Timing the Buzz: How Lineup Announcements Influence Engagement in Electronic Music Festivals

A Quantitative Study on the Impact of Lineup Announcements and Their Role in Shaping Festival Buzz across Benelux and Germany (2022–2024)

Student Name: Paraschiv Elena Raluca

Student Number: 739825

Supervisor: Prof. Dr. Christian Handke

Erasmus School of History, Culture and Communication
Erasmus University Rotterdam

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ABSTRACT

In the increasingly competitive economic landscape of the music and entertainment industry, electronic music festivals have evolved as powerful cultural and commercial platforms. As the market becomes more saturated and festival lineups exhibit growing homogeneity, organisers are faced with a pressing strategic dilemma: How does the digital buzz surrounding electronic music festivals translate into the event's perceived attractiveness and consequently impact ticket sales in the contemporary attention economy? Despite their cultural and economic relevance, electronic music festivals remain underexplored particularly regarding the role of lineup announcement strategies in shaping audience interest and influencing ticket purchase behaviour.

This paper addresses a central puzzle: To what extent do lineup announcements generate significant changes in online audience engagement and shape the buzz for the electronic music festivals in the Benelux region and Germany? While anecdotal industry wisdom often suggests that much of a festival's hype is driven by star headliners, empirical research on this phenomenon remains limited.

To test this, the study analyses a dataset encompassing 20 festivals in the Benelux region and Germany from 2022 to 2024. The research employs a quantitative approach, using panel data regression techniques to examine the relationship between festival promotion strategies and public attention measured via Google Trends.

By offering a data-driven assessment of how lineup announcements influence online search behaviour, this study contributes to the fields of event marketing, digital consumer engagement and media analytics. The findings are particularly relevant for festival organisers seeking to optimize the timing, format and visibility of promotional campaigns in order to maximise audience attention and ultimately drive ticket demand.

Keywords: Lineup Announcement Strategy, Headliner's Influence, Digital Audience Engagement, Electronic Music Festival Marketing, Digital Hype Effect

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1. Introduction

Over the past two decades, electronic music festivals have progressively evolved from niche gatherings into large-scale cultural phenomena characterised by hyper-competitiveness and an increasing emphasis on artist exclusivity. Within the broader discourse of cultural economics and the sociology of popular culture, lineup announcements have always represented not only a marketing tool but also a signal of artistic and economic value. This study investigates how different lineup announcement strategies influence audience engagement, as measured through digital metrics such as Google Trends. This research focuses on electronic music festivals across the Benelux region and Germany between 2022 and 2024. Furthermore, this paper examines the extent to which lineup announcements alongside the digital prominence of headlining artists contribute to shifts in public attention. By integrating principles from attention economics with empirical analysis of Google search behaviour, the study offers insights into how strategic timing and artist visibility interact to shape audience engagement within the contemporary festival landscape.

The roots of music festivals can be traced back to various historical and cultural contexts, with the modern ones primarily emerging in the 20th century. While music festival models were initially centred around classical music traditions, the format has morphed to incorporate multiple genres such as pop, rock and electronic music, therefore creating a melting pot of musical experiences (Vinnicombe & Sou, 2017). The genesis of electronic music events can be attributed to the underground movements of the 1980s in Detroit and Chicago, USA, which eventually led to the emergence of Detroit Electronic Music Festival (Bader & Scharenberg, 2010), considered one of the first festivals of its kind.

Urban environment transformations have also deeply influenced the development of these festivals, shaping the dynamics of the electronic music scene and facilitating its growth amidst the remnants of industrial legacies and socio-political changes. In the context of the Benelux region and Germany, both considered electronic music hubs nowadays in Europe, the scene developed along slightly distinct trajectories in each of the aforementioned urban settings, but shares cultural and spatial factors that underpinned the broader expansion of electronic music events. Berlin for instance, marked by a surplus of vacant spaces and supportive cultural policies, enabled the post-reunification urban environment to emerge as a dynamic and club-based music scene. Conversely, the regulated urban framework of Amsterdam and its spatial constraints led to a shift toward large-scale, festival-driven formats (Dorst, 2015). Naturally, the festival sector continued to expand, with over 800 festivals taking place annually in more than 50 countries prior to the COVID-19 pandemic (Gajanan, 2019).

Consequently, the highly competitive nature of this sector requires festival organisers to employ creative strategies to capture and retain audiences, with headliners' selection playing a crucial role in this process. The calibre of the headliners set to perform at a music festival can increase ticket sales and therefore, the economic viability of the event. Previous research shows that festivals with prominent headliners on the lineup tend to have higher overall attendance rates which are further reflected in various ancillary services such as accommodation and food, subsequently generating pecuniary benefits for the local communities (Čekrlija & Milić, 2024). As such, festivals heavily market their headliners, serving as symbolic anchors around which the identity of the event is being constructed. Their influence goes beyond mere entertainment, representing key factors in both the audience's and organisers' decision-making processes.

Furthermore, the digital paradigm has shaped how the excitement around headliners is generated, facilitating digital engagement and a buzz that transcends the borders of the festival and promotes broader cultural dialogues (Danielsen & Kjus, 2017). Digital platforms such as Instagram allow for real-time sharing of experiences and engagement with digital music content, therefore shaping immersive narratives and increasing festival visibility (Baek et al., 2017). Apart from the impressive number of followers that headliners possess across multiple platforms, they also have the capacity to influence audience perceptions and engagement through the electronic word-of-mouth (eWOM) surrounding their performances (Rossetti, 2021). In addition to this, social media platforms usually amplify content related to popular headliners via specific algorithms that further creates a feedback loop perpetuating digital buzz.

While existing literature has examined topics around social media engagement and festival attendance (Tan, Ho, Sim, & Hii, 2025; Kinnunen et al., 2021), they primarily relied on qualitative assessments or web surveys rather than focusing on empirical data which results in a significant gap that persists in establishing a causal relationship between headliner appeal, digital platforms' dynamics and real-time data regarding shifts in audience interest. This study addresses exactly this limitation by configuring a comprehensive dataset that includes engagement related data from Instagram, Spotify and Google Trends. Through the use of econometric modelling, the aim of this paper is to explore how different lineup announcements affect digital buzz, leading to a clearer understanding of audience behaviour in the context of electronic music festivals.

The central research question guiding this study is: "To what extent do lineup announcements generate significant changes in online audience engagement and shape the buzz for the electronic music festivals in the Benelux region and Germany?". This question foregrounds the impact of lineup announcements on audience festival-related attention, by comparing the pre- and post-announcement periods.

Beyond that, this study introduces a causal, treatment-based research design that regards lineup announcements as critical intervention points. It contrasts "Big Bang" type of announcement strategies, where headliners are revealed *en masse*, with "Staged" approaches that release artist names gradually. This kind of distinction is important for a more nuanced understanding of how anticipation and audience engagement evolve throughout different announcement phases.

1.1 Explanation of concepts

The main research question employs multiple concepts that will be further explained for a more detailed understanding. The term "buzz", in our study, is defined as the surge in public attention surrounding lineup announcements, which plays a crucial role in building anticipation and driving engagement. The study also uses a data-driven engagement approach, measuring audience interest through Google search trends to assess how and when the public responds to promotional efforts.

1.2 Relevant Subquestion

To effectively address the main research question, there is primary subquestion that will be explored throughout this thesis. This question is: "To what extent do post-announcement changes in Google Trends Scores differ between festivals using a *Big Bang* announcement strategy and those employing a *Staged* approach?". This inquiry will examine the structure of lineup announcements, specifically comparing the *Big Bang* versus *Staged* strategies and examine the different levels of audience engagement during the post-announcement period. By tracking the changes in Google Trends Scores, this study seeks to assess which announcement strategy elicits a more substantial online response, in an effort to provide practical implications for the strategic design of communication strategies within festival marketing contexts.

1.3 Personal Motivation

The motivation for this research stems from a personal fascination with the transformative role of electronic music festivals within contemporary cultural dynamics. The Western Europe area is specifically of interest, regions such as Benelux and Germany being well-known for their significant contributions to the electronic music scene. This geographical focal point is pivotal, as it represents an area that throughout history has cultivated a considerable number of top-tier DJs recognized globally. For instance, a relevant example would be the Netherlands which has the most substantial representation of Dutch DJs in the 2024 DJ Mag Top 100 rankings (DJ Mag, 2024). The DJ Mag Top 100 is an annual public poll organised by DJ Magazine, one of the most prestigious electronic music publications worldwide that ranks world's most popular DJs based on fan votes, therefore considering audience interest and engagement as well. Notable figures such as Armin van Buuren, Martin Garrix and Hardwell have repeatedly been voted as the number one DJ of the world, alongside consistent presence of Dutch talent occupying the top spots in the rankings.

The context of post-pandemic recovery (2022-2024) is also particularly compelling for this inquiry. As a distinctive confluence of art and technology, post-pandemic festivals provide an interesting perspective on audience behaviour, with many events re-emerging through hybrid models that adopt both live and virtual experiences. Standing as pathbreakers for innovation, electronic music festivals have always been at the forefront of technological advancements in various areas including stage design, immersive visual experiences and state-of-the-art ticketing solutions (Srivastava, n.d.). Recent evidence shows that the integration of data-driven algorithms and social media platforms is shaping audience engagement with cultural events, thus making festivals highly responsive to digital trends. Not only does this dynamic revolutionise the nexus of human interaction and data-driven insight, but it also enables the identification of nuanced patterns in consumption tendencies, audience behaviour and cultivation of festival buzz via online environments.

1.4 Research Contribution

In light of the aforementioned factors, the contribution of this Master thesis lies in its potential to deepen the understanding of audience interest dynamics in electronic music festivals through a data-driven lens. From an academic standpoint, this research builds on existing literature that examines the convergence of audience behaviour, marketing strategies, data-supported findings and the real-world outcome of digital hype. By integrating econometric techniques, this research aligns with state-of-the-art practices and proposes an innovative solution for addressing multiple treatments and diverse lineup announcement strategies.

This study aims to bridge theoretical frameworks with practical applications, yielding contributions that are both academically and socially relevant. Its findings will offer valuable guidance for further academic research and it will deliver actionable insights for effective marketing strategies within the electronic music sector, implications capable of stimulating economic growth and supporting communities through increased music festival participation.

2. Theoretical Framework

This chapter establishes the theoretical basis for understanding how festival lineups, with particular emphasis on the headliners, shape audience attention, drawing on applied research and key cultural economic theories. It synthesises prior empirical research that has measured attention through digital metrics, accounting for specific factors that are able to influence the outcome. Moreover, characteristics of performances and lineup announcements that shape audience interest have been analysed employing relevant theoretical frameworks such as: demand theory, experience economy, superstars effects, the attention economy and data-driven decision making.

2.1 Experience Economy and Demand Theory Contextualised for Festivals

In order to assess the influence of headliners on audience interest in the electronic music industry, it is essential to situate music festivals within the context of the Experience Economy. As mentioned by Pine & Gilmore (1998) festivals represent immersive experiences that extend beyond the mere consumption of a product. They create emotional value and therefore audience engagement is heavily influenced by the experiential and narrative frameworks developed around these kinds of events, with headliners acting as catalysts in amplifying the festival's emotional appeal. To further ground the analysis in the economic context, Theory of Demand is employed. This theory states that the demanded quantity of a good or service depends on its price, income levels and the characteristics of the good itself (Varian, 2014). Specifically, demand is influenced not only by the price of a good or service but also by income and consumer preferences. For instance, consumers' willingness to pay and their level of interest may vary depending on whether the festival features international acts or local performers, as well as the overall perceived quality and uniqueness of the festival experience (Borges, Rodrigues, & Matias, 2016). Within the scope of this research, the "goods" are represented by the performances or experiences offered by the artists. Some of the characteristics of these performances that shape demand could be genre, artist popularity or festival atmosphere. However, justification and a sense of direction regarding the choice of the attributes will be further discussed based on relevant prior academic research.

2.2 Characteristics of performances

In the case of music festivals, performances exhibit distinct attributes which resonate with specific market segments. Notably, as articulated by Montoro-Pons and García (2020) the artist lineup and the geographical location of the festival are key characteristics that affect audience interest and attendance. In their study, Montoro-Pons and García focus on the online search behaviour of music festival tourists, analysing the dynamic facilitating the diffusion of information. The data set employed consists of Google Trends indexes googled by prospective attendees of three different Spanish music festivals: Festival Internacional de Benicassim, Primavera Sound and Sónar. Moreover, the factors taken into account for this research serve as critical attractors that shape pre-event audience attention. First, the "lineup proposal" can be divided into two distinct types: "niche" lineups, where the main focus is on a specific music genre and "general appeal" lineups that, as the term goes, suggests a broader spectrum of music genres. The latter are particularly relevant as they are often connected with increased audience diversity, thus catering for a wider range of preferences (Nunes & Birdsall, 2021). In the current research, lineup is considered a key determinant in enhancing festival attractiveness. However, rather than limiting our research to the dichotomous distinction between "niche" and "general appeal" lineups, we will extend our study by diving into the temporal dynamics of lineup announcements, more precisely the timing and the phasing of lineup releases. In addition to this, our research will strictly cover electronic music festivals, situating it within the "niche" category. Given the objective of examining cross-country and regional variations, it is of utmost importance the we narrow the genre scope, thereby minimising the genre-related variability, which provides a clear rationale for selecting electronic music as the focal genre of our selection.

The other relevant factor employed in Montoro-Pons and García's (2021) paper is the festival location. Bearing this mind, two categories of festivals can be distinguished: the ones held in urban environments such as Primavera Sound and Sónar in Barcelona, and the others situated in a rural area. Supporting this, Dragin-Jensen et al. (2018) prove that spatial proximity to an event has a strong influence on the motivational dimensions for attendance. According to his study, findings reveal that individuals residing closer to the event location place greater emphasis on socialisation, interest in the event theme and the overall geographical setting of the event. Conversely, people travelling from greater distances are motivated by loyalty-driven factors such as the devoted fans' strong sense of affiliation with a certain festival.

Furthermore, the literature stresses that factors such as the elapsed time since a band's debut album release, genre of the performer, average web search index, average ratio of awareness and the edition of the festival may significantly influence the level of attention received by a festival. In this regard, another study by Montoro-Pons and García (2020) specifically addresses music festivals as intermediaries and explores their role in shaping consumer awareness.

The data used in this study are drawn from the Primavera Sound Festival in Barcelona, including 73 headliners from the 2016, 2017 and 2018 editions. They were chosen based on their placement in the festival's official lineup poster, covering a diverse array of performers ranging from well-established acts to emerging ones. This selection does not suggest uniform superstar status among the artists, rather it reflects considerable heterogeneity in their popularity levels. In this way, potential biases associated with the Google Trends index, particularly the issue wherein search terms with insufficient query volume receive a value of zero, thereby introducing a downward bias in the data. Regarding the temporal scope of the research, each performer spans a five-year period, which begins with 253 weeks prior to the festival and it ends six weeks after the event.

The genre classification functions as a core variable in the analysis, with the potential to capture public interest. This variable comprises the following musical categories: rock, pop, electronic, rap, experimental, RnB and metal. With regard to the year of the first release, the selected period spans from 1977 to 2015, ensuring a good mix of both established and emerging artists, thereby increasing the relevance of the sample. The authors also introduce an interesting relative awareness ratio which compares the Google search volume of each performer to that of the corresponding festival over the same time frame. This ratio serves as an effective indicator of the informational leverage of a festival and its potential spillover effects on artist visibility. A ratio that is greater than one indicates that the artist generated more search interest on its own than the festival during that period, while a ratio below one shows that the festival managed to attract greater attention. Overall, this measure reflects the artist's salience relative to the festival and emphasises the festival's role in amplifying performer visibility.

Once the aforementioned ratio of awareness has been calculated, the authors proceed to classify the performers in order to evaluate their status within the sample. Then, performers are grouped into four categories: "lesser known", "middle class", "upper class" and "superstars". It is also important to mention that, this typology captures the relative visibility of artists compared to the festival, using Google search volume metrics. In order to enhance the robustness of the research, the study incorporated several control variables including: (i) the web search index for each performer in Australia, employed as a control geography, (ii) a dummy variable accounting for potential spikes in searches during the week when the lineup is revealed and (iii) the number of years since the release of a performer's debut album, alongside its squared term in order to capture potential nonlinear effects.

This approach aligns with previous studies that highlight the central role of the festival lineup in modelling audience perception and satisfaction levels. Through these lenses, Tan et al. (2020) found, based on 288 participants, that the festival programme was the main factor driving attendees' satisfaction.

Building on previous knowledge, our study introduces a novel methodological approach in order to examine whether different festival lineup reveal strategies, referring to the *Big Bang* versus *Staged* announcements, impact the timing and scale of audience engagement. Unlike prior studies, which have largely neglected communication strategies such those previously mentioned, our analysis incorporates multiple treatments and is moving beyond the standard practice of the literature.

In addition to this, a measure of popularity is constructed by creating a composite index that integrates Spotify monthly listeners and Instagram followers. Moreover, whereas prior studies have predominantly focused on measuring the impact of festivals on artists, often overlooking the festival as a branded event, our study aims to assess the influence of headliners on the overall festival buzz. This methodology is consistent with theoretical perspectives that emphasise the generation of “buzz” around performers via the activation of social, cultural and symbolic capital (Scott, 2012). These forms of capital collectively enhance an artist’s popularity and desirability, which subsequently contribute to the festival’s prominence by attracting media attention, audience engagement and broader public interest.

2.3 Superstar Effects in Cultural Markets

Cultural and creative industries, particularly the music and live entertainment sector, are characterised by a significant concentration of attention and rewards among a limited number of highly prominent individuals. The phenomenon is referred to as the “superstars effect”. As originally theorised by Rosen (1981), even marginal differences in talent, exposure or perceived prestige might result in significant discrepancies in outcomes, especially in contexts where consumption is highly scalable, such as social media and digital platforms. In these types of markets, performers regarded as “the best” not only do they achieve a better performance compared to their peers, instead they manage to capture a disproportionately large share of total. Therefore, usually rather a small number of headliners benefit from an unequal share of attention and rewards, driven by scale effects, prestige and mechanism of networked consumption. In practical terms, the presence and pre-eminence of superstar headliners are likely to exert a significant impact on the level of public interest in a festival. By grounding our research in superstar theory we might be able to explain potential nonlinear and concentrated effects observed in the data, as few major artists generate greater levels of audience engagement compared to lesser-known performers.

Beyond that, Adler (2006) extended this theory by highlighting the role of social consumption. He argues that individuals prefer to consume the same content as others, not because of the intrinsic quality of the product, but because of the status signalling and coordination benefits. Previous research findings suggest that festival attributes such as the quality of amenities, programming and the quality of entertainment exert both direct and indirect effects on attendees’ levels of satisfaction, experiential outcomes and their likelihood of returning to the next edition of the festival (Cole and Chancellor, 2009; Cole and Illum, 2006). This creates a self-reinforcing cycle in which a performer’s recognition serves both as an outcome and a catalyst for increased attention, wherein visibility constitutes a form of symbolic capital. In the context of electronic music, headliners act as strategic resources integral to the festival’s branding and promotional efforts, as their inclusion on the lineup signals status. As a result, headliners exert a considerable impact on audience behaviour, especially regarding ticket purchasing decisions.

2.4 Attention Economy and Cultural Visibility

In today’s oversaturated content environment, attention is a scarce and very valuable resource, as stated by Lanham (2006). In the “economy of attention” the challenge is not accessing information but capturing and holding the focus of the audience. Moreover, early “digital optimism” as articulated by Anderson (2004) in the “Long Tail” stated that digital platforms would democratise cultural consumption by increasing the availability of niche content and reducing the dominance of superstars. Through the lens of this theory, the internet would lower distribution costs and there would allow for many lesser-known artists to reach audiences, flattening attention inequalities as a result. However, more recent empirical research shows that social proof, viral dynamics and algorithmic curation reinforced the concentration of attention on the so called “superstars” (Epstein, 2017). This can be translated as the persistence of strong superstar effects despite the promise of the long tail.

2.5 Electronic Word-of-Mouth (eWOM) and Peer Influence

Staying within the sphere of “buzz” formation and attention, electronic word-of-mouth (eWOM) is a critical driver of audience engagement, particularly in the cultural markets. Early responses to festival lineup announcements, disseminated via peer sharing on social media and other online platforms are pivotal in generating “buzz” and impacting audience interest and ticket sales (Chevalier & Mayzlin, 2006). Such social exchanges serve to produce network effects, facilitating the diffusion of influence throughout interconnected audiences.

This peer-driven buzz shapes the search behaviour of audiences and the attention spikes captured by Google Trends, making electronic word-of-mouth critical for understanding fluctuations in festival interest. Artists possessing higher social media visibility and greater industry recognition tend to stimulate stronger eWOM, which leads to an increase in festival demand. This mechanism corresponds with the theoretical frameworks of social proof and networked consumption, which state that collective endorsements increase cultural value beyond traditional marketing approaches.

2.6 Data-Driven Decision-Making in Festival Lineups

As industries increasingly revolve more and more around data, the adoption of digital strategies grounded in data-driven decision-making has become a pervasive and essential practice. As Jones and Elsden (n.d.) highlight in their analysis of live events and digital innovation, festival organisers are increasingly harnessing the power of digital metrics such as but not limited to: social media follower counts, streaming metrics and algorithmic engagement indicators with the aim of guiding the selection of headliners. In doing so, event organisers enhance the precision of audience targeting while facilitating evidence-based marketing strategies that can be further tailored to the evolving consumer behaviours.

2.7 Algorithmic Visibility and Platform Bias

Furthermore, algorithmic visibility on digital platforms including Instagram and Spotify play a pivotal role in shaping artist exposure. Headlining acts that manage to achieve a favourable positioning within these platforms benefit from increased organic reach, which then generates buzz and search activity (Singh, 2023). Being aware of these dynamics is essential for this study, as it forms the basis for defining and measuring the Instagram popularity metrics. This framework further elucidates why particular artists induce more pronounced variations in festival interest. Therefore, by integrating these elements, the research invites for a thorough investigation into how digital data and algorithmic biases affect audience engagement within the contemporary festival setting.

2.8 Hypotheses

In terms of hypotheses, the following ones will be tested in a panel regression analysis, in an effort to assess the impact of lineup announcement strategies and data-driven audience engagement on the hype generated within the electronic music festivals sector in the Benelux region and Germany.

H1: There is a significant increase in the GTS score in the post-announcement period compared to the pre-announcement period.

The rationale behind this hypothesis would be that lineup announcements represent key marketing events. A significant surge in the Goole Trends Score is expected immediately following a lineup announcement, pointing at an increased public search interest. This assumption is rooted in the agenda-setting theory and temporal attention dynamics. Media events, including official lineup releases are known to generate spikes in attention due to the novelty and the relevant nature of the information (McCombs & Shaw, 1972).

H2: The treatment is more immediate but less durable for the Big Bang lineup announcements, whereas for Staged announcements it is more gradual.

Important mention for the H2 hypothesis would be that a the *Big Bang* strategy concentrates media exposure, which can potentially produce a sharper spike in public attention during the announcement window. Intensified media presence may further influence the stakeholders' cognitive and evaluative responses to the information, thus creating a feedback loop in which increased online visibility amplifies engagement. In contrast, *Staged* announcements align with theories of spaced exposure and retention (Ebbinghaus, 1913).

H3: Festivals that announce headliners earlier in the season generate higher audience attention compared to late announcers.

This hypothesis is grounded in the temporal primacy effect and first-mover advantage theory in information campaigns. Earlier announcements are expected to benefit from higher public attention and potentially less competitive noise (Carpenter & Nakamoto, 1989).

H4: Public interest starts to increase in the weeks leading up to the lineup announcement, suggesting the presence of anticipatory effects.

This hypothesis draws on informal signals and expectancy theory positing that attention may increase prior to the actual announcement due to speculative cues (Loewenstein, 1987). Thereby, challenging the conventional assumption of no pre-treatment effects in causal inference frameworks including event studies.

H5: The difference in GTS between Big Bang and Staged strategies becomes statistically indistinguishable over time.

If festival organisers align communication style with festival identity, both *Big Bang* and *Staged* strategies may converge in long-term effectiveness because as the initial lineup announcement effects fade, organic drivers such as the lineup appeal and electronic word-of-mouth may level out public attention patterns, essentially making GTS differences statistically negligible over time (Sormaz, Okul, Musaeva, & Soylu, 2025).

3. Methodology

This chapter outlines the methodological framework used in the present study, providing a detailed account of the research design implemented to explore the influence of lineup announcements on audience attention towards electronic music festivals in the Benelux region and Germany, operationalised through Google Trends search data. It delineates the research objectives, the methodological approach, data collection and analysis methods, as well as the rationale behind each methodological decision. Additionally, the chapter addresses potential limitations and underscores the suitability of the selected approach in effectively guiding the investigation.

3.1 Methods

3.1.1 Research Strategy and Design

The research follows a quantitative strategy and a deductive research approach, employing a structured econometric analysis with a longitudinal design based on panel data. Moreover, causal experimental research design has been adopted in this study.

The decision to opt for a quantitative analysis stems from the primary research objective that is to test theory-driven hypotheses with regard to what extent festival-related interest, as expressed through online search behaviour, changes in the post-announcement period compared to the pre-announcement one. The variables examined can clearly be operationalised and expressed numerically, allowing for the precise measurement and investigation.

The rationale for using panel data lies in the fact that panel data studies remain an influential and rapidly evolving area within econometrics. Rising availability of micro- and macro- panel datasets, has spurred demand for more sophisticated analytical methods among researchers (Baltagi, 2008). This growth has been further reinforced by technological advancements in statistical software, especially through accessibility to open-source software such as R. Reflecting the continued international engagement with the field, several major events on panel data econometrics are already scheduled for 2025. The 30th International Panel Data Conference (IPDC) will take place France in June while the EC^2 conference, another prominent event, will be held in Switzerland, from December 5 to 6 (Conference2Go, n.d.).

Panel data represents a combination of longitudinal and cross-sectional data. They contain multiple observations over a certain period of time for each unit of analysis (Baltagi, 2008). A longitudinal research design is particularly suited for capturing the temporal ordering of variables, therefore leading to an increased potential for establishing causal relationships. As noted by Bryman (2016), longitudinal studies imply collecting data from a sample on at least two occasions and it may include multiple types of cases within the panel. This format supports a more nuanced analysis of potential change over time and highlights the dynamics between key variables. The longitudinal structure of the panel dataset, which encompasses multiple observations per festival over a period of 3 years, bolsters the robustness of the findings by accounting for within-unit variation and potential unobserved heterogeneity.

As previously mentioned, the dataset used in this study comprises observations on 20 distinct electronic music festivals over a three-year period: 2022, 2023, 2024. Technically, each year represents a cross-sectional snapshot of all festivals, thus facilitating comparative analysis across different entities at a given point in time. Concurrently, the longitudinal component is introduced by the repeated observation of the same set of festivals over three years, enabling the investigation of temporal dynamics and intra-festival evolution.

Established literature on panel data analysis has provided relevant methodological guidance for the development of the current study. In that sense, the framework presented in the "Using Panel Data to Estimate the Effects of Events" (Allison, 1994) offers valuable insights regarding panel-based causal analysis, particularly in settings where discrete changes are applied over time. The study focuses on how multi-wave panel-data can be leveraged to assess the causal impact of specific interventions or events, employing econometrics techniques such as fixed effects models and difference-in-differences. Therefore, Allison (1994) demonstrates that fixed effects models in panel data analysis allow for credible causal inference by controlling for unobserved, time-invariant factors. This can be particularly useful for evaluating the impact of specific events or changes over time in non-experimental settings.

Furthermore, this study incorporates two distinct treatments: one related to pre- and post-lineup announcement periods and the other with regard to the lineup announcement strategies. Thus, insights can be gained by comparing the post-treatment GTS score observations with their pre-treatment counterparts so as to determine whether this treatment generates significant changes. Besides, the "Big Bang" and "Staged" distinction is used for marking the lineup announcement strategy. They both represent lineup announcement strategies with *Staged* treatment involving multiple phases of announcements, where artists are gradually revealed over time and the *Big Bang* strategy, which, in contrast, refers to instances where a single announcement includes at least 20 artists, as considered in this study.

As highlighted by Díaz, Henríquez and Winkelried (2022), it is true that heterogenous treatment effects show that changes in search behaviour can vary significantly by different characteristics, in their case socioeconomic and regional ones. Their paper focuses on how dynamic COVID-19 quarantines affected population well-being across Chilean municipalities. Using panel data and Google Trends search volumes as proxies for mental health, they implemented a DiD analysis in an effort to compare pre- and post- treatment periods across regions exposed to distinct levels of restrictions. Given the nature of this study and the models employed, this study similarly investigates how two distinct strategies affect online public engagement measured through GTS.

3.2 Data collection

3.2.1 Data

Data for this study has been collected exclusively from secondary, non-reactive sources, in line with Bryman's (2016) classification of unobstructive data and official statistics. The dependent variable responsible for determining festival-related interest ("GTS") was operationalised through Google Trends metrics. Google Trends data reflects weekly online search volumes over a period of time. Specifically, the Google Trends index represents a standardised measure for the relative online search volume with regard to a specific term or phrase on Google within a specified temporal interval and geographic region (Choi & Varian, 2012). In the present analysis, it serves as an indicator of festival-related audience interest and attention by illustrating temporal fluctuations in online search activity for a specific festival.

The data used were collected manually from official online sources. GTS weekly observations have been extracted from Google Trends official website for the period 2022-2024 for each of the 20 selected electronic music festivals. A brief note is that the exact analysed period of time ranges from 2021-12-26 to 2024-12-22. This timeframe has been considered in order to conduct research on the most recent available data so that it reflects the latest trends for the majority of festivals. The decision not to include the year 2025 stems from the fact most festivals in Europe are typically held during the summer months, particularly in July and August (Resident Advisor, n.d.).

Therefore, relevant data would not have been available for all festivals at the time of the study. Moreover, the date 2021-12-26 was also included for symmetry reasons across the defined periods, namely pre-lineup announcement, post-lineup announcement and post-festival. A snippet of the GTS score observation of a subset of the selected electronic music festivals has been provided in the Appendix section in order to illustrate the structure of the data (*see Appendix B, Section B.3*). The full set of observations was not appended in its entirety due to formatting considerations and to maintain the overall reliability of the document. The complete dataset is, however, available upon request.

With the aim of constructing a Fame Index, consisting of two quantitative indicators, Instagram followers and monthly Spotify listeners have been collected manually for each of the top three headliners at every selected festival. Headliner Instagram follower counts were extracted from each headliner’s public Instagram profile. Similarly, monthly Spotify listeners were retrieved by consulting the artists’ individual Spotify profiles. Further information regarding lineup posters, including headliner identification and announcement strategy, was obtained from the official festival Instagram account, Facebook account and the festivals' official websites.

The electronic music festivals included in the sample were randomly selected in order to ensure representation of medium- to large-scale events within the Benelux region and Germany. The selection focused primarily on music festivals that are not necessarily sold out every year, allowing for meaningful variation in both audience engagement and artist exposure. Headliners were identified based on the official festival lineup posters, with the top three artists selected according to typographic prominence. Specifically, the artists displayed in the largest font size were chosen. In the analysis, were included only electronic music festivals with hierarchically structured posters, where a clear distinction between headliners and the rest of the acts was made.

In order to classify the type of announcement each festival employs, the *BigBang_Announcement* variable was created. This is a dummy variable coded as 0 for *Staged* lineup announcements and 1 for *Big Bang* announcements. The distinction between these two announcements types has been previously stated in the *3.1.1 Research Strategy and Design* section.

Additionally, this study uses a categorical variable called "*Period*". This variable captured four distinct timeframes: the periods before and after the lineup announcement, the period following the festival, as well as the event week itself. Regarding the time-based segmentation,

the majority of observations are concentrated in the Post-Festival (43.3%) and Post-Announcement (41.4%) periods, the Pre-Announcement phase represents 13.1%, while the Event period accounts for only 2.2% of the dataset.

The descriptive statistics for all numerical variables are presented in the table below (*Table 1. Descriptive Statistics for Main Variables*).

Table 1. Descriptive Statistics for Main Variables

Variable	N	Mean	SD	Median	Min	Max	Range	Skew	Kurtosis
GTS	3140	7.06	13.90	2.00	0.00	100.00	100.00	4.21	21.41
Fame_Index_Median	3140	201.20	203.65	110.12	12.38	654.16	641.78	-0.38	3.63
BigBang_Announcement	3140	0.40	0.49	0.00	0.00	1.00	1.00	0.41	-1.83

Note: GTS = Google Trends Score. Fame_Index_Median = Median score of the Fame Index. BigBang_Announcement is a binary variable (0 = No, 1 = Yes). SD = Standard Deviation.

The descriptive statistics reveal important aspects such as variability and skewness within the dataset. The Google Trends Score (GTS) has a mean of 7.06, a standard deviation of 13.90, with a median of 2.00, indicating a right-skewed distribution and as expected, reflects the presence of some extreme values since the GTS ranges from 0 to 100. These GTS score observations capture real-world audience attention directed at a specific music festival during a given week, which inherently allows for high sensitivity to fluctuations in public interest over time. Regarding the *Fame_Index_Median*, this variable shows a right-skewed distribution (skewness = 1.04), with a mean of 201.20 and a maximum value of 654.16 that suggests notable dispersion across observations. By contrast, the binary variable *BigBang_Announcement* displays a relatively balanced distribution with a mean of 0.40, which obviously aligns with its dichotomous nature.

Because *Period* is a categorical variable, the descriptive statistics for it were analysed separately for each phase to assess how audience interest evolved over time based on GTS data (see *Table 2*). Consequently, before the lineup announcement (N = 411), audience attention was minimal, with a low mean GTS of 3.69 and a median of 1.00, accompanied by a right-skewed (1.92) and moderately leptokurtic (3.62) distribution. This is an indication of sparse but occasionally heightened online search activity. Following the announcement, interest rose substantially (N = 1301), with the mean increasing to 8.37 and the median to 7.00. During the Event week (N = 69), public engagement peaked dramatically, as shown by a mean of 66.45 and a median of 81.00, with a relatively symmetric (skewness = -0.91) and slightly platykurtic (kurtosis = -0.81) distribution.

Thus, these statistics demonstrate significant and widespread public attention during the event itself. In the Post-Festival phase (N = 1359), online search activity sharply declined, with the mean dropping to 3.82 and the median to 0.00. The distribution exhibited right-skewness (4.58) and marked leptokurtosis (25.00), signifying a return to low levels of audience attention, punctuated by isolated cases of residual interest. Therefore, these dynamics illustrate a sharp, short-lived surge in public attention around the event period, which suggests that the event itself is the main driver of festival-related interest, with limited sustained engagement thereafter.

Table 2. Descriptive Statistics of GTS across Study Periods

Period	N	Mean	SD	Median	Min	Max	Range	Skew	Kurtosis
Pre-Announcement	411	3.69	5.60	1	0	31	31	1.92	3.62
Post-Announcement	1301	8.37	8.72	7	0	100	100	2.25	13.32
Event	69	66.45	37.96	81	0	100	100	-0.91	-0.81
Post-Festival	1359	3.82	9.86	0	0	100	100	4.58	25.00

Note: GTS = Google Trends Score. SD = Standard Deviation. Periods are based on predefined phases related to the event timeline.

In the following section, each variable will be examined and discussed individually in order to provide a detailed preliminary analysis of the dataset.

3.2.2 Google Trends Score

This research will analyse 20 electronic music festivals situated in the Benelux area (the Netherlands, Belgium, Luxembourg) and Germany during 2022, 2023 and 2024. Besides this, Christmas Day is deliberately chosen as a neutral reference point for normalising Google Trends values, as it is generally considered that during major holidays, entertainment consumption patterns shift towards family-related activities rather than event planning, resulting in a period with a fairly low festival public attention. To further enhance the accuracy of the study, upon entering the festival name, the recommended related search term “Music Festival”, presented below the query input, was taken into consideration in order to refine the search parameters. The “Arts & Entertainment” category filter was applied with the intention of minimising potential contamination from totally unrelated subjects and homonymous terms, assisting in the refinement of data filtering by topic and keyword.

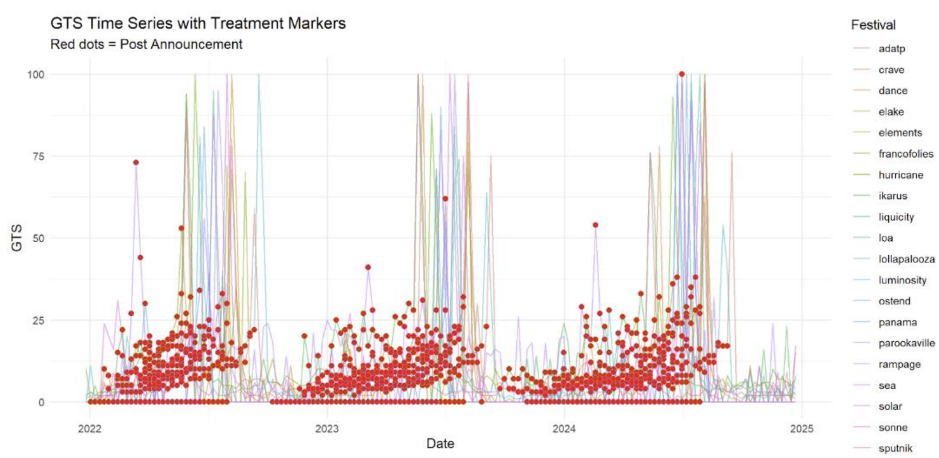


Fig. 1 GTS time series plot

The time series plot displays weekly GTS scores for all music festivals considered over the period 2022-2024, with red dots marking the post-lineup announcement period. Clear seasonal spikes are visible, typically aligning with the week of each festival (Event). This aspect indicates a surge in audience interest coinciding with festival dates. The dense clustering of red markers prior to these spikes (in most cases) suggests that most announcements occur shortly before the festivals. However, the variability in GTS levels across festivals implies heterogeneity in marketing reach and overall festival popularity. These large event-week (Event) peaks act as visual outliers and justify their exclusion from the post-treatment analysis to avoid overstating announcement effects.

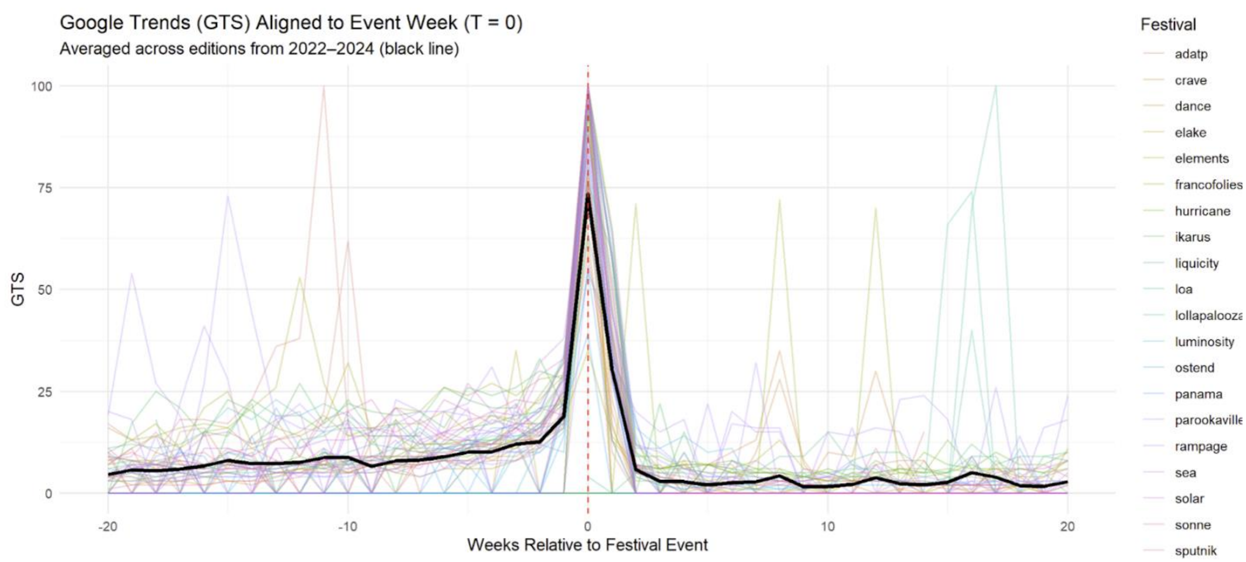


Fig. 2 GTS time series event

This plot (*Fig. 2*) aligns weekly Google Trends Score (GTS) data relative to each festival's event week (T = 0), with individual festival patterns shown in light lines and the overall average (2022–2024) marked by the bold black line. A distinct and recurrent peak emerges at T = 0, where GTS values frequently reach or approach the maximum score of 100. Therefore, it signals a highly reliable peak in public attention during the event week (Event), reinforcing that the festival serves as the primary focal point of search activity.

As mentioned already, these peaks further provide strong justification for excluding the event week (Event) from post-treatment analyses. Including it would risk conflating baseline event-driven visibility with the effects of specific treatments, such as lineup announcements. By excluding it, we isolate the causal impact of such treatments as it eliminates the influence of predictable and universal spikes in attention.

Despite the regularity observed in the aggregated trend, there is considerable variation across individual festivals, with some of them showing more dispersed or multiple peaks. This heterogeneity likely stems from differences in promotional strategies, festival size or audience engagement patterns. As such, the figure supports the bivariate narrative by confirming that the event week consistently generates the highest attention, while also underscoring the need to control for inter-festival differences in subsequent analysis.

Initial visual inspection of the time series plots revealed that, in many cases, online search interest appeared to increase not only immediately after the lineup announcement but also in the weeks leading up to it. This pattern raised the possibility of an anticipatory effect. As users begin actively searching for the festival ahead of the lineup announcement, behaviour that might potentially be driven by either intrinsic curiosity or social media speculation. To formally test this idea, we implemented a shifted treatment window that would begin three weeks prior to the official lineup announcement date. While the choice of three weeks is somewhat arbitrary, it was guided by the visible pre-announcement patterns observed in the data and the fact that in the festival context, fans are usually highly engaged, especially during the build-up phase, exactly when rumours or maybe even unofficial leaks begin flooding the social media environment. Moreover, strictly from a visual standpoint, a three-week window will make interpretation of the shifts in search behaviour easier, as it will provide a clearer separation between baseline and post-treatment dynamics. However, future research could extend this approach by experimenting with different time windows (for instance, 1-2 weeks) to assess the robustness and timing of the effect.

Table 3. Linear Regression Results for GTS (Shifted Treatment Period)

Variable	Estimate	Std. Error	t value	Pr(> $\|t\|$)
(Intercept)	18.2710	13.4411	1.359	0.174
treatment_shifted	5.4691	1.1341	4.822	$< 0.001^{***}$
log_Fame_Index_Median	-3.4138	2.9885	-1.142	0.253
Crave Festival	-6.3193	4.2617	-1.483	0.138
Dance Valley	-0.1901	3.2546	-0.586	0.715
E-Lake Festival	-12.8711	5.8143	-2.086	0.037^{*}
Elements Festival	4.8824	1.4308	3.412	0.001^{***}
Les Francofolies	-2.4808	4.2296	-0.587	0.558
Hurricane Festival	8.6262	5.6997	1.513	0.130
Ikarus Festival	3.4754	1.7910	1.940	0.052
Liquicity	4.4755	3.4750	1.288	0.199
Luxembourg Open Air	-6.6565	1.4348	-4.611	$< 0.001^{***}$
Lollapalooza Berlin	5.9719	6.1060	0.979	0.328
Luminosity Beach	-9.9727	4.9766	-2.004	0.045^{*}
Ostend Beach Festival	-8.8407	1.4689	-6.020	$< 0.001^{***}$
Panama Open Air	5.9457	7.3207	0.742	0.458
Parookaville	3.5885	3.7225	0.964	0.335
Rampage	5.0541	1.4430	3.502	$< 0.001^{***}$
Sea You Festival	-4.4728	3.4480	-1.297	0.194
Solar Weekend Festival	0.8416	1.5240	0.552	0.589
Sonne Mond Sterne	7.3879	5.6399	1.310	0.190
Sputnik Spring Break	NA	NA	NA	NA

Note: Significance levels: $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

The table above (*Table 3*) shows whether search interest increases during the three weeks leading up to the official lineup announcement. This linear regression model includes a shifted treatment indicator (*treatment_shifted*) and a control for festival popularity, but legitimised (a full explanation for this variable can be found in the *Fame Index* section of this paper). The coefficient for *treatment_shifted* is 5.47 and highly significant (p<0.001) which indicates a clear increase in GTS scores during the anticipatory period. This finding empirically support the presence of a precursory effect, as audience attention starts rising before the official lineup announcement, likely due to speculation and growing anticipation within festival community. However, this effect should be further analysed.

Therefore, in the figures below (*Fig. 3, Fig. 4*) we explore how public interest operationalised via Google Trends Score evolves around the time of lineup announcements. The aim of these plots is to track changes in public attention and to assess whether lineup announcements are consistently associated with spikes in online search activity.

Across the full set of festivals (*Fig. 3*), the observations aim at a common seasonal pattern, with visible increases in GTS around announcement dates. Nevertheless, the magnitude and shape of this pattern vary considerably. For instance, in the case of *A day at the park Festival* (top-left), there is a dramatic rise in search interest during the last year (2024), contrasting with the relatively low levels in previous editions. However, this contrast may be attributed to a significant growth in the festival's overall popularity.

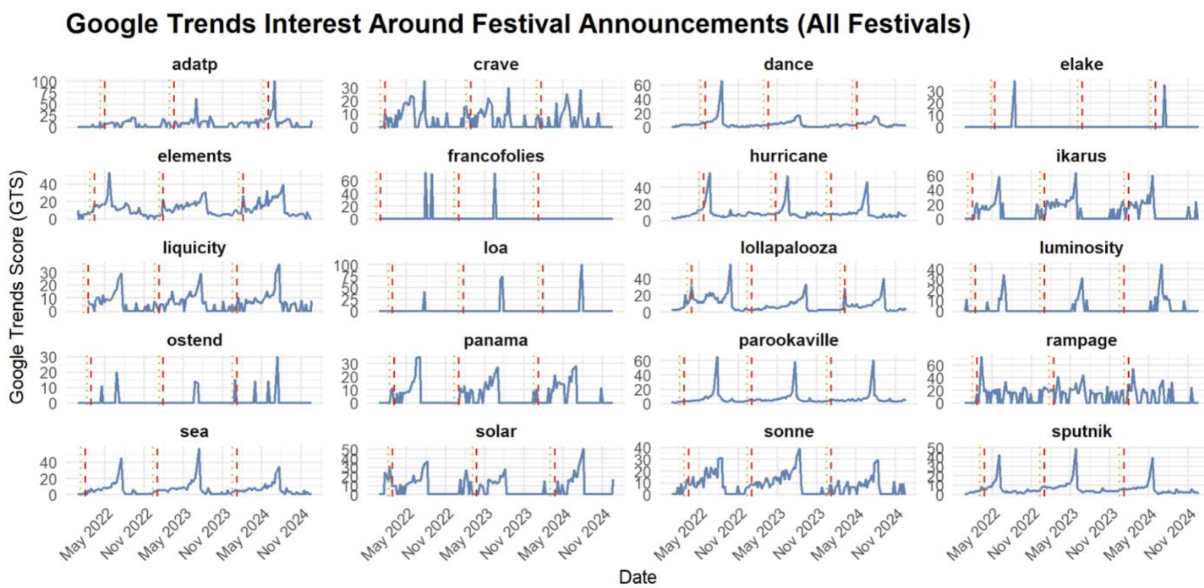


Fig. 3 GTS all festivals

In *Figure 4*, in order to improve clarity and interpretability, a separate plot that zooms in on a detailed subset of four festivals is presented below. Each red dashed line marks the official lineup announcement of a festival, while the dotted purple lines denote the beginning of the treatment window, specifically three weeks prior to the real lineup announcement. Judging from the plot, we observe that Lollapalooza Berlin, Elements Festival and Hurricane Festival exhibit not only post-lineup announcement increase but also noticeable upward trends in the weeks leading up to the festival. However, Rampage show noisier patterns, potentially due to a more fragmented fan base, but this remains speculative and would require dedicated investigation.

Overall, these exploratory plots confirm that festival lineup announcements are often associated with observable shifts in audience attention and usually they are also preceded by a period of anticipatory effects.

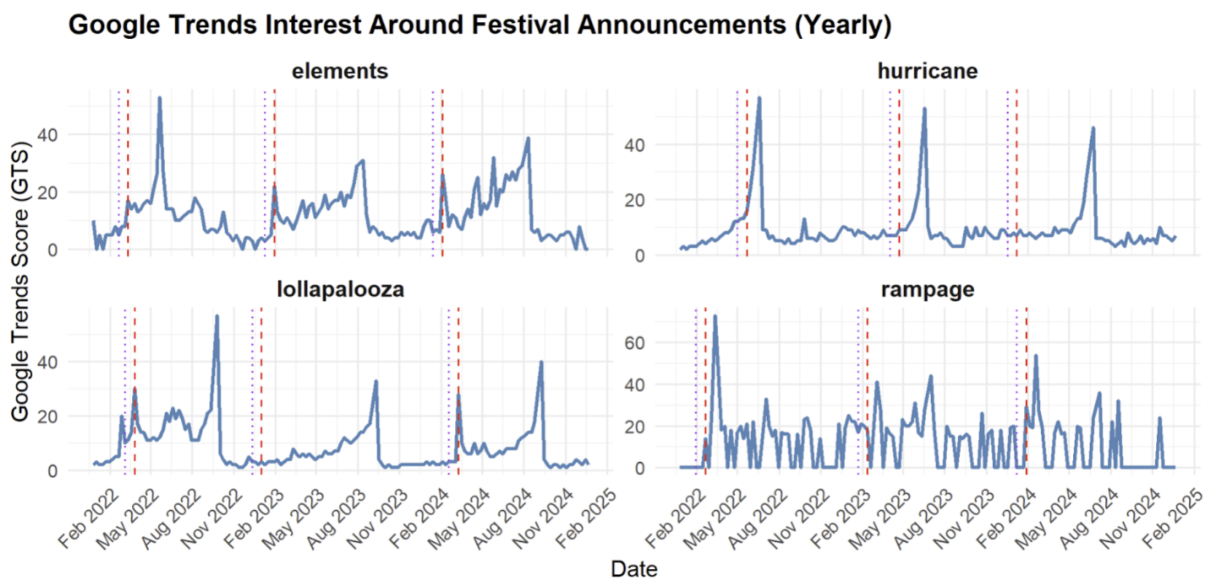


Fig. 4 GTS 4 festivals

3.2.3 Big Bang Announcement

One of the independent variables used in this study is a *BigBang_Announcement* which is a binary variable coded as 1 for “big bang” lineup announcement strategies and 0 for “staged”. The *Big Bang* strategy entails the release of all or the majority of headliners in a single communication event, whereas the *Staged* strategy involves announcing artists over a longer period of time. An important mention is that for *Staged* lineup announcements, the reference point is represented by the date of the first wave of headliners revealed. For future research, staged lineup announcement could be treated gradually in a sense that, each announcement wave would be considered a separate treatment point. Possibly, a multiple treatment difference-in-differences (DiD) approach could be used as it would capture the cumulative or diminishing effects of staged announcement. However, our dummy (*BigBang_Announcement*) serves as a key independent predictor, enabling us to examine whether the type of lineup announcement shapes public attention.

Table 4. Google Trends Score by Announcement Type and Period

Announcement Type	Period	Mean GTS	SD GTS	N
Big Bang	Post_Announcement	9.75	9.16	436
Big Bang	Post_Festival	3.47	9.99	540
Big Bang	Pre_Announcement	3.96	5.88	248
Staged	Post_Announcement	7.67	8.41	865
Staged	Post_Festival	4.06	9.78	819
Staged	Pre_Announcement	3.46	5.21	152

Note: Values represent mean and standard deviation of *Google Trends Score* (GTS) across different announcement strategies and temporal phases surrounding the festival.

The analysis presented in *Table 4*. illustrates the GTS scores across different announcement strategies and temporal phases. In the Post-Announcement phase, the Big Bang strategy generated the highest average GTS (M = 9.75, SD = 9.16, N = 436), outperforming the Staged approach (M = 7.67, SD = 8.41, N = 865). This consequent implications would be that concentrated, one-time announcements are more effective at creating immediate online search interest. However, in the Post-Festival period, Staged lineup announcements yielded a slightly higher mean GTS (M = 4.06, SD = 9.78, N = 819) than Big Bang (M = 3.47, SD = 9.99, N = 540), suggesting that staged releases may help sustain audience attention after the event has ended. Moreover, in the Pre-Announcement phase, both strategies showed comparably low GTS values: Big Bang (M = 3.96, SD = 5.88, N = 248) and Staged (M = 3.46, SD = 5.21, N = 152). Given the fact that GTS ranges from 0 to 100 and represents normalised public online search interest over time, these findings hint at the short-term impact of Big Bang campaigns and the potential for prolonged engagement acquired with Staged strategies. Thus, this particular distinction might have implications for festival promotion planning depending on the timing and longevity of desired audience engagement.

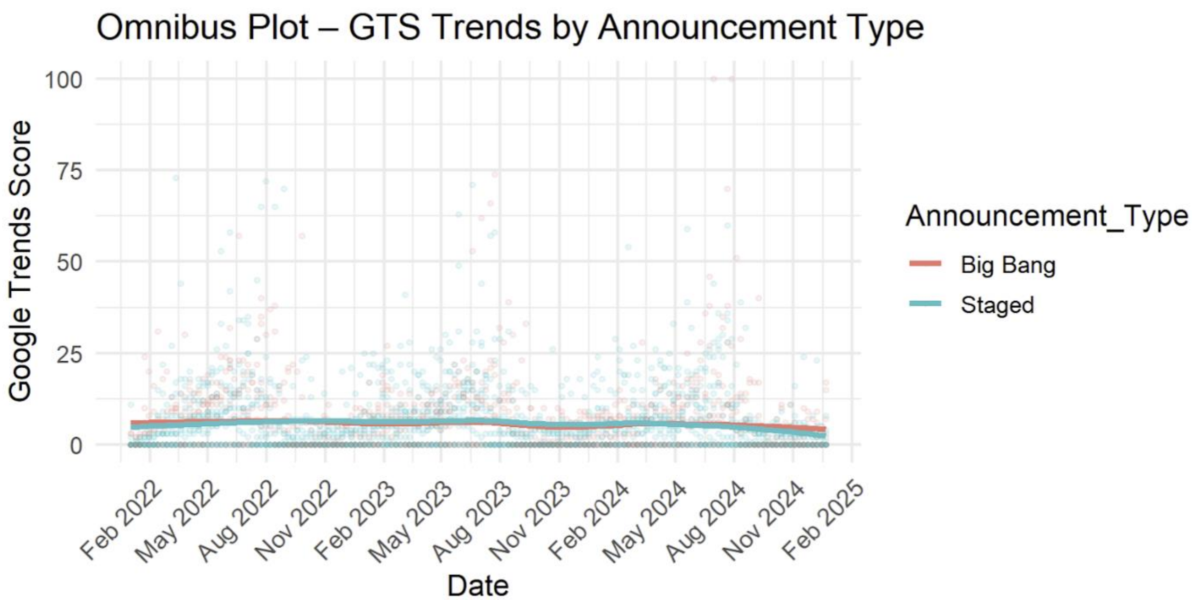


Fig. 5 Omnibus

In addition to the aforementioned period-specific comparisons, an omnibus time series plot was employed as to examine the longitudinal evolution of public attention across both Big Bang and Staged lineup announcement strategies. As shown in Figure, despite sporadic spikes in interest, the overall trendlines (LOESS smoothing) for both strategies seem to remain relatively stable and low throughout the observed period. Notably, Staged lineup announcements are associated with a slightly higher average trendline, indicating a more consistent, though moderate, level of audience engagement over the analysed period.

A large share of GTS score observations cluster around zero, as evidenced by the dense overlap at the bottom of the plot. Therefore, the pattern shown here is that search interest is often minimal in the absence of active communication or festival-related stimuli. The lack of sustained peaks across time further implies that while both Big Bang and Staged announcements can trigger short-term bursts of attention, neither appears to generate long-term or recurrent public interest at scale.

Moreover, another visual inspection element we could use in order to account for the effect of Big Bang and Staged announcements in the post-announcement period is the bar plot below. As we are mainly interested in the comparison between pre-announcement and post-announcement, it is noticeable that both strategies generate similarly low levels of public interest in the pre-announcement phase (GTS ≈ 3.5–4.0), but an increase in the post-announcement period is observed, especially particularly for the Big Bang announcements (M ≈ 9.8), that yield higher values than Staged announcements (M ≈ 7.7). Therefore these results suggest that the lineup announcement strategy itself plays a role in driving immediate public attention, with strategic bulk disclosure of headliners proving more effective in generating fans engagement in the post-announcement period.

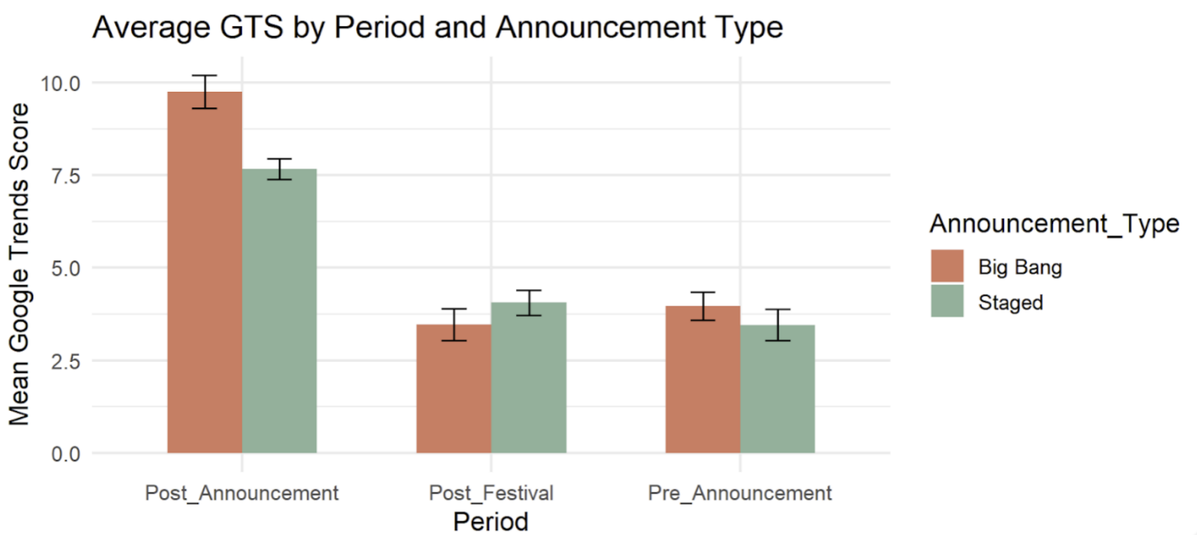


Fig. 6 Bar plot GTS

Additionally, an OLS regression was performed to examine whether the timing of Big Bang announcements influences their treatment effect on public interest (*see Appendix, Section A.4*). A variable *Timing_Group* was used in order to categorise the timing of Big Bang lineup announcements as: early, medium or late. After performing the regression, no results indicate statistically significant differences between the these timing groups. The intercept ($\beta = 3.434$, $p=0.055$) represents the average treatment effect for early announcements and is marginally significant, reflecting a potentially meaningful but statistically borderline increase in public attention for early-time announcements. However, the other timing groups show no statistically significant difference relative to early announcements. These estimates point to the conclusion that the timing of Big Bang announcements does not significantly influence their impact on attention, even though early announcements may provide a modest advantage that needs to be further investigated.

To gain a more precise understanding of how festival-related interest evolves around the time of an announcement, we shifted to a dynamic event-study design. The aim is to also determine, apart from the need to identify whether the announcement leads to a spike in attention, when this effect emerges and how long it persists.

An event study is a method used to estimate the causal effect of an event, by tracking changes in an outcome variable over time, but relative to the event date (T = 0). First, the analysis defines a time window around the event and compares each period (pre-event and post-event) to a baseline, usually set as the week prior to the event (T = –1). By interacting week indicators with a treatment the model produces event-time coefficients that reflect the marginal effect of the treatment in each period. When a control group is included, the method controls for underlying trends and isolates the treatment effect more reliably, thus offering a robust and time-sensitive approach to capturing both short- and medium-term effects of a treatment (MacKinlay, 1997).

Therefore, in our case, the event-study estimates week-by-week deviations in GTS scores relative to a baseline, usually one week prior to the event. By interacting week indicators with the Big Bang treatment variable, the model compares treated festivals (Big Bang) to control festivals (Staged), while controlling for fame and fixed effects. Importantly, as we previously reported, we are aware of the pre-treatment trend and we adjust the event-study plot accordingly, by correcting it. In the graph, we focus on the closest time window to the announcement, spanning from 9 weeks before (T=-9) to 8 weeks after (T=+8). Prior to the event itself (T=0), coefficients for the treated group (Big Bang) fall below the control group baseline but this does not represent a real decline, but the result of adjusting for the previously identified upward trend in the treated group. However, from the moment of the announcement a statistically significant increase in GTS scores is observed, peaking between weeks +3 and +5. This result shows that Big Bang lineup announcements produce a strong but transient increase in audience interest. In subsequent weeks, this effect tapers off, indicating that usually concentrated announcements do generate a brief surge in attention, but then they return to baseline.

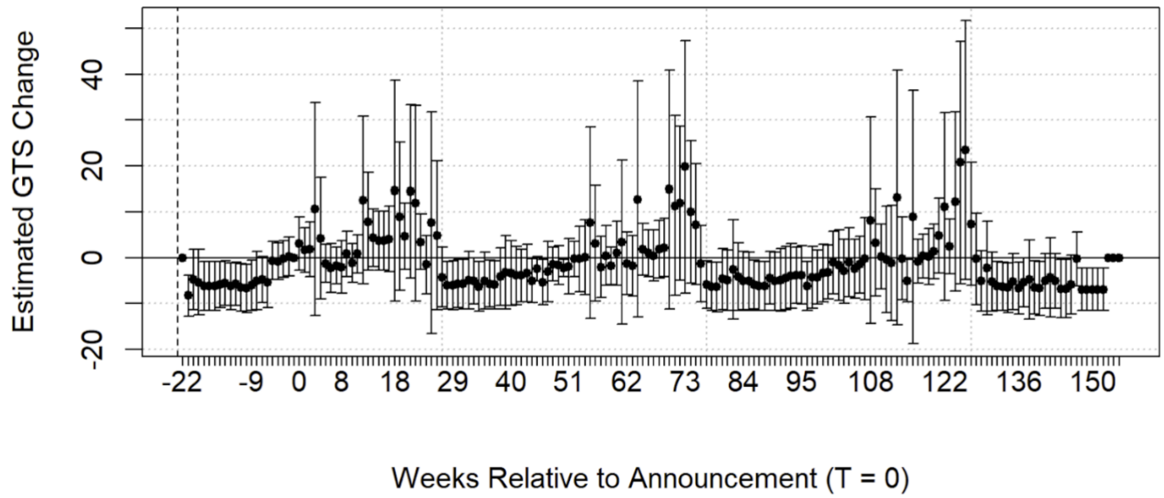


Fig. 7 Event study plot

3.2.4 Period

The variable Period represents the position of each calendar week within the festival's promotional and post-event timeline. This variable can take one of the following four categorical values: Pre-Announcement, Post-Announcement, Event and Post-Festival. As discussed earlier, the Event week consistently registers extreme spikes in GTS which are largely driven by event-related public attention. To prevent these peaks from inflating post-treatment effects and conflating baseline festival visibility with the actual impact of lineup announcements, we exclude the event week (Event) from all post-treatment analyses. Consequently, the analytical focus remains primarily on the pre-announcement and post-announcement periods.

To facilitate analysis, this initially categorical variable is operationalized into three dummy variables:

- Pre_Announcement: takes the value 1 if the week falls within the pre-announcement window for a specific festival and 0 otherwise.
- Post_Announcement is 1 if the week follows the announcement but precedes the festival.
- Post_Festival is 1 for all weeks after the event up until Christmas Day of the same year.
- For the week of the event, all dummy variables are zero, as we exclude this period.

For every festival, each week from 2022 to 2024 is assigned values for these dummy variables accordingly. Importantly, the week in which the lineup is announced is treated as part of the Post-Announcement phase, as announcement effects may begin to manifest immediately within that week. Moreover, we define the event week as the calendar week containing the majority of festival days, even though in some cases this may slightly overlap into a neighbouring week.
To ensure feasibility and clarity in the analysis, each week must be assigned to one and only one treatment status. In cases where overlap occurs, for instance, when the post-announcement period from one edition intersects with the pre-announcement phase of the following edition we apply then following prioritization logic in order to resolve conflicts:
Festival_Week > Post_Announcement > Post_Festival > Pre_Announcement.

This rule ensures that overlapping weeks are consistently attributed to the most behaviourally relevant phase. Additionally, for simplicity and due to time constraints, the announcement date is defined as the first release of headliners. Furthermore, although some electronic music festivals use staged announcements with multiple waves of artist releases, in this analysis, we treat the initial announcement as the treatment trigger, recognizing this simplification as a trade-off between precision and efficiency.

3.2.5 Fame Index

Yet another variable incorporated in the study is the Fame Index, which, as the name suggests, represents the operationalization of the concept of fame. To account for the a festival's online popularity, we constructed an index based on two indicators: the number of Instagram followers and the number of Spotify monthly listeners. Since both metrics offer imperfect but complementary proxies for artist fame, combining them into an index allows for a more balanced and robust representation of a festival's online visibility.

The reason behind constructing this index, rather than including the raw indicators separately in the models, lies in the concerns about potential multicollinearity. Thus, it would mean that Instagram and Spotify fame measures are correlated and could distort regression estimates if entered simultaneously. Furthermore, treating Spotify listeners as a standalone measure risks overweighting it, since one listen may represent a much lower unit of attention than one social media follower, where a follower may correspond to sustained and repeated engagement on Spotify. Consequently, the fame index offers a solution that preserves information from both sources while minimising distortions in interpretation.

The Fame Index was computed as follows. For each edition of every festival, we extracted the top three headliners, totalling nine headline acts across three years (*see Appendix, Section A.1*). For each artist, we collected the number of Instagram followers and monthly Spotify listeners. Then, the average was calculated per edition, separately for Instagram and Spotify. However, for efficiency and consistency across editions, we assign the same average per festival (based on all its editions) for both indictors. This simplification implies treating fame as a time-invariant variable, which we acknowledge as a limitation but accept for practical reasons.

Once the average values per festival were obtained (*Avg_Instagram_Fest* and *Avg_Spotify_Listeners_Fest*), we normalised each against the median value of the respective variable across all festivals. The choice of using the median rather than the maximum or mean is due to the fact that the median reduces the impact of outliers, present in the upper tail of the distribution. Unlike the mean, which can be skewed by extreme values, the median provides a more robust central tendency for dispersed or skewed data. We then combine the two normalised components with equal weights, reflecting the decision to treat both sources of fame as equally informative. This yielded the final form:

$$Fame\_Index = 100 \times \left(0.5 \times \mathrm{norm}_{\mathrm{Instagram}} + 0.5 \times \mathrm{norm}_{\mathrm{Spotify}}\right)$$

Multiplying by 100 expresses the index as a percentage relative to the median, allowing for more interpretable coefficients.

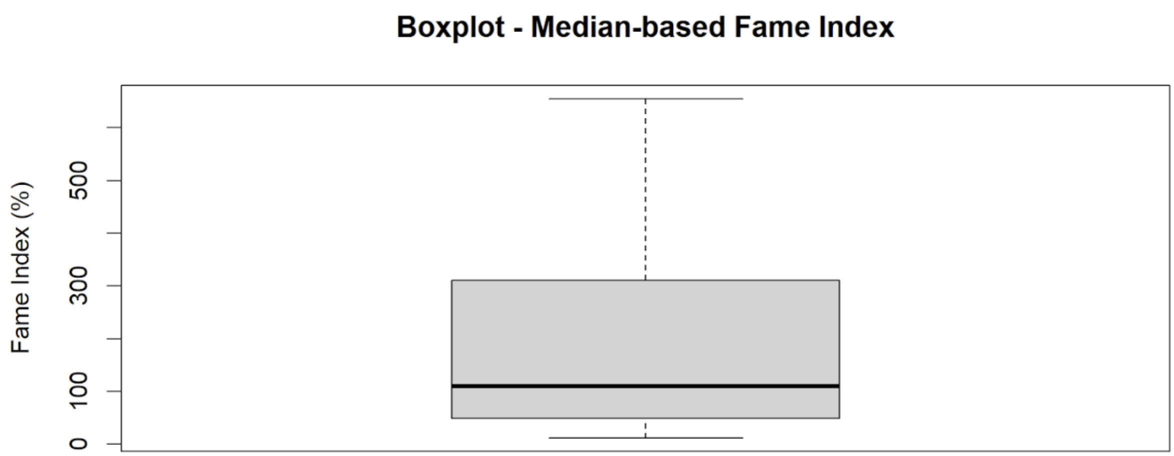


Fig. 8 Boxplot Fame

The boxplot above (*Fig. 8*) illustrates the distribution of the Fame Index. This visualisation is able to identify potential outliers and assess the overall spread of festival popularity. By looking at the boxplot we observe that one festival has a Fame Index value approaching 700%, while another lies significantly below the lower whisker. Upon inspection, the upper outlier corresponds to Lollapalooza Berlin, while the lower outlier is E-Lake Festival, a niche festival with limited international exposure.

To address the potential influence of these outliers on model estimates, we considered excluding them and re-estimating the regression models. A robustness check was performed by rerunning the DiD model, without these two extreme values. The results (*see Appendix, Section A.2*) showed that the coefficients and significance levels remained stable, indicating that the findings are robust to the presence of outliers.

Given this robustness, we opted to retain the outliers in the main analysis. This decision ensures that the analysis remains inclusive of the full spectrum of festival types, ranging from highly niche to globally dominant events, therefore capturing the true variation in audience response. In addition to this, from a theoretical standpoint, removing Lollapalooza Berlin would risk excluding a central case in which announcement-driven attention is particularly relevant. Thus, including all festivals provides a better representation of the market dynamics and preserves the validity of the estimates.

However, to enhance the methodological rigor of the study and account for the extreme values and skewed distribution of the Fame Index, a natural logarithmic transformation was applied. This transformation reduces the effect of outliers, an observation that can also be inferred from the visual inspection of the figure below (*Fig. 9*), as the values are now clustered within a range of approximately [2.5 – 6.5].

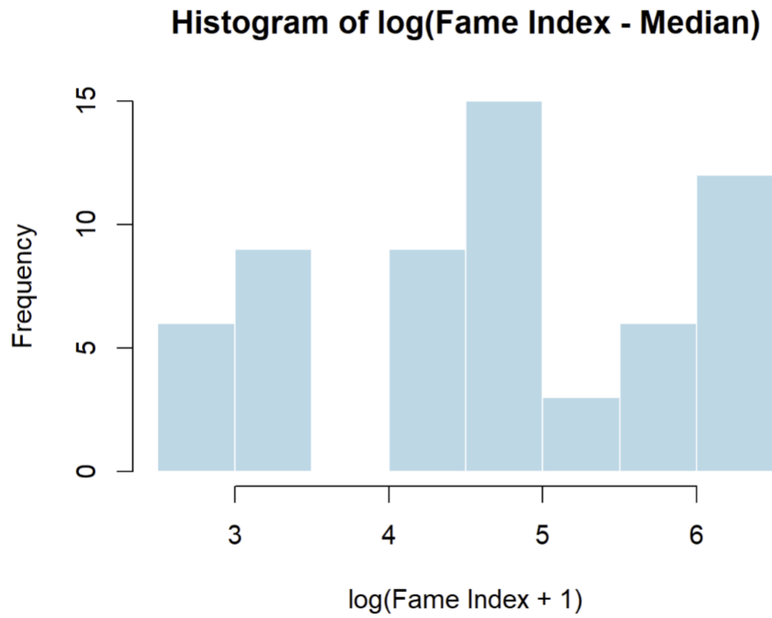


Fig. 9 Histogram Fame

3.3 Data Analysis

This chapter outlines the procedures employed to investigate the relationships within the dataset. We begin by presenting the detrending process of the aforementioned upward trend in the pre-treatment period, ensuring the integrity of subsequent statistical analyses. Following this, we implement both Fixed Effects and Random Effects models, accompanied by diagnostic tests for autocorrelation and heteroscedasticity to validate model assumptions. Finally, we advance to a Difference-in-Differences (DiD) framework, which enables us to estimate the causal impact of the treatment. Importantly, all statistical analyses and visualisations presented in this study were conducted using the R statistical software environment. The results of these analyses are then systematically examined and interpreted.

3.3.1 Detrending process

In order to identify the treatment effect of lineup announcements while controlling for underlying time trends, we implement a detrending strategy. As we are already aware of the upward trend in the pre-treatment, the chosen method by which the detrending is done was the residual analysis (Bobbitt, 2021). As also shown in *Figure 10*, pre-announcement weeks exhibit lower but slightly increasing GTS levels, consistent with a modest upwards trend prior to the treatment, whereas the post-announcement weeks show the highest variability and frequent spikes, suggesting short-term attention surges after the treatment.

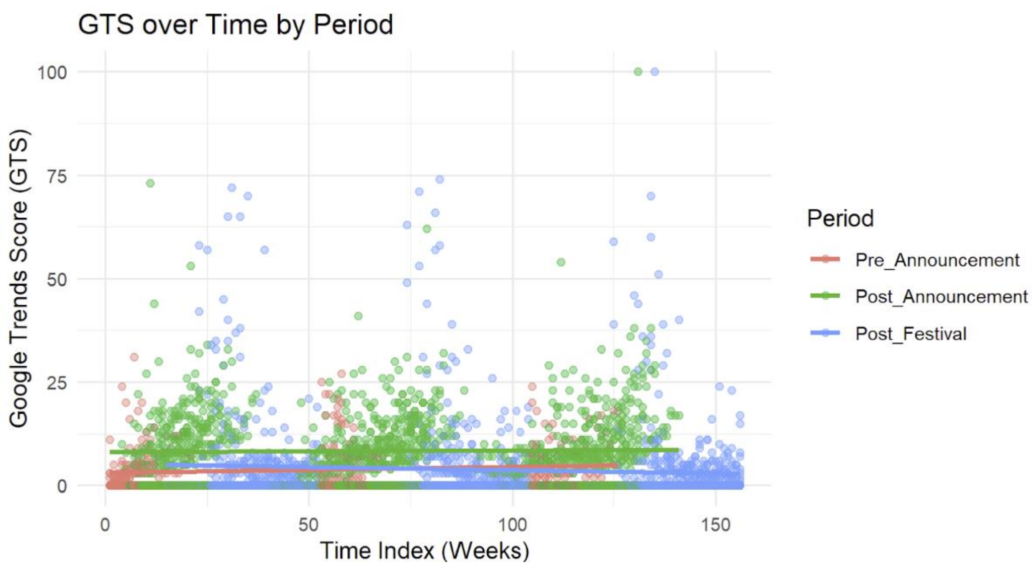


Fig. 10 GTS over time

A linear model for the Pre-Announcement period was employed, regressing GTS on a continuous time variable (*Time_Index*) to capture any pre-existing trend. This reported a statistically significant, positive trend coefficient ($\beta = 0.014$, $p = 0.025$), indicating that prior to the announcement, audience interest was gradually increasing (*Table 5*). Then, we extrapolated this baseline trend to the post-announcement period to estimate what GTS levels would have been in the absence of the treatment. Therefore, by subtracting the projected values from the actual post-announcement GTS scores, we obtained a series of residuals that represent the deviations from the pre-existing trend.

Next, these residuals were regressed on *Time_Index* within the post-announcement period so as to check whether the treatment caused a change in attention. This model (Residuals Post) captures two key components: the intercept, which reflects the immediate level shift attributable to the treatment and the slope, which measures the rate of change in residuals over time. The intercept was highly significant ($p < 0.001$), indicating a positive level shift in online search interest immediately after the lineup announcement. Conversely, the trend coefficient in the post period was negative and marginally significant ($\beta = -0.010$, $p = 0.085$). These values hint at the fact that the effect of the treatment, decayed in time, although the lineup announcement produced a spike in attention. In other words, the treatment appears to have induced a temporary boost in interest, which gradually diminishes as the event approaches.

Table 5. Linear Regression Models for GTS – Full, Pre-Announcement and Post-Announcement Residuals

Variable	Model Full	Model Pre	Residuals Post
Intercept	-0.071 (0.807)	3.083 (0.415)***	5.001 (0.499)***
Post_Announcement	4.687 (0.526)***	–	–
Post_Festival	0.280 (0.538)	–	–
Time_Index	-0.004 (0.004)	0.014 (0.006)*	-0.010 (0.006)
log(Fame_Index_Median)	0.804 (0.137)***	–	–
BigBang_Announcement	0.566 (0.334)	–	–
R-squared	0.0719	0.0126	0.0023
Adj. R-squared	0.0703	0.0101	0.0015
F-statistic (df)	47.29 (5, 3054)	5.08 (1, 398)	2.98 (1, 1299)
p-value (F)	< 0.001	0.025	0.085

Note: Each cell shows coefficient estimate with standard error in parentheses. *Model Full* includes all predictors. *Model Pre* is restricted to the Pre_Announcement period. *Residuals Post* regresses residuals on time in the Post_Announcement period. Significance: $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

3.3.2 Fixed Effects and Random Effects

In the context of panel data, such as repeated weekly observations for multiple music festivals over time, applying fixed or random effects models is essential to account for unobserved heterogeneity across units, in this case, festivals. Baseline popularity, marketing strategies such as lineup announcement types and audience type are a few characteristics that remain constant over time but may strongly influence GTS scores. A fixed effects model controls for these time-invariant differences by allowing each festival to have its own intercept, therefore focusing solely on within-festival variation. In contrast, the random effects model assumes that individual-specific effects are uncorrelated with explanatory variables and allows for the inclusion of time-invariant covariates such as the aforementioned ones (Schmidheiny & Basel, 2011).

Given these differences, usually fixed effects are preferred when the goal is to estimate causal relationships robust to omitted variable bias, while the random effects are more efficient under the assumption of exogeneity. In this settings, both models will be performed and investigated in order to offer our study robustness and help assessing the sensitivity of the estimated treatment effects to unobserved heterogeneity across the 20 music festivals observed over 153 weeks.

The fixed effects (FE) panel regression analysis (*Table 6*) explores the impact of different campaign phases on public interest, as measured by GTS. The results indicate a statistically significant and substantial increase in GTS during the Post_Announcement phase, with an estimated coefficient of 4.77 ($p < 0.001$) suggesting that the lineup announcement is associated with a rise in online search activity, immediately following the promotional reveal. A very similar situation happens in the random effects model as well (coefficient = 4.76, $p < 0.001$). However, the Post_Festival phase does not exhibit a statistically significant effect in either model implying that public attention does not significantly persist or intensify in the aftermath of the event compared to the pre-announcement period. Both models explain approximately 6.1% of the variation in GTS scores ($R^2 = 0.061$).

Table 6. Fixed and Random Effects Models for Google Trends Score (GTS)

Variable	**Fixed Effects Model**	**Random Effects Model**
Post_Announcement	4.774 (0.513)***	4.765 (0.511)***
Post_Festival	0.371 (0.504)	0.359 (0.503)
log(Fame_Index_Median)	–	0.803 (0.626)
BigBang_Announcement	–	0.576 (1.504)
R-squared	0.061	0.061
Adj. R-squared	0.055	0.060
F-statistic / Chi2	99.02 (2, 3038)	200.85 (4 df)
p-value (model)	< 0.001	< 0.001

Note: Coefficient estimates shown with standard errors in parentheses. Fixed effects model uses within transformation. Random effects model uses Swamy–Arora's method.
Hausman test: $\chi^2(2) = 0.179$, $p = 0.915$.
Significance levels: $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Furthermore, in the random effects (RE) model, additional time-invariant controls are included. In this study the time-invariant variables are Fame_Index and BigBang_Announcement. Neither of them is statistically significant, which translates to variation in the GTS scores is explained festival popularity or announcement large-scale announcement strategies. However, this interpretation should not be considered as conclusive yet since it is possible that the influence of these variables interacts with other unobserved or time-varying actors or even manifest differently depending on festival characteristics. As such, further investigation, potentially involving interaction terms or sub-group analyses may yield better results.

To further explore whether the impact of announcement timing depends on the lineup announcement strategy, an interaction model was estimated (*Table 7*). Results show a surge in search interest during the Post_Announcement period ($\beta = 5.15$, $p < 0.001$), primarily driven by Staged festivals. However, the interaction with BigBang_Announcement is not significant ($\beta = -0.29$, $p = 0.783$), indicating no meaningful difference in post-announcement effects across announcement strategies. Interestingly, the interaction for Post_Festival is marginally significant and negative ($\beta = -1.89$, $p = 0.064$), suggesting that online search interest declines more sharply after "big bang" festivals. Other covariates, including BigBang_Announcement and Fame Index, remain non-significant. Consequently, while the timing of lineup announcements has a clear effect on public attention, there is limited empirical evidence that a specific type of announcement moderates this relationship.

Table 7. Interaction Announcement Strategy × Period

Variable	**Estimate (SE)**	**Pr(> |z|)**
Intercept	-0.948 (3.267)	0.772
Post_Announcement	5.153 (0.773)***	< 0.001
Post_Festival	1.311 (0.770)	0.089
BigBang_Announcement	1.566 (1.770)	0.376
log(Fame_Index_Median)	0.779 (0.649)	0.229
Post_Announcement × BigBang	-0.288 (1.043)	0.783
Post_Festival × BigBang	-1.894 (1.023)	0.064
R-squared		0.0637
Adj. R-squared		0.0619
Chi-squared (df)		207.70 (6)
p-value (model)		< 0.001

Note: Estimates are based on a random effects panel model with interaction terms between announcement strategy (Big Bang) and festival period. The model controls for *Fame Index*. Significance levels: $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Next, in order to guide the model selection between fixed and random effects, the Hausman test is conducted. The hypotheses are as follows:

(H_0): The random effects model is consistent and appropriate to use.

(H_1): The random effects model is inconsistent, therefore, the fixed effects model is more reliable.

According to our results (*Table 6*), since the p-value is very high (0.9145), we fail to reject the null hypothesis which means that the random effects model is preferred in this case.

3.3.2.1 Autocorrelation and heteroskedasticity

Autocorrelation and heteroskedasticity represent two common violations of classical regression assumptions that can distort inference. Autocorrelation occurs when error terms are correlated over time, resulting in underestimated standard errors and potential overstated significance. On the other hand, heteroskedasticity refers to the unequal variance of the error terms which often results in inefficient estimates or invalid standard errors (Schmidheiny & Basel, 2011).

Table 8. Diagnostic Tests and Robust Coefficient Estimates for Panel Models

Test / Variable	Fixed Effects (FE)	Random Effects (RE)
Autocorrelation (Wooldridge)	$F = 145.64$, $p < 0.001$	–
Heteroscedasticity (BP)	$BP = 8.920$, $p = 0.012$	–
Post_Announcement	4.774 (0.696)***	4.764 (0.692)***
Post_Festival	0.371 (0.564)	0.359 (0.556)
log(Fame_Index)	–	0.803 (0.404)*
BigBang_Announcement	–	0.576 (1.124)

Note: Tests for serial correlation and heteroscedasticity indicate both are present (FE model). Cluster-robust standard errors (HC1) were used to correct for these issues. Values are coefficient estimates with robust standard errors in parentheses. Significance: $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

In the fixed model, we use the Wooldridge's test for serial correlation in FE panels. Because of the extremely low p-value, the null hypothesis of no autocorrelation is strongly rejected, therefore the presence of serial correlation in the residuals is detected.

In an attempt to check for heteroskedasticity, the Breusch-Pagan test is implemented. With the p-value below the conventional 0.05 significance level, we reject the null hypothesis of heteroskedasticity, suggesting that the variance of the error terms is not constant.

In summary, we have to correct for both autocorrelation and heteroskedasticity using cluster-robust standard errors at the festival level. The coefficient for the Post_Announcement period remains highly statistically significant with a value of 4.77 (p< 0.001) implying that there is a strong increase in GTS scores after lineup announcement of a festival has been revealed. Conversely, the Post_Festival coefficient is not statistically significant (p = 0.5107), indicating that any observed changes in GTS after the festival are not reliably distinguishable from zero once statistical corrections are applied. Ultimately, the results reinforce the robustness of the pre-event hype effect while casting doubt on the persistence of audience attention after the event.

Similarly for the random effects model, after correcting for heteroskedasticity and autocorrelation using cluster-robust standard errors, this model confirms a strong positive effect of the Post_Announcement period on search interest ($p < 0.001$), while Post_Festival remains insignificant. Notably, the Fame_Index becomes significant alluding to the fact that more prominent festivals tend to attract higher baseline attention, regardless of timing.

Although the Hausman test favours the RE model, the presence of both autocorrelation and heteroskedasticity, plus the fact that the FE model has the ability to account for unobserved heterogeneity across festivals, make the FE model with robust standard errors a more reliable and conservative choice.

Furthermore, to evaluate whether the effect of the treatment varies by announcement strategy, separate fixed effects regressions were estimated both for Big bang and Staged festivals, with standard errors adjusted for heteroskedasticity and autocorrelation via clustering (*see Appendix, Section A3*). Although both promotional strategies effectively increase online search interest after the lineup announcement and prior to the event, only Staged announcements appear to be linked to a residual post-festival attention effect. All things considered, the results suggest that Staged communication may increase prolonged audience engagement, whereas, Big Bang strategies tend generate short-term interest before the event itself.

3.3.3. Difference-in-Differences

Difference-in-Differences (DiD) is an econometric technique used to estimate the causal effects of a treatment, in our case the lineup announcement by comparing the changes over time between a treatment group and a control group. This method relies on the parallel trends assumption which states that in the absence of the treatment, both the control group and treatment group would have followed parallel trends (Donald & Lang, 2007).
As we are already familiar with the fact that our raw data presented a upward trend in the pre-period, the detrended data will be used for DiD.
DiD successfully isolates the effect of the treatment from time-related confounders, by subtracting the pre-post difference in the treatment group.

Table 9. Difference-in-Differences Model: Post $\times$ Treated (Big Bang)

Variable	**Estimate**	**Std. Error**	**Pr(> |t|)**
(Intercept)	-2.882	2.568	0.262
Post	3.734	1.612	0.021*
Treated	0.292	0.499	0.559
Post $\times$ Treated	1.417	2.183	0.516
log(Fame_Index_Median)	0.590	0.532	0.268

Note: Difference-in-Differences model estimates the interaction effect of being treated (Big Bang strategy) in the post period.
Significance levels: $^{*}p < 0.05$

Table 9 reports the results of the DiD model estimating the interaction (Post x Treated) effect of being treated with the Big Bang announcement strategy in the post-announcement period. The interaction term is positive (1.417), indicating a higher post-period GTS for treated festivals but the coefficient is not statistically significant (p = 0.516). This suggests that, on average, there is no robust evidence of a differential post-treatment effect attributable to the Big Bang strategy when compared to the control group.

The Post coefficient (p = 0.021) is statistically significant, implying that GTS increased in the post-announcement period regardless of treatment. This may also reflect general attention patterns close to the announcement weeks, perhaps independent of the specific strategy employed. The Treated coefficient and the control variable (log(Fame_Index_Median)) are both non-significant, indicating no systematic baseline differences between groups and no direct effect of artist fame on GTS in this specification.

In the light of the above, even though the Big Bang strategy may show a positive directional effect, the lack of statistical significance in the DiD interaction term implies that the average treatment effect appears too modest and inconsistent to warrant strong causal interpretations in the context of the current analysis.

4. Results

This section of the paper presents the empirical findings of this study and interprets them in relation to the research question and the formulated hypotheses. To begin with, from the visual inspection of *Fig. 2* where the Google Trends Scores are aligned to the event week we can confirm that public attention peaks reliably during the event week (T=0), marking the festival as the primary determinant of audience interest. Despite this common peak, notable heterogeneity was observed, with some of the festivals showing multiple or more dispersed peak, which indicates variability in audience behaviour.

With the aim of testing Hypothesis 1 and assess the impact of the lineup announcements on audience attention, we considered residuals regressed on Time_Index within the pre-period. In this model, the intercept, accounting for the immediate level shift in the online search interest was highly significant ($p < 0.001$) which means that there is a substantial and sudden increase in Google search activity generated by the lineup announcement, while the slope, indicating the evolution of this effect over time, was negative and marginally significant ($\beta = -0.010$, $p = 0.085$), thus concluding that this effect gradually decayed over subsequent weeks.

After correcting the autocorrelation and heteroskedasticity using cluster robust standard errors at the festival level, the coefficient for the Post_Announcement period was highly statistically significant with a value of 4.77 ($p< 0.001$) suggesting that there is a strong increase in GTS scores after announcement. In addition to this, the Post_Festival coefficient is not statistically significant ($p = 0.5107$) therefore any observed changes in GTS after the festival are not reliably distinguishable from zero.

Empirical findings regarding the random effects model, confirm particularly strong positive effect of the Post_Announcement period on search interest ($p < 0.001$). However, the Post_Festival coefficient remains insignificant.

In the DiD analysis the Post coefficient ($p = 0.021$) was statistically significant, pointing to a general post-announcement increase in GTS independently of whether the treatment was applied.

Across all models, the results confirm Hypothesis 1, indicating that lineup announcements significantly increase public attention in the short term, supporting agenda-setting theory (McCombs & Shaw, 1972).

With respect to the second hypothesis, Mean GTS values show that Big Bang announcements produce the highest sudden increase ($M = 9.75$) in the Post_Announcement phase, outperforming the Staged strategy ($M = 7.67$). However, the event study and LOESS trendlines suggest that this effect is short-lived. From approximately week +3 onward (according to the event-study plot), interest for Big Bang festivals declines more rapidly than for Staged ones. This is also supported by the post-period trend coefficient ($\beta = -0.010$, $p = 0.085$), suggesting a decay in public interest over time. Considering all the aforementioned findings we can confirm Hypothesis 2: Big Bang campaigns trigger a strong, immediate response, but one that fades quickly. Conversely, the Staged strategy generates more sustained, though moderate, engagement over time.

Importantly, the interaction term from the DiD model (Post × Treated) was positive but not statistically significant ($\beta = 1.42$, $p = 0.516$), and the interaction in the regression model also fails to reach significance ($\beta = -0.29$, $p = 0.783$). These results indicate that although Big Bang lineup announcements appear to be more impactful at first glance, the difference between strategies becomes statistically indistinguishable over time, thereby supporting Hypothesis 5.

To be able to evaluate Hypothesis 3, we assessed whether earlier lineup announcements can drive more attention. The intercept for early announcements was marginally significant ($\beta = 3.43$, $p = 0.055$), suggesting a possible advantage for early announcements, but further research should be conducted in order to explore additional moderating variables or contextual factors that may moderate the impact of announcement timing. No statistically significant differences were found between early and late timing groups, implying that while timing may have modest practical effects, it is not a robust predictor across the sample. Hence, Hypothesis 3 receives partial support.

In order to evaluate the remaining assumption, Hypothesis 4, we look at the initial time series plots that even only upon visual inspection suggested that search interest often began increasing before the official lineup announcement. The treatment window was shifted to begin three weeks prior so as to test the aforementioned supposition. The model reveals a highly significant anticipatory effect ($\beta = 5.47$, $p < 0.001$), confirming Hypothesis 4 as audience attention starts rising in the weeks preceding the official announcement, likely driven by speculation, unofficial leaks and overall community anticipation, fully consistent with Loewenstein (1987).

5. Conclusion

This study set out to investigate the extent to which lineup announcement strategies influence public attention in the context of electronic music festivals in the Benelux region and Germany. Drawing on event study methodology, fixed effects panel regression, as well as random effects and difference-in-differences (DiD), the research effectively examined and responded to the core research question and its subsequent sub-question.

The overall findings provide clear empirical support for the claim that lineup announcements significantly increase public attention in the immediate post-announcement period, thereby confirming the main research question. Furthermore, while Big Bang announcements yield stronger immediate surges, Staged announcements tend to sustain attention for longer periods, a distinction with meaningful theoretical and managerial implications. Notably, the research also uncovered anticipatory effects marked by a rise in public attention in the weeks leading up to the official announcement. Interestingly, this aspect is rarely accounted for in prior literature but highly consistent with expectancy theory and media salience frameworks.

With regard to the practical implications, the results offer actionable insights for festival organizers and marketers. The choice between Big Bang and Staged announcements should be made based on strategic communication goals. If the objective is to maximize short-term media impact and digital buzz, concentrated Big Bang releases may be preferable according to this study. Conversely, for building longer-term engagement and spreading attention over time, Staged releases appear more effective. Additionally, recognizing and leveraging anticipatory behaviour could allow organizers to subtly signal information and build momentum prior to formal announcements.

Moreover, the use of real-time attention metrics like GTS illustrates the viability of digital trace data in assessing campaign effectiveness, offering an affordable and scalable alternative to traditional audience measurement tools.

In terms of limitations, we include Google Trends accuracy as an indirect, aggregate-level proxy for public interest that is very limited in capacity and therefore cannot capture audience subgroups or motivations. Because of the fact that the festival analysed are all located in Europe, we may not generalise to other geographical contexts. Third, despite the efforts to control for confounding factors, unobserved time-varying variables such as but not limited to parallel media events or competing festivals may still influence the outcome.

Building on the current findings, future research could apply more advanced causal inference methods and richer data sources. A particularly promising avenue for research would be the Generalized Synthetic Control Method (GSCM) (Xu, 2017), which constructs synthetic counterfactuals using pre-treatment dynamics and accommodates time-varying effects and unbalanced panels. Moreover, future studies might also incorporate other social media engagement metrics and apply machine learning techniques such as causal forests to uncover heterogeneous treatment effects and further investigate how announcement timing interacts with artist fame.

To conclude, this paper contributes to the growing body of research on digital announcement strategies within cultural event marketing, providing both empirical evidence and strategic insights into how festival lineup announcements shape audience attention. By integrating causal inference methodologies with temporally granular data, this study highlights the temporal mechanics of attention formation and establishes a robust empirical foundation for the future development of data-driven, audience-centric promotional strategies in the electronic music festival industry.

References

Adler, M. (2006). Stardom and talent. *Handbook of the Economics of Art and Culture*, *1*, 895-906.

Allison, P. D. (1994). Using panel data to estimate the effects of events. *Sociological Methods & Research*, *23*(2), 174-199.

Bader, I., & Scharenberg, A. (2010). The sound of Berlin: Subculture and the global music industry. *International Journal of Urban and Regional Research*, *34*(1), 76-91.

Baek, H., Oh, S., Yang, H. D., & Ahn, J. (2017). Electronic word-of-mouth, box office revenue and social media. *Electronic Commerce Research and Applications*, *22*, 13-23.

Baltagi, B. H., & Baltagi, B. H. (2008). *Econometric analysis of panel data* (Vol. 4, pp. 135-145). Chichester: John wiley & sons.

Bobbitt, Z. (2021, January 20). *How to detrend data (with examples)*. Statology. https://www.statology.org/detrend-data/

Borges, A. P., Rodrigues, P., & Matias, A. (2016). Customer satisfaction and expenditure behaviour in musical festivals: The optimus primavera sound case study. *Tourism Economics*, *22*(4), 825-836.

Bryman, A. (2016). *Social research methods*. Oxford university press.

Carpenter, G. S., & Nakamoto, K. (1989). Consumer preference formation and pioneering advantage. *Journal of Marketing research*, *26*(3), 285-298.

Čekrlija, S., & Milić, Z. (2024). The Significance of Tourist Consumption From The Perspective Of Organizing Music Festivals. *SCIENCE International Journal*, *3*(1), 133-137.

Chevalier, J. A., & Mayzlin, D. (2006). The effect of word of mouth on sales: Online book reviews. *Journal of marketing research*, *43*(3), 345-354.

Choi, H., & Varian, H. (2012). Predicting the present with Google Trends. *Economic record*, *88*, 2-9.

Cole, S. T., & Chancellor, H. C. (2009). Examining the festival attributes that impact visitor experience, satisfaction and re-visit intention. *Journal of vacation marketing*, *15*(4), 323-333.

Cole, S. T., & Illum, S. F. (2006). Examining the mediating role of festival visitors' satisfaction in the relationship between service quality and behavioral intentions. *Journal of Vacation Marketing*, *12*(2), 160-173.

Conference2Go. (n.d.). *Economics conferences calendar | Economics conferences alerts*. Retrieved June 11, 2025, from https://www.conference2go.com/economics

Danielsen, A., & Kjus, Y. (2019). The mediated festival: Live music as trigger of streaming and social media engagement. *Convergence*, *25*(4), 714-734.

Díaz, F., Henríquez, P. A., & Winkelried, D. (2022). Heterogeneous responses in Google Trends measures of well-being to the COVID-19 dynamic quarantines in Chile. *Scientific Reports*, *12*(1), 14514.

DJ Mag. (2024). DJ Mag Top 100 DJs 2024. Retrieved May 2025, from https://djmag.com/features/dj-mag-top-100-djs-2024-record-breaking-numbers-vote-our-annual-poll-of-worlds-best-djs

Donald, S. G., & Lang, K. (2007). Inference with difference-in-differences and other panel data. *The review of Economics and Statistics*, *89*(2), 221-233.

Dorst, H. (2015). Electronic music scenes: A comparison of the diverging spatial contexts of the electronic dance music scenes of Berlin and Amsterdam. *Journal of urban cultural studies*, *2*(1-2), 57-74.

Dragin-Jensen, C., Schnittka, O., Feddersen, A., Kottemann, P., & Rezvani, Z. (2018). They come from near and far: The impact of spatial distance to event location on event attendance motivations. *Scandinavian Journal of Hospitality and Tourism*, *18*(sup1), S87-S100.

Ebbinghaus, H. (1913). A contribution to experimental psychology. *New York, NY: Teachers College, Columbia University*.

Epstein, G. *(2017).* Winner takes all. *The Economist,* 11th February 2017.

Gajanan, M. (2019). How music festivals became a massive business in the 50 years since Woodstock. *Time*. Retrieved from https://time.com/5651255/businessof-music-festivals/

Jones, V., & Elsden, C. Live events, digital technologies, and data-driven innovation. Professor Christopher Smith, Executive Chair of the Arts, 219.

Kinnunen, M., Honkanen, A., & Luonila, M. (2021). Frequent music festival attendance: festival fandom and career development. *International Journal of Event and Festival Management*, *12*(2), 128-147.

Loewenstein, G. (1987). Anticipation and the valuation of delayed consumption. *The Economic Journal*, *97*(387), 666-684.

MacKinlay, A. C. (1997). Event studies in economics and finance. *Journal of economic literature*, *35*(1), 13-39.

McCombs, M. E., & Shaw, D. L. (1972). The agenda-setting function of mass media. *Public opinion quarterly*, *36*(2), 176-187.

Montoro-Pons, J. D., & Cuadrado-García, M. (2020). Music festivals as mediators and their influence on consumer awareness. *Poetics*, *80*, 101424.

Montoro-Pons, J. D., & Cuadrado-García, M. (2021). Analyzing online search patterns of music festival tourists. *Tourism Economics*, *27*(6), 1276-1300.

Nunes, P., & Birdsall, C. (2022). Curating the urban music festival: Festivalisation, the 'shuffle' logic, and digitally-shaped music consumption. *European Journal of Cultural Studies*, *25*(2), 679-702.

Pine, B. J., & Gilmore, J. H. (1998). *Welcome to the experience economy* (Vol. 76, No. 4, pp. 97-105). Cambridge, MA, USA: Harvard Business Review Press.

Resident Advisor. (n.d.). *Electronic music festivals*. Retrieved June 12, 2025, from https://ra.co/festivals

Rosen, S. (1981). The economics of superstars. *The American economic review*, *71*(5), 845-858.

Rossetti, G. (2021). The role of literary festival attendance in generating attendees' health and well-being. *International Journal of Event and Festival Management*, *12*(3), 265-278.

Schmidheiny, K., & Basel, U. (2011). Panel data: fixed and random effects. *Short guides to microeconometrics*, *7*(1), 2-7.

Scott, M. (2012). Cultural entrepreneurs, cultural entrepreneurship: Music producers mobilising and converting Bourdieu's alternative capitals. *Poetics*, *40*(3), 237-255.

Singh, D. P. (2023). The algorithmic bias of social media. *The Motley Undergraduate Journal*, *1*(2).

Sormaz, U., Okul, T., Musaeva, T., & Soylu, A. G. (2025). What affects revisit intention and word of mouth at international ethno-fest? An experience approach in Kyrgyzstan. *Geojournal of Tourism and Geosites*, *59*(2), 759-768.

Srivastava, S. Exploring the Role of Technology in Event Management and Exhibition Industry: Challenges and Opportunities from Global Perspectives.

Tan, K. L., Ho, J. M., Sim, A. K., & Hii, I. S. (2025). Fear of missing out and beyond: Unveiling theoretical dimensions in post-pandemic festival events and community engagement dynamics. *Event Management.*

Tan, K. L., Sim, A. K., Chai, D., & Beck, L. (2020). Participant well-being and local festivals: the case of the Miri country music festival, Malaysia. *International Journal of Event and Festival Management*, *11*(4), 433-451.

Varian, H. R. (2014). *Intermediate microeconomics with calculus: a modern approach*. WW norton & company.

Vinnicombe, T., & Sou, P. U. J. (2017). Socialization or genre appreciation: the motives of music festival participants. *International Journal of Event and Festival Management*, *8*(3), 274-291.

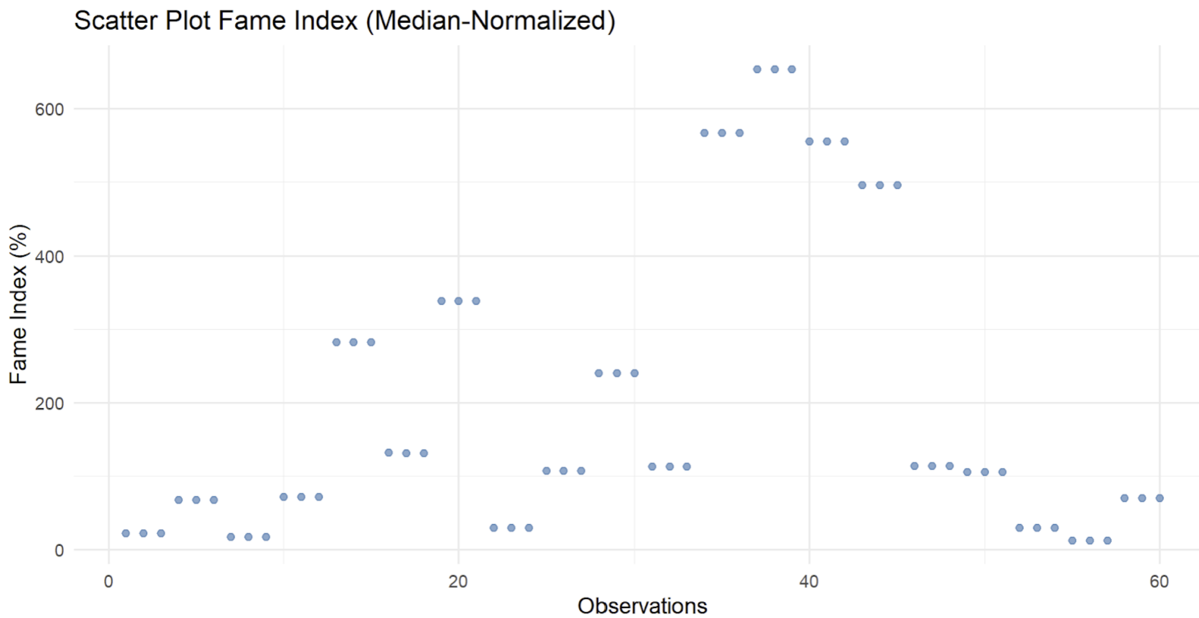
Wei, S. (2023). Research on the application of big data analysis in music enterprises. *Academic Journal of Business & Management*, *5*(16), 46-51.

Xu, Y. (2017). Generalized synthetic control method: Causal inference with interactive fixed effects models. *Political Analysis*, *25*(1), 57-76.

Appendix

Appendix A.

A.1 Scatter Plot Fame Index



A.2 Diff-in-Diff without Ouliers

Table 1: Diff-in-Diff Results without Outliers

Variable	Estimate	Std. Error	t value	Pr(> |t|)
(Intercept)	-2.12	3.46	-0.61	0.539
Post	2.43	1.62	1.50	0.134
Treated	0.02	0.22	0.07	0.942
Post × Treated	2.36	1.97	1.20	0.231
log(Fame Index Median)	0.43	0.71	0.61	0.542

Note: The interaction term *Post × Treated* is the DiD estimator. *log(Fame Index Median)* is log-transformed.

A.3 FE By Announcement Strategy

Table 2. FE Results by Announcement Strategy (Cluster-Robust SE)

Variable	**Estimate**	**Std. Error**	**t value**	**Pr($>|t|$)**
Model 1: BigBang Strategy				
PeriodPost_Announcement	4.850	0.681	7.127	$< 0.001^{***}$
PeriodPost_Festival	-0.579	0.838	-0.691	0.489
Model 2: Staged Strategy				
PeriodPost_Announcement	5.186	1.051	4.934	$< 0.001^{***}$
PeriodPost_Festival	1.338	0.691	1.935	0.053

Note.
$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

A.4 Timing of Big Bang Announcement

Table 3. OLS Regression: Timing of the Big Bang Announcement

Variable	**Estimate**	**Std. Error**	**t value**	**Pr($>|t|$)**
(Intercept)	3.434	1.375	2.498	$0.055^{\dagger}$
Timing_Groupmedium	3.626	3.074	1.180	0.291
Timing_Grouplate	0.765	2.100	0.364	0.731

Appendix B.

B1. Fame Data

Festival	**Instagram (Norm.)**	**Spotify (Norm.)**	**Fame Index (Log.)**
A day at the park	0.47	0.88	4.23
Crave Festival	0.37	0.06	3.13
Dance Valley	2.22	2.58	5.48
E-Lake Festival	0.13	0.12	2.59
Elements Festival	0.71	1.40	4.67
Hurricane Festival	7.44	3.90	6.34
Ikarus Festival	1.70	0.93	4.89
Les Francofolies Esch/Alzette Festival	3.52	3.24	5.83
Liquicity	0.08	0.05	3.41
Lollapalooza Berlin	7.35	5.74	6.48
Luminosity Beach Festival	0.20	0.14	2.88
Luxembourg Open Air	0.16	0.11	4.29
Ostend Beach Festival	0.39	1.02	4.27
Panama Open Air	6.74	3.19	6.21
Parookaville	3.18	2.47	5.65
Rampage	1.63	0.51	4.68
Sea You Festival	0.34	0.26	3.42
Solar Weekend Festival	0.32	1.95	4.74
Sonne Mond Sterne Festival	6.11	5.00	6.32
Sputnik Spring Break	1.29	0.98	4.74

B2. Artists

Festival	Year	Artists	Announcement	Country
A day at the park	2022	Jamie Jones, Loco Dice, Meduza	Big Bang	NL
A day at the park	2023	Pawsa, James Hype, Dennis Cruz	Big Bang	NL
A day at the park	2024	Hot Sice 82, Joris Voorn, Amme	Big Bang	NL
Crave Festival	2022	Nina Kraviz, Jeff Mills, Honey Dijon	Big Bang	NL
Crave Festival	2023	Anetha, Ben Sims, 999999999	Big Bang	NL
Crave Festival	2024	Ben Ufo, Djrum, DJ Heartstring	Big Bang	NL
Dance Valley	2022	Dimitri Vegas & Like Mike, Nicky Romero, Paul van Dyk	Staged	NL
Dance Valley	2023	Dimitri Vegas & Like Mike, Nicky Romero, Paul van Dyk	Staged	NL
Dance Valley	2024	Tiesto, Ben Nicky, D-Block	Staged	NL
E-Lake Festival	2022	Die Orsons, Paul van Dyk, Scheppe Siwen	Big Bang	LU
E-Lake Festival	2023	Grossstadtgefluster, Ferry Corsten, Scheppe Siwen	Big Bang	LU
E-Lake Festival	2024	Og Keemo, Markus Schulz, Scheppe Siwen	Big Bang	LU
Elements Festival	2022	Fisher, Kaskade, Zeds Dead	Staged	DE
Elements Festival	2023	Chris Lake, Ganja White Night, John Summit	Staged	DE
Elements Festival	2024	Chris Lake, Cloonee, Excision	Staged	DE
Hurricane Festival	2022	Seeed, Martin Garrix, The Killers	Big Bang	DE
Hurricane Festival	2023	Billy Talent, KraftKlub, Peter Fox	Big Bang	DE
Hurricane Festival	2024	Ed Sheeran, K.I.Z, Avril Lavigne	Big Bang	DE

Continued from previous page

Festival	Year	Artists	Announcement	Country
Ikarus Festival	2022	Adam Beyer, Fritz Kalkbrenner, Carl Cox	Staged	DE
Ikarus Festival	2023	Neelix, Paul Kalkbrenner, Timmy Trumpet	Staged	DE
Ikarus Festival	2024	Hardwell, Boris Brejcha, Dimitri Vegas & Like Mike	Staged	DE
Les Francofolies Esch/Alzette Festival	2022	PNL, Damso, Clara Luciani	Staged	LU
Les Francofolies Esch/Alzette Festival	2023	DJ Snake, Orelsan, Angele	Staged	LU
Les Francofolies Esch/Alzette Festival	2024	David Guetta, Ninho, Shaka Ponk	Staged	LU
Liquicity	2022	Netsky, Sub Focus, Camo & Krooked	Staged	NL
Liquicity	2023	Pendulum, Andy C, Dimension	Staged	NL
Liquicity	2024	Netsky, Wilkinson, DJ Marky	Staged	NL
Lollapalooza Berlin	2022	Annenmaykantereit, KraftKlub, Machine Gun Kelly	Big Bang	DE
Lollapalooza Berlin	2023	Imagine Dragons, David Guetta, SDP	Big Bang	DE
Lollapalooza Berlin	2024	Sam Smith, Martin Garrix, Burna Boy	Big Bang	DE
Luminosity Beach Festival	2022	Aly & Fila, Ferry Corsten, Gareth Emery	Staged	NL
Luminosity Beach Festival	2023	Aly & Fila, Bryan Kearney, Ferry Corsten	Staged	NL
Luminosity Beach Festival	2024	Bryan Kearney, Giuseppe Ottaviani, Ally & Fila	Staged	NL
Luxembourg Open Air	2022	Fedde LeGrand, Blasterjaxx, Tujamo	Big Bang	LU
Luxembourg Open Air	2023	Bassjackers, Topic, Tchami	Big Bang	LU
Luxembourg Open Air	2024	Will Sparks, Blasterjaxx, Malaa	Big Bang	LU

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Festival	Year	Artists	Announcement	Country
Ostend Beach Festival	2022	Bilal Wahib, Len Faki, Bob Sinclar	Staged	BE
Ostend Beach Festival	2023	Purple Disco Machine, Sunnery James & Ryan Marciano, Oliver Heldens	Staged	BE
Ostend Beach Festival	2024	Armand van Helden, Eli Brown, Omdat Het Kan & Average Bob	Staged	BE
Panama Open Air	2022	Bastille, Alle Farben, Acraze	Staged	DE
Panama Open Air	2023	Martin Garrix, Wiz Khalifa, Skrillex	Staged	DE
Panama Open Air	2024	Swedish House Mafia, Bonez MC, David Puentez	Staged	DE
Parookaville	2022	Armin van Buuren, Scooter, Fisher	Staged	DE
Parookaville	2023	Hardwell, Steve Aoki, Timmy Trumpet	Staged	DE
Parookaville	2024	Timmy Trumpet, W&W, Armin van Buuren	Staged	DE
Rampage	2022	Macky Gee, Modestep, Andy C	Staged	BE
Rampage	2023	Subtronics, Wilkinson, Hedex	Staged	BE
Rampage	2024	Andy C, Rudim3ntal, Svdden Death	Staged	BE
Sea You Festival	2022	Neelix, Liquid Soul, Ace Ventura	Staged	DE
Sea You Festival	2023	Ben Bohmer, Klaudia Gawlas, Alle Farben	Staged	DE
Sea You Festival	2024	Lilly Palmer, Klaudia Gawlas, Pan-Pot	Staged	DE
Solar Weekend Festival	2022	Chris Liebing, De Staat, Donnie & Joost XL	Big Bang	NL
Solar Weekend Festival	2023	999999999, Airod, Antoon	Big Bang	NL
Solar Weekend Festival	2024	6ejou, Adje, Afro Bros	Big Bang	NL

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Festival	Year	Artists	Announcement	Country
Sonne Mond Sterne Festival	2022	Martin Garrix, The Chainsmokers, Timmy Trumpet	Big Bang	DE
Sonne Mond Sterne Festival	2023	Macklemore, Amelie Lens, Armin van Buuren	Big Bang	DE
Sonne Mond Sterne Festival	2024	Hardwell, Steve Aoki, Calvin Harris	Big Bang	DE
Sputnik Spring Break	2022	Seeed, Apache 207, Capital Bra	Staged	DE
Sputnik Spring Break	2023	Kraftklub, Peter Fox, Kontra K	Staged	DE
Sputnik Spring Break	2024	Cro, Dimitri Vegas, Raf Camora	Staged	DE

B3. GTS Sample

Date	A day at the park	Crave Festival	Dance Valley	E-Lake Festival	Elements Festival	Hurricane Festival
2021-12-26	0	0	0	0	10	2
2022-01-02	0	0	0	0	0	3
2022-01-09	0	0	0	0	5	2
2022-01-16	0	0	2	0	0	3
2022-01-23	0	10	1	0	5	3
2022-01-30	0	8	2	0	5	3
2022-02-06	0	0	3	0	5	4
2022-02-13	0	7	3	0	8	5
2022-02-20	0	7	3	0	5	4
2022-02-27	0	0	3	0	8	5
2022-03-06	6	0	3	0	8	6
2022-03-13	0	9	3	0	17	5
2022-03-20	0	0	4	0	14	6
2022-03-27	0	13	2	0	16	7
2022-04-03	0	6	3	0	13	8
2022-04-10	12	9	3	0	14	8
2022-04-17	0	15	4	0	16	9
2022-04-24	0	18	3	0	17	12
2022-05-01	8	19	3	0	16	12
2022-05-08	6	17	5	0	21	13
2022-05-15	8	17	5	0	26	13
2022-05-22	7	24	7	0	53	16
2022-05-29	10	94	5	0	27	24
2022-06-05	11	23	7	0	14	32
2022-06-12	8	0	7	0	14	100
2022-06-19	0	0	7	0	14	57
2022-06-26	10	0	8	0	10	9
2022-07-03	7	7	8	0	10	9
2022-07-10	0	10	11	0	11	6
2022-07-17	0	13	11	0	12	7
2022-07-24	10	35	15	0	13	5
2022-07-31	11	7	24	0	13	5
2022-08-07	13	0	100	71	18	5
2022-08-14	12	0	65	38	35	4
2022-08-21	16	0	5	0	14	6
2022-08-28	12	0	3	0	7	4
2022-09-04	20	8	2	0	6	4
2022-09-11	59	0	1	0	7	5
2022-09-18	20	0	0	0	7	5
2022-09-25	0	7	2	0	6	13
2022-10-02	0	0	3	0	8	6
2022-10-09	7	0	2	0	13	6
2022-10-16	0	0	1	0	6	6
2022-10-23	0	0	2	0	5	5
2022-10-30	0	0	0	0	3	8
2022-11-06	6	11	0	0	5	7
2022-11-13	0	0	0	0	3	6
2022-11-20	0	0	2	0	0	5
2022-11-27	0	0	0	0	4	5
2022-12-04	0	0	0	0	4	6
2022-12-11	0	1	0	0	1	0
2022-12-18	0	1	0	0	1	0
2022-12-25	0	0	0	0	1	0
2023-01-01	0	0	0	0	1	0
2023-01-08	0	0	0	0	1	0

Date	A day at the park	Crave Festival	Dance Valley	E-Lake Festival	Elements Festival	Hurricane Festival
2023-01-15	0	0	0	0	1	0
2023-01-22	0	0	0	0	1	0
2023-01-29	0	0	0	0	1	0
2023-02-05	0	0	0	0	1	0
2023-02-12	0	7	1	0	10	7
2023-02-19	8	10	2	0	9	6
2023-02-26	11	0	2	0	11	7
2023-03-05	0	7	2	0	9	6
2023-03-12	0	0	2	0	7	7
2023-03-19	0	9	4	0	10	9
2023-03-26	13	0	5	0	13	7
2023-04-02	8	11	3	0	17	7
2023-04-09	0	11	4	0	11	7
2023-04-16	0	14	5	0	15	7
2023-04-23	8	11	5	0	16	9
2023-04-30	10	8	4	0	11	9
2023-05-07	7	11	5	0	13	9
2023-05-14	9	16	6	0	15	11
2023-05-21	10	22	6	0	19	13
2023-05-28	6	100	5	0	14	17
2023-06-04	14	17	5	0	16	23
2023-06-11	18	0	6	0	17	88
2023-06-18	9	0	7	0	17	53
2023-06-25	20	0	8	0	20	10
2023-07-02	62	7	6	0	15	6
2023-07-09	7	7	9	0	19	7
2023-07-16	0	0	9	0	18	7
2023-07-23	8	0	13	0	23	8
2023-07-30	12	0	16	0	29	6
2023-08-06	12	10	79	98	71	6
2023-08-13	12	9	16	0	31	4
2023-08-20	12	30	3	0	12	3
2023-08-27	0	10	3	0	6	3
2023-09-03	23	0	0	0	8	3
2023-09-10	75	0	2	0	7	3
2023-09-17	10	0	0	0	5	10
2023-09-24	0	0	0	0	6	7
2023-10-01	0	0	0	0	4	6
2023-10-08	0	0	1	0	4	10
2023-10-15	0	0	0	0	3	7
2023-10-22	0	0	0	0	4	7
2023-10-29	0	0	0	0	4	10
2023-11-05	0	9	1	0	6	8
2023-11-12	0	0	0	0	5	7
2023-11-19	0	0	0	0	6	6
2023-11-26	0	0	0	0	5	6
2023-12-03	7	0	1	0	6	9
2023-12-10	8	0	2	0	4	9
2023-12-17	8	0	0	0	4	7
2023-12-24	0	0	0	0	8	7
2023-12-31	0	7	2	0	10	8
2024-01-07	0	9	2	0	10	7
2024-01-14	7	0	3	0	6	9
2024-01-21	8	7	2	0	7	7
2024-01-28	11	0	3	0	6	7
2024-02-04	12	0	5	0	26	8
2024-02-11	7	0	3	0	17	7

Date	A day at the park	Crave Festival	Dance Valley	E-Lake Festival	Elements Festival	Hurricane Festival
2024-02-18	10	0	0	0	8	6
2024-02-25	11	8	2	0	12	7
2024-03-03	0	0	3	0	11	8
2024-03-10	11	0	3	0	8	7
2024-03-17	8	0	4	0	7	7
2024-03-24	11	0	4	0	11	7
2024-03-31	9	18	2	0	14	10
2024-04-07	16	0	3	0	11	8
2024-04-14	0	0	2	0	21	9
2024-04-21	14	7	3	0	25	9
2024-04-28	17	11	2	0	12	9
2024-05-05	13	13	4	0	16	8
2024-05-12	10	16	6	0	14	11
2024-05-19	18	25	5	0	17	13
2024-05-26	18	78	5	0	32	13
2024-06-02	17	13	7	0	15	19
2024-06-09	23	0	5	0	21	28
2024-06-16	36	0	4	0	20	93
2024-06-23	38	8	6	0	26	46
2024-06-30	100	0	6	0	24	6
2024-07-07	17	0	6	0	27	6
2024-07-14	0	10	8	35	24	6
2024-07-21	11	28	11	0	28	5
2024-07-28	10	8	16	0	29	5
2024-08-04	9	0	63	100	100	4
2024-08-11	12	0	13	0	39	3
2024-08-18	12	0	6	0	7	4
2024-08-25	17	7	4	0	6	5
2024-09-01	17	0	3	0	7	3
2024-09-08	17	0	2	0	3	8
2024-09-15	76	0	1	0	4	5
2024-09-22	0	0	1	0	5	4
2024-09-29	0	0	0	0	5	5
2024-10-06	0	0	2	0	4	7
2024-10-13	10	11	0	0	3	4
2024-10-20	0	0	3	0	5	6
2024-10-27	0	0	3	0	5	5
2024-11-03	0	0	3	0	6	6
2024-11-10	0	0	3	0	6	4
2024-11-17	0	0	2	0	4	10
2024-11-24	0	0	2	0	0	7
2024-12-01	0	0	2	0	8	7
2024-12-08	0	0	2	0	4	6
2024-12-15	0	0	2	0	0	5
2024-12-22	15	0	3	0	0	7