATIO + 0.4586 * PE\_RATIO - \; 0.52 * TRADE\_VOLUME \\ & -0.427 * \; TURNOVER + 0.246 * AUTO\_INDEX\_NEWS\_SENTIMENT \end{aligned} \tag{7}$$

The results are presented in Table 8.

Table 8
Integrated Sentiment Index.

Variable	PC1
ADVANCE_DECLINE_RATIO	0.0595
AUTO_INDEX_NEWS_SENTIMENT	0.246
FOREIGN_INSTITUTIONAL_NET_FLOW	-0.087
PB_RATIO	0.511
PE_RATIO	0.458
TRADE_VOLUME	-0.525
TURNOVER	-0.426

3.2.2.2. Findings and market implications of the integrated sentiment index. Fig. 7 shows the causality of the ISI on Nifty Auto Index movement based on data obtained through the regression plot shown in Table 3. Fig. 8 evinces the better explanatory power of the ISI compared with the CSI.

The predicted stock prices are calculated for both the financial proxy-based CSI and the ISI using their respective regression models illustrated in Fig. 8. We compare the performance of the indices with the actual stock price of the Nifty Auto Index to determine whether the ISI explains the stock market movement more accurately than the financial proxy-based CSI. Comparing the ISI's R^2 of 0.272 and the CSI's R^2 of 0.232 evinces the higher explanatory power of the former.

3.2.3. Construction of the Enhanced Integrated Sentiment Index (EISI) using consumer reviews

To further augment the ISI, we mine expert reviews, influencer ratings, and customer reviews from car review websites and comments on social media sites as inputs for the extraction of consumer sentiment. Specifically, we extract reviews for each car model produced by Maruti Suzuki (Alto, WagonR, Swift Dzire, and Ertiga) and Tata Motors (Tata Nano, Tata Zest, and Land Rover) from Indian-based websites cardekho.com, carwale.com, and zingwheels.com along with comments below videos of new car model launches on YouTube. These reviews and comments are combined with Nifty Auto Index news from the EMIS database to predict stock movements on the Nifty Auto Index.

We first conduct a limited survey to determine whether the data analyzed in Section 3.1 accurately reflects the customer pulse and product perceptions. We survey 300 respondents belonging to different age groups, economic statuses, and educational backgrounds to confirm the reliability of the reviews based on a complete participation interview approach. The respondents are automobile enthusiasts in the age group of 25–45 with middle to high economic status background. The results corroborate that consumers consult expert and customer reviews before making automobile acquisition decisions. As indicated by a large number of responses awarding a score of 4 or 5 on a 1–5 scale, Figs. 9 and 10 illustrate that most of the customers rely on such sources, thereby justifying the sources chosen for extracting customer sentiment. Moreover, although not confirmed in the survey, when automobile companies launch new car models, the online influencer websites that display reviews and ratings about the models influence consumers to purchase the product by highlighting features that target specific demographic and psychographic customer segments. Hence, we also take influencers' ratings into account when constructing the model.

We then examine sentiment polarity extracted from customer reviews of each of four models produced by Maruti Suzuki (Alto, WagonR, Swift Dzire, and Ertiga) and three models made by Tata Motors (Tata Nano, Tata Zest, and Land Rover) from India-based websites and social media comments concerning product launches. Initially, the reviews are imported into the N-Vivo tool with the help of the N—Capture plugin that exports the reviews, performs paragraph-wise auto-coding, and generates the distribution of references into the above-mentioned sentiment grades (see 3.2.2.1). The number of views/impressions is considered for the customer review ratings to normalize the impact of ratings for each car model of Maruti and Tata Motors, from different sources. We eliminate reviews having less than 1000 viewers for a lack of impact on consumer purchasing decisions.

We calculate the sentiment polarity for each month from 2013 to 2018 according to the below formula:

$$\text{REVIEW\_SCORE} = \sum \textit{Net sentiment scores for each car model} * \textit{Number of views per car model} \Big/ \textit{Total number of views across each car model}, \tag{8}$$

where the Net sentiment scores equal:

$$\begin{aligned}&(\textit{Number of Positive references} * 1 + \textit{Number of Moderately positive references} * 0.5) + \\ &(\textit{Negative references} * -1 + \textit{Moderately negative references} * 0.5)\end{aligned} \tag{9}$$

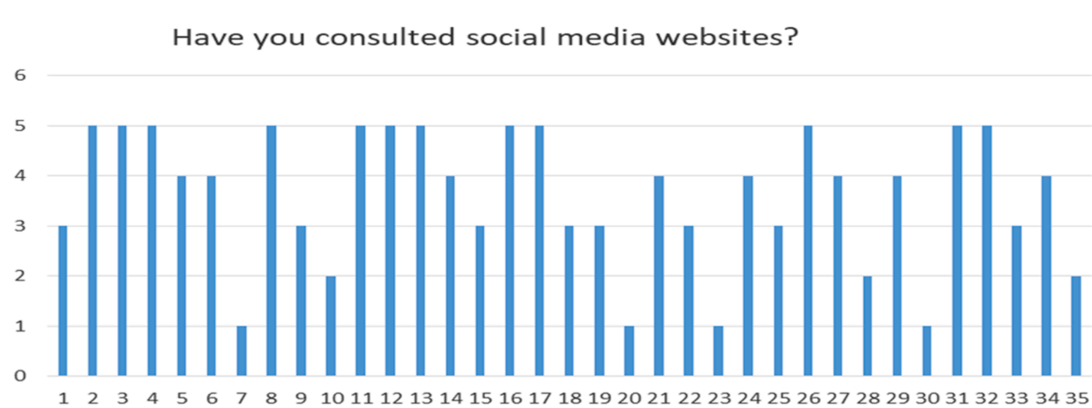

Fig. 9. Responses to whether customers consult social media website reviews [1–5].

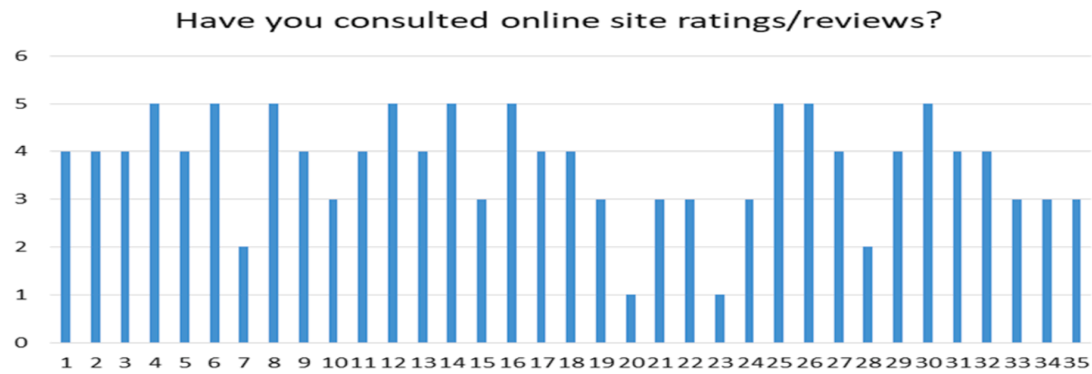

Fig. 10. Responses to whether customers consult online website influencer ratings and expert reviews [1–5].

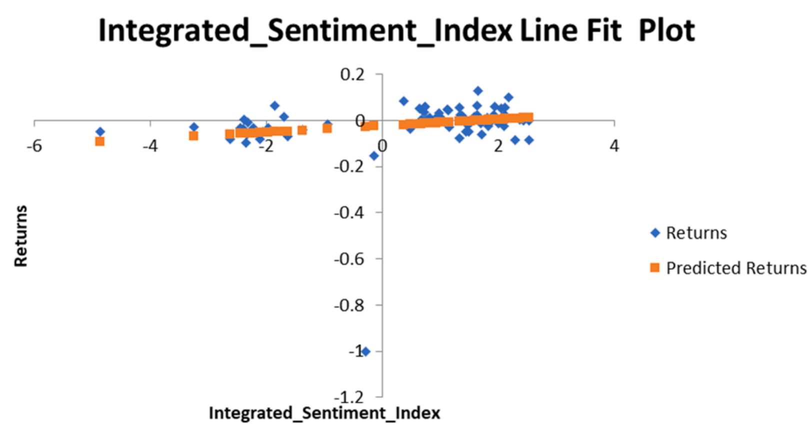

Fig. 11. Line fit plot for actual vs. predicted nifty price for EISI.

Table 9
Enhanced Integrated Sentiment Index.

Variable	PC1
ADVANCE_DECLINE_RATIO	0.0735
AUTO_INDEX_NEWS_SENTIMENT	0.266
EXPERT_REVIEWS_SCORE	0.0596
FOREIGN_INSTITUTIONAL_NET_FLOW	-0.071
PB_RATIO	0.511
PE_RATIO	0.457
TRADE_VOLUME	-0.519
TURNOVER	-0.417

We incorporate the sentiment score as the variable REVIEW_SCORE along with the proxy financial indicators and NSE Auto Index news to construct a reviews-augmented integrated sentiment index:

We perform principal component analysis on the reviews enhanced integrated dataset and consider the first principal component, which has an eigenvalue > 1, to construct the Enhanced Integrated Sentiment Index:

$$\text{EISI} = \sum Factor\ Loading_i * i \Big/ Stdev_i, \tag{10}$$

where i/Stdev_i represents the normalized indicator value for a particular

Table 10
Regression model results.

Variables	Baseline Sentiment Index	News-Enhanced Sentiment Index	News and Reviews-Enhanced Sentiment Index	VIF
Foreign Institutional Net Flow	0.0062***(0.025)	0.0069***(0.025)	0.00574***(0.025)	1.13
PE Ratio	-0.006***(0.03)	-0.0057***(0.03)	-0.0069***(0.03)	1.05
PB Ratio	0.049***(0.04)	0.034***(0.04)	0.067***(0.04)	1.63
Advance/Decline Ratio	0.021(0.59)	0.031 (0.59)	0.044 (0.59)	2.25
Turnover	0.0033***(0.01)	0.0043***(0.01)	0.0089***(0.01)	1.04
Trade Volume	-0.0147***(0.001)	-0.0149***(0.001)	-0.0157***(0.001)	4.8
AUTO_INDEX_NEWS_SENTIMENT_POLARITY		0.367***(0.0006)	0.787***(0.0006)	5.4
REVIEWS_SCORE			19.032***(0.0004)	3.26
Adj. R-Square	0.544	0.649	0.853	
DW	2.01(0.45)	2.65(0.1)	2.86(0.2)	
LM	4.78(0.74)	4.67(0.23)	4.85 (0.43)	

month and factor loading is from the principal component. The EISE is regressed on the Nifty Auto Index prices and compared with the CSI and ISI to determine the extent to which it explains the stock returns (Fig. 11).

Further, to examine how customer and expert reviews influence the firm performance measured in terms of stock returns, we develop three least square regression models. The first baseline model captures only the financial indicators considered in the composite sentiment index and how they explain the stock returns. The second model additionally incorporates the Auto index news and related events as NSEAUTO-NEWS_SENTIMENT. The final model incorporates the REVIEW_SCORE variable to assess the incremental contribution of this variable, as illustrated in the Enhanced Integrated Sentiment Index in formula 11 and Table 9:

$$\begin{aligned} &INT\_SENT2 = 0.0735 * ADVANCE\_DECLINE\_RATIO - 0.07066 * FII\_FLOW \\ &+0.511 * PB\_RATIO + 0.4576 * PE\_RATIO - 0.51 * TRADE\_VOLUME \\ &-0.417 * TURNOVER + 0.059 * EXPERT\_REVIEWS\_SCORE \end{aligned} \tag{11}$$

The results of the three indices (composite, integrated, and review-augmented integrated indices) and the regression models are summarized in Table 10 below. As a comparison of R^2 values indicates, the third model explains market performance better than the first two methods.

Table 10 reports the coefficients and significance value (in p-value) for the three models: "Baseline Model", "News-Enhanced Sentiment Index" and "News and Reviews-Enhanced Sentiment Index". *** indicates a 0.1 (10%) significance. The regression results assumptions autocorrelation, homoskedasticity, and multi-collinearity are validated by Durbin Watson (DW), Lagrange Multiplier (LM), and Variance Inflation Factor (VIF).

The important variables identified from the machine learning models are taken as dependent variables in Baseline Sentiment Index. The results of the Baseline Sentiment Index support the inferences drawn from the machine learning models. The explanatory power of Model I is 0.544, as indicated through Adjusted R-Square. This means that the identified dependent variables contribute to 54.4% variations in the model.

$$\begin{aligned} &Coefficient\ of\ AUTO\_Index\_News\_Sentiment\_Polarity * \\ &Standard\ Deviation\ of\ AUTO\_Index\_News\_Sentiment\_Polarity / Standard\ Deviation\ of\ NIFTY\ price \\ &= 0.367 * 0.0857/0.678 = 0.0463 \end{aligned} \tag{12}$$

In this context, for the baseline model, the Durbin Watson value (DW) is 2.01 with a p-value of 0.45, and the significance value rho is 0.001 indicating no autocorrelation with the rule that DW must lie between 2 and 4 and rho must be equivalent to 0. The Lagrange Multiplier (LM) is 4.78 with a p-value of 0.74 (> the level of significance alpha = 0.05 i.e.,5%) implying homoscedasticity.

The news-enhanced Sentiment Index incrementally builds on the baseline model by including sentiment polarity from the news. The variables included in the baseline model are still found to be significant. Adj.R-Squared improves with a value of 0.649. This demonstrates that news-based sentiment is additionally influencing the stock market. For the News-enhanced Sentiment Index, the regression assumptions are found to be valid similarly.

News and Reviews-Enhanced Sentiment Index includes customer reviews sentiment corresponding to Table 10. The sentiment is found significant. Adjusted R-Squared improves with a value of 0.853. The regression assumptions continue to be valid. The VIF can be computed for the variable points by performing a multiple linear regression and by the formula: 1 / (1 – R Square). The dataset is found to be multi-collinear with VIF less than threshold value 10.

3.2.4. Validating the sentiment indices with Nifty Auto market developments

The regression plot of the Review-enhanced Integrated Sentiment Index in Fig. 12 indicates that customer reviews have augmented the Integrated Sentiment Index to better explain the stock returns with an R^2 of 0.65.

Table 10 shows that customer sentiment plays a vital role in explaining stock market movement as characterized by a significant influence of the REVIEWS_SCORE variable and the highest adjusted R^2 value among the three indices. Thus, hypothesis H_{1b} is rejected at the market level.

Below, the economic significance of both the News-enhanced Integrated Sentiment Index and Enhanced Integrated Sentiment Index (Table 10) are compared to gage the sensitivity of the News-Enhanced Integrated Sentiment Index (ISI) and Reviews-Enhanced Integrated Sentiment Index (EISI) to Nifty Auto index direction. For Table 10, the Economic Significance for News-enhanced Integrated Sentiment Index equals:

According to the coefficient, the ISI positively influences trends in the Nifty stock market. Further, the economic significance is 0.0463, which implies that for every one standard deviation change in Nifty prices, there is a change of approximately (0.0463/0/678) units i.e., 0.0684 units in the News-enhanced Integrated Sentiment Index (ISI).

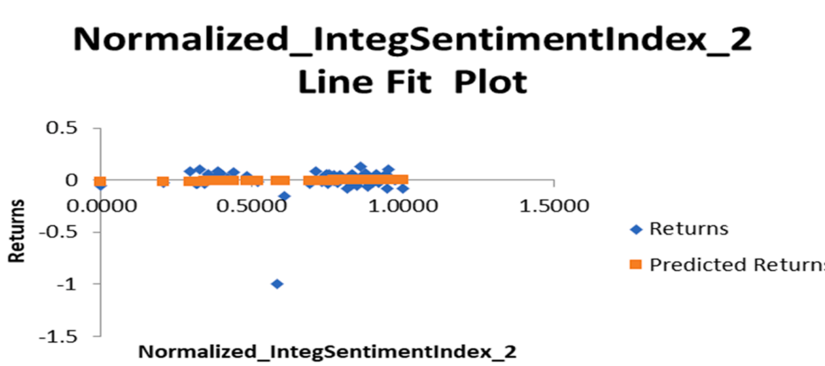

Fig. 12. Regression plot of Enhanced Integrated Sentiment Index.

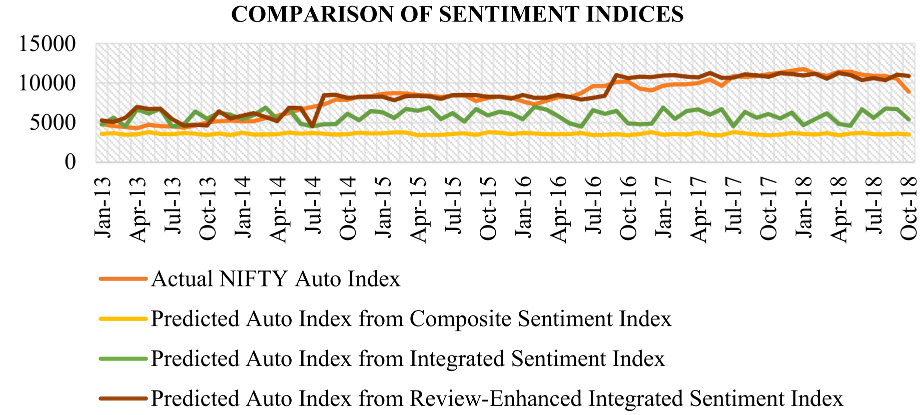

Fig. 13. Comparison of Sentiment Indices for Nifty Auto index.

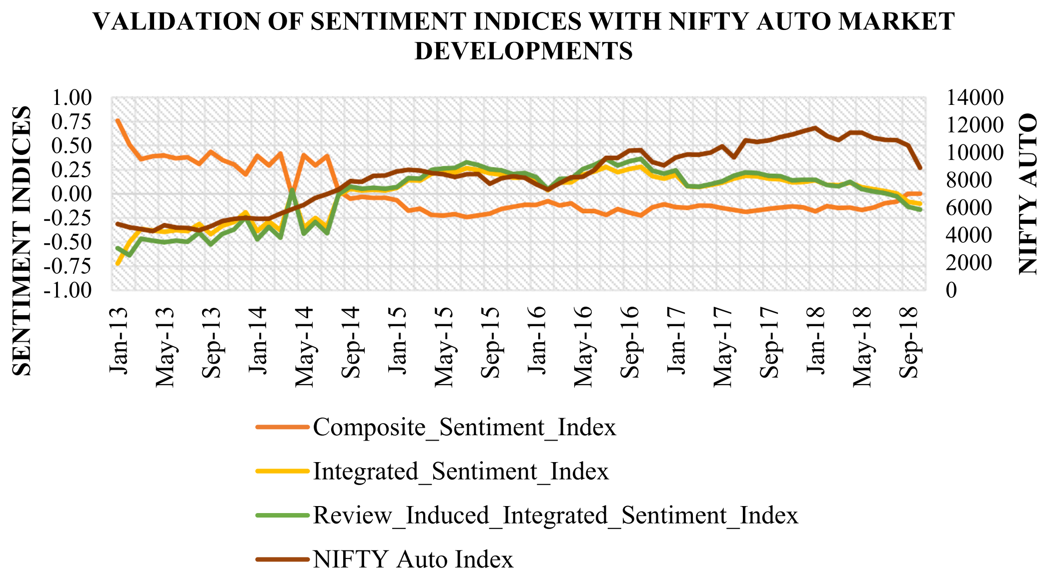

Fig. 14. Validating the sentiment indices with Nifty Auto market developments.

Similarly, for Table 10, the Economic Significance for Reviews-enhanced Integrated Sentiment Index is calculated according to the following formula

$$\textit{Coefficient of REVIEWS\_SCORE} * \textit{Standard Deviation of REVIEWS\_SCORE} / \textit{Standard Deviation of NIFTY price} \tag{13}$$

$$\text{Theresult} = 1109 * 1628/1178 = 1532.64$$

Again, the positive coefficient indicates that the ESI positively influences the direction of the Nifty stock market. Further, the economic significance is 1532.64, which implies that for every one standard deviation change in Nifty prices, there is a change of approximately 1.3 units in the EISI. We compare the actual Nifty Auto Index prices from January 2013 to December 2018 with the predicted prices computed from the regression models in Table 10 (Fig. 13). The predicted Nifty Auto price computed from the EISI is closer to the actual Nifty Auto index price than the predicted prices computed from the CSI and ISI. Fig. 13 reveals a relatively flat market path if only financial indicators are considered (yellow line). However, when the polarity from customer sentiment is considered, the market reaches elevated levels (brown line) and synchronized with the actual market (red line), thereby evincing that customer sentiment impacts firm return.

Fig. 14 shows the movement of the unit normalized integrated sentiment indices (integrated and review-enhanced integrated indices)

Table 11
Results and inferences.

S. No.	Hypothesis	Inference
H_{1a}	Customer sentiment polarity developed from various product or customer-centric announcements from automobile firms and firm-specific news does not impact firm returns.	The hypothesis is rejected for Maruti Suzuki and Tata Motors but not for Eicher Motors.
H_{1b}	Apart from industry news, customer and expert reviews do not incrementally impact NIFTY AUTO sectoral index returns.	The hypothesis is rejected at the stock market level for the NIFTY AUTO index.

along with the Indian Nifty Auto Index. These data represent the anecdotal account of the impact of customer sentiment on market movement. The results indicate that the indices developed in the paper have reflected market developments to a substantial degree, thereby demonstrating the impact of customer sentiment on market returns.

The period from January–September 2013 is relatively stable, with Nifty Auto prices ranging between 4000 and 5000 basis points, as reflected in changes in the ISI and EISI (trending toward 0 and ending up at -0.5 and -0.38, respectively, thereby indicating no significant sentiment fluctuations). However, the product launch of Maruti WagonR Stingray in September 2013 lifted the Nifty Auto market to over 5000 basis points, improving the ISI and EISI to -0.28 and -0.25, respectively due to positive reviews by users and experts. The momentum continues until June 2014, when the Index is further boosted to 6700 points due to announcements of six new Maruti Suzuki products, in particular Maruti Suzuki Ciaz. The integrated and review-enhanced integrated sentiment indices also increased to 0.05 and 0.03, respectively harboring positive sentiment. In September 2015, the steadily climbing NSE Auto market suddenly plummets from 8427 points to 7700 points due to a sudden product recall of 33,098 Maruti Suzuki vehicles (Alto 800 and Alto K-10), and the ISI and EISI capture the market shock due to the product recall, decreasing from 0.13 to 0.05 to -0.12 and -0.13, respectively. A similar situation is observable in November 2016 with the Nifty Auto Index decreasing from 10,164 points to 9300 points due to the difficulties Tata Motors experienced with its car model, the Nano. This situation is reflected in a decrease in the ISO and EISI to 0.25 and 0.13 from 0.38 to 0.27. Thus, the anecdotal evidence validates the correspondence of the integrated (ISI) and review-enhanced integrated (EISI) sentiment indices with Nifty Auto market events. We find that the principal component of this index further improves the accuracy of the model to explain NSE Auto Index returns, thereby evincing that customer and expert reviews have an impact on the Auto Index.

3.2.5. Results and implications

We showed that the Reviews-Enhanced Integrated Sentiment Index (EISI) is more economically influential than the News-Enhanced Integrated Sentiment Index (ISI), and that it better predicts movement in the Nifty Auto Index.

The overall inferences from the above studies are summarized below in Table 11.

For H1a, it is found that in the case of Maruti Suzuki and Tata Motors, the alternate hypothesis is rejected (i.e., customer sentiment from firm announcements and news impacts firm returns). However, the same alternate hypothesis is accepted for Eicher (i.e., no impact of customer sentiment observed). This is due to the fact the major volume of customer reviews for firms comes from owners of passenger vehicles (Jochem et al., al.,2018). These are the higher economic class, educated and opinionated strata of consumers who depend on online website customer reviews for making automobile purchase decisions. On the other hand, truck drivers and heavy commercial vehicle owners do not belong to the same strata. They are not reliant on online customer reviews but rely directly on the brand and specifications of the heavy commercial vehicles. Maruti Suzuki (Jeyabharathy and Ramesh,2021) and Tata Motors (Prateek and Ruparao,2019) being major passenger vehicle manufacturers belong to the first strata of customers thus leading to the rejection of H1a. Eicher motors are not dedicated to passenger vehicles (Kumar et al., al.,2021) but also manufacture heavy commercial vehicles and have a lesser proportion of customers relying on online reviews, thus accepting H1a.

Thus, the study validates both the hypotheses that customer sentiment impacts the stock market returns rejecting the hypothesis at both the firm and market levels.

4. Conclusion and implications

4.1. Key results

This paper investigated and validated the hypotheses that customer sentiment impacts stock returns both at the firm level and for the aggregate Auto index of the National Stock Exchange (NSE). We find that the Composite Sentiment Index (CSI), developed using the financial proxies of investor sentiment as a baseline, explains 23.2% of the variance in asset prices. Nevertheless, when the CSI is augmented with NSE Auto market-related news to develop a news-integrated sentiment index (ISI), the index explains d 27.2% of the variance in the auto index. Thus, auto news has a marginal impact on investor sentiment. Next, we developed a Reviews-Enhanced Integrated Sentiment Index (EISE) incorporating customer reviews and product reviews of experts, which explains 65% of the variance in the NSE Auto Index, such that the auto index positively changes in accordance with polarities in customer sentiment, and the Reviews-Enhanced Integrated Sentiment Index is a robust indicator of the potential of customer sentiment to influence firm returns. This finding is corroborated by regression models of the individual factors considered as explanatory variables, which show that the statistical significance of RISE is corroborated in terms of economic significance.

4.2. Implications and contribution to the customer satisfaction literature

The paper presents a holistic approach for obtaining definite conclusions on the role of customer satisfaction or dissatisfaction (i.e. customer sentiment) in improving both firm performance and overall stock market performance. Firms that monitor and strive to improve their customer sentiment index will produce improved firm returns. The polarity of customer reviews shows a measure of customer satisfaction, and the polarity of expert reviews indicates their possible impact on customer sentiment (confidence) before making a purchasing decision. Thus, by computing the polarity of both the pre-purchase mood and the post-purchase feeling, we conducted a granular study of customers' incremental influence on firm returns after eliminating investor sentiment due to market news on financial proxy indicators. We directly relate investor sentiment to customer reaction at the firm and industry levels to establish that customer satisfaction and polarity from customer sentiment positively impact firm returns, which is a departure from related studies based on ACSI (Fornell, 2006; O'Sullivan et al., 2012; Peng et al., 2015). Studies based on ACSI illuminate that the index plays a crucial role during pessimistic periods and propose that managers increase investment in customer satisfaction to counter pessimistic investor sentiment with a purpose to protect firm value from diminishing. This study is the first to adopt an integrated approach consisting of quantitative finance indicators and qualitative customer-centric data sets to demonstrate that customer sentiment can influence stock returns. The study overcomes the limitation of the lack of time-series data for customer review scores in the Indian automobile sector.

4.3. Managerial and practical implications

Thus, marketing managers respond by contemplating strategies to enhance customer satisfaction depending on product life cycles, economic phases, and investor sentiment. Knowing customer sentiment provides many benefits to a firm. Managers desirous of safeguarding the interests of all their stakeholders strive to improve customer-centric policies, as customer satisfaction is an essential driver of business performance and firm value. Marketing managers typically contemplate strategies to enhance customer satisfaction depending on product life cycles, economic phases, and investor sentiment. However, technological advances have changed consumer outlook, thereby rendering many traditional strategies redundant. Data science plays a critical role in knowing the customer with a 360° view (Rambocas and Pacheco, 2018).

The results of this study show that managers can evaluate investments made in improving product quality and strategic marketing and develop data-driven marketing strategies across all geographical regions and demographic groups to learn more about the strategies of industry leaders and influencers. Understanding potential customers help firms secure competitive advantage by framing acceptable investment policies and pursuing strategies to arrive at harmony among all functional areas.

4.4. Limitations and scope for future research

Marketing managers should define their data requirements and data reach. Multiple data sources like news, views, reviews, blogs, and indicators that can reveal key result areas in marketing decisions may be analyzed, but as warned by Schweidel and Moe (2014), mere aggregation of data from multiple sources may not eliminate sampling error and robust statistical tools need to be deployed for analysis. Smaller firm managers cannot afford to avail services of specialized vendors to evaluate brands and hence should look for open-source text-analytics like NVivo, Watson Natural language, Python, NLTK, 'RapidMiner'. Improved machine learning tools for translation services are handy (Grimes,2014; Gopaldas,2014; Chen and Skiena,2014) for cultural understanding. Whereas as a community we need to uphold data privacy norms while using other data for marketing research, Holmes(2009) suggests a method to avoid stigma from using data without authentication. Sentiment analysis is to be conducted with caution and after understanding various limitations.

Though appear simple, related works have discussed the difficulties in measuring customer satisfaction as there is ample scope for furthering the research in this area (Westbrook and Oliver, 1981; Westbrook and Olive,1991; Westbrook,2000). Scope for developing industry-wise a benchmark customer satisfaction index in line with ACSI may be explored by future researchers. The findings can be extended to other industrial sectors using the Deep learning approach. While evaluating sentiment at a firm level, we have not considered customer reviews and product reviews as the outcome of the analysis would be limited to customer sentiment of the new vehicle model that may impact the stock market in the long horizon. According to Fama(1998), the market reaction on the arrival of new information like news and announcements would result in price adjustments immediately and any subsequent information like customer reviews/ reviews would have already reached the market from the media. In the words of (Samuelson,1965), "in competitive markets, there is a buyer for every seller. If one can be sure that price will rise, it would have already risen." But any intense negative news from the reviews would impact the market price in the long run. Hence, we captured datasets sources from a broader perspective of news and announcements which have a bearing on investor sentiment. However, while computing sentiment at the industry index level, we have extracted sentiment from all sources including customer reviews and product reviews.

CRediT authorship contribution statement

Prajwal Eachempati: Conceptualization, Writing – original draft, Writing – review & editing. **Praveen Ranjan Srivastava:** Conceptualization, Supervision, Writing – original draft, Writing – review & editing. **Ajay Kumar:** Conceptualization, Supervision, Writing – review & editing. **Javier Muñoz de Prat:** Supervision, Writing – review & editing. **Dursun Delen:** Writing – review & editing.

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