The Impact of Twitter on Consumption: Evidence from museums

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July 3, 2023

1 Introduction

In our paper we measure the impact of Twitter on consumption, that is one of the most important economic decision. We focus on cultural consumption and we study the causal effect of the activity on Twitter on the number of visitors to museums. Nowadays consumers receive news and information via social media platforms (Facebook, Twitter, Wikipedia, Tik Tok, Instagram, etc) that are replacing or supplementing more traditional media. In these platforms Twitter, with over 330 million active monthly users, is considered one of the most

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powerful social media marketing channel and is the most suitable to provide timely information. “People love to use Twitter to discover new things, make recommendations, and share their experiences with the world” (Twitter website). It is the most used social platform by the US journalists and can be considered “a compilation of the best and most relevant news on the web”. While Facebook, the other prominent social media, networks people, Twitter networks topics. [1]

As terms of use of Facebook and Instagram prohibited data scraping, the official Meta Researcher API was in its closed beta phase. Due to these feasibility reasons, we focus our research on Twitter. (NON SI CAPISCE. DA RISCRIVERE) Data for tweets was collected using Twitter API. We focus on cultural events because i) there is a large variability over time in what they offer, which implies that timely information might be very important, ii) they significantly affect the local economy and generate positive spillovers. iii) they have been hit very hard by the COVID-19 pandemic that has posed new challenges and opportunities, especially for digital technologies.

We use information on eight museums in the metropolitan area of the Italian city of Turin that has recently changed its vocation from an industrial to a smart city where innovation and culture do play a prominent role. SCRIVERE QUALCOSA SULLA VARIABILITA' NEL TEMPO DELL'OFFERTA DEI MUSEI, SU GLI EFFETTI DEI MUSEI SULL'ECONOMIA, MENZIONANDO IL TURISMO. Although the role of museums in attracting tourists might be sizeable (see Campaniello 2017), it is not the only important impact on the economy of a region. There is widespread evidence in the economic literature that highly educated and skilled people (the so called “human capital”) are the main drivers of economic development. The presence of amenities and culturally creative individuals (the

[1] Twitter allows users to post quick, frequent messages, called *Tweets*, that might be up to 140 characters long, and follow the messages of other users on their Twitter feed. People can upload photos, videos, text, share links and send private messages to people they follow. Messages are searchable on Twitter search and can be *retweeted* easily. It is mainly used to communicate with other individuals with similar interests.

bohemia) together with openness to diversity and tolerance make a region more attractive to other talented individuals (Florida, Mellander and Stolarick, 2008; Florida 2002). Clusters of talented individuals, in turn, increase regional productivity (Borowiecki, 2013; Moretti, 2019). For all the mentioned reasons, it is extremely important to use all the possible tools to implement the best strategies to make museums as competitive and attractive as possible. Social media are considered modern and powerful tools to promote the museums, engaging the public and expanding the audience.The use of social media by museums is related to the more general tendency of expanding the relations between museums and visitors thanks to the cultural organizations' digital transformation. The contamination between technology and museums has started recently and has dramatically accelerated during the COVID-19 pandemic when cultural institutions tried their best to maintain a dialogue with their public. A very successful example is the Getty Museum in Los Angeles that challenged its followers on social media (Twitter, Instagram and Facebook) to re-create famous artworks using people and objects in their home using the hastag #GettyMuseumChallenge. The challenge went viral mainly on Twitter, where the Getty Museum has the largest number of followers (over 1.3 million). The tweet that first introduced the challenge got an extraordinarily high engagement: 26,700 likes, 14,500 retweets, and 4,900 replies in total. The process of digital transformation for museums cannot be reversed and,nowadays, is a fundamental part of the cultural experience for visitors. Social media are an integral part of this process and have been increasingly been used by most of the museums worldwide[2]. Museums are expected to increase the number of visitors that has fallen to zero during the lockdowns and they struggle to go back to their pre-pandemic numbers. We find that investing in social media planning is a good strategy to increase the number of visitors.

Our paper is structured as follows: in section ....

[2]Even small museums are attracting large audiences on social media. For example, the Museum of Rural Life in England shared a picture of a really big sheep that was liked by over 112,000 people and shared by over 25,000.

2 Literature Review

The rise of social media platforms has changed the way consumers receive and interact with news and content. User-generated content (UGC) is a common feature across all social media platforms, where users are both consumers and contributors. Luca (2015) in the Handbook of Media Economics dedicates a whole chapter on this topic. In particular, he highlights how there is now a significant amount of evidence that supports the existence of a causal relationship between user-generated reviews and the demand for products in many different areas. Luca (2016) investigates the impact of online consumer reviews on the demand for restaurants. The author combines information from Yelp.com reviews and restaurant data from the Washington State Department of Revenue. The analysis reveals that a one-star increase in Yelp rating leads to a 5-9% increase in revenue, indicating that online consumer reviews act as substitute for traditional forms of reputation. Interestingly, this effect appeared to be significant only for independent restaurants, as opposed to those with chain affiliation. Additionally, consumers respond more strongly to ratings that contain more information.

Another piece of literature related to the effect of consumer reviews on revenue is Chevalier and Mayzlin (2006)'s work. The authors analyze the influence of online reviews on books sales on Amazon and Barnes & Noble's platforms. Their study concluded that various review-related variables, such as the number of reviews, average review rating, fraction of one-star reviews and fraction of five-star reviews, had a significant impact on book sales. Moreover, their findings indicate that a positive review can lead to an increase in relative sales, and one-star reviews had a greater impact than five-star reviews.

The causal impact of online information on real-world economic outcomes is explored by Hinnosaar et al. (2021).The authors conducted a randomized field experiment, in which they analyzed the relationship between additional content on cities Wikipedia pages and tourists' final consumption, accounted as overnight stays in treated cities compared to nontreated cities. The experiment included 240 Wikipedia pages (60 Spanish cities in four different languages). According to their results, the treatment led to a 9% increase in hotel stays on average (estimates of the treatment effect for the entire sample), which translates into an increase of about 270 nights per month. This result implies a considerable impact on local hotels and the overall local tourism industry. Overall, this study emphasizes the importance of online presence and suggests that the return on investment is relatively large compared to the minimal costs of improving online information.

Our study is closely related to the growing body of literature developing around the interlinkages between museums and social networks. Vassiliadis and Belenioti (2017) reviews a series of publications on the issue and identifies four relevant effects on this connection. First, and rather obvious, social media enhance the communication opportunities available to museums, providing a cost-effective and targeted option. Second, they can increase the museums' teaching power, enhancing their educational role. The third and fourth effects, instead, focus on the pattern of use of social media by museums and barriers they face when trying to extend their presence on platforms. Carvalho and Raposo (2012) insists on the market opportunities offered by social media, stressing the fact that museums cannot be indifferent to the innovations brought along by these platforms. The authors pay particular attention to the cost-effective nature of social media advertising and engagement, a relevant merit especially in times of crisis. Finally, these opportunities reflect the need for museums to show their dynamic adaptability needing profound reforms in order to meet new challenges. Chung, Marcketti and Fiore (2014) explores the use of social media by museums by conducting interviews with a panel of 12 midwestern museums. A pattern emerge among the collected answers: although platforms are perceived to be very effective in building engagement among the possible pool of visitors, it is often difficult to assign employees on a permanent basis to develop these activities. A successful use of social media entails a three-step plan: building awareness among the employees about the best possible use of the platform according to its characteristics, aim at enhancing the comprehension of the museum scope through it and, finally, build engagement among the visitors. Moreover, Hausmann (2012) discusses the importance that word of mouth (WoM) strategies have in empowering museums' marketing strategies. Through social media platforms, these techniques allow to reach a potentially unlimited number of people, thus allowing museums to be competitive in the entertainment arena not only with other arts organizations, but with a number of different providers.

This paper...

Our contribution is ..., we find that...

NOT SO SURE THE NEXT PARAGRAPHS FIT According to Liu et al. (2015)' framework brand messages are transmitted to opinion leaders, such as influencers and bloggers, who are then responsible to readdress them to the pool of consumers. Influencers thus assume a connective communication role, being deemed trust-worthy by the pool of consumers trusting them. Important contributions in literature are about the role and effect of social media influencers (SMI), which try to disentangle how they can shift public perceptions of particular products and services. Freberg et al. (2011) identifies the perceived core characteristics of a sample of SMIs in being verbal, smart, ambitious, productive, and poised. This set of characteristics significantly overlaps with those generally assigned to companies' CEOs of successful brands.

? explore how public opinion is usually influenced by celebrity endorsements. The authors conducted a nationwide Twitter experiment in Indonesia to promote vaccination. The experiment involved 46 high-profile celebrities and organizations with a total of 7.8 million followers. Results indicate that tweets written by celebrities received significantly higher levels of engagement (higher likes and retweets by users) compared to similar tweets without celebrity influence. Moreover, the authors found that explicitly citing sources in tweets had a negative effect on diffusion. By randomizing which celebrities tweeted and their timing in doing so, the results indicate that increased exposure to the vaccination campaign may affect user beliefs and knowledge regarding vaccination-seeking behavior.

The effect of museums' digital presence on the number of on-site visits is, a priori, ambiguous. In fact, the use of digital platforms might be either a complement or a substitute to the traditional museums' visits. Allcott et al. (2020) conducted a large-scale randomized evaluation by constructing a treatment group that had Facebook deactivated for four weeks in the run up to the 2018 US midterm election. The treatment group saw the use of Facebook-related social media declining on average by one hour, with a shift toward offline activities, signaling a strong substitution effect. [3]. Deactivation, in particular, was strongly and significantly correlated with an improvement in self-reported well-being.

? adds its contribution to the use of social media in enhancing museums' experience by analysing content generated online during a school visit to a museum. From the analysis, it arises that interactions with microblogging platforms improved students' impressions and participation. Furthermore, there is no evidence that they distracted them from the actual content and purposes of the museums. The publication thus gives strong credibility to the idea of the museum as a learning tool, a consistent pattern in the literature.

According to Liu et al. (2015)' framework brand messages are transmitted to opinion leaders, such as influencers and bloggers, who are then responsible to readdress them to the pool of consumers. Influencers thus assume a connective communication role, being deemed trust-worthy by the pool of consumers trusting them. Since the key ingredients of this relationship are trust and mutual understanding, brands are responsible in transferring value to opinion leaders in order to leverage their marketing power and breed it so that it does not run the risk of being eroded over time.

[3] In addition, measures of political engagement and political polarization declined significantly with respect to the control group

Our study is closely related to the growing body of literature developing around the role and effect of social media influencers (SMI), trying to disentangle how they can shift public perceptions of particular products and services. Freberg et al. (2011) identifies the perceived core characteristics of a sample of SMIs in being verbal, smart, ambitious, productive, and poised. This set of characteristics significantly overlaps with those generally assigned to companies' CEOs of successful brands. Liu et al. (2015), recognizes the power of word-of-mouth advertising in driving consumers' choices. In particular, the core assumption is that influencers' trust is confined to specific domains and cannot be universally applied to different market segments. Additionally, the power of influencers in swaying people's decisions is not constant over time and can be significantly affected by the rise of competitors and fading trust.

3 Data

Data on Twitter were collected from its official website using the Twitter Research Access API [4]. They are available for the period 2012-2021 but we have to exclude the years of the COVID-19 pandemic (2020-2021) because museums were forced to be closed. We collected, on a daily basis, the information about tweets published from 01.01.2012 till 31.12.2019 mentioning at least one of the museums through the use of a set of keywords, including direct tags of the museums' official Twitter accounts. We ended up with 400,506 tweets as shown in Table 1. These data contain the text of the tweet, the date, the user ID, counts of the likes, retweets, replies, and quotes of the tweet. Then we parsed the Twitter's accounts that mentioned at least one museum using the users ID and web-scraped publicly available data on the username, status, number of followers and of following.

There are different actions a user can perform on the Twitter social media platform, besides

[4] https://developer.twitter.com/en/products/twitter-api/academic-research

writing a tweet. These actions, usually referred to as "engagement" in the literature are: "to like" (introduced in 2015 to replace the "favorite" button) , "to quote" (introduced in 2015), "to reply" and "to retweet" (introduced in 2009) a tweet. In our analysis, we refer to an inclusive definition of engagement as the number of retweets and other actions, which means how many times a tweet has been read by users, reposted, replied, liked or quoted by them on their private Twitter profile. In our dataset the average engagement is equal to 155 as shown in Table 1 [5]. We also collected information on the characteristics of each tweet: the number of characters (every symbol used, including spaces and punctuation), hashtags (#), tags (@), websites linked, photos, videos and gifs. We also computed the number of words in each tweet, net of all the symbols and the links to websites [6].

Table 1: SUMMARY STATISTICS

	(1) Mean	Median	S.D.	N
engagement	155.2	1	6156.4	400506
retweet	27.5	0	1344.8	400506
replies	9.27	0	412.0	400506
likes	112.1	0	4569.8	400506
quotes	6.34	0	313.3	400506
n_hashtags	0.80	0	1.61	400506
n_tags	1.52	0	3.62	400506
n_sites	0.69	1	0.63	400506
clear n_words	13.6	12	9.89	400506
photos	0.19	0	0.39	400506
videos	0.0041	0	0.064	400506
gifs	0.0037	0	0.061	400506

Notes: The top panel presents summary statistics for the data. The unit of observation is a single tweet post.

We selected all the museums in the metropolitan area of the city of Turin (Italy) that have a Twitter account and have reported at least 100,000 visits per year. We ended up

[5] We perform and discuss a robustness analysis using a less inclusive definition of engagement in the appendix. Here, the focus is on retweeting because it represents the most powerful tool to spread information

[6] $n\_words - (n\_hashtags + n\_tags + n\_websites)$

with 8 museums that, altogether, account for 64% of the total visits in this area (Report Annuale 2019, Osservatorio Culturale Piemonte): Galleria di Arte Moderna (GAM), Museo di Arte Orientale (MAO), Museo dell' Automobile di Torino (MAUTO), Museo Nazionale del Cinema, Museo Egizio, Palazzo Madama, Castello di Rivoli and Reggia di Venaria Reale.

The Osservatorio Culturale Piemonte (OCP) provided us with a dataset with daily and monthly information on visits and admission prices for each museum. Since daily data are not available for all the museums over the period considered, in our analysis we use monthly data. Table 2 shows the summary statistics. The number of observations (768) refers to the monthly data gathered from the 8 museums over a 8-years period (2012-2019). The average number of visits in a month for a museum is about 30,331 with a median of 17,586 and a standard deviation of 29,803.

We define our variable of interest, *Activity on Twitter*, as $(tweets + engagement)$: the sum of the number of tweets tweeted by users who mentioned one of the 8 museums through a hashtag, tag, or a web link and the engagement variable. *Activity on Twitter* is collapsed at the museum - month level. Its mean value, for the 8 museums altogether, is about 1,685, with a median of 420 and a standard deviation of 15,874, as reported in 2.

We now provide a description of the explanatory variables used in the baseline regressions. They are all measured on a monthly basis.

Exhibitions indicates the number of exhibitions set up within a single museum in each month. The OCP provides a database that reports the name of each exhibition, its starting and ending date, and the number of visitors who attended it. *Popularity of the Exhibition* ranks the exhibitions according to their popularity measured through Google Trends[7]. We searched for the title of each exhibition on Google Trends, selecting the Piedmont region area, and related to Picasso's searches in the same area to provide a common base. In other

[7]Google Trends normalizes data and index them from 0 to 100, where 100 is the maximum search interest for the time and location selected.

words, everything is defined in terms of % of Picasso's popularity. The final popularity score, which ranges between 0 and 100, is equal to the average of all the single monthly scores in the 6 months before the start of the exhibition.

Monthly museum tweets represents the number of tweets written by the 8 museums each month. Instead, the control variable *Monthly authors* indicates the monthly number of authors, whose tweets mention at least one of the 8 museums.

We control for two weather variables, namely *Average temperature* (in Celsius degrees) and *Days of rain*. We collected information on monthly values of weather data in the metropolitan area of Turin from the Archivio Meteo Torino (IlMeteo).

Finally, since most visits take place during weekends, we generate a dummy, *5th WE*, which is equal to 1 if a month has an extra weekend (meaning 5 Saturdays and 5 Sundays) and 0 otherwise.

Table 2: Summary statistics

	(1) Mean	Median	S.D.	Iqr	N
Monthly visits	30489.0	17133	30121.9	36319.5	768
Monthly activity	1083.0	338	15952.5	465.5	768
Monthly exhibitions	1.35	1	1.50	2	768
Monthly Museum Twe s	32.3	10.5	64.3	37	768
Average temperature	13.4	13.7	7.44	14.1	768
Days of rain	10.3	10.5	4.96	5	768
Monthly authors	303.5	265	233.2	212	768
5th WE	0.21	0	0.41	0	768

Notes: The top panel presents summary statistics for the data. The unit of observation is museum - month. An *activity on Twitter* outlier relative to MAUTO, year 2016 month 10, equal to 426010 is excluded from the sample

Tab Notes (DA RISCRIVERE): Monthly visits measures the number of people visiting a specific museum in a certain month. Monthly activity variable is given by *tweet + engagement*: the number of tweets tweeted by users tagging a specific museum added to the engagement variable. l.Tot is a dummy variable, representing whether the account writing the tweet is either a touristic and/or cultural page, an art Twitter account or a Museum (not one of the 8 included in our analysis, which are excluded from the panel). Foll is the number of followers that each person twitting has on his/her Twitter account, at the present day. The compound score measures the overall sentiment of a text, Typical threshold values used in the literature are a positive sentiment for compound score greater than 0.05, a neutral sentiment with a compound score between -0.05 and 0.05, and a negative sentiment with compound score lesser than -0.05. Monthly exhibitions is the number of simultaneously exhibitions set up within a single museum. Score ranks the single exhibitions from 0 to 100 according to their popularity among people. The logavgtemp is the average temperature in Celsius degrees, monthly registered values for each specific year in the Turin geographic area. The logdaysrain is the number of days in which rain was recorded, monthly registered values for each specific year in the Turin geographic area.

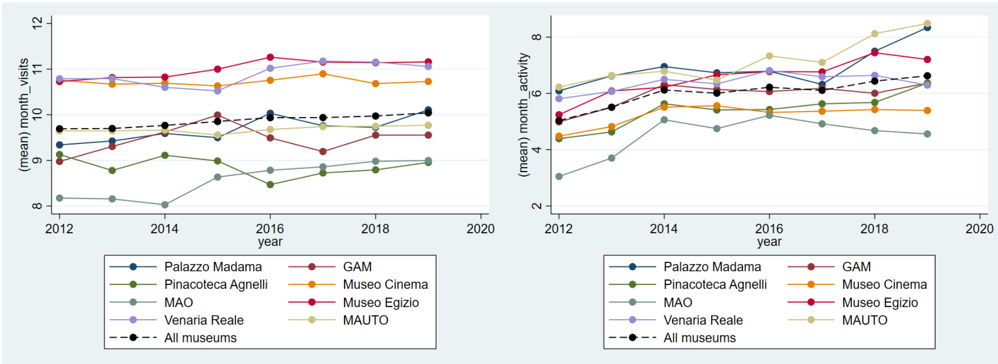
4 Empirical Analysis

4.1 Descriptive evidence and empirical strategy

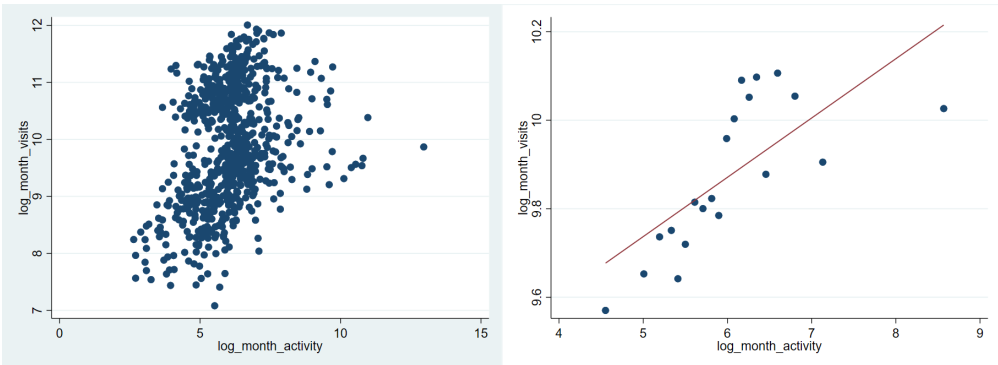
As a first preliminary evidence of the relationship between activity on Twitter and museum visits, we show raw data and simple correlations. The top panel of Fig.**??** shows the trends of the (mean) number of monthly visits and Twitter activity for each of the museums included in our analysis over the period 2012-2019. The brown line represents the average for the 8 museums altogether. Museo Egizio, Reggia di Venaria Reale and Museo del Cinema have a number of visitors that is larger than the average one. Museo Egizio has considerably increased the number of visits in 2016, a few months after the 5 years renovation works had finally been completed. Reggia di Venaria Reale has experienced a significant increase in the number of visitors in 2015...

In the bottom panels of ?? we show a positive correlation between monthly visits to museums and activity on Twitter using both a parse and a binned scatter plot. But in these figures, we do not control for other variables, observable and unobservable, that could affect museums visits and bias our results.

Figure 1: Twitter activity and cultural consumption.



(1) *Yearly Visits* (b) *Yearly Activity*



(2) *Scatter plot* (3) *Binscatter*

Notes: The table reports ...

Even though we control for many observables that are likely to be correlated with both the number of visits at museums and activity on Twitter, our results might still be biased by unobservable factors. First, reverse causality might be at play if individuals increase their Twitter activities about museums after they visit them. Second, the measure of activity could be a noisy proxy for the set of characteristics that would ideally measure the twitter activity around museum, for example, due to multiple or fake accounts. At least in part, we address potential endogeneity by exploiting the panel structure of the data and using fixed effects. But fixed effects specifications may not be able to capture time varying unobserved heterogeneity. To address the potential endogeneity problem, and isolate a causal effect, we adopt a Two Stage Least Squares (2SLS) approach in the spirit of the "judge fixed effects" literature (Bhuller et al. (2020), Kling (2006), Dobbie, Goldin and Yang (2018)). The idea is to randomly assign tweeters, who differ systematically in their ability to generate engagement, to museums. Our exclusion restriction is the randomness in pairing a museum and a high-engagement Tweeter. ALTRA COSA PER RIDURRE ENDOGENEITY: HO ESCLUSO TUTTI GLI AUTORI DEI TWEET IL CUI PROFILO E' SEGUITO DA ALMENO UNO DEGLI 8 MUSEI. For each individual who tweets about museums, we construct an index measuring his/her average ability to engage people. Engagement is measured as the sum of retweets, replies, quote, and likes. Our instrument is constructed selecting the 10 top Tweeters who generated the highest average engagement per tweet writing something about one of the 8 museums of our study over the period 2012-2019. To avoid concerns of endogeneity we have calculated the leave one out mean:

$$\frac{\sum_{t=1}^{96}\sum_{m=1}^{8} e_{i,t,m}}{\sum_{t=1}^{96}\sum_{m=1}^{8} T_{i,t,m} - T_{i,t,m}} - \frac{e_{i,t,m}}{\sum_{t=1}^{96}\sum_{m=1}^{8} T_{i,t,m} - T_{i,t,m}} = \bar{e}_{i,t,m}$$

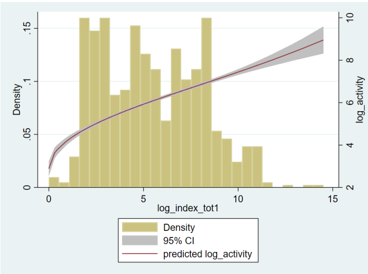
where e is the engagement and T the count of tweets, i is the Tweeter, t is the month and m is one of the 8 museums, under the condition that we have at least two observation in our sample.

We use as instrumental variables the 10 tweeters with the largest index $\bar{e}_{i,t,m}$. *Index1* refers to the tweeter who generates the highest average engagement. *Index10* to the one who generates the lowest one. The instruments' descriptive statistics are outlined in Table

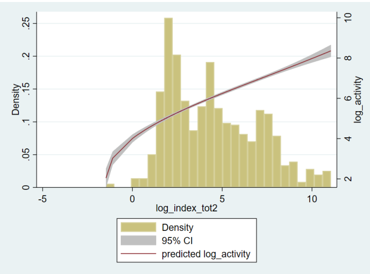
3. The mean of the first index, *Index1*, is 7869 (with a standard deviation of 78330) and, by construction, it decreases going from the first index to the last one (the mean of *Index10* is 221 with a standard deviation of 1002).

Figure 2 is a graphical representation of the first stage, that shows, in each panel, the relationship between each instrument and the *Activity on Twitter*. The correlation between the two variables is clearly positive and approximately linear in each panel.

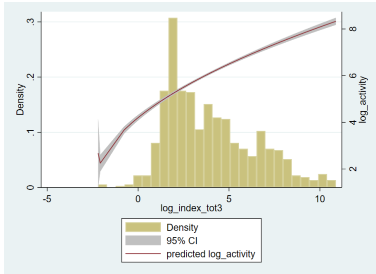
Figure 2: Visual first stage



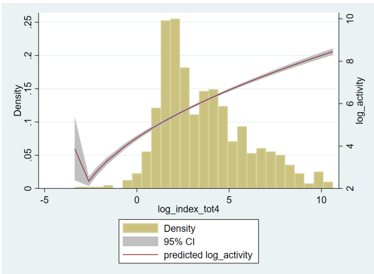
1st Author



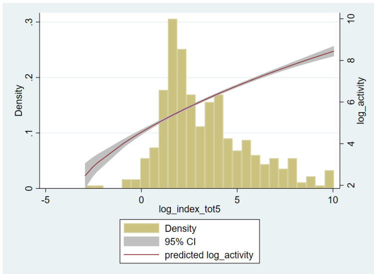
2nd Author



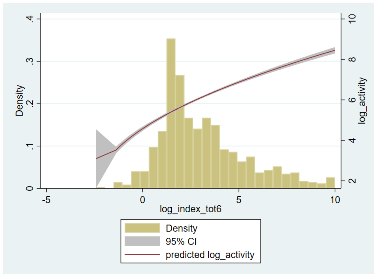
3rd Author



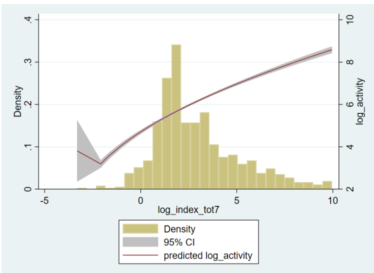
4th Author



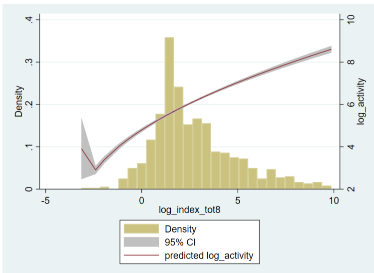
5th Author



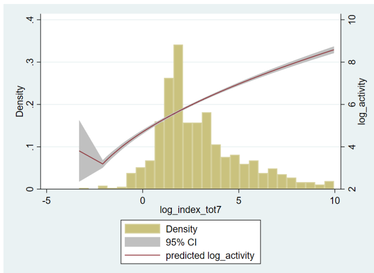
6th Author



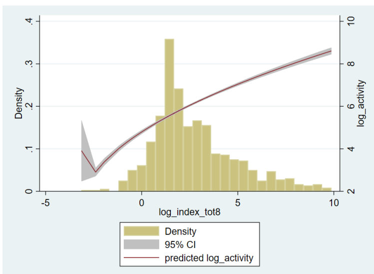
7th Author



8th Author



9th Author



10th Author

Notes: The table reports the distribution of average and .

We created three variables that describe some of the characteristics of the top tweeters and the content of their messages: *Followers*, *Art-related* and *Sentiment score*. Table 3 shows their summary statistics.

Followers indicates the number of followers of each Twitter account [8]. The number of followers decreases from the first index (with a mean of 50515 followers) to the last one (with a mean of about 3600 followers). This is in line with the fact that the first index refers to the person who generate a high engagement, while index10 to the one with the lowest one. The only exception are the last 3 indexes, where this pattern does not appear.

Art-related is a dummy variable equal to 1 if the Twitter account is either an art, touristic and/or cultural page [9].

Finally, we conduct a sentiment analysis to look at the emotions expressed in the tweets. We use VADER (Valence Aware Dictionary and sentiment Reasoner) which is a lexicon and rule-based tool designed to score sentiments expressed in social media (Hutto and Gilbert, 2014). VADER assigns scores according to a dictionary that associates each word to a certain sentiment. The compound score, *Sentiment score*, measures the overall sentiment of a text. It is computed by summing the scores of each word in the lexicon, adjusted according to the rules (e.g. negations, amplifications, and emoticons), and then normalized to be between -1 (most extreme negative) and +1 (most extreme positive). The scores are ratios for proportions of text that fall in each category. Typical threshold values used in the literature are a positive sentiment for compound score greater than 0.05, a neutral sentiment with a compound score between -0.05 and 0.05, and a negative sentiment with compound score lower than -0.05. All tweets show a positive sentiment with values that range between 0.126 and 0.171 (standard deviations range between 0.33 and 0.38).

NELLE SUMMARY STATISTICS DELLA TABELLA 3 POTREMMO USARE I LOG PER RIDURRE GLI STANDARD ERROR (NEI LIVELLI CI SONO MOLTISSIMI ZERI!)

[8] Since it is not possible to collect the number of followers over time, their number is that of December 1, 2022.

[9] The Twitter account of the 8 museums of our study are not included in our dataset.

Table 3: Summary Statistics of the instrumental variables

	(1)		(2)		(3)		(4)		(5)	
	1		2		3		4		5	
	Mean/p50	Sd/Iqr	Mean/p50	Sd/Iqr	Mean/p50	Sd/Iqr	Mean/p50	Sd/Iqr	Mean/p50	Sd/Iqr
Instrument	7869.5	78330.3	1802.7	6668.3	1148.7	4684.3	796.3	3338.8	593.5	2575.6
	(174.7)	(2249.0)	(67.7)	(592.7)	(28.3)	(229.4)	(20.7)	(134.5)	(14.2)	(85.1)
Sentiment score	0.11	0.23	0.12	0.24	0.12	0.21	0.11	0.23	0.095	0.25
	(0.087)	(0.20)	(0.093)	(0.22)	(0.091)	(0.21)	(0.089)	(0.21)	(0.086)	(0.20)
Followers	2239977.8	9689184.3	1163415.1	7336705.3	796948.2	4250087.5	593190.2	2667865.7	502649.0	2753800.5
	(79163.5)	(763472)	(28519)	(163791.5)	(17921)	(120854)	(16195)	(95633)	(8428)	(65298.5)
Art-related	0.13	0.33	0.15	0.36	0.15	0.35	0.17	0.38	0.15	0.36
	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
Observations	762		764		765		763		764	

	(1)		(2)		(3)		(4)		(5)	
	6		7		8		9		10	
	Mean/p50	Sd/Iqr	Mean/p50	Sd/Iqr	Mean/p50	Sd/Iqr	Mean/p50	Sd/Iqr	Mean/p50	Sd/Iqr
Instrument	493.9	2217.6	394.5	1834.2	324.2	1520.5	249.2	1098.0	221.2	1001.7
	(12.8)	(65.7)	(10)	(50.2)	(8)	(37.3)	(7.11)	(28.6)	(6.84)	(26.8)
Sentiment score	0.10	0.19	0.11	0.23	0.11	0.21	0.12	0.23	0.092	0.20
	(0.078)	(0.18)	(0.085)	(0.19)	(0.085)	(0.20)	(0.096)	(0.21)	(0.071)	(0.17)
Followers	512570.2	2975261.9	447343.3	3423800.5	356312.3	2516420.9	246992.2	1246506.2	238854.5	1102203.5
	(7484)	(47099)	(7682)	(47265)	(6271)	(44265)	(5229)	(28317)	(5325.5)	(32591)
Art-related	0.16	0.36	0.14	0.35	0.17	0.38	0.14	0.35	0.17	0.38
	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
Observations	762		758		757		749		730	

Notes: The table presents summary statistics of the instruments employed in the IV analysis. Means and standard deviations in parentheses.

4.2 OLS results

To investigate the relationship between Twitter activity and visits to museums, we estimate the following linear regression model:

$$Museums\_visits_{it} = \beta \, Activity\_on\_Twitter_{it} + \theta \, \mathbf{X_{it}} + \kappa_i + \tau_t + \varepsilon_{it} \qquad (1)$$

where $Museums\_visits_{it}$ and $Activity\_on\_Twitter_{it}$ are, respectively, the natural logarithms of the number of museums monthly visits and of the activity on Twitter related to museums. The matrix $\mathbf{X_{it}}$ includes controls for the number and quality of temporary exhibitions, weather and temperature condition, as well as extra weekend days in a month, SENTIMENT E' IL SENTIMENT MEDIO DEI POST DEI 10 INDICI (QUINDI PER CIASCUN MUSEO IN CIASCUN MESE) . Continuous variables are transformed in logs.

κ_i and τ_t are, respectively, museum and time fixed effects.

With 12 museums and 64 time periods what we really have is closer to multiple time series. Therefore, we employ Driscoll-Kraay standard errors, which allow any correlation across firm and general serial correlation across time, in place of clustered standard errors. Month fixed effects are ambitious to estimate with 12 observations available for each period, we use in our baseline models year fixed effects, we provide estimates with month fixed effects in table 15 of the Appendix.

We present the results of the baseline model in Table 4. The inclusion of controls slightly affect the sample size of each model (BY HOW MUCH?). In Column 1 we use information on all Tweeters, while in the other columns we restrict our sample to the top 10 Tweeters. SPIEGARE BENE che in una colonna (QUALE? immagino LA 1) CI SONO TUTTI I TWEETERS. SPIEGARE PERCHE' NELLA COLONNA 1 NON CI SONO I CONTROLLI PER LA SENTIMENT ANALYSIS, I FOLLOWERS E ART-RELATED (TOT). NOI STIAMO CONSIDERANDO TUTTI GLI ACCOUNT TWEETER cambiare il label "TOT" CON "ART RELATED"

Table 4: OLS

	(1) log_visits	(2) log_visits	(3) log_visits	(4) log_visits	(5) log_visits	(6) log_visits	(7) log_visits	(8) log_visits	(9) log_visits	(10) log_visits	(11) log_visits
log_activity	0.161***	0.156***	0.165***	0.167***	0.161***	0.159***	0.156***	0.165***	0.159***	0.155***	0.152***
	(0.0530)	(0.0532)	(0.0578)	(0.0538)	(0.0544)	(0.0541)	(0.0522)	(0.0548)	(0.0525)	(0.0516)	(0.0547)
log_num_mostre	0.177***	0.176***	0.180***	0.186***	0.174***	0.176***	0.176***	0.170***	0.172***	0.175***	0.172***
	(0.0484)	(0.0475)	(0.0468)	(0.0485)	(0.0484)	(0.0487)	(0.0484)	(0.0483)	(0.0470)	(0.0476)	(0.0472)
score	0.00499**	0.00491**	0.00516**	0.00471**	0.00508**	0.00477*	0.00479**	0.00450*	0.00485**	0.00511**	0.00482**
	(0.00227)	(0.00227)	(0.00228)	(0.00236)	(0.00228)	(0.00245)	(0.00231)	(0.00233)	(0.00235)	(0.00230)	(0.00234)
c.log_num_mostre#c.score	-0.00122	-0.00122	-0.00134	-0.00119	-0.00121	-0.00118	-0.00108	-0.000982	-0.00109	-0.00117	-0.00113
	(0.00102)	(0.00104)	(0.00102)	(0.00103)	(0.00103)	(0.00106)	(0.00101)	(0.00105)	(0.00104)	(0.00104)	(0.00103)
Sunday_5	0.0672	0.0761	0.0677	0.0727	0.0765	0.0655	0.0705	0.0753	0.0636	0.0717	0.0756
	(0.0500)	(0.0488)	(0.0500)	(0.0495)	(0.0511)	(0.0509)	(0.0505)	(0.0499)	(0.0512)	(0.0526)	(0.0529)
log_avg_temp	-0.187***	-0.188***	-0.186***	-0.191***	-0.188***	-0.184***	-0.186***	-0.185***	-0.181***	-0.181***	-0.178***
	(0.0505)	(0.0511)	(0.0504)	(0.0516)	(0.0485)	(0.0513)	(0.0510)	(0.0500)	(0.0518)	(0.0517)	(0.0509)
log_days_rain	0.120**	0.121**	0.126**	0.119**	0.122**	0.116**	0.121**	0.118**	0.119**	0.116**	0.107**
	(0.0533)	(0.0534)	(0.0534)	(0.0535)	(0.0524)	(0.0540)	(0.0530)	(0.0516)	(0.0531)	(0.0539)	(0.0504)
log_museum_tweets	-0.00433	-0.00484	-0.00426	-0.00431	-0.00301	-0.00405	-0.00412	-0.00310	-0.00427	-0.00193	-0.00570
	(0.0111)	(0.0111)	(0.0107)	(0.0112)	(0.0113)	(0.0112)	(0.0113)	(0.0114)	(0.0112)	(0.0116)	(0.0107)
sent_tot		0.0871	-0.153**	0.0812	-0.0105	-0.0156	-0.113	0.0799	0.0586	-0.0630	0.0340
		(0.0757)	(0.0735)	(0.0758)	(0.0639)	(0.0642)	(0.134)	(0.0660)	(0.0703)	(0.0751)	(0.0802)
foll		0.00829	-0.0152*	-0.0135	-0.00129	-0.00726	0.00413	-0.00915	-0.00467	-0.0103	-0.00308
		(0.00798)	(0.00847)	(0.00897)	(0.00773)	(0.00856)	(0.00913)	(0.00783)	(0.00930)	(0.0101)	(0.0106)
Tot		0.0706	-0.0265	-0.0543	-0.139**	0.0583	-0.0238	-0.124**	0.0383	0.0658	-0.0465
		(0.0472)	(0.0518)	(0.0542)	(0.0555)	(0.0472)	(0.0473)	(0.0522)	(0.0537)	(0.0667)	(0.0473)
obs	753	747	748	748	745	745	741	737	732	722	711
R2 adj	.19	.2	.2	.2	.2	.19	.18	.19	.18	.18	.17
Museum FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses

Notes: Standard errors are clustered at museum-year level. All models include ... * Significant at the 10% level; ** Significant at the 5% level; *** Significant at the 1% level.

In line with the descriptive evidence, we find a positive relationship between the activity on Twitter and visits to museums. In particular, a doubling of the activity on Twitter would increase the monthly number of visits to museums by around 9%.

(Continuare il commento di OLS.to be SOLVED)

5 2SLS results

Table 5 reports the reduded form, first stage and IV estimates. Panel **??** shows the estimates for the reduced form. The coefficient on the instrument is positive and significant. According to the estimates, doubling the *engagement* causes an increase between 1.5% and 5.1% of monthly museums visits across the first ten Twitter contributors. Crucial for the validity of our instruments is that that the engagement of top contributors' affects *monthly visits* only through *Activity on Twitter*. In our context, this hinges on how the engagement mechanism works. For example, a tweet from a famous person could be taken up by traditional media or by other social media. ANCHE SE COSI' FOSSE SAREBBE COMUNQUE UN EFFETTO (INDIRETTO) GENERATO DA TWITTER.

Panel **??** shows that the estimates for the first-stage regressions are in line with the graphical representation in 2. A doubling in *engagement* causes an increase between 12% and 29% of the monthly *Activity on Twitter* across the first ten contributors. Standard statistical tests on the performance of these instruments are reported at the bottom of Table 5. The F-statistic increases almost monotonically from ranked 1st contributor to ranked 10th contributor. The instruments are relevant, with an F-statistic that ranges between 32 and 145. We can speculate that lowest rankest contributors' *engagement* multiplier is more and more relevant instrument. POICHE' LA f STATISTICA AUMENTA CON IL RANK DELLLL'AUTORE, LO STRUMENTO E' PIU' RELEVANT. GLI AUTORI PIU' BASSI NEL RANKING SONNO QUELLI PIU' ESOGENI . IL MOTIVO POTREBBE ESSERE CHE, PUR CREANDO MENO ENGAGEMENT, IL LORO ENGAGEMENT E' DI MIGLIORE QUALITA'. GLI AUTORI CHE CREANO PIU' ENGAGEMENT POTREBBERO ESSERE PIU' ENDOGENI (AD ESEMPIO E' PROBABILE CHE SIANO PAGATI DAI MUSEI) OPPURE QUELLI CHE SEGUONO GLI AUTORI CON MENO FOLLOWER (PIU' IN BASSO NEL RANKING DEGLI IDNICIC) HANNO UN SENSO DI APPARTENENZA PIU' GRANDE E QUINDI SEGUONO DI PIU' I CONSIGLI (PIVOTAL).

Panel **??** reports the IV estimates: a 100% increase in *Activity on Twitter* increases *museums visits* by 10% - 20%. Compared to the average OLS estimate, the average effect is downward biased by 50%. To offer a more transparent economic interpretation of the estimates, we can then consider what would happen if we were to use them to infer the effect of lifting the level of twitter activity .... from all museums to that of the museums at the 90th percentile of this distribution. ![10] This implies a ... in YYY of on average per ...QUESTO LO SCRIVE VINCENZO!! Indeed, IV estimates differing when using different instruments, is an indication of heterogeneous treatment effects due to different compliers associated with the instruments (Angrist, Imbens and Rubin (1996)). Possible compliers in our setting are museums increasing or decreasing their twitter activity if and only if they experience a shock in their best contributors' engagement; this is unlikely because museums have very constrained budget and rigid recruiting procedure, so it is difficult to rapidly increase or decrease the effort spent in social management activities, in particular, when they have to deal with several social media. MA I NOSTRI TWEETERS NON SONO LA FERRAGNI. AUMENTARE L'ATTIVITA' DI SOCIAL ACTIVITY POTREBBE NON ESSERE FACILE NEL BREVISSIOMO PERIODO.TWITTER GENERA UNO SCAMBIO DI INFORMAZIONI MOLTO VELOCE CHE RENEREBBE DIFFICILE UNA REAZIONE IMMEDIATA DA PARTE DEI MUSIE.

[10]The museum at the 90th percentile of the cross-sectional distribution of *twitter activity* is ...

Table 5: Baseline Results

(a) Reduced Form regressions

	(1) log_visits	(2) log_visits	(3) log_visits	(4) log_visits	(5) log_visits	(6) log_visits	(7) log_visits	(8) log_visits	(9) log_visits	(10) log_visits
log_index_tot	0.0134	0.0324*	0.0391**	0.0253	0.0478***	0.0298*	0.0550***	0.0492***	0.0519***	0.0453**
	(0.0131)	(0.0174)	(0.0161)	(0.0181)	(0.0150)	(0.0159)	(0.0204)	(0.0155)	(0.0140)	(0.0191)
obs	747	748	748	745	745	741	737	732	722	711
R2 adj	.17	.17	.17	.17	.17	.16	.17	.16	.16	.15

Standard errors in parentheses

(b) First Stage regressions

	log_activity	log_activity	log_activity	log_activity	log_activity	log_activity	log_activity	log_activity	log_activity	log_activity
log_index_tot	0.106***	0.130***	0.143***	0.177***	0.206***	0.195***	0.206***	0.219***	0.232***	0.240***
	(0.0274)	(0.0222)	(0.0222)	(0.0245)	(0.0230)	(0.0223)	(0.0226)	(0.0216)	(0.0188)	(0.0242)
obs	747	748	748	745	745	741	737	732	722	711
R2 adj	.31	.31	.31	.32	.34	.32	.34	.34	.35	.36

Standard errors in parentheses

(c) IV regressions

	log_visits	log_visits	log_visits	log_visits	log_visits	log_visits	log_visits	log_visits	log_visits	log_visits
log_activity	0.127	0.249**	0.274***	0.142	0.232***	0.153**	0.267***	0.224***	0.224***	0.189**
	(0.130)	(0.122)	(0.102)	(0.0968)	(0.0697)	(0.0766)	(0.0883)	(0.0667)	(0.0576)	(0.0723)
obs	747	748	748	745	745	741	737	732	722	711
Cragg	36.97	45.02	50.52	80.17	110.6	95.22	105.12	125.89	144.62	153.55
Museum FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses

Notes: In Columns ... we present the first stage for each IV regression from Table ??. Both y and characteristics are replaced by their logs. Standard errors are clustered by ... and t-stats (SONO I P-VALUE) are in parentheses. Instruments are:. Columns (n) report IV ... All models include controls for ... * Significant at the 10% level; ** Significant at the 5% level; *** Significant at the 1% level. The underidentification test is an LM test of whether the equation is identified, i.e., that the excluded instruments are relevant, meaning correlated with the endogenous regressors. The test is essentially the test of the rank of a matrix: under the null hypothesis that the equation is underidentified, the matrix of reduced form coefficients on the L1 excluded instruments has rank=K1-1 where K1 is the number of endogenous regressors. Under the null, the statistic is distributed as chi-squared with degrees of freedom equal to (L1-K1+1). A rejection of the null indicates that the matrix is full column rank (model is identified). The Sargan statistic is calculated as N*R-squared from a regression of the IV residuals on the full set of instruments. All models include controls for..., fixed effects for ... * Significant at the 10% level; ** Significant at the 5% level; *** significant at the 1% level.

Given the crucial role that we have identified for XXX, it would be important to develop a deeper understanding of what factors can promote this .....

We conclude this section with a brief summary of insights from the main robustness checks among those presented in the appendix. We refer to the appendix for a more exhaustive description of both these robustness checks and the additional ones presented there. To simplify the exposition, we present the findings by categorizing them in ... groups.

The ... group of robustness checks involves threats to the causal identification of the estimates. First, we assess the reliability of the inference conducted on the estimated parameters by applying the recently proposed method by Young, Alwyn (2017)... to be done. SOLVED?

For the second group of robustness checks, we also consider the possibility of alternative strategies to an IV...to be done. SOLVED?

6 Heterogeneity

Age: we use info on visitors with Carta Abbonamento Musei

Gender: we use info on visitors with Carta Abbonamento Musei

cap?

Table 6: IV REGRESSIONS, AGE_CAT AMTP DATA

	log__18_24	log__18_24	log__18_24	log__18_24	log__18_24	log__18_24	log__18_24	log__18_24	log__18_24	log__18_24
log_activity	-0.146	0.137	0.291**	0.198	0.140	0.319*	0.295**	0.256**	0.238	0.184
	(0.195)	(0.176)	(0.120)	(0.129)	(0.121)	(0.164)	(0.148)	(0.114)	(0.145)	(0.119)
obs	626	629	629	629	631	631	630	628	620	615
Cragg	40.87	59.46	51.68	82.02	109.14	95.56	102.79	122.37	146.36	154.25
Museum FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses

Notes: Instruments are:. Columns (n) report IV ... All models include controls for ... * Significant at the 10% level; ** Significant at the 5% level; *** Significant at the 1% level. The underidentification test is an LM test of whether the equation is identified, i.e., that the excluded instruments are relevant, meaning correlated with the endogenous regressors. The test is essentially the test of the rank of a matrix: under the null hypothesis that the equation is underidentified, the matrix of reduced form coefficients on the L1 excluded instruments has rank=K1-1 where K1 is the number of endogenous regressors. Under the null, the statistic is distributed as chi-squared with degrees of freedom equal to (L1-K1+1). A rejection of the null indicates that the matrix is full column rank (model is identified). The Sargan statistic is calculated as N*R-squared from a regression of the IV residuals on the full set of instruments.

Table 7: IV REGRESSIONS, SEX_CAT AMTP DATA

	log_Female_visit_count	log_Female_visit_count	log_Female_visit_count	log_Female_visit_count	log_Female_visit_count	log_Female_visit_count	log_Female_visit_count	log_Female_visit_count	log_Female_visit_count	log_Female_visit_count
log_activity	-0.0842	-0.0265	0.0463	-0.0599	0.00720	-0.0255	0.171	0.178	0.182	0.189
	(0.241)	(0.198)	(0.146)	(0.133)	(0.107)	(0.159)	(0.159)	(0.177)	(0.175)	(0.120)
obs	649	652	652	652	654	654	653	650	641	634
Cragg	42.58	55.77	49.93	81.16	110.26	95.43000000000001	108.58	126.34	147.16	158.4
Museum FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses

Notes: Instruments are:. Columns (n) report IV ... All models include controls for ... * Significant at the 10% level; ** Significant at the 5% level; *** Significant at the 1% level. The underidentification test is an LM test of whether the equation is identified, i.e., that the excluded instruments are relevant, meaning correlated with the endogenous regressors. The test is essentially the test of the rank of a matrix: under the null hypothesis that the equation is underidentified, the matrix of reduced form coefficients on the L1 excluded instruments has rank=K1-1 where K1 is the number of endogenous regressors. Under the null, the statistic is distributed as chi-squared with degrees of freedom equal to (L1-K1+1). A rejection of the null indicates that the matrix is full column rank (model is identified). The Sargan statistic is calculated as N*R-squared from a regression of the IV residuals on the full set of instruments.

7 Channels and Welfare:?

GUARDARE PAPER HINNOSAAR: CONVERSION RATE (a larger share of readers choosing the destination)VS BROADER AUDIENCE VS INCREASED interest in the destination via indirect effects, such as word of mouth. SE CI FOSSERO DATI SUL NUMERO DI VISITATORI DEI SITI INTERNET DEI MUSEI SI POTREBBE MISURARE SE C'E' EFFETTO SOSTITUZIONE O EFFETTO COMPLEMENTARE TRA VISITE ONLINE E IN PRESENZA. L'IDEA E' CHE TWITTER SPIGE LE PERSONE A VISITARE I SITI DEI MUSEI WELFARE EFFECTS (who are the winners and the losers among customers, workers and businesses)?

Table 8: Placebo IVs: other museums (quale gruppo: ora ï¿½ il 2)

	log_visis_nt	log_visis_nt	log_visis_nt	log_visis_nt	log_visis_nt	log_visis_nt	log_visis_nt	log_visis_nt	log_visis_nt	log_visis_nt
log_activity	0.0607	0.0767	0.108*	0.0380	0.104**	0.0537	0.145***	0.110***	0.126***	0.0893**
	(0.0789)	(0.0562)	(0.0597)	(0.0556)	(0.0425)	(0.0498)	(0.0474)	(0.0411)	(0.0392)	(0.0447)
obs	762	763	763	760	760	756	752	747	737	726
Cragg	38.9	48.44	53.38	82.62	113.05	99.76000000000001	110.98	130.32	150.53	158.83
Museum FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses

Notes: In Columns ... we present the reduced form for... Both y and characteristics are replaced by their logs. Standard errors are clustered by ... and t-stats are in parentheses. All models include controls for..., fixed effects for ... * Significant at the 10% level; ** Significant at the 5% level; *** significant at the 1% level.

In table 9 we present the dis-aggregated reduced form Regressions for *engagement*, its components, and monthly *activity*. We divided the sample dropping observations with an engagement that fell within the last percentile of its distribution. These observations strongly bias the descriptive analysis in levels of tweets, with the side effect that only authors fixed effects can explain the variation in the data. Table 14 in the appendix shows a similar analysis, but conducted using only observation of the last percentile. The first two columns show *engagement* as dependent variable regressed on several characteristics of tweets. Column (1) includes the *followers* and *following* explanatory variable, while column (2) includes tweet-author fixed effects. The last three columns report the regressions having *activity* as dependent variable; columns (3) and (4) using linear models, respectively with and without the followers variable. In Column (5) we estimate the same model of column (4) using a pseudo-Poisson approach. As mentioned above, *engagement* is the number of monthly retweets, while *activity* is the sum of retweets and written tweets in a month. From Table 9 we infer that the number of *hashtags* and *clear number of words* have not significant impact, but the effect is positive on *engagement* and *activity* ;the effect of the number of included *sites* when a tweet is written are, instead, highly significant and negative related to the *engagement* and *activity*. Multimedia objects (*gif*, *photos*, and *videos*), look very author specific contents since their impact on the *engagement* flip the sign (from positive to negative) when we control for authors fixed effects. Regarding the sentiment analysis, the reference value is the neutral one, while 0.sentiment refers to negative tweets and 2.sentiment to positive ones. As Table 7 shows, the relationship between non-neutral tweets and the dependent variables is negative, with higher reduction for the positive sentiment. The followers control variable, which counts the number of followers a person has on his/her Twitter account, is positively correlated with both total *engagement* and *activity*. (Questi risultati sono un po' strani e vanno compresi meglio. to be SOLVED)

Table 9: Reduced Form Regressions

	(1) tot_engagement	(2) tot_engagement	(3) retweet_count	(4) reply_count	(5) like_count	(6) quote_count	(7) month_activity	(8) month_activity	(9) month_activity
hashtags	0.382**	0.719***	0.280***	-0.00543	0.434***	0.0105*	1.146***	1.295***	0.0570***
	(0.165)	(0.133)	(0.0349)	(0.0171)	(0.0893)	(0.00599)	(0.200)	(0.303)	(0.0120)
tags	-0.151**	-0.391***	-0.0365	-0.0342***	-0.308***	-0.0124***	0.536**	-0.551	-0.0145**
	(0.0754)	(0.109)	(0.0305)	(0.00911)	(0.0756)	(0.00300)	(0.214)	(0.353)	(0.00622)
sites	4.379***	3.281***	1.245***	0.264***	1.637***	0.135***	5.128***	2.485*	0.0145
	(0.671)	(0.663)	(0.163)	(0.0835)	(0.439)	(0.0419)	(0.953)	(1.351)	(0.0274)
clear_num_of_words	0.418***	0.308***	0.0818***	0.00913*	0.207***	0.00969***	0.551***	0.518***	0.00710***
	(0.0322)	(0.0366)	(0.00802)	(0.00530)	(0.0252)	(0.00374)	(0.0392)	(0.0752)	(0.00135)
gifs	-4.733	-1.032	-0.341	-0.430***	-0.107	-0.154***	13.35	40.49***	0.801***
	(3.042)	(1.794)	(0.474)	(0.0979)	(1.279)	(0.0427)	(9.579)	(14.34)	(0.194)
photos	-11.00***	-1.810**	-0.302	-0.627***	-0.679	-0.201***	-7.607***	4.696	0.225***
	(1.048)	(0.739)	(0.186)	(0.0799)	(0.497)	(0.0375)	(2.499)	(2.863)	(0.0747)
videos	-13.40***	-1.328	0.156	-1.087***	-0.123	-0.273***	-13.27***	-1.035	-0.0434
	(2.493)	(2.281)	(0.564)	(0.196)	(1.586)	(0.0792)	(4.172)	(5.882)	(0.138)
0.sentiment	4.312***	2.519***	0.633***	0.468***	1.471***	-0.0539	6.630***	6.573***	0.328***
	(0.541)	(0.477)	(0.109)	(0.122)	(0.309)	(0.0723)	(0.734)	(1.090)	(0.0357)
2.sentiment	-1.405***	0.0817	0.0286	0.0914**	0.0218	-0.0602**	4.129***	6.653***	0.357***
	(0.399)	(0.189)	(0.0414)	(0.0364)	(0.129)	(0.0271)	(1.181)	(0.925)	(0.0378)
log_foll	7.720***						13.89***		
	(0.534)						(0.741)		
log_folling	-3.051***						-5.398***		
	(0.345)						(0.493)		
obs	396354	396503	396503	396503	396503	396503	246952	247099	247099
R2 adj	.11	.52	.48	.39	.51	.28	.1	.3	.77
Museum FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Author FE	No	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes

Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

Notes: In Columns ... we present the reduced form for... Both y and characteristics are replaced by their logs. Standard errors are clustered by ... and t-stats are in parentheses. All models include controls for..., fixed effects for ... * Significant at the 10% level; ** Significant at the 5% level; *** significant at the 1% level.

8 Robustness

We run censored regressions to show that our results are not driven by influencers.

Table 10: IV REGRESSIONS, CENSORED TWEET DISTRIBUTION

(a) IV regressions q95

	log_visits	log_visits	log_visits	log_visits	log_visits	log_visits	log_visits	log_visits	log_visits	log_visits
log_activity	0.114	0.221*	0.234***	0.165*	0.206***	0.201***	0.253**	0.235***	0.250***	0.192***
	(0.134)	(0.121)	(0.0844)	(0.0952)	(0.0739)	(0.0731)	(0.103)	(0.0683)	(0.0701)	(0.0729)
obs	746	747	746	744	742	740	729	705	658	546
Cragg	34.59	46.74	53.46	80.04000000000001	109.92	103.25	104.47	112.66	119.59	102.33
Museum FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses

(b) IV regressions q90

	log_visits	log_visits	log_visits	log_visits	log_visits	log_visits	log_visits	log_visits	log_visits	log_visits
log_activity	0.0850	0.195*	0.271***	0.199**	0.266***	0.301***	0.162**	0.175**	0.290***	0.221**
	(0.143)	(0.108)	(0.0872)	(0.0867)	(0.0845)	(0.0853)	(0.0777)	(0.0749)	(0.0986)	(0.0864)
obs	746	746	745	739	729	710	684	603	511	395
Cragg	27.1	40.91	57.12	79.33	99.39	104.72	103.93	84.19	68.56	62.32
Museum FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses

(c) IV regressions q75

	log_visits	log_visits	log_visits	log_visits	log_visits	log_visits	log_visits	log_visits	log_visits	log_visits
log_activity	0.0596	0.211**	0.232***	0.139*	0.398***	0.247**	0.156	0.352*	0.179	0.331***
	(0.134)	(0.105)	(0.0757)	(0.0759)	(0.111)	(0.106)	(0.105)	(0.181)	(0.133)	(0.104)
obs	738	735	705	640	535	400	305	244	196	177
Cragg	23.32	45.29	84.29000000000001	86.15000000000001	70.44	31.37	38.09	38.71	36.2	67.37
Museum FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses

Notes: Instruments are:. Columns (n) report IV ... All models include controls for ... * Significant at the 10% level; ** Significant at the 5% level; *** Significant at the 1% level. The underidentification test is an LM test of whether the equation is identified, i.e., that the excluded instruments are relevant, meaning correlated with the endogenous regressors. The test is essentially the test of the rank of a matrix: under the null hypothesis that the equation is underidentified, the matrix of reduced form coefficients on the L1 excluded instruments has rank=K1-1 where K1 is the number of endogenous regressors. Under the null, the statistic is distributed as chi-squared with degrees of freedom equal to (L1-K1+1). A rejection of the null indicates that the matrix is full column rank (model is identified). The Sargan statistic is calculated as N*R-squared from a regression of the IV residuals on the full set of instruments.

Table 11: IV REGRESSIONS, RESIDUAL ENGAGEMENT

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	log_visits	log_visits	log_visits	log_visits	log_visits	log_visits	log_visits	log_visits	log_visits	log_visits
log_activity	0.121	0.0539	0.190**	0.226**	0.193***	0.130*	0.194***	0.167**	0.136**	0.166***
	(0.0781)	(0.0690)	(0.0724)	(0.101)	(0.0712)	(0.0702)	(0.0666)	(0.0636)	(0.0614)	(0.0627)
obs	752	750	748	740	738	733	729	723	716	710
Cragg	69.88	69.27	55.28	37.03	89.97	82.61	80.16	105.97	76.26000000000001	63.73

Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

Notes: Instruments are:. Columns (n) report IV ... All models include controls for ... * Significant at the 10% level; ** Significant at the 5% level; *** Significant at the 1% level. The underidentification test is an LM test of whether the equation is identified, i.e., that the excluded instruments are relevant, meaning correlated with the endogenous regressors. The test is essentially the test of the rank of a matrix: under the null hypothesis that the equation is underidentified, the matrix of reduced form coefficients on the L1 excluded instruments has rank=K1-1 where K1 is the number of endogenous regressors. Under the null, the statistic is distributed as chi-squared with degrees of freedom equal to (L1-K1+1). A rejection of the null indicates that the matrix is full column rank (model is identified). The Sargan statistic is calculated as N*R-squared from a regression of the IV residuals on the full set of instruments.

Table 12: Placebo IVs: lead f1

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	log_visits	log_visits	log_visits	log_visits	log_visits	log_visits	log_visits	log_visits	log_visits	log_visits
F.log_activity	-0.00256	-0.00817	0.0296	-0.0380	-0.00804	-0.0350	0.0146	0.0621	0.0658	0.0269
	(0.103)	(0.102)	(0.0782)	(0.0899)	(0.0715)	(0.0765)	(0.0713)	(0.0588)	(0.0584)	(0.0621)
log_num_mostre	0.165***	0.167***	0.180***	0.161***	0.165***	0.158***	0.154***	0.165***	0.168***	0.168***
	(0.0503)	(0.0487)	(0.0513)	(0.0500)	(0.0517)	(0.0518)	(0.0516)	(0.0498)	(0.0510)	(0.0514)
score	0.00561**	0.00597**	0.00562**	0.00578**	0.00554**	0.00546**	0.00541**	0.00581**	0.00599***	0.00583**
	(0.00226)	(0.00232)	(0.00239)	(0.00229)	(0.00247)	(0.00234)	(0.00236)	(0.00234)	(0.00225)	(0.00233)
c.log_num_mostre#c.score	-0.00120	-0.00131	-0.00132	-0.00107	-0.00118	-0.000929	-0.00100	-0.00131	-0.00138	-0.00139
	(0.00109)	(0.00112)	(0.00112)	(0.00103)	(0.00115)	(0.00109)	(0.00112)	(0.00108)	(0.00106)	(0.00110)
Sunday_5	0.0673	0.0565	0.0608	0.0665	0.0558	0.0632	0.0612	0.0601	0.0657	0.0582
	(0.0543)	(0.0548)	(0.0540)	(0.0547)	(0.0547)	(0.0549)	(0.0535)	(0.0546)	(0.0569)	(0.0561)
log_avg_temp	-0.204***	-0.202***	-0.202***	-0.206***	-0.201***	-0.208***	-0.201***	-0.195***	-0.194***	-0.183***
	(0.0550)	(0.0525)	(0.0538)	(0.0507)	(0.0537)	(0.0519)	(0.0528)	(0.0543)	(0.0548)	(0.0544)
log_days_rain	0.137**	0.143**	0.132**	0.139**	0.130**	0.137**	0.132**	0.132**	0.130**	0.114**
	(0.0557)	(0.0548)	(0.0549)	(0.0544)	(0.0565)	(0.0553)	(0.0543)	(0.0561)	(0.0575)	(0.0532)
log_museum_tweets	0.00104	0.00291	0.000970	0.00445	0.00262	0.00393	0.00139	-0.000192	0.000470	-0.00255
	(0.0116)	(0.0118)	(0.0119)	(0.0130)	(0.0122)	(0.0123)	(0.0125)	(0.0121)	(0.0119)	(0.0118)
obs	739	740	741	737	736	731	725	719	706	679
Cragg	55.69	63.52	62.68	80.37	92.57000000000001	93.23999999999999	128.22	137.54	148.64	164.02
Museum FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses

Notes: In Columns ... we present the reduced form for... Both y and characteristics are replaced by their logs. Standard errors are clustered by ... and t-stats are in parentheses. All models include controls for..., fixed effects for ... * Significant at the 10% level; ** Significant at the 5% level; *** significant at the 1% level.

9 Conclusions

DO THEY STEAL VISITORS FROM OTHER MUSEUMS? BACK OF THE ENVELOPE CALCULATION ON THE EFFECT ON THE LOCAL ECONOMY

Appendix A

AAA

Table 13: Reduced Form Regressions: Outliers

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	tot_engagement	tot_engagement	retweet_count	reply_count	like_count	quote_count	month_activity	month_activity	month_activity
hashtags	1360.2	85.77	79.34	5.849	-21.46	22.03	1645.5	1193.9	-0.0625
	(1453.4)	(808.1)	(147.0)	(69.58)	(618.8)	(25.65)	(1750.9)	(2608.4)	(0.0643)
tags	-3934.3***	-1269.3	-181.8*	-400.7	-672.1	-14.71	-5042.9***	-2969.0**	-0.279**
	(1001.9)	(772.4)	(110.0)	(372.0)	(462.9)	(27.15)	(1222.0)	(1407.8)	(0.108)
sites	-2393.1**	-4596.1***	-511.6***	35.55	-4085.2***	-34.78	-967.5	-7177.0**	-0.236***
	(1135.7)	(1264.3)	(178.4)	(245.4)	(1028.4)	(51.62)	(1324.3)	(2843.2)	(0.0691)
clear_num_of_words	-311.2**	6.046	6.470	3.080	0.348	-3.852**	-385.4**	-97.68	0.000209
	(125.8)	(44.39)	(7.125)	(3.564)	(34.63)	(1.935)	(162.7)	(95.92)	(0.00327)
gifs	3757.7	-3361.4	-404.3	-538.1	-2452.1	33.04	26258.1	-26970.0	-1.318
	(10490.4)	(3396.8)	(530.6)	(346.9)	(2733.1)	(140.9)	(39815.8)	(20603.9)	(1.298)
photos	-3435.4	-1518.3	-412.9	-408.7	-565.5	-131.3	-7264.2	-4083.9	-0.900
	(3531.5)	(4507.5)	(708.3)	(330.6)	(3555.2)	(177.7)	(4638.7)	(6706.8)	(0.600)
videos	-1618.3	4312.7	184.1	-89.94	4294.3	-75.81	-1108.2	7978.0	-1.653*
	(7923.8)	(3968.0)	(536.8)	(494.7)	(3395.6)	(148.6)	(6931.2)	(11574.3)	(0.928)
0.sentiment	-2833.3	-947.4	-80.79	233.2	-1093.4	-6.465	-3042.7	-2519.8	0.119
	(3640.8)	(2166.5)	(386.5)	(321.3)	(1657.2)	(99.24)	(4676.3)	(5724.3)	(0.122)
2.sentiment	-2158.1	-4268.6	-860.2	191.9	-3466.4	-133.9*	-1230.0	-7235.5	0.100
	(3607.1)	(3475.1)	(631.3)	(466.9)	(2664.1)	(72.67)	(4802.5)	(9581.3)	(0.131)
log_foll	2089.3*						3681.7**		
	(1072.9)						(1461.3)		
log_folling	-1437.4**						-1385.4*		
	(644.0)						(805.3)		
obs	3991	4003	4003	4003	4003	4003	3243	3255	3255
R2 adj	.03	.78	.85	.25	.77	.29	.02	.52	.8300000000000001
Museum FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Author FE	No	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes

Standard errors in parentheses

* p<0.10, ** p<0.05, *** p<0.01

Notes: In Columns ... we present the reduced form for... Both y and characteristics are replaced by their logs. Standard errors are clustered by ... and t-stats are in parentheses. All models include controls for..., fixed effects for ... * Significant at the 10% level; ** Significant at the 5% level; *** significant at the 1% level.

Table 14: IVs: full set of covariate

	(1) log_visits	(2) log_visits	(3) log_visits	(4) log_visits	(5) log_visits	(6) log_visits	(7) log_visits	(8) log_visits	(9) log_visits	(10) log_visits
log_activity	0.127	0.249**	0.274***	0.142	0.232***	0.153**	0.267***	0.224***	0.224***	0.189**
	(0.130)	(0.122)	(0.102)	(0.0968)	(0.0697)	(0.0766)	(0.0883)	(0.0667)	(0.0576)	(0.0723)
log_num_mostre	0.174***	0.186***	0.192***	0.173***	0.179***	0.176***	0.176***	0.175***	0.179***	0.174***
	(0.0491)	(0.0469)	(0.0496)	(0.0488)	(0.0498)	(0.0494)	(0.0481)	(0.0478)	(0.0481)	(0.0486)
score	0.00497**	0.00498**	0.00443*	0.00512**	0.00462*	0.00479**	0.00422*	0.00471**	0.00500**	0.00474**
	(0.00225)	(0.00222)	(0.00228)	(0.00226)	(0.00241)	(0.00227)	(0.00232)	(0.00228)	(0.00228)	(0.00227)
c.log_num_mostre#c.score	-0.00120	-0.00140	-0.00123	-0.00119	-0.00121	-0.00108	-0.00104	-0.00114	-0.00122	-0.00114
	(0.00104)	(0.00102)	(0.00105)	(0.00101)	(0.00106)	(0.00101)	(0.00106)	(0.00104)	(0.00103)	(0.00104)
Sunday_5	0.0753	0.0710	0.0771	0.0760	0.0687	0.0704	0.0823	0.0652	0.0745	0.0767
	(0.0527)	(0.0537)	(0.0539)	(0.0548)	(0.0550)	(0.0547)	(0.0533)	(0.0548)	(0.0559)	(0.0569)
log_avg_temp	-0.189***	-0.183***	-0.187***	-0.189***	-0.181***	-0.186***	-0.181***	-0.180***	-0.181***	-0.177***
	(0.0503)	(0.0497)	(0.0515)	(0.0488)	(0.0506)	(0.0501)	(0.0482)	(0.0504)	(0.0505)	(0.0501)
log_days_rain	0.123**	0.122**	0.114**	0.123**	0.113**	0.121**	0.114**	0.116**	0.113**	0.105**
	(0.0530)	(0.0538)	(0.0538)	(0.0542)	(0.0540)	(0.0538)	(0.0508)	(0.0534)	(0.0536)	(0.0516)
log_museum_tweets	-0.00396	-0.00716	-0.00750	-0.00244	-0.00608	-0.00402	-0.00512	-0.00584	-0.00364	-0.00644
	(0.0121)	(0.0121)	(0.0120)	(0.0128)	(0.0117)	(0.0121)	(0.0115)	(0.0116)	(0.0119)	(0.0111)
obs	747	748	748	745	745	741	737	732	722	711
Cragg	36.97	45.02	50.52	80.17	110.6	95.22	105.12	125.89	144.62	153.55
Museum FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses

Notes: In Columns ... we present the reduced form for... Both y and characteristics are replaced by their logs. Standard errors are clustered by ... and t-stats are in parentheses. All models include controls for..., fixed effects for ... * Significant at the 10% level; ** Significant at the 5% level; *** significant at the 1% level.

Table 15: IVs: Month Fe

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	log_visits	log_visits	log_visits	log_visits	log_visits	log_visits	log_visits	log_visits	log_visits	log_visits
log_activity	0.117	0.227*	0.228**	0.118	0.185***	0.162**	0.198**	0.154**	0.146**	0.130
	(0.121)	(0.123)	(0.0904)	(0.0937)	(0.0690)	(0.0635)	(0.0942)	(0.0705)	(0.0569)	(0.0800)
log_num_mostre	0.127***	0.142***	0.149***	0.120***	0.137***	0.137***	0.133***	0.125***	0.123***	0.121***
	(0.0455)	(0.0421)	(0.0434)	(0.0428)	(0.0441)	(0.0449)	(0.0432)	(0.0433)	(0.0419)	(0.0438)
score	0.00644***	0.00623***	0.00583***	0.00656***	0.00623***	0.00628***	0.00591***	0.00620***	0.00630***	0.00627***
	(0.00221)	(0.00214)	(0.00215)	(0.00222)	(0.00231)	(0.00219)	(0.00220)	(0.00222)	(0.00221)	(0.00216)
c.log_num_mostre#c.score	-0.00177	-0.00188*	-0.00182*	-0.00174	-0.00186*	-0.00177	-0.00167	-0.00166	-0.00163	-0.00167
	(0.00110)	(0.00106)	(0.00108)	(0.00106)	(0.00109)	(0.00107)	(0.00109)	(0.00110)	(0.00109)	(0.00109)
Sunday_5	-0.101	-0.124	-0.0766	-0.0909	-0.0932	-0.100	-0.0685	-0.102	-0.0896	-0.0963
	(0.265)	(0.244)	(0.277)	(0.262)	(0.260)	(0.260)	(0.231)	(0.252)	(0.260)	(0.261)
log_avg_temp	0.196	0.274	0.280	0.278	0.267	0.216	0.177	0.213	0.214	0.220
	(0.335)	(0.320)	(0.361)	(0.274)	(0.334)	(0.336)	(0.328)	(0.335)	(0.333)	(0.330)
log_days_rain	-0.908*	-0.802*	-0.978**	-0.914**	-0.895*	-0.876*	-0.831*	-0.890*	-0.921*	-0.894*
	(0.486)	(0.473)	(0.469)	(0.396)	(0.456)	(0.481)	(0.464)	(0.485)	(0.499)	(0.477)
log_museum_tweets	-0.00774	-0.00622	-0.00645	-0.00417	-0.00599	-0.00706	-0.00608	-0.00648	-0.00526	-0.00809
	(0.0126)	(0.0126)	(0.0127)	(0.0136)	(0.0127)	(0.0130)	(0.0133)	(0.0128)	(0.0131)	(0.0127)
obs	747	748	748	745	745	741	737	732	722	711
Cragg	39.94	44.82	50.74	82.79000000000001	116.34	99.81	95.69	126.93	154.79	153.51
Museum FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses

Notes: In Columns ... we present the reduced form for... Both y and characteristics are replaced by their logs. Standard errors are clustered by ... and t-stats are in parentheses. All models include controls for..., fixed effects for ... * Significant at the 10% level; ** Significant at the 5% level; *** significant at the 1% level.

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