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The impact of Twitter on consumption: Evidence from museums

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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, 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.

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1 Introduction

In our study, we investigate the impact of Twitter activity [1] 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, Twitter, TikTok, and Instagram to receive news and information, supplementing or even replacing traditional media. Twitter, with its vast user base of over 330 million active monthly users, stands out as a powerful social media marketing channel, offering timely information. According to the Twitter website, users utilize the platform to discover new things, share recommendations, and narrate their experiences, making it a valuable tool for museums to engage with the public. We collected tweet data using the Twitter API. Unfortunately, due to platform restrictions, we couldn't include data from other social media platforms like Facebook and Instagram in our analysis.

Our research focuses on museums for several reasons. Firstly, museums exhibit considerable variability over time, making timely information crucial. Secondly, they significantly impact the local economy and generate positive spillover effects. Thirdly, museums have faced unprecedented challenges and opportunities during the COVID-19 pandemic, especially in the realm of digital technologies.

Social media platforms have become indispensable tools for museums worldwide. 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.

[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.

In our study, we focus on eight 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 city, where innovation and culture play pivotal roles in its development. These museums faced significant challenges during the pandemic-induced lockdowns, with visitor numbers dropping to zero. They are now striving to regain their pre-pandemic attendance levels. These cultural institutions host both permanent and temporary exhibitions, encouraging visitors to return by offering varied and changing artistic experiences.

Employing an instrumental variable approach, 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. Increased Twitter activity concerning these eight museums also positively impacts visits to other museums, resulting in a 9% - 14% rise.

This finding holds significant importance. Museums not only enhance visitation rates and attract tourism, as demonstrated by (Campaniello and Richiardi, 2018), but also generate positive externalities through the arts. Extensive evidence in economic literature supports the idea that highly educated and skilled individuals, often referred to as "human capital" are key drivers of economic development. Regions offering cultural amenities and fostering creativity and diversity, often associated with "the bohemia", become attractive to talented individuals (Florida, Mellander and Stolarick (2008); Florida (2002)). Clusters of talented individuals, in turn, increase regional productivity (Borowiecki (2013); Moretti (2021)). In summary, our research underscores the importance of social media, particularly Twitter, in driving cultural consumption, benefitting museums, local economies, and fostering a thriving cultural ecosystem.

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

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.

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 Wikipedia pages about cities 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 inter-linkages between museums and social networks. Vassiliadis and Belenioti (2017) review a series of publications on the issue and identify 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) insist 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) explore 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. 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 trustworthy 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.

Alatas et al. (2019) 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 [2]. Deactivation, in particular, was strongly and significantly correlated with an improvement in self-reported well-being.

Charitonos et al. (2012) 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.

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

3 Data

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.

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 1 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.

Table 1: Summary statistics

	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
# Museum 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
# Authors	303.5	265	233.2	212	768
5th Weekend	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. *Visits*, *Activity*, *Exhibitions* and *Museums' tweets* are variables all considered at a monthly level. *Visits* measure the number of people visiting a specific museum in a certain month. *Activity* 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. *Museums' 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 WE* is a dummy variable equal to 1 if a month has an extra weekend (meaning 5 Saturdays and 5 Sundays) and 0 otherwise.

Data on Twitter were collected from its official website using the Twitter Research Access API [3]. 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 2. 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

[3]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 [4]. We 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 [5]. Table 2 shows the summary statistics about data on Twitter. The average engagement is equal to 155 and the most common action is "to like" (with an average of around 112).

Table 2: Summary statistics

	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
# 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

Notes: The top panel presents summary statistics for the data. The unit of observation is a single tweet post.*Engagement* represents how users interact with a tweet, and it can include different actions that can be performed: *Retweet*, *Reply*, *Like* and *Quote* the tweet. The summary statistics of the characteristics of each tweet are also outlined, such as the average number of *Hashtags* (#), *Tags* (@) and *Websites* used. The most common action among these is to tag (other users or pages on Twitter). textitWords is the number of words written in. *Photos*, *Videos* and *Gifs* are variables indicating the presence of any of these elements in a tweet, and they are dummy variables equal to 1 if a tweet includes them 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

[4] 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.

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

link and the engagement variable [6]. *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 Table 1.
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 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, *5th WE*, which is equal to 1 if a month has an extra weekend (meaning 5 Saturdays and 5 Sundays) and 0 otherwise.

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

[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.

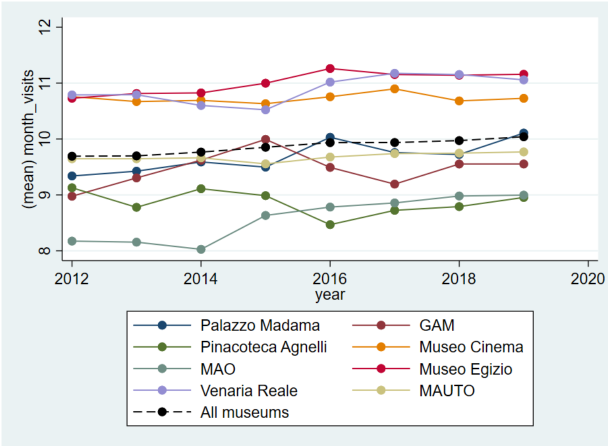
4 Empirical Strategy and Results

4.1 Descriptive evidence and empirical strategy

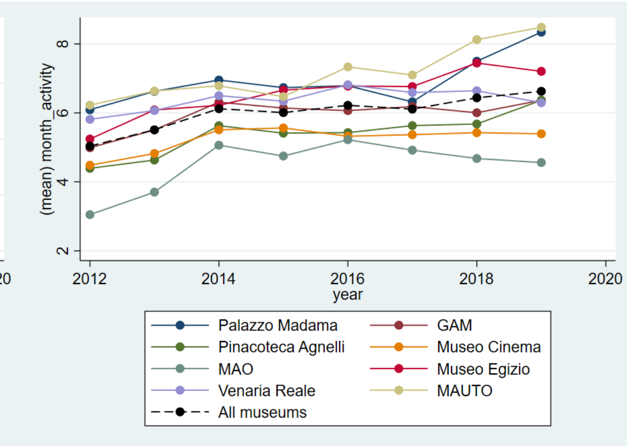
As a first preliminary evidence of the relationship between activity on Twitter and museum visits, we show raw data and simple correlations. The top panel of Fig.3 shows the trends of the (mean) number of monthly visits and Twitter activity for each of the museums included in our analysis over the period 2012-2019. The 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 3 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.

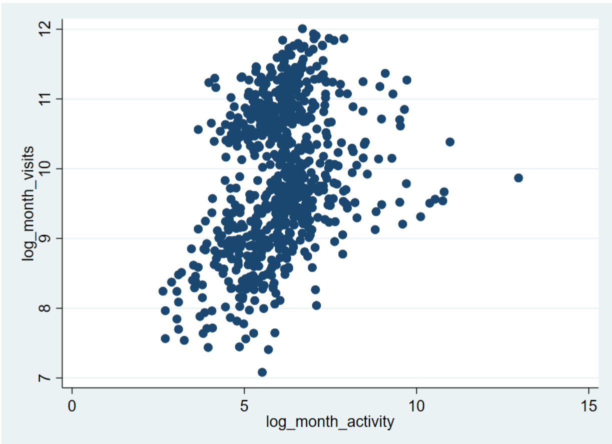
Figure 1: Twitter activity and cultural consumption.



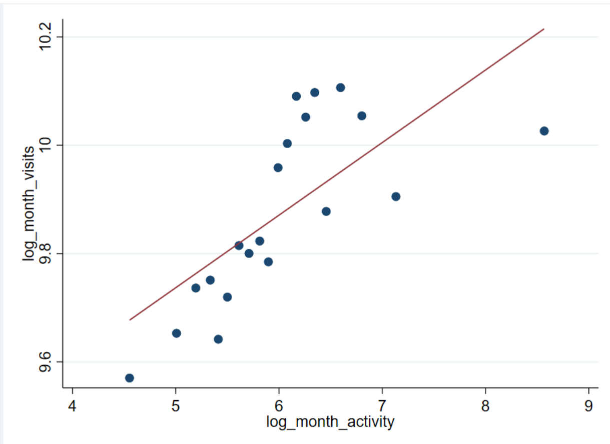
(1) *Yearly Visits*



(2) *Yearly Activity*



(3) *Scatter plot*



(4) *Binscatter*

Notes: The table reports raw data and simple correlations regarding our data. The top panel shows the trends of the natural logarithms of yearly museum visits (1) and Twitter activity (2) 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. The bottom panels show a positive correlation between log visits and log Activity on Twitter using both a parse (3) and a binned scatter plot (4). Figures 4 contains museum fixed effects.

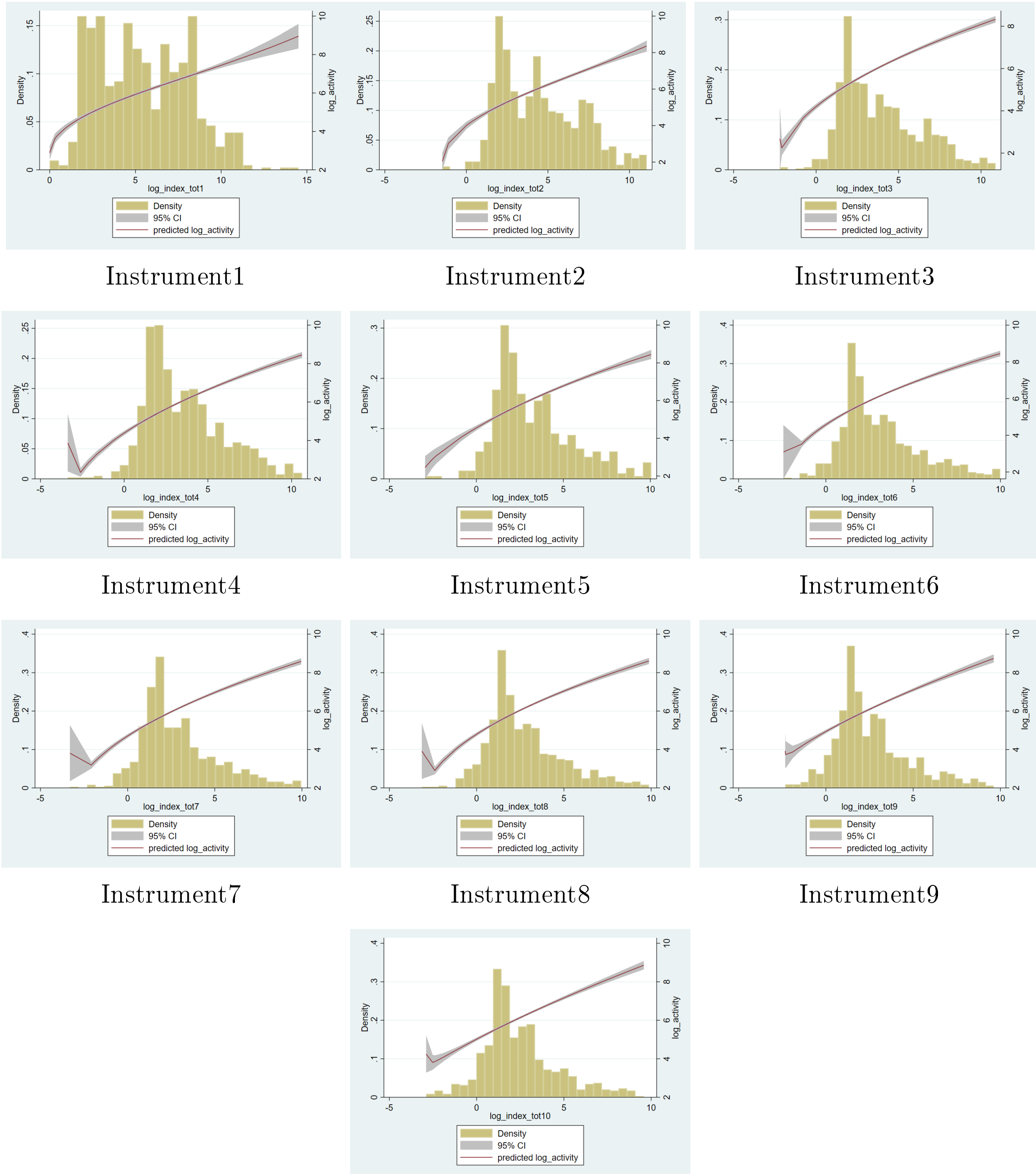
Even though we control for many observables that are likely to be correlated with both the number of visits at museums and activity on Twitter, our results might still be biased by unobservable factors. First, reverse causality might be at play if individuals increase their Twitter activities about museums 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. For each individual who tweeted about one of the 8 museums of our study over the period 2012-2019, we construct an index of engagement, $\bar{e}_{i,t,m}$, that measures his/her average ability to engage people. Engagement is measured as the sum of retweets, replies, quote, and likes. To avoid concerns of endogeneity we construct the index of engagement calculating the leave one out mean:

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

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.

As instrumental variables we use 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. The instruments' descriptive statistics are outlined in Table 3. The mean of the first index, *Instrument1*, is 7869 (with a standard deviation of 78330) 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 1002).

Figure 2: Visual first stage



Instrument1 Instrument2 Instrument3

Instrument4 Instrument5 Instrument6

Instrument7 Instrument8 Instrument9

Instrument10

Notes: The above Figure graphically represent the first stage, showing the relationship between the natural logarithm of *Activity on Twitter* and each of the 10 instrumental variables, one in each panel. *Instrument1* refers to the tweeter who generates the highest average engagement. *Instrument10* to the one who generates the lowest one. The graphs show a positive and approximately linear correlation between the two variables.

Figure 2 is a graphical representation of the first stage, that shows, in each panel, the relationship between each of the 10 instruments and the natural logarithm of *Activity on Twitter*. The correlation between the two variables is clearly positive and approximately linear in each panel.

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 and we control for three variables that describe some of the characteristics of the top 10 tweeters and the content of their messages: *Followers*, *Art-related* and *Sentiment score*. Table 3 shows their summary statistics.

Followers represents the number of followers of each Twitter account [8]. The number of followers decreases from the *Instrument1* (with a mean of 50,515 followers) to the *Instrument10* (with a mean of about 3,600 followers). This is in line with the fact that *Instrument1* refers to the individual who generates the highest engagement, while *Instrument10* to the one with the lowest one.

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

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

Table 3: Summary Statistics of the instrumental variables and their characteristics

	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 presents summary statistics of the instruments and the three control variables employed in the IV analysis. Means, standard deviations and the number of observations of these variables are outlined; median and interquartile range are in parenthesis. The table lists 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. *Sentiment 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. *Followers* indicates the number of followers of each Twitter account; *Art-related* is a dummy variable equal to 1 if the Twitter account is either an art, touristic and/or cultural page.

Finally, we conduct a sentiment analysis to study 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).

4.2 OLS results

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

$$museums\,visits_{it} = \beta\, activity\, on\, twitter_{it} + \theta\, \mathbf{X_{it}} + \kappa_i + \tau_t + \varepsilon_{it} \tag{1}$$

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 popularity of temporary exhibitions, 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 6).

We present the results of the baseline model in Table 4. In Column 1 we use information on all Tweeters altogether, while in the other columns we restrict our sample to the top 10 Tweeters (one in each column). Since Followers, Art-related ad Sentiment score are Tweeter-specific, they do not apper as controls in column 1.

Table 4: 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)
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)
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)
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)
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: Activity on Twitter is the number of monthly tweets tweeted by users tagging a specific museum added to the engagement generated. *activity on twitter* is logged. *exhibitions* is the log of the number of simultaneous exhibitions set up within a single museum in a specific 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 log average monthly registered temperatures for each specific year (in Celsius degrees). days of rain is the log number of days in which rain was recorded. Both *average temperature* and *days of rain* refer to values registered in the Turin geographic area. *museums tweets* represents the log number of tweets written by the 8 museums each month. *Sentiment 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. *followers* is the log number of followers that each person twitting has on his/her Twitter account, at the present day. *Art-related* 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).
In Column 1 the information regards all Tweeters, while in the other columns the sample is restricted to the top 10 Tweeters. 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

Table 5 reports the reduced form, first stage and IV estimates. Panel 5a shows the estimates for the reduced form. The coefficient on the instrument is positive and significant in 8 out of 10 cases. According to the estimates, doubling the *engagement* causes an increase between around 3% and 5% of monthly museums visits across the top Tweeters. Panel 5b shows that the estimates for the first-stage regressions are in line with the graphical representation in Figure 2. A doubling in *engagement* causes an increase between 10% and 24% of the monthly *Activity on Twitter* across the first ten contributors. Panel 5c 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%.

In Table 13 in 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 5: Baseline Results

(a) Reduced Form regressions

	(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 regressions

	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 regressions

	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 5c we present iv regressions along with the reduced form in panel 5a and the first stage in panel 5b. 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. *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. * Significant at the 10% level; ** Significant at the 5% level; *** Significant at the 1% level. 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.

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 5c. 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*.

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 6 shows that the coefficient on the instrument is significant in 7 out of 10 cases and the magnitude is sligthly lower than in Table 5.

Table 6: IVs: 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 presents the results of IV regressions with the use of month fixed effects. 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 users tagging a specific museum added to the engagement generated. *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. * Significant at the 10% level; ** Significant at the 5% level; *** significant at the 1% level. 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.

As a second robustness check, to make sure that our results are not driven by the top Twitter influencers, in Tables 7 and 8, 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 Tweeter contributions mechanically reduces the ranks of authors increasing the number of missing observations when we consider lower rank contributors for our instruments. Results are in line with those of Table 5. The coefficients remain positive and statistically significant in most of the specifications in any of the panels of Tables 7 and 8.

Table 7: IV regressions, censored tweeters' 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 IV regressions using the 75th, 90th and the 95th percentiles of the Tweeters' engagement distribution, using year fixed effects. All variables in lower case are expressed by their logs. Driscoll-Kraay standard error are in parentheses. 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. 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. * Significant at the 10% level; ** Significant at the 5% level; *** Significant at the 1% level. 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.

Table 8: IV regressions, censored tweeters' followers distribution

(a) IV regressions q95

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	museum visits									
log_activity	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									
log_activity	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 IV regressions using the 75th, 90th and the 95th percentiles of the Tweeters' engagement distribution, using year fixed effects. All variables in lower case are expressed by their logs. Driscoll-Kraay standard error are in parentheses. 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. 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. * Significant at the 10% level; ** Significant at the 5% level; *** Significant at the 1% level. 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.

We provide a further robustness check exercise in Table 9, where we construct the instruments using the residuals from a regression of engagement on tweets' characteristics [9]. After controlling for the characteristics of tweets, the only residual monthly variation is due to contributors' 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.

[9] These characteristics are analyzed and discussed in the Appendix in Tables 14 and 15.

Table 9: IV REGRESSIONS, 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 provides results of IV regressions 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. Moreover, they also refer to the number of followers and following of the user that is tweeting, and the relative sentiment analysis of his tweet. Once we control for the characteristics of the tweets, the residual monthly variation depends just on the contributors' characteristics. 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. *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. * Significant at the 10% level; ** Significant at the 5% level; *** Significant at the 1% level. 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.

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 10.

Table 10: Placebon test IVs: lead of the Activity on Twitter

	museum visits									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
F1, 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 provides results of IV regressions using lead of order 1 of the instruments to instrument lead of order 1 of *activity on twitter*. All variables in lower case are expressed by their logs. 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, and the number of museum's tweets in a month. 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. Driscoll-Kraay standard error are in parentheses. * Significant at the 10% level; ** Significant at the 5% level; *** Significant at the 1% level. 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.

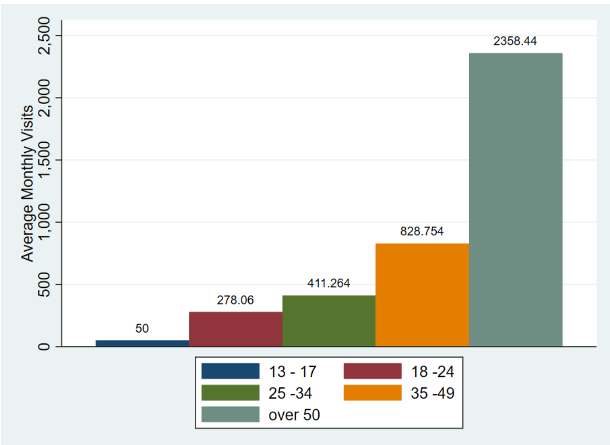
6 Heterogeneity

To investigate whether there is heterogeneity of the effect in age and gender, we use from the Associazione Abbonamento Musei that collects information about the socio-demographic characteristics of visitors who enter the museums through the single tickets bought at the ticket office and through 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) [10] .

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 count the number of museums' visitors at month-museum level.

Panel (a) of Table 11 shows that the activity on Twitter, with just one exception, increases visits to museums just for young people aged 18 -24 (tables that show results for the other age groups are in the Appendix).

Figure 3: Cultural consumption of AMP members by age



Notes: The figure shows average museum's monthly visits divided by age cohorts

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

Table 11: IV REGRESSIONS, HETEROGENEITY

(a) IV regressions 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) IV regressions, female visitor

	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) IV regressions, male 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) IV regressions, female 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 11a and 11b we present iv regressions for 18-24 and female subgroups. In panel 11c and 11d 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. *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. * Significant at the 10% level; ** Significant at the 5% level; *** Significant at the 1% level. 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.

The result is statistically significant in 4 out of 10 cases. When we look at gender heterogeneity in this age group, 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 as shown in Figure 3 representing just around 7% of the total number of visitors.

7 Mechanisms

We analyze the mechanisms by which the activity on Twitter does increase the number of visits to museums. 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 5c but, as for the variables related to museums, we use data on all the museums that were not included in the activity on Twitter.

We selected the museums involved in this analysis using the following criteria: they do not have a Twitter account and their montly visits data are complete. We ended up with sixteen museums [11].

We find that Twitter activity about the eight museums that we use in our analysis, not only increases the visits to the eight museums, but also to the other ones (the sixteen museums mentioned above). Table 12 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

[11] 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.

demand mostly through additional visits.

Table 12: IV regressions: other museums

	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

Standard errors in parentheses

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 added 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. * Significant at the 10% level; ** Significant at the 5% level; *** Significant at the 1% level. 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.

8 Conclusions

We measure the impact of online user generated information on real world economic outcomes. We find that doubling the activity on Twitter about museums would increase their visitors by 15 - 27%. Furthermore, we perform a back-of-the-envelope calculation to measure the impact of increasing museums' *activity on Twitter* from the first 8 deciles to the 9th one[12]. We find that the average museum in our sample would increase the number of visitors by 20,747 units. [13]. Since the average minimum and maximum ticket price for the eight museums of our analysis is, respectively, 8.579$ and 13.778$, an increase of 20,747 visitors would translate into an increase of museums' revenues ranging between 177,988.51$ and 285,852.17$. As for the mechanism, we show that there is no evidence of a displacement effect and that the activity on Twitter increases museums demand mostly through additional visits. Moreover, 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 number increase by 9 - 15%).

In our work we have measured the average effect of activity on Twitter on visits to museums. How could museums increase activity on Twitter? Online presence and collaboration with social media influencers who generate a strong engagement might be effective ways to boost activity on Twitter and, in turn, to increase visits and revenues.

Finally, it is worth mentioning that the benefits of cultural consumptions are not just related to an increase in revenues for museums (and in tourism for the city). 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

[12]The museum at the 9th decile of the distribution of *activity on Twitter* is La Venaria Reale

[13]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 5c, equal to 0.2054. The total average variation, 0.68, times the mean of total visitors, 30,849, results in 20,747 units.

(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.

9 Appendix

Table 13 show the IV results with all the controls.

Table 13: IVs: 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 5c with the full list of control variables. Each Column report the estimates using the relative instrument for the just-identified IV. *Activity on Twitter* is the number of monthly tweets tweeted by users tagging a specific museum added to the engagement generated. *activity on twitter* is logged. *exhibitions* is the log of the number of simultaneous exhibitions set up within a single museum in a specific 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 log average monthly registered temperatures for each specific year (in Celsius degrees). days of rain is the log number of days in which rain was recorded. Both *average temperature* and *days of rain* refer to values registered in the Turin geographic area. *museums tweets* represents the log number of tweets written by the 8 museums each month. *Sentiment 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. *followers* is the log number of followers that each person twitting has on his/her Twitter account, at the present day. Driscoll-Kraay standard error are in parentheses. * Significant at the 10% level; ** Significant at the 5% level; *** significant at the 1% level. 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.

In our analysis, we examine the characteristics of tweets that impact engagement, individual actions (retweets, replies, likes, or quotes), and overall Twitter activity. To differentiate between micro-influencers - individuals with thousands of followers and niche interests [14] - and other accounts, we divide our sample into two parts. In the first subset, we exclude observations falling within the last percentile of the engagement distribution. In the second subset, we focus on observations below the 99th percentile. This division allows us to distinguish between micro-influencers and other accounts, as micro-influencers often have highly engaged and trustful followers, potentially leading *Tweeter fixed effects* to capture the entire variation in the data.

Tables 14 and 15 present our findings for values below and above the 99th percentile, respectively. In the first two columns of both tables, *engagement* serves as the dependent variable, regressed against various tweet characteristics. Column (1) includes *followers* and *following* as explanatory variables, while column (2) introduces *Tweeter fixed effects.* Columns (3) to (6) present results for dependent variables *retweet*, *reply*, *like*, and *quote*, respectively. The last three columns (7, 8, and 9) focus on *Activity on Twitter* as the dependent variable, using linear and Poisson estimators, with column (7) and (8) including *followers* and *following* as explanatory variables and column (9) incorporating *Tweeter fixed effects.* Table 14 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). Additionally, we conducted sentiment analysis by creating a categorical variable where the reference level is the neutral sentiment.

Tweets with negative content exert a stronger positive effect on the dependent variables

[14] In our data, micro-influencers might be well known in the art world, but less well known to the general public.

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).

In Table 15, it is evident that most explanatory variables are not significant for micro-influencers. The only exceptions are the number of *tags*, *websites linked*, *words*, and *followers*. As anticipated, *Tweeter fixed effects* account for a significant portion of the variability.

Table 14

	Engagement		# Retweet	# Replies	# Likes	# Quotes	Author Monthly Activity		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
# 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)
# Websites	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)
# 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)
Sentiment: negative	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)
Sentiment: positive	-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)
followers	7.720***						13.89***		
	(0.534)						(0.741)		
followings	-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: 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. Columns (7), (8) and (9) report the results when you aggregate tweets by authors every month. The dependent variable is regressed on averaged characteristics using respectively a linear model in column 7 and 8, and a Poisson model in column 9. In particular, column (7) and (8) include, as explanatory variables, the averaged number of followers and following, while column (9) includes the Tweeter (Author) fixed effects. 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 15: Reduced Form Regressions: Outliers

	Engagement		# Retweet	# Replies	# Likes	# Quotes	Author Monthly Activity		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
# 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)
# Websites	-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)
# 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)
Sentiment: negative	-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)
Sentiment: positive	-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)
followers	2089.3*						3681.7**		
	(1072.9)						(1461.3)		
followings	-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	.83
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: 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. Columns (7), (8) and (9) report the results when you aggregate tweets by authors every month. The dependent variable is regressed on averaged characteristics using respectively a linear model in column 7 and 8, and a Poisson model in column 9. In particular, column (7) and (8) include, as explanatory variables, the averaged number of followers and following, while column (9) includes the Tweeter (Author) fixed effects. 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.

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