Art fair participation impact on online attention

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A study on the impact that participating in Art Basel Miami Beach art fair have for artists and galleries online attention.

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ABSTRACT

Art fairs are a rather important element in the art market. Hundreds of galleries and artists come together to offer art lovers a chance to appreciate and buy art, all complied in one event. With the advent of the Internet and social media platforms it is interesting to assess the impact that those events have online.

Using data retrieved from Google Trends, the effect that an offline event (as an art fair) has on online attention is going to be measured. In other words, we study the impact that Art Basel Miami Beach participation might have on galleries' and artists' online attention. In essence the empirical findings of this dissertation suggest that there are three main conclusions: from a descriptive perspective, the time-series analysis acknowledges that participation in ABMB does not seem to have an impact on online attention; there is solely a short-term impact for galleries online attention after participating in ABMB and lastly participation in ABMB has a long-term impact on online attention for artists exhibiting in one booth with two peers or less, compared with artists that exhibit in groups of more than three artists.The findings of this dissertation suggest that there is a slight effect, however not greatly pronounced.

Keywords: art fair, online impact, Art Basel Miami Beach, artist, gallery, Google Trends.

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1.Introduction

There is a lot that has been written about the Internet, web 2.0 and the cultural sector especially: interactive websites, the increasing use of social media by cultural organizations, or the new value that innovative virtual cultural experiences might add. The aim of this thesis is not to touch on any of the points above, but rather to look to the overall picture as the online attention that cultural organizations have been receiving. More important than having a Facebook page or an interactive website is actually to realize how much online attention cultural organizations are attracting. Rather than being focused on online strategies adopted by the cultural sector, this research is going to assess the effect that an offline cultural event might have on the participants' online attention.

This issue is particularly interesting in the art market, since this sector is considered rather subjective and secretive (Arora and Vermeylen, 2011), where a great part of the deals are not disclosed. In addition, due to the subjectivity of art itself, it is not easy to predict trends or the next conceptual artist. However, gallerists and art dealers are now starting to adopt online techniques in order to disseminate information about their goods. Although not as rapidly and innovative as museums, most galleries have now their own website and social media profiles. To note, most art galleries have an exclusive list of clients, thus they are not interested to appeal to the masses. Nevertheless, the great majority seems to start to want to have a presence online.

Looking to the art market as a whole, art fairs are by far the sector that tries to explore the most all the possibilities that the World Wide Web can offer. Being a once-a-year temporary event, massive online campaigns begin to emerge a couple of weeks before the event, in order to start a conversation between the organizers and the audience (Klamer, 2012) and attract visitors. However this research will not be focused on the effect that online campaigns have on actual visitor numbers, but quite the opposite: the effect that participating in an event has on online attention. In essence, I will examine the relationship between offline events and online attention. The assumption is that after participation in an art fair, online attention towards galleries and artists might increase. Hence the research question: does participation in an art fair have an impact on art galleries' and artists' online attention?

There is a considerable amount of research on the effect that digital campaigns might have in cultural organizations' attendance (Hume and Mills, 2011; Thomas and Carey, 2005), however online attention as an effect of participation in such events seems to be overlooked. The effect that an offline event might have on online attention is going to be measured with an interrupted time-series, comparing the online attention in the period before, during and after the art fair. Time-series enables measurements of successive points in time, separated by equal intervals (Cook and Campbell,1979). This dissertation is going to be focused on one of the most popular art fairs: Art Basel Miami Beach 2012 (ABMB) (Thompson, 2008). The second chapter complies a literature review on cultural organizations online adoption and its impact, followed by the main research question of this study, and an introductory note on the art fair chosen for this study: ABMB. The fifth chapter addresses the research design and its limitations, followed by the descriptive and inferential data analysis and its meaning. Lastly a summary of the empirical findings and general limitations of this research will be discussed in the conclusion. This dissertation aims to contribute to empirical research on the impact that digital resources might have in the art market.

2. Literature Review

2.1 Internet in the cultural sector

The world is connected through the Internet, as people communicate through websites, blogs, social media platforms and so forth. It is argued that in this century, a networked communication system will define the global power (Hodsoll, 2009). The Internet paves the way to do so. Any organization that is competing to increase its demand has a heavy online presence. This presence is achieved not only with complex and up-to-date websites, but also through trying to engage with the consumer through various social media platforms. Therefore, an organization's online adoption has not only a marketing purpose but also economic reasoning.

The World Wide Web is an amazing marketing tool since it disseminates information without boundaries, since a physical space is not needed (Kidd, 2010). Place and time are not a constraint, since online information can arrive at any connected household in the world, 24 hours per day, 7 days a week. The other advantages for marketing are word-of-month and bandwagon (or snowball) effects that the Internet offers (Haussman, 2012, Towse, 2010). Bandwagon or snowball effects occur when consumers follow the masses and make decisions influenced by others, instead of making individual decisions (Towse, 2010). Those effects spread easily and rapidly through the World Wide Web. In the end, organizations want to create awareness of their product or service, so they disseminate information to attract new customers. Related to bandwagon and snowball effects is word-of-month: a form of informal learning about a product by consumers (Haussman, 2012). This is a marketing tool often used by organizations, especially since the advent of social media platforms, defined by Haussmann (2012) as eWord-of-Mouth.

Another reason for the fast-growing Internet adoption by organizations is the economic advantages. The Internet is also a powerful tool to reduce search costs (Klein, 1998 and Towse, 2010). Search costs are essentially the time and money spent to search for a product and to assess its quality. Towse (2003) gives the example of buying a CD: before the Internet, one had to spend time and money to commute to the local music store and then spend time listening to some tracks to evaluate whether it was a product worth buying. From the consumer point of view, it is an advantage since the Internet enables consumers to have a sample of the products or service online.

In the last years, cultural institutions are also adopting Internet marketing strategies. In the last decade, cultural organizations' mindset has been shifting, with emphasis on education and access to information, making these instructions more relevant and inclusive to society. As a result, Internet Communication Technologies (ICT) and the Internet play a vital role in organizations' external communication (Loran, 2005). According to Loran (2005), ICTs supply new opportunities by giving easy access to organizations' services and knowledge, and by helping the audience enhance their participation in the cultural sector. The dissemination of knowledge is now possible on a scale bigger than ever. The author also states that online presence can also increase cultural organizations audiences, and educate visitors (Loran, 2005). Marty (2007) goes even further and acknowledges that there was a need to create a new set of individuals that would deal with new information resources, tools and technologies in the cultural sector. Due to the massive adoption of online resources, new content, technology and expertise is needed.

It can be argued that a shift is occurring in the relationship between the Internet and arts organizations. Instead of using the Internet only as a content provider, these institutions aim to create a relationship with the consumer (Vargo and Lusch, 2004 and Cowen, 2008). The role of the visitor shifted from being merely regarded as the recipient of goods, to being the co-creator of goods (Vargo and Lusch, 2004). Generally speaking, this shift is positively linked with the adoption of online resources by cultural organizations. Web 2.0 has enabled arts organizations to engage with its visitors, creating an online experience.

Cowen (2008) also examines the potential and power that the Internet supplies to cultural organizations. His thesis endorses the idea that consumer's online participation positively changes the connection that one has to culture and to cultural organizations - strengthening the connection. Social media platforms as Facebook, Twitter, Instagram, Pinterest, Linkedin and others, especially enable the demand to use culture and connect with others, sharing and shaping it (Cowen, 2008). It is a fact that culture helps to shape individuals tastes and character. By having presence online, cultural organizations enable consumers to not only appreciate culture online, but also easily sharing it with their peers.

In a report about art organizations and digital technologies, Pew Research Center (2013) concludes that such organizations are using online resources for marketing education, to grow their audience, sell tickets or even to raise funds online, exploiting this medium as much as possible. In research on more than 1000 arts organizations in the US between 2007 and 2011, it was concluded that 99% of arts organizations have their own website, 97% use social media and 69% of these organizations have individual employees to create exclusive content for this platforms. In addition, 94% of the organizations post pictures online about their services or products, and 72% sell tickets online (Pew Research Center [PRC], 2013). As a note, these results comply different types of cultural organizations, from art museums and art galleries, to performing arts and media arts centers. Nevertheless, it can be concluded that cultural organizations have been embracing and exploiting all the advantages that the World Wide Web has to offer.

2.2 Internet in the art market

The art market is known for being rather indefinite or imprecise, being one of the reasons for the subjectivity of art valuation (Arora and Vermeylen, 2011, Ginsburgh, 2003, Yogev and

Grund, 2012). The ‘nobody knows property’ (Caves, 2000) states the fact that no one can predict whether or not a good will be successful, is rather adequate for the art market. Trends and fads change, and it is always a surprise who will be the next big star in the art market.

As explained above, in the last years a shift has occurred (Vargo and Lusch, 2004). , where the consumer is regarded as an active player in the art market (Arora and Vermeylen, 2011). Engagement and cultural participation are now words part of the arts organizations vocabulary. Through digital platforms, and the so-called Web 2.0, consumers are now able to communicate directly with artists (Arora and Vermeylen, 2011). This “participatory culture” enables every consumer to have a voice. Due to the low entry barriers that internet offers (Towse, 2010), any individual with internet access can participate in the online art valuation process: “this new medium where walls between high and low culture crumble, where individuals and institutions become blurred and where producer and consumer share power in this new liberated sphere (Arora and Vermeylen, 2011, p,8). The question then arises whether Internet users are replacing art critics? Arora and Vermeylen (2011) have an interesting theory when trying to assess the impact that the World Wide Web might have for the art market. According to the authors, the appearance of a new wave of lowbrow, self-made art critics are not replacing the traditional ones, but rather create the necessity of valid and trustworthy professionals. Out of the thousands of voices heard about art and about what is good, there is a need for expertise to assess what is valuable and what is not.

As it was acknowledged in the previous section, cultural organizations are largely adopting online resources, impacting the way they interact with their audience. There several studies on museums’ online usage and impact, from their website to social media strategies (Marty, 2006; Loran, 2005; Haussmann, 2012; Schweibwnz, 2004; Santos, 1999). However there are very few specifically about the art market. Arora and Vermeylen (2011) examined the relationship between the art market and the advent of Internet, however it was only analyzed from the consumer’s perspective as content creators. There is a lack of research on online strategies in the art market from the supply side.

This fact leads to the conclusion that art galleries, visual artists and art fairs are not yet keen in being part of the world wide web. Initial research for this thesis showed that 34,67% of the art galleries that took part in Art Basel 2012 do not have, for example a Facebook page. Most artists or art galleries have a website, however these are considered what is commonly known as a brochure website (Pedro, 2009). Brochure websites supply basic information about the gallery, such as opening hours, contact information and artists represented. The aim of the brochure website is solely to inform potential visitors (Pedro, 2009).

Compared with museums, art galleries do not have the same relationship with the audience then the former. Museums are open institutions that supply a service for the community, and most of the time are even considered a public good (Towse, 2003). On the other hand, art galleries represent and sell exclusive works of art. The first has a one-to-million relationship with the audience; art galleries in contrast have a one-to-one relationship with potential buyers. Art galleries do not aim to attract the masses, but rather the wealthy players interested in art.

Nevertheless, due to competition and the economic crisis, art galleries have been making an effort to enhance their websites, and/or to have some presence on social media platforms. Due to the current economic crisis, the need for a more commercial understanding is increasing. Not only cultural organizations, but also visual artists are starting to find new ways to promote and sell their work. Applying Fillis (2004) theory, artists would need to use innovation, creativity, entrepreneurial thinking and network to do so.

2.3 The case of art fairs

Art fairs have a special "status" in the art market. In essence, galleries, the intermediaries represent artists, generally in return keep 50% of the price of piece of art (Velthuis, 2003). One of the most important events for art galleries are art fairs. In essence, art fairs are events that enable galleries to showcase their best works to a rather large number of arts enthusiasts. Having in one event a rather large group of galleries, attracts art lovers and collectors, since search costs are lowered (Towse, 2003) by having the chance to see art from more than a hundred galleries in one space (Thompson, 2012).

According to Graddy (2009), in Thompsons famous book "*The $12 million stuffed shark: The curious economics of contemporary art*" the author considers that the role of the art fairs has been increasing over the last years, becoming one of the key events in this market. In addition, art fairs are considered an "equalized force" (p.235, Graddy, 2009) for the art dealers to be able to compete with auction houses, stating that the quantity and quality of works of art presented in the best contemporary fairs, is the same in an auction's house entire season. However, it is also a necessary expense that galleries have to remain in the art circuit. Participating in a fair enables galleries and artists to not only meet potential buyers, but also as a sign of quality, for being featured in such event (Velthuis, 2003). Contemporary art fairs are nowadays so important that they actually add value to the contemporary art market. The only downside is that art fairs are time consuming and are rather expensive for art dealers (Thompson, 2012).

Broadly speaking, the art market seems not to be adopting online strategies similar to other cultural organizations. This conclusion is drawn after comparing museums, performing arts and other media related cultural industries with organizations in the art market. Since fairs are normally a once a year event, a lot is invested in promoting the event a few days before, and during the event. Before the event, the website is renovated with innovative features, and a massive social media campaign is initiated. An example is the media campaign noticed during Rotterdam Art Week 2013. Four major art fairs in Rotterdam were rather silent throughout the year, but in the first week of February, they exploded onto social media platforms. Another example is one of the most known art fairs: Art Basel Miami Beach. During the year, the social media activity was rather low every month, and the data during the event shows that several posts are generated per day.

Concerning academic research, there is a lack of literature concerning art fairs and their online strategies or impact. In fact, most of the articles that touch upon the art fair phenomenon either study the globalization issu,e or the network effects that are created in such event. The first acknowledges the fact that despite art fairs investment in internationalization (in terms of the participatory art galleries), the “territorial dimension” is still quite present. In essence, the national dimension is still most present than the international one (Quemin, 2013). On the same theme, van Hest (2013) is interested in territorial factors on art fairs and biennales. As a conclusion of this study, it was acknowledged that the most visible countries in terms of internationalization are the United States, Germany and United Kingdom. Therefore, it is most pertinent to examine these nations when concerning internalization.

Yogev and Grund (2012) studied art fair networking and assessed whether two fairs are interrelated, if a minimum number of galleries participate in both fairs. The authors concluded that galleries are more prone to attend two art fairs when there is an indirect relationship between the fairs. In addition, age and status of the artists are positively correlated with galleries attending the same fair (Yogev and Grund, 2012), forming an age and status cluster. Although these studies are rather interesting for the art market, they merely touch upon globalization and network effects. No study was found that would combine online strategies or their impact with art fairs or galleries.

According to Thompson (2008) the reason why art fairs invest heavily on branding and marketing is to overcome being associated solely with a blockbuster gallery. Art fairs have now their own identity, being considered the decade of the art fair (Thompson, 2008). In essence Thompson’s ackownledgements (2008) are related to what Aurora and Vermeylen (2011) assess, since art fairs have their own identity (Thompson, 2008), but it can be disrupted due to the rise of the online consumer/producer who can also use Internet to build unauthorized identity for the cultural organizations through sharing their own input on their own social networks (Aurora & Vermeylen, 2011).

By investing heavily on marketing and by its growing importance, it is rather interesting to research on art fairs and their online impact. However, this research will not touch upon the impact that these strategies have on the art fair itself, but rather the impact that participating in art fair has for artists and galleries online attention. In essence, this thesis examines the impact that an offline event has online. The two main dimensions in this research are online impact and art fairs.

3. THE CASE OF ABMB

Art fairs are rather important events in the art market, since it complies a great number of art galleries offering specialized works (Thompson, 2013). Different galleries are complied in one event, giving the opportunity to art collectors to see (and possible purchase) some of the best works of art at once, being rather comfortable and reducing search and other related costs (Klein,1998). According to Thompson, (2013) there are nowadays four major art fairs: TEFAF, the European Fine Art Foundation Fair held in Maastricht; Art Basel organized in Basel; Art Basel Miami Beach, considered an Art Basel 'descendant' and finally Frieze fair held in London (Thompson, 2013). This research is going to be based on Art Basel Miami Beach (2012 edition).

One of the reasons for the choice of ABMB was the fact that it is considered the biggest contemporary art fair in the world, with more than 200 galleries exhibiting from Moscow to Los Angeles. For this dissertation it is important to have a representative fair, complying galleries from all over the world, ABMB seemed to be the best choice. Secondly, this fair is rather interesting since it bridges European/north American galleries with less known south American dealers. Hence, Miami is considered the place that connects the Americas and links them to Europe through the Atlantic Ocean (Thopmson, 2013). ABMB is especially interesting, since it mixes dealers from developing countries (as Brazil) where the art market is still developing but growing exponentially (Phillips, 2012) with well-established western galleries. In addition, ABMB is also considered a social event, where various exhibitions, performances and social gatherings take place in Miami during the fair.

ABMB 2012 was held between the 3rd and 8th December, being divided in seven distinct sectors: Galleries, Nova, Positions and Kabinett were concerned to galleries exhibitions and Editions, Public, Video and Magazines showcasing other mediums. This research will exclusively deal with Art Galleries, Nova and Positions. Art galleries is the most important sector where are featured 201 galleries and more than 4000 artists, displaying paintings, drawings, sculptures, installations, prints, photography, video or other digital medium (Villareal, 2012). This section is rather similar to any other art fair where dealers choose their best artists to represent the gallery. In Art Nova, art galleries have the possibility to present only a small sample of the artists they represent, featuring art works created recently, up to three years ago. The idea of this sector is to feature recent or never seen before art pieces came directly from the artist's studio (Art Basel Miami Beach, 2012). The idea is to bring a fresh look to the fair with brand new art. Art Positions invite art dealers to discover a new talent, giving the opportunity to exhibit his/her work. Art Positions includes only 16 galleries and it is considered a rather especial sector since dealers had the opportunity to only present one artist, almost as a single-exhibition artist (Russeth, 2012).

4. Research question and hypothesis

The aim of this research is to analyze the relationship between two main concepts: the art market and online impact. In essence, I aim to examine whether in the art market, an offline event has an impact in the online sphere. The most characteristic offline event in the art market is the art fair where thousands of art enthusiasts, lovers, and critics appreciate the work of artists represented by galleries. Therefore this study will be solely focused on art fairs. Hence, the research question: does participation in an art fair has an impact in art galleries' and artists' online attention?

The assumptions of potential findings in this research raise the following hypothesis:

- Online attention is greater for art galleries and artists participating in the fair in the post-period compared to the pre-period;
- Artists participating in the art fair, exhibiting together in a smaller group, are more likely to have more online attention in the art fair post-period than artists that exhibit in larger groups.

5. RESEARCH DESIGN

5. 1 Conceptualization

5.1.1 Quantitative analysis

Research projects aim to understand a situation and explain it by choosing a topic of investigation, researching what other studies say about the subject, gathering data and analyzing it, intending to not only explain the situation, but also to make inferential statements and provide explanations for the outcome (Zhou and Sloan, 2011). When doing research there are essentially two ways to perform it: either qualitative or quantitative. This research will be quantitative, since the process of 'quantification' (Babbie, 2008) will be explored through transforming the data to numerical form. In other words, the numerical format will be used to help describe and explain the phenomenon being studied. By using numbers instead of words (qualitative method), the data will be easily read and prepared by a computer, helping to draw statistically significant conclusions from the research (Babbie, 2008). As a consequence, quantitative variables are characterized by counting or measuring (Marascuilo and Serlin, 1988). This study is considered quantitative by nature, since the outcome from Google Trends is already numerical.

In addition, this research is also non-obtrusive, since social behavior or activities are studied without affecting them (Babbie, 2008). This is a rather important issue since intruding in the object of study may alter the data, hence jeopardizing the research. However there are some limitations when dealing with unobtrusive methods, as one cannot get answers in order to explain 'why' the communication message is the way it is (Zhou and Sloan, 2011). In other words, the fact that an individual looked on Google for a gallery or artists name in the same period as ABMB 2012, does not necessarily mean that the two moments are correlated. However, due to the importance of the event it is assumed that there is a relationship between the two.

Being a time-series analysis, this research is considered a longitudinal study. Contrary to cross-sectional studies, longitudinal research implies data collection over time. In other words, observations of the same phenomenon are made over different points in time (Babbie, 2008). In this research, observation of online attention to galleries and artists that participated inABMB 2012 are going to be collected in different points in time. Within longitudinal studies are trend studies, cohort studies and panel studies. Although the three studies might have similar features, this dissertation can be considered a panel study. Similar, to a trend or cohort, the panel study compiles longitudinal data collected from the same sample at different points in time (Babbie, 2008).

5.1.2 Quasi-experimental design

5.1.2.1. Definition of quasi-experimental design

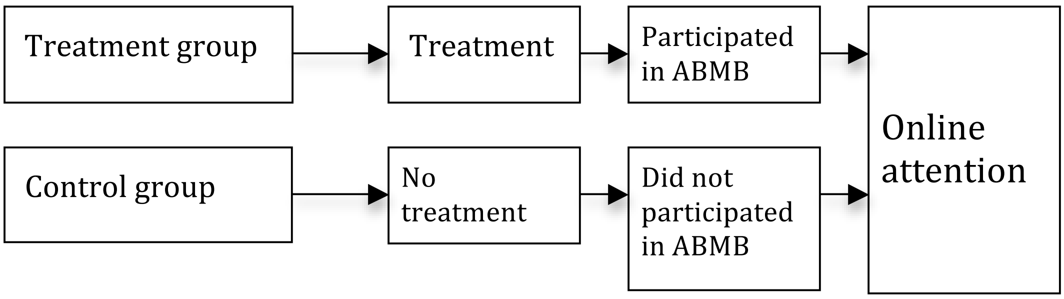
By definition, the word ‘experimentation’ implies a test. As a rule, a test implies a causal relationship (Campbell and Cook, 1979). One would perform a task with the intention of assessing what it would cause: a simple example is an artist that decides to work two hours extra in his/hers art in order to assess whether the work will be more successful. In this example, the artist wants to test whether extra hours of work would have an impact in the quality and success of the painting. The previous example entails an experiment; however this research will be based on a quasi-experimental design.

A quasi-experimental design is considered to be an experiment, but not in the full sense of the word. This type of design is commonly known as a similar model to the experimental design, however lacking a random assignment (Trochim, 2006); in other words, having basically all the characteristics of an experiment, but being always dependent on the previous selection of the group that is going to receive a treatment (Box and Jenkins, 1970). According to Campbell and Cook (1979) quasi-experiments are considered as “experiments that have treatments, outcome measures, and experimental units, but do not use random assignment to create the comparisons from which treatment-caused change is inferred” (p.6). In this case, the research touches upon the causal relationship between the participation in an offline event and the online attention of the participants. This could be an experiment, except for the fact that the independent variable (the participation on the art fair) was not randomly chosen. Therefore, the sample is previously dictated.

One of the limitations of this design is the fact that all the threats that random assignment rules out by nature, can be a threat in quasi-experimentations (Campbell and Cook,1979). Hence, these threats to internal or external validity will be further explained in the next pages.

5.1.2.2. Non-equivalent group design

There are two types of quasi-experiments: non-equivalent group design (Campbell and Cook, 1979; Box and Jenkins, 1970) and interrupted time series analysis (Campbell and Cook, 1979). The first is normally used when there is a treatment group, and another group that was not subjected to this treatment, commonly known as control group. With this model, both groups are measured before and after the treatment, and conclusions are drawn (Campbell and Cook, 1979). According to X (Box and Jenkins, 1970) this research can also be considered a non-equivalent control group design with a pre-test, since galleries are not only going to be analyzed after the art fair, but also before. This is a rather important aspect, since the before and after values of each group will be compared. This method would be further explained, as it is going to be used when comparing a sample of similar galleries that participated in ABMB 2012, and other art fairs that did not receive this treatment. By comparing both groups in time, before and after the time period that the fair occurred, it will be possible to estabelish whether ABMB participation has on average an effect on attention.



In essence a part of this research is going to use an interrupted time-series is to compare ABMB 2012 the control and treatment groups, during pre and post-periods. Although the treatment and a control group process is the same as in non-equivalent group designs, each group is presented in an interrupted time-series.

5.1.2.3.Interrupted time-series analysis

Interrupted time-series analysis assesses the effect of a treatment during a certain period of time, comparing the performance before and after the treatment in several data points. In essence, a time series is used to observe diverse points in time (Campbell and Cook, 1979), being a set of quantitative observations evenly spread in time and measured in a time sequence (Senter, 2008).

Interrupted time-series analysis acknowledges a specific point in time when the treatment took place and the idea behind this method is to assess whether the treatment had indeed an impact (Campbell and Cook, 1979). For this research, the treatment is ABMB 2012, and the online attention mean values, before and after the event, will then be inferred. In this research, a simple interrupted time-series will be used, which is the most simple form of time-series (Campbell and Cook, 1979). The diagram of the design is present below:

$$T_1 \quad T_2 \quad T_3 \quad T_4 \quad T_5 \quad X \quad T_6 \quad T_7 \quad T_8 \quad T_9 \quad T_{10}$$

For every unit of the sample (either art galleries or artists), eleven data points in time will be collected concerning online attention. The T_x indicates different points in time and X the event, in this case ABMB 2012. Time-series analysis has some advantages over other types of quasi-experimental analysis, namely for the fact that it can assess trends prior to the treatment (Campbell and Cook, 1979). By looking to what happened in the past, it is easier to compare with the present and perhaps, make predictions about the future.

5.1.2.4.Internal validity and other limitations

In a standard experiment, the random assignment element would exclude possible threats to internal validity. As explained above, in quasi-experimentation analysis the independent variable is not randomly assignment (Campbell and Cook, 1979) hence there is a need to point out and explain possible threats to internal validity such as history, maturation, testing, instrumentation, statistical regression, selection, mortality and interactions with selection. These threats will be acknowledged as limitations and will not be considered as a setback once clarified and adapted to this research.

<u>Threats to internal validity - history</u>

A first overview will explain all the possible threats to internal validity that can occur when dealing with a quasi-experimental design, followed by the adaptation of those to this specific research. According to Campbell and Cook (1979) history can be a threat for the validity of a sample, since the impact observed can be due to an event between the pre and the pro-test that was not considered. When dealing with interrupted time-series analysis, the impact of an event is analyzed throughout diverse time points before and after it happened; however this does not exclude the possibility of another major event taking place immediately after or before the event being studied, jeopardizing the results. In this case it cannot be stated that there is a causal relationship between the variables, since important events were not taken in consideration. In this research there are two different metrics being used, thus the need to be analyzed separately. Concerning the six-daily data, history does not seem to be a threat since the data points before and after are only six days apart. Within this scope, the most important event for every gallery and artist would be Art Basel Miami Beach, so any result on the online attention will most likely be an effect of the art fair. To note that the time people researched online for galleries or artists may not necessarily be the days immediately after the fair. It may happen that one sees an exhibition in November and only researched about it in December. However, due to the advance of technology and the fact that a big part of the population owns a smartphone or a computer, it is rather likely that not a long time will pass between having interest in the gallery or artist and research about it (McEleny, 2009). In this fast changing world, with overwhelming amount of new information every hour, the world wide web is all about the immediate, what is it happening at the moment. As a result, it can be concluded that individuals are prone to researching a subject online right after exposure to it, than after a couple of weeks, hence history may be excluded as a threat to internal validity.

The data retrieved monthly is more difficult to analyze, since there is one time point every 30 days, instead of every six days. With this metric, December is acknowledged as the data point when the event took place, November as the point in time ‘before’ and January ‘after’. This is a long-term approach and during these three months some other events may have occurred that had an impact on art galleries’ and artists’ online attention. According to Campbell and Cook (1979) history is one of the major threats to internal validity in simple time-series. This is a rather important not only to internal validity, but also to the validity of the research as a whole, due to this fact it is going to be analyzed in detail.

Concerning exhibitions in a gallery, or exhibitions anywhere else by artists that participated in ABMB, it is rather difficult to assess whether there were any between November and January that would bias the results. However due to the big scope of ABMB it is safe to state that the fair would attract more online and offline attention than any single exhibition. Concerning any other major events, according to Kendzulak (n.d.), out of the top ten most influential art fairs and top 15 most popular art biennales, only India Art Fair is in January, however there seems to be no overlap since the two art fairs operate in different art circuits. To conclude, there seems to be no major art events that would have an impact in the art galleries’ and artists’ online attention during the time period analyzed. History as a threat to internal validity should be acknowledged as a small limitation, since it is not possible within the scope of this thesis to control for every event in the art sphere.

Other threats to internal validity

Instrumentation can be considered a threat to internal validity, acknowledging a change in the instrument that is going to be measured between the pre and the post-periods (Campbell and Cook, 1979). This can be a limitation to internal validity when for instance, humans that are part of the experience became more knowledgeable between the two tests, or whether different metrics are used between the pre and post periods. In essence it is a change in “administrative procedures” (Campbell and Cook, 1979, page 212) while the experiment is being taken. Instrumentation is not a great threat to this research’s internal validity: being unobtrusive research (Babbie, 2008) human beings are not being studied directly, so the research does not intervene in their lives. Instrumentation can also be a threat when different metrics are used between the pre and post-test, however Google Search uses the same metrics over time, so this is also not considered an issue.

Selection as a threat to internal validity is a concern when an effect may be caused by the differences between the different units of analysis in each group. Most of the time, selection is a problem due to change in the composition of the experimental group at the time of the intervention (Campbell and Cook, 1979). In this research, problems with selection are in the sense that the results from galleries and artists’ Google searches may be different concerning the art fair they participate in. However, the composition of the experimental group did not suffer any changes at the time of the intervention.

Maturation can also be an issue, since it explores the fact that the respondent growing older, wiser or with more experience might influence the results of the experience (Campbell and Cook, 1979). This can be an issue concerning the use of the Internet. Over the time, art lovers might be more experienced in using the World Wide Web, hence the results in galleries and artists' online attention can increase. However due to the short time span, maturation is not likely to be a big influence in the research. In essence, history is the bigger limitation in quasi-experiment research, and it should be acknowledged as such.

5.1.3 Sample

A sample is commonly known as a part of the population that is going to be studied (Babbie, 2008). Generally the population contains a rather large number of cases to be feasible to analyze them all, hence the need to choose a representative group of cases, smaller than the population, but big enough to draw significant conclusions. The "representativeness" (Babbie, 2008) of a sample is a rather important issue, since it is crucial that the sample have similar characteristics than the population from which was selected. In this research there are two types of sampling methods, since there are two different units of analysis.

A unit of analysis is what (or who) is going to be studied. Individual people are normally the typical units of analysis (Babbie, 2008). In this research there are two units of analysis: art galleries and artists that participated in Art Basel Miami Beach 2012. Hence, the population for the first is all the art galleries that participated in ABMB 2012 and for the second, the population is all the artists that participated in the fair. Due to the small size of the population for art galleries that participated in ABMB, the sample and the population will be the same. In other words for art galleries, there is no sampling method since it is possible to research all the cases (the whole population). Last year, 252 galleries participated in ABMB, however not all can be included in the research due to Google Trends constraints. As explained above, Google Trends computes the number of searches of a certain term, relative to the total number of searches that have been done over time ([Analizing data on Google Trends]). However there are certain terms that do not have enough search volume to be featured in Google Trends, most likely smaller galleries that are less popular. Due to this fact, out of the 256 galleries, 187 were analyzed.

The number of artists that participated in ABMB 2012 is rather greater than the numer of participating galleries, being almost 2000. Due to the greater number a sampling method is needed. The sample method chosen was a nonprobability sampling (Babbie, 2008), which states that the sample was selected without recurring to the probability theory. In other words, the sample was not randomly chosen. In order to have a representative sample, it was important to have artists from every gallery, hence the quota-sampling method. Since it is intended to try and represent artists from all galleries, the quota sampling method ackowledges that the sample was chosen based on prespecified characterists (Babbie, 2008).

Since some galleries only exhibit two or three artists, and others more than ten, the sampling method was based on the artists featured in the ABMB 2012 catalogue. The catalogue features a picture with artwork from one artist, being already a sample from the population. This is considered a good sampling method, since it was already done by the organization itself. However, it is important to recognize that one of the limitations of this method might be the bias of the organization with selecting which artists would be featured in the catalogue. Due to Google Trends constraints, out of the 256 possible artists, 195 had enough data to be featured in this research.

5.2 Google Trends data

As explained above, this research method uses content analysis as the only data resource using Google Trends. Google Trends is a website developed by Google that measures the number of times an individual entered a certain keyword over time. The data is presented over time, from 2004 until the present. According to Google, Google Trends computes how many searches have been done for a certain keyword, relative to the total number of searches over time. The idea is that this analysis shows the likelihood of a random user to search a particular term. In order to assess a credible level of someone's interest over a certain term, the Google Trends system eliminates repeated queries with the same keyword by a single user over a short period of time ([Analizing data on Google Trends]).

The data retrieved from Google Trends is displayed on a scale from 0 to 100. This data is normalized, meaning that sets of data are divided by a common variable (not disclosed by Google) in order to annul the variable's effect on the data. Each point is then divided by the highest value and multiplied by 100 ([Analizing data on Google Trends]). Hence, a graph is presented with the normalized number of searches for a specific term over time. According to the volume of searches, the data is presented either monthly or six-daily: the bigger the interest in a term, the more detailed the data is. This is the reason why in this research, each test of both galleries and artists are divided into two groups: either monthly or six-daily.

When there is not enough data in a specific term, Google Trends is unable to show any data. Hence the sample of artists and galleries is not as large as planned, since some of the units of analysis did not have enough search volume to be featured in Google Trends, decreasing the sample size.

Google Trends measures the number of queries on a specific term over time. In other words, the site measures the interest individuals have on a specific term or subject. This research aims to understand if the participation in art fair had an online impact on the galleries and artists. The purpose is to assess the impact that an offline event has online. Google Trends is used in this research since it is considered a good indicator to evaluate online impact, as it measures individual online interest on a subject over a period of time. Since estimating online impact is a rather vague concept, measuring the interest that the global population have on a specific term by looking for it on Google is an interesting indicator of online impact. Google is one of the most (if not the most) powerful tools on the World Wide Web; by wanting to know more about an artist or gallery seen in an art fair, the probability of the first online contact being over Google is rather high, reaching 500 million queries per day (Farber, 2013).

However, it should be acknowledged that Google alone does not represent online impact as a whole. By researching people's interest in looking for a subject on Google, several other online platforms were not taken into consideration such as Bing, Facebook, Twitter or direct traffic to the website of interest.

6. THE IMPACT ABMB 2012 PARTICIPATION ON ONLINE ATTENTION FOR GALLERIES AND ARTISTS

6.1 Variables and tests overview

In this research there are two distinct variables: the date and the number of Google searches. As explained above, data from Google Trends is retrieved in different metrics: either monthly or six-daily. Each metric is going to be analyzed separately. Concerning monthly data, a time-series was created between July 2012 and April 2013. Six-daily data examined the number of Google searches between 28 October 2012 and 26 January 2013. These dates were chosen giving the fact ABMB 2012 took place between December 6th and 9th.

In addition there are two ways of assessing the number of Google searches: absolute values and first differences. The first indicates the value supplied by Google Trends, whereas in the second variables are formed by subtracting the absolute value of two neighbor data points. Since Google Trends analyzes the number of Google searches over time and the data is normalized, the absolute value of each data point may differ over time, however the fluctuations between data points remain the same, hence the importance of first difference values.

Lastly, online attention over time is also going to be analyzed according to the number of artists represented per gallery in the art fair. Therefore, artists will be divided into two groups: 'multi' and 'up to three'. The first complies art galleries that exhibited in one booth the work of four or more artists, whereas in 'up to three' galleries exhibit a maximum of three artists, giving them more exposure. As explained in the research question section, both art galleries and artists that participated in ABMB 2012 are going to be analyzed. For each of them, different tests will measure: monthly online attention absolute values, six-daily online attention absolute values, monthly online attention first differences and six-daily online attention first differences.

The descriptive analysis complies an interrupted time-line of each of the above categories, a descriptive table, two complement scatterplots that analyze the trend-line in the ABMB pre and post-period, and a box-plot for the absolute value to assess the dispersion of the values. The inferential analysis will be performed with two-paired sample t-tests and independent F tests.

6.2 Galleries descriptive analysis

Out of the more than 2000 art galleries throughout the world that applied to participate in the art fair, only 257 galleries were accepted to exhibit at ABMB 2012 (Art Basel Miami Beach, 2012). Out of the 257 galleries, 126 have data available monthly, 73 have data that is presented six-daily, and 58 galleries did not have enough search volume for Google Trends to show a graph. The fact that the last galleries are not featured in Google Trends might be an indicator of being less known or popular. Regarding this research, only galleries featured in Google Trends will be taken in consideration.

6.2.1. Art galleries monthly analysis

6.2.1.1. Art galleries monthly absolute values

The monthly data analysis can be considered less detailed and more orientated to long-term effect and/or impact, since it explores 11 data points between July 2012 and April 2013.

Starting with the galleries for which data was available monthly, the first three graphs show the absolute values from the 126 galleries, whereas the second set of three graphs depicts the first differences. Being an interrupted time-series design (Cook and Campbell, 1979), in the first graph, the black line represents the point in time when the event took place. The idea is to assess whether there is a significant change in online attention during or after the event compared to the period before. In other words, I am comparing the pre-period with the treatment, or post-period.

Graph 1 and Table 1 give a general overview of the online attention from July 2012 to April 2013, presented with an interrupted time-series. The graph helps to get an idea of the impact in the pre and post-periods. From preliminary analysis, it can be concluded that in the pre-period, the online attention mean concerning the art galleries dropped slightly, from 53,9 (sd=29,73) in November to 50,97 (sd=28,22) in December. However in January, I detected an increase to 56,47 (sd=28,74), followed by a long-term stable increase to 59,88 (sd=66,28) during February (graph 1 and table 1).

A box-plot is a statistical diagram to asses the distibutionn of scores of different variables (Cramer & Howitt, 2004). The middle lines represent the medias of each variable and rectangles represent the middle half of the data, going from the 25th to the 75th percentile (Robins, 2012). In essence, box-plots are a a rather simpre way to depict mulitple data distributionsin one graph. This representation is rather interesting to assess the differences in concentration in the different months analyzed. As it can be ssen in graph 2, all boxes overlap with medians, hence no major difference can be claimed (Naylannd College Mathematics, 2011). In addition, the values of each month do not seem to differ greatly from one another. It can also be assessed that January (considered the post-period) seems to be slightly greater than December (treatmenst-period) however this difference dosen't seem no be striking.

Although the attention decreased in the post-period, it seems that the event had an impact on the galleries' online attention, since it augmented in the data points right after the event. However, looking to the box-plot (graph 2) the median of all the months is rather similar amongst each other.

What changes then, is the distribution between months. Hence, the dispersion between months does not seem to be great.

Graph1

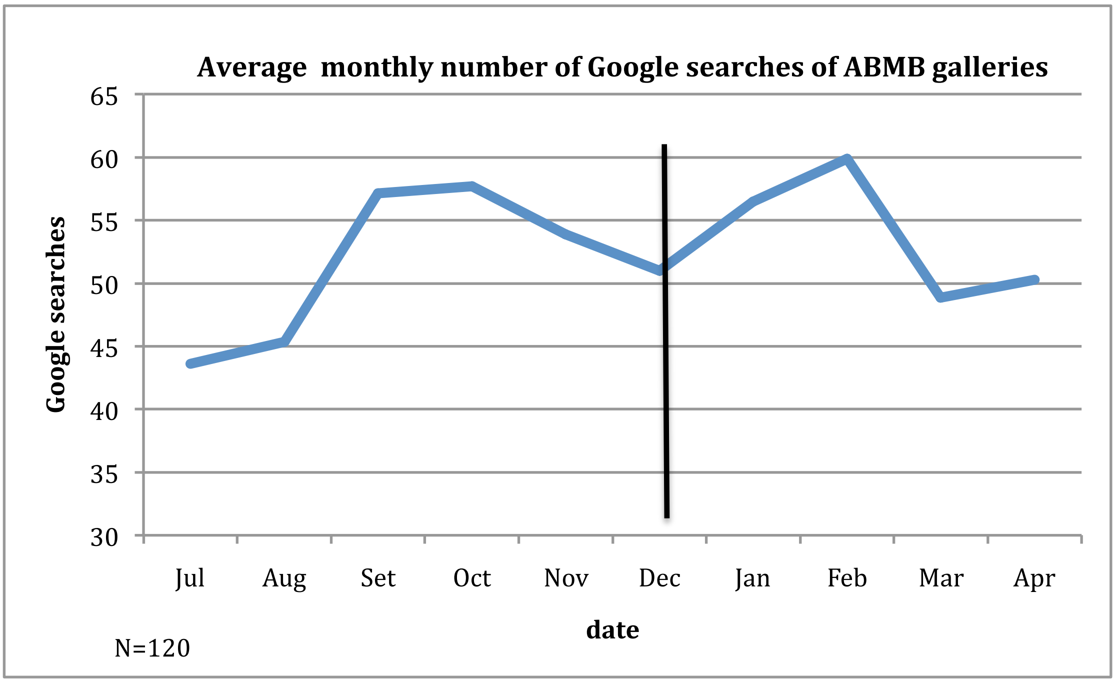
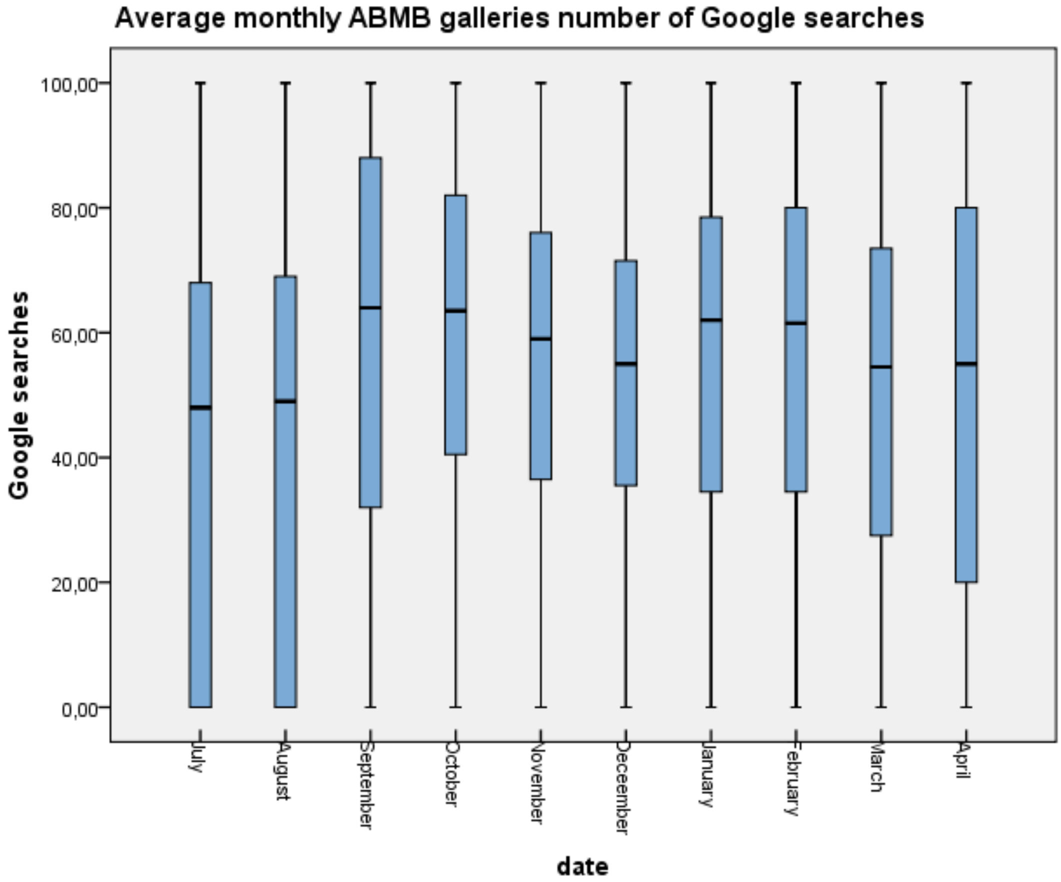


Table1. ABMB galleries monthly number of Google searches descriptive analysis

date	N	Minimum	Maximum	Mean	Std. Deviation
Jul	120	0	100	43.62	32.33
Aug	120	0	100	45.36	31.36
Set	120	0	100	57.16	35.16
Oct	120	0	100	57.71	32.23
Nov	120	0	100	53.90	29.73
Dec	120	0	100	50.97	28.22
Jan	120	0	100	56.47	28.74
Feb	120	0	696	59.88	66.28
Mar	120	0	100	50.30	34.00
April	120	0	100	48.88	30.76

Graph 2



6.2.1.2. Art galleries monthly first differences

Graph 3 and table 2 showcase the first differences between two data points. With this graph it is possible to assess the fluctuations in time. As concluded before, there is a slightly significant increase in online attention between December and January, the second being higher in the scope of this analysis (July 2012 and April 2013). Whereas in the ABMB pre-period on average, there was a decrease of -2.93 (sd=21.75), but after the event, the online attention increased 5.51 (sd=21.46). This peak continues until February, with the online attention augmenting 3.41 (sd=60.85). In essence, the monthly descriptive analysis concerning galleries that participate in ABMB acknowledges that there is, on average, a decrease in the number of Google searches during the entire time period, but that this trend is reverted shortly around ABMB.

Graph 3

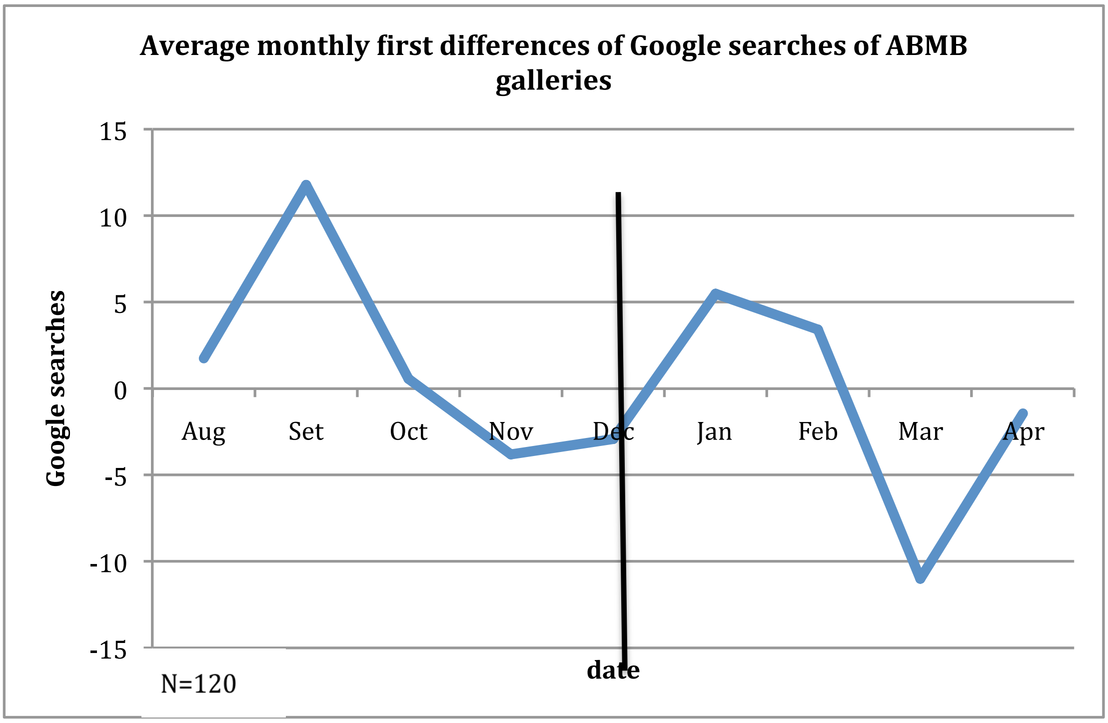


Table 2. ABMB galleries monthly first differences of Google searches average descriptive analysis.

date	N	Minimum	Maximum	Mean	Std. Deviation
Aug	120	-45.00	100.00	1.74	19.42
Set	120	-29.00	100.00	11,80	24.50
Oct	120	-64.00	100.00	0.55	26.28
Nov	120	-69.00	84.00	-3.81	22.44
Dec	120	-87.00	100.00	-2.93	21.75
Jan	120	-100.00	100.00	5.51	21.46
Feb	120	-100.00	627.00	3.41	60.85
Apr	120	-646.00	64.00	-11.00	63.43
Mar	120	-89.00	100.00	1.42	27.35

6.2.2. Art galleries six-daily analysis

6.2.2.1. Art galleries six-daily absolute values

The six-daily analysis is more detailed since it takes into consideration 13 points in time, between 28 October 2012 and 20 January 2013. The same model as the monthly analysis will be followed: first an overview of the absolute values, followed by the first differences. As observed in the monthly analysis, shown in Graph 4, it can be determined that in the ABMB pre-period, the online attention decreases, or stays rather stable, until the date of the event. In the six days immediately before the event, the online attention average is 53.93 (sd=23.33), decreasing to 49.9 (sd=21.71) during the period the event takes place. The post-ABMB period does not seem to have a short-term impact, since the values are roughly the same (m=49.61 sd=24.89). In the long-term, the treatment period is followed by a decrease in the number of Google searches by the end of December (m=45.36, sd=23.45) and an ascendant increase until the end of the post-period (graph 4, table 3).

As observed in the graph and tables above, the box-plot representation (graph 5) does not present major differences between the average online attention every month, given the fact that each median overlap with other months' boxes being rather difficult to assess if there is a difference between each variable (Naylannd College Mathematics, 2011).

Graph 4

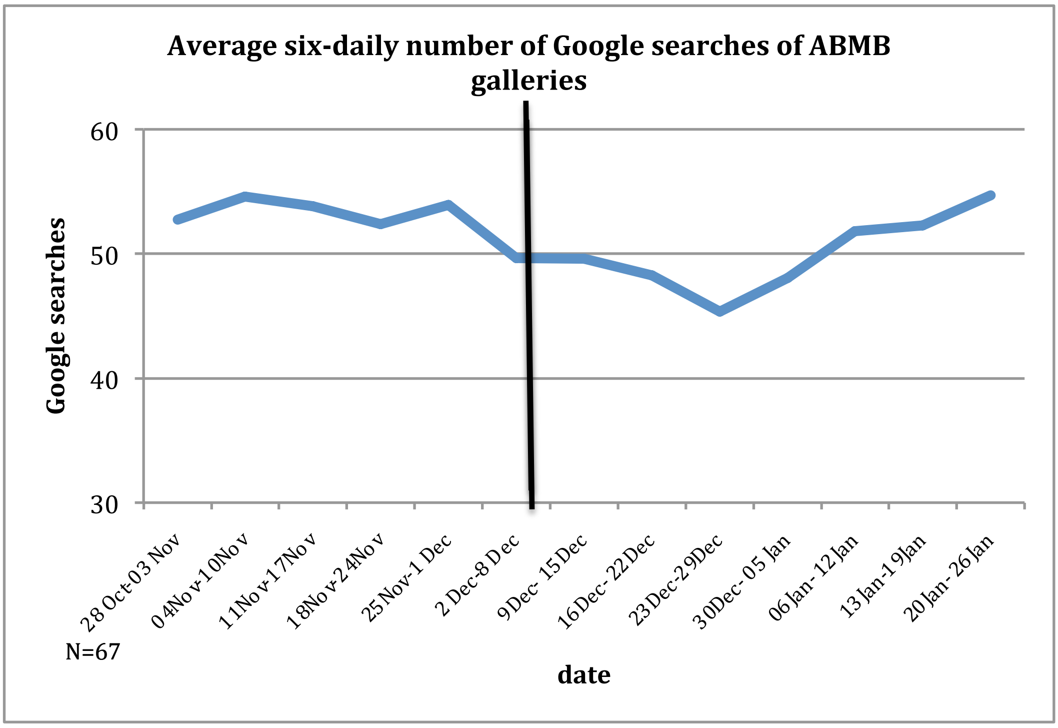
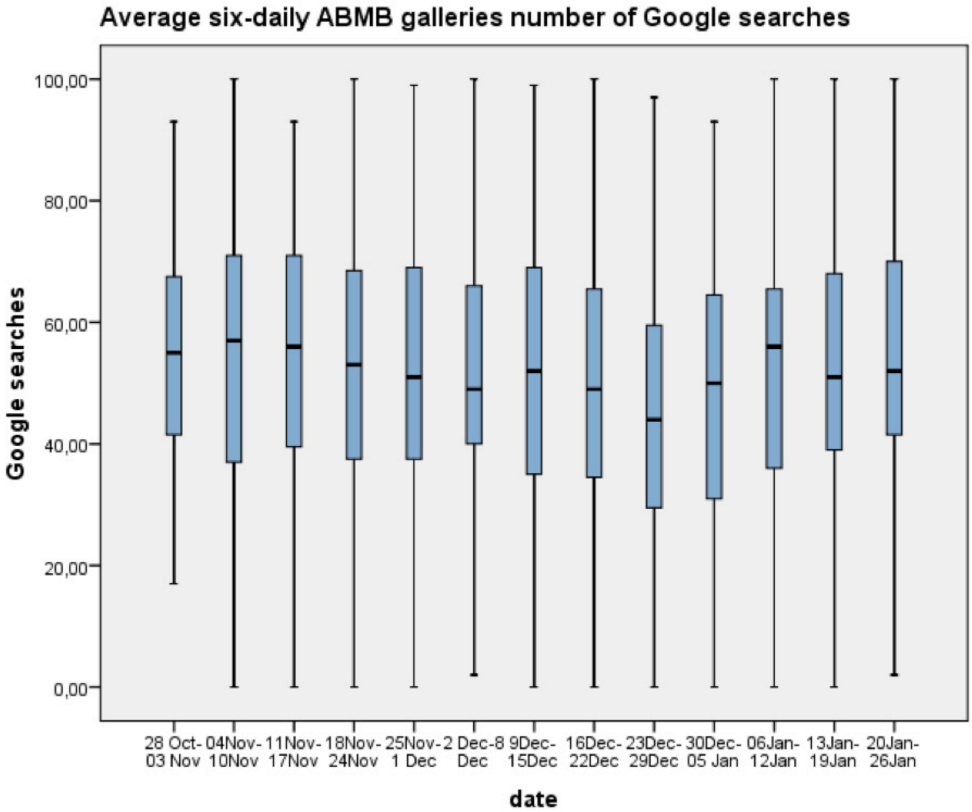


Table 3. ABMB galleries six-daily number of Google searches descriptive analysis

date	N	Minimum	Maximum	Mean	Std. Deviation
October 28- November 03	67	0	93.00	52.76	21.49
November 04-November 10	67	0	100.00	54.63	24.59
November 11-November 17	67	0	93.00	53.84	23.79
November 18-November 24	67	0	100.00	52.39	24.70
November 25-December 01	67	0	99.00	53.93	23.33
December 02-December 08	67	0	100.00	49.69	21.71
December 09- December 15	67	0	99.00	49.61	24.89
December 16- December 22	67	0	100.00	48.28	23.05
December 23 – December 29	67	0	97.00	45.36	23.45
December 30 – January 05	67	0	93.00	48.07	23.74
January 06 – January 12	67	0	100.00	51.85	24.60
January 13 – January 19	67	0	100.00	52.28	22.11
January 20 – January 26	67	2.00	100.00	54.69	21.35

Graph 5



6.2.2.2. Art galleries six-monthly first differences

From the first differences graph, it seems that there is a short-term impact in ABMB galleries online attention. While in the treatment-period there is in average a decrease in Google searches of 4.24 (m=-4.24 sd=18.16), there is an increase in the post-period to -0.07 (sd=17.96), experiencing another immediate decrease six days later (m=-1.32 sd=14.10). ABMB only seems to have an impact in online attention after 30 December (graph 6).

Graph 6

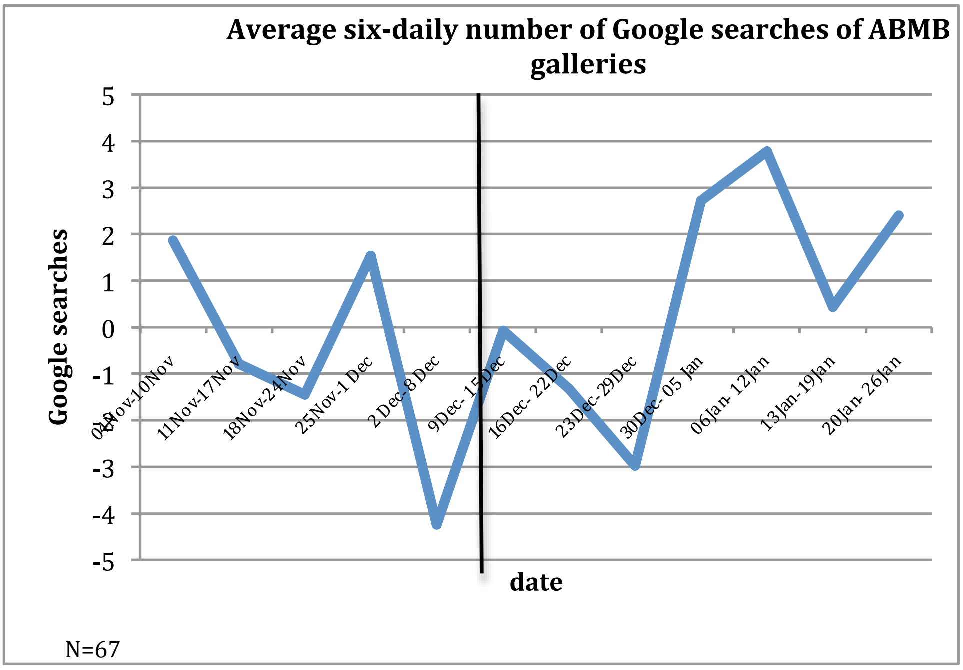


Table3. ABMB galleries six-daily number of Google searches descriptive analysis

date	N	Minimum	Maximum	Mean	Std. Deviation
November 04-November 10	67	-59.00	58.00	1.87	16.82
November 11-November 17	67	-50.00	44.00	-0.79	15.30
November 18-November 24	67	-34.00	52.00	-1.45	16.28
November 25-December 01	67	-36.00	84.00	1.54	16.66
December 02-December 08	67	-65.00	65.00	-4.24	18.16
December 09- December 15	67	-62.00	41.00	-0.07	17.96
December 16- December 22	67	-36.00	39.00	-1.33	14.11
December 23 – December 29	67	-35.00	27.00	-2.93	10.82
December 30 – January 05	67	-30.00	32.00	2.72	10.45
January 06 – January 12	67	-33.00	39.00	3.78	12.61
January 13 – January 19	67	-47.00	78.00	0.43	19.04
January 20 – January 26	67	-37.00	60.00	2.40	17.77

6.3 Artists descriptive analysis

After assessing art galleries’ online attention during ABMB, it is also interesting to determine what is the ABMB’s online impact for artists. Art galleries are the intermediaries that enable artists to actually participate in an art fair, however it can be argued that individuals have more interest in the artists rather than in the gallery itself. In order to evaluate the impact that ABMB has on online attention, researching the artists is fundamental. During ABMB, around 2000 artists exhibit their work . Due to the great number of the population of artists, sampling is required.

The sampling method is this case is rather transparent: the sample consists of all the artists featured in the catalogue. The ABMB 2012 catalogue features every gallery and a prominent picture of an artist's piece exhibited in the art fair. Since there are 256 (Art Basel Miami Beach catalogue 2012) galleries participating in the art fair, the sample will consist of one artist per gallery. As it was already explained, for certain keywords that do not have enough search volume, Google Trends is unable to determine any values. Out of the 256 galleries, 51 did not have enough volume so they will not be featured in the sample.

6.3.1. Artists monthly

6.3.1.1. Artists monthly absolute values

The structure will follow the same pattern as the section above, including a descriptive analysis of the interrupted time-series and its descriptive table.

As can be assessed from graph 7, there seems to be a short-term impact on the average monthly Google searches for artists' after the participation in the fair. Although there was a decrease in the treatment-period, from 55.72 (sd=31.45) to 48.37 (sd=29.45) in December, it was not prominent. In the post-period, the online attention seemed to increase slightly to 53.19 (sd=29.14) in January. This upward trend continues until the end of February (m= 54.87, sd=31,74) (table 4). In other words, there is indeed a short-term increase in the artists' online attention in the post-period, however it is not permanent, since the number of Google searches decreases after February. These results can be also acknowledged by the box-plot (graph 8). In addition, the dispersion of number of Google searches for artists is smaller in December and January.Lastly, graph 8 also complies the conclusion that there is not a pronounced different between every month average values, due to the similar position in the graph that every box-plot present. However, it is rather interesting that July and August do not present a lower whisker and present the lower average values from the months analyzed.

Graph 7

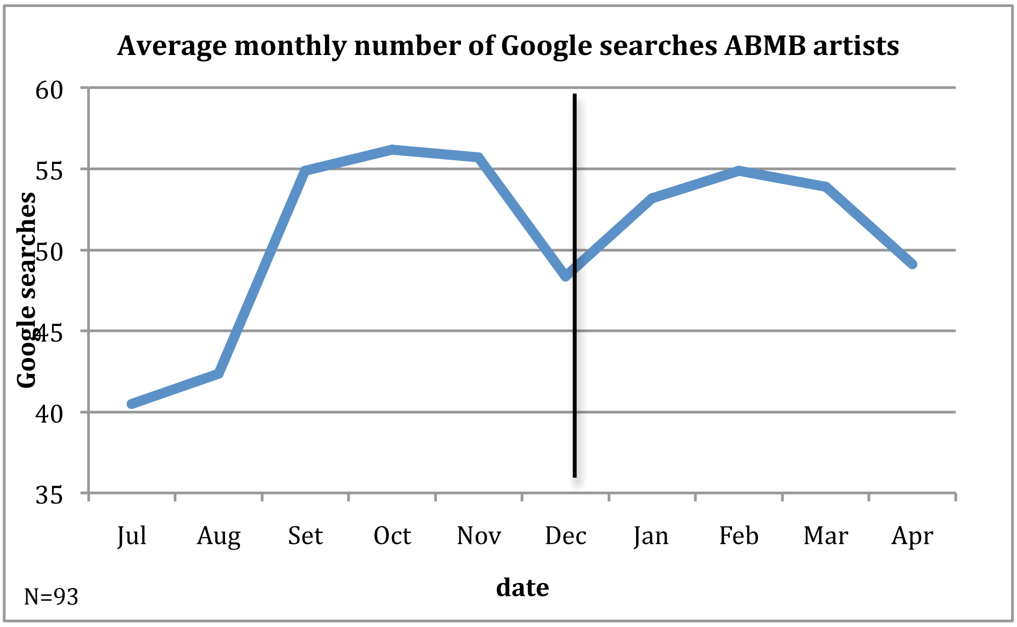
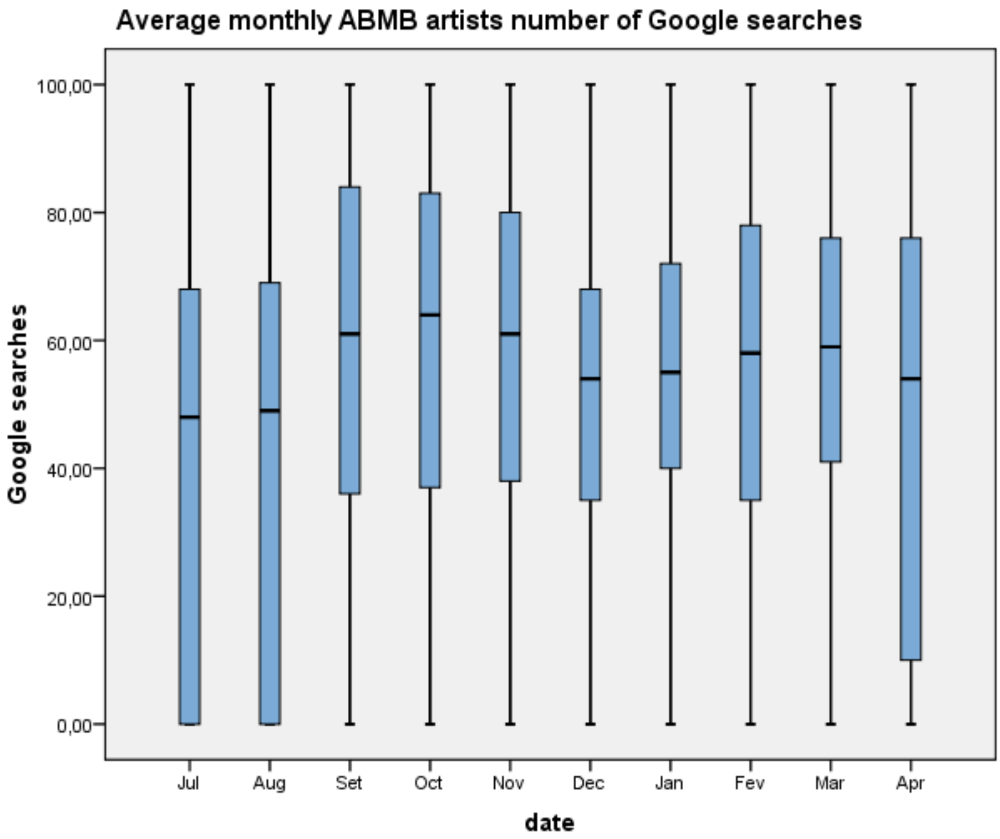


Table 4. ABMB artists monthly number of Google searches descriptive analysis

date	N	Minimum	Maximum	Mean	Std. Deviation
July	93	0	100.00	40.49	33.34
August	93	0	100.00	42.37	33.58
September	93	0	100.00	54.87	33.07
October	93	0	100.00	56.18	32.99
November	93	0	100.00	55.72	31.45
December	93	0	100.00	48.37	29.07
January	93	0	100.00	53.19	29.14
February	93	0	100.00	54.87	31.74
March	93	0	100.00	53.90	30.13
April	93	0	100.00	49.13	33.79

Graph 8



6.3.1.2. Artists monthly first differences

Looking to the absolute numbers it seems that ABMB has, to a certain extent, an effect in artists' online attention. There is a clear decrease in the pre-period between the average in September first differences online attention (m= 12.51, sd= 28.23) and December (m=-7.35, sd= 22.33). This trend is reverted in the post-period, where the difference of the means between the treatment and post-periods (December and January) is actually 4.83 (sd=18.45), the second highest positive value between July 2012 and April 2013. This is depicted in graph 9 with a peak right after the treatment-period. However, the number of Google searches tends to decrease in the following months. It can be concluded that participation in ABMB has only a short-term impact on the artist's monthly online attention.

Graph 9

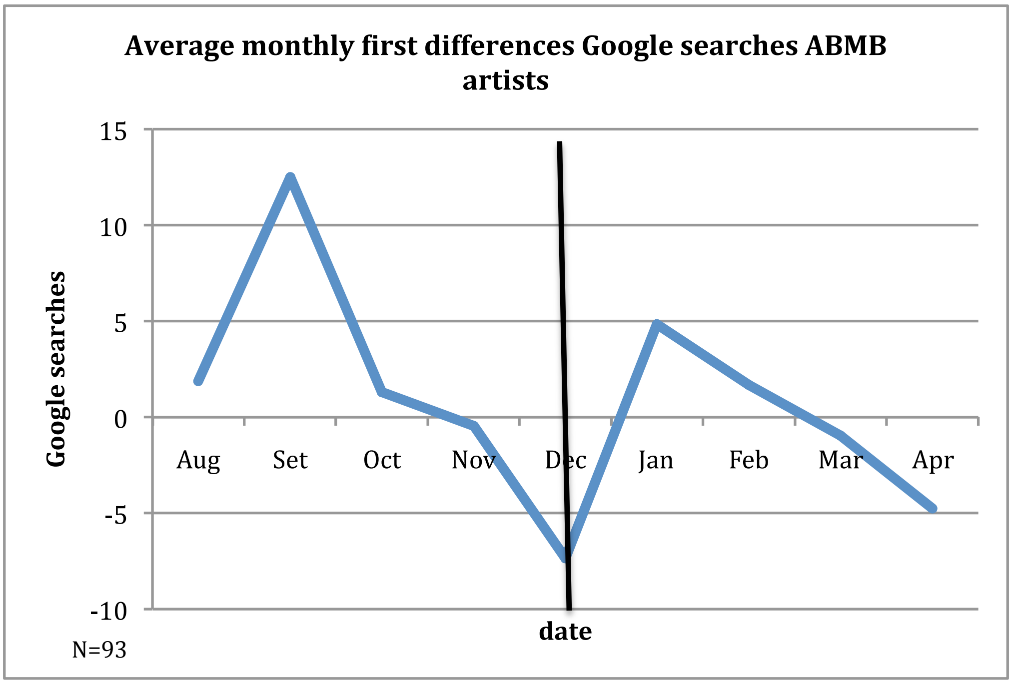


Table 5. ABMB artists' monthly first differences of Google searches average descriptive analysis.

date	N	Minimum	Maximum	Mean	Std. Deviation
Aug	93	-87.00	86.00	1.87	23.33
Set	93	-57.00	100.00	12.51	28.23
Oct	93	-100.00	90.00	1.31	25.56
Nov	93	-47.00	100.00	-0.46	23.70
Dec	93	-100.00	48.00	-7.35	22.33
Jan	93	-33.00	100.00	4.83	18.45
Feb	93	-93.00	100.00	1.68	29.16
Apr	93	-100.00	100.00	-0.97	30.42
Mar	93	-100.00	100.00	-4.77	31.51

6.3.2. Artists six-daily analysis

6.3.2.1. Artists six-daily absolute values

When analyzing the impact of online attention in form of Google search queries, the six-daily values do not quite match the monthly ones. As it can be assessed by the six daily absolute values graph (graph 10), the values between the pre and treatment period do not seem to differ greatly. Looking closer to the impact between the pre, treatment, and post-period, there seems to be no significant differences: 52.14 (sd=24.80) in the pre-period, 50.76 (sd=25.45) in the treatment period and 50.43 (sd=43.58) (table 5) in the post-period. The stable number of Google searches value is followed by a significant decrease towards the end of December, reaching an average of 38.07 (sd=21.66). As it was assessed in the previous box-plots, Graph 11 is also in line with the descriptive findings, since the boxes of every variable overlap with each other. In otder words, there is not a major difference in values from month to month. In essence the dispersion between the numbers of Google searches between all the data points (graph 11) is rather small. The box-plots are included in this research in order to illustrate that, although online attention averages change slighty from month to month, this changes are not quite pronounced.

Graph 10

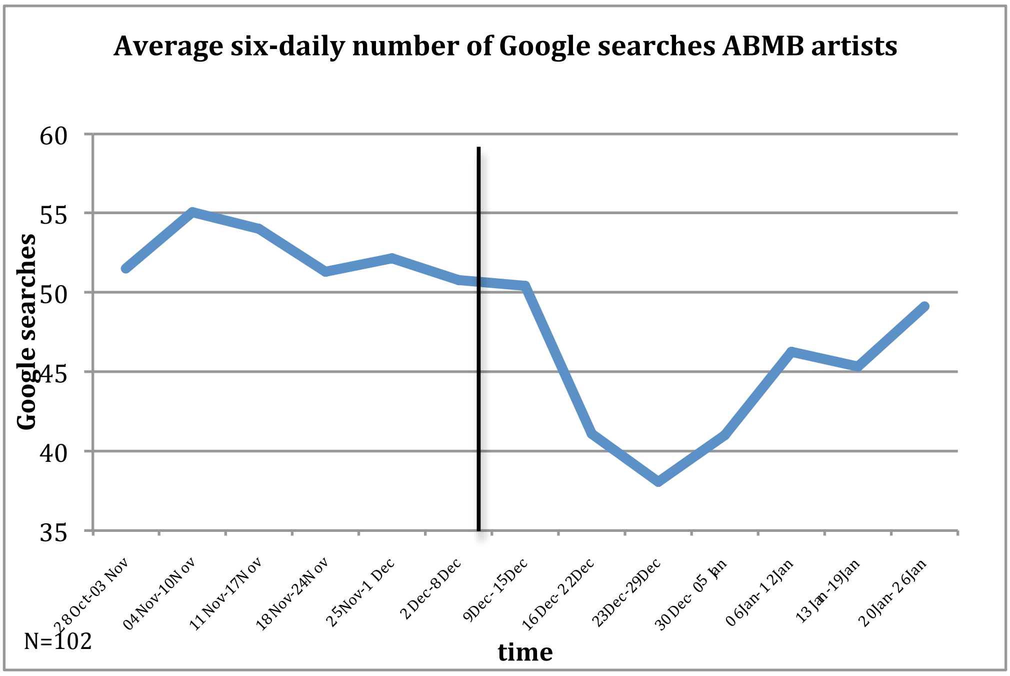
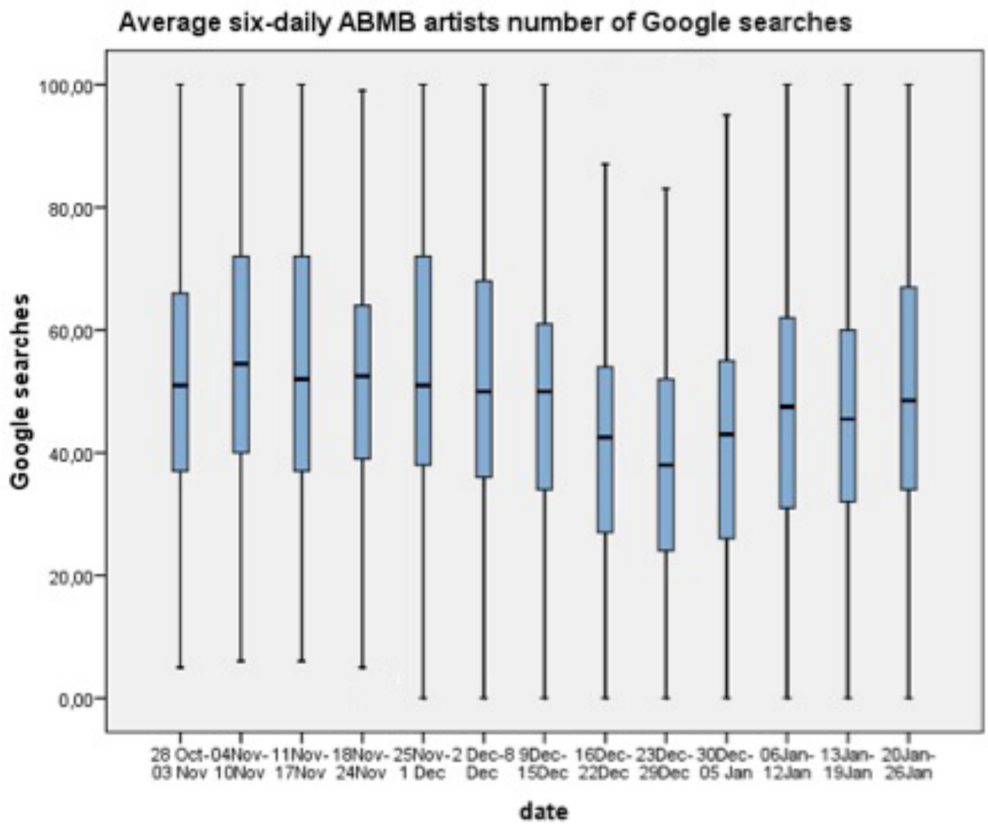


Table 5. ABMB artists six-daily number of Google searches descriptive analysis

date	N	Minimum	Maximum	Mean	Std. Deviation
October 28- November 03	102	5.00	100.00	51.52	21.93
November 04-November 10	102	6.00	100.00	55.04	23.36
November 11-November 17	102	6.00	100.00	54.09	23.72
November 18-November 24	102	0.00	99.00	51.32	21.98
November 25-December 01	102	0.00	100.00	52.14	24.80
December 02-December 08	102	0.00	100.00	50.76	25.45
December 09- December 15	102	0.00	422.00	50.43	43.58
December 16- December 22	102	0.00	100.00	41.09	22.50
December 23 – December 29	102	0.00	100.00	38.07	21.66
December 30 – January 05	102	0.00	95.00	41.01	22.76
January 06 – January 12	102	0.00	100.00	46.24	24.04
January 13 – January 19	102	0.00	100.00	45.34	22.97
January 20 – January 26	102	0.00	100.00	49.11	25.60

Graph 11



6.3.2.2 Artists six-daily first differences

From the first differences graph (graph 12), it can be assessed that there is a short-term increase in artists' online attention, although it is not permanent. The first differences mean increases slightly between the treatment and the post period, from -1.37 (sd=16.82) to -0.33 (sd=40.78) (table 6), however it is followed by a great decrease towards the end of December (m= -9.34, sd= 42.10). In essence, the number of Google searches has a slight increase after ABMB, however this impact is not acknowledged in the long-term. This trend is shortly reverted, when the number of Google searches augmented significantly until the second week of January (m=5.23, sd=12.30). However it is hard to assess whether the second peak is correlated with ABMB participation.

Graph 11 is consistent with the results above since it also indicates that there is not a pronounced difference in the average number of Google searches comparing the months analyzed to each other. Once again, the boxes overlap the median of each month represented (Naylannd College Mathematics, 2011), being rather complicated to assess a significant difference between variables.

To sum up, the monthly number of Google searches on the artists' that participated in ABMB seemed to have a greater impact than artists with six-daily data. Both metrics present a rather small but positive impact in the number of Google searches after participation in ABMB, however monthly data seems to be more prominent.

Graph 12

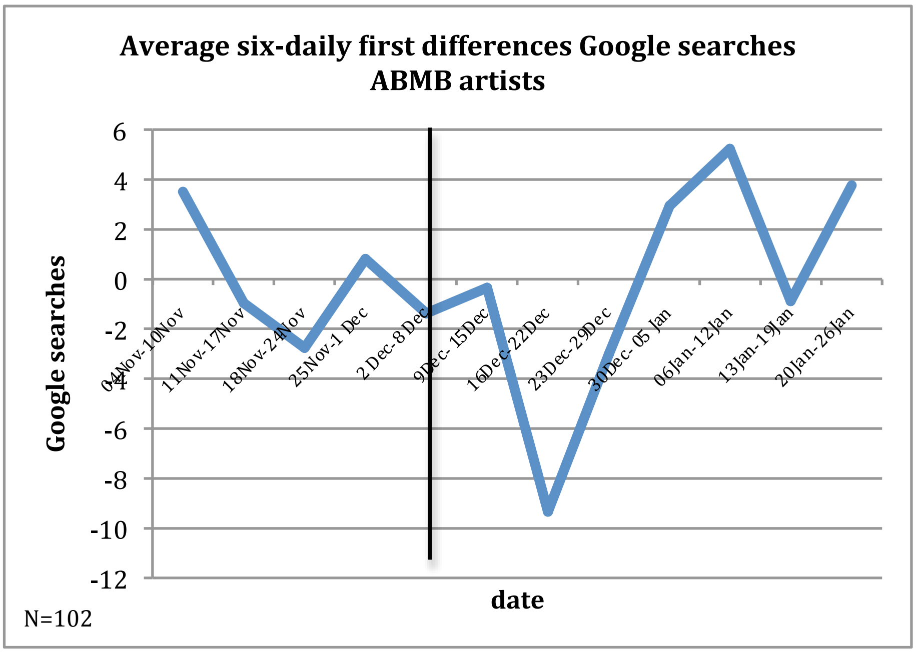


Table 6. ABMB artists six-daily first differences Google searches descriptive analysis

date	N	Minimum	Maximum	Mean	Std. Deviation
November 04-November 10	102	-39.00	38.00	3.52	12.83
November 11-November 17	102	-49.00	57.00	-0.95	15.75
November 18-November 24	102	-100.00	48.00	-2.76	17.66
November 25-December 01	102	-45.00	54.00	0.81	15.56
December 02-December 08	102	-77.00	42.00	-1.37	16.82
December 09- December 15	102	-57.00	37.00	-0.33	40.78
December 16- December 22	102	-39.00	61.00	-9.34	42.10
December 23 – December 29	102	-77.00	31.00	-3.02	14.75
December 30 – January 05	102	-24.00	41.00	2.94	10.65
January 06 – January 12	102	-25.00	41.00	5.22	12.30
January 13 – January 19	102	-67.00	41.00	-0.89	14.68
January 20 – January 26	102	-42.00	87.00	3.76	18.21

The interrupted time-series analysis and the descriptive analysis indicates that there is a slight increase in the number of Google searches in the ABMB post-period, both for artists and galleries. However, this increase doesn’t seem to be pronounced. What it is rather interesting in this analysis is the fact that in most of the graphs, the amount of Google searches in the post-period is preceded by an abrupt decrease. In other words, the treatment-period is characterized by a decrease in online attention. In addition, the referred increase in online attention in the post-period should be carefully acknowledged, since its prominence is accentuated by the low values in the treatment-period.

Being unobtrusive research, it is rather complicated to assess the cause of the low number of Google searches during ABMB, however one could argue that the interest in knowing more about an artists or gallery will be developed exclusively after the first contact with the participants in ABMB. Taking the assumption that art lovers will learn about a specific artist or gallery during the fair, interest in having more information will logically come after visiting the fair (in the post-period). This fact helps to build up the explanation on the sudden decrease in online attention during the fair, since individuals are actually visiting the physical space and appreciating art rather than looking up for more information on it.

However this dissertation does not concern exclusively actual ABMB visitors that were interested in looking for information online; but also art enthusiasts that did not necessarily attended the fair, but where aroused to know more about a specific player in the art market after galleries and artists media exposure concerning ABMB participation. Therefore, media exposure can also be an indicator for the decrease in Google searches in the treatment-period. The two periods when artists and galleries receive more attention concerning the participation in a specific event is when the list of participants is out to the public, and by the time the fair has closed and final reviews, opinions and critics start to emerge. In short, in the period before and after the event takes place. Due to the popularity and increasing media coverage that ABMB attracts, it is logical to speculate that in such periods of time, the names of participants being largely advertised raise some curiosity; hence the number of Google searches.

This media attention can be an explanation for the number of individuals searching for an artist or gallery name, however the graphs depict that this is not an extraordinary increase: comparing with the previous and following months, the online attention values immediately before and after ABMB are quite standard. Given the fact that both visitors and media are ‘busy’ visiting the fair, the number of Google searches decreases exponentially in the treatment-period. These acknowledgements should be considered as merely speculative reasons for the decrease online attention during the time ABMB takes place.

6.4. Inferential variables and tests overview

Inferential analysis aims to generalize a measure tested in a small sample to a larger number of cases that weren’t observed, commonly known as population (Antonius, 2003). As explained above, it is intended to assess to whether ABMB 2012 has an impact in online attention, the latter measured in the amount of gallery and artists names searched in Google. In other words, these tests aim to acknowledge whether there is a statistically significant mean difference before and after the art fair. In order to assess its significance a paired difference t-test is going to be performed. It is also commonly known as a matched pair or two-sample t-test for dependent samples (Sirkin, 2006; Marascuilo and Serlin, 1988). This test is different to the independent t-test in the sense that it tests/examines a one-sample t-test with the differences in each pair of scores (Sirkin, 2006). In essence, it will give a paired student t-test, giving a confidence interval for the difference between two means that are paired.

The matched pair t-test is commonly used when the values from two different samples/groups are collected from the same individuals. In essence, two values are given by an individual or case, one for each group . Hence, this test is normally used in before-after experiments when the samples are not independent but dependent, being a one-sample t-test that tries to understand the differences in every pair of scores (Sirkin, 2006, Field, 2000).

With this type of analysis, the first step is to look to the descriptive values, in this case to the mean of both before and after the experiment. According to the greater mean value between before or after the experiment, the null and alternative hypotheses are formed. If the mean value is bigger before the experiment the hypothesis are formed as

$$H_0\text{: } \mu_{before} = \mu_{after} \text{ and } H_1\text{: } \mu_{before} > \mu_{after},$$

whereas if the after mean value is greater the hypothesis are formed the other way around:

$$H_0\text{: } \mu_{before} = \mu_{after} \text{ and } H_1\text{: } \mu_{before} < \mu_{after}$$

However looking closely, the question is not whether the two means are different but rather if there is a difference between them, the hypothesis will be express as follow:

$$H_0\text{: } \mu_D = 0 \text{ and } H_1\text{: } \mu_D \neq 0$$

The μ_D stands for the difference between the two means. Hence, if the difference between the two means is positive, meaning that the score after is higher; and accordingly if the mean difference is negative, then the before value is higher (Sirkin, 2006).

Since this research is based in a quasi-experimental interrupted time-series (Box and Jenkins, 1970) where the impact before and after an event is going to be measured, the paired difference t-test seemed to be the most appropriate test to perform. Every gallery and artist's number of Google searches was analyzed before and after ABMB 2012 in different metrics (as explained above). Hence the same individual or case has two values for each point in time, either before or after the event. By following the same procedure to all the paired sample t-tests, it will be possible to assess whether the differences before and after ABMB 2012 are statistically significant. According to the data available, the tests will be performed in the four distinct groups: galleries with monthly data, galleries with six-daily data, artists with monthly data and artists with six-daily data. For every group with equal metrics, the same tests will be performed: four paired difference t-tests for each group (table 15 and table 16).

Table 15 . Overview of monthly pre-period and post-period inferential analysis.

Time period	Pre/Post
Overall period	Pre event
	Post event
3 months	Pre event
	Post event
2 months	Pre event
	Post event
1 month	Pre event
	Post event

Table 16 . Overview of six-daily pre-period and post-period inferential analysis.

Time period	Pre/Post
Overall period	Pre event
	Post event
18 days	Pre event
	Post event
16 days	Pre event
	Post event
6 days	Pre event
	Post event

In essence, to confirm the assumption that ABMB has an impact in online attention in the population, two criteria must be met: first the mean difference between pre and post- period must be negative, in other words the mean of the post-period must be higher than the mean of the pre-period; and secondly this difference must be statistically significant.

6.5 Galleries inferential analysis

6.5.1.Galleries with monthly data

Data was gathered from all the galleries that participated in ABMB 2012 and are featured in Google Trends. As explained before, Google Trends provides data either monthly or six-daily. For the monthly data, four different points in time are considered pre-ABMB, and are going to be compared with their match: post-ABMB. Hence the general research question: Does ABMB have an impact on galleries' online attention (monthly data)?

Tables 17, 18 and 19 show an overview of the four pairs concerning galleries' online attention with monthly data, however each paired difference t-test will be analyzed separately. To note, due to the fact that Google Trends do not present absolute values concerning the amount of searches of a certain keyword, but rather a normalized number according to the overall amount of Google searches over the time, the values in the dataset for the tests are not the absolute values given by Google but rather the first differences.

Table 17 shows some important characteristics from the sample.

The paired differences t test also gives information about the correlation between the two variables. This test is featured in this analysis, given the fact that when repeated measures are used, there is a chance of a correlation since the data in each moment in time came from the same unit of analysis (Field, 2000). SPSS gives the value of Pearson's r and its significance value. The last test that will analyze whether the difference between the means is statically significant (table 19) (Field, 2000). In other words, the aim is to assess whether the difference between the means before and after ABMB can be inferred to the population.

Table 17. Galleries monthly descriptive data

		Mean	Sample size (N)	Standard deviation
Total	Pre event	2.57	120	7.81
	Post event	-0.17	120	9.35
3 month	Pre event	2.85	120	9.61
	Post event	-0.69	120	9.56
2 month	Pre event	-1.63	120	15.41
	Post event	4.46	120	29.33
1 month	Pre event	-3.81	120	22.44
	Post event	5.51	120	1.96

Table 18. Galleries monthly correlation

	Sample size (N)	Correlation	P-value
Pre and post event	120	-0.01	0.88
3 months pre and 3 months post	120	-0.07	0.48
2 months pre and 2 months post	120	-0.10	0.28
1 month pre and 1 month post	120	-0.06	0.53

Table 19. Galleries monthly matched pair t-test

	Mean	T	Degrees of Freedom	P- value
Pre and post event	2.74	2.44	119	0.01
3 months pre and 3 months post	3.54	2.77	119	0.01
2 months pre and 2 months post	-6.09	-1.93	119	0.55
1 month pre and 1 month post	-9.31	-3.20	119	0.002

Hence the hypothesis:

H_0: $\mu_{(\text{pre event – post event})} = 0$ and H_1: $\mu_{D(\text{pre event – post event})} \neq 0$

H_0: $\mu_{(\text{3 months pre event – 3 months post event})} = 0$ and H_1: $\mu_{(\text{3 months pre-event – 3 months post-event})} \neq 0$

H_0: $\mu_{(\text{2 months pre event – 2 months post event})} = 0$ and H_1: $\mu_{(\text{2 months pre-event – 2 months post-event})} \neq 0$

H_0: $\mu_{(\text{1 month pre event – 1 month post event})} = 0$ and H_1: $\mu_{(\text{1month pre-event – 1month post-event})} \neq 0$

Firstly, by looking to table 18, it can be concluded that there is a fairly weak or no correlation at all between the two variables in the four time periods. Furthermore, this correlation is not statically significant, due to the rather high p-value of each test (p =>0.05). In essence, these results cannot be inferred to the population.

Both in the comparison between the total pre and post periods, and 3 months in the pre and post-periods, the null hypothesis is rejected and the alternative hypothesis accepted, given the fact that the p-value is < than 0.05 (t(119)=2.44, p (0.01)< 0.05 and t(119)= 2.77, p (0.01)<0.05 (table 19), accordingly) . In essence, there is a difference between the two paired data points in time in the population. However, due to the positive value of the difference between the paired means, the period before ABMB has a greater number of searches than in the post period. Although the tests are statistically significant, in the population, ABMB doesn’t have an impact on galleries’ online attention, comparing the entire time and 3 month pre and post-periods.

When analyzing short-term effects it can also be concluded that the null hypothesis can be rejected, and the alternative one accepted. In the comparison of one month pre and post-periods, the p-value is smaller than the significance value: $t(119)=-3.19$, $p\ (0.02)<0.05$. Contrasting with the previous two tests, the differences between the two variable means are negative, meaning that the mean of the post-period is greater than the pre-period. In other words, the ABMB participation has a positive impact in the short-term number of Google searches.

6.5.2. Galleries with six-daily data

This section will analyze galleries online attention with data six-daily data retrieved from Google Trends. As in the section before, the data will be analyzed in four different points in time, before and after ABMB: 24 days, 18 days, 12 days and 6 days. Hence the research question: Does ABMB have an impact on galleries' online attention (six-daily data)?

Table 20 will assess the descriptive statistics of each variable, whereas table 21 will acknowledge whether there is a correlation between the paired variables. Lastly, table 22 will display the results of the paired difference t test.

Table 20. Galleries six-daily descriptive data

		Mean	Sample size (N)	Standard deviation
Total	Pre event	0.29	67	5.41
	Post event	0.71	67	2.96
18 days	Pre event	-0.23	67	7.85
	Post event	-1.44	67	5.45
12 days	Pre event	0.04	67	10.75
	Post event	-0.70	67	8.80
6 days	Pre event	1.54	67	16.66
	Post event	-0.07	67	17.96

Table 21. Galleries six-daily correlation

	Sample size (N)	Correlation	P-value
Pre and post event	67	-0.02	0.88
18 days pre and 18 days post	67	0.12	0.32
12 days pre and 12 days post	67	0.15	0.23
6 days pre and 6 days post	67	0.27	0.03

Table 22. Galleries six-daily matched pair t-test

	Mean	t	Degrees of Freedom	P- value
Pre and post event	-0.42	-0.56	66	0.58
18 days pre and 18 days post	1,20	1.10	66	0.28
12 days pre and 12 days post	,75	0.48	66	0.63
6 days pre and 6 days post	1,61	0.63	66	0.53

Hence the hypothesis:

H_0: $\mu_{(\text{pre event – post event})} = 0$ and H_1: $\mu_{(\text{pre event – post event})} \neq 0$.

H_0: $\mu_{(\text{18 days pre event – 18 days post event})} = 0$ and H_1: $\mu_{(\text{18 days pre-event – 18 days post-event})} \neq 0$

H_0: $\mu_{(\text{12 days pre event – 12 days post event})} = 0$ and H_1: $\mu_{(\text{12 days pre-event – 12 days post-event})} \neq 0$

H_0: $\mu_{(\text{6 days pre event – 6 days post event})} = 0$ and H_1: $\mu_{(\text{6 days pre-event – 6 days post-event})} \neq 0$

Looking to table 21, it can be assessed that there is a weak, or no correlation at all between the two variables, however these results cannot be extrapolated to the population since they are not statistically significant.

Contrary to the monthly data in the previous section, galleries with six-daily data results did not present any statistically significant results. The p-value of the four paired tests is greater than 0.05 on the four time periods: t (66)= -0.56, p value (0.58) > 0.05 for the comparison between the total pre and post-periods; t(66)= 1.10, p (0.27) >0.05 comparing 18 days prior and after the event; t(66)=0.48, p value (0.67)>0.05 for the 12 days analysis and finally t(66)=0.63, p value (0,53)>0.05 (table 22) for the short-term 6 days pre and post-ABMB.

From the sample means (table 21) it seems that ABMB might have a long-term impact in galleries online attention, since the mean of the post-period is higher than the mean of the pre-period in both total period and 18 days analysis. However, as acknowledged above, these mean differences are not statistically significant. In other words, in the population ABMB does not have an impact in galleries online attention with six-daily data.

6.6 Artists inferential analysis

6.6.1 Artists with monthly data

As mentioned before, not only galleries that participated in ABMB are part of this study but also artists. Online attention is then measured by the amount of Google searches by the name of an artist that participated in the art fair. Once again Google Trends provides data in two different metrics: monthly and six-daily. The artist's analysis will be divided into two distinct sections: artists with monthly data and with six-daily data. Hence the first research question: Does ABMB have an impact on artists' online attention (monthly data)?

The methodology will follow the same lines as galleries with monthly data. The first table (table 23) will show some descriptive data about the two variables, and table 24 will expose the correlation between the two. Lastly table 25 will showcase the paired differences t test.

Table 23. Artists monthly online attention descriptive data

		Mean	Sample size (N)	Standard deviation
Total	Pre event	3.80	93	8.94
	Post event	0.19	93	7.80
3 month	Pre event	4.45	93	11.49
	Post event	1.85	93	9.61
2 month	Pre event	0.42	93	15.39
	Post event	3.25	93	14.34
1 month	Pre event	-0.46	93	23.70
	Post event	4.83	93	18.45

Table 24. Artists' monthly paired sample correlations

	Sample size (N)	Correlation	P-value
Pre and post event	93	-0.30	0.003
3 months pre and 3 months post	93	-0.23	0.03
2 months pre and 2 months post	93	-0.09	0.37
1 month pre and 1 month post	93	-0.02	0.84

Table 25. Artists monthly matched pair t-test

	Mean	t	Degrees of Freedom	P- value
Pre and post event	3,61	2.58	92	0.01
3 months pre and 3 months post	2,61	1.52	92	0.13
2 months pre and 2 months post	-2,83	-1.24	92	0.22
1 month pre and 1 month post	-5,29	-1.68	92	0.10

Following the same line as the sections above, the following tests have as hypothesis:

H_0: $\mu_{(\text{pre event – post event})} = 0$ and H_1: $\mu_{D(\text{pre event – post event})} \neq 0$

H_0: $\mu_{(\text{3 months pre event – 3 months post event})} = 0$ and H_1: $\mu_{(\text{3 months pre-event – 3 months post-event})} \neq 0$.

H_0: $\mu_{(\text{2 months pre event – 2 months post event})} = 0$ and H_1: $\mu_{(\text{2 months pre-event – 2 months post-event})} \neq 0$

H_0: $\mu_{(\text{1 month pre event – 1 month post event})} = 0$ and H_1: $\mu_{(\text{1month pre-event – 1month post-event})} \neq 0$

Concerning the correlation between the variables, the pair that complies the total period before and after ABMB have a moderate negative correlation according to Pearson's R table (table 24), and pairing that analysis with the 3 months in the pre and post-periods, there is a weak negative correlation. Furthermore, both tests are statistically significant. There is no relationship between the variables of the remaining two pairs, and this result is not statistically significant.

Participation in ABMB appears to only have a long-term impact in artists with monthly data, since it is the only pair that is statistically significant within 5% the confidence interval: since $t(92)=2.58$, p value $(0.01)<0.05$. The null hypothesis is rejected and the alternative one accepted. In other words, in the population there is a difference between the two variables. However, since the pre-period mean is greater than the post period, it is also concluded that in the population ABMB does not have a long-term impact in online attention. Or has a nehative impaxt in online attention.

Although in the sample the comparison between 3 months in the pre and post-periods shows that ABMB has indeed an impact in online attention, this result is not statistically significant: $t(92)= 1.51$, p value $(0.13)<0.05$. The two remaining pairs assess that in the sample ABMB does not have an impact in monthly artists online attention, since the number of Google searches in the pre-period is greater than in the post-period (table 24). However these results are not statistically significant: $t(92)=-1.24$, p value $(0.22)>0.05$ for the comparison between 2 months and $t(92)= -1.68$, p value $(0.10)<0.05$ regarding 1 month in the pre and post-periods.

6.6.2. Artists with six-daily data

Following the same methodology as the previous sections, this part will analyze the impact that ABMB might have in online attention for artists with six-daily data. Four different pairs are going to be analyzed: before and after the event, 18 days before and after, 12 days before and after and 6 days before and after. Hence the research question: Does ABMB has an impact in artists' online attention (six-daily data)?

This section will follow the same model as the previous: table 26 depicts descriptive data, whereas table 27 assesses the relationship between the variables. Lastly, table 28 showcases the paired differences t test.

Table 26. Artists six-daily descriptive data

		Mean	Sample size (N)	Standard deviation
Total	Pre event	0.15	102	5.32
	Post event	-0.24	102	3.05
18 days	Pre event	-0.97	102	6.77
	Post event	-4.23	102	7.18
12 days	Pre event	-0.98	102	10.45
	Post event	-4.84	102	10.68
6 days	Pre event	0.81	102	15.56
	Post event	-0.33	102	40.78

Table 27. Artists six-daily correlation

	Sample size (N)	Correlation	P-value
Pre and post event	102	-0.09	0.40
18 days pre and 18 days post	102	-0.12	0.24
12 days pre and 12 days post	102	-0.12	0.24
6 days pre and 6 days post	102	0.08	0.41

Table 28. Artists six-daily matched pair t-test

	Mean difference	t	Degrees of Freedom	P- value
Pre and post event	0.39	0,62	101	0.54
18 days pre and 18 days post	3.26	3,16	101	0.002
12 days pre and 12 days post	3.86	2,47	101	0.02
6 days pre and 6 days post	1.15	0,27	101	0.79

To measure artist's with six-daily data number of Google searches, the following hypothesis are going to be tested:

H_0: $\mu_{(\text{pre event – post event})} = 0$ and H_1: $\mu_{(\text{pre event – post event})} \neq 0$

H_0: $\mu_{(\text{18 days pre event – 18 days post event})} = 0$ and H_1: $\mu_{(\text{18 days pre-event – 18 days post-event})} \neq 0$.

H_0: $\mu_{(\text{12 days pre event – 12 days post event})} = 0$ and H_1: $\mu_{(\text{12 days pre-event – 12 days post-event})} \neq 0$

H_0: $\mu_{(\text{6 days pre event – 6 days post event})} = 0$ and H_1: $\mu_{(\text{6 days pre-event – 6 days post-event})} \neq 0$

Firstly, in the four pairs there isn’t a correlation between the variables. However these results are not statistically significant (table 25). Concerning the significance tests for the comparison between the overall and 6 days pre and post-periods, the results appear to be not statistically significant: $t(101)=0.62$, p value $(0.54)>0{,}05$ and $t(101)=0.27$, p value $(0.79)<0.05$, accordingly. On the contrary, the comparison between 18 and 12 days in the pre and post-periods is statistically significant, since: $t(101)=3{,}159$, p value $(0.002)<0.05$ and $t(101)=2.47$, p value $(0.02)<0.05$ (table 28). Although these results can be extrapolated to the population, they did not confirm the assumption that ABMB has an impact on artists’ number of Google searches, since the mean of the pre-period is greater than the post-period. This resuts are rather suprising since it seems that ABMB is not a powerful tool to ensure a great amount of online attention, in these time periods.

In brief, it can be concluded that ABMB solely has a short-term impact on galleries online attention and doesn’t present any evidences concerning artists’ online attention. The empirical tests above determine that the number of Google searches in ABMB post-period is greater than in the pre-period in the short-term. In addition, it can also be inferred that art lovers were more interested in searching for the name of gallery rather than the artist’s name. Since the artist is the producer of the art work itself, and the gallery regarded as the gatekeeper, this result might be surprising. However, contrary to the artists exhibition, an art fair is a gallery-orientated event (Thompson, 2008) where art galleries are highlighted, is a possible explanation for the results.

7.1 Test overview

As explained above, ABMB 2012 was divided in three major sections: Art Galleries, Art Nova and Art Positions. The main differences between the three sections is the fact that, whereas the first galleries could choose to exhibit a rather large number of artists, Art Nova and Art Positions showcase special exhibitions of one, two or three artists. Galleries chosen to exhibit in the Art Nova section are able to show the work of a maximum of three artists. The idea behind this sector is to feature new works created within the last three years, often pieces that were never seen, being almost as a fresh of breath air, with pieces directly from the artist's studio. Art Positions was created to discover new talents, where galleries chose a single artist, having the possibility to create a major project (Art Basel Miami Beach, 2012). Thus, the two sections celebrate the work of one, two or three artists, having more attention and exposure. Due to this fact, it is interesting to assess whether online attention after ABMB is greater for artists that exhibit in a small group (solo or up to three artists) comparing to artists that exhibit with a larger number. In essence, this section will assess whether different types of ABMB participation are associated with greater growth in online attention, hence the sub-question: do artists that exhibit solo or in a small group have more online attention after ABMB?

In order to answer to this question, independent t-tests are going to be performed. The difference between this test and the paired difference t-test is the fact that this one does not measure pairs, but rather whether the two means from different cases is statistically significant (Field, 2000). The variables used are the same as those used in the previous section with the addition of variable 'number of artists' that acknowledges whether artists exhibited in a multi-artists gallery, or with a small group of up to three artists.

The analysis of this test will start with a descriptive analysis, measuring which of the variables has a higher mean in the sample. With the independent t-test it going to be assessed whether it is statistically significant in the population. Normally an independent t test follows the hypothesis: H0: $\mu_1 = \mu_2$ H1: $\mu_1 \neq \mu_2$. Adapting the hypothesis to these variables:

$$H0: \mu_{\text{up to 3 artists}} = \mu_{\text{multi artists}} \quad H1: \mu_{\text{up to 3 artists}} \neq \mu_{\text{multi artists}}.$$

Contrary to the the paired differences significance test, in this section all the independent t tests have the same hypothesis since the same values in the variable "number of artists" is being measured. The difference between each test is the period of time being analyzed. A limitation is the fact that the variable 'up to three artists' has a rather small sample (monthly data n=23, six-daily n=11), which can make the results less reliable.

7.2 Data analysis

7.2.1 Monthly data

Table 29. Number of artists monthly data analysis

	Number artists	N	Mean	Standart deviation
Overview post	Up to 3	23	2.82	7.32
	Multi	70	-0.67	7.81
Post 3 months	Up to 3	23	6.55	10.49
	Multi	70	0.30	8.84
Post 2 months	Up to 3	23	2.28	10.96
	Multi	70	3.57	15.34
Post 1 month	Up to 3	23	7.57	25.41
	Multi	70	3.93	15.65

Table 30. Number of artists monthly independent f-test

		Levene's test for equality of variances		T test for equality of means		
		F	P value	t	df	P value
Overview post	Equal variances assumed	0.54	0.46	1.89	91	0.06
	Equl variances not assumed			1.95	39.74	0.06
Post 3 months	Equal variances assumed	1.71	0.20	2.81	91	0,006
	Equl variances not assumed			2.57	32.91	0.02
Post 2 months	Equal variances assumed	1.80	0.18	-0.37	91	0.71
	Equl variances not assumed			-0.44	52.50	0.66
Post 1 month	Equal variances assumed	2.95	0.09	0.82	91	0.42
	Equl variances not assumed			0.65	27.69	0.52

From the four tests only the 'post 3 months' is statistically significant.
Due to the high Levene's test p-value (0.20) equal variances are assumed, hence t(91)=2,807, p value (0,006)<0,05 (table 30). The null hypothesis is rejected and the alternative accepted. Since the mean of the artists' online attention 3 months after the event that exhibits with a maximum of 3 artists (m=6,551 sd=10,487), is larger than artists exhibiting with a larger group (m=0,300 sd=8,843) (table 29), It can be concluded that in the population, the means of the two variables are

different. In essence, concerning the 3 months post-ABMB, artists that exhibit with less peers in ABMB attract more online attention.

On the other hand, the other time periods did not present statistical significant results.

7.2.2 Six-daily data

Table 31. Number of artists six-daily descriptive data

	Number artists	N	Mean	Standard deviation
Overview post	Up to 3	11	-0.65	2.12
	Multi	91	-0.19	3.15
Post 18 days	Up to 3	11	-1.67	8.37
	Multi	91	-4.54	7.01
Post 12 days	Up to 3	11	-6.32	11.12
	Multi	91	-4.66	10.66
Post 6 days	Up to 3	11	-2.55	9.78
	Multi	91	-0.07	43.07

Table 32. Number of artists six-daily independent t-tet

		Levene's test for equality of variances		T test for equality of means		
		F	P value	t	df	P value
Overview post	Equal variances assumed	1.55	0.22	-1.75	100	0.08
	Equal variances not assumed			-2.87	20.66	0.009
Post 18 days	Equal variances assumed	0.02	0.89	1.26	100	0.21
	Equal variances not assumed			1.09	11.76	0.30
Post 12 days	Equal variances assumed	0.06	0.80	-0.49	100	0.63
	Equal variances not assumed			-0.47	12.30	0.65
Post 6 days	Equal variances assumed	0.31	0.58	-0.19	100	0.85
	Equal variances not assumed			-0.46	69.42	0.65

Firstly it should be acknowledge that due to the small sample of one variable ('up to 3 artists with six-daily data n=11) the results might not be statistically significant. Nevertheless, they are an important part of this section and should be acknowledged.

The inferential analysis also shows that this difference is not statistically significant, since all the Levene's test showed that equal variances were assumed in every test, hence a high t-test p-value of each test: overview post period p value (0.08)>0.05; 18 days post-period p value (0.21)>0.05; 12 days post-period p value (0.63)>0.05 and 6 days post-period p value (0.85)>0.05. In essence, the null hypothesis cannot be rejected and the mean differences of the variables are not statistically significant in the population. To note that the sample size is rather small for the variable "up to 3" (n=11), can be one of reasons for the lack of statistically significant results.

In essence, it can be concluded that artists that exhibit with fewer peers have indeed more online attention after ABMB, however these results are solely significant in a long-term analysis (3 months). This result should be interpreted carefully, given the fact that in a 3 month period, other events such as art fairs, exhibitions or major media exposure might also affect the amount of Google searches of the referred artists. As explained in the methodology, history is one of the limitations of quasi-experiment analysis with an interrupted time-series, especially when a long period of time (as 3 months) is considered.

8. Comparing ABMB galleries with non-ABMB galleries online attention

Because ABMB 2012 took place during December, one could argue that its attention online could increase due to seasonality issues, especially due to Christmas time. In time series analysis, normally related to sales, seasonality can be an issue: increasing in December, related to Christmas, and decreasing during summer time. In order to check for seasonality and other trends that the number of Google searches for galleries may be subject to it was needed to create a control group. The 'control group galleries' are galleries that did not participated in the art fair, whereas 'treatment group galleries' participated in ABMB.

'The world's best 100 galleries' (Bermeo, 2012) was used to create control and treatment groups. This top was created based on galleries' media attention and participation in art fairs. Because this group of galleries was featured in this top, they can be compared with each other. Out of the 100 galleries, 54 belong to the control group and 37 to the treatment group. The 9 galleries that are missing did not have enough search volume to be featured in Google Trends. In essence, from the list mentioned above, ABMB participants comply the treatment group and galleries that did not participated in the art fair formed the control group.

In order to assess the impact of ABMB the difference between the treatment and control groups, a test of significance should be performed. However, since both groups were formed based on a top 100 best galleries, the number of cases of each group is not enough to perform a test of significance, since the sample sizes for each group are rather small. Due to this fact, a descriptive analysis is going to be performed instead. This section attempts to answer to the question: are the treatment and alternative groups different? The general idea behind this question is to assess whether all the galleries in the sample had the same Google search values (represented by the control group) or whether the ones that participated in ABMB perform differently (treatment group).

Again, the data retrieved from Google Trends comes with two different metrics: either monthly or six-daily. The major difference is the fact that the monthly data will cover a rather big scope, from July to April; and the six-daily data will cover from 28 October to 26 January. For the sake of this research, both metrics will be presented separately and taken in consideration evenly.

8.1. Monthly data absolute values

In this section, short-term impact analysis is going to be undertaken by showcasing an overview of the complete time-series, both for the control and treatment groups. In order to analyze the long-term or trends impact the time-series will be divided in a pre and post-ABMB trend line graph. To note, the notion of short and long-term effects will vary according to the date being presented monthly or six-daily data.

Analyzing the monthly control group there seems to be no significant difference between November, December and January, since its absolute values average varies between 46.83 (sd=31.34), 44.79 (sd=30.30) and 45.45 (32.50) (graph 13).

On the other hand, by looking to the treatment group monthly graph, the average online attention of galleries that participated in ABMB seemed to augmented slightly between December and January, 54.76 (sd=26.30) and 67.18 (sd= 23.23), accordingly (graph 14). Although it is not a great increase, there seems to be an increase in attention for treatment galleries after their participation in ABMB.

Two major conclusions can be taken from this simple analysis. Firstly, the control art galleries online attention does not augment or diminish during Christmas (in this case during December) being an indicator that seasonality cannot be applied in this situation. As explained above, seasonality states that in certain times of the year values can change due to the season that they are in, as summer or Christmas and can be analyzed in the monthly control group graph, this seems not to be applied in this situation since the values are rather stable during these months.

Secondly, from the comparison between the absolute values between the control and treatment groups, it can also be argued that there might be an impact in galleries' online attention that attended ABMB 2012. Whereas the control group galleries' online attention don't seem to vary before or after December, the treatment group galleries'' online attention augmented slightly right after its participation in the art fair. Hence, in this sample, it can be argued that there is an impact in online attention for the galleries than participated in ABMB.

Graph 13

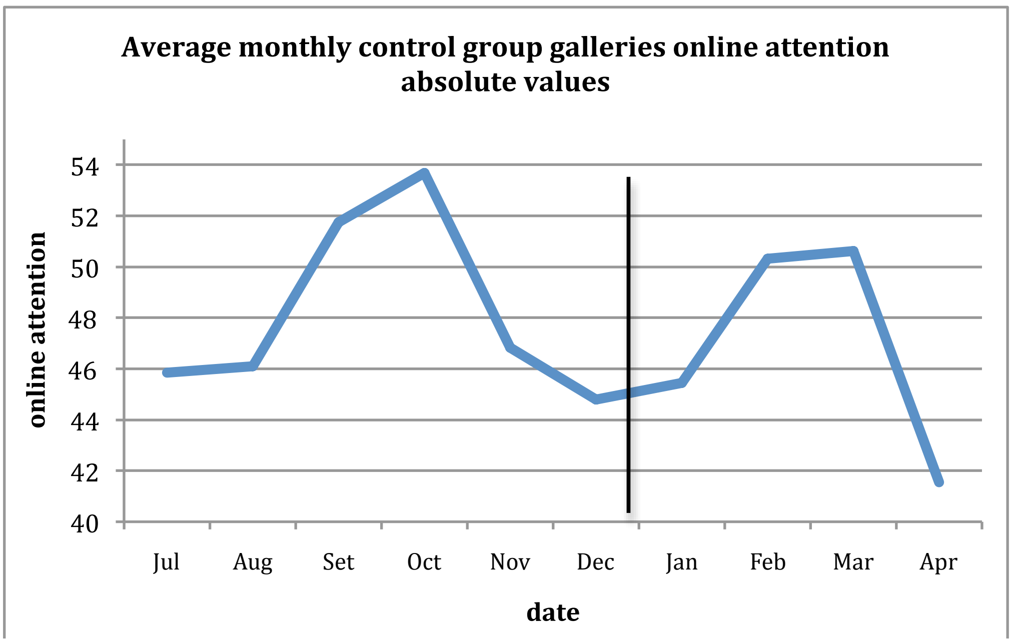


Table 33. Control group monthly number of Google searches descriptive analysis

date	N	Minimum	Maximum	Mean	Std. Deviation
July	29	0.00	100.00	45.86	34.04
August	29	0.00	100.00	46.10	35.27
September	29	0.00	100.00	51.76	35.70
October	29	0.00	100.00	53.69	35.51
November	29	0.00	100.00	46.83	31.34
December	29	0.00	100.00	44.79	30.30
January	29	0.00	100.00	45.45	32.50
February	29	0.00	100.00	50.31	34.44
March	29	0.00	100.00	51.31	31.69
April	29	0.00	100.00	41.55	37.78

Graph 14

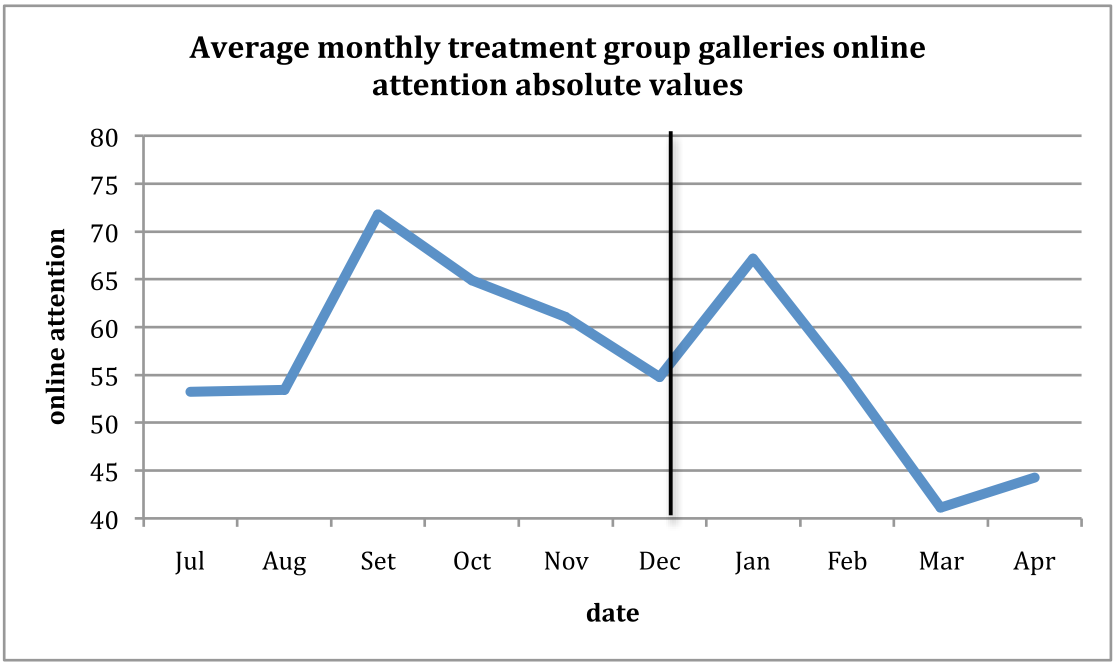


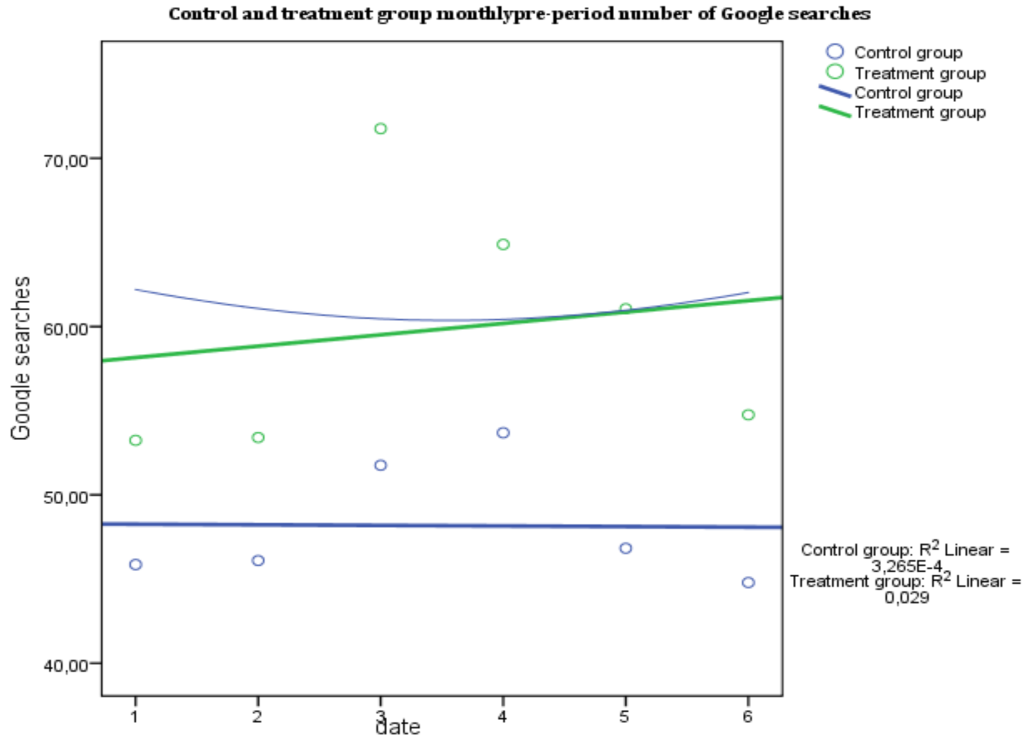
Table 34. Treatment group monthly number of Google searches descriptive analysis

date	N	Minimum	Maximum	Mean	Std. Deviation
July	17	00.00	100.00	53.24	32.05
August	17	00.00	100.00	53.41	30.81
September	17	00.00	100.00	71.76	31.92
October	17	00.00	100.00	64.88	29.98
November	17	00.00	91.00	61.06	26.82
December	17	00.00	88.00	54.76	26.30
January	17	35.00	100.00	67.18	23.23
February	17	00.00	100.00	54.64	30.85
March	17	00.00	81.00	41.11	32.54
April	17	00.00	100.00	44.29	37.10

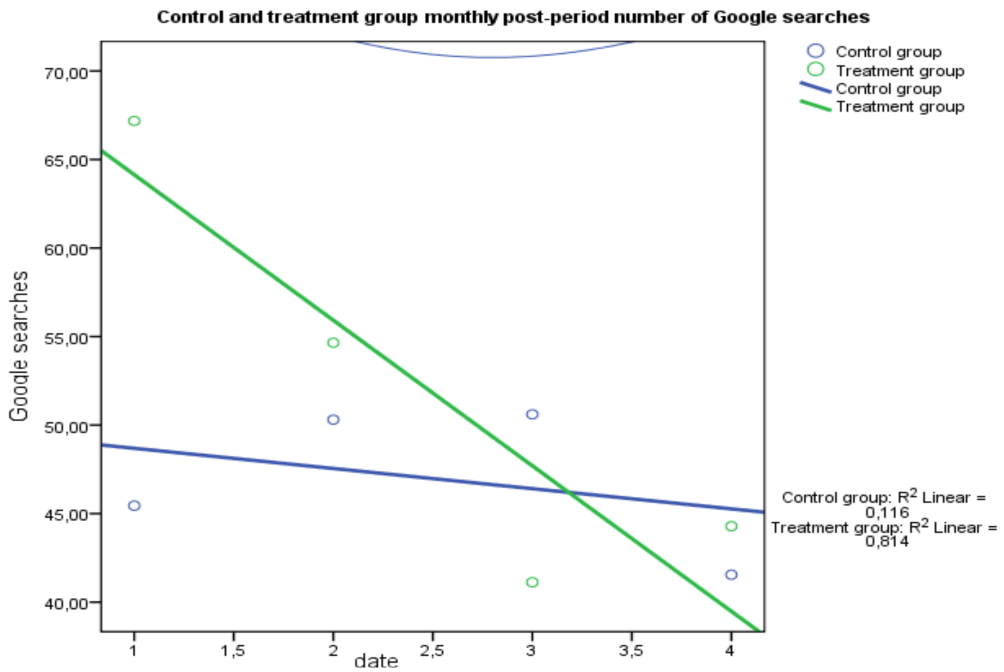
Concerning the long-term effect for absolute values, both groups present rather similar results. Whereas before the event the control group exhibited a horizontal slope indicating a stable trend (graph 15), the post-ABMB period has a negative slope denoting a negative trend towards online attention (graph 31).

To conclude, in the long-term the impact of ABMB seems to be rather similar comparing the control and treatment groups. In other words, the online attention of galleries from the two groups does not have a long-term impact after the ABMB time period.

Graph 15



Graph 16



8.2 Monthly data first differences

The graphs below represent the differences between search values over time. These graphs help to give a clear overview of the changes between months. In the control group there is a small increase in the post-period (m=-6.86 sd=31.79), comparing to the treatment period (m=-2.03 sd=12.23), (graph 17, table 35). Although there is a slight increase, it is not significant. The treatment group presents some differences between December and January. The average of the treatment period is 6.29 (sd=19.80), increasing to 12.41 in the post-period (graph 18, table 36). In other words, in the short-term, ABMB seems to have impact in galleries' online attention since it increases in the treatment group. It can also be concluded that the impact is not in every gallery, but exclusive for the galleries that participated in ABMB, since the control group galleries do not present the same results.

Graph 17

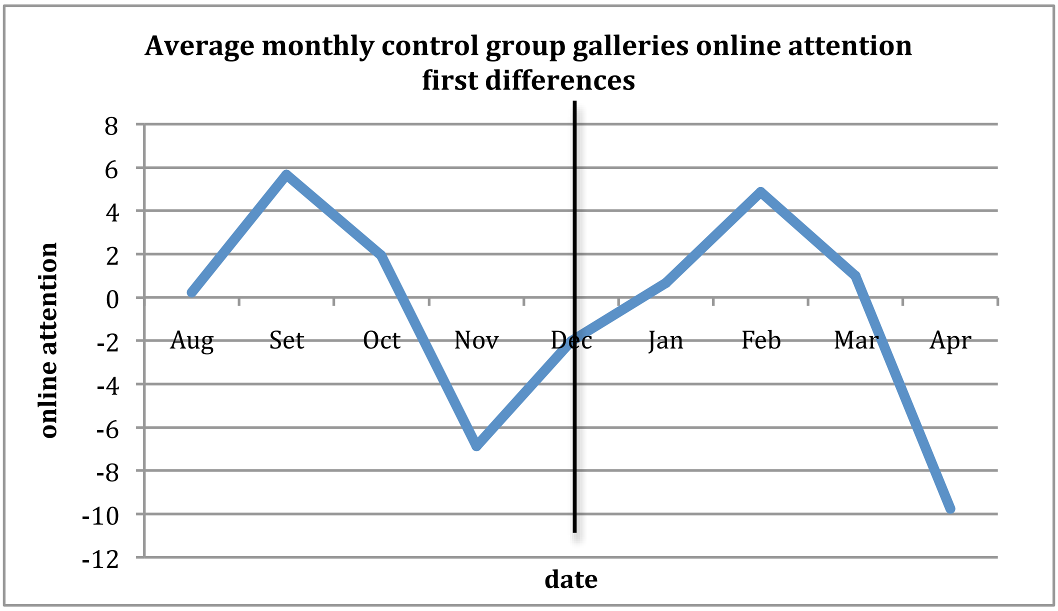


Table 35. Control group monthly Google searches first differences descriptive analysis

date	N	Minimum	Maximum	Mean	Std. Deviation
August	29	-53.00	54.00	.24	21.34
September	29	-43.00	51.00	5.66	22.20
October	29	-68.00	100.00	1.93	36.95
November	29	-100.00	100.00	-6.86	31.79
December	29	-37.00	24.00	-2.03	12.23
January	29	-47.00	32.00	.66	16.00
February	29	-48.00	66.00	4.86	22.72
March	29	-85.00	100.00	1.00	34.24
April	29	-100.00	35.00	-9.76	32.18

Graph 18

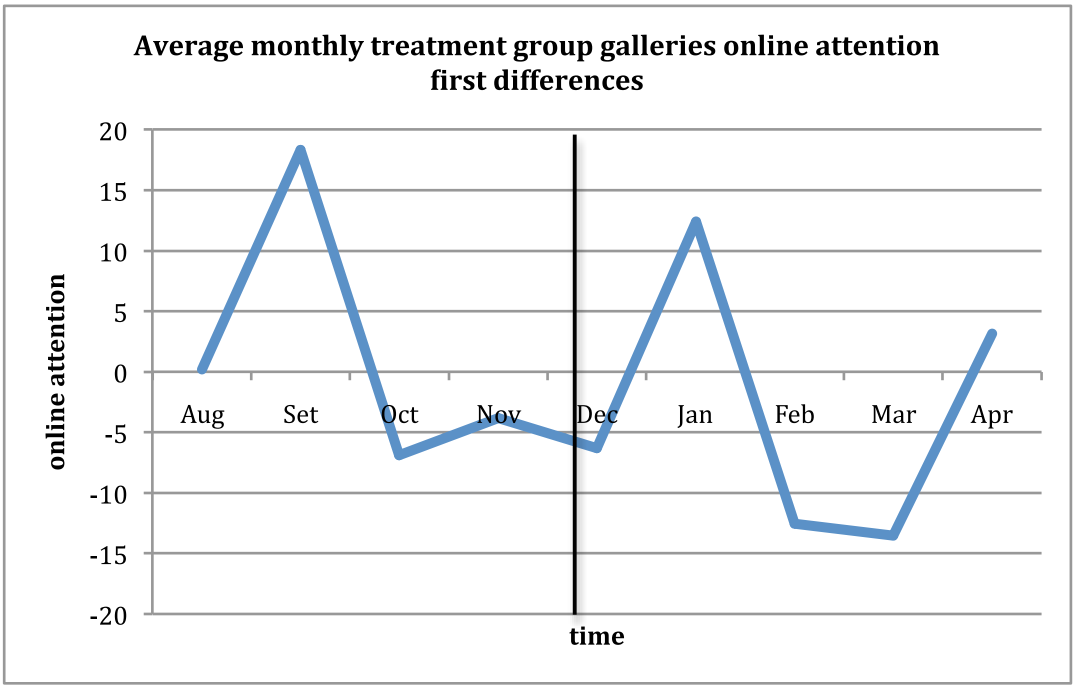


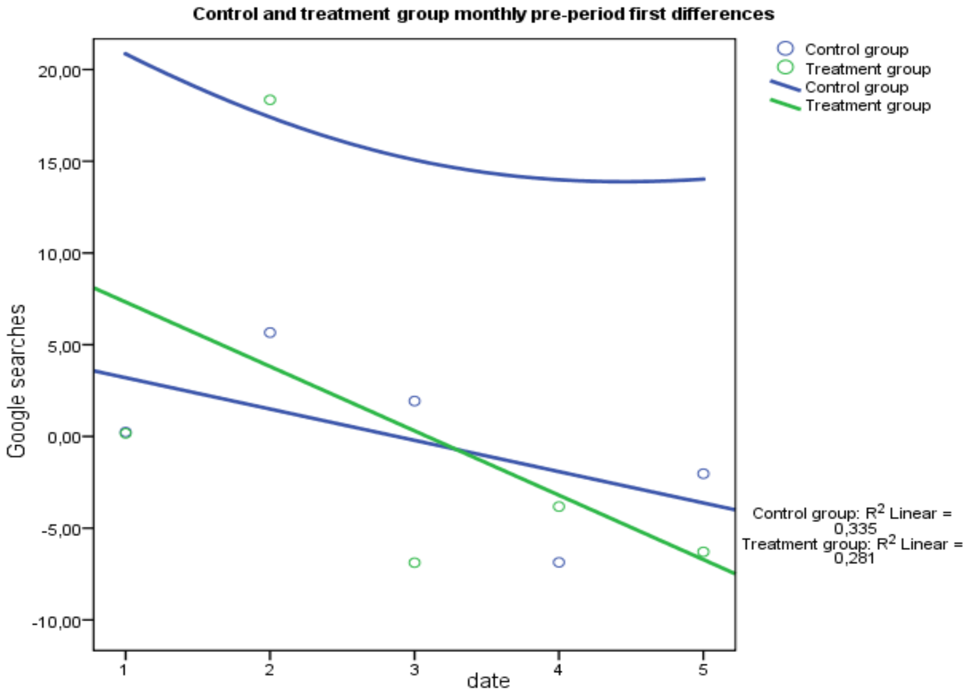
Table 36. Treatment group monthly Google searches first differences descriptive analysis

date	N	Minimum	Maximum	Mean	Std. Deviation
August	17	-37.00	35.00	0.17	15.13
September	17	-18.00	92.00	18.35	28.85
October	17	-38.00	8.00	-6.88	13.53
November	17	-44.00	35.00	-3.82	20.61
December	17	-54.00	30.00	-6.29	19.80
January	17	-36.00	50.00	12.41	21.68
February	17	-89.00	33.00	-12.53	27.58
March	17	-100.00	26.00	-13.53	35.26
April	17	-20.00	52.00	3.18	15.69

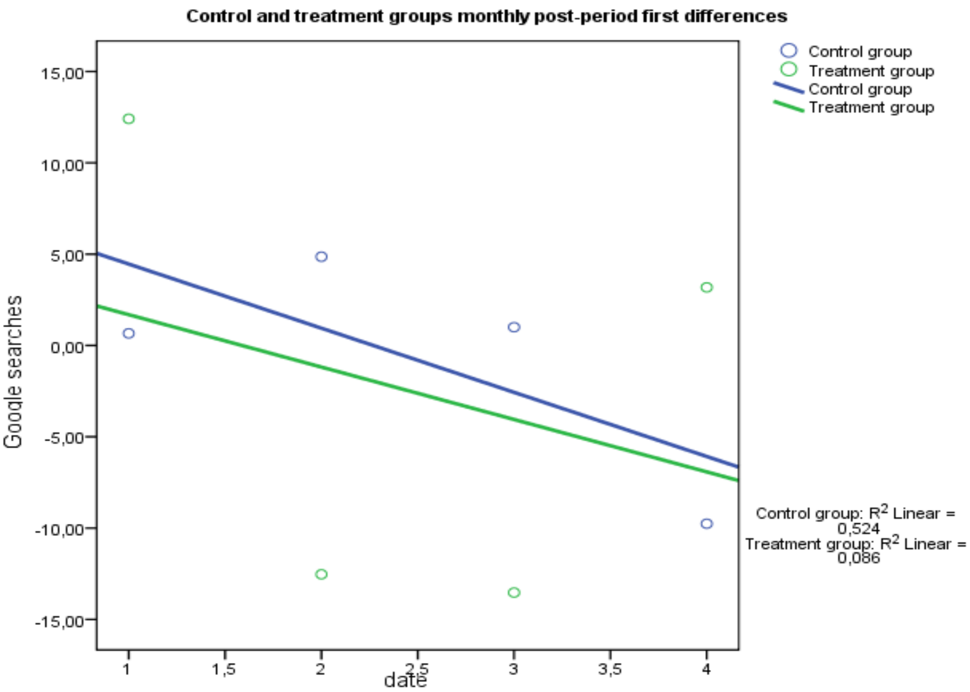
Concerning the long-term effects, both the control and treatment groups (graph 19 and 20) have a trend line with a negative slope. In other words, the long-term effect on the control and treatment groups' galleries pre and post-ABMB is has a decreasing trend, meaning that the long-term online attention is decreasing. To note that the confidence intervals on the graphs are rather wide (in graph 19 it is pointed as the blue curve, whereas in the other do not even appear in the graph). This leads to the conclusion that while this trendlines can help to have an overview of the online attention long-term impact, it is not possible to be sure at a reasonable level of confidence the slope of the trendline.

However it should be acknowledged that this long-term analysis with monthly data covers a wide time span. Since this research is based on online attention, it is likely that after one month since the event, the online attention will not be due the art fair. With the increase of smart-phones and the instant mindset that is linked with the World Wide Web, one could not assume that an individual would look for a gallery online as a sequence of an art fair that occurred three months ago.

Graph 19



Graph 20



8.3. Six-daily data absolute values

The graphs below represent the online attention from the control and treatment groups with six-daily data. The difference between monthly and six daily is that the latter is more detailed and accurate. Note that since this is a six-daily analysis; before the art fair is the time period between 25 November to 1 December, during is considered 2 to 8 December and after from 9 to 14 December. ABMB took place between the 6 and 9 December, however due to Google Trends metrics, it was decided to embrace 2 to 8 December as the period 'during'.

Looking to the six-daily data in the short-term, the control group values during, after and before seem not to vary much, since their averages are: 49.48 (sd=25.51), 46.36 (sd=26.23) and 44.88 (sd=25.23), accordingly (graph 21). Concerning the treatment group, however small, there is actually a decrease in online attention after the event. As it was concluded in the monthly analysis, seasonality seems not to be a limitation in this case, since there are no major fluctuations during this time period. Contrasting with the monthly data, the six-daily data for the treatment group does not seem to have major fluctuations, as the average before ABMB decreases from an average of 50.90 (sd=17.05) to 50.50 (sd=20.25) in the post-period (graph 22, table 38). Both control and treatment galleries are rather similar in terms of six-daily absolute values, since the number of Google searches seems to decrease after ABMB period.

Graph 21

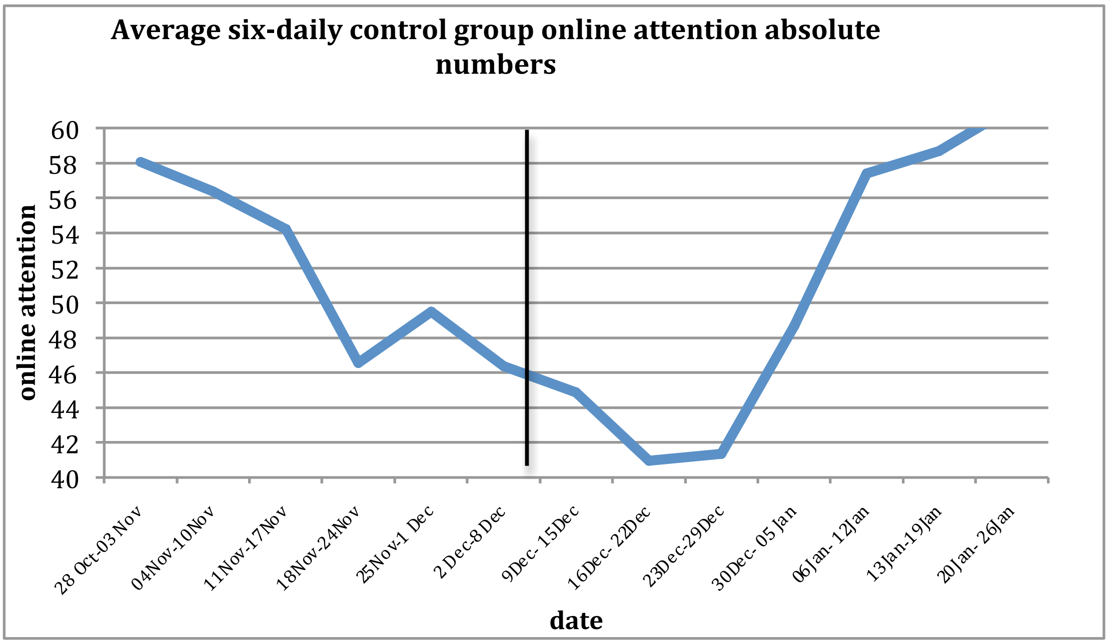


Table 37. Control group galleries six-daily number of Google searches descriptive analysis

date	N	Minimum	Maximum	Mean	Std. Deviation
October 28- November 03	25	0.00	100.00	58.08	25.06
November 04-November 10	25	0.00	82.00	56.40	22.21
November 11-November 17	25	0.00	90.00	54.24	21.92
November 18-November 24	25	0.00	80.00	46.56	25.70
November 25-December 01	25	0.00	83.00	49.48	25.51
December 02-December 08	25	0.00	78.00	46.36	26.23
December 09- December 15	25	0.00	78.00	44.88	25.23
December 16- December 22	25	0.00	73.00	40.96	24.53
December 23 – December 29	25	0.00	84.00	41.36	25.64
December 30 – January 05	25	0.00	97.00	48.68	31.73
January 06 – January 12	25	0.00	100.00	57.40	26.31
January 13 – January 19	25	0.00	91.00	58.68	23.70
January 20 – January 26	25	0.00	100.00	61.20	25.12

Graph 22

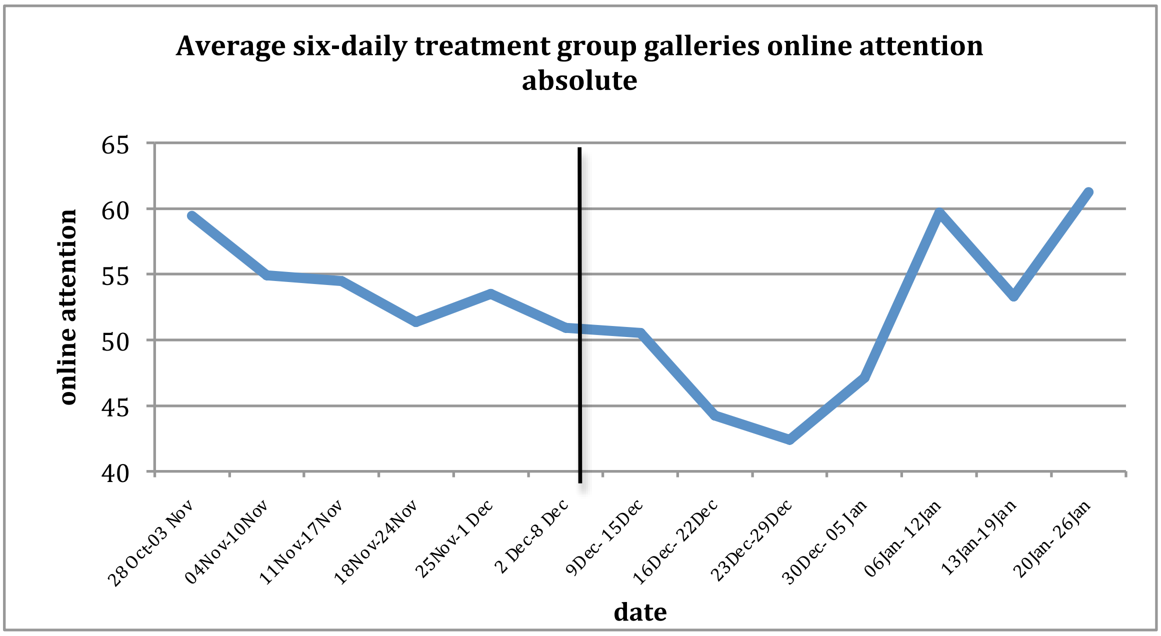
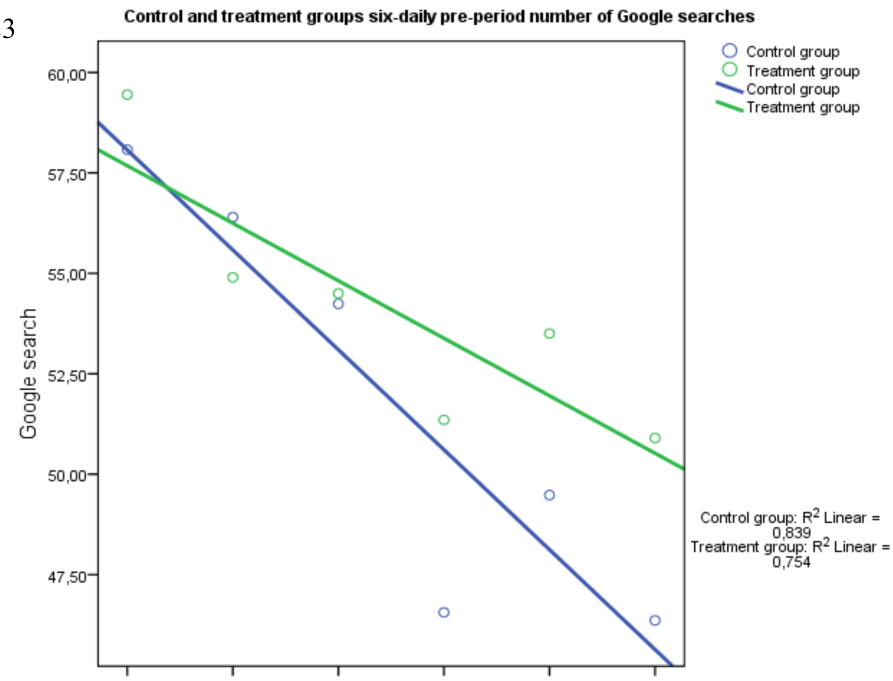


Table 38. Treatment group galleries six-daily number of Google searches descriptive analysis

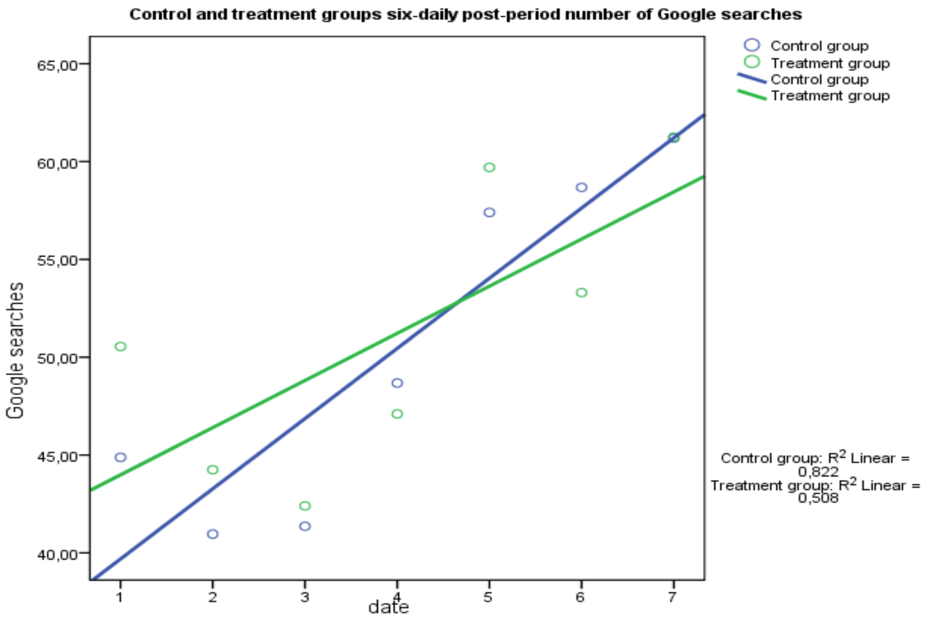
date	N	Minimum	Maximum	Mean	Std. Deviation
October 28- November 03	20	23.00	93.00	59.45	18.87
November 04-November 10	20	00.00	98.00	54.90	20.69
November 11-November 17	20	00.00	80.00	54.50	19.59
November 18-November 24	20	00.00	100.00	51.35	22.38
November 25-December 01	20	00.00	91.00	53.50	21.14
December 02-December 08	20	00.00	77.00	50.90	17.05
December 09- December 15	20	00.00	74.00	50.55	20.25
December 16- December 22	20	00.00	78.00	44.25	19.54
December 23 – December 29	20	00.00	81.00	42.40	20.09
December 30 – January 05	20	00.00	84.00	47.10	20.56
January 06 – January 12	20	34.00	88.00	59.70	15.90
January 13 – January 19	20	30.00	90.00	53.30	16.77
January 20 – January 26	20	33.00	100.00	61.25	19.00

Although there is a minor change between the control and treatment groups in the short-term analysis, in the long-term there seems to be no difference. Whereas the short-term analysis indicated there was no impact post-ABMB, the long-term analysis indicates the contrary: both control and treatment groups (graph 23 and 24) present a negative slope pre-ABMB but a positive one in the post period. In other words, the absolute value of galleries online attention seems to decrease before the art fair and to augment after. Contrary to the monthly data, the six-daily control group does not present major differences with the treatment group. To conclude, ABMB does not seem to have a clear online attention impact, since the results of the control group are quite similar to the results of the treatment group.

Graph 23



Graph 24



8.4. Six-daily first differences

Looking to the first differences the same conclusions can be drawn. The graphs below represent these differences. This type of graph is particularly interesting since the fluctuations between two data points are particularly visible, giving a better overview of an event's impact in time. The data points of particular interest are the ones representing the period before ABMB (2–8 December) and the period after the fair (9-15 December). In both control and treatment groups there seems to be a not very prominent positive impact in online attention in ABMB, comparing the treatment with the post-period. In the control group, the average increases from -3.12 in the treatment period (sd= 19.01) to -1.46 (sd=10.76) in the post-period (graph 25, table 39). However, there is a rather large increase in the following weeks.

The treatment group is roughly the same, where there is an increase from -2.6 (sd= 16.30) in the treatment-period to -0.35 (sd=11.68) in the post-period (graph 26, table 40). In both groups the number of Google searches augmented slightly right after ABMB period, however both experienced a peak in the beginning of January.

To conclude ABMB seems not to have an effect for this group of galleries since the number of Google searches of both control and treatment group galleries is rather similar. In essence, the participation of ABMB was not the cause for these results.

Graph 25

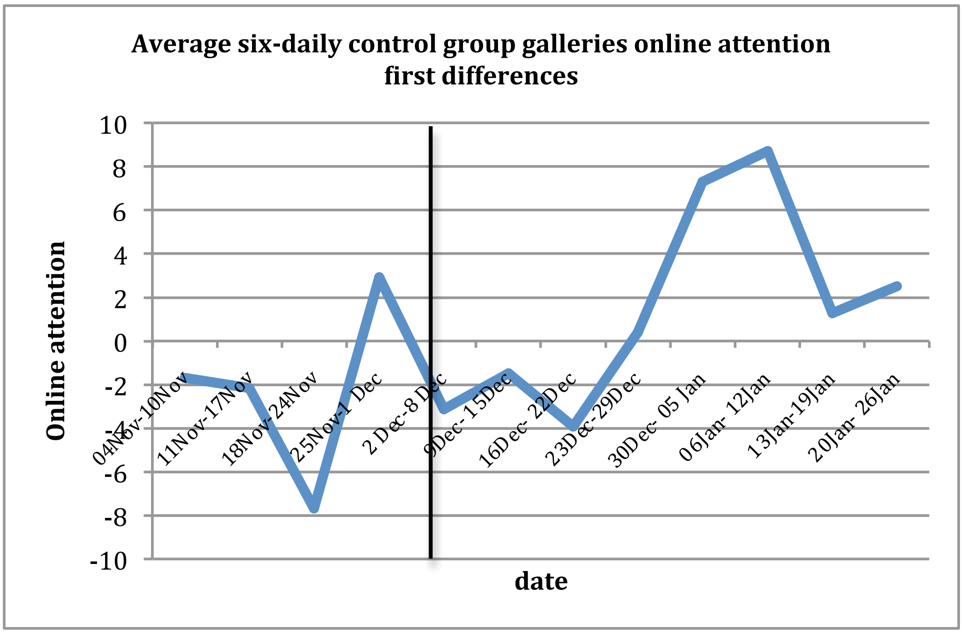


Table 39. Control group galleries six-daily first differences descriptive analysis

date	N	Minimum	Maximum	Mean	Std. Deviation
November 04-November 10	25	-34.00	40.00	-1.68	15.52
November 11-November 17	25	-30.00	21.00	-2.16	11.97
November 18-November 24	25	-82.00	43.00	-7.68	25.19
November 25-December 01	25	-18.00	28.00	2.92	9.74
December 02-December 08	25	-71.00	22.00	-3.12	19.01
December 09- December 15	25	-30.00	21.00	-1.48	10.76
December 16- December 22	25	-27.00	15.00	-3.92	10.65
December 23 – December 29	25	-28.00	15.00	0.40	9.10
December 30 – January 05	25	-9.00	38.00	7.32	11.29
January 06 – January 12	25	-55.00	100.00	8.72	30.86
January 13 – January 19	25	-71.00	81.00	1.28	25.61
January 20 – January 26	25	-29.00	35.00	2.52	15.31

Graph 26

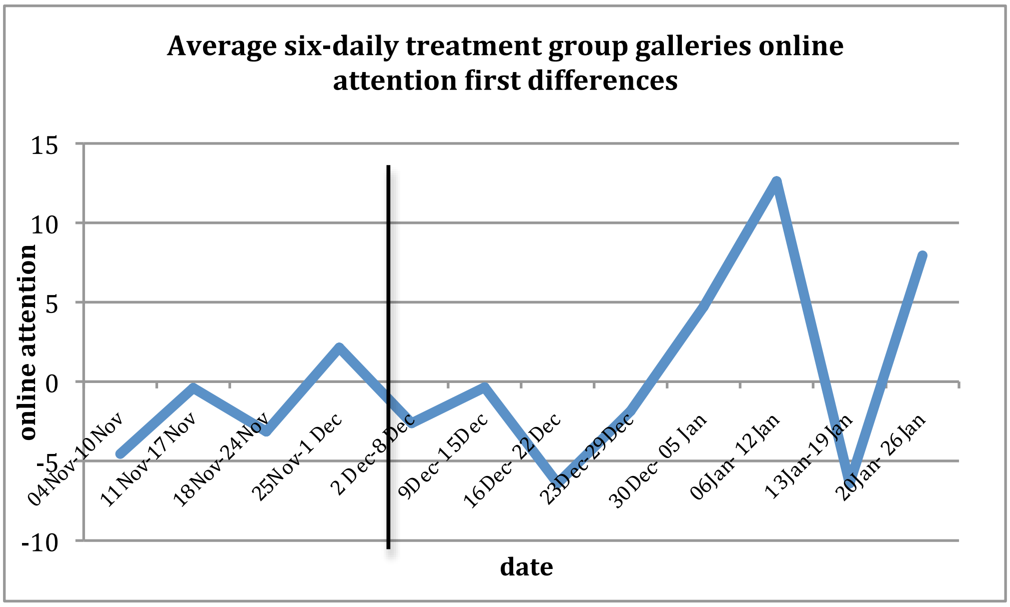
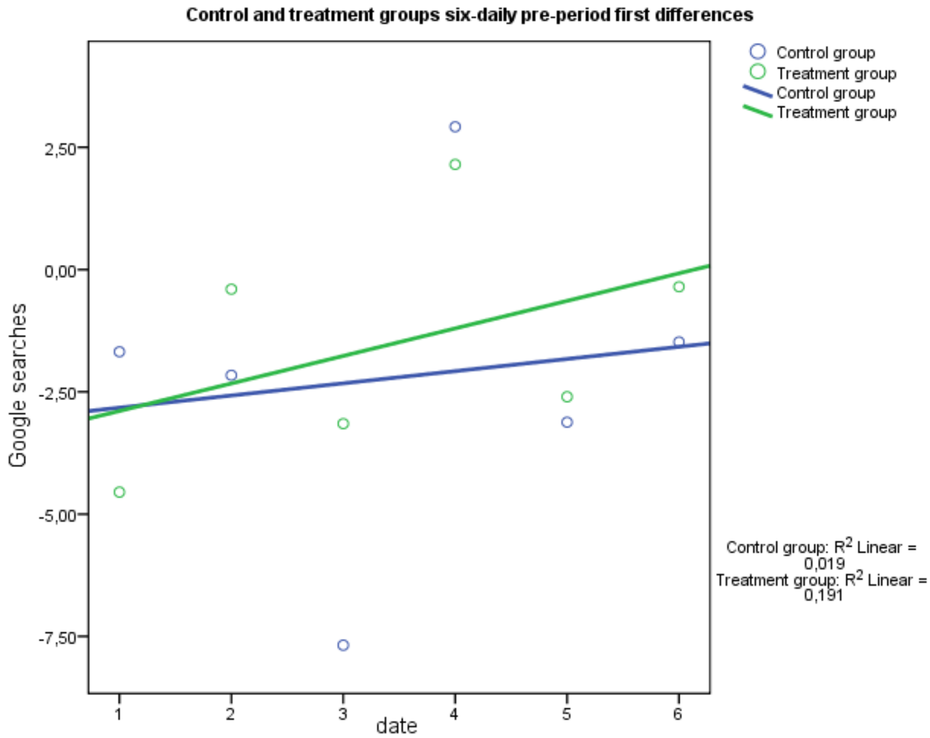


Table 40. Treatment group galleries six-daily first differences descriptive analysis

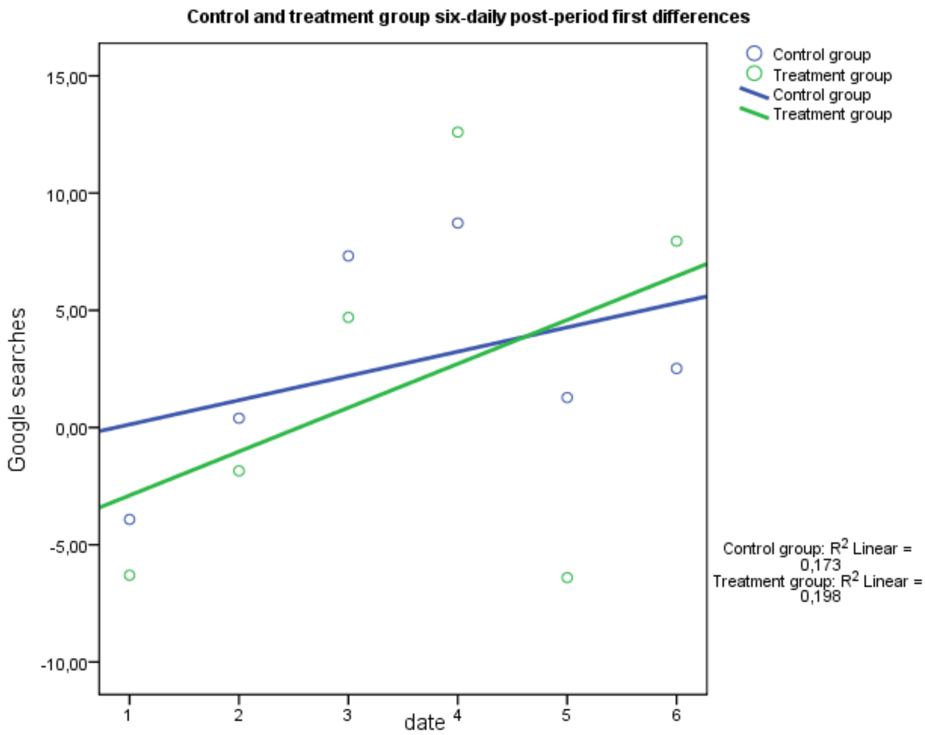
date	N	Minimum	Maximum	Mean	Std. Deviation
November 04-November 10	20	-89.00	17.00	-4.55	23.32
November 11-November 17	20	-29.00	44.00	-.40	15.67
November 18-November 24	20	-34.00	51.00	-3.15	20.40
November 25-December 01	20	-24.00	22.00	2.15	10.89
December 02-December 08	20	-47.00	19.00	-2.60	16.30
December 09- December 15	20	-28.00	20.00	-.35	11.68
December 16- December 22	20	-31.00	16.00	-6.30	12.17
December 23 – December 29	20	-17.00	13.00	-1.85	6.85
December 30 – January 05	20	-4.00	24.00	4.70	7.59
January 06 – January 12	20	-21.00	88.00	12.60	22.450
January 13 – January 19	20	-24.00	6.00	-6.40	8.06
January 20 – January 26	20	-18.00	43.00	7.95	13.79

By looking to the following trend lines, it can be concluded that both control and treatment groups have an increase in online attention in the pre and post-period, since the slope of both trend lines is positive (graph 27 and 28). However, this is an indication that the impact is not due to ABMB participation, since the control group galleries' online attention is also increasing in the long-term. Again, it should be ackownledge that is not possible to be confident about the slope of the trendlines. In essence, these graphs are included to supply an overview of the similarities between control and treatment groups.

Graph 27



Graph 28



Briefly, from the comparison between the control and treatment groups, it can be assessed that ABMB does not present clear signs of having an effect in galleries' online attention, giving the fact that the number of Google searches does not seem to vary greatly from galleries' online attention that did not participate in the art fair.

9. CONCLUSIONS

In this study the impact that art fairs have on galleries and artists online attention was measured. Starting from a simple interrupted time series analysis it was possible to assess the online impact on artists and galleries that participated in ABMB, using data from Google Trends.

In essence the empirical findings of this dissertation suggest three main conclusions: from a descriptive perspective, the time-series analysis acknowledges that participation in ABMB does not seem to have an impact on online attention; there is solely a short-term impact for galleries online attention after participating in ABMB, since the number of Google searches in the post-period is greater compared to the pre-period; and lastly participation in ABMB has a long-term impact on online attention for artists exhibiting in one booth with two peers or less, compared with artists that exhibit in groups of more than three artists.

From the interrupted time-series analysis, galleries and artists, both with six-daily and monthly data, presented rather similar results: a slight increase in the number of Google searches in the ABMB post-period. However, this increase doesn't seem to be pronounced. Interestingly, this analysis is also characterized by a decrease in online attention in the treatment-period. This fact leads to the conclusion that the referred increased values in the post-period are accentuated by the low values in the treatment-period.

One of the limitations of this research is the fact that it is not possible to determine the cause of the sudden decrease in online attention during the fair, however, possible assumptions can be addressed. Logically, the first explanation is that possible art enthusiasts interested, search for more information on an artists or galleries are actually visiting the art fair, and not looking for more information online. However this assumption also has some limitations, given the fact that nowadays mobile devices are largely used and any individual with a smartphone is able to go online at the same time as visiting the art fair (and appreciating art). Another possible explanation of this phenomenon would be that online attention is correlated with media exposure. Assuming that ABMB participants would have increased media coverage before the fair (when the list of participants becomes public) and by the end of the fair (where art critics give their opinion on the fair), hence the low values during the treatment-period. To note, these are merely assumptions and further research on the reasons why online attention seems to decrease during the time ABMB takes place would be necessary.

An inferential analysis was realized in order to assess whether there is empirical evidence that online attention is greater for art galleries and artists participating in the fair in the art fair post-period, compared to the pre-period. In almost two dozens of tests of significance it was concluded that participation in ABMB had solely a short-term online impact concerning galleries' online attention. In essence, this research proved that looking to one month after ABMB, the online attention in this period was greater than one month before.

Besides proving that ABMB have, to a certain extent, an impact on online attention, these tests also acknowledge that in the population, the gallery name attracts more online visitors than the actual artist name. It can be argued that that the name of the actual artists can sometimes be more popular than its gatekeeper (in this case, the gallery). However, this research determines that only galleries have an impact in online attention after ABMB participation, whereas artists' online attention do not seem alter after ABMB. It can be argued that being a gallery-orientated event, where the gallery name appears rather highlighted (contrasting with a small label with the artist's name under the work of art) the results are not surprising. However, one can say that the artist, as the creative mind behind the work of art, would receive more attention. This is a rather interesting issue that could be further developed in future research.

Another conclusion is the fact that artists that exhibit together in smaller groups, tend to have a greater amount of online attention after ABMB. When comparing the amount of online attention between artists that exhibit in one booth with three peers or less, with artists that share the same gallery space with up to 20 other professionals, the first has indeed a greater number of Google searches. However, this difference is not quite pronounced, since this was acknowledged as a long-term effect: 3 months after participation in the fair. Although statistically significant, this long-term effect might have some limitations giving the fact that 3 months after ABMB other important events in the art market might have taken place and affected artist's online attention. As mentioned above, history is one of the principal limitations concerning time-series analysis.

All arguments considered, the empirical findings of this dissertation suggest that ABMB has some impacton artists and galleries online attention, however the effect is not greatly pronounced. A control group was therefore used in order to test differences between galleries that participated in ABMB and galleries that did not receive the same treatment. In essence, the amount of online attention received after the art fair did not vary much between the two groups. Although ABMB galleries present a slight increase in the number of Google searches after participation in the event, its effect is not pronounced enough to assert that ABMB had an effect in its participants' online attention. To note that this research aimed to investigate the impact that an offline event had online, however not only actual ABMB visitors should be considered, but also individuals that were not physically present in the fair, but all the exposure as a consequence of ABMB participation led them to search for more information about a gallery or artists online.

Contrasting with other cultural organizations, the art market did not adopt digital strategies extensively. This might be due to the fact that this is a rather particular market where gallerists and other gatekeepers are not interested in attracting the masses, but rather few crucial potential buyers;

thus their model is mostly focused on one-to-one relationships. This could be one of the reasons why art events do not seem to have a great impact in its participant's online attention. However, due to the importance that art fairs have nowadays, not only in the art market, but in the cultural sector in general, further research on the effects that art fairs have in this sector must be taken in consideration.

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11. APPENDIX

List of ABMB galleries

Galleria Zero	Frank Elbaz	David Kordansky Gallery	Overduin and Kite
Eva Presenhuber	Eleven Rivington	Tomio Koyama Gallery	Praz Delavallade
Chantal Crousel	Konrad Fischer Galerie	galerie Krinzinger	Ramiken Crucible
Campoli Presti	Stephen Friedman Gallery	Kukje Gallery	Michel Rein
Andrew Kreps	Gemini gel	L M Arts	Roberts Tilton
Bortolami	Galerie Gmurzynska	La Central galeria	Galeria Nara Roesler
Meyer Riegger	Elvira González	Labor gallery	Andrea Rosen Gallery
Fortes Vilaca	Richard Gray Gallery	Simon Lee Gallery	Lia Rumma
Proyectos Monclova	Greenberg Van Doren	Galeria Leme	SCAI The Bathhouse
Galerie Kamm	Greene Naftali Gallery	Marlborough Fine Art	Esther Schipper
A Gentil Carioca	Galerie Karsten Greve	Mary Anne Martin	Bruce Silverstein
alexander and bonin	Hammer Galleries	McKee Gallery	Craig Starr Gallery
Ruth Benzacar	Harris Lieberman	Anthony Meier	Sevenson gallery
John Berggruen Gallery	Rhona Hoffman	Urs Meile	Galeria Luisa Strina
Marianne Boesky Gallery	Max Hetzler	Galeria Millan	Galerie Daniel Templon
Tanya Bonakdar Gallery	Hirschl Adler	Robert Miller Gallery	Tilton Gallery
Mary Boone Gallery	Edwynn Houk Gallery	Francesca Minini	Tornabuoni Art
luciana brito galeria	Xavier Hufkens	Mitchell-Innes Nash	Nicolai Wallner
Carlier gebauer	Alison Jacques Gallery	Stuart Shave	Washburn Gallery
James Cohan Gallery	Martin Janda	Stephan Rosemarie	Wentrup
Pilar Corrias	Rodolphe Janssen	Edward Tyler Nahem	UNTITLED gallery
CRG Gallery	Annely Juda	Helly Nahmad Gallery	Valentin gallery
DAN Galeria	Casey Kaplan	Leandro Navarro	Buchmann Galerie
Thomas Dane Gallery	Paul Kasmin Gallery	neugerriemschneider	Susanne Vielmetter
Maxwell Davidson	Anton Kern Gallery	Franco Noero	Howard Greenberg Gallery
Guillermo de Osma	Kewenig	David Nolan Gallery	Cherry and Martin
	Sabine Knust	Nordenhake	Galleria Continua

Friedrich Petzel
Galerie Thaddaeus Ropac
Michael Rosenfeld Gallery
Sikkema Jenkins
Sommer gallery
Zeno X Gallery
Fitzroy Gallery
Galerie Eigen
kurimanzutto
Kavi Gupta
Gavin Brown Enterprise
shanghart
Marian Goodman
Sadie Coles HQ
Herald St
Sperone Westwater
McCaffrey Fine Art
Metro Pictures
303 gallery
Paula Cooper

Team
Pace gallery
White Cube
Hauser & Wirth
Gagosian gallery
David Zwirner
The modern institute
blum and poe
Casa Triangulo
Wallspace
Michael Werner
Acquarella
Antony and the Johnsons
Art : Concept
Galerie Buchholz
Cheim Read
Silvia Cintra + Box4
Contemporary Fine Arts
Massimo De Carlo
Fonti

Peter Freeman
Gladstone Gallery
Goodman Gallery
Cristina Guerra
Johann König
Karma International
Sean Kelly Gallery
Klosterfelde
Yvon Lambert
Lehmann Maupin
Galerie Lelong
Lisson Gallery
Luhring Augustine
Mai-36
Jorge Mara
Matthew Marks Gallery
kamel mennour
Victoria Miro Gallery
Schwarzwälder
Nelson Freeman
NON gallery

Galerie Perrotin
Simon Preston
Almine Rech
Regen Projects
Regina Gallery
Salon 94
Thomas Schulte
Sicardi
Sies + Höke
Thomas Solomon
Sprüth Magers
Standard (OSLO)
Christian Stein
gallery Sur
Galerie Thomas
Van de Weghe
Vermelho galeria
Jack Shainman Gallery

List of ABMB artists in the sample

thiago rocha pitta	rosangela renno	keltie ferris	jonathan monk
pamela rosenkranz	rita ackermann	nina beier	florian meisenberg
eugenio dittborn	matt connors	julieta aranda	hao liang
hubert duprat	carla accardi	manolo millares	mendez blake
claudia andujar	Marianne Vitale	pawel althamer	agnes denes
eduardo basualdo	saul fletcher	jorinde voigt	carlito carvalhosa
Derek Sullivan	charlie hammond	pekka turunen	nina yuen
Kon trubkovich	giorgio griffa	gabriel de la mora	matt johnson
Nelson Leirner	tobias madison	dominique gonzalez-foerster	brice marden
clare woods	makoto saito	farhad moshiri	patrick lee
jutta koether	judith hopf	enoc perez	thomas hirschhorn
mariana palma	laurent grasso	philippe decrauzat	john baldessari
jitish kallat	jorge macchi	oscar tuazon	Matt Keegan
john armleder	christian jankowski	hans schabus	carroll dunham
jonathan horowitz	Mathieu Mercier	ivan seal	matt saunders
gert uwe tobias	gert uwe tobias	andra ursuta	tomas saraceno
carlos garaicoa	valentin carron	latoya ruby frazier	peter saul
juliao sarmento	andrea bowers	georg baselitz	al taylor
heather rowe	hans op de beeck	zhang ding	hector zamora
carlos cruz-diez	markus schinwald	ulrich wulff	laura owens
Gaudel de Stampa/Jessica Warboys	zilvinas kempinas	analia saban	jack goldstein
davide balula	richard learoyd	yael bartana	Julio Le Parc
pedro teran	ana sacerdote	silvio wolf	tal R
jan dibbets	mircea cantor	jon kessler	bill viola
colby bird	evariste richer	pier paolo calzolari	kelley walker
ged quinn	latifa echakhch	pablo atchugarry	rirkrit tiravanija
eija-liisa ahtila	mandla reuter	simone leigh	lygia clark
gunther forg	becky beasley	anna oppermann	arturo herrera
	barnaby furnas	jack whitten	alighiero boetti

neo rauch	jannis kounellis	gary simmons	antonio asis
lucia laguna	bernd hilla becher	rodrigo andrade	kara walker
catherine murphy	bruce conner	oscar murillo	cindy sherman
ged quinn	katharina grosse	keith haring	barry ball
man ray	gabriel serra	sarah sze	jenny holzer
anish kapoor	barbara kruger	jim lambie	victor man
wifredo lam	felipe arturo	antoni tapies	chuck close
uta barth	picaso	gary hume	lygia pape
frank stella	robin rhode	john mclaughlin	ivan navarro
joel meyerowitz	carmen herrera	wade guyton	lyonel feininger
richard diebenkorn	A Kassen	nathan peter	n dash
adam fuss	joel sternfeld	joel morrison	basquiat
theaster gates	katharina fritsch	lawrence weiner	robert indiana
rene magritte	thomas ruff	jerry martin	michael riedel
alexander calder	richard estes	melanie smith	harry dodge
rebecca warren	yayoi kusama	ryan trecartin	ray parker
adam fuss	tony oursler	ryan trecartin	per kirkeby
robert motherwell	leonardo drew	marina abramovic	antony gormley
wim delvoye	tony oursler	nathan carter	rodrigo matheus
jim lambie	adriano costa	kerry james marshall	lee kit

List of galleries in the control group

Carmichael Gallery
Rodeo gallery
Klughaus Gallery
Freymond-Guth
Johann Konig
Gisela Capitain
Isabella Bortolozzi
Gio Marconi
Franco Noero
Balice Hertling
Peres projects
Praz-Delavallade
Esther Schipper
Richard Telles
White Columns
Joshua Liner Gallery
Reena Spaulings
Labor

Space 1026
PRISM
Broadway 1602
White Walls
Miguel Abreu
Jack Hanley Gallery
New Jerseyy
V1 Gallery
Lazarides Gallery
Barbara Gladstone
Gering and Lopez
The Third Line
FFDG
Jan Mot
Known Gallery
Gaga Gallery
Air de Paris
gb agency

The Modern Institute
General Hotel
Maureen Paley
Lisson Gallery
Cabinet Gallery
Alex Zachary
greene naftali gallery
Renwick gallery
Ks art
Bureau gallery
Cherry & Martin
Murray Guy
Blum and Poe
Modern Art Gallery
Elizabeth Dee
Emmanuel Perrotin
47 canal
Jonathan LeVine

List of galleries in the treatment group

Galleria Zero
Eva Presenhuber
Luciana Brito
Chantal Crousel
Kurimanzutto
Daniel Buchholz
Campoli Presti
Spruth Magers
Ramiken Crucible
Andrew Kreps
Bortolami
Meyer Riegger
Fortes Vilaca
Proyectos Monclova
Friedrich Petzel
Galerie Kamm
Marian Goodman
Sadie Coles HQ

David Kordansky
Yvon Lambert
Herald St
Sperone Westwater
Andrea Rosen
McCaffrey Fine Art
Anton Kern
Metro Pictures
303 gallery
Paula Cooper
Team
Pace gallery
White Cube
Hauser & Wirth
Gagosian gallery
David Zwirner
The modern institute
Standard