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Going digital? The impact of social media marketing on retail website traffic, orders and sales

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ABSTRACT

Given the rapid proliferation of digital technology, social media has become a key digital marketing strategy to promote business products, with the ultimate aim of maximising profits. Yet, empirical evidence on the impact of social media as a marketing tool remains underexplored. Using unique data over a 12-month period from a major online retailer, this paper examines the impact of daily social media activity on daily business outcomes: website traffic, orders and sales. Key findings reveal that social media leads to increased web traffic, but it does not produce a significant rise in product orders and sale income. Though, larger social media campaigns tend to result in significantly higher number of orders and sale income, and Facebook emerges as the most effective channel. Our results also reveal that the effectiveness of social media marketing varies across products depending on their complexity, cost and brand status. Taken together, these results offer a better understanding of the ways social media marketing impact businesses and provide intelligence on how to allocate resources to develop marketing campaigns.

1. Introduction

In the past decade, the way consumer goods are marketed and sold has been markedly altered with various technological factors primarily driving the change. In November 2018, online sales reached 20% of total sales for the first time in the UK (ONS, 2018). Retailers are constantly searching for new and innovative ways to reach new customers and improve the consumer experience. An increasingly popular approach involves the use of social media to communicate with customers, endorse brands and promote products through digital marketing campaigns and online (e) word-of-mouth (Grewal et al., 2017).

Social network sites experienced an explosive growth. In 2018, a total of 3.03 billion active social media users was estimated globally (Smith, 2018). In 2016, 99% of Britons aged 16–24 indicated to use social media sites in the past week (Carson, 2017). The amount of daily content shared on social media increased from 27 million pieces of content in 2011 to 3.2 billion in 2018 (Smith, 2018). This increase in individuals and activity on social media has led to businesses using sites such as Facebook (FB) - the most popular social media platform with 2.3 billion users globally (Smith, 2018) - to benefit their company via communication and marketing. Research shows that 79% of surveyed companies had presence on social media (Baird and Parasnis, 2011) and 38% of companies planned on spending more than 20% of their total advertising budgets on social media channels in 2015 (Smith, 2018). This implies that in the era of digital merchandising, social media platforms play increasingly important role and tend to alter the way retailers market their goods and communicate with customers.

Existing research on social media and digital marketing has predominantly focussed on digital technologies creating value for customers and how this impacts their purchase decisions e.g. customer satisfaction, brand equity (Kim and Ko, 2012). Other studies examined the impact digital technologies have on demand by examining consumer online search behaviour e.g. best-selling products (Bronnenberg et al., 2016). Yet, only a small number of studies have explored the effects of social media marketing on the business outcomes such as sales volume, profit or growth rate.

This study aims to quantify the relationship between social media activities and business outcomes for a major British online retail company. Drawing on a time series of twelve-month of detailed social media activity, website traffic and product-level sales data, we measure the impact of social media marketing campaigns on website visits, orders and sales. Using an autoregressive integrated moving average (ARIMA)

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with explanatory variables (i.e. ARIMAX) modelling framework and its seasonal extension (i.e. SARIMAX) a suite of regression models are used to capture daily relationships between business outcomes (i.e. website visits, orders and sales) and a set of social media variables, including likes, blog clicks, impressions, amount spent and reach at two levels: overall company level, and campaign-specific level. For the campaign-specific models, three brands are used (i.e. Apple, Ideal Home and Toy Time) to evaluate differences in the effectiveness of social media campaigns according to the product family (consumer electronics, home furniture and children toys). Our study seeks to address three key research questions:

i) How, and to what extent, do social media interactions affect business outcomes?
ii) How the effects of social media marketing vary across different demographics?
iii) What is the impact of social media campaigns on different product types?

The paper is structured as follows: Section 2 provides a literature review which highlights the current discussion and studies surrounding social media and digital marketing. The study design and models specifications are then explained in Section 3 and Section 4 respectively, followed by Section 5, which presents and describes results, and Section 6, where these results are interpreted and discussed in the context of the broader literature. Section 7 provides some concluding remarks and implications of the evidence reported in this paper.

2. Literature review

2.1. Digitalisation of retail activities

Retail landscape has undergone a large transformation in the past decade due to a substantial growth in the Internet sales and other technological innovations such as digital marketing, artificial intelligence or virtual reality shopping platforms (Wrigley and Lambiri, 2015; Singleton et al., 2016; Dolega et al., 2019). These changes have altered profoundly the ways in which consumer goods are traded (Dolega and Lord, 2020) and how retailers communicate with customers to boost business profits. New forms of retailing such as omni-channel retailing, digital marketing and click & collect facilities have emerged changing the customers' shopping experience. Customer can now access to purchasing and browsing goods 'on the go' through mobile applications, and although some demographics prefer physical 'brick and mortar' retailing, a hybrid combination of online and physical channels has become increasingly popular (Patano and Priporas, 2016). Often referred to as omni-channel retailing, this new approach to selling and buying goods has augmented the channels of company-consumer interaction by using the complementary strengths of both online and offline channels e.g. 24/7 shopping convenience, instant price comparison or click and collect facilities (Chopra, 2016; Davies et al., 2019).

One way the major retailers have adapted to these changes is through creation of digital content, identification of effective social media channels and their integration into marketing strategies (Tiago and Veríssimo, 2014). There seems to be a consensus amongst larger retailers that adopting omni-channel strategy (Lee et al., 2018) ensures the needs of the new age customers that frequently use a mixture of different marketing platforms are considered (Kannan and Li, 2017; Hossain et al., 2017). The omni-channel strategy for marketing relates to the way each marketing channel is linked and integrated with each other to create a seamless experience for the brand (Lee et al., 2018). Furthermore, this integrated approach has reportedly increased sales by in some case as much as 31% (Rigby, 2016), suggesting that such approach and the introduction of not just physical but also digital marketing can enhance both customer experience and sales.

The integration of social media into business marketing operations has been key to this new approach. Social media is viewed as inherently powerful tool for both retailers and customers (Kaplan and Haenlein, 2010; Kietzmann et al., 2011). The key advantages of such approach include enabling companies to create, co-create, share and discuss user-generated content and augment their visibility in a global scale. It also accelerates dissemination of information on new and existing products and services and facilitates company-consumer interaction and consumer-to-consumer online recommendation (Chou et al., 2016). Yet, the exact impact of social media marketing on business trading outcomes is not fully understood and in particular, quantitative research pertaining to this phenomenon is sparse.

2.2. Benefits and effectiveness of social media marketing

The increasing evidence base from qualitative research indicate that to better understand the benefits of social media marketing and its effectiveness on business outcomes, companies implement various mechanisms and use numerous metrics. These vary from a more general enhanced communication with customers through mechanisms such as e-word of mouth to metrics tracking the progress, success and engagement of particular campaigns.

A common benefit of retailers engaging with social media marketing is an enhanced power of communication (Kietzmann et al., 2011; Neti, 2011; Kim and Ko, 2012) with various platforms creating the ability to communicate with customers and spreading relevant information. Customer feedback obtained through social media platforms helps a company to reduce misunderstandings towards a brand or a product (Kim and Ko, 2012). Similarly, customer enquiries can easily be addressed by the relevant company or other customers. Communication shared on social media can also be a good opportunity for retailers to personally connect with existing and prospective customers, unlike other one-direction company-to-customer marketing channels, such as email or television (e.g. Neti, 2011). The effective use of social media marketing is argued to involve an interactive relationship with customers based on trust and compassion. This may require a change of a company's approach to a more social collaborative strategy in which customers more actively engage with social media content (Baird and Parasnis, 2011).

Another key benefit of using social media marketing relates to brand reputation: the ways in which customers communicate with each other and endorse a brand, spreading good and bad comments about a company. The advantage of social media to enhance brand reputation is potentially extensive geographical and population scale of e-word of mouth as consumers can share opinions and reviews, which can easily be visualised and reshared by other users across the world (Nieto et al., 2014). As an outcome, this self-feeding process may influence individual purchasing behaviour but also have a domino effect inducing purchases of the same or related products from other web users (Kim and Ko, 2012). Companies can leverage on this domino effect by building strong online-based relationships with customers to encourage involvement in e-word of mouth activities (Barreto, 2015). Through e word-of-mouth, brand relationship strengthens as companies gain exposure by allowing people to freely discuss a brand (Kim and Ko, 2012). Highly exposed brands make buying more appealing to other consumers, due to exposure via peer referrals (Zhang et al., 2017). Promoted e-word of mouth works well when communication is positive. However, communication can also be negative and poor reviews on a company and services and product offer can spread as quickly, or sometimes faster than positive reviews. This may mean that trust between a brand and their customers can be lost just as quickly as it is created (Kietzmann et al., 2011). Building the appropriate strategy for social media communication is important to build trust as the volatile nature of relationships and reputation can be destroyed as quickly as information travels through online platforms and generate significant long-term implications (Kim and Ko, 2012).

2.3. The effectiveness of social media marketing on business outcomes

A growing body of research is devoted to understanding the integration of social media into the current day marketing strategy. However, existing studies are predominantly qualitative in nature. They tend to focus on digital touchpoints in the marketing process including customer satisfaction in relation to dedicated digital marketing campaigns (Lee et al., 2018), new product launch (Baum et al., 2018) and on comparison analysis between online and offline consumer behaviour (Kannan and Li, 2017). Findings indicate that using social media platforms can extend offline customer journeys by longer consideration and evaluation stages (Edelman and Singer, 2015) and influence customer purchasing behaviour depending on a number of marketing platforms encountered (Kushwaha and Shankar, 2013).

Few quantitative empirical studies exist assessing the impact of online marketing on business outcomes. A key study by Sonnier et al. (2011) investigating the impact of positive, negative and neutral online communications on sales and found a statistically significant effect. The examination of the impact of firm-generated content in social media, alongside the TV and email marketing by Kumar et al. (2016) demonstrated that they have a positive and significant effect on consumer spending, especially those that are tech-savvy and social media-prone. Related research has also shown that successful digital marketing strategy requires a good understanding of their consumers. To this end, knowledge of the ranging from demographic profiles and location of customers is required (Singleton and Spielman, 2014; Patias et al., 2019) as well as well-defined marketing funnel strategies (Haydon et al., 2012). These business analytics and marketing strategies seek to help a company cater more effective marketing material for appropriate geodemographics at all stages of the buying process (Kumar et al., 2016). For instance, advertisements will change for customers depending on what stage of the marketing funnel they are in, or what geodemographic group they belong to, in order to ensure the relevant content is shown to relevant customers (Haydon et al., 2012). However, many companies still lack a full understanding of the application of such strategies on new digital platforms such as social media and how they vary across different geodemographics.

There is a clear research gap that needs to be addressed pertaining to the effectiveness of digital marketing on business outcomes and the extent to which this vary across space and time need to be investigated. The dearth of quantitative evidence assessing the impact of social media on business outcomes, and the relationship to the existing customer base characteristics is primarily due to the absence of detailed data relating to both business outcomes and social media activity across various social platforms. This information is not freely accessible and is considered commercially sensitive. Existing studies analysing social media data typically use Twitter web Application Programming Interfaces (APIs), which is the most widely accessible social media data option). However, social media data gathered in a passive manner, with researchers unable to control what data they can collect have some major implications (Huang and Wong, 2016). This may include individuals attempting to protect their identity online, which is problematic for companies when selecting the right social media tool to their customer base (Kietzmann et al., 2011) Understanding this relationship is key to developing more targeted and cost-efficient marketing strategies and ultimately expand the existing customer base and improve consumer satisfaction.

3. Study design

This study presents a rare opportunity to link two detailed datasets from a single retail company together to enable unique exploration of a poorly understood relationship between using social media marketing and business outcomes. More specifically, this paper draws on access to a unique database from a large online, retail company, which makes use of social media as a main marketing strategy. Facebook (FB) and Instagram (IG) represent the two main platforms. We had access to data on daily business and social media campaign activity and consumers and users engaging in these activities over a period of 12 months extending from January to December 2017.

3.1. Business outcomes measures

To address the research questions, we employ time-series modelling techniques, ARIMAX and its seasonal variant, SARIMAX. Three key indicators were used to measure business outcomes: website visits, product orders and gross sales. Specifically, we used daily counts of the number of visits to the retail website, the number of product orders, and gross sales. Furthermore, the empirical analysis is comprised of two key components. First, the company-wide models to assess the impact of social media marketing campaigns across the entire business product portfolio. Here we used aggregated data for the business outcome metrics across products. Second, the campaign-specific models to assess the impact of targeted social media campaigns on the key business outcomes of specific products and brands. For this analysis we used data on three different brands and product type to capture differences in the effectiveness of social media campaigns according to the product complexity, cost and brand status. Apple (a consumer electronics brand) data were used to represent a highly complex technical product with a well-established, highly desirable brand at the high end of the price bracket. Toy Time (a children toys brand) is used to represent an everyday type of product of a less recognisable brand and of lower cost. Ideal Home (a home furniture brand) is used to represent products at an intermediate level i.e. less complex than a technological product but with some level of sophistication and relatively more expensive than children's toys.

For the campaign-specific analysis, only two business outcomes were used: website visits and gross sales. Product orders could not be computed as orders include a mix of products so it is difficult to identify products of a particular brand. Gross sales was measured as the amount of units in pounds that left the warehouse excluding cancellations, and website visits were computed based on the number of entry visits onto the URLs relating to the product advertised in the product campaign.

3.2. Social media users

In this study we also explore the relationship between various demographics and social media marketing effectiveness, measured by visiting the website visit and purchase of the company's products. The demographics were captured in our model by a number of socio-economic factors such as age, gender, cash or credit customer and the ACORN demographic segmentation group provided by CACI (https://acorn.caci.co.uk/) each visitor fell into. There are five major ACORN groups starting with the "Wealthy Achievers" in category one (most affluent) to "Hard Pressed" in category five (least affluent), for people in the poorest areas in the UK. For the macro scale overall model, the demographic variables were aggregated daily counts for 2017. For the micro scale, the counts for each trading variable and demographic variable relate to the products advertised in the campaign and span a month before and after the campaign was live.

3.3. Social media data

The social media data for this study was acquired from multiple sources including data downloaded from social media API links, available from the company's shared drive. These files contained daily counts of paid social media metrics (Table 1) for Facebook (which is the principal social media platform used by the company) and Instagram, which is predominantly used by the company to advertise women's clothing. Figs. 1 and 2 show the daily social media metrics for the retail company throughout 2017. Further social media metrics were downloaded from the Facebook Business Manager platform (Table 1) including metrics related to performance of specific campaigns. Typically, social media

Table 1
Summary of data sources and metrics.

Data source	Social media platform	Metrics	Definition
Company database	NA	Visits	An aggregated count of the number of visitors onto the website each day
		Orders	An aggregated count of the number of orders placed each day
		Sales	An aggregated daily count of the demand for units (number of products) to leave the warehouse after confirmation of each order on that day.
Company database	NA	ACORN Group 1	Wealthy Achievers – some of the most successful and affluent people in the UK
		ACORN Group 2	Urban Prosperity – Well educated and mostly prosperous people
		ACORN Group 3	Comfortably Off – May not be wealthy but have few major financial worries.
		ACORN Group 4	Moderate means – Many people are still employed in traditional, blue collar occupations or service and retail jobs. Incomes fall below the national average.
		ACORN Group 5	Hard Pressed – The poorest areas in the UK where unemployment is above national average
Stored files	Facebook and Instagram	Cost	The estimated amount spent per day or week
		Paid Impressions	The number of times an advert is seen (total count)
		Paid Clicks	The number of clicks on social media content (total count)
Facebook Business Manager	Facebook-Campaign variables	Reach	The number of people who saw an advert at least once (unique users)
		Impressions	The number of times an advert is seen (total count)
		Frequency	The average number of times a person saw a certain advert (total count)
		Result - rate, amount of and Cost per result	The number of times that an advert achieved a set outcome based on the objective and settings selected. The company has selected the result to be website purchases (total count). Rate- The percentage of results received out of all views of a certain advert (total count)
		Amount spent (Cost)	
		Social reach and impressions	The value of reach (unique users) and impressions (total count) of a certain advert that was shown with social information, which shows Facebook friends who engaged with that page or advert
		Amount of actions and people taking action and cost per action	The total number of actions people take that are attributed to adverts. Actions may include engagement, clicks or comments (total count)
		Clicks	The number of clicks on social media content (total count)
		CPC (all)	The average cost for each click
		CTR (all)	The percentage of times people saw a certain advert and performed a click (total count)
		Cost per 1000 people reached	The average cost to reach 1000 people
		CPM (cost per 1000 impressions)	The average cost for 1000 impressions
	Facebook-Daily overview variables	New Likes	The number of new people who have liked your Page (unique users)
		Unlikes	
		Engaged Users	The number of people who engaged with your Page. Engagement includes any click or story created. (unique users)
		Total, Paid and Organic	Organic social media is using social medias free tools to schedule posts and interact. Paid posts are paid to target certain demographics certain demographics cost more to advertise to.
		Reach	The number of people who saw an advert at least once (unique users)
		Impressions	The number of times an advert is seen (total count)
		Total Consumers	The number of people who clicked on any company social media content (unique users)
		Page Consumptions	The number of clicks on social media content (total count)
		Organic Video Views	The number of times a video has been viewed due to organic reach (total count)

variables are highly correlated, therefore we have selected only those less correlated, which capture distinct dimensions of customer-business social media interaction. Pearson's correlation coefficient was used to calculate the relationship between the dependent and independent variables and only those with the coefficient of less than 0.8 were retained.

Some researchers point out a number of considerations related to the quality of data generated by social media platforms including a passive manner in which is gathered (Huang and Wong, 2016), individuals attempting to protect their identity online by creating false identities or presenting an alternate version of themselves to suit the platform they are using (Kietzmann et al., 2011). Different social media platforms attract different groups of people, often creating a sample that is not large enough and as such prone to a population bias such as age, gender or socio economic status (Ruths and Pfeffer, 2014). Often, social media

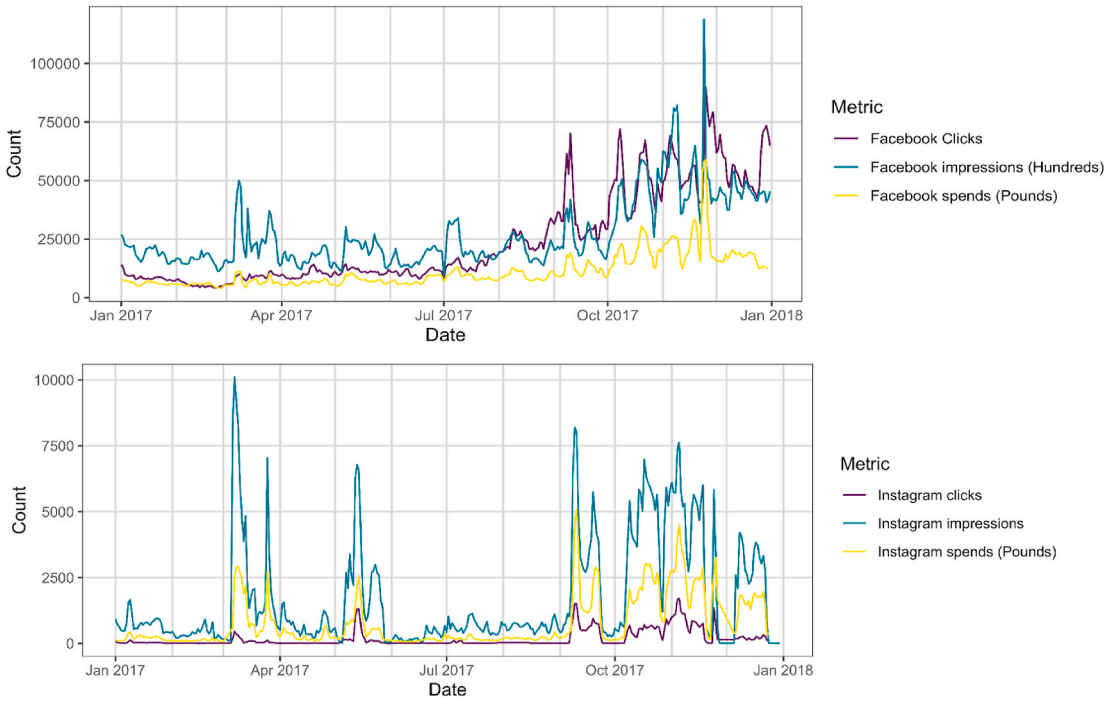

Fig. 1. Daily Paid Facebook (top) and Instagram (bottom) metrics from stored files.

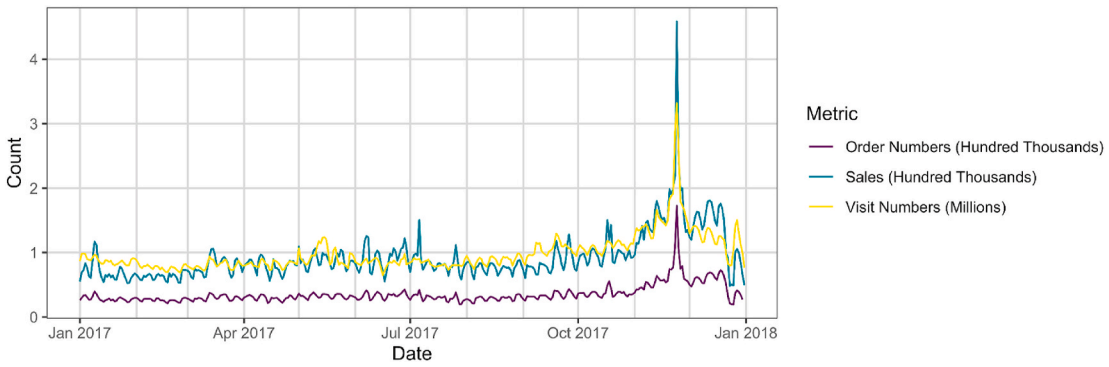

Fig. 2. Daily business outcomes.

companies tend to release carefully curated data, which presents a question of whether the way the data is collected and presented for business use distorts the human behaviour of interest (Ruths and Pfeffer, 2014). However, the social media data acquired is largely unaffected by the issues of social media data outlined above. The data used is not from a publicly accessible source, but directly from a company's social media profile, meaning that the data available is not limited to a small percentage like public APIs such as Twitter (Huang and Wong, 2016). The social media data used by this study correspond to counts of actions and costs of social media activity for the company, resulting in privacy settings of individuals not being an issue.

4. Models specification

4.1. ARIMAX and SARIMAX models

Multiple linear regression modelling is inappropriate to study the relationship between social media campaign activity and business outcomes. This approach treats temporally continuous business trading activity as independent incidents and in doing so neglects the existence of temporal self-dependency. Yet, there is strong temporal synchronicity in trading activity patterns. Sale patterns for a day, for instance, tend to be associated with sale patterns of the previous day. Failing to take account of such temporal autocorrelation is likely to generate biased estimates of the impacts of social media marketing on business outcomes. Given that business trading outcomes normally exhibit systematically recurring temporal patterns in accordance with different times of day (e.g., day and night) and days of week (e.g., weekday and weekends), it is necessary to employ a modelling technique that has the capacity to minimise autocorrelation, while effectively capturing the impacts of social media marketing on business outcomes.

To meet these requirements, time-series modelling approaches were employed, specifically ARIMAX and SARIMAX models. To introduce these modelling techniques, basic understanding of some key concepts is first required - see Hyndman and Athanasopoulos (2018) for a more detailed description. ARIMAX and SARIMAX models are derived from the ARIMA model (Box and Jenkins, 1970). An ARIMA model comprises three components: an autoregressive (AR) process, a moving average (MA) and an integrated (I) element. Intuitively, these components capture the long-term, stochastic and short-term trends of a time series, respectively. Formally, the AR and MA components control for temporal autocorrelation in a time series resulting from two mechanisms. The first

assumes a variable (Y) at time t (Y_t) is explained by its past value(s) (e.g., Y_{t-1}, Y_{t-2}, ⋯, Y_{t-p}). The second assumes Y_t is a function of current and past moving averages of error terms (e.g., u_{t-1}, u_{t-2}, ⋯, u_{t-q}); that is, current deviations from the mean depends on previous deviations. An general ARMA(p, q) model takes the form of:

$$Y_t = \gamma + \alpha_1 Y_{t-1} + \cdots + \alpha_p Y_{t-p} - \theta_1 u_{t-1} - \cdots - \theta_q u_{t-q} + u_t \quad (1)$$

The subscript p and q denote the order of the autoregressive and moving average terms, respectively. Fitting a time series in a model containing AR and MA parameters (or an ARMA model) requires the data to be weakly stationary. Weakly stationary is characterised by: (1) constant mean and variance of $Y_t$over time; and, (2) the covariance of Y_t to be time-invariant i.e. to only depend on the lag between the current and past value and not the actual time at which the covariance is computed (Hyndman and Athanasopoulos, 2018). However, weakly stationarity in time series is rare. They have an integrated (I) time series; that is, time series have to be differentiated to be stationarity so its statistical properties, such as mean, variance and autocorrelation are constant over time. Mathematically, Equation (1) can be modified to represent a general ARIMA(p, d, p) model:

$$y_t = \theta + \varphi_1 y_{t-1} + \cdots + \varphi_p y_{t-p} - \beta_1 u_{t-1} \cdots - \beta_q u_{t-q} + u_t \quad (2)$$

where: $y_t = Y_t - Y_{t-1}$ for a first order differencing model, and d denotes the degree of first differencing.

A time series also often exhibits seasonal recurring patterns, such as a yearly increase in sale activity during Christmas. To account for this, an ARIMA model can be expanded to a seasonal ARIMA (or SARIMA) model by adding seasonal operators; that is, differencing or backshift AR, MA and/or I terms at a seasonal lag(s). These additional seasonal operators are multiplied with the non-seasonal terms.

The ARIMA and SARIMA models were originally developed to model and forecast univariate time series. Our study aims to measure the impacts of exogenous variables on a time series, so we estimated ARIMAX (or SARIMAX) models. These models incorporate the time-series components of an ARIMA (or SARIMA) process into a multiple regression model as follows:

$$y_t = \theta + \beta X_t + \varphi_1 y_{t-1} + \cdots + \varphi_p y_{t-p} - \beta_1 u_{t-1} \cdots - \beta_q u_{t-q} + u_t \quad (3)$$

where X_t is a vector of covariates at time t. β is the associated vector of coefficients, and u_t is a white noise process; that is, it has a zero mean and is independent and identically distributed. ARIMAX (or SARIMAX) models serve as the main analytical tools to assess the impacts of social media marketing on daily business outcomes, effectively account for the long-term tendency, temporal dependency and seasonality changes in our time series. We analyse three outcome variables: web visits, orders and sales; and, explore the effects of 14 social media marketing variables capturing consumers' interaction and responses to online social media content. Additionally, we include consumers' demographic attributes in the models to capture differences in purchasing behaviour across age groups, gender, use of cash and socio-economic status according to the ACORN classification. In addition to the concurrent impacts of social media variables, we investigated the their lagged effects on daily business outcomes by including variables of social media activity of the previous day. We argue that while website traffic may be impacted by concurrent social media marketing activity, orders and sales may also be influenced more heavily by social media marketing activity hours or days earlier. This may particularly apply to more complex products, such as computers and cars as consumers may need time to process and compare alternatives. Yet, to our knowledge these effects of social media marketing has not been tested.

4.2. Campaign-specific models

The effectiveness of social media marketing may vary by the level of product complexity and brand. Hence, we estimated models for three specific campaigns: Apple, Ideal Home and Toy Time Event. These campaigns were entirely based on social media content and extended from March 22nd to 27th, 2017 for Apple; from August 31st to September 24th, 2017 for Ideal Home; and, from April 28th to May 5th, 2017 for Toy Time Event. To enable the analysis of the impact of these campaigns, data of the advertised products for one month before and after a campaign were used. Analysis of data only for the campaign period would not reveal changes in business outcomes linked to increased social media content. We analysed the impact of campaign-specific social media advertising on website visits and sales. Data on orders were unavailable. Separate ARIMAX or SARIMAX models were configured and fitted to the total daily website visits and sales for each of the three campaigns.

5. Results and discussion

Results are presented in two parts: First, we report the results for the company-wide models, followed by those for campaign-specific models.

5.1. Company-wide models

We first visually inspected daily web visit, order and sale patterns over a twelve-month period from January 2017 to January 2018. All three business outcomes, shown in Fig. 2 display the same general trend. A higher average level of activity occurs during the retail golden quarter (October–December), with gradually increasing trend in October, global peak on Black Friday and less pronounced peaks in the days before Christmas. Except for this pattern of high activity, a strong recurrent weekly cyclical pattern of daily web visits, orders and sales, with moderate peaks on Thursdays, Fridays and Saturdays, and drops on Mondays and Tuesdays, persists from January to October. Hence differencing of all three business outcomes is needed to achieve stationarity. By plotting the autocorrelation function (ACF) of the three daily business outcomes, we identified significant autocorrelations (i.e., correlation coefficients above 0.7 at a 5% significance level) for daily business outcomes on 24hr intervals. To address these autocorrelation effects, daily business outcomes were differenced to remove the observed periodicity and achieve more stationary time series. Specifically, times series were differenced at the 24hr lag for all three business outcomes. After this differencing process, re-examining the ACF of the differenced ridership revealed that most of the temporal dependence was then removed and insignificant at the 0.05 level.

Following the differencing of the daily time series for the three business outcomes, SARIMA models were next estimated including social media marketing and customer demographic variables as explanatory variables. Seasonal and non-seasonal AR and MA parameters were determined through examining the ACF and partial ACF (PACF) of model residuals. A range of modelling trials were carried out, which entailed adding statistically significant (i.e. p value < 0.05) AR and MA parameters to, and excluding statistically insignificant terms from our models with the aim of minimising the Akaike's Information Criterion (AIC) score. The lowest AIC score for all three business outcomes was provided by a model including a 1 order autoregressive term to control for autocorrelation; a 1 order differencing term to ensure stationarity; and, a 1 order seasonal term of a seven-day interval to account for the recurrent weekly cycle in business outcomes. We used the Ljung–Box tests for detection of serial autocorrelation. The results showed that absence of significant autocorrelation in the residuals of the each business outcome model.

Table 2 reports the modelling results. Coefficients are interpreted as the estimated change in daily business outcomes given a one-unit change in one of our explanatory variables. Examining the concurrent coefficients for social media reveals a significantly positive relationship between FB consumers and web visits, but a significantly negative association with orders and sales. The results suggest that while FB

Table 2
Results of company-wide modelling: website visits, orders and sales.

Variables	Web visits		Orders		Sales	
	Coefficient	P value	Coefficients:	p value	Coefficients:	p value
Autoregressive of Order 1	0.6993	0.000 ***	0.7313	0.000 ***	0.5993	0.000 ***
Seasonal Moving Average of Order 1	−0.6419	0.000 ***	−0.6591	0.000 ***	−0.5608	0.000 ***
Female	0.5114	0.421	0.0298	0.408	0.3485	0.004 **
Cash Customer	8.9152	0.000 ***	0.4105	0.000 ***	0.6003	0.019 *
Age 18-24	−1.2606	0.518	−0.0886	0.436	−0.0707	0.847
Age 25-34	−0.8141	0.498	−0.3284	0.000 ***	−1.513	0.000 ***
Age 35-44	1.2901	0.451	−0.0192	0.845	−0.002	0.995
Age 45-54	0.0326	0.981	0.0237	0.759	0.0593	0.822
Age 55-64	−7.0382	0.109	−0.3002	0.228	−0.8827	0.299
ACORN Group 2	−5.3618	0.094.	0.0429	0.815	−0.9652	0.115
ACORN Group 3	2.2947	0.041 *	−0.0265	0.683	0.2444	0.245
ACORN Group 4	1.4033	0.510	0.5253	0.000 ***	1.0725	0.008 **
ACORN Group 5	0.7042	0.562	0.1422	0.042 *	0.6572	0.005 **
Facebook Total Impressions	0.0041	0.441	−0.0004	0.196	−0.0007	0.479
Facebook Organic Impressions	−0.0567	0.481	0.0021	0.641	0.0168	0.260
Facebook Total Consumers	1.3344	0.056.	−0.1538	0.000 ***	−0.3117	0.017 *
Facebook Unlikes	360.4181	0.054.	−5.0399	0.638	−80.4908	0.024 *
Facebook Organic Video Views	2.102	0.200	−0.0291	0.759	0.1297	0.672
Facebook Costs	−1.0017	0.616	0.4153	0.000 ***	1.2854	0.000 ***
Instagram Cost	17.2499	0.094.	0.4327	0.463	−2.1929	0.250
Facebook Total Impressions lag 1 day	0.0114	0.033 *	0.0007	0.033 *	0.0008	0.429
Facebook Organic Impressions lag 1 day	−0.1179	0.140	0.0028	0.542	0.0005	0.975
Facebook Total Consumers lag 1 day	−0.5812	0.398	−0.1150	0.004 **	−0.2817	0.026 *
Facebook Unlikes lag 1 day	324.1286	0.089.	−11.5333	0.292	−12.3324	0.732
Facebook Organic Video Views lag 1 day	2.7887	0.091.	−0.1613	0.089.	−0.5247	0.088.
Facebook Costs lag 1 day	0.449	0.792	−0.0258	0.790	−0.2482	0.437
Instagram Cost lag 1 day	9.0835	0.420	−0.4316	0.503	4.015	0.055.

Significance levels: p-value < 0.0 5*, p-value < 0.0 1**, p-value = 0.00***.

marketing leads to a greater number of consumers engaging in website visits, it does not seem to generate a higher number of orders and larger sale income streams. For FB cost, a significantly negative coefficient with web visits but statistically significant positive association with orders and sales indicates that a £1 increase in FB advertisement content expenditure leads to a 0.42 rise in the number of orders and a £1.29 increase in sale income.

Lagged effects of social media are largely statistically insignificant, except for lagged coefficients for FB consumers and impressions. Coefficients for the lag of FB consumers are negatively associated with orders and sales suggesting that a large number of consumers engaging with FB marketing content in the day before is less likely to result in an increase in orders and sales.

In terms of the association of business outcome with various demographics, Table 2 shows that cash customers, Acorn groups 4 (moderate means – income below the national average) and Acorn group 4 (Hard pressed – least affluent demographics) and females have been found to have positive impact on business outcome metrics. In the case of cash customers, all three measures have been found to be positively associated with daily business outcome, while both Acorn groups show positive association with daily orders and sales and females with daily sales only. On a contrary, only one age group 35–24 was found to show statistically significant levels of negative association with daily orders and sales.

5.2. Campaign-specific models

We assessed the impact of three product-, brand-specific campaigns: Apple, Ideal Home and Toy Time Event. These campaigns were conversion campaigns aimed at lower funnel customers seeking to convert website visits into product purchases Haydon et al. (2012). The campaigns comprise different generic product types: electricals, furniture and toys which enable capturing differences in the impact of social media marketing on product-, brand-specific business outcomes for products of varying complexity and brand recognition. Apple products involve relatively complex and expensive electrical products with a wide range of product attributes, and a globally recognised brand. Ideal Home involves expensive products of mid-range complexity and a less well-known brand. Toy Time Event encompasses a wide range of everyday affordable products of a number of brands.

Table 3 details the length of the three campaigns and the type of ARIMAX and SARIMAX models identifying the order of autoregressive, moving average and seasonality terms used. As indicated in the data section, the product-, brand-specific number of orders could not be identified as orders tend to include products from various brands not related to the campaigns. So we focus the analysis on two business outcomes: website visits and gross sales. Social media variables for campaign-specific models are highly correlated. The number of impressions tends to correlate with the number of people who see an advert at least once (reach) and the average number of times a person has seen a certain advert (frequency). To avoid these problems of multicollinearity, we followed a similar strategy to Tao et al. (2018) and estimated separate models for each of our social media variables. We report two model fitting indicators: Akaike Information Criterion (AIC) and mean square error (MSE) to provide a measure of fit for our models. Tables 4–6 report the results for the regression results for the three campaigns, Apple (Table 4, Ideal Home (Table 5 and Toy Time Event (Table 6). Consumer demographic variables were included in campaign-specific regression models but not displayed in the tables.

The results reveal significant differences across product campaigns.

Table 3
Summary about each campaign along with model orders used.

Campaign	Length of Campaign	Trading variable	Model orders
Apple	22nd – 27th March 2017	Sales	(1,1,1)
		Website visits	(1,1,1)
Ideal Home	31st August – 24th September 2017	Sales	(0,1,1)
			$(1,0,1)_{[7]}$
		Website visits	(0,1,1)
Toy Time Event	28th April – 5th May 2017	Sales	(2,1,1)
		Website visits	(1,1,1)

Table 4
Model results for Apple campaign: Website visits (left) and sales (right).

Model	Variable	Website Visits				Sales			
		Coefficient	P-value	AIC	RMSE	Coefficient	P-value	AIC	RMSE
1	Actions	−0.0001	0.968	862.79	152.72	0.0261	0.000***	845.41	136.29
2	Amount Spent	0.0676	0.686	862.62	152.55	1.7454	0.000***	852.73	143.88
3	Clicks	0.0085	0.858	862.76	152.69	0.5507	0.000***	825.81	125.87
4	Cost per action	714.4669	0.897	862.77	152.71	77151.0000	0.000***	841.45	129.76
5	Cost per result	12.5042	0.917	862.78	152.71	1471.7000	0.000***	849.01	137.77
6	Cost per thousand reached	−2.6568	0.898	862.77	152.70	238.1100	0.000***	839.30	129.58
7	CPC	−9.9672	0.973	862.79	152.72	1.1439	0.000***	841.64	132.30
8	CPM	−7.7272	0.815	862.73	152.65	377.9200	0.000***	837.88	126.44
9	CTR	−51.9633	0.575	862.47	152.34	1016.6300	0.000***	808.77	100.78
10	Frequency	−10.8954	0.838	862.75	152.66	652.4300	0.000***	825.00	116.11
11	Impressions	0.0001	0.733	862.67	152.60	0.0043	0.000***	850.05	140.91
12	People taking action	0.0043	0.784	862.71	152.66	0.1662	0.000***	844.54	135.18
13	Reach	0.0002	0.817	862.73	152.67	0.0064	0.000***	857.70	151.68
14	Result rate	−150.7614	0.485	862.31	152.11	2625.0000	0.000***	806.36	100.68
15	Results	0.0068	0.952	862.79	152.72	1.2063	0.000***	842.99	133.78
16	Social impressions	0.0004	0.691	862.63	152.56	0.0094	0.000***	857.92	149.56
17	Social reach	0.0002	0.837	862.75	152.69	0.0116	0.000***	853.79	144.98

Table 5
Model results for Ideal Home campaign: Website visits (left) and sales (right).

Model	Variable	Website Visits				Sales			
		Coefficient	P-value	AIC	RMSE	Coefficient	P-value	AIC	RMSE
1	Actions	0.0115	0.002**	1222.44	255.77	0.0006	0.097.	795.59	17.98
2	Amount Spent	0.7806	0.007**	1224.21	258.50	0.0103	0.721	803.14	20.57
3	Clicks	0.5554	0.000***	1220.08	252.09	0.0306	0.031 *	794.96	17.91
4	Cost per action	23474.6300	0.010*	1225.59	260.47	187.0966	0.844	803.23	20.58
5	Cost per result	219.0503	0.004**	1224.29	258.31	1.6705	0.820	803.22	20.57
6	Cost per thousand reached	64.4498	0.009**	1224.37	258.79	0.7648	0.749	803.17	20.57
7	CPC	339.2968	0.109	1228.17	264.88	2.1572	0.909	803.25	20.58
8	CPM	85.4667	0.009**	1224.58	259.11	0.2148	0.945	803.26	20.59
9	CTR	698.0370	0.000***	1218.95	250.37	3.6544	0.844	803.23	20.58
10	Frequency	302.3023	0.002**	1222.61	255.95	3.5503	0.731	803.15	20.56
11	Impressions	0.0350	0.002**	1222.98	256.49	0.0002	0.000***	794.95	17.87
12	People taking action	0.0558	0.000***	1220.49	252.62	0.0005	0.781	803.19	20.58
13	Reach	0.0050	0.002**	1222.73	256.14	0.0000	0.915	803.25	20.59
14	Result rate	1382.5487	0.017*	1224.32	259.04	−3.4710	0.939	803.26	20.59
15	Results	1.1755	0.008**	1224.00	258.28	0.0839	0.011*	793.95	17.76
16	Social impressions	0.0041	0.003**	1223.13	256.73	0.0003	0.000***	794.90	17.87
17	Social reach	0.0059	0.002**	1222.96	256.48	0.0000	0.949	803.26	20.59

Table 6
Model results for Toy Time Event campaign: Website visits (left) and sales (right).

Model	Variable	Website Visits				Sales			
		Coefficient	P-value	AIC	RMSE	Coefficient	P-value	AIC	RMSE
1	Actions	0.0012	0.000***	383.98	3.05	0.0052	0.857	1048.60	353.86
2	Amount Spent	0.1641	0.000***	374.00	2.84	−0.1212	0.973	1048.63	353.94
3	Clicks	0.0370	0.000***	398.29	3.38	0.1030	0.921	1048.63	353.92
4	Cost per action	1951.3984	0.000***	380.26	2.96	−20500.0900	0.654	1048.43	353.39
5	Cost per result	13.9832	0.000***	373.63	2.83	−57.4761	0.832	1048.59	353.81
6	Cost per thousand reached	3.6036	0.000***	380.13	2.97	−13.0343	0.863	1048.61	353.86
7	CPC	54.2195	0.000***	370.67	2.77	−264.2522	0.817	1048.58	353.79
8	CPM	6.2171	0.000***	375.40	2.87	−16.7206	0.894	1048.62	353.90
9	CTR	11.6134	0.000***	398.14	3.39	31.7291	0.911	1048.62	353.91
10	Frequency	8.1386	0.000***	392.00	3.23	−24.1676	0.909	1048.62	353.91
11	Impressions	0.0004	0.000***	385.97	3.09	−0.0016	0.878	1048.61	353.88
12	People taking action	0.0102	0.000***	384.18	3.06	0.0601	0.806	1048.58	353.79
13	Reach	0.0007	0.000***	381.19	2.98	−0.0016	0.922	1048.63	353.91
14	Result rate	58.9454	0.000***	391.77	3.23	193.7448	0.901	1048.62	353.90
15	Results	0.1551	0.000***	391.94	3.23	0.1146	0.979	1048.63	353.94
16	Social impressions	0.0010	0.001**	376.13	2.87	−0.0058	0.803	1048.57	353.77
17	Social reach	0.0012	0.000***	376.28	2.87	−0.0057	0.838	1048.59	353.83

Significance levels: p-value < 0.0 5*, p-value < 0.0 1**, p-value = 0.00***.

For Apple, coefficients are insignificant for website visits but statistically significant across the whole range of social media variables for sales. This result indicates that while social media campaigns may not boost website visits, they increase Apple product sales. The coefficient for amount spent indicates that for every pound spent on a social media marketing campaign increases Apple sales by 1.7 pounds. Similarly, the coefficient for frequency indicates that the average number that a customer sees an advert increases by 1, sales of Apple products will rise by more than £600 pounds and increase by 1 cost per action will lead to a significant rise of over £77 thousand in sales.

In contrast, social media coefficients for Ideal Home and Toy Time sales are largely insignificant, while a statistically significant correlation exists for website visits. These results indicate that social media marketing provides increased exposure for Ideal Home and Toy Time products but they do not significantly effect purchases. Though, four of the seventeen social media campaign metrics for Ideal Home -clicks, impressions, social impressions and results-display a statistical relationship with sales, suggesting that certain aspects of the campaign significantly impact gross demand. For instance, the amount of times that customers see and click on an advert significantly increases Ideal Home product sales, but this seems to be unrelated to the amount spent on a specific campaign. The coefficient for amount spent displays a statistically insignificant relationship with sales, indicating that even with an increased investment in an Ideal Home campaign, increases in sales would be modest.

6. Discussion

The results of our model exploring the extent to which social media metrics affect business outcome variables on a macro scale are complex. Although there is no simple significant effect for one of the three trading variables, we find some significant associations. This suggests that for this company at least, investment into social media marketing is working in some respect - meaning that, to an extent, a suitable strategy for managing the highly complex nature of communication through social media marketing has been developed (Kietzmann et al., 2011; Kumar et al., 2016). More specifically, the model indicates that FB could be a convenient cost-effective marketing strategy to increase sales. By contrast, coefficients for IG cost are insignificant for all three business outcomes, indicating that IG is a less effective mechanism to influence consumer behaviour compared to FB. Coefficients for impressions and video views are also insignificant suggesting that an increase in the number of impressions and video plays of social media marketing posts does not necessarily induce a significant rise in website visits, orders, or sale income. This finding is important as it offers guidance for the development of online social media marketing content. While videos provide effective graphical tool to present content, they are relatively expensive and do not seem to represent an effective way to generate sales.

Another interesting finding pertains to the coefficients for the lag effect of FB marketing on consumer purchasing behaviour. The general expectation is that consumers need time to process product information and evaluate alternatives so that product offers promoted through social media platforms may not effect an impulsive purchasing response (Baumeister, 2002). The model indicate that consumers may need a longer timeframe than 24 h to complete compare and evaluate alternatives. Additionally, the results show that users' past impression activity of FB advertising posts correlate with website visits and orders suggesting that consumers reacting to FB posts tend to visit the company website and place an order within the next 24 h. Yet these associations appear to be marginal, leading to a 0.01 rise in the number of web visits and 0.0007 increase in the number of orders.

What is of central importance to this study, is that the customer demographic coefficients reveal the profile of online shoppers that is most susceptible to the effects of social media marketing. Females, cash customers and the less affluent socio-economic groups are more likely to engage in online shopping including placing orders and buying online. Some of these findings correspond well with the wider trends in consumer purchasing behaviour e.g. there is well-established evidence documenting females' higher propensity to engage in hedonic and impulsive shopping (Tifferet and Herstein, 2012). However, the higher engagement in online shopping activities of the less affluent geodemographic groups are is more specific to this study. There is little empirical evidence on how online shopping varies across different geodemographic groups. Our findings that the price sensitive and deal conscious demographics engage more in online shopping than other groups although novel, it may pertain to particular activities such as price comparison and browsing for special offers.

While useful, company-wide business outcomes tend to conceal variations in the impact of product- and brand-specific social media marketing campaigns. Brand recognition and product complexity are widely acknowledge to shape consumer behaviour and hence to moderate the effect of advertising on consumers' purchasing patterns (Kim and Ko, 2012; Kietzmann et al., 2011). Marketing offers are likely to trigger a more immediate response on low-cost, less complex products, such as kids' toys, compared to more expensive, more complex products, such as a laptop or insurance. In contrast, high-end, more complex products are likely to require a longer evaluation and consideration process of comparing a range of different alternatives.

The results from our campaign-specific models provide some valuable insights in that respect. They suggest that social media marketing is more effective in affecting sales for premium, more expensive and complex products, like Apple than lower-end, cheaper products, such as toys. This may seem counterintuitive as higher end, more complex and expensive products may require a longer psychological purchase process than less complex and inexpensive products. More complex products are also likely to require careful consideration of a large number of attributes. Buying a laptop, for instance, could involve assessing screen size, storage capacity, number of USB ports, battery durability and processing efficiency specifications. Evaluating these specifications may mediate the influence of social media marketing on triggering an impulsive purchase response (Baumeister, 2002). Consistently, such type of spontaneous responses are more likely for everyday, less expensive products, like toys which generally entail a shorter consumer evaluation process, little financial investment and are easily accessible. However, this same process of careful evaluation may trigger a purchase reaction, if customers may have already completed this process and have been waiting for an offer to realise a purchase. Additionally, the exclusivity and reputation of Apple products may prompt a purchase when a discount offer is made. Apple products are only sold in selected stores, authorised sellers must adhere to a strict recommended retail price, and as such, shopping around for opportunities are limited. Offered discounts via social media campaigns on exclusive brands are thus likely to trigger a purchase response from interested customers (Kim and Ko, 2012).

On a contrary, our model implies that social media campaigns have a limited impact on increasing sales for less complex products and less exclusive brands. For instance, social media marketing does not seem to generate positive impacts on sales for Ideal Home products. It may be because while the same furniture product may not be available at various retailers, similar furniture products may be available at a cheaper price. This lower level of exclusivity, coupled with lower brand reputation and greater availability, appear to limit the impact of social media marketing campaigns, driving an increase in website visit traffic but not leading to a significant rise in product sales.

Finally, the nature of products seems to moderate the impact of social media marketing campaigns on product sales. Apple and other leading electronic and technological brands encompass cutting edged nature of products. They release regular product upgrades, creating a constant need for product updates for existing customers and enticing new customers. This constant desire to know of new product updates increases engagement with advertisements. On the other hand, the

lower-end, simpler products including toys are cheap and easily available from a range of competing retailers. As a result, customers may not necessarily wait for a social media campaign offer to purchase these products or they may shop around for toys after seeing an advertisement of a product. Lower-end products are also regularly bought throughout the year, and hence, while a social media campaign leads to increase in website traffic, it does not generate significantly larger sales.

7. Conclusion

The growing proliferation of social media networking sites has led to an increase in the use social media platforms as marketing tool to augment consumer reach with the hopes to foster business outcomes. Yet, limited empirical evidence exists as to how social media impact these outcomes. Previous research has typically employed qualitative methods or publicly available data from APIs to estimate effects of various social media campaigns. Drawing on unprecedented access to a large retail company database, we analysed the impacts of social media marketing campaigns on business outcomes: web traffic, product orders and income sales. The findings from this analysis are set to benefit both the company and wider research community, as it provides the first to our knowledge robust quantitative analysis which specifically assesses the effects of social media marketing strategies on business outcomes.

So within that context, our most important findings pertained to the fact that social media are partially effective as they lead to increased web traffic but only marginally increase product order and sales. However, the larger social media campaigns generate markedly greater number of orders with the primary social media site - Facebook outperforming the less used platforms such as Instagram. This indicates that using Facebook for digital marketing is beneficial to the company and provides a more cost-effective platform to convert money spent into valuable trading outcomes. Other key contributions of this study include quantification of the extent to which social media metrics impact business outcomes, how they differ for each trading variable and investigation of a time lag importance. Of high importance is the finding that video content does not results in significant increase of orders and sale income. This valuable insight provides useful guidelines to a more effective development of digital marketing strategy, in particular better understanding how effective a specific online content is and where the potential lies. Contrary to our expectations, the lagged effect from social media campaigns is relatively week and short lived, as it tends to be most significant within the 24 h of consumers having been exposed to the campaign.

Finally, we find that the effectiveness of social media varies across products according to their complexity, cost and brand status. Overall the product and brand specific social media campaigns have more influence on business outcomes, however, the type of product mediates the influence of social media campaigns. Typically, the more complex, premium products drive demand of campaigns more than cheaper, everyday products. The impact of social media marketing on business outcomes appears to be more significant when the need for shopping around is reduced or eliminated due to limited availability or strict pricing.

Our social media data only enable identifying if a social media advertisement campaign led to an order or sale; that is, if users action an order or purchase via clicking on a social media advertisement campaign. The data do not allow tracking if a user saw an advertisement on a social media application but decided to use Google to find the company' website and place a purchase order. While this may lead to an underestimation of the influence of social media on orders and sales in our study, we argue that this underestimation is likely to be marginal as anecdotal evidence collected through focus groups conducted by the company which provided the data used in this study indicate customers are more likely to use social media to place an order if they see a social media advertisement campaign than through the company's website directly.

The results of this study will allow the company to develop a more effective strategy for managing the highly complex nature of communication through social media marketing (Kietzmann et al., 2011; Kumar et al., 2016). Essentially, to better target their social media campaigns for more cost effective and efficient marketing, and to better allocate resources to the more complex product campaigns that have a larger effect on achieving the desired outcome of increased product demand. This study has also created the groundwork for avenues of further research. While our results based on data from a single retail company, they represent novel, robust empirical evidence on the impacts of social media marketing on business outcomes, and provide a methodological framework to expand research on the effects of social media campaigns on business outcomes to other companies of varying sizes and market niches.

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