How Context Moderates the Sales Impact of Social Media

A study in the Electronic Dance Music Industry

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Abstract

Although several studies have examined and established a positive effect of social media on sales, most of these studies use only one social media dimension in their assessment. Addressing all possible effects, this article jointly investigates how metrics within the three social media dimension Fans, Electronic Word of Mouth (EWOM) individually influence sales, and develops hypotheses on how these effects may be moderated by context characteristics. The research is applied in the electronic dance music (EDM) industry. Daily ticket sales are used as the dependent variable, and the context characteristics are four different event characteristics: (1) the size of an event, (2) the sub-genre of an event, (3) the average age of the buyers of event tickets, and (4) the number of days tickets for the event are on sale. To test the hypotheses, the authors follow a two-step procedure. In the first stage, the social media metrics and covariates are regressed on ticket sales. The standardized elasticities of the social media metrics are used as dependent variables in the second stage, where weighted least squares (WLS) is used to account for possible heteroscedasticity and the uncertainty of the parameter estimates of the first stage. The authors find that Fans decrease sales, and that eWOM boost sales. Consumption does not seem to affect sales. Managers' social media incentive should therefore focus on enhancing eWOM rather than fans, followers or online music consumption. The authors also find that the event characteristics moderate the effects of social media on sales, which suggests that managers in other industries should also assess which context characteristics influence the effect social media has on sales.

INTRODUCTION AND CONTRIBUTION TO THE LITERATURE

The explosive growth in online social networking has provided researchers and marketers an opportunity to gain valuable insights into user behaviour and preferences (Bhatt et al. 2010). From a firm's perspective, online communications are observable, facilitate the measurement and allow the assessment of their influence on sales and other quantities of interest (Sonnier, McAlister and Rutz 2011). Nevertheless, the majority of companies are not yet using this data to gain more insights in the behaviour of their consumers. However, as a result of the enormous and still growing count of social media users, it is crucial for companies to start incorporating the data generated on these social media in their explanatory and predictive consumer behaviour models to enhance performance. The sales function has the potential to be one of the most dramatically changed by these technological advancements (Andzulis, Panagopoulos and Rapp, 2012). Though ample research declares that social media activities influence sales, the majority only considers one social media dimension in the assessment. In this paper, we jointly investigate how metrics within the three social media dimensions Fans, Electronic Word of Mouth (EWOM), and Consumption individually affect sales, and how these effects may be moderated by context characteristics.

An emerging body of research has shown that social media affects sales. Table 1 presents the relevant literature. This study relates to three streams in the existing literature. The first and major set of articles examines the effect of electronic word of mouth (eWOM) on sales (e.g., Goel and Goldstein 2014, Chevalier and Mayzlin 2009, Sonnier, McAlister, and Rutz 2011, Schweidel and Moe 2014, Stephen and Galak 2012). For example, Chevalier and Mayzlin (2009) find that positive online reviews and ratings improve the sales of books. This relationship is also established by Babić, Sotgiu, de Valck, and Bijmolt (2015), who find a correlation of .091 between eWOM and sales.

Table 1: Position of this study compared to previous work on the relation between social media metrics and sales

		Social Media Dimensions			*Variable Operalization*			*Social Media Channels*		
Article	**Context**	**eWOM**	**Fans**	**Consumption**	**Individual effects of SM**	**Effect of**	**Effect on**	**#**	**Specified**	**Method**
Putler and Lele (2003)	Theater	—	—	—	N.A.	Event Awareness	Ticket Sales	N.A.	N.A.	Non-Linear Tobit
Beckman et al. (2012)	Baseball	—	✓	—	N.A.	Fans	Ticket Sales	N.A.	N.A.	Censored Normal Regression
Babić et al. (2015)	Online Platforms	✓	—	—	No	eWOM on SM	Sales	6	Amazon, Facebook, MSN, MySpace, Twitter, YouTube	Meta-analysis
Chevalier and Mayzlin (2006)	Books	✓	—	—	Yes	eWOM	Sales	2	Amazon, Barnes & Noble	Differences-in-Differences
Goel and Goldstein (2014)	Retail Purchases	✓	—	—	No	eWOM on SM	Individual Behaviour	1	Yahoo!	Top-k Analysis, Logit Regression
Schweidel and Moe (2014)	Tele-communications	✓	—	—	No	eWOM on SM	Brand Sentiment	—	Unknown	Ordered Probit
Smith, Fischer, and Yongjian (2012)	Social Media	✓	—	—	Yes	SM Platform Type	eWOM	3	Facebook, Twitter, YouTube	Poisson
Sonnier, McAlister, and Rutz (2011)	Firm, unknown	✓	—	—	No	Online Communications	Sales	—	Unknown	LIV
Stephen and Galak (2012)	Social Lending	✓	—	—	Yes	eWOM	Sales	1	Kiva	Zero-inflated Multivariate Autoregressive Double Poisson
Dewenter, Haucap, and Wenzel (2012)	Music	—	—	✓	N.A.	File Sharing	Ticket Sales	N.A.	N.A.	Hotelling
Nguyen, Dejean, and Moreau (2014)	Music	—	—	✓	No	Free Streaming	Ticket Sales	—	YouTube, Spotify, Deezer (Answer to the question: "Do you stream online music?")	Recursive Multivariate Tobit
Saboo, Kumar, and Ramani (2015)	Music	✓	✓	✓	No	eWOM, Fans and Consumption on SM	Sales	5	MySpace, Last.FM, YouTube, Facebook, Twitter	Arellano-Bond / GMM
THIS STUDY (2016)	Music	✓	✓	✓	Yes	eWOM, Fans and Consumption on SM	Ticket Sales	5	Facebook, Twitter, SoundCloud, YouTube, Google Analytics	VAR

The second stream of literature investigates the music industry and if consumption on social media enhances music sales. For example, Dewenter, Haucap and Wenzel (2012) find that file sharing can lead to increased profits through increased concert ticket demand. Furthermore, Nguyen, Dejean and Moreau (2014) show that consuming music on free streaming services has a positive effect on music attendance for national and international artists that are more likely to be available on streaming services.

We position our own work in the third stream in the literature, which investigates both the effect of eWOM and consumption on music sales. Additionally, the social media dimension Fans is also taken into consideration. Saboo, Kumar and Ramani (2015) include each of the three social media dimensions as a combination of the related metrics. They find that on the one hand, fans and eWOM have a significant positive effect on music sales, and on the other hand, consumption has a significant negative effect on music sales.

The contribution of this study to the existing literature is threefold. Firstly, this study includes different social media dimensions instead of one in isolation. The social media dimensions in this paper consist of eWOM, fans and consumption, whereas in previous studies only the effect of one of these dimensions was considered. This article thereby avoids unnecessary model assumptions, as it considers all social media dimensions that could possibly influence sales. Only one prior research by Saboo, Kumar and Ramani (2015) includes the effect of all three social media dimensions. Using MySpace, Last.FM, Facebook, Twitter and YouTube, they define three metrics: SWOM, SFANS, and SPLAYS. These correspond to the more general metrics eWOM, fans, and consumption as defined in this paper. The major drawback of the study by Saboo, Kumar and Ramani (2015) is that the metrics are combined within each dimension, rather than measured individually. For example, they aggregate the metrics from all the channels into one eWOM dimension, and then test its influence on sales.

The second contribution of this study therefore lies in the measurement of social media on sales. Although studies have examined the effects of different social media dimensions, the dimensions have mostly been defined as aggregations of different social media metrics (e.g., Babić et al. 2015, Goel and Goldstein 2014; Nguyen, Dejean, and Moreau 2014, Saboo, Kumar, and Ramani 2015). This study aims to identify the individual effect of each unique social media metric on sales. For example, both Facebook Fans and Twitter Followers are metrics within the Fans dimension, however their influence on sales will be measured individually rather than combined. This is important, because, as Smith, Fisher and Yongjian (2012, p. 111) find: brand-related eWOM tends to differ across sites when investigating Twitter, Facebook and YouTube. Furthermore, they state that Twitter, Facebook, and YouTube represent different types of social media, and users visit these sites with slightly different intentions, and interact in diverse ways. Moreover, measuring individually enables the possibility to compare the relative influence of each unique metric across the different social media dimensions and channels.

The third contribution of this study relates to the number and relevance of social media channels taken into account. Smith, Fisher and Yongjian (2012, p. 102) state that although scholars have studied certain social media channels in isolation, few have incorporated multiple types into a single study for comparative purposes. Furthermore, Goel and Goldstein (2014, p. 92) conclude that it is likely one would find even more predictive value from incorporating social data from additional sources, as they only use two communication networks. Thus, the importance of a broader scope of today's popular social media channels is substantial, yet hardly implemented in the current literature. Therefore, this study uses 5 social media channels, which is more than in the majority of preceding studies (e.g. Smith, Fisher, and Yongjian 2012, Chevalier and Mayzlin 2006). The only ones to achieve or exceed this number with respectively 6 and 5 channels, are Babić et al. (2015) and

Saboo, Kumar, and Ramani (2015). However, our set of social media channels is more up-to-date on this subject than all of the preceding studies, because we use the most popular and largest social media of today: Facebook, Twitter, SoundCloud, and YouTube. Trends Expert Elise Moreau states in a recent online article on the top 25 social media networking sites people are using, that we have moved on from the days of MySpace, and places Facebook, Twitter, SoundCloud and YouTube in the top 25 (2016). Previous works only include one or two of these nowadays more relevant channels. Moreover, we also include events' brands' website statistics from Google Analytics.[1]

In summary, we investigate how the different social media metrics influence sales, and if these effects are affected by context characteristics. This research is applied in the setting of the Electronic Dance Music (EDM) industry. More specifically, we aim to capture the effects of social media on the ticket sales for EDM events, and explore how these effects are moderated by event characteristics. We include three social media dimensions eWOM, fans, and consumption and investigate the individual unique effects across social media channels, whereas previous research typically includes only one social media dimension, aggregating its effect across the social media channels included. Moreover, compared to prior works, we increase the number and relevance of the social media channels studied, making the setting up-to-date.

Our findings are based on event and social media data for 78 national and international EDM events. The data is collected by a large EDM event organizer, and we are the first to use this data. We find that only two of six significant social media metrics enhance event ticket sales. Thus, we establish more evidence for an opposite statement that increased social media interaction decreases sales. Furthermore, we find that context characteristics, which in our study are event characteristics, moderate the effects of social media on sales.

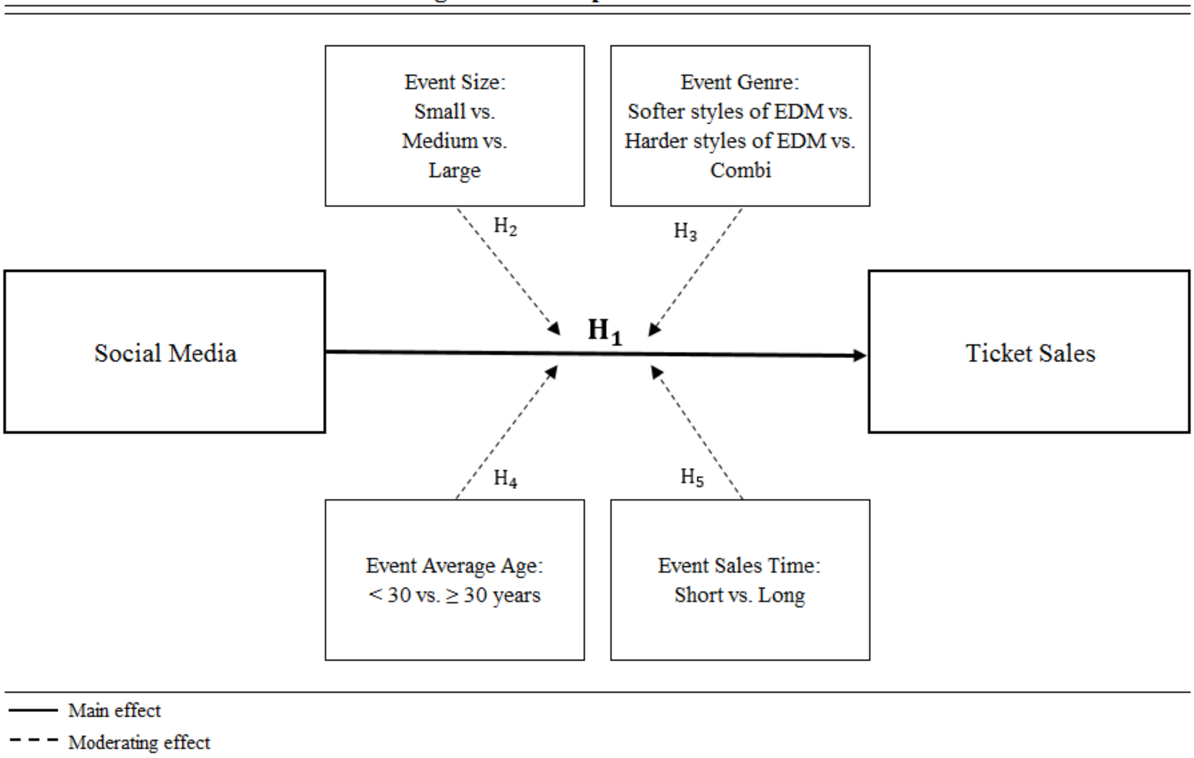
[1] When we talk about social media metrics in the remainder of this paper, we also consider the website statistics of Google Analytics.

The findings suggest that managers should focus less on increasing fans and followers, and more on enhancing eWOM on social media. Furthermore, these findings offer managers in the music industry the opportunity to better target their audiences on social media based on particular event characteristics. Lastly, the results propose to managers in other industries that context characteristics are worth exploring when establishing the effect of social media on sales.

CONCEPTUAL FRAMEWORK AND HYPOTHESES

Figure 1 presents the conceptual framework for this research. The core of the framework consists of the main effects of social media metrics on event ticket sales, moderated by event characteristics (e.g., small versus large events).

Figure 1: Conceptual Framework



In assessing the influence of social media metrics on sales, we consider the direction and magnitude of the effects. Additionally, we reason that these effects may be influenced by particular characteristics of events, i.e. (1) the size of the event, (2) the genre of the event, (3) the average age of the buyers of event tickets, and (4) the length of an event's sales period (i.e. the number of days tickets are on sale).

Event size. We distinguish three types of event sizes based on the number of total tickets available for the event: (1) small events with less than 10,000 tickets available, (2) medium events with 10,000 or more, but less than 30,000 tickets available, and (3) large events with 30,000 or more tickets available. Events belonging to the same brand may differ in size. For example, Defqon (large event), Qapital (medium event), and Qult (small event) all belong to the brand Q-Dance.

Event genre. We differentiate three types of Electronic Dance Music (EDM) events based on sub-genres: (1) events offering the softer styles of EDM, such as Trance, House, Dubstep, Techno, Electro, etc. (e.g. Sensation), (2) events offering the harder styles of EDM, such as Hardstyle, Hardcore and Hard Trance (e.g. Defqon), and (3) events offering both softer and harder styles of EDM (e.g. TomorrowLand). We classified the different events according to their brands' official websites.

Event average age. We also want to distinguish the events in this research according to the average age of the tickets' buyers. We distinguish two types of events based on average buyer age: (1) events with the average age of buyers below 30, and (2) events with the average age of buyers equal or above 30.

Event sales period. We also classify the events according to the number of days tickets are on sale. We distinguish two types of events based on the lengths of their sales periods: (1) events with a short sales period of 105 days (15 weeks) or less, and (2) events with a long sales period of more than 105 days.

Differences in the Effects of Social Media

This research builds upon the expectation that the effects of social media interaction on sales depend on context moderation. The context moderators in this study consist of event characteristics. Our hypotheses are based on findings in the existing literature and our own expectations.

Main effects of social media on ticket sales. The existing literature already established a significant effect of social media on sales (e.g. Babić et al. 2015, Dewenter et al. 2012, Saboo et al. 2015, Goel and Goldstein 2014). As claimed by previous research, increased eWOM improves sales (e.g. Chevalier & Mayzlin 2009, Babic et al. 2015, Saboo, Kumar & Ramani 2015). Also, according to Saboo, Kumar and Ramani (2015), a higher level of fans on social media has a positive effect on sales. The same research found that online music samples reduced the appeal of the original music, reducing overall sales. On the other hand, other studies established that online consumption through file sharing and free streaming have a positive effect on ticket sales (Dewenter, Haucap & Wenzel 2012, Nguyen, Dejean & Moreau 2014).

Moreover, we argue that interaction on social media indicates that people are interested in the event, and otherwise are becoming more aware of the event. Furthermore, we think that especially social media interaction within the Fans and Consumption dimension indicates potential buyers, and thus indirectly enhances sales. However, based on previous findings, we also expect eWOM to enhance sales. Nevertheless, we should take into account that eWOM can be negative as well. Unfortunately, we could not account for the sentiment of eWOM in this study. Due to the majority of aforementioned arguments, we hypothesize the following:

H_1: Social media enhances sales.

Impact of event size on social media effects. We argue that smaller events negatively moderate the sales impact of social media. We imagine that successful niche events, or new events that start off small, could gain a lot of social media attention. For example, 22tracks, an online music discovery service got very popular on social media, and decided to host their own festival in 2015 (22tracks.com, 2016). However, large events are more well-known, and will be more often subject of the online conversation. For example, Nguyen, Dejean and Moreau (2015) found that consumption on social media increases ticket demand for concerts by national and international stars, but has no effect on concerts of niche content or local artists. More (popular) artists are performing at large events than at small events, which implies a broader scope of fans will be interacting on social media. Also, large events will have a better marketing budget. Consequently, large events can reach out to a bigger audience and make use of more (and more advertisement on) social media. In summary, we hypothesize as follows:

H_2: Smaller events have a negative impact on the effects of social media on ticket sales.

Impact of event genre on social media effects. While the genres in this study are not considerably different from each other and belong to the all-embracing EDM genre, we expect that the sub-genre harder EDM negatively impacts the social media effects on sales. A study by Eventbrite (2014) established that EDM-fans are the most social of music fans – both online and offline. They are hyperactive in their social media usage, and significantly more active on Twitter than general music fans. Although no research is available on the social media interaction of EDM sub-genres' fans, a study on EDM genre preferences by EDM.com (2015) showed that the softer styles are more popular than the harder styles of EDM. This is also established by data from Beatport (2014), where the softer styles of EDM are higher up in the top-selling EDM genres. Based on the aforementioned, we expect the fan base of the softer EDM styles to be larger and to interact more on social media than the fan base of the harder EDM styles. As we expect a positive moderation of the softer EDM styles and a negative moderation of the harder EDM styles, the existence and direction of a moderating impact of the events that offer both styles, such as TomorrowLand, is yet ambiguous to us. In summary, we expect the following:

> H_3: The events that offer only the harder styles of EDM have a negative impact on the effects of social media on ticket sales.

Impact of event average age on social media effects. We also expect that the average age of the buyers of event tickets may moderate the effects of social media on sales. First, we argue that a larger share of younger individuals is active on social media. This is confirmed by Lenhart et al. in 2010, who found that 72% of online individuals younger than 30 used social networking websites. This percentage was significantly higher than the 39% of online individuals of 30 years and older. More recently, Duggan and Brenner (2013) also confirm that individuals below 30 years are most active on social media. Second, as individuals younger than 30 were growing up during the development of social media in the last decade, we think that they are most familiar with activities and interactions on social media. Their networks on social media, mostly consisting of peers, are larger and more active. Also, they are more used to search and to share information on social media and spend more time on social media. These statements are confirmed by a research on adults' media use by Ofcom (2015), which shows that individuals younger than 30 spend more than 27 hours per week online and among all age groups are most likely to visit social media at least 10 times a day. As a result, we expect the following:

> H_4: Events with an average age of buyers of 30 or above have a negative impact on the effects of social media on ticket sales.

Impact of event sales period on social media effects. The time event tickets are on sale may also affect the sales impact of social media. We argue that social media interaction is highest in the beginning of the sales period. Potential buyers are creating a lot of eWOM and sharing the event with relatives to question if they should attend. Additionally, we think a similar spike occurs in the days before the event takes place, as attendees get excited about the event. Though, we can expect these spikes in both short and long sales periods. Therefore, we first reason that a long sales period covers a longer time span in which people can interact about the event on social media. However, we also argue that when a sales period is longer, potential buyers have more time to think about the event. The event is still long ahead, and they might lose interest in interacting about it on social media for a while. Consequently, less people are talking about the event at the same time, and less hype is built up on social media. Furthermore, events with short sales periods may have increased incentive to advertise more and to boost social media interaction to get sold out. Events with longer sales periods may expect they will sell out anyways, because they cover such a large time span. In summary, we hypothesize the following:

> H_5: Events with a sales period longer than 105 days have a negative impact on the effects of social media on ticket sales.

DATA

Study Context

To test our conceptual framework, we examine sales data of national and international EDM events, and the social media data of the corresponding events' brands. We define our dependent variable *Sales* as the number of daily tickets sold by an event obtained from the sales records of a large EDM event organizer. This data also includes event details and customer details, such as event location, number of tickets available, age and gender of customers.

Furthermore, we measure the effect of social media through three social media dimensions: fans, eWOM and consumption. These social media dimensions are based on metrics from the largest social media sources of today: Facebook, Twitter, YouTube, SoundCloud, and Google Analytics. Detailed definitions of the included social media metrics are provided in Table 2. As opposed to sales data, which is available for each individual event, the social media data are based on the events' brands' social media pages.

Brands. As we are dealing with events instead of concerts, various artists are performing and they may differ each year. To measure the effect of social media on event ticket sales, we need to consider the actual kind of event rather than the individual artists performing. We use the term brand to identify the overarching kind of event. For example, Q-Base and Qapital are both events that belong to the brand Q-Dance. Furthermore, for several brands the only difference is the year the events take place. However, for other brands, the events are dissimilar (in e.g. location, venue, tickets available, etc), but still belong to the same brand. For example, Sensation Japan, Sensation Amsterdam, and Sensation South-Africa all belong to the brand Sensation.

Table 2: Detailed Descriptions of Social Media Metrics

Dimension	Metric	Description
Fans	Facebook Fans	The number of individuals that has liked and thereby has subscribed to the event's brand's Facebook Page.
Fans	SoundCloud Followers	The number of individuals that has subscribed to the event's brand's SoundCloud Page.
Fans	Twitter Followers	The number of individuals that has subscribed to the event's brand's Tweets.
Fans	YouTube Subscribers	The number of individuals that has subscribed to the event's brand's YouTube Channel.
EWOM	Facebook Page Views	The number of times the event's brand's page was viewed.
EWOM	Google Analytics Page Views	The number of pages that visitors displayed on the website of the event's brand.
EWOM	Twitter Mentions	The number of times the event's brand's username is mentioned in tweets of other Twitter users.
EWOM	YouTube Likes	The number of positive ratings given to a video of the event's brand's YouTube channel.
Consumption	YouTube Views	The number of times a video of the event's brand's YouTube channel was played.

Fans. We define *Fans* as the number of individuals that subscribed to the event's brand's social media page by clicking a like-, follow- or subscribe-button. More specifically, the metrics that belong to the social media dimension *Fans* are: Facebook Fans, Soundcloud Followers, Twitter Followers, and YouTube Subscribers.

EWOM. We define eWOM as the direct electronic word of mouth, as well as the indirect electronic word of mouth on or about the events' brand's social media page. For example, we consider mentions and comments as direct eWOM, and views and post likes as indirect eWOM. In this study, the direct eWOM metrics are based on quantity rather than the sentiment.[2] The metrics that are considered as eWOM in this research consist of: Facebook Views, Twitter Mentions, YouTube Likes, and Google Analytics Page Views.

Consumption. This dimension represents the number of times a video or track is played on the event's brand's social media page, and their derivatives, such as average play time. The only metric belonging to this social media dimension is YouTube Views.

Data Set

From an initial set of daily sales for 234 events, we retained a subset of 78 events (33%) based on several criteria. First, as we aim to establish the effect of social media on sales, we exclude all events for which no social media information was available. Second, we eliminated all events for which missing or incorrect sales data or social media data was present.[3] We retained 80 events that took place between 2010 and 2016. However, we only study the events that took place between 2012 and 2016, because the social media data contains many missing or erroneous values before 2012. The remaining 78 events belong to 12 different brands and took place between July 7, 2012 and January 30, 2016. Furthermore,

[2] The EDM event organizer that provided us with data only provided quantitative eWOM metrics.
[3] For some events the sales data was not daily registered, but rather with gaps of a few days. Also, for several events sales decreased at some points, which indicated incorrect sales data.

Table 3: Descriptive Statistics

	N	Date Range	Min	Max	Mean	SD
Dependent Variables						
Ticket sales	8233	19/03/2012 - 30/01/2016	0	25667	122	598
Social Media Variables[1]						
Fans						
Facebook Fans	7519	19/03/2012 - 30/01/2016	- 208758	359552	950	9266
SoundCloud Followers	4418	06/01/2014 - 30/01/2016	-753	561	55	55
Twitter Followers	7950	19/03/2012 – 30/01/2016	-342967	343030	133	5454
YouTube Subscribers	7378	30/09/2013 - 30/01/2016	-6133	115390	351	1999
eWOM						
Facebook Views	4707	19/03/2012 - 28/04/2015	0	78402	2046	3458
Google Analytics Page Views	3294	14/01/2014 - 30/01/2016	2	4551248	38107	121945
Twitter Mentions	7439	19/03/2012 - 30/01/2016	1	3406	67	135
YouTube Likes	6109	30/09/2013 - 30/01/2016	0	114992	594	2420
Consumption						
YouTube Views	7477	06/05/2012 - 30/01/2016	0	120720524	125344	2448528
Control Variables						
Sales period (in days)	8233	19/03/2012 - 30/01/2016	45	319	125	60
Sold out[2]	8233	19/03/2012 - 30/01/2016	0	1	0.43	0.5
Total tickets available for event	8233	19/03/2012 - 30/01/2016	850	150000	27311	31556
Average age of customers	6608	19/03/2012 - 30/01/2016	14	89	27.5	8.5
Average % males among customers	6922	19/03/2012 - 30/01/2016	0%	100%	68%	18%
ID Variables						
Events	78	19/03/2012 - 30/01/2016				
Brands	12	19/03/2012 - 30/01/2016				

[1] We only describe the Social Media Variables that are in our final model. The Social Media Variables are based on the events' brands rather than unique events. The 78 events in the data belong to 12 different brands.
[2] Sold out dummy = 1 if sold out, = 0 otherwise.

these events have corresponding sales and social media data between March 19, 2012 and January 30, 2016. Table 3 lists all summary statistics of the variables in the data.

We converted ticket sales and all cumulatively registered social media metrics to first differences, so that we have daily ticket sales and social media data. On average, 122 tickets are sold on a daily basis. The period tickets for an event are on sale has a mean of 125 days. We specify an event to be sold out if at least 95% of the available tickets got sold.[4] According to this measure, 33 of 78 (43%) of the events got sold out. Also, we aggregate the ticket orders of each day and acquire daily average age and the daily average percentage of male customers for each event. [5] The customers consist on average of 68% males and are on

[4] We discussed this with the EDM event organizer and reason as follows. Tickets may be given away to sponsors or in marketing effort. These tickets are not registered in the daily sales, however are included in the specified number of total tickets available. Therefore, if at least 95 % of the total tickets available is sold, we may consider it to be sold out.
[5] Age and gender of consumers are specified per transaction record, and we average them over each day of sales.

average 27.5 years old.

The social media information is only available per brand, implying all events belonging to the same brand have identical social media data. The social media data available consists of 53 different social media metrics from the channels Facebook, Google Analytics, Google Plus, Instagram, Klout, SoundCloud, Twitter and YouTube. We retain 9 metrics (17%) that are categorized according to the social media dimension they belong to: 4 metrics belong to the *Fans* dimension, 4 metrics belong to the *eWOM* dimension, and 1 metric belongs to the *Consumption* dimension.

We applied several criteria for the retention of the social media metrics. First, the metrics were collected over considerably varying time periods.[6] We excluded 5 metrics that were recorded before 2012, because these metrics were recorded with many gaps, and also seemed to have a considerable amount of inaccurate values. Among the 48 remaining metrics, we removed another 13 metrics that had no or almost no data. Next, we still uncovered that several metrics had many erroneous values or gaps of a few days or even a few months. If these metrics were cumulatively recorded, we corrected for the inappropriate (small) gaps, spikes, and drops by continuing the trend. In case of gaps, we extracted the difference in value, divided it by the number of days that nothing was recorded, and assigned this average to each missing record in the gap. In case of inappropriate spikes and drops, we ignored the spike or drop and set the value to 0. Next, we extracted the difference in value from the next record and divided it by two. This average was then assigned to the record of the spike or drop, and to the record following the spike or drop. Note that 15 of the metrics were instantaneously recorded, which would have made corrections equivalent to speculations. Therefore we excluded them from this analysis.

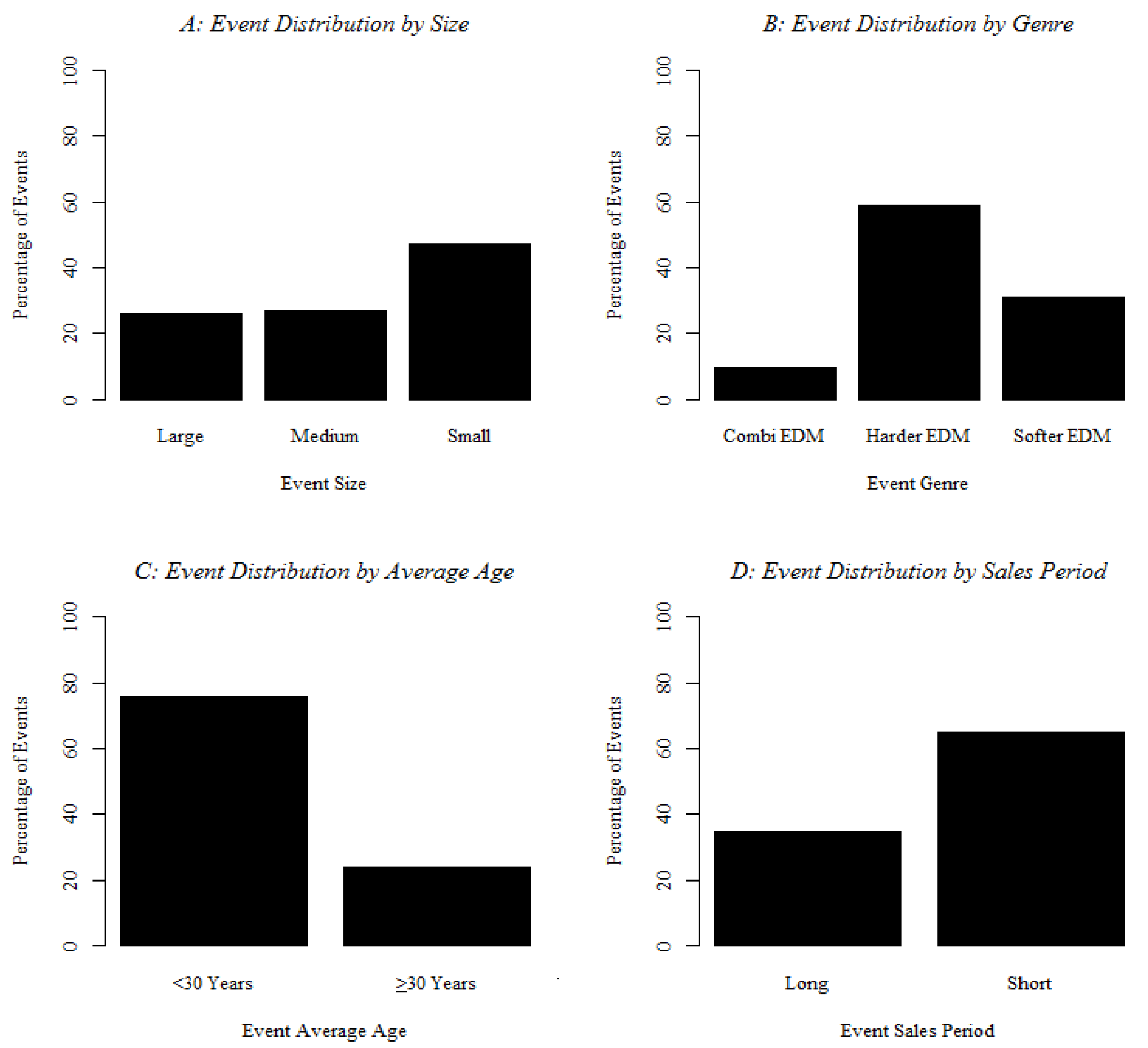
Moreover, as many of the remaining 20 metrics are derivatives or combinations of

[6] For example, data for Soundcloud and Google Analytics metrics was only collected since 2014, and Facebook Views were only recorded until May, 2015. This information is also provided in Table 3.

each other, including all of them would incite multicollinearity. We retained 9 metrics with the highest number of observations, and that were almost not or not at all derived from another metric. For example, we exclude Klout Score, which accumulates metrics from eight different social media channels (among which Facebook, Twitter, Instagram and Google+) and uses an algorithm to translate these into an online influence score (Klout, 2016).

Finally, we summarize the events according to different event characteristics. The distribution of the events according to their event characteristics is as follows. The average age of buyers is for 19 events (24%) 30 or higher, and for 59 events (75%) below 30. Furthermore, 46 events (59%) offer the harder styles of EDM, 24 events (31%) offer the softer styles of EDM, and 8 events (10%) offer both. Also, 37 events (47%) are considered as small events with less than 10,000 tickets available, 21 events (27%) are considered as medium events with 10,000 or more and less than 30,000 tickets available, and 20 events (26%) are considered as large events with 10,000 or more tickets available. Moreover, 51 events (65%) have a short sales period of 105 days (15 weeks) or less, and 27 events (35%) have a long sales period of more than 105 days. Figure 2 also visualizes the distribution of the events according to these event characteristics.

Figure 2: Event Distribution by Event Characteristics



MODEL

Vector Autoregressive Model. In order to test our hypotheses, we construct a model that examines the effects of social media on ticket sales, and how event characteristics moderate these effects. We follow a similar approach as Nijs et al. (2001) and Steenkamp et al. (2005). Considering the non-linear nature of our dependent variable ticket sales and the combination of cross-section and time-series data, we estimate a vector autoregressive (VAR) approach for each event i (i = 1, …, N), using ordinary least squares (OLS) to assess the effects of social media on ticket sales. Then, we estimate a second stage with weighted least squares (WLS) to account for the uncertainty of the parameter estimates of the first stage that may yield biased results if the residuals exhibit heteroscedasticity (Nijs et al. 2001, p. 7, Steenkamp et al. 2005, p. 43), and examine how event characteristics moderate the effects of social media on ticket sales. In the next paragraphs we show our complete models, and discuss all individual model components.

First Stage Model. As our time-series variables were recorded for different time intervals, we are dealing with a substantial amount of missing values over the full time period. Therefore, we construct a rule that requires each time-series variable to have at least 80% of observations per event. For example, if Google Analytics Page Views is available for less than 80% of the records for event i, we do not include it in the event-specific model of event i. This implies we will have different models with different sets of independent variables and numbers of observations.

We present the following general VAR model that, for each day t, tests the effects of social media of event i on ticket sales for event i:

$$
\begin{aligned}
(2)\quad & TicketSales_{it} \\
&= \alpha_{it} + \beta_{1i} FacebookFans_{it} + \beta_{2i} SoundCloudFollowers_{it} \\
&+ \beta_{3i} TwitterFollowers_{it} + \beta_{4i} YouTubeSubscribers_{it} \\
&+ \beta_{5i} FacebookViews_{it} + \beta_{6i} GoogleAnalyticsPageViews_{it} \\
&+ \beta_{7i} TwitterMentions_{it} + \beta_{8i} YouTubeLikes_{it} + \beta_{9i} YouTubeViews_{it} \\
&+ \beta_{10i} BuyersAge_{it} + \beta_{11i} BuyersMale_{it} + \beta_{12i} DaysToEvent_{it} \\
&+ \beta_{13i-ki} TicketSales_{it-k} + \varepsilon_{it}
\end{aligned}
$$

where α_{it} presents the event-specific time-variant intercept, β_{1-9} the set of predictors, β_{10-12} the set of control variables, β_{13-k} the set of lagged dependent variables, and ε_{it} the event-specific time-variant error component.

Predictors. We test how each individual social media metric for event i influences ticket sales of event i at day t (H_1). Due to per event missing observations, we have 78 event-specific models with different combinations of social media metrics.

Lagged Dependent Variables. We include lags of the dependent variable ticket sales $TicketSales_{it-k}$ for event i on day t – k, as several research has established that past behaviour is a strong predictor of future behaviour (e.g. Brown 1952, Ouellette and Wood 1998), or more specifically, future sales (e.g. Saboo, Kumar and Ramani 2015, Goel and Goldstein 2014). We follow the approach of Nijs et al. (2001) and Steenkamp et al. (2005), and use k equal to up to four, six, and eight lags. In the next section, we use model selection criteria to make a final decision on the number of lags included.

Covariates. We include a set of covariates. First, as we have aggregated the ticket orders per day, we use the average age of buyers of event i on day t, $BuyersAge_{it}$. Also, we include the average percentage of male buyers of event i on day t, $BuyersMale_{it}$. Furthermore, we expect that the highest sales take place at the beginning of the sales period and decrease each day closer to the event. To control for this trend of ticket sales we include a variable that captures the days to the event left for event i on each day t, $DaysToEvent_{it}$.

Second Stage Model. In the second stage of our approach, we test the moderating impact of event characteristics on each social media dimension's effect on sales, and on each individual social media metric's effect on sales. First, we transform the event-specific coefficients and standard errors of the first-stage model to elasticities to enable cross-event comparison (see e.g. Steenkamp et al. 2005). We include our new coefficients and standard errors:

$$Elast_{ij} = \beta_{ij} \frac{\mu_j}{\mu_{tickets}} \qquad SE_{Elast_{ij}} = SE_{\beta_{ij}} \left|\frac{\mu_j}{\mu_{tickets}}\right|$$

where β_{ij} present the first stage event-specific coefficients, $SE_{\beta_{ij}}$ present the first stage event-specific standard errors, μ_j equals the mean of variable j, and $\mu_{tickets}$ equals the mean of the dependent variable ticket sales.

Second, we standardize the elasticities by subtracting the mean and dividing by the standard deviation of each variable. We do this, because the social media metrics are measured at different scales and do not contribute equally to the analysis. For example, Facebook Fans range between 0 and 8285000, whereas SoundCloud Followers range between 0 and 124200. The Facebook Fans variable will outweigh SoundCloud Followers. Walsh (1990) states that comparing regression coefficients with respect to size is rather like comparing apples and oranges when the variables have different units of measurement. Afifi and Clark (1990) add that comparing the unstandardized coefficients does not achieve this because of the different units and degrees of variability of the variables. Converting the data to equivalent scales can avoid this (e.g. Afifi and Clark 1990, Bring 1994, Gelman 2008, Walsh 1990). We use the standardized elasticities as inputs for the dependent variables in the second stage models.

As our dependent variables in the second stage are estimated parameters, we need to account for estimation uncertainty. Furthermore, the differing accuracy of these estimated parameters yields biased estimates of the second stage if heteroscedasticity is present (Steenman et al. 2001, p. 7, Steenkamp et al. 2005, p. 43). According to the event-specific Breusch-Pagan tests, which are included in Appendix I, heteroscedasticity is present in 18 of 78 (23%) models ($p < .05$). Thus, in the majority of cases we cannot reject the null hypothesis of homoscedasticity. However, keeping in mind the uncertainty of the estimates and the 23% heteroscedasticity in our quite small set of data, we use both OLS and weighted least squares (WLS), and choose the best estimation method based on model fit. WLS weights each dependent and independent variable in the equation with the inverse standard error of the dependent variable.

We carry out the second stage on per social media dimension aggregated social media metrics, and on individual social media metrics. The first models thus examine the effect of event characteristics on each social media dimension: Fans, EWOM, and Consumption, whereas the latter models use individual social media metrics as dependent variables.

We present the following second stage models. In Equation (3) we apply OLS and test the moderating effect of each event characteristic on the effect of social media dimension j (in the case of aggregated metrics per social media dimension) or social media metric j (in the case of individual metrics). Equation (4) is equivalent to Equation (3), however WLS is applied.

$$(3)\ Social\ Media\ Elasticity_j = \alpha_j + \beta_{1j} EventSize_j + \beta_{2j} EventGenre_j + \beta_{3j} EventBuyersAge_j + \beta_{4j} EventSalesPeriod_j + \varepsilon_j$$

and

$$(4)\ w_j * (3), \qquad with\ w_j = \frac{1}{SE_j}$$

where α_j presents the intercept, β_{1-4} the set of moderating parameters, and ε_j the error component. The weights w_j present the inverse standard errors of the dependent variables j.

Moderating Variables. We test how each of the event characteristics (1) size, (2) genre, (3) buyers' average age, and (4) sales period's length impact the effect of social media on ticket sales (H_{2-5}). We assess the magnitude and direction of each moderating effect.

EMPIRICAL RESULTS

First Stage Model Performance and Model Selection. Table 4 presents the model selection criteria for our first stage models. We compared the values of all 78 event-specific models' Akaike Information Criteria (AIC) and Bayesian Information Criteria (BIC) and report the percentages of lowest and thus best values for each number of lags. As both AIC and BIC report the highest percentage for the model with four lags, we concentrate on this model in the remainder of our study. Table 9A and 9B in Appendix I provide all 78 event-specific models' AIC and BIC values.

Table 4: Selection of First Stage VAR Model Dimension

	AIC			*BIC*		
	4 lags	6 lags	8 lags	4 lags	6 lags	8 lags
Selected %[1]	**50%**	19%	31%	**68%**	14%	18%

[1] We highlight the best model fit in boldface.

Figure 3 presents an overview of the R-squares of all event-specific first stage models. All specific values are provided in Table 10 in Appendix I. Because of different parameters in reasonable, we argue that our models may have omitted variables that decrease model performance. We further discuss limitations of our model in the last section of this paper. Furthermore, we check event-specific variation inflation factors (VIF) to assess the degree of multicollinearity. According to these VIFs, only 5.6% is equal or higher than 10, and only 14.6% of the VIFs is equal or higher than 6. Thus, we may conclude that in the majority of cases we have no multicollinearity.

Main effects. Table 5 describes the results of our first stage models. We estimated 78 event-specific models and report for each variable in how many models it was included, its weighted standardized elasticity, and its percentages of significant positive elasticities and significant negative elasticities. These percentages reflect the proportion of estimated elasticities that were found to differ significantly from zero ($p < .1$). We also report the percentage of models in which no significance was established. We first discuss the main effect of social media on sales, and then address the effects of the lagged dependent variables and control variables.

Figure 3: Model Fit First Stage Event-Specific Regression Models

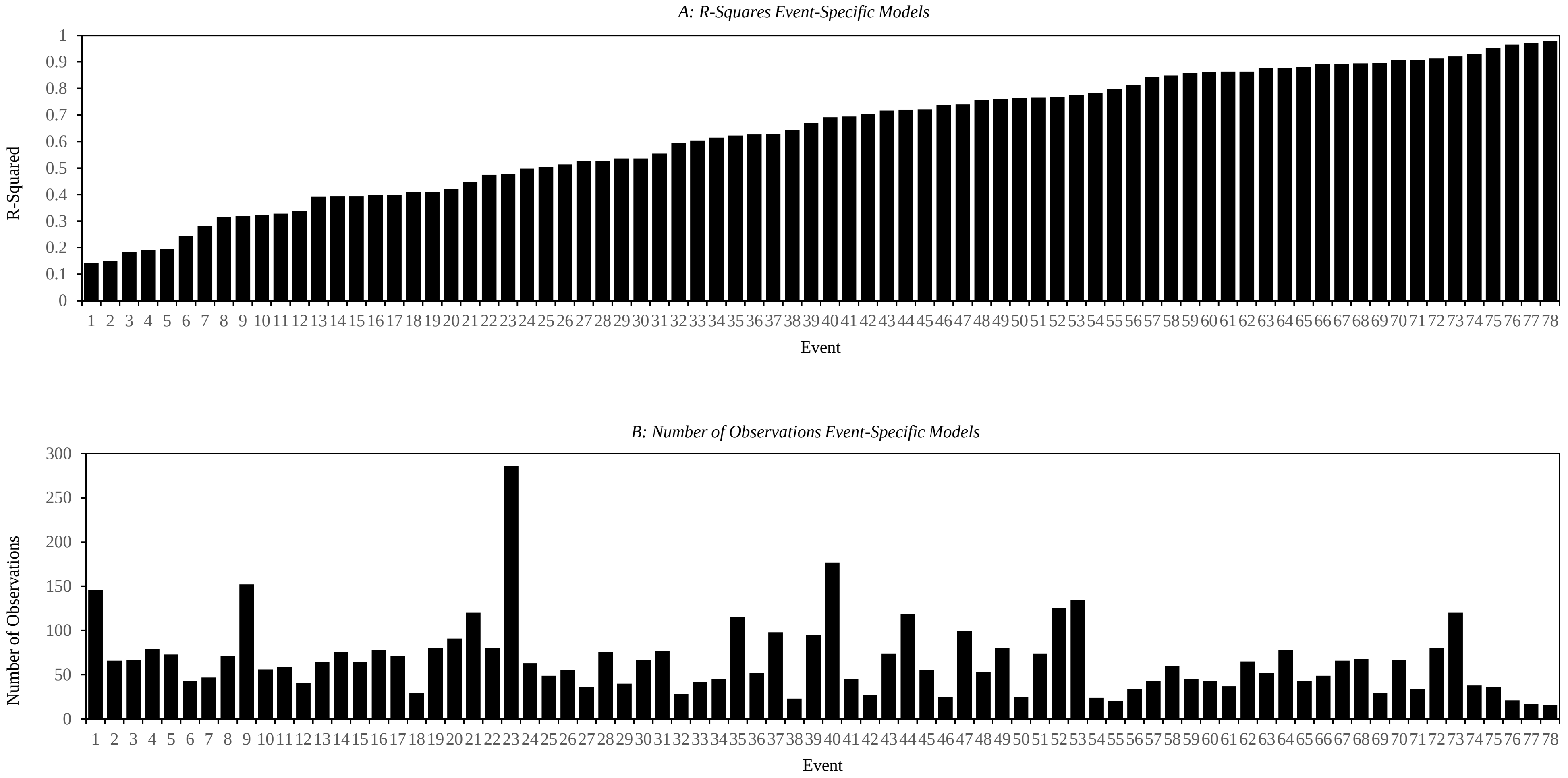


Table 5: Main Effects of Social Media on Ticket Sales

		N	b[1]	Positive Significant		Negative Significant		Not Significant	
				N	*%*	*N*	*%*	*N*	*%*
Social Media Predictors									
Facebook Fans	$H_1 > 0$	71	-.048*	5	7%	4	6%	62	87%
SoundCloud Followers	$H_1 > 0$	40	-.088	1	2.5%	1	2.5%	38	95%
Twitter Followers	$H_1 > 0$	74	-.161***	5	7%	8	11%	61	82%
YouTube Subscribers	$H_1 > 0$	69	-.171**	3	5%	5	7%	61	88%
Facebook Views	$H_1 > 0$	49	.207*	10	20%	3	6%	36	74%
Google Analytics Page Views	$H_1 > 0$	29	.576**	10	35%	1	3%	18	62%
Twitter Mentions	$H_1 > 0$	74	-.058	10	14%	7	9%	57	77%
YouTube Likes	$H_1 > 0$	53	-.161**	2	4%	6	11%	45	85%
YouTube Views	$H_1 > 0$	69	-.047	6	9%	1	1%	62	90%
Lagged Dependent Variable									
Ticket Sales (t-1)		76	.379***	37	49%	5	6%	34	45%
Ticket Sales (t-2)		76	.006	5	7%	4	5%	67	88%
Ticket Sales (t-3)		76	.014	12	16%	2	3%	62	82%
Ticket Sales (t-4)		76	.005	9	12%	6	8%	61	80%
Covariates									
Buyers Age		73	-.400	2	3%	8	11%	63	86%
Buyers Gender		73	-.208	4	5%	5	7%	64	88%
Days To Event		76	-.254*	8	11%	12	16%	56	74%

* p < .10.
** p < .05.
*** p < .01.
[1] This is the weighted standardized elasticity.

The results do not unanimously confirm the expectation of social media enhancing ticket sales (H_1). Actually, only two of six significant social media effects on sales have a positive sign.

Within the Fans dimension, SoundCloud Followers do not affect ticket sales (*b* = -.088, *p* = .377). This may be due to the fact that SoundCloud has only become really popular after 2014, when they reached more than 175 million unique listeners each month (Rusli, Karp & MacMillan 2014). Furthermore, this metric was available for only 41 of our models (53%). In a larger and more complete set, we may find a significant effect on ticket sales. Facebook Fans (*b* = -.048, *p* = .038), Twitter Followers (*b* = -.161, *p* = .377), and YouTube Subscribers (*b* = -.171, *p* = .008) negatively affect ticket sales. These findings contradict our hypothesis and the existing literature. Saboo, Kumar, and Ramani (2015) established that Fans have a positive impact on sales, but at a diminishing rate. We measure our metrics instantaneously (daily), rather than cumulatively. It may be, that the brands in our data already have reached such a number of fans or followers, that an additional fan or follower would not impact sales anymore. Nevertheless, significance is established, and we would have at least expected very small positive effects on sales. Therefore, we think that either our estimation method is unfitting or that our model suffers from omitted variable bias.

Within the EWOM dimension, we find that Facebook Views, Google Analytics Page Views, and YouTube Likes affect sales, but that Twitter Mentions' weighted elasticity is insignificant ($b = -.058$, $p = .308$). The impact of both Facebook Views ($b = .207$, $p = .019$) and Google Analytics Page Views ($b = .682$, $p = .000$) is positive, which is consistent with the previous findings that eWOM enhances sales (e.g. Babić et al. 2015). YouTube Likes reports a negative sign ($b = -.161$, $p = 0.001$), and again contradicts our hypothesis. As this eWOM metric actually indicates a positive rating for a music video, we cannot imagine that this finding is right. Therefore, we further expect that our model is not correctly estimated, which we will further discuss in our last section.

Within the Consumption dimension, YouTube Views has a positive significant value in 9% of the models, and a negative significant value in 1% of the models. Nevertheless, the weighted elasticity of YouTube Views indicates that this metric does not affect ticket sales ($b = -.047$, $p = .450$). We reason that this is because of even newer online music sampling services, such as Spotify, whose users are increasing. We think that if we study these newer services, we may find a positive effect on ticket sales.

The four lags of ticket sales all have positive signs. However, only the first lag actually influences ticket sales ($b = .379$, $p < .001$). The second lag ($b = .006$, $p = .875$), third lag ($b = .014$, $p = .711$), and fourth lag ($b = .005$, $p = .882$) are very insignificant, and seem to not influence sales on day t. Our findings confirm the study of Brown (1952, p. 370), who established that the influence of past behaviour from sales decreases continuously for each additional time period and that only the first lag actually affects sales. Our covariates, Buyers Age ($b = -.400$, p = .297) and Buyers Gender ($b = -.208$, $p = .336$) do not influence ticket sales. This might be due to the aggregation of these variables in the data. These covariates reflect daily averages, and this way of measurement might explain the insignificance. Lastly, the trend variable Days to Event negatively affects sales (b = -.254, p = .032). This effect is the largest at the start of sales, and the smallest in the days just before the event takes place.

Second Stage Model Performance and Model Selection. For our second stage model, in which we assess the moderating impact of event characteristics on the effects of social media on ticket sales, we compare two estimation methods (OLS vs. WLS). We do this for the per social media dimension aggregated models. To assess model performance, we evaluate two fit measures: R-squared, and Adjusted R-squared. Table 6 shows that WLS estimation outperforms OLS estimation for 2 of 3 models. Moreover, as our previous described Breusch-Pagan tests established heteroscedasticity for 23% of the models, and especially as we need to account for the uncertainty of the first stage estimates, we focus on WLS as the best estimation method in our second stage.

Moderating impact on aggregated social media effects. Table 7 describes the results of second stage models that assesses the moderating impact of event characteristics on per dimension aggregated social media effects of our first stage models. We estimated 3 different models and again report the parameter estimates, the standard errors of the event characteristics and the number of observations. We discuss the relationships of the conceptual framework with respect to the effects of the different social media dimensions on ticket sales.

In support of H_2, we find that events of both small size (b = -.093, p = .094) and medium size (b = -.087, p = .089) negatively impact the social media effect of the Fans dimension on ticket sales. This can be explained by the fact that these events are less well-known, and a relative small number of artists that are not that popular is performing.

Table 6: Selection of Model for Second Stage

		OLS			*WLS (Selected Model)*		
Social Media Dimension		Fans	EWOM	Cons.	Fans	EWOM	Cons.
		b	*b*	*b*	*b*	*b*	*b*
Intercept		.406	.175	-.096	.139***	.130	-.165***
Moderators							
Event Size: Small	$H_2 < 0$	-.203	-.115	-.036	-.093*	-.052	.051
Event Size: Medium	$H_2 < 0$	-.243	-.098	-.071	-.087*	-.021	.053
Event Genre: Harder EDM	$H_3 < 0$	-.239	-.086	.074	-.078***	-.096*	.020
Event Genre: Combi EDM	$H_3 = ?$	-.893***	-.265	1.183**	-.075*	-.116*	.021
Event Age: ≥ 30	$H_4 < 0$	.169	-.021	-.070	.120**	.014	-.090*
Event Sales Period: Long	$H_5 < 0$	-.195	-.023	-.069	-.131***	-.079	.043
Model Fit[1]							
R-Squared		.079	.005	**.137**	**.136**	**.045**	.086
Adjusted R-Squared		.057	-.024	**.056**	**.116**	**.017**	-.001

* p < .10.
** p < .05.
*** p < .01.
[1] We highlight the best model fit in boldface.

Table 7: Moderating Effects of Event Characteristics on Aggregated Social Media Effects

Social Media Dimension		Fans		EWOM		Consumption	
		b	*SE*	*b*	*SE*	*b*	*SE*
Intercept		.139***	.051	.130	.080	-.165***	.060
Moderators							
Event Size: Small	$H_2 < 0$	-.093*	.055	-.052	.061	.051	.045
Event Size: Medium	$H_2 < 0$	-.087*	.051	-.021	.056	.053	.043
Event Genre: Harder EDM	$H_3 < 0$	-.078***	.029	-.096*	.052	.020	.041
Event Genre: Combi EDM	$H_3 = ?$	-.075*	.043	-.116*	.059	.021	.051
Event Age: ≥ 30	$H_4 < 0$	.120**	.054	.014	.066	-.090*	.053
Event Sales Period: Long	$H_5 < 0$	-.131***	.046	-.079	.061	.043	.044
N		258		209		70	
R-Squared		.136		.045		.086	
Adjusted R-Squared		.116		.017		-.001	

* p < .10.
** p < .05.
*** p < .01.

Consequently, these events' brands will have less fans and followers compared to the large events' brands.

The results strongly confirm our H_3, which stated that events that only offer the harder styles of EDM negatively moderate the social media effects on sales. In our second stage models, the softer EDM genre is our reference category. We find a negative moderating impact of events that only offer the harder styles of EDM on both the Fans- (*b* = -.078, p = .008) and EWOM (*b* = -.096, *p* = .064) dimension. Similarly, events of the combi EDM genre also negatively impact both the social media effect of the Fans- (*b* = -.075, *p* = .082) and Consumption (*b* = -.096, *p* = .064) dimension. Apparently, the negative impact of the hard EDM genre outweighs the positive impact of the soft EDM genre.

In line with H_4, we find that a higher age of buyers of event tickets negatively impacts the effect the Consumption dimension has on ticket sales (*b* = -.090, *p* = .095). This effect confirms the existing literature, which established that individuals of 30 years and older are less active on social media (e.g. Lenhart et al. 2010, Pew Research Center 2015). Contradicting our H_4, we find a positive moderating impact of individuals of 30 years and older on the Fans dimension (*b* = .120, *p* = .026). This may be explained by a study by Ofcom (2015), which states that although individuals between 16 and 24 years old have always shown the highest levels of social media use compared to older ages, the most marked increase over the last eight years has been among the individuals between 30 and 44 years old – a 68 percentage point increase from 12% to 80%. These individuals could therefore be more active in the Fans dimension on social media than younger individuals that have already subscribed to the social media page in the past.

In support of H_5, we find a significant moderating impact of an event's sales period on the effect of Fans' social media metrics on ticket sales. Indeed, a sales period longer than 105 days negatively affects the effect of the Fans dimension on ticket sales (*b* = -.131, *p* = .005). Possibly these events are, contrary to our expectation, very active on social media during their whole long sales periods. Consequently, people may get annoyed by the many updates and unsubscribe, or even not subscribe at all.

Moderating impact on individual social media effects. Table 8 describes the results of our second stage models that assess the moderating impact of event characteristics on the individual social media effects of our first stage models. We estimated 9 different models and report for each model the parameter estimates, the standard errors of the event characteristics and the number of observations. We establish only two significant moderations.

Both significant effects involve H_4. A negative moderation on the effect of YouTube Views (*b* = -.090, *p* = .095) supports our expectation and is in line with previous findings that individuals of 30 years and older interact less on social media than younger people (e.g. Ofcom 2015, Smart Insights 2015). However, we also find that the effect of a higher age of ticket buyers positively affects the effect Google Analytics Page Views has on ticket sales (*b* = .300, *p* = .005). Thus, the results are twofold. A possible explanation for the positive impact on Google Analytics Page Views is that individuals of 30 years and older are more inclined to check event's brand's websites for information about the events, whereas individuals younger than 30 years old are more active on the actual social media.

In summary, we find more evidence against than in favour of H_1. Furthermore, the results of the per social media dimension aggregated models support H_2, H_3, and H_5, but establish both supporting and contradicting results for H_4. The results of the individual models provide little evidence of moderation. Similar as in the aggregated models, these models establish effects both in favour and against H_4.

Table 8: Moderating Effects of Event Characteristics on Individual Social Media Effects

Social Media Metric	Facebook Fans		SoundCloud Followers		Twitter Followers		YouTube Subscribers		Facebook Views		Google Analytics Page Views		Twitter Mentions		YouTube Likes		YouTube Views	
	b	*SE*	*b*	*SE*	*b*	*SE*	*b*	*SE*	*b*	*SE*	*b*	*SE*	*b*	*SE*	*b*	*SE*	*b*	*SE*
Intercept	.140**	.048	.138	.210	.032	.108	-.030	.115	-.001	.112	-.331*	.176	.274*	.140	-.098	.214	-.165***	.060
Moderators																		
Event Size: Small	-.007	.046	-.138	.172	.015	.111	-.096	.104	.104	.090	-.062	.068	-.130	.123	-.058	.121	.051	.045
Event Size: Medium	-.010	.047	-.092	.135	.021	.108	-.089	.096	.084	.081	-.003	.066	-.103	.113	-.046	.108	.053	.043
Event Genre: Harder EDM	-.010	.023	-.098	.159	-.011	.056	.015	.066	-.040	.069	.119	.151	-.088	.084	.074	.150	.020	.041
Event Genre: Combi EDM	-.019	.050	-.004	.081	.066	.113	.006	.095	-.029	.116	.126	.151	-.092	.115	.025	.123	.021	.051
Event Age: ≥ 30	.004	.045	.277	.173	.004	.114	.130	.096	-.080	.085	.300***	.097	.041	.133	.081	.139	-.090*	.053
Event Sales Period: Long	-.003	.045	-.198	.197	-.022	.090	-.102	.089	.069	.088	-.014	.071	-.119	.117	-.000	.145	.043	.044
N	73		41		75		71		51		31		76		55		71	
R-Squared	.006		.102		.010		.037		.051		.387		.036		.016		.086	
Adjusted R-Squared	-.086		-.056		-.077		-.055		-.082		.228		-.049		-.109		-.001	

* p < .10.
** p < .05.
*** p < .01.

DISCUSSION

Although several studies have established that social media enhances sales (e.g. Babić et al. 2015, Dewenter et al 2012, Saboo et al. 2015, Goel & Goldstein 2014), almost no one has jointly studied all three social media dimensions Fans, EWOM, and Consumption. This research includes metrics from each dimension, and assesses the effect of the individual social media metrics on sales, rather than the per dimension aggregated effects. Additionally, we see how the effects of social media on sales are affected by context characteristics. We make the setting more up-to-date by including 5 of the nowadays most popular social media channels: Facebook, Google Analytics, SoundCloud, Twitter, and YouTube, whereas previous studies contain only one or two of the nowadays most popular networks.

We apply our research in the setting of the EDM music industry, and use a unique set of event-, sales- and social media data, which has not been studied before. We first estimate a vector autoregressive model to assess the effects of individual social media metrics on sales. Second, we assess the moderating effect of event characteristics. The event characteristics we use consist of (1) the size of an event, (2) the sub-genre of an event, (3), the average age of buyers of event tickets, and (4) the length of an event's sales period. We standardize our first stage elasticities to account for the different scales of the social media metrics, and use these as our dependent variables in the second stage. Accounting for the uncertainty of the estimated parameters and heteroscedasticity among our first stage estimates, we use weighted least squares (WLS) in our second stage.

We find varying results with respect to our expectation that social media enhances sales. Only two of six social media metrics enhance ticket sales. Both of these metrics belong to the EWOM dimension. This is in line with the majority of findings in previous literature, that found positive effects of eWOM on sales (e.g. Chevalier & Mayzlin 2009). Furthermore, as the metrics considered are all in terms of quantity rather than sentiment, we think that this finding is quite intuitive. We argue that when the quantity of interaction on social media increases, this indicates that consumers are interested in the event and may be inclined to buy tickets. Nevertheless, four of six significant metrics actually contradict our hypothesis, and do not confirm that social media enhances sales. Most of these metrics belong to the Fans dimension. As all previous literature has established that social media enhances sales, and we cannot find arguments for an opposite statement, we expect that this is due to some error in our estimation method. It is possible that our model exhibits residual autocorrelation because of the lagged dependent variables. This would imply that the estimates are biased downwards (e.g. Maddala & Rao 1973, Achen 2000, Keele & Kelly 2005), and may explain the negative signs of the majority of the social media metrics.

In our second stage we confirm that smaller and medium events negatively impact the effects of the social media dimension Fans on ticket sales. Second, events that offer the harder styles of EDM, with respect to events that only offer the softer styles of EDM, negatively affect the effects of social media on ticket sales. Third, support is found for the fact that events that have buyers of an average age of 30 years and older, negatively moderate the effect of social media on ticket sales. This may be due to the fact that the number of social media adopters has always been higher among the individuals below 30 years old, according to a global social media research summary by Smart Insights (2016). Furthermore, according to statistics by the Pew Research Center (2015), the percentages of social media users on Facebook, Twitter and YouTube are highest among individuals in the 18-29 category. Nevertheless, we also find that events with an average age of buyers of 30 years and older positively impact the effect of Google Analytics on ticket sales. We suggest that this is because Google Analytics measures websites statistics, rather than actual social media interaction, and that individuals of 30 years and older are more inclined to find information about events on the event’s brand’s website. Finally, the events that have a longer sales period (of more than 105 days), have a negative moderating effect on the effect of social media on ticket sales.

Managerial Implications

Our study has several key managerial implications. We contradict the literature that states that social media enhances sales. We establish that almost every individual metric included decreases sales. The majority of these metrics belong to the Fans dimension. The only two metrics that do enhance sales, belong to the eWOM dimension. According to our findings, managers should focus on increasing eWOM, rather than Fans or Consumption. Moreover, managers should not forget about their brand's websites. Although one may expect brands' websites to lose audience with the continuously increasing popularity of social media networks, our results suggest that websites are actually actively used by the older potential buyers.

Furthermore, we do establish that the effects of social media on sales depend on context characteristics in the aggregated models. This is extremely important, as one can set out different selling strategies based on the impacts of context characteristics on sales. Moreover, particular target groups can be differentiated and reached out to in diverse ways. As our results only apply to the EDM industry, managers should aim to establish for their own industry which context characteristics influence the effects of social media on sales.

Our analysis also offers insights for the music industry in particular and which factors play a role in the way social media affects event ticket sales. We find that the Fans dimension is negatively affected by events of small and medium size and implies that they have a negative impact on the effect of fans and followers on ticket sales. The music industry should focus on increasing the number of fans and followers of large events.

Furthermore, the average age of buyers of tickets of an event is important in different ways. We find that individuals of 30 years and older positively moderate the effect of Google

Analytics on ticket sales. We argue that this is because these are statistics of the event's brand's website and older individuals visit the website rather than social media for information. On the other hand, we find a negative moderating impact on the sales effect of YouTube Views. We argue that this may be due to the fact that the older individuals are less aware of online music services. Events can now target their audiences more effectively by increasing website interaction among older potential buyers, and by increasing online music consumption among the younger potential buyers.

Also, we establish that a longer sales period has a negative impact on the effects of social media on ticket sales. We argue that a shorter sales period keeps the interaction on social media lively and active, and therefore positively impacts the effects of social media on ticket sales. Events, but probably the whole music industry, should consider shorter sales periods (of less than 105 days, or 15 weeks). However, this would only positively affect the effects of social media on ticket sales. We did not assess the main effect of the length of an event's sales period on sales.

Lastly, our results concerning the moderating impact of the event's genre are very significant, however apply particularly to the EDM industry. Therefore, we only suggest that genre is important and affects the effect of social media on ticket sales, but that our results cannot be generalized and are not as useful as the other insights we have provided.

Limitations and Further Research

Our work is the first to assess the moderating impact of event characteristics on the effect of social media on event ticket sales. The main limitation of our study is that our data set is not rich enough. First, we had many errors and missing data in our original data set, implying we only could include 78 of the 234 (33%) events. Second, in the first stage model we include covariates for daily average age and average percentage of males among the ticket buyers. These effects are insignificant, and we argue that this is because these daily averages are aggregates of all the ticket orders on each day. We think this way of measurement may decrease the strength of our first stage models as we do not really capture all the information. Third, the R-squares of our second stage models are very low, which implies we are missing out in important variables. For example, future research could assess the effect of the event venues, the nationalities of ticket buyers, expected weather for the events, the prices of event tickets, etc.

Second, we think we use a wrong estimation method in our first stage regression. Because we include lagged dependent variables in an OLS estimation, we may have residual autocorrelation that biases our coefficients downwards (e.g. Keele & Kelly 2005). Future researches could replicate our study, using a better fitting model.

Third, further research should consider to include social media metrics based on valence, rather than only on quantity. Several studies have investigated the effect of the valence of social media interaction, and have found positive results (e.g. Chevalier & Mayzlin 2006, Ludwig et al. 2013, Schweidel & Moe 2015). As the event organizer that collected and provided us with the data did not collect any sentiment data, we were not able to include metrics based on valence. Future studies could include sentiment data, and see how context characteristics influence these social media effects on sales.

Finally, further research could replicate this research in other settings within the music industry, but also in complete other context. Our study is only based on one genre events, which is the EDM industry. Therefore, we are sceptical about generalizing the findings for the whole music industry. However, as we have established that context characteristics influence the effects of social media on sales, future studies could investigate how and which context characteristics are moderators in other industries. For example, in the restaurant sector, one could see how social media interaction affects the number of bookings and visits, and how restaurant characteristics moderate these effects.

In summary, we assess the effects of individual social media metrics on event ticket sales. Our results suggest that increased eWOM interaction enhances ticket sales, but that additional Fans or Followers decrease sales. Furthermore, our findings offer managers new insights on how context characteristics actually influence the effect of social media on sales, and that it is important to establish which context characteristics will drive or negatively impact the effect of social media on sales in each industry.

APPENDIX I

Table 9A: Selection of the VAR Model Dimension: AIC

Model	4 lags	6 lags	8 lags	Model	4 lags	6 lags	8 lags
1	**623.822**	626.654	629.168	40	392.258	**390.900**	394.485
2	219.659	222.108	**166.003**	41	**384.447**	387.415	390.739
3	**295.417**	297.302	299.627	42	**901.191**	904.824	908.231
4	334.741	**331.325**	332.155	43	**534.310**	535.029	537.184
5	**801.318**	805.162	806.374	44	**557.085**	560.326	560.398
6	522.085	**521.464**	524.975	45	**628.239**	632.044	633.778
7	787.470	787.555	**778.690**	46	**612.193**	613.643	616.795
8	1075.422	1078.938	**1072.368**	47	367.846	355.827	**348.722**
9	**691.144**	694.250	697.832	48	**503.596**	505.199	507.307
10	**782.077**	783.704	787.009	49	244.935	**221.871**	223.800
11	502.744	501.805	**441.385**	50	411.388	412.273	**407.079**
12	671.560	666.643	**662.328**	51	**1344.571**	1348.115	1351.719
13	**2382.811**	2386.599	2387.544	52	**216.848**	NA	NA
14	1721.563	1694.770	**1667.452**	53	**696.749**	700.149	703.224
15	**1405.866**	1407.714	1409.004	54	**3535.625**	3538.566	3541.869
16	1249.321	1245.100	**1230.721**	55	110.760	**98.325**	99.094
17	**851.068**	854.922	857.627	56	675.740	678.743	**668.793**
18	574.701	**570.837**	574.516	57	**212.290**	NA	NA
19	**326.698**	330.313	328.025	58	330.203	325.396	**305.097**
20	**418.030**	420.346	420.865	59	2160.042	**2146.042**	2149.757
21	**778.715**	782.194	785.972	60	1348.570	1337.086	**1323.830**
22	**649.583**	652.067	654.559	61	**1005.933**	1009.759	1012.637
23	229.654	**228.626**	232.479	62	**912.522**	914.889	917.619
24	**432.214**	434.907	434.899	63	918.053	**914.267**	918.188
25	**494.535**	496.714	498.698	64	**1032.136**	1035.964	1038.305
26	662.197	**648.449**	651.992	65	**822.922**	825.958	829.426
27	649.108	649.416	**631.772**	66	**332.519**	335.404	338.336
28	320.485	314.395	**305.119**	67	357.636	353.967	**351.818**
29	2488.372	2472.589	**2471.450**	68	641.427	**635.268**	638.914
30	848.780	842.173	**827.634**	69	522.148	**521.797**	525.300
31	444.374	421.708	**414.116**	70	**531.154**	531.941	535.891
32	1148.078	**1141.043**	1144.711	71	**564.255**	567.530	569.866
33	**937.303**	940.628	942.104	72	810.657	814.610	**798.327**
34	**1162.526**	1165.010	1162.940	73	321.130	**314.856**	315.572
35	1706.096	1695.140	**1695.475**	74	336.470	**335.920**	336.619
36	**520.911**	524.655	527.908	75	**617.112**	620.554	622.731
37	251.446	239.576	**238.284**	76	521.307	517.756	**517.063**
38	**692.640**	692.551	693.350	77	**257.682**	258.664	261.418
39	667.205	670.695	**663.325**	78	876.220	861.526	**860.001**

We highlight the best value in boldface.

Table 9B: Selection of the VAR Model Dimension: BIC

Model	4 lags	6 lags	8 lags	Model	4 lags	6 lags	8 lags
1	**653.143**	660.163	666.867	40	**427.723**	430.306	437.832
2	234.595	239.035	**184.922**	41	**413.353**	419.935	426.872
3	**313.088**	317.329	322.010	42	**940.875**	948.918	956.734
4	**352.302**	352.788	357.521	43	**570.442**	575.176	581.346
5	**837.049**	845.656	851.632	44	**585.939**	593.618	598.130
6	**548.361**	552.119	560.009	45	**667.099**	675.222	681.273
7	**820.819**	825.668	821.567	46	**648.649**	654.151	661.353
8	**1114.349**	1123.055	1121.675	47	396.026	387.529	**383.946**
9	**726.874**	734.745	743.091	48	**546.473**	552.840	559.712
10	**817.427**	823.768	831.786	49	263.102	**242.310**	246.510
11	521.395	523.120	**465.365**	50	**441.658**	446.326	444.915
12	697.656	696.753	**696.453**	51	**1394.746**	1403.864	1413.044
13	**2421.598**	2431.353	2438.265	52	**231.013**	NA	NA
14	1763.987	1742.851	**1721.190**	53	**733.450**	741.168	748.560
15	**1447.553**	1454.960	1461.808	54	**3594.121**	3604.374	3614.989
16	1288.096	1289.045	**1279.835**	55	128.517	**118.171**	121.029
17	**880.483**	888.862	896.093	56	705.217	711.495	**704.820**
18	**602.968**	603.453	611.481	57	**243.865**	NA	NA
19	**349.594**	356.261	357.025	58	352.142	349.774	**331.913**
20	**441.783**	447.265	450.952	59	2210.860	**2203.212**	2213.280
21	**816.007**	824.147	832.586	60	1395.957	1390.048	**1382.368**
22	**679.587**	686.357	693.135	61	**1046.106**	1054.955	1062.854
23	**244.281**	245.690	251.981	62	**949.169**	956.117	963.428
24	**460.017**	466.185	469.652	63	**958.915**	960.236	969.265
25	**522.287**	528.166	533.850	64	**1070.047**	1078.614	1085.694
26	697.515	**687.922**	695.620	65	**857.957**	865.372	873.219
27	678.104	681.635	**667.212**	66	**361.230**	367.493	373.803
28	342.362	339.006	**332.465**	67	**389.797**	389.912	391.547
29	2536.755	**2527.018**	2531.927	68	674.497	**672.748**	680.803
30	887.949	885.951	**876.019**	69	**551.055**	554.317	561.434
31	476.076	456.932	**452.862**	70	**559.333**	563.643	571.115
32	1190.032	**1187.658**	1195.987	71	**592.434**	599.232	605.090
33	**979.492**	987.504	993.667	72	841.370	848.937	**836.266**
34	**1209.190**	1217.164	1220.583	73	346.467	**343.360**	347.242
35	1758.257	**1753.097**	1759.227	74	**358.499**	360.541	363.831
36	**551.755**	558.926	565.607	75	**643.568**	651.420	658.006
37	275.868	**267.050**	268.811	76	**552.527**	552.879	556.088
38	**733.368**	737.804	743.129	77	**280.926**	284.643	290.131
39	**709.626**	717.829	715.173	78	913.085	**902.999**	906.082

We highlight the best value in boldface.

Table 10: First Stage Models R-Squares and Breusch-Pagan Results

Model	Number of Obs.	R^2	Breusch-Pagan	p	Model	Number of Obs.	R^2	Breusch-Pagan	p
1	146	0.144	12.911	0.299	40	177	0.691	12.783	0.308
2	66	0.150	6.775	0.817	41	45	0.695	38.846	0.000
3	67	0.183	6.533	0.836	42	27	0.703	13.487	0.263
4	79	0.192	2.220	0.998	43	74	0.717	23.741	0.014
5	73	0.195	4.339	0.959	44	119	0.721	14.524	0.205
6	43	0.246	6.945	0.804	45	55	0.722	8.705	0.649
7	47	0.281	6.857	0.811	46	25	0.738	14.365	0.214
8	71	0.317	5.980	0.875	47	99	0.740	29.313	0.002
9	152	0.319	23.487	0.015	48	53	0.756	14.755	0.194
10	56	0.325	25.058	0.009	49	80	0.761	23.592	0.015
11	59	0.329	15.892	0.145	50	25	0.764	14.645	0.199
12	41	0.339	17.012	0.108	51	74	0.766	23.971	0.013
13	64	0.393	8.918	0.630	52	125	0.769	10.600	0.477
14	76	0.395	19.472	0.053	53	134	0.776	15.216	0.173
15	64	0.395	11.432	0.408	54	24	0.782	4.152	0.965
16	78	0.399	22.796	0.019	55	20	0.797	9.527	0.573
17	71	0.400	8.510	0.667	56	34	0.813	5.904	0.880
18	29	0.410	9.401	0.585	57	43	0.846	29.353	0.002
19	80	0.410	7.025	0.797	58	60	0.849	46.567	0.000
20	91	0.421	4.331	0.959	59	45	0.858	19.169	0.058
21	120	0.447	43.085	0.000	60	43	0.861	12.134	0.354
22	80	0.475	9.796	0.549	61	37	0.863	6.409	0.845
23	286	0.479	4.959	0.933	62	65	0.864	12.685	0.314
24	63	0.498	8.428	0.675	63	52	0.877	21.671	0.027
25	49	0.505	10.784	0.462	64	78	0.877	17.028	0.107
26	55	0.514	3.140	0.989	65	43	0.880	10.590	0.478
27	36	0.527	10.254	0.508	66	49	0.892	23.588	0.015
28	76	0.528	55.377	0.000	67	66	0.893	8.083	0.706
29	40	0.536	20.629	0.037	68	68	0.894	7.318	0.773
30	67	0.537	17.346	0.098	69	29	0.896	6.828	0.813
31	77	0.555	37.957	0.000	70	67	0.906	10.956	0.447
32	28	0.594	2.858	0.992	71	34	0.908	12.653	0.317
33	42	0.604	9.439	0.581	72	80	0.913	7.421	0.764
34	45	0.615	9.399	0.585	73	120	0.921	31.973	0.001
35	115	0.623	4.260	0.962	74	38	0.929	10.638	0.474
36	52	0.626	3.948	0.971	75	36	0.952	22.493	0.021
37	98	0.630	6.261	0.855	76	21	0.965	5.659	0.895
38	23	0.644	15.553	0.159	77	17	0.972	9.989	0.531
39	95	0.669	8.123	0.702	78	16	0.980	9.557	0.571

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