The Impact of Twitter on Cultural Consumption

Nadia Campaniello*

Sara Ciarlantini†

Vincenzo Mollisi‡

March 12, 2024

Abstract

We show evidence of the causal impact of Twitter on consumption, that is one of the most important economic decisions. In particular, we focus on cultural consumption analyzing data on eight museums of the metropolitan area of Torino (the fourth largest city in Italy), that altogether account for 64% of the total museums' visits in the area. Using an IV strategy that randomly pairs tweeters who generate the highest engagement to a museum, we document that a doubling of the activity on Twitter leads to an increase in visits between 15% and 27%. We do not find evidence of a displacement effect. Indeed, activity on Twitter increases the total number of museums' visitors in the metropolitan area of Torino.

Keywords: consumption, Twitter, social media, museums

JEL Codes: D12, L82, Z11

*University of Turin (ESOMAS Department) and Collegio Carlo Alberto; nadia.campaniello@unito.it

†Polytechnic University of Turin; sara.ciarlantini@polito.it

‡University of Turin (ESOMAS Department); vincenzo.mollisi@unito.it

1 Introduction

We investigate the impact of Twitter activity on consumption, a crucial economic decision. We specifically concentrate on cultural consumption, exploring the causal relationship between Twitter activity and museums' attendance.

In today's digital age, consumers rely on social media platforms such as Facebook, Instagram [1] and Tik Tok to receive news and information, supplementing or even replacing traditional media. Twitter [2], with its vast user base of over 520 million active monthly users, stands out as a powerful social media marketing channel, offering timely information. According to Twitter website, people use the platform to discover new things, share recommendations, and narrate their experiences making it a valuable tool for museums to engage with the public and to increase their number of visitors. In our work, we focus on museums for several reasons. First, museums host both permanent and temporary exhibitions, encouraging visitors to return by offering varied and changing artistic experiences. In other words, museums exhibit considerable variability over time, making timely information crucial. Second, they are experience goods. Potential visitors rely on various sources of information such as online reviews, recommendations from friends or experts, official museum websites, and social media posts to gather insights about the exhibits, collections, and overall visitor experience. Therefore, pre-purchase information might significantly influence visitors' choices. Third, museums have faced unprecedented challenges and opportunities in the realm of digital technologies. Social media platforms have become indispensable tools for museums worldwide [3]. Even smaller museums attract large audiences on platforms like Twitter. For instance, the Museum of Rural Life in England garnered widespread attention by challenging its followers on social media to recreate famous artworks using household items, a campaign that went viral, particularly on Twitter. Fourth, museums significantly impact the local economy and generate positive spillover effects.

We use data on 8 museums located in the metropolitan area of Turin, Italy - the fourth largest city in the country. Turin has recently transitioned from an industrial hub to a smart

[1] Due to platform restrictions, we couldn't include in our analysis data from Facebook and Instagram

[2] 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.

[3] Vassiliadis and Belenioti (2017), Carvalho and Raposo (2012) highlight that social media enhance the communication opportunities available to museums, providing a cost-effective and targeted option to traditional communication strategies.

city, where innovation and culture play pivotal roles in its development.

We employ an instrumental variable approach that follows the framework outlined in the "judge fixed effect" literature. The approach involves random assignment of tweeters, who exhibit systematic differences in their engagement-generating abilities, to various museums. Our analysis reveals compelling insights: doubling the Twitter activity related to these museums leads to a 16% increase in museum visits in ordinary least squares (OLS) regressions and a 15% - 27% increase in two-stage least squares (2SLS) regressions. Notably, our investigation indicates the absence of a displacement effect. Twitter activity also positively impacts visits to other museums, resulting in a 9% - 14% rise in attendance. When we look at the heterogeneity of the effect, we find that women in the age cohort 18-24, are the most affected by Twitter activity.

Our paper is structured as follows: in Section 2 we present the literature review, in Section 3 the data and in Section 4 the empirical strategy and the results. In Section 5 we do some robustness checks, in Section 6 we look at the heterogeneity of the effect, while in Section 7 we analyse the mechanisms. Finally, in Section 8, we present the conclusions.

2 Literature Review

Our paper is related to the recent and still scant literature on the existence of a causal relationship between User-Generated Content (UGC) and the demand for products and services. (Luca, 2016) investigates the impact of online consumer reviews on the demand for restaurants. 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, consumers respond more strongly to ratings that contain more information.

Hinnosaar et al. (2021) conducted a randomized field experiment, in which they analyzed the relationship between additional content on Wikipedia pages about cities and tourists' final consumption, accounted as overnight stays in treated cities compared to nontreated cities. According to their results, the treatment led to a 9% increase in hotel stays.

Finally, Reimers and Waldfogel (2021) analyze and compare the relative influence of professional critics and crowd-based Amazon star ratings on consumer behaviour and welfare in the book market. They show that they both have a positive effect on book sales. Their findings reveal that, in the aggregate, the impact of star ratings on consumer surplus is more than ten times larger than that of traditional review outlets.

In line with the cited papers, we investigate the impact of UGC platforms on consumption for experience goods in the leisure/hospitality industry. But our work focuses on a different typology of user generated content, Twitter, that is not just devoted to customer ratings and reviews like "Amazon", and "Yelp" and is not an encyclopedia like Wikipedia. Furthermore, we use an instrumental variable that has never been used in the field of research on social media. As in Hinnosaar et al. (2021) and in (Luca, 2016), when we analyse the characteristics of tweets (Table 13 of the Appendix), we show that providing more information (using more words or the link to a website) generate a higher engagement on Twitter.

Our contribution is close to the strand of literature that investigates the relationship between online and offline experiences. The effect of the digital presence of museums (i.e. photos published on Twitter or links to the museums' websites) 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. On this regard, 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. In our work we do not find evidence of a substitution effect: Twitter activity does increase museums' audience.

Our study is also related to the growing body of literature about the role and effect of social media influencers, that tries to disentangle how they can shift public perceptions of particular products and services. Freberg et al. (2011) identify the perceived core characteristics of a sample of social media influencers. They are found to be 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. Even though we do not directly study the role of social media influencer, in Tables 6 and 7 we show that the effect of Twitter activity on museums' visit is not driven by the top influencers in our dataset. Furthermore, in the Appendix of our work (Table 14) we show that engagement is strongly and positevely influenced by the chacteristics of the tweets (number of words, hastags, of links to websites) for tweeters below the 99% percentile of the engagement distribution, while for tweeters in the top 1% (top influencers) individual fixed effects absorb most of the variability.

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. There are different actions a user can perform on the Twitter social media platform, besides 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 [5]. Accordingly, we web-scraped the text of the tweet, the date, the user ID, the number of followers and of followings, the number of "likes", "retweets", "replies", and "quotes" of the tweet. 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, gifs and the number of words in each tweet (net of all the symbols and the links to websites) [6]. Table 1 shows the summary statistics. The average engagement is equal to 155 and the most common action is "to like" with an average of around 112.

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

[5]In the robustness checks we perform and discuss an analysis using a less inclusive definition of engagement that is just focussed on retweeting that represents the most powerful tool on Twitter to spread information.

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

Table 1: Summary statistics

(a) Twitter

	Mean	Median	S.D.	N
Engagement	155.2	1	6156.4	400506
Retweets	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
Hashtags	0.80	0	1.61	400506
Tags	1.52	0	3.62	400506
Websites	0.69	1	0.63	400506
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

(b) Museums

	Mean	Median	S.D.	Iqr	N
Museum visits	30489.0	17133	30121.9	36319.5	768
Activity on Twitter	1083.0	338	15952.5	465.5	768
Exhibitions	1.35	1	1.50	2	768
Museums' tweets	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
Tweeters	303.5	265	233.2	212	768
5th weekend	0.21	0	0.41	0	768

Notes: Panel 1a show the summary statistics for Twitter. The unit of observation is a single tweet. Panel 1b] shows the summary statistics for our . All variables are a monthly leve An *activity on Twitter* outlier relative to MAUTO, year 2016 month 10, equal to 426010 is excluded from the sample. *Museum Visits*, *Activity on Twitter*, *Exhibitions* and *Museums Tweets* are variables all considered at a monthly level. *Museum Visits* measure the number of people visiting a specific museum in a certain month. *Activity on Twitter* is given by $tweet + engagement$: the number of tweets tweeted by users tagging a specific museum added to the engagement generated. *Exhibitions* is the number of simultaneous exhibitions set up within a single museum in a specific month. *Museum Tweets* represents the number of tweets written by the 8 museums each month. *Average temperature* is measured in Celsius degrees, and it represents the average monthly registered temperatures for each specific year. *Days of rain* is the number of days in which rain was recorded. Both *Average temperature* and *Days of rain* refer to values registered in the Turin geographic area. *Authors* is the number of people that wrote at least one tweet tagging a specific museum in a single month. *5th Weekend* is a dummy variable equal to 1 if a month has an extra weekend (meaning 5 Saturdays and 5 Sundays) and 0 otherwise.

We define our variable of interest, *Activity on Twitter*, as 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 [7]. *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 panel 1a of table 1

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 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.

Museums' visits is the dependent variable that measure cultural consumption. 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.

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[8]. 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 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.

Museums' tweets represents the number of tweets written by the 8 museums each month.

Tweeters indicates the number of people who wrote at least one tweet about one of the 8 museums in a single month. We also 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,

[7] *Activity on Twitter= tweets + engagement*

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

5th WE, which is equal to 1 if a month has an extra weekend (meaning 5 Saturdays and 5 Sundays) and 0 otherwise.

Panel 1b of table 1 shows the summary statistics. The number of observations (768) refers to the monthly data gathered from the 8 museums over a 8-year period (2012-2019). The average number of visits in a month for a museum is about 30,489 with a standard deviation of 30,122.

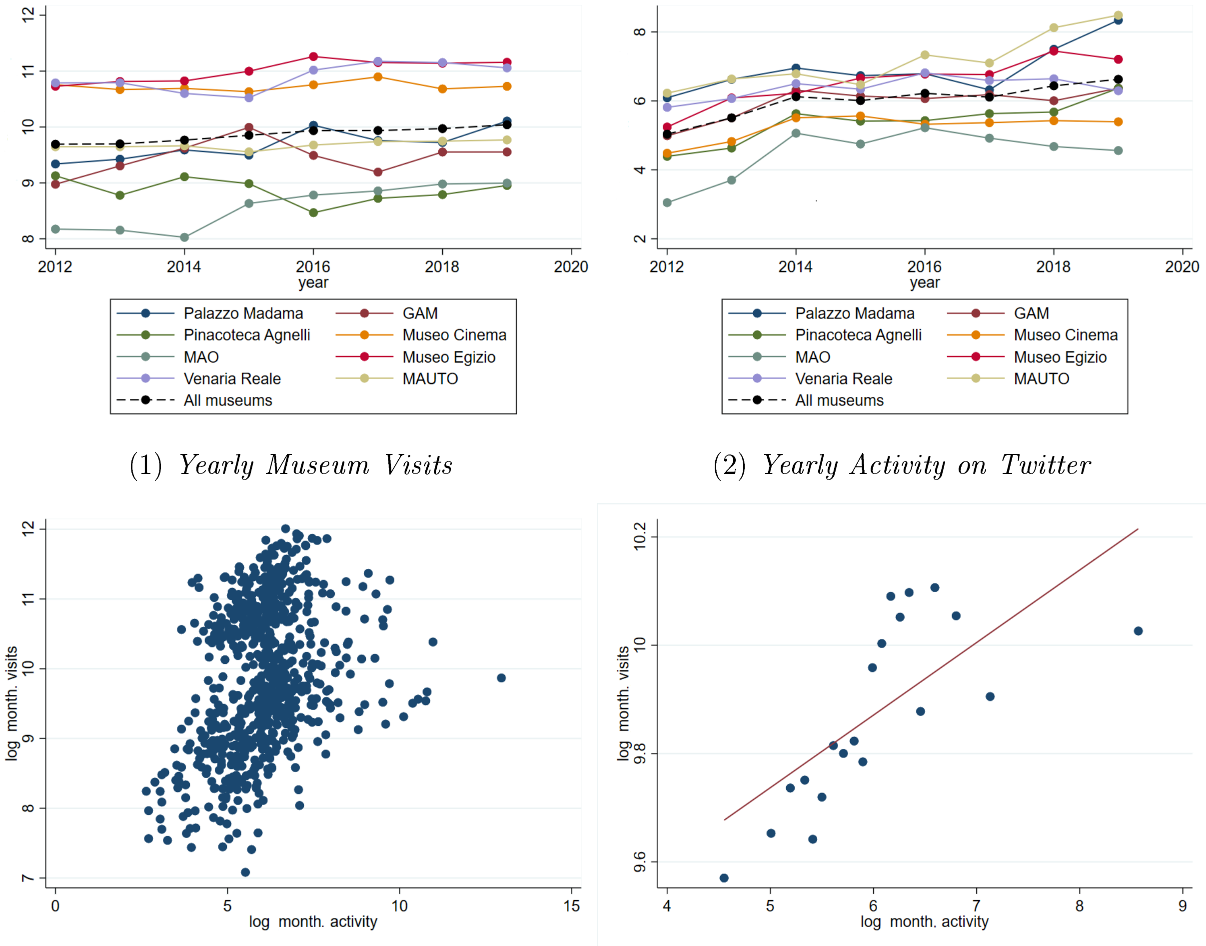
4 Empirical Strategy and Results

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 panels of Figure 1 show 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 black dashed line represents the average for the 8 museums altogether. Museo Egizio, Reggia di Venaria Reale and Museo del Cinema had a number of visitors that is larger than the average one. The activity on Twitter has been almost constantly increasing for all museums, mirroring the general trend of the digital transformation for the cultural sector. The activity on Twitter has been more intense than the average for MAUTO, Palazzo Madama, Reggia di Venaria Reale and Museo Egizio.

In the bottom panels of Figure 1 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 Museum Visits* (2) *Yearly Activity on Twitter*

(3) *Scatter plot* (4) *Binscatter*

Notes: The figures show raw data and simple correlations. The top panels illustrate the trends of the natural logarithms of yearly *Museum Visits* (1) and yearly *Activity on Twitter* (2) for each of the museums included in our analysis over the period 2012-2019. The black dashed line represents the average for the eight museums altogether. The bottom panels show a positive correlation between log *Museum Visits* and log *Activity on Twitter* using both a parse (3) and a binned scatter plot (4). Figure 4 includes museum fixed effects.

Our first empirical strategy is an Ordinary Least Squares (OLS) model. Even though, in the OLS, 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 exploit random pairing of tweeters, who differ systematically in their ability to generate engagement (that is measured as the sum of retweets, replies, quote, and likes), to museums. Our exclusion restriction is the randomness in pairing a museum and a high-engagement tweeter. For each individual who tweeted about one of the 8 museums of our study over the period 2012-2019 [9], we construct an index of engagement, $\bar{e}_{i,t,m}$, that measures his/her average ability to engage people in the past and in the future:

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

where e is the engagement and C is the number of tweets, i is the tweeter, t is the month and m is one of the eight museums. To avoid concerns of endogeneity we construct the index of engagement calculating the leave one out mean with respect to the unit of observation museum-month.

Each instrumental variable is the index of engagement of the top ten tweeters associated with museum, m, in month, t. *Instrument1* refers to the index of the tweeter who generates the highest average engagement for the museum, m, in month, t. *Instrument10* refers to the index of the tweeter who generates the lowest average engagement for the museum, m, in month, t. Table 2 shows the summary statistics of the instrumental variables. The mean of the first index, *Instrument1*, is 7,869 (with a standard deviation of 78,330) and, by construction, the mean decreases going from the first index to the last one (the mean of *Instrument10* is 221 with a standard deviation of 1,002). In the 2SLS strategy, we control for three variables that describe some of the characteristics of the top ten tweeters and the content of their messages: *Followers*, *Art-related* and *Sentiment score*. Their summary statistics are reported in Table 2.

Followers represents the number of followers of each of the 10 top tweeters [10]. The number

[9] To make sure to isolate the impact of the activity on Twitter on museums' visitors, we do not take into account those tweeters who are followed by the museums and, potentially, paid by them to be promoted.

[10] Since it is not possible to collect the number of followers over time, we use the data recorded on December 1, 2022.

of followers decreases from *Instrument1* (with a mean of 2,239,978 followers) to *Instrument10* (with a mean of about 238,854 followers). This is in line with the fact that *Instrument1* refers to the individual who generates the highest average engagement, while *Instrument10* to the one that generates the lowest average engagement.

Art-related is a dummy variable equal to 1 if the Twitter account is either an art, touristic and/or cultural Twitter account. Around 13 -17% of the accounts are art-related.

To study the emotions expressed in the tweets we conduct a sentiment analysis. 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 [11]. 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 in our sample show a positive sentiment with values that range between 0.092 and 0.17.

[11] 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.

Table 2: Summary Statistics: 2SLS.

	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	

	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 shows the summary statistics of the ten instruments (one in each column) and the three additional control variables that we use in the 2SLS analysis. *Instrument1* is the tweeter who generates the highest average engagement, *Instrument10* is the one who generates the lowest one. *Sentiment score* measures the sentiment of a text: positive sentiment for compound score larger than 0.05, a neutral sentiment with a score between -0.05 and 0.05, and a negative sentiment with a score lower than -0.05. *Followers* indicates the number of followers of each of the top 10 tweeter; *Art-related* is a dummy variable equal to 1 if the tweeter is either an art, touristic and/or cultural page.

4.2 OLS results

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

$$museum\_visits_{it} = \beta\, activity\_on\_twitter_{it} + \theta\, \mathbf{X_{it}} + \kappa_i + \tau_t + \varepsilon_{it} \tag{1}$$

where $museums\, visits_{it}$ and $activity\, on\, twitter_{it}$ are, respectively, the natural logarithms of museums monthly visits and of the activity on Twitter. The matrix $\mathbf{X_{it}}$ includes controls for the number and popularity of temporary exhibitions, tweets from the eight museums' Twitter accounts, weather and temperature condition, as well as an extra weekend in a month. Continuous variables are transformed in logs. κ_i and τ_t are, respectively, museum and time fixed effects.

Our panel data, that consists of 8 museums and 98 time periods, is close to multiple time series that exhibit cross-sectional and serial correlation. For this reason we do not use clustered standard errors but the Driscoll-Kraay standard errors that are robust to very general forms of cross-sectional and temporal dependence when the time dimension becomes large Driscoll and Kraay (1998). Since month fixed effects are ambitious to estimate with 8 observations available for each period, in our baseline models we use year fixed effects, but we provide estimates with month fixed effects in the robustness checks (Table 5).

We present the results of the baseline model in Table 3. In Column 1 we use information on the full sample of tweeters, while in the other columns we restrict the sample to the top 10 tweeters (one in each column). Since the number of *Followers*, whether the Twitter account is *Art-related* and the *Sentiment score* are tweeter-specific, they do not apper as controls in column 1.

Table 3: OLS

		museum visits									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
activity on twitter	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)
exhibitions	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)
exhibitions#Popularity	-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)
Popularity of the Exhibition	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)
5th Weekend	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)
average temperature	-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)
days of 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)
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)
Sentiment score		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)
followers		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)
Art Related		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)
Observations	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

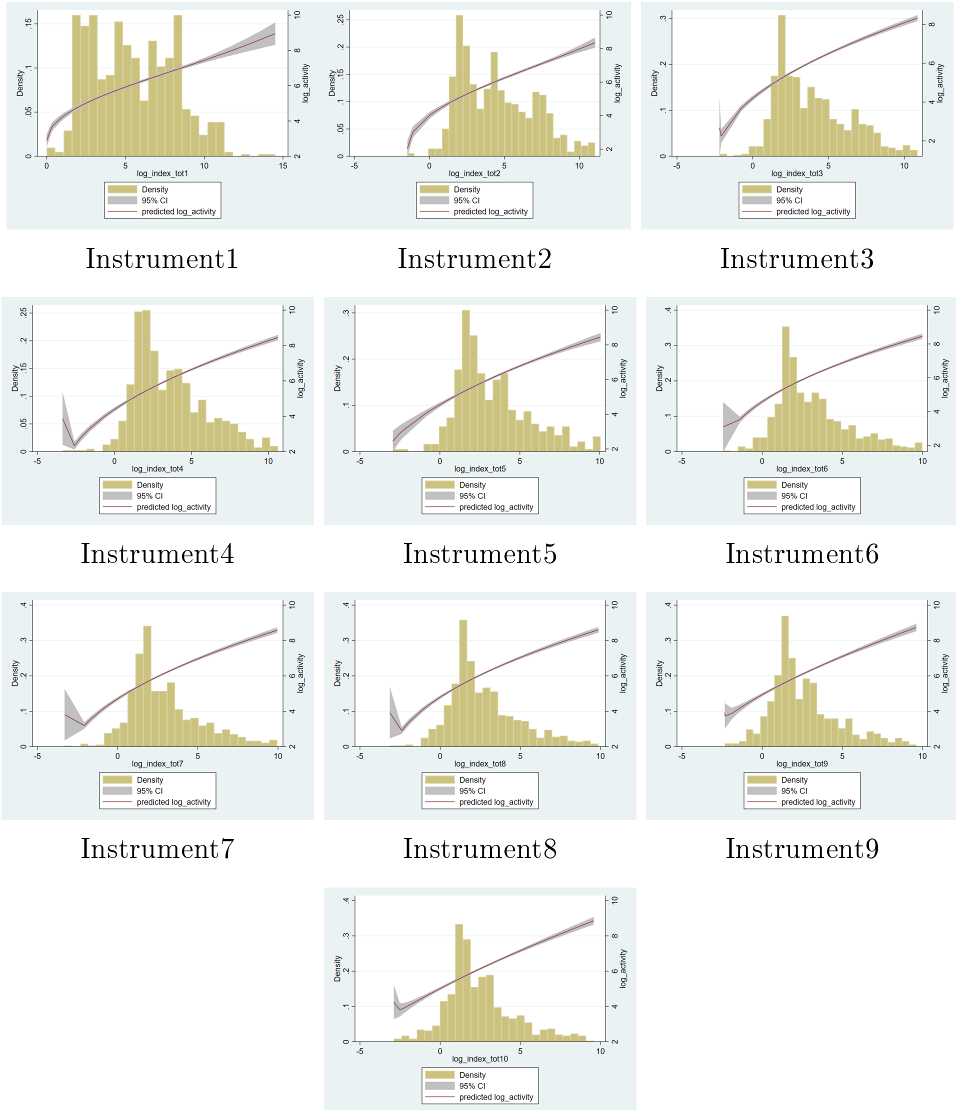
Notes: In Column 1 we use information about all tweeters, while in the other columns the sample is restricted to the top 10 tweeters who generate the highest engagement. All variables in lower case are log transformed. *activity on twitter* is equal to the sum of tweets and engagement, *exhibitions* is the number of exhibitions hosted by each museum in a given month, *Popularity of the Exhibition* ranks the exhibitions according to their popularity relative to Picasso searches on Google trends, *5th WE* is a dummy variable equal to 1 if a month has an extra weekend (meaning 5 Saturdays and 5 Sundays) and 0 otherwise, *exhibitions#Popularity* is the interaction between the number of exhibitions and their popularity.*average temperature* is the average temperatures (in Celsius degrees) in Turin and *days of rain* is the number of rainy days in Turin. The variable *museums tweets* is the number of tweets tweeted by the 8 museums. In columns (2) - (11) we use additional controls that are tweeter-specific. *Sentiment score* measures the sentiment of a text: positive sentiment for compound score larger than 0.05, a neutral sentiment with a score between -0.05 and 0.05, and a negative sentiment with a score lower than -0.05. *followers* is the number of followers of each of the 10 top tweeters. *Art-related* is a dummy variable equal to 1 if the tweeter is either an art, touristic and/or cultural Twitter account. Driscoll-Kraay standard error are in parentheses. * 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 16%. The magnitude of the coefficient on the variable of interest is pretty stable in all the specifications. Both the number of exhibitions and their popularity are positively correlated with the flows of museums' visitors. As expected, weather has an impact on museum attendance. In rainy days people look for indoor activities and museums get busier than usual. This is true also in our data. Instead, average temperature is negatively related to the number of visitors because people tend to choose outdoor activities when the weather is good.

4.3 2SLS results

As a preliminary evidence of the relevance of our IVs, we show the relationship between each of the 10 instruments and the natural logarithm of *Activity on Twitter*. Figure 2 is a graphical representation of the first stage. The correlation between the two variables is clearly positive and approximately linear in each panel.

Figure 2: FIRST STAGE



Instrument1 Instrument2 Instrument3

Instrument4 Instrument5 Instrument6

Instrument7 Instrument8 Instrument9

Instrument10

Notes: The figure shows the relationship between each of the 10 instrumental variables and the natural logarithm of *Activity on Twitter*. Each instrumental variable is the index of engagement (the average tweeter's ability to engage people in the past and in the future) generated by the top 10 tweeters associated with a museum, m, in a month, t. Among the top ten tweeters, *Instrument1* is the one who generates the highest average engagement, while *Instrument10* is the one who generates the lowest average engagement. The graphs show a positive and approximately linear correlation between the each of the ten instrumental variable and activity on Twitter.

We now turn to the estimates for the reduced form, the first stage and the IV. Panel 4a of Table 4 reports the estimates for the reduced form. The coefficient on the instrument is positive and significant in 8 out of 10 cases. Panel 4b shows that the estimates for the first-stage regressions are always significant and are in line with the graphical representation in Figure 2. Finally, panel 4c reports the IV estimates that are significant 8 out of 10 times. A doubling of *Activity on Twitter* would increase *museums' visits* by 15% - 27%. Compared to the IV estimates, the OLS effect is downward biased by around 50%.

IV estimates are different across the different instruments, indicating heterogeneous treatment effects due to different compliers associated with the instruments. Standard statistical tests on the performance of the 10 instruments are reported in panel 4c. The instruments are relevant, with an F-statistic that ranges between 37 and 154 which is well above the rule of thumb value of 10 indicated by the literature on weak instruments Stock and Yogo (2002). The F-statistic increases almost monotonically from *Instrument1* to *Instrument10*: the relevance of the instrument is higher for the top 10 tweeters who generate the lowest engagement.

In Table 12 in the subsection 9.2 of the Appendix we show the IV results with all the controls. The coefficients on the controls are in line with those of the OLS.

Table 4: 2SLS

(a) Reduced form

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	museum visits									
instrument	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

	activity on twitter									
instrument	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

	museum visits									
activity on twitter	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 Panel 4c we show the estimates for the 2SLS model. In panel 4a and in 4b we show, respectively, the estimates for the reduced form and the first stage. All variables in lower case are log transformed. *activity on twitter* is the sum of tweets and engagement, *museum visits* is the number of monthly visits for each museum. The estimates for each of the 10 instruments (the top 10 tweeters with the largest engagement index) are shown in columns (1-10). *Instrument1* is the tweeter with the highest average engagement, *Instrument10* is the one with the lowest average engagement. All specifications include controls for the number of exhibitions, popularity of the exhibitions, their interaction, months with a 5th weekend, average temperature, days of rain, the number of museum's tweets in a month, tweeter's average sentiment score, number of followers, and whether a Twitter account is art-related. Driscoll-Kraay standard error are in parentheses. The F- statistic ranges between 37 and 154, that is well above the rule of thumb of 10. * Significant at the 10% level; ** Significant at the 5% level; *** Significant at the 1% level.

5 Robustness checks

To make sure that our results are not biased by the particular specification we use, in this section we perform different robustness checks. As a first robustness check, we use month fixed effects instead of year fixed effects in the 2SLS regressions. Table 5 shows that the coefficient on the instrument is significant in 7 out of 10 cases and the magnitude is sligthly lower than in Table 4.

Table 5: 2SLS. MONTH FE

	museum visits									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
activity on twitter	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)
obs	747	748	748	745	745	741	737	732	722	711
Cragg	39.94	44.82	50.74	82.79	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

Notes: The table shows the stimates for the 2SLS model with month fixed effects. All specifications include controls for the number of exhibitions, popularity of the exhibitions, their interaction, months with a 5th weekend, average temperature, days of rain, the number of museum's tweets in a month, tweeter's average sentiment score, followers, and art-related account. All variables in lower case are log tranformed. Driscoll-Kraay standard error are in parentheses. * Significant at the 10% level; ** Significant at the 5% level; *** significant at the 1% level.

As a second robustness check, to make sure that our results are not driven by the top Twitter influencers, in Tables 6 and 7, we use, respectively, observations below the 90th and 95th percentiles of the tweeters' engagement and followers distribution. It is important to highlight that reducing the number of tweeters' contributions mechanically reduces the ranks of tweeters increasing the number of missing observations when we consider lower rank contributors for our instruments. Results are in line with those of Table 4. The coefficients are positive and statistically significant in most of the specifications in any of the panels of Tables 6 and 7. Overall, they are even larger than the coefficients in our main 2SLS regression in Table 4c indicating that the top influencers in our sample do not drive our results.

Table 6: 2SLS. CENSORED ENGAGEMENT DISTRIBUTION

(a) IV regressions q95

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	museum visits									
activity on twitter	0.0788	0.129	0.173*	0.226**	0.259**	0.282***	0.264***	0.221**	0.223**	0.165*
	(0.160)	(0.136)	(0.100)	(0.0958)	(0.100)	(0.0751)	(0.0948)	(0.0998)	(0.110)	(0.0990)
obs	670	670	657	666	643	621	614	581	520	464
Cragg	42.17	71.32	96.74	91.32	135.83	165.04	171.13	112.31	93.53	73.18
Museum FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

(b) IV regressions q90

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	museum visits									
activity on twitter	0.227	0.273**	0.189**	0.146*	0.294***	0.243***	0.243**	0.245***	0.248**	0.284**
	(0.151)	(0.104)	(0.0848)	(0.0844)	(0.0884)	(0.0883)	(0.117)	(0.0930)	(0.109)	(0.133)
obs	556	556	551	542	512	476	459	435	375	361
Cragg	43.84	65.67	103.88	100.85	142.42	125.02	73.66	121.74	74.89	43.08
Museum FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The table presents the results of Ithe 2SLS model using the 90th and the 95th percentiles of the tweeters' engagement distribution. *activity on twitter* is given the sum of tweets and engagement. All models include controls for the number of exhibitions, popularity of the exhibitions, their interaction, months with a 5th weekend, average temperature, days of rain, the number of museum's tweets in a month, the tweeter's average sentiment score, the number of followers, whether a Twitter account is art-related, year fixed effects. All variables in lower case are log tranformed. Driscoll-Kraay standard error are in parentheses. * Significant at the 10% level; ** Significant at the 5% level; *** Significant at the 1% level.

Table 7: 2SLS. CENSORED FOLLOWERS' DISTRIBUTION

(a) IV regressions q95

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	museum visits									
activity on Twitter	0.173*	0.216**	0.228**	0.214***	0.254***	0.287***	0.284***	0.202***	0.149**	0.147
	(0.102)	(0.1000)	(0.0873)	(0.0719)	(0.0864)	(0.0735)	(0.0731)	(0.0747)	(0.0669)	(0.0903)
obs	747	733	711	686	665	614	607	542	494	428
Cragg	28.33	47.03	86.96	134.27	111.81	209.51	163.53	228.96	194.46	137.12
Museum FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

(b) IV regressions q90

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	museum visits									
activity on Twitter	0.229**	0.382***	0.265***	0.308***	0.326***	0.232***	0.140	0.270**	0.251**	0.359**
	(0.109)	(0.129)	(0.0768)	(0.0845)	(0.0745)	(0.0873)	(0.0895)	(0.103)	(0.0996)	(0.158)
obs	723	686	634	602	579	530	480	443	397	294
Cragg	33.35	40.59	110.26	117.89	163.85	157.71	159.09	104.92	87.45	34.74
Museum FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The table presents the results of the 2SLS model using the 90th and the 95th percentiles of the tweeters' followers distribution. All specifications include controls for the number of exhibitions, popularity of the exhibitions, their interaction, months with a 5th weekend, average temperature, days of rain, the number of museum's tweets in a month, tweeter's average sentiment score, the number of followers, whether a Twitter account is art-related, year fixed effects, year fixed effects. All variables in lower case are log tranformed. Driscoll-Kraay standard error are in parentheses. * Significant at the 10% level; ** Significant at the 5% level; *** Significant at the 1% level.

We provide a further robustness check exercise in Table 8, where we construct the instruments using the residuals from a regression of engagement on tweets' characteristics [12]. After controlling for the characteristics of tweets, the only residual monthly variation is due to Tweeters' characteristics (for example, the size of their network, their exposure, their expertise on a particular topic etc.). The effect is still positive and statistically significant for the most of the specifications, even though it tends to be smaller.

[12] These characteristics are analyzed and discussed in Tables 13 and 14 in the subsection 9.2 of the Appendix

Table 8: 2SLS. RESIDUAL ENGAGEMENT

	museum visits									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
activity on twitter	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	76.2	63.73
Museum FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table presents the results of the 2SLS model using the residuals from a regression of *engagement* on tweets' characteristics. These characteristics include the number of hashtags, tags, websites, words and the presence of gifs, photos and videos. We include in the regression the number of followers and following of the tweeter, and the score of the sentiment analysis. Once we control for the characteristics of the tweets, the residual monthly variation depends just on the tweeter's characteristics. All models include controls for the number of exhibitions, popularity of the exhibitions, their interaction, months with a 5th weekend, average temperature, days of rain, the number of museum's tweets in a month, tweeter's average sentiment score, followers, and art-related account. All variables in lower case are log tranformed. Driscoll-Kraay standard error are in parentheses. * Significant at the 10% level; ** Significant at the 5% level; *** Significant at the 1% level.

We also do a placebo test using, as a treatment that should not affect the outcomes, the lead of the Activity on Twitter. The idea is that future activity on Twitter should not affect the past number of museums' visitors. As expected, we do not find any effect. The coefficient on $Activity\_on\_Twitter_{it+1}$ is not significant in any of the specifications, as reported Table 9.

Table 9: 2SLS. PLACEBO TEST

	museum visits									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
activity on twitter	-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)
obs	739	740	741	737	736	731	725	719	706	679
Cragg	55.69	63.52	62.68	80.37	92.57	93.24	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

Notes: This table presenst results of 2SLS model using the lead of each of the 10 indexes of engagement to instrument for the lead of activity on Twitter ($Activity\_on\_Twitter_{it+1}$). All variables in lower case are log trasnformed. All specifications include controls for the number of exhibitions, popularity of the exhibitions, their interaction, months with a 5th weekend, average temperature, days of rain, the number of museum's tweets in a month, tweeter's average sentiment score, the number of followers, whether a Twitter account is art-related, year fixed effects, year fixed effects. Driscoll-Kraay standard error are in parentheses. * Significant at the 10% level; ** Significant at the 5% level; *** Significant at the 1% level.

6 Heterogeneity

To investigate whether there is heterogeneity of the effect in age and gender, we use data from the “Associazione Abbonamento Musei” (AAM) that collects information about the socio-demographic characteristics of visitors who enter the museums with the “Carta Abbonamento Musei” (a museums membership card that gives the customer free entry to museums, castles, special exhibitions in Piedmont for one year from the date of purchase) [13] .

Even though members of the “Associazione Abbonamento Musei” are a positive selection of individuals in terms of cultural consumption, other things being equal, they might decide to visit a museum because they get some information via Twitter. We divide individuals in 5 different age groups (13-17, 18-24, 25-34, 35-49, over 50) and we aggregate the number of museums' visitors at month-museum level.

Panel (a) of Table 10 shows that the activity on Twitter, with just one exception, increases visits to museums just for young people aged 18 -24 (see table 12 in the Appendix for the other age groups). The result is statistically significant in 4 out of 10 cases. When we look at gender heterogeneity in the age group 18-24, we find that the effect is driven by women and it is significant in 8 out of 10 cases (panel (d)). Doubling the activity on Twitter increases their visits to museums by 21 - 40%. This is an important result if we consider that young people are the ones who go less to museums representing just around 7% of the total number of visitors who bought the “Carta Abbonamento Musei" (see Figure 3) and this is also true in the US ((AMACAD, 2017)). In countries like the US, where philanthropic contributions are the primary source of funding for most art organizations, the absence of young people from museums might turn out to be an existential threat. As the older generation, major donors to museums, steps back or passes away, art leaders are grappling with attracting the interest of their heirs (Halperin (2024)). Being able to engage a young audience now, increases the likelihood of their future visits and, ideally, sets them on the path to becoming donors. According to a case study done by (Mock, 2023) one of the reasons why younger generations do not go to museums is that “advertisements about museums are not present, they are not loud enough, not bright enough” and an easy access to information about museums thorugh social media could be an effective strategy to bring young people closer to cultural institutions. Our results support this idea.

[13]Data from the Osservatorio Culturale del Piemonte do not provide information about age and gender of the museums' visitors.

Table 10: HETEROGENEITY

(a) Cohort 18-24

	18-24 Visits									
activity on twitter	0.160	0.175	0.311***	0.172	0.115	0.282*	0.326*	0.302*	0.254	0.174
	(0.142)	(0.178)	(0.116)	(0.129)	(0.116)	(0.158)	(0.165)	(0.157)	(0.164)	(0.126)
obs	649	652	652	652	654	654	653	650	641	634
Cragg	42.58	55.77	49.93	81.16	110.26	95.43	108.58	126.34	147.16	158.4

Standard errors in parentheses

(b) Females

	Female Visits									
activity on twitter	-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	95.43	108.58	126.34	147.16	158.4

(c) Males 18-24

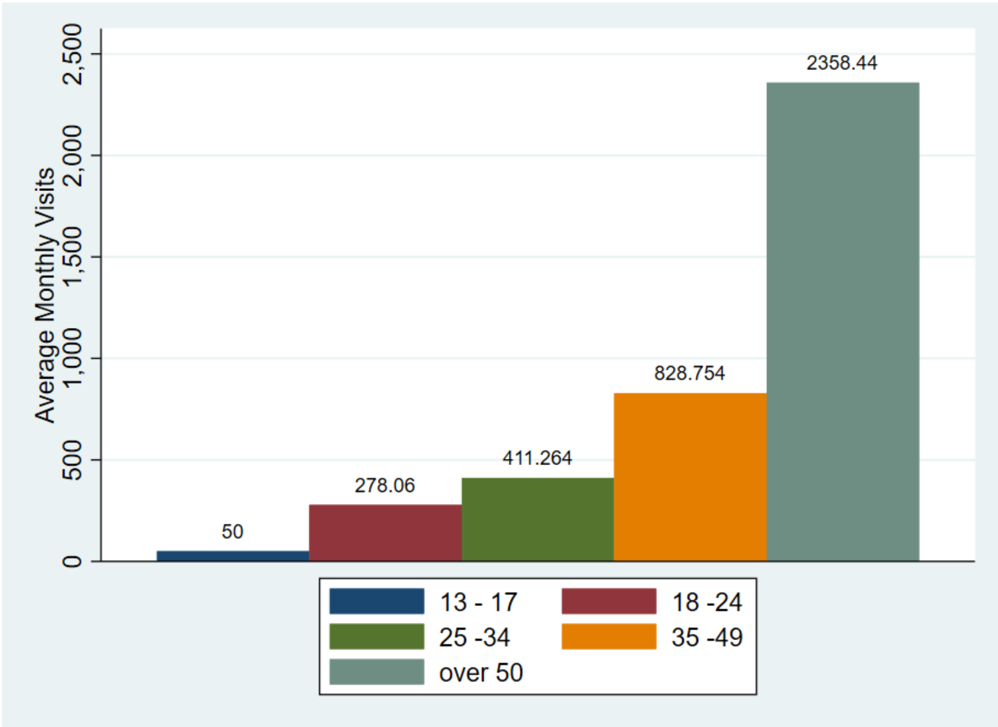
	Male 18-24									
activity on twitter	-0.00356	0.104	0.225**	0.0741	0.0705	0.208	0.200	0.213	0.190	0.108
	(0.135)	(0.168)	(0.107)	(0.125)	(0.101)	(0.145)	(0.152)	(0.148)	(0.148)	(0.117)
obs	649	652	652	652	654	654	653	650	641	634
Cragg	42.58	55.77	49.93	81.16	110.26	95.43	108.58	126.34	147.16	158.4

(d) Females 18-24

	Female 18-24									
activity on twitter	0.151	0.248	0.405***	0.270**	0.208*	0.370**	0.407**	0.361**	0.317*	0.239*
	(0.132)	(0.170)	(0.116)	(0.122)	(0.110)	(0.161)	(0.165)	(0.147)	(0.166)	(0.125)
obs	649	652	652	652	654	654	653	650	641	634
Cragg	42.58	55.77	49.93	81.16	110.26	95.4	108.58	126.34	147.16	158.4

Notes: In panel 10a and 10b we present iv regressions for 18-24 and female subgroups. In panel 10c and 10d there are iv regressions for the interactions of the two subgroups. All variables in lower case are expressed by their logs. The logged variable *activity on twitter* is given by $tweet + engagement$: the number of monthly tweets tweeted by users tagging a specific museum added to the engagement generated. The variable *museum visits* is the log count of monthly visits for each museum. Columns between 1 and 10 report the instrument for the just-identified IV. The instruments are the top 10 tweeters with the largest index. *Instrument1* refers to the tweeter who generates the highest average engagement. *Instrument10* to the one who generates the lowest one. All models include controls for the number of exhibitions, popularity of the exhibitions, their interaction, months with a 5th weekend, average temperature, days of rain, the number of museum's tweets in a month, tweeter's average sentiment score, followers, and art-related account. Driscoll-Kraay standard error are in parentheses. The Cragg statistic combines information from the first-stage F-statistic and the overidentification test to provide an overall assessment of the instruments. It is essentially an F-test of the null hypothesis that the instruments are weak or irrelevant. Under the specific null the instruments are weak, indicating that they do not explain a significant portion of the variation in the endogenous variable. * Significant at the 10% level; ** Significant at the 5% level; *** Significant at the 1% level.

Figure 3: MUSEUMS' VISITS BY AGE GROUP



Notes: The figure shows average museum's monthly visits by age group for members of "Associazione Abbonamento Musei"

7 Mechanisms

We analyze some potential mechanisms that might drive our results. We consider two main channels. First of all, activity on Twitter could lead to a displacement effect by bringing about some degree of reduction in the number of visitors in other museums that are not involved in any Twitter activity. Alternatively, Twitter could increase the total number of museums' visitors. To identify the mechanism we estimate the same 2SLS regression equation as in Panel 4c but we use data on all the museums that do not have a Twitter account and for which we have information on montly visits over the entire time span. We ended up with sixteen museums [14].

[14] Borgo e Rocca Medievale, Castello Ducale di Agliè, Castello Reale di Racconigi, Museo Accorsi-Ometto, Museo Civico Pietro Micca e dell'Assedio di Torino del 1706, Museo del Carcere Le Nuove, Museo della Frutta Francesco Garnier Valletti, Museo della Sindone, Museo di Anatomia Umana Luigi Rolando, Museo di Antropologia Criminale Cesare Lombroso, Museo Diffuso della Resistenza, della Deportazione, della Guerra, dei Diritti e delle Libertà, Museo Faa di Bruno, Museo Nazionale della Montagna Duca degli Abruzzi, Orto Botanico, Parco del Castello di Racconigi, Villa della Regina.

We find that Twitter activity about the eight museums that we use in our analysis, not only increases the visits those eight museums, but also to the other ones (the sixteen museums mentioned above). Table 11 shows that the effect is always positive and it is significant in 6 out of 10 cases with a coefficient that ranges between 9% and 15%. We conclude that there is no evidence of a displacement effect and that the activity on Twitter increases museums demand mostly through additional visits. The increase in museums' attendance for the sixteen museums might be explained by their geographical proximity to one of the eight museums that are affected by activity on Twitter or by the theories of addiction and learning by consuming applied to the arts [15]. **?** says that the arts are addictive "in the sense that an increase in an individuals present consumption will increase over time with exposure." The theory predicts that as consumers get more knowledgeable about art they will consume more of it. According to both theories, if museums' attendance increases, we should expect, other things being equal, an increase in future demand for museums' exhibitions.

Table 11: MECHANISMS

	other museums									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
activity on twitter	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	99.76	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

Notes: This table provides results of IV regressions using aggregated visits of museum that do not use twitter. All variables in lower case are expressed by their logs. The logged variable *activity on twitter* is given by $tweet + engagement$: the number of monthly tweets tweeted by users tagging a specific museum plus to the engagement generated. *other museums* is the log of aggregated monthly visits for each museum that do not use twitter. Columns between 1 and 10 report the instrument for the just-identified IV.The instruments are the top 10 tweeters with the largest index. *Instrument1* refers to the tweeter who generates the highest average engagement. *Instrument10* to the one who generates the lowest one. All models include controls for the number of exhibitions, popularity of the exhibitions, their interaction, months with a 5th weekend, average temperature, days of rain, the number of museum's tweets in a month, tweeter's average sentiment score, followers, and art-related account. Driscoll-Kraay standard error are in parentheses. The Cragg statistic combines information from the first-stage F-statistic and the overidentification test to provide an overall assessment of the instruments. It is essentially an F-test of the null hypothesis that the instruments are weak or irrelevant. Under the specific null the instruments are weak, indicating that they do not explain a significant portion of the variation in the endogenous variable. * Significant at the 10% level; ** Significant at the 5% level; *** Significant at the 1% level.

[15] People get addicted not only to alcohol, cocaine, and cigarettes but also to work, eating, music, television, their standard of living, other people, religion, and many other activities (Becker and Murphy (1988))

8 Conclusions

We measure the impact of online user generated information on real world economic outcomes. We find that doubling the activity on Twitter would increase the number of visitors by 15 - 27%. We also perform a back-of-the-envelope calculation: moving from the first 8 deciles in Twitter activity to the 9th one[16], a museum would increase the number of visitors by 20,747 units [17]. Since the average minimum and maximum ticket price for the eight museums of our analysis is, respectively, 8.579$ and 13.778$, an increase of 20,747 visitors would translate into an increase in revenues ranging between 177,988.51$ and 285,852.17$ for each museum. It is important to stress that the benefits of cultural consumptions go far beyond an increase in revenues for museums (and in tourism for the city, see Campaniello and Richiardi (2018)). Culture generates positive spillovers - the beneficial effects that engaging in cultural activities have on individuals and society beyond the direct experience itself - enhancing tolerance and fighting prejudice, thus reducing social exclusion (Ferraro et al. (2019), Denti, Crociata and Faggian (2023)), spurring innovation through new ideas or processes, improving well-being, health and cognitive skills (OECD (2022). But their measure is out of the scope of our work.

As for the mechanisms, we show that there is no evidence of a displacement effect and that the activity on Twitter increases museums demand mostly through additional visits. Activity on Twitter about the eight museums of our study, generate positive spillovers on the visits to museums of the metropolitan area of Torino that are not present on Twitter (their attendance increases by 9 - 15%). We find that the cultural consumption of young people, in the 18-24 cohort, mainly women, is the most positevely affected by Twitter activity. It is an important result considering that young people are largely absent from museums and that in countries, like the US, where museums are highly dependent on patronage, this might pose a threat to their future existence.

Word of mouth strategies have a significant role in empowering museums' marketing strategies. Through social media platforms, these techniques allow to reach a potentially unlimited number of people Hausmann (2012). But how could museums increase activity on Twitter? Online presence and skilled media managers who are able to engage their followers might be effective ways to boost activity on Twitter and, in turn, to increase visits, revenues and the

[16]The museum at the 9th decile of the distribution of *activity on Twitter* is Reggia di Venaria Reale

[17]We calculated each deviation between the 9th decile and the other deciles of the distribution, then we averaged the deviations and multiplied for the mean of coefficients from panel 4c, equal to 0.2054. The total average variation, 0.68, times the mean of total visitors, 30,849, results in 20,747 units.

number of new donors.

9 Appendix

9.1 IV regressions with all the controls

Table 12 show the IV results with all the controls.

Table 12: 2SLS. FULL SET OF COVARIATES

	museum visits									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
activity on twitter	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)
exhibitions	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)
popularity of the exhibition	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)
exhibitions#popularity	-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)
5th Weekend	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)
average temperature	-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)
days of 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)
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)
Sentiment score	0.0904	-0.153**	0.0736	-0.0104	-0.00626	-0.112	0.0818	0.0578	-0.0528	0.0337
	(0.0742)	(0.0746)	(0.0780)	(0.0683)	(0.0635)	(0.137)	(0.0648)	(0.0706)	(0.0737)	(0.0823)
followers	0.00948	-0.0191*	-0.0178*	-0.000648	-0.00911	0.00425	-0.0146	-0.00779	-0.0131	-0.00497
	(0.00904)	(0.0107)	(0.00982)	(0.00951)	(0.00881)	(0.0102)	(0.00991)	(0.01000)	(0.0106)	(0.0119)
Art Related	0.0691	-0.0223	-0.0475	-0.140**	0.0468	-0.0242	-0.118**	0.0402	0.0605	-0.0429
	(0.0503)	(0.0533)	(0.0544)	(0.0553)	(0.0475)	(0.0504)	(0.0527)	(0.0523)	(0.0686)	(0.0472)
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

Notes: The table presents the results of IV regressions in 4c with the full list of control variables. Each Column report the estimates using the relative instrument for the just-identified IV. All variables in lower case are expressed by their logs. The logged variable *activity on twitter* is given by $tweet + engagement$: the number of monthly tweets tweeted by tweeter tagging a specific museum plus the engagement generated. The variable*exhibitions* is the log number of exhibitions hosted by each museum, *Popularity of the Exhibition* ranks the exhibitions according to their popularity relative to Picasso searches on Google trends, *5th WE* is a dummy variable equal to 1 if a month has an extra weekend (meaning 5 Saturdays and 5 Sundays) and 0 otherwise, *exhibitions#Popularity* is the interaction between the number of exhibitions and their popularity. The *average temperature* is the average temperatures (in Celsius degrees) in Turin and *days of rain* is the log of rainy days in Turin. The variable *museums tweets* is the log number of tweets tweeted by the eight museums. *Sentiment score* measures the 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, *followers* is the log number of followers of tweeters, and *Art-related* is a dummy variable equal to 1 if the Twitter account is either an art, touristic and/or cultural Twitter account. Driscoll-Kraay standard error are in parentheses. The Cragg statistic combines information from the first-stage F-statistic and the overidentification test to provide an overall assessment of the instruments. It is essentially an F-test of the null hypothesis that the instruments are weak or irrelevant. Under the specific null the instruments are weak, indicating that they do not explain a significant portion of the variation in the endogenous variable. * Significant at the 10% level; ** Significant at the 5% level; *** significant at the 1% level.

9.2 Characteristics of tweets

We examine the characteristics of tweets that affect engagement, individual actions (retweets, replies, likes, or quotes), and Activity on Twitter. To differentiate between top influencers and other accounts, we divide our sample into two parts. In Table 13, we use observations below the 99th percentile of the engagement distribution while in Table 14, we use observations in the top 1% of the engagement distribution.

In the first two columns of both tables, the dependent variable is *engagement* and is regressed against various tweet characteristics: number of hashtags, tags, websites, words, gifs, photos, videos, followers and followings, emotions expressed in the tweet (positive, negative, neutral) [18]. Column (1) includes *followers* and *following* as explanatory variables, while column (2) introduces *Tweeter fixed effects.*
In columns 3 - 6 the dependent variables are *retweet*, *reply*, *like*, and *quote*, respectively.
The dependent variable in the last three columns (7, 8, and 9) is *Activity on Twitter.* We use linear and Poisson estimators. In particular, in column (7) and (8) we include *followers* and *following* as explanatory variables and, in column (9), we control for *Tweeter fixed effects.*
Table 13 shows that the number of *hashtags*, *words*, *websites linked* and of *followers* positively influence the dependent variable. On the other hand, the number of *tags* exhibits a negative correlation with the dependent variables in all cases except one (column 7). Tweets with negative content generate a larger positive effect on the dependent variables than neutral ones, while the opposite holds true for tweets with positive content. Multimedia objects (*gifs*, *photos*, and *videos*) consistently exhibit a negative relationship with the dependent variable, with the exception of specifications in columns (8) and (9) where the dependent variable is *Activity on Twitter.*

In Table 14, it is evident that most explanatory variables are not significant for top influencers. The only exceptions are the number of *tags*, *websites linked*, *words*, and *followers.* *Tweeter fixed effects* account for a significant portion of the variability. Top influencers generate engagement because they have devote followers who trust their honest opinions and experiences.

[18] We conduct a sentiment analysis by creating a categorical variable where the reference category is neutral sentiment)

Table 13: CHARACTERISTICS OF TWEETS. 99% OF THE DISTRIBUTION

	Engagement		# Retweet	# Replies	# Likes	# Quotes
	(1)	(2)	(3)	(4)	(5)	(6)
	tot_engagement	tot_engagement	retweet_count	reply_count	like_count	quote_count
hashtags	0.382**	0.719***	0.280***	-0.00543	0.434***	0.0105*
	(0.165)	(0.133)	(0.0349)	(0.0171)	(0.0893)	(0.00599)
tags	-0.151**	-0.391***	-0.0365	-0.0342***	-0.308***	-0.0124***
	(0.0754)	(0.109)	(0.0305)	(0.00911)	(0.0756)	(0.00300)
sites	4.379***	3.281***	1.245***	0.264***	1.637***	0.135***
	(0.671)	(0.663)	(0.163)	(0.0835)	(0.439)	(0.0419)
clear_num_of_words	0.418***	0.308***	0.0818***	0.00913*	0.207***	0.00969***
	(0.0322)	(0.0366)	(0.00802)	(0.00530)	(0.0252)	(0.00374)
gifs	-4.733	-1.032	-0.341	-0.430***	-0.107	-0.154***
	(3.042)	(1.794)	(0.474)	(0.0979)	(1.279)	(0.0427)
photos	-11.00***	-1.810**	-0.302	-0.627***	-0.679	-0.201***
	(1.048)	(0.739)	(0.186)	(0.0799)	(0.497)	(0.0375)
videos	-13.40***	-1.328	0.156	-1.087***	-0.123	-0.273***
	(2.493)	(2.281)	(0.564)	(0.196)	(1.586)	(0.0792)
0.sentiment	4.312***	2.519***	0.633***	0.468***	1.471***	-0.0539
	(0.541)	(0.477)	(0.109)	(0.122)	(0.309)	(0.0723)
2.sentiment	-1.405***	0.0817	0.0286	0.0914**	0.0218	-0.0602**
	(0.399)	(0.189)	(0.0414)	(0.0364)	(0.129)	(0.0271)
log_foll	7.720***					
	(0.534)					
log_folling	-3.051***					
	(0.345)					
obs	396354	396503	396503	396503	396503	396503
R2 adj	.11	.52	.48	.39	.51	.28
Museum FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Author FE	No	Yes	Yes	Yes	Yes	Yes

Notes: This table provides correlation evidence between twitter activities and tweets' characteristics. These regressions do not consider observations associated with engagement above the 99th percentile. *Engagement* is the count of several actions: *Retweet*, *Reply*, *Like* and *Quote* the tweet. Column (1) includes, as extra explanatory variables, the number of followers the user has and the number of accounts he follows. Column (2) includes the Tweeter (Author) fixed effects. Columns (3), (4), (5) and (6) show outputs when the dependent variable is, respectively, a retweet, reply, like and quote. The characteristics of each tweet are the number of *Hashtags* (#), *Tags* (@) and *Websites* used in a single tweet, while textitWords is the number of complex words written in it. *Gifs*, *Photos* and *Videos* are dummy variables indicating the presence of any of these elements in a tweet. Sentiment is a categorical variable (negative, neutral, and positive), which takes the neutral level as reference. Clustered standard errors at the author level are in parentheses. * Significant at the 10% level; ** Significant at the 5% level; *** Significant at the 1% level.

Table 14: CHARACTERISTICS OF TWEETS. TOP 1% OF THE DISTRIBUTION

	Engagement		# Retweet	# Replies	# Likes	# Quotes
	(1)	(2)	(3)	(4)	(5)	(6)
	tot_engagement	tot_engagement	retweet_count	reply_count	like_count	quote_count
hashtags	1360.2	85.77	79.34	5.849	-21.46	22.03
	(1453.4)	(808.1)	(147.0)	(69.58)	(618.8)	(25.65)
tags	-3934.3***	-1269.3	-181.8*	-400.7	-672.1	-14.71
	(1001.9)	(772.4)	(110.0)	(372.0)	(462.9)	(27.15)
sites	-2393.1**	-4596.1***	-511.6***	35.55	-4085.2***	-34.78
	(1135.7)	(1264.3)	(178.4)	(245.4)	(1028.4)	(51.62)
clear_num_of_words	-311.2**	6.046	6.470	3.080	0.348	-3.852**
	(125.8)	(44.39)	(7.125)	(3.564)	(34.63)	(1.935)
gifs	3757.7	-3361.4	-404.3	-538.1	-2452.1	33.04
	(10490.4)	(3396.8)	(530.6)	(346.9)	(2733.1)	(140.9)
photos	-3435.4	-1518.3	-412.9	-408.7	-565.5	-131.3
	(3531.5)	(4507.5)	(708.3)	(330.6)	(3555.2)	(177.7)
videos	-1618.3	4312.7	184.1	-89.94	4294.3	-75.81
	(7923.8)	(3968.0)	(536.8)	(494.7)	(3395.6)	(148.6)
0.sentiment	-2833.3	-947.4	-80.79	233.2	-1093.4	-6.465
	(3640.8)	(2166.5)	(386.5)	(321.3)	(1657.2)	(99.24)
2.sentiment	-2158.1	-4268.6	-860.2	191.9	-3466.4	-133.9*
	(3607.1)	(3475.1)	(631.3)	(466.9)	(2664.1)	(72.67)
log_foll	2089.3*					
	(1072.9)					
log_folling	-1437.4**					
	(644.0)					
obs	3991	4003	4003	4003	4003	4003
R2 adj	.03	.78	.85	.25	.77	.29
Museum FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Author FE	No	Yes	Yes	Yes	Yes	Yes

Notes: This table provides correlation evidence between twitter activities and tweets' characteristics. These regressions consider observations associated with engagement above the 99th percentile. *Engagement* is the count of several actions: *Retweet*, *Reply*, *Like* and *Quote* the tweet. Column (1) includes, as extra explanatory variables, the number of followers the user has and the number of accounts he follows. Column (2) includes the Tweeter (Author) fixed effects. Columns (3), (4), (5) and (6) show outputs when the dependent variable is, respectively, a retweet, reply, like and quote. The characteristics of each tweet are the number of *Hashtags* (#), *Tags* (@) and *Websites* used in a single tweet, while textitWords is the number of complex words written in it. *Gifs*, *Photos* and *Videos* are dummy variables indicating the presence of any of these elements in a tweet. Sentiment is a categorical variable (negative, neutral, and positive), which takes the neutral level as reference. Clustered standard errors at the author level are in parentheses. * Significant at the 10% level; ** Significant at the 5% level; *** Significant at the 1% level.

References

Allcott, Hunt, Luca Braghieri, Sarah Eichmeyer, and Matthew Gentzkow. 2020. "The Welfare Effects of Social Media." *American Economic Review*, 110(3): 629–76.

AMACAD. 2017. "Why Millennials Aren't Going To Museums." *American Academy of Arts and Sciences.*

Becker, Gary S, and Kevin M Murphy. 1988. "A theory of rational addiction." *Journal of Political Economy*, 96(4): 675–700.

Bhuller, Manudeep, Gordon B Dahl, Katrine V Løken, and Magne Mogstad. 2020. "Incarceration, recidivism, and employment." *Journal of Political Economy*, 128(4): 1269–1324.

Campaniello, Nadia, and Matteo Richiardi. 2018. "The role of museums in bilateral tourist flows: evidence from Italy." *Oxford Economic Papers*, 70(3): 658–679.

Carvalho, Joana, and Rui Raposo. 2012. "The adoption of social media by museums as a communication tool: helping museums get into the game." Vol. 10.

Denti, Daria, Alessandro Crociata, and Alessandra Faggian. 2023. "Knocking on Hell's door: dismantling hate with cultural consumption." *Journal of Cultural Economics*, 47(2): 303–349.

Dobbie, Will, Jacob Goldin, and Crystal S Yang. 2018. "The effects of pre-trial detention on conviction, future crime, and employment: Evidence from randomly assigned judges." *American Economic Review*, 108(2): 201–240.

Driscoll, John C, and Aart C Kraay. 1998. "Consistent covariance matrix estimation with spatially dependent panel data." *Review of economics and statistics*, 80(4): 549–560.

Ferraro, Aniello, Massimiliano Cerciello, Massimiliano Agovino, and Antonio Garofalo. 2019. "The role of cultural consumption in reducing social exclusion: empirical evidence from Italy in a spatial framework." *Economia Politica*, 36(1): 139–166.

Freberg, Karen, Kristin Graham, Karen McGaughey, and Laura A. Freberg. 2011. "Who are the social media influencers? A study of public perceptions of personality." *Public Relations Review*, 37(1): 90–92.

Halperin, J. 2024. "The hangover after the museum party: institutions in the US are facing a funding crisis." *The Art Newspaper.*

Hausmann, Andrea. 2012. "The Importance of Word of Mouth for Museums: An Analytical Framework." *International Journal of Arts Management*, 14: 32–43.

Hinnosaar, Marit, Toomas Hinnosaar, Michael Kummer, and Olga Slivko. 2021. "Wikipedia matters." *Journal of Economics & Management Strategy*, n/a(n/a).

Hutto, C., and Eric Gilbert. 2014. "VADER: A Parsimonious Rule-Based Model for Sentiment Analysis of Social Media Text." *Proceedings of the International AAAI Conference on Web and Social Media*, 8(1): 216–225.

Kling, Jeffrey R. 2006. "Incarceration length, employment, and earnings." *American Economic Review*, 96(3): 863–876.

Liu, Shixi, Cuiqing Jiang, Zhangxi Lin, Yong Ding, Rui Duan, and Zhicai Xu. 2015. "Identifying effective influencers based on trust for electronic word-of-mouth marketing: A domain-aware approach." *Information Sciences*, 306: 34–52.

Luca, Michael. 2016. "Reviews, reputation, and revenue: The case of Yelp. com." *Com (March 15, 2016). Harvard Business School NOM Unit Working Paper*, , (12-016).

Mock, S. 2023. "What is causing the lower frequency of millennials visiting museums?" *Medium.*

OECD. 2022. *The Culture Fix.*

Reimers, Imke, and Joel Waldfogel. 2021. "Digitization and pre-purchase information: the causal and welfare impacts of reviews and crowd ratings." *American Economic Review*, 111(6): 1944–1971.

Stock, James H, and Motohiro Yogo. 2002. "Testing for weak instruments in linear IV regression."

Vassiliadis, Chris, and Zoe-Charis Belenioti. 2017. "Museums & cultural heritage via social media: an integrated literature review." *Tourismos*, 12(3): 97–132.