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The impact of Cultural Events in Airbnb Supply and Reviews

Evidence from Porto and Lisbon Using the Generalized Synthetic Control Method

Ema Beatriz José Velosa Costa

Project Work

presented as partial requirement for obtaining a Master's Degree in Information Management

NOVA Information Management School
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Universidade Nova de Lisboa

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Project Work presented as partial requirement for obtaining the Master's degree in Information Management, with a specialisation in Business Intelligence

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STATEMENT OF INTEGRITY

I hereby declare having conducted this academic work with integrity. I confirm that I have not used plagiarism, any form of undue use of information or falsification of results along the process leading to its elaboration. I further declare that I have fully acknowledged the Rules of Conduct and Code of Honor from the NOVA Information Management School.

Lisbon, July 15th, 2025

Ema Costa

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ABSTRACT

This study investigates the causal impact of major cultural events on the dynamics of Airbnb listings in the Portuguese cities of Lisbon and Porto. Drawing on data from Inside Airbnb and applying the Generalized Synthetic Control (GSC) method, the analysis focuses on two key outcomes: the daily supply of available listings and the sentiment expressed in guest reviews. The research considers six multi-day events in 2024, including music festivals and large-scale concerts, and defines treated neighbourhoods using a 2 km spatial buffer and listing density criteria. Results reveal a statistically significant reduction in the number of available listings during event periods, suggesting increased booking activity in response to demand shocks. In contrast, no significant change was detected in average review sentiment, possibly reflecting measurement limitations or genuine stability in guest satisfaction. This dissertation contributes to the growing body of research on peer-to-peer accommodation and urban tourism, demonstrating the value of causal inference methods in measuring the effects of temporary shocks. It also points out the need for improved data granularity to better understand how platforms like Airbnb interact with evolving patterns of urban tourism.

KEYWORDS

Airbnb; Event Management; Urban Planning; Impact Analysis; Generalized Synthetic Control; Portugal

Sustainable Development Goals (SDG):

11 SUSTAINABLE CITIES AND COMMUNITIES

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LIST OF ABBREVIATIONS AND ACRONYMS

ADR	Average Daily Rate
ATT	Average Treatment effect on the Treated
DID	Difference-in-Differences
eWOM	Electronic Word-of-Mouth
GSC	Generalized Synthetic control
KM	Kilometre
KPI	Key Performance Indicator
MPSE	Mean Squared Prediction Error
Nco	Number of Control Units
NLP	Natural Language Processing
Ntr	Number of Treated Units
Occ%	Occupancy Percentage
OLS	Ordinary Least Squares
QR	Quantile Regression
RevPAR	Revenue per Available Room
STR	Smith Travel Research
USA	United States of America

1. INTRODUCTION

Cultural events such as music festivals, international concerts, and city-wide celebrations have become powerful catalysts for urban tourism. These moments generate temporary yet intense shifts in visitor flows, local consumption, and accommodation demand (Getz, 2008). Beyond their economic impact, cultural festivals are increasingly used by cities as tools for destination branding and to strengthen emotional engagement with visitors (Richards & King, 2022). While much of the academic literature has traditionally focused on the hotel sector's response to such demand shocks, peer-to-peer platforms like Airbnb now play an equally central (even if less studied) role in how cities absorb and redistribute these surges.

Unlike conventional hotels, individual hosts disperse, manage, and govern Airbnb listings under different incentives and constraints. This makes the platform particularly agile during event periods but also more difficult to monitor and regulate (Fairley & Dolnicar, 2017). Although Airbnb has been widely studied (Guttentag, 2019), little is known about its dynamics during temporary urban shocks such as large-scale cultural events.

Portugal, and in particular the cities of Lisbon and Porto, provides a compelling case for examining this dynamic. These cities are not only key cultural hubs but also prominent destinations within the Airbnb ecosystem. They have recently hosted globally significant events like the Taylor Swift Tour, NOS Alive, and MEO Kalorama, all of which had quantifiable effects on public space and tourism infrastructure. However, there is still limited causal evidence on how these events affect the short-term rental market in concrete terms.

This dissertation aims to fill that gap by investigating whether major cultural events in Lisbon and Porto lead to measurable changes in two specific dimensions of Airbnb activity: the daily supply of available listings and the sentiment expressed by guests in online reviews. These two outcomes capture distinct but complementary perspectives on the effects of events: one structural (availability), the other experiential (sentiment).

To answer this question, the study uses the Generalized Synthetic Control (GSC) method (Xu, 2017), which has become popular for estimating cause-and-effect relationships in situations where there are complicated, unseen factors (Maamoun, 2019). Unlike traditional Difference-in-Differences models, GSC allows for heterogeneous treatment timing and latent time-varying confounders, making it particularly suitable for the study of platforms like Airbnb, where market conditions evolve rapidly and unevenly across space.

Six major cultural events held in 2024 were selected for analysis, and treated areas were defined as neighbourhoods within a 2 km radius of the event venue, with at least 70% of listings falling within that buffer. By comparing the evolution of supply and sentiment in treated areas against a synthetic counterfactual constructed from control neighbourhoods, the study seeks to identify whether Airbnb dynamics are measurably altered by the presence of high-profile events.

In doing so, this research contributes to the study of urban tourism and digital platforms. While subject to data and methodological constraints, the findings offer a replicable framework for evaluating event impacts in other cities where tourism and housing markets coexist in delicate balance.

The remainder of this thesis is organised as follows. Chapter 2 presents a review of the existing literature on the impact of Airbnb and major events on urban accommodation markets, identifying key research gaps. Chapter 3 outlines the methodology, including a description of the datasets and the rationale for using the Generalized Synthetic Control method. Chapter 4 introduces the selected events, details the construction of variables, and defines the treatment and control groups. Chapter 5 discusses the main empirical results and robustness checks. Finally, Chapter 6 summarises the key findings, highlights limitations, and suggests directions for future research. This structure supports a clear and logical progression from theoretical foundations to empirical results and final reflections.

2. LITERATURE REVIEW

Urban events which can range from cultural festivals to mega-sporting events, play various roles, from community building and urban renewal to revitalizing national identity through cultural development processes (Getz, 2008). Organizing events has been proven an effective solution to encourage visitors to travel during off-peak seasons (Dalir, 2023), enhancing their experiences and promoting destination loyalty (Gautam, 2022); it also has a positive effect on the destination's image (Richards & King, 2022).

During periods of high demand, such as major events, the flexibility of peer-to-peer platforms like Airbnb allows cities to rapidly expand their temporary accommodation supply, covering any potential shortages or gaps in conventional hotel capacity (Fairley & Dolnicar, 2017). This, therefore, plays a vital role in ensuring adequate lodging, but it also showcases one of the increasing shifts in how urban destinations manage tourism demand for events. As it'll be illustrated in this literature review, while many studies have been carried out on the impact major events have on more conventional accommodation sectors, such as hotels, little attention has been given to understanding the implication for peer-to-peer accommodations. This represents a knowledge gap, since such platforms, like Airbnb, could also show peculiarities in pricing and supply dynamics compared to the hotel industry, besides constituting a supplementary solution during such surges.

2.1. RESEARCH ON AIRBNB AND ITS IMPACT ON DESTINATIONS

Airbnb, recognized by most as the pioneer of the sharing economy (Barron et al., 2020), has changed the way people travel and find accommodation, as it is the most successful peer-to-peer accommodation network internationally (Dolnicar, 2017), which has triggered an increase in research into its broad impact on the hospitality industry and local economies. Major events such as festivals, sporting tournaments, and conferences bring large crowds to cities, thus changing the dynamics of the listings in Airbnb (Airbnb, 2024). Researchers have explored how this peer-to-peer platform challenges existing hotels, influences how tourists make decisions, and shapes the character of destinations, showing that Airbnb is not just a competitor for established hotel chains but also a driver of economic and social transformation.

Guttentag (2019) analysed 132 peer-reviewed studies on Airbnb, categorizing them into six themes: guests, hosts, supply impacts, regulation, tourism sector effects, and the company itself. The review brought attention to Airbnb's transformative role in tourism, with research focusing on guest motivations like cost savings and authenticity, as well as regulatory challenges. Similarly, Ding et al. (2023) conducted a systematic literature review to investigate the evolution of research related to Airbnb. Adopting the structural topic modelling approach, a text-mining method designed for social sciences. They analysed 1,021 articles from 416 journals published between 2015 and 2022. Their methodology included preprocessing text data to identify underlying research concepts, assessing their prevalence in both hospitality and non-hospitality journals, and tracking their progression over time. Two key research areas were highlighted by this study: Airbnb's operational procedures, such as pricing strategies and trust-building techniques, and its effects on industries, including hotels, housing markets, and urban tourism. The results revealed significant trends, including a decline in comprehensive business model studies and an increase in user experience and pricing strategies. This study provides valuable information about the evolving academic environment surrounding Airbnb and lays foundations for further research.

Building on these thematic overviews, several empirical studies have focused specifically on Airbnb's impact on housing markets. Benítez-Aurioles and Tussyadiah (2021) developed a theoretical model of segmented housing supply and tested it using borough-level data from London. Their findings indicate that for every additional 100 Airbnb listings, house prices increased by 0.032%, with effects on rents being weaker but still statistically relevant. This suggests that short-term rentals crowd out long-term housing, thereby intensifying affordability concerns. In a similar vein, Garcia-López et al. (2020) examined the case of Barcelona using spatial econometrics and panel data, estimating that Airbnb activity contributed to a 4% increase in rents and notable rises in both asking and transaction prices, particularly in city centre areas popular with tourists. Expanding the geographical scope, Gárate Alvarez & Pennington-Cross (2023) investigated a less tourism-dependent region in the U.S., analysing neighbourhood-level data from Wisconsin. They found that doubling the number of Airbnb listings led to an 11% increase in house prices, although this effect was concentrated in low-density neighbourhoods with high house prices, and absent in urban cores. Taken together, these investigations illuminate a consistent pattern: as short-term rentals become more profitable and widespread, they reshape expectations and incentives in the housing market, ultimately putting upward pressure on property values and reducing the availability of affordable housing.

The platform's expansion has not only reshaped housing dynamics but also triggered competitive pressures in adjacent industries, most notably, the hotel sector. Dogru et al. (2020) examined the impact of Airbnb listings on hotel performance metrics, including RevPAR, ADR, and OCC, in four major international markets: London, Paris, Sydney, and Tokyo. Using panel data with ordinary least squares (OLS) regression and fixed-effects modelling, they incorporated Airbnb listing data from AirDNA and hotel performance metrics from STR spanning 2001 to 2017. They discovered that a 1% increase in Airbnb listings resulted in a 0.016% to 0.031% fall in RevPAR and a decline in OCC, while ADR remained practically unaffected. The evidence suggests that while hotels experienced reduced occupancy and revenue, they were slow to adjust their pricing strategies in response to Airbnb’s growth. Zervas et al. (2017) took a different approach, using a difference-in-differences (DID) model to study the effect of Airbnb’s entry on hotel revenues in Texas from 2003 to 2014. They used data from Airbnb, the Texas Comptroller's Office, STR, and other auxiliary sources. Their findings revealed that a 10% rise in Airbnb listings resulted in a 0.39% drop in hotel revenue; in Austin, the effect was most noticeable, with hotel revenues dropping by 8–10%. Together, these studies illustrate Airbnb's disruptive impact on established hotel industries on a regional and global scale.

Beyond hotel performance, Airbnb influences local economies and employment within the hospitality sector. According to research, despite the competition it presents for hotels, Airbnb has shown positive effects on employment in some hospitality-related areas. Dogru et al. (2020) described this phenomenon as the “Airbnb paradox,” whereby Airbnb’s growth indirectly boosts employment by increasing demand for auxiliary services like cleaning, maintenance, and local dining. The study analysed panel data from 12 major U.S. metropolitan statistical areas between 2008 and 2018, incorporating Airbnb listings data from AirDNA and employment statistics from the Bureau of Labor Statistics. The authors employed a fixed-effects regression model to investigate the effects of changes in Airbnb supply on employment in industries such as hotels, food services, entertainment, and the arts. Macroeconomic variables such as wages, income levels, airport arrivals, and labour force size were considered in the analysis. The results show that a 1% increase in Airbnb supply leads to a 0.015% increase in employment in these industries. This demonstrates Airbnb's capacity to promote employment expansion despite disrupting lodging markets.

As for Airbnb's pricing strategies, Wang and Nicolau (2017) analysed 180,533 Airbnb listings across 33 cities (retrieved from Inside Airbnb site) using both ordinary least squares (OLS) and quantile regression models (QR). Their study determined that host features, site and property characteristics, amenities and services, rental regulations, and internet review ratings are the five main factors that affect pricing. For example, listings managed by "super hosts" on average were priced higher, whilst houses tended to be cheaper each kilometre further away from the city centre. Building on these findings, Falk et al. (2019) studied the factors that influence Airbnb pricing in Switzerland's urban and rural marketplaces, using a hedonic pricing model and panel data analysis. They discovered that qualities like luxury and penthouse status resulted in 20–70% higher pricing, depending on the location and price range. Collectively, these studies suggest that Airbnb pricing reflects not only host credibility and locational convenience, but also market-specific valuation of exclusivity and property typology.

While these mostly concern the physical and easily measurable aspects of a listing, more recent studies have begun to explore how less tangible elements, like the tone and content of guest reviews can also shape pricing decisions. Online reviews, as expressions of guest experience and trust, are considered powerful signals in Airbnb's marketplace. Lin and Yang (2024) examined how customer reviews content affects pricing by looking at 99,084 Airbnb listings across 26 U.S. areas, retrieved from Inside Airbnb site. By combining sentiment analysis, topic modelling, and hedonistic pricing with quantile regression, they discovered that negative reviews had double the effect on prices compared with positive reviews, especially for lower-priced rentals. Furthermore, ratings that focused on location and amenities had the biggest impact on prices. This study emphasizes how complex electronic word-of-mouth (eWOM) can influence Airbnb's pricing policies, particularly in metropolitan markets where competition is strong. Similarly, Cheng and Jin (2019) analysed 170,124 Airbnb reviews from Sydney using text mining and sentiment analysis, identifying location, amenities, and host as key themes, with location being most prominent. Despite comparisons to hotels, price was not a significant factor. Reviews showed a positivity bias, with negative feedback focusing on noise, maintenance, and unmet expectations. The study emphasizes the value of trust-building and personalized services in shaping Airbnb experiences. Table 1 provides a summary of key studies examining the impact of Airbnb on travel destinations, outlining the data sources, methodological approaches, and main findings.

Table 1 - Summary of Studies on Airbnb and its impact on Destinations

Sources	Data Used	Methods	Conclusions	Explanatory variables
Guttentag (2019)	132 peer-reviewed articles	Thematic literature review	Categorized Airbnb research into six themes; emphasised guest motivations (authenticity, price), host behaviour, regulation, and tourism impact.	N.A.
Ding et al. (2023)	1,021 articles from 416 journals (2015–2022)	Text-mining	Key areas of research: Airbnb's operational strategies (e.g., pricing, trust) and its impacts on industries, with growing focus on user experience and pricing.	N.A.
Benítez-Aurioles & Tussyadiah (2021)	Airbnb + housing market data from London boroughs	Theoretical modelling + System GMM	Airbnb raises house prices more than rents; 100 new listings increase house prices by 0.032%. Illustrates crowding-out of long-term rentals.	Density of Airbnb listings per borough; instrumental variables (tourism establishments and hotels × Google Trends); demographic and structural controls (property style, age, number of rooms, garage, water
Garcia-López et al. (2020)	Airbnb and housing data from Barcelona	Panel data; Spatial econometrics	Airbnb activity linked to 4% rent increase, 3.7% rise in asking prices, and 4.6% in transaction prices; strongest in tourist neighbourhoods.	Number of Airbnb listings per neighbourhood; distance to city centre; sociodemographic variables (income, average age, share of foreigners); neighbourhood and time fixed effects
Alvarez & Pennington-Cross (2023)	Airbnb and housing data from Wisconsin (USA)	2SLS IV regression	Doubling listings raises prices by 11%; effects concentrated in low-density, high-value areas. No significant effect in dense urban centres.	Airbnb density per neighbourhood (Airbnb per 100 housing units); transaction type (cash, short sale, FHA/VA); property features (size, age, style, pool, garage, water); demographic controls (income, ethnicity, education, unemployment)
Dogru et al. (2020) -Hotel Performanc**e**	AirDNA + STR data from London, Paris, Sydney, Tokyo (2001–2017)	OLS; Fixed-effects modelling	Increase in Airbnb listings led to a drop in RevPAR and OCC but no significant ADR change, reflecting Airbnb's disruption in hotel revenues.	Number of Airbnb listings; city and time fixed effects; macroeconomic controls: average wage, income level, air arrivals, labour force size

Sources	Data Used	Methods	Conclusions	Explanatory variables
Zervas et al. (2017)	Airbnb, Texas Comptroller, STR, and auxiliary data (2003–2014)	DID	Rise in Airbnb listings caused a revenue drop in hotels. Showed Airbnb's disruptive impact on regional hotel revenues.	Number of Airbnb listings per city/year; city and time fixed effects; hotel market characteristics
Dogru et al. (2020) – Airbnb Paradox	AirDNA listings; employment data from 12 U.S. cities (2008–2018)	Fixed-effects regression model	An increase in Airbnb supply led to a rise in hospitality-related employment.	Number of Airbnb listings; employment by sector; macroeconomic variables: wages, income, air arrivals, labour force; fixed effects
Wang and Nicolau (2017)	Airbnb listings from 33 cities (Inside Airbnb)	OLS; QR	Key price factors: host features, property traits, amenities, rules, and reviews. Super host status raised prices; greater distance to city centre lowered them.	Host characteristics (super host, number of reviews); property features (location, amenities, type); cancellation policies; rating; distance to city centre
Falk et al. (2019)	Airbnb listings in Switzerland	Hedonic pricing model; Panel data analysis	Pricing decisions are influenced by host credibility, property location convenience, and specific amenities.	Property type; room type; max occupancy; time dummies (month/year); location type (urban, rural); thematic attributes (Old Town, Ski, Nature, Lake, etc.); host multi-listing dummy
Lin and Yang (2024)	Airbnb listing reviews from 26 U.S. areas (InsideAirbnb)	Sentiment analysis; Topic Modelling; Hedonic Pricing; QR	Negative reviews had double the price impact of positive reviews, especially for low-priced rentals. Reviews on location and amenities had the strongest effect on pricing.	Sentiment metrics (Posword, Negword); review score; distance to city centre; host attributes (Super host); property size/type; amenities; rental rules; city fixed effects
Cheng and Jin (2019)	Airbnb reviews from Sydney	Text mining; Sentiment analysis	Reviews displayed positivity bias, while negative feedback focused on noise, maintenance, and unmet expectations.	Review-based themes: location (proximity to transport/shops), amenities (e.g. kitchen, bed), host traits (e.g. friendliness), room characteristics (e.g. noise, cleanliness); sentiment polarity by topic

Research shows that Airbnb has had a significant impact on the accommodation industry, disrupting hotel occupancy, pricing, and revenue by providing passengers with a flexible and scalable alternative (Dogru et al., 2020; Zervas et al., 2017). Besides competing with traditional hotels, Airbnb has boosted economic growth by creating jobs, both directly on its platform and indirectly through increased demand for services like cleaning, maintenance, and dining (Dogru et al., 2020). Furthermore, Airbnb's dynamic pricing strategies, influenced by factors such as host credibility, property location, and amenities, have reshaped how accommodations respond to market demands (Falk et al., 2019; Wang & Nicolau, 2017). These findings emphasize Airbnb's dual role as a disruptor of traditional lodging markets and a catalyst for broader economic change.

2.2. Impact of Events on Hotels & Short-Term Rentals

While the literature on the impact of events on peer-to-peer accommodation platforms such as Airbnb is still emerging, the hotel industry has been closely studied in many areas, including pricing strategies, occupancy rates, and revenue shifts during such events. This chapter will examine existing literature on these dynamics in the hotel industry, laying the foundation for meaningful comparisons with Airbnb. By drawing this parallel, the analysis aims to provide helpful perspectives into the different roles and behaviours of traditional hotels and peer-to-peer platforms such as Airbnb in the context of event-driven tourism.

Research has shown that hotels adjust their pricing strategies to capitalize on increased demand during major events. Piga and Melis (2021) studied the impact of cultural events on hotel performance by collecting data via a web crawler from Booking.com; the factors were based on hotel pricing, features, and location within a radius of 2.5 km from Nottingham's city centre for two consecutive years of the 'Robin Hood Beer and Cider Festival' and 'Nottingham Octoberfest' in 2016 and 2017. The researchers employed ordinary least squares (OLS) regression models to compare hotel room prices and occupancy during event weeks, intermediate weeks, and non-event weeks. They found that hotels raised their prices during events for which demand is very high, like during the Beer and Cider Festival, but showed less consistent changes for Oktoberfest.

Barreda et al. (2017) analysed hotel room pricing strategies during the 2014 FIFA World Cup, employing a methodology focused on percentage changes in key performance indicators (KPIs). Using data from STR (Smith Travel Research), the researchers examine a range of variations: supply, demand, occupancy percentage (Occ %), average daily rate (ADR), revenue per available room (RevPAR), and room revenue. In this paper, the authors measure the performance of hotels in nine host cities in Brazil during the period of the World Cup by matching the performance against the same period of three preceding years and one subsequent year. The findings showed significant increases in ADR and RevPAR during the event period due to guests seemed less sensitive to high rates. However, the study underlined some disparities across cities on some KPIs and further outlined a sharp decline of key performance indicators after the events, emphasizing the importance of strategic pricing and that any mega-event benefits are usually short- term. Chalupa et al. (2024) examined the impact of UEFA club competition finals on local hospitality performance using data from STR. The key performance indicators of occupancy rates, ADR, and RevPAR were analysed for several finals, such as the 2015 Europa League final in Warsaw and the 2022 Champions League final in Paris. These results showed significant price increases, with ADR growing up to 297.79% for the event day, while the changes in occupancy rates were more modest. This study has established that these events create short-run increases in hospitality performance that do not lead to long-term impacts.

Heller and Stephenson (2021) analysed the economic impact of the Super Bowl on hotel markets in four host cities (2015–2018) using daily hotel occupancy data from STR. Their regression analysis revealed substantial variations in room demand, prices, and revenues across cities. While the Super Bowl consistently increased room rates and generated $40–$50 million in hotel revenue for game nights, the net gain in room rentals was significantly lower than gross rentals, and effects varied by proximity to the stadium. Notably, 90% of the revenue gain stemmed from price increases, raising concerns about economic leakages from host city economies. Collins et al. (2022) discussed the various impacts on the Austin hotel market for selected sporting and cultural events. Six classes of hotels were considered, ranging from economy to luxury, using daily data from the years 2010 to 2017 derived from STR. The authors have estimated room rentals and revenue changes during events such as SXSW, Formula One, and UT football games using OLS regression with Newey-West corrections. Results showed event-specific effects: SXSW had a positive impact on room demand at all tiers, whereas Formula One benefited higher-tier hotels disproportionately. The study underlined nuanced effects, noting variations in visitor profiles and tax revenues, and emphasized the importance of event selection for maximizing economic benefits.

Falk and Vieru (2021) examined the short-term effects of sporting events on hotel room prices by employing a difference-in-differences (DID) approach, analysing more than 220,000 room bookings from a nine-hotel chain in Finnish Lapland. The DID analysis focused on treated hotels located near eight major sporting events, with a control group of hotels situated further away. The researchers adjusted for attributes particular to guests and bookings to isolate the influence of these occurrences. The robust regression results showed a 14% average increase in hotel room prices during event periods. While no noticeable price effects were observed in the pre-event period, a price reduction of roughly 6% was identified post-event.

Jakar and Binesh (2023) used a central place theory framework to examine how college sport events impacted the demand for short-term rentals. Their research relied on intensive big data analysis of over 350,000 observations from Ann Arbor, Michigan. Using detailed data from AirDNA (which includes information from sites like Airbnb and Vrbo) and college event schedules, they used logistic regression and ordinary least squares (OLS) models to explore how short-term rental demand is related to factors like location, property features, and college football games. Their findings showed that sporting events were positively correlated with higher short-term rental bookings and revenues, underscoring the important economic impact of university sports on regional hospitality sectors. Extending on the research of event-driven demand, Depken and Stephenson (2018) analysed daily hotel occupancy data from Charlotte (2005–2014) using ordinary least squares (OLS) regression models to measure the impacts of sporting events on hotel demand, prices, and revenues. Results showed significant increases for high-profile events like NASCAR races but limited effects for smaller-scale events, with most benefits restricted to event days. Similarly, Chikish et al. (2019) used the spatial regression methods to analyse the impact of NBA and NHL games in Los Angeles at the Staples Center and found demand concentration for nearby hotels while displacement effects at those farther away.

The documented spikes in demand surrounding major events naturally lead to questions about supply-side responsiveness. Fairley and Dolnicar (2017) argued that to meet surges in demand created by large events, peer-to-peer platforms such as Airbnb must have the capacity to flexibly and temporarily increase accommodation supply. The research results suggest that hotels can respond to surges in demand that are predictable; however, peer-to-peer platforms have the unique advantage of being able to provide immediate fulfilment of short-term lodging needs that cannot always be provided by traditional hotels. This conclusion is supported by their analysis of various case studies and interviews with event organizers, which show the special role that peer-to-peer platforms play in the solution to accommodation problems during major events. The authors recognized that while hotels depend on preplanned expansions to meet predictable demand, peer-to-peer platforms like Airbnb can mobilize unused residential spaces virtually overnight; hence, they represent a scalable and flexible solution. Furthermore, their findings highlight how concerns regarding quality control and regulatory compliance are preventing event planners and destination marketers from utilizing these platforms to their full potential. Nonetheless, the evidence provided indicates that these platforms play a critical role in addressing accommodation shortages, especially during short-term demand surges that surpass the existing capacity of conventional hotels. Table 2 summarizes relevant studies on the effects of events on hotels and short-term rentals, detailing the data used, methodological choices, and key conclusions.

Table 2 - Summary of Studies on Impacts of events on Hotels and Short-term Rentals

Sources	**Data**	**Methods**	**Conclusions**	**Explanatory variables**
Piga and Melis (2021)	Hotel data from Booking.com (via web crawler)	OLS	Hotels increased prices during Beer and Cider Festival but showed less consistent changes for Octoberfest.	Event dummies; hotel fixed effects; day-of-week fixed effects; year dummies; interaction terms
Barreda et al. (2017)	Performance of Brazilian Hotels from STR	Analysis of variations in Hotel KPIs	Increases in ADR and RevPAR during the event, sharp post-event KPI declines.	Event period dummies (pre/during/post-event); KPIs: Occupancy, ADR, RevPAR; year fixed effects
Chalupa et al. (2024)	STR data on UEFA club competition finals	Analysis of occupancy rates, ADR, RevPAR	ADR increased on event days, with modest occupancy changes. Effects were short-term and did not lead to long-term impacts.	Event date indicators; comparisons across years; KPIs (Occupancy, ADR, RevPAR); STR benchmarking data
Heller and Stephenson (2021)	STR daily hotel occupancy data from four Super Bowl host cities	Regression analysis	Super Bowl increased room rates. 90% of revenue gain came from price increases. Effects varied by proximity to the stadium.	Event dummy (Super Bowl); distance to stadium; time fixed effects; hotel fixed effects
Collins et al. (2022)	STR daily data on six hotel classes in Austin	OLS regression with Newey-West corrections	SXSW increased room demand at all tiers, while Formula One benefited higher-tier hotels unevenly.	Event dummy (SXSW, F1); hotel class dummies; time dummies (day-of-week, month); Newey-West corrected standard errors
Falk and Vieru (2021)	Finnish Lapland Hotel Room bookings	DID	Event periods led to an increase in room prices and a price reduction occurred post-event.	Event dummy (pre/during/post); year fixed effects; interaction terms with time and location

Sources	Data	Methods	Conclusions	Explanatory variables
Jakar and Binesh (2023)	Michigan short-term rental booking data from AirDNA; Event schedules	Logistic regression; OLS	Sporting events positively correlated with higher bookings and revenues for short-term rentals.	Football event dummy; holiday and university event dummies; property-level variables (distance to stadium/downtown, price, rating, cleaning fee, type of unit); time fixed effects (month, day); opponent team dummies
Depken and Stephenson (2018)	Daily hotel occupancy data from Charlotte	OLS	High-profile events like NASCAR boosted demand, prices, and revenues; smaller events had limited, event days specific impacts.	Event dummies (NBA, NHL, concerts); lockout dummies; spatial fixed effects (3 distance bands); day-of-week, month, and year fixed effects; interaction terms (event × distance)
Chikish et al. (2019)	Hotel demand data from Los Angeles during NBA and NHL games	Spatial regression methods	High demand concentrated near the arena, while displacement effects occurred for hotels farther away.	Event dummies (sports, political, weather); 2 leads and 2 lags; real gasoline price; US unemployment rate; snowfall dummy; day, month, and year fixed effects; separate models by area
Fairley and Dolnicar (2017)	Case studies and interviews with event organizers	Qualitative analysis	Peer-to-peer platforms flexibly increase supply for event demand surges but face regulatory challenges.	N.A.

While Airbnb has been extensively studied for its broader impacts on tourism, housing, and hotel markets, relatively few studies have explored how the platform operates in the context of large-scale cultural events. These events create short-term but intense shifts in demand, where platforms like Airbnb may respond differently than traditional hotels, especially in terms of supply flexibility and pricing strategies (Fairley & Dolnicar, 2017). Yet, most research has focused on hotel responses, leaving a gap in the understanding of how peer-to-peer accommodations, like Airbnb, behave under these conditions.

To help close this gap, this study will analyse how large events affect Airbnb supply, prices, and guest sentiment in Lisbon and Porto, offering a closer look at how the platform adapts when cities experience sudden surges in demand.

3. METHODOLOGY

3.1. DATA DESCRIPTION

This empirical analysis draws on data from Inside Airbnb a widely used and publicly available source that compiles detailed information on short-term rental listings worldwide (Inside Airbnb, 2024). The dataset offers granular observations into listing characteristics, pricing, availability, and guest reviews. For this study, data was collected for Lisbon and Porto, with a focus on the year 2024.

The analysis relies on several key files provided by Inside Airbnb, each containing different but complementary dimensions of information about the listings:

Table 3 - Inside Airbnb Datasets

File Name	Description
listings	Summary file containing fundamental attributes of each listing, including location, nightly price, number of bedrooms, and host characteristics.
calendar	Dataset capturing daily pricing, availability, and information on minimum and maximum nights for each listing
reviews_details	Comprises detailed information on guest reviews

Given the aim of analysing price, supply, and guest reviews, the datasets were selected to ensure the adequacy and consistency of the analysis, as presented in Table 3. The calendar dataset contains listing-level information on daily prices and availability, allowing an overview of how these variables change over time. Inside Airbnb offers two formats for the listings and reviews dataset: a summary version and a detailed version. The summary version was chosen for the listings, as it includes key attributes such as listing location, host characteristics, and neighbourhood identifiers, suitable for spatial and contextual analysis. For guest reviews, the detailed dataset was used, as this version includes the full text of review comments, allowing for sentiment classification.

The data sets were available on a quarterly basis and required careful selection to accurately reflect user behaviour during each event period. For example, the March 2024 dataset was chosen to look at events that happened in May 2024 because it was the best snapshot of the time before the events. But for reviews, the 2025 dataset was used to include past stays. Earlier snapshots, such as those from March 2024, could not include reviews of stays from past snapshots because they only covered a short period of time.

The outcome variables chosen are availability, price, and guest sentiment. These variables were constructed from the previously mentioned datasets and aggregated by neighbourhood and day, as this is the most granular geographic unit available in the data. Analysing data at the neighbourhood level helps ensure consistent comparisons across time and place, and avoids the noise and gaps that can occur with listing-level data.

3.2. GSC MODEL

To investigate the causal impact of large cultural events on Airbnb's pricing, supply, and host reviews in Porto and Lisbon, this study employs the Generalized Synthetic Control (GSC) method developed by Xu (2017). Airbnb markets are complex and change quickly; listings vary a lot between neighbourhoods, guests, hosts, and over time. Traditional methods like Difference-in-Differences (DID) assume that treated and control groups would follow the same trend if no event had happened (parallel trend). But with something as dynamic as Airbnb, that assumption often doesn't hold.

The original Synthetic Control method, proposed by Abadie and Gardeazabal (2003) is a good alternative when there's only have one treated unit and a very stable setting. However, this study focuses on multiple events across different neighbourhoods and time periods, often with several treated units at once. This makes GSC suitable in for the research. It accommodates varying treatment timings, heterogeneous effects across units, and unobserved factors that evolve over time, such as tourism flows or changes in host behaviour.

As Maamoun (2019) explains when using GSC to evaluate the Kyoto Protocol, this method is especially useful when the treatment isn't randomly assigned and when the data is affected by hidden trends, a similar situation to the dynamics of cultural events and Airbnb markets. This parallels the structure of the present study, where large events follow non-random patterns and affect Airbnb markets through subtle, often hidden dynamics.

By addressing these challenges, GSC allows us to construct more credible counterfactuals, that is, plausible scenarios of what would have happened in the absence of an event. Instead of assuming perfect balance or clean, parallel trends between groups, it adapts to the complexity of real-world data, making it a robust and flexible tool for estimating the impact of short-term cultural events on local Airbnb activity.

3.2.1. MODEL SPECIFICATION

Let Y_{it} denote the observed outcome (price, availability, or aggregated review score) for listing i at time t. The GSC model assumes the following structure:

$$Y_{it} = \delta_{it} D_{it} + X'_{it}\beta + \lambda'_i f_t + \varepsilon_{it}$$

Where:

- D_{it} is a binary treatment indicator equal to 1 if unit *i* is exposed to the event at time t, 0 otherwise;
- $\delta_{it}$is the (potentially heterogeneous) treatment effect;
- X_{it} are observed covariates (listing and time characteristics);
- β is the unknown parameters
- f_t are latent common factors (e.g., market-wide trends);
- λ_i are unit-specific factor loadings;
- ε_{it} is an idiosyncratic error term.

The key idea is that in the absence of treatment, the outcome Y_{it} is driven by both observable variables and unobserved dynamic patterns captured by the interactive fixed effect's structure $\lambda'_i f_t$. These unobserved patterns allow the model to flexibly account for heterogeneity and hidden trends across neighbourhoods and over time.

To estimate what would have happened without the event (i.e., the counterfactual $Y_{it}(0)$), the GSC model first uses only the pre-treatment periods and untreated units to learn the structure of $\widehat{f_t}$, $\widehat{\lambda_i}$ and $\hat{\beta}$ It then projects the untreated potential outcome forward to the post-treatment period. The average treatment effect on the treated (ATT) at time t is then computed as the difference between the observed outcome and the estimated counterfactual:

$$ATT_t = \frac{1}{N_{tr}} \sum_{\{i \in T} \left(Y_{it} - \widehat{Y_{it}(0)}\right)$$

Where τ is the set of treated units, and Ntr is the number of treated units.

The model was estimated using the gsynth package in R, following the steps described by Xu (2017), which included using only control units for estimation, projecting treated units onto a hidden factor space, and counterfactuals imputation. Cross-validation and bootstrapping were applied to enhance robustness.

3.2.2. IDENTIFICATION ASSUMPTIONS

For the Generalized Synthetic Control (GSC) model to support valid causal inference, several key assumptions must hold:

- **Latent Factor Structure**: It is assumed that all unobserved, time-dependent factors that influence the outcome operate through a small number of shared latent factors. These factors influence all units, but to different extents. This configuration enables the model to identify complex trends, including seasonal influences or patterns of tourism across a city, without the need for direct observation or measurement of these factors.
- **No Interference Between Units (SUTVA)**: The Stable Unit Treatment Value Assumption says that the intervention administered to one unit doesn't change the outcomes for other units. In this context, it indicates that the impact of an event in a specific area (for example, a neighbourhood) is presumed not to extend into adjacent areas that are not being treated.
- **Conditional Exogeneity**: The assignment of treatment (i.e., proximity to an event) must be unrelated to unobserved shocks in the outcome variable, once observed covariates and the latent factor structure are accounted for. This ensures that any post-treatment divergence between treated and control units can be attributed to the event itself, rather than to omitted variables.
- **Overlap in the Latent Space**: For treated units to be meaningfully compared to control units, their underlying dynamics (captured by the latent factors) must lie within the range of variation observed among control units. This ensures the model compares treated areas to control areas with similar patterns, rather than making predictions based on unrelated or very different cases, improving the credibility of the results.

These assumptions are stronger than those required by simple Difference-in-Differences, but they are also more flexible in accounting for unit-specific trends and time-varying unobserved confounders.

4. EMPIRICAL STUDY

4.1. CONTEXT AND EVENTS UNDER STUDY

This empirical study focuses on the effect of large-scale cultural events on the short-term rental market in Portugal, specifically in Porto and Lisbon. The selected events serve as external shocks to local demand that are expected to affect short-term rental markets, offering a suitable context for estimating causal effects using the Generalized Synthetic Control method.

Six major festivals and concerts scheduled for 2024 were selected for analysis, as shown in Table 4. All are multi-day events with large audiences and national relevance, capable of generating sharp, short-term increases in local tourist inflow. Their selection was guided by their scale, duration, and geographic dispersion, as well as their expected impact on accommodation demand in the surrounding areas.

Table 4 - Events Overview

Event	Location	Dates
Taylor Swift Concert	Lisbon (Estádio da Luz)	24–25 May 2024
North Music Festival	Porto (Parque de Serralves)	24–26 May 2024
NOS Primavera Sound	Porto (Parque da Cidade)	6–8 June 2024
NOS Alive	Oeiras (Passeio Marítimo de Algés)	11–13 July 2024
MEO Marés Vivas	Vila Nova de Gaia (Parque Urbano da Madalena)	19–21 July 2024
MEO Kalorama	Lisbon (Parque Bela Vista)	29-31 August 2024

To better understand the spatial distribution of the selected events, Figures 1 and 2 show their locations within the municipal boundaries of Lisbon and Porto. Each event is represented by a coloured star, allowing visual identification of the respective hosting neighbourhoods. The neighbourhood boundaries were obtained from the GeoJSON files provided by Inside Airbnb, while the coordinates of the event venues were manually collected based on their official addresses.

The maps illustrate the spatial distribution of the selected events across different areas of Lisbon and Porto, ranging from central neighbourhoods to peripheral or riverside locations. This dispersion helps explain the importance of adopting a neighbourhood-level approach when analysing the effects of each event, rather than considering the city as a whole.

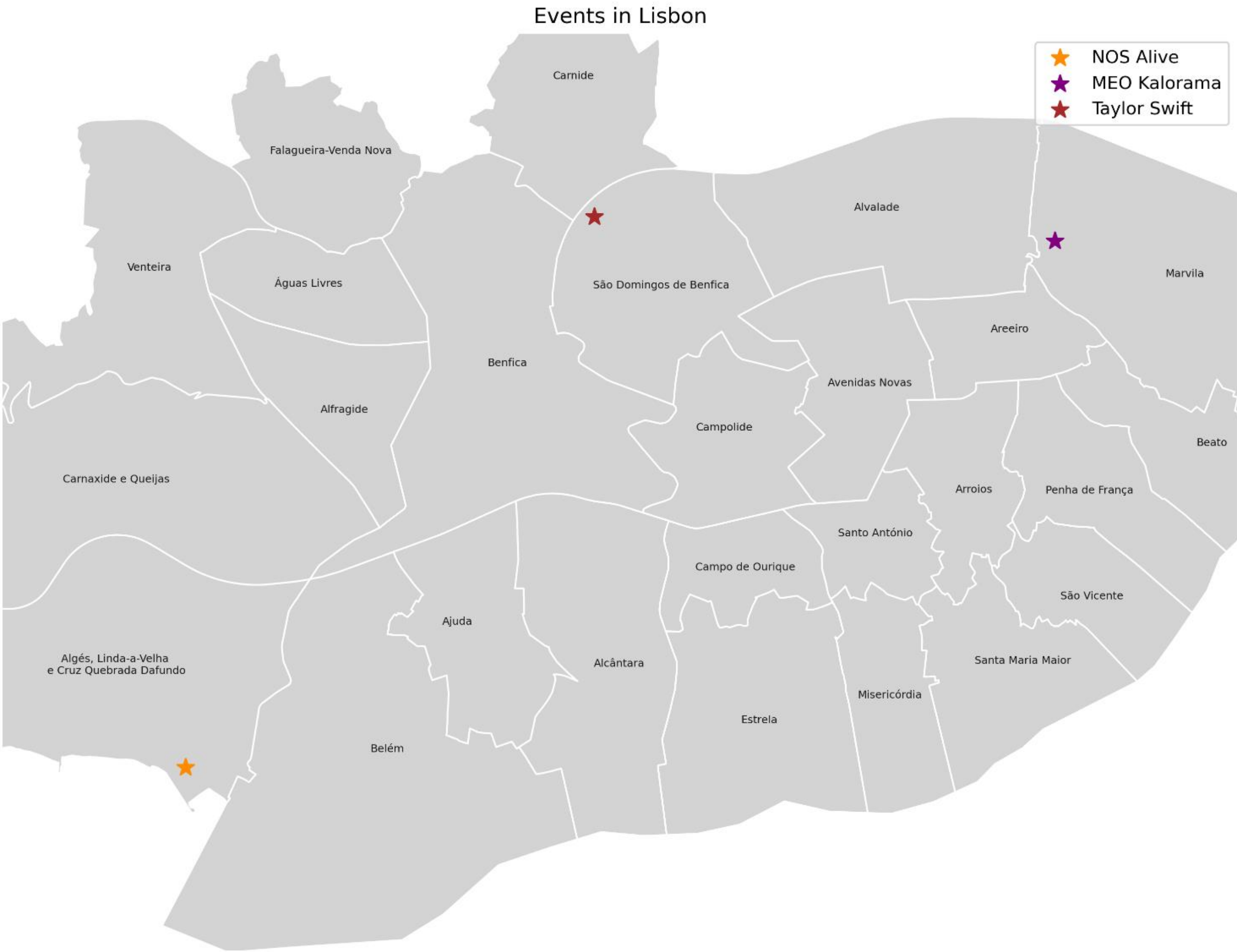

Figure 1 - Events Location in Lisbon

Events in Porto

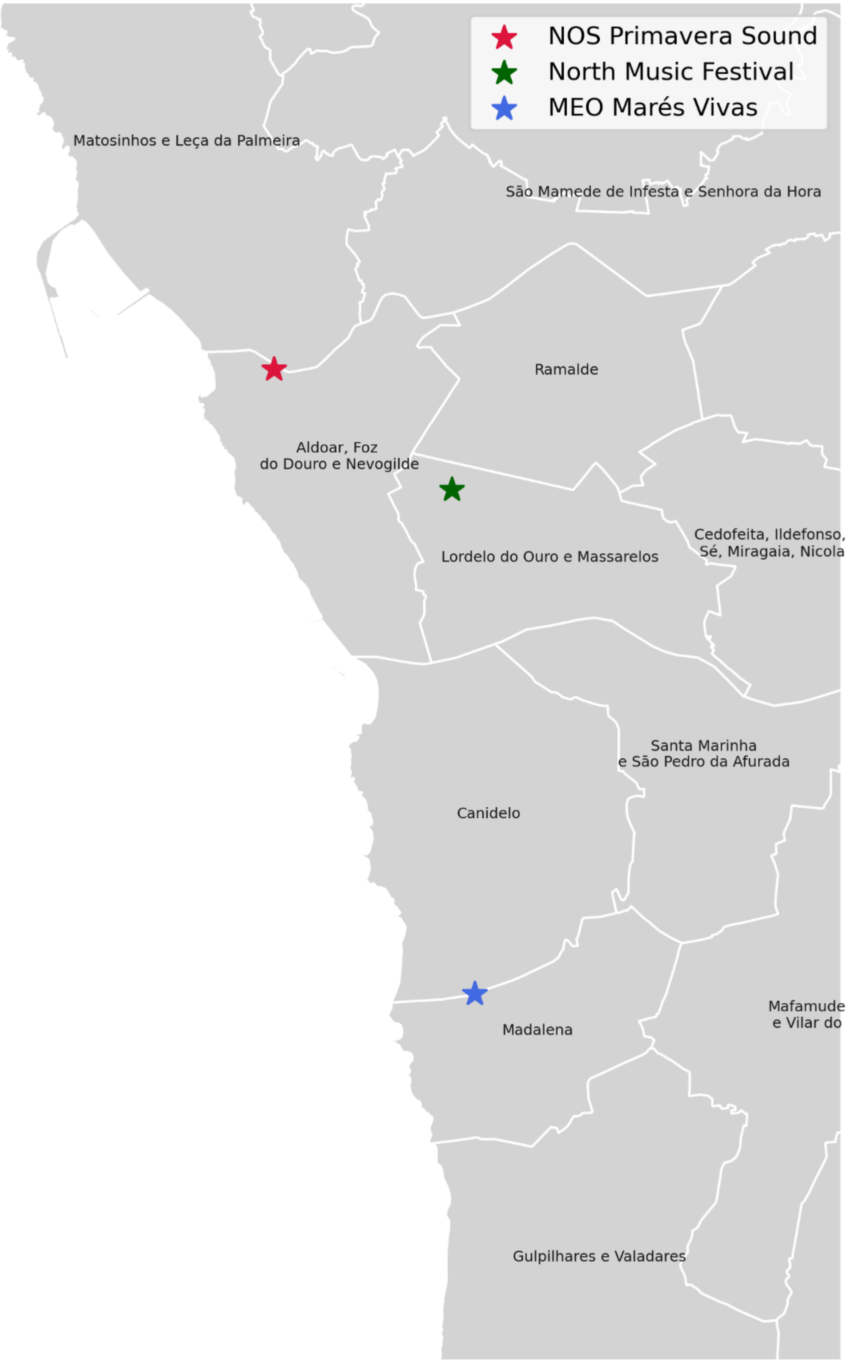

Figure 2 - Events location in Porto

4.2. Exploratory Data Analysis

Since the events being studied take place from May 2024 to August 2024, this Exploratory Data Analysis aims to explore the datasets selected for analysis in the previous chapter. This analysis aims to find patterns in the target variables and create the research hypothesis.

Although listing price was initially considered as a potential outcome, preliminary analysis revealed limited variation during the event periods, with many listings displaying static or infrequently updated prices. As such, price was excluded from the final model specification, as it did not provide sufficient signal to support robust causal inference. The analysis will therefore focus on two variables: daily supply of available listings and the sentiment expressed in guest reviews.

4.2.1. Supply

To analyse Airbnb supply, we used the variable "available", which indicates whether a listing was available (t) or not (f) on a given day. The supply was measured as the total number of listings available per day. Figure 3 presents the daily sum of available listings for Lisbon and Porto, with dashed vertical lines marking the beginning of six major cultural events (as per Table 4).

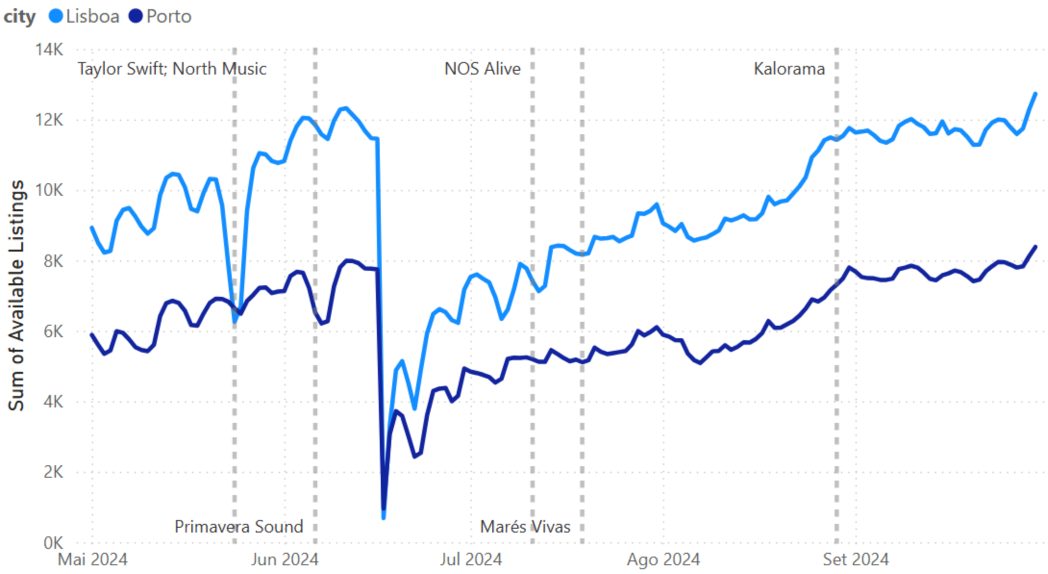

Figure 3 - Evolution of available Airbnb listings in Lisbon and Porto

To ensure the most up-to-date information, we combined datasets exported in March and June. However, this merging process introduced a visible drop in the number of available listings around mid-June, which results from the transition between data sources rather than a real change in supply. Although this break may limit the suitability of the data for causal inference methods such as the Generalized Synthetic Control (GSC), the unified dataset was retained for analysis for two main reasons. First, none of the events under study coincide with the date of the discontinuity (17th of June), which reduces the likelihood of biasing the estimation of treatment effects. Second, the merged dataset offers a more comprehensive observation window, which enhances the reliability of model estimation and the comparability across events. The discontinuity is acknowledged as a limitation and is considered when interpreting the results.

Notably, a sharp decrease in available listings in Lisbon is observed around 24–25 May, coinciding with Taylor Swift's concerts. A similar, although smaller, reduction appears in Porto around 6 June, during the NOS Primavera Sound festival. While these patterns may not be entirely attributable to the events themselves, they suggest a potential relationship between cultural events and local accommodation supply.

Despite short-term fluctuations, there is an overall increase in the number of available listings over time. This trend is expected given that the datasets were exported on a quarterly basis and reflect availability calendars rather than real-time bookings. Therefore, some listings may appear available in the data even if they ended up being booked later, especially for dates further in the future.

4.2.2. REVIEWS

To begin uncovering patterns in Airbnb user sentiment across cities, Figure 4 displays the daily average review score derived from sentiment analysis between May and early September 2024. Each review was processed using the transformer-based multilingual sentiment model available at Hugging Face (tabularisai/multilingual-sentiment-analysis), which classifies text into one of five categories: very negative, negative, neutral, positive, and very positive (Tabularis AI, n.d.). These categories were then mapped onto a numerical scale from 1 to 5, for analytical purposes, allowing for daily aggregation of sentiment at the city level. This transformation enabled the construction of a continuous, interpretable time series to track how guest sentiment evolved throughout the study period. Overall, Porto consistently shows higher sentiment scores than Lisbon. In both cities, the average ratings remain within a relatively narrow band, suggesting stable guest satisfaction over time.

There are no clear or consistent shifts in sentiment that visibly coincide with the event periods marked by dashed vertical lines. This visual pattern supports the preliminary impression that, cultural events do not appear to strongly affect how guests rate their stays. However, these results must be interpreted with caution. Aggregating ratings at the city level may smooth out localised effects that occur only in specific neighbourhoods or listings closer to the event locations. Whether the observed stability reflects genuine consistency in guest satisfaction, or instead the limitations of sentiment scoring and spatial aggregation, will be examined in the following chapter through a formal causal framework.

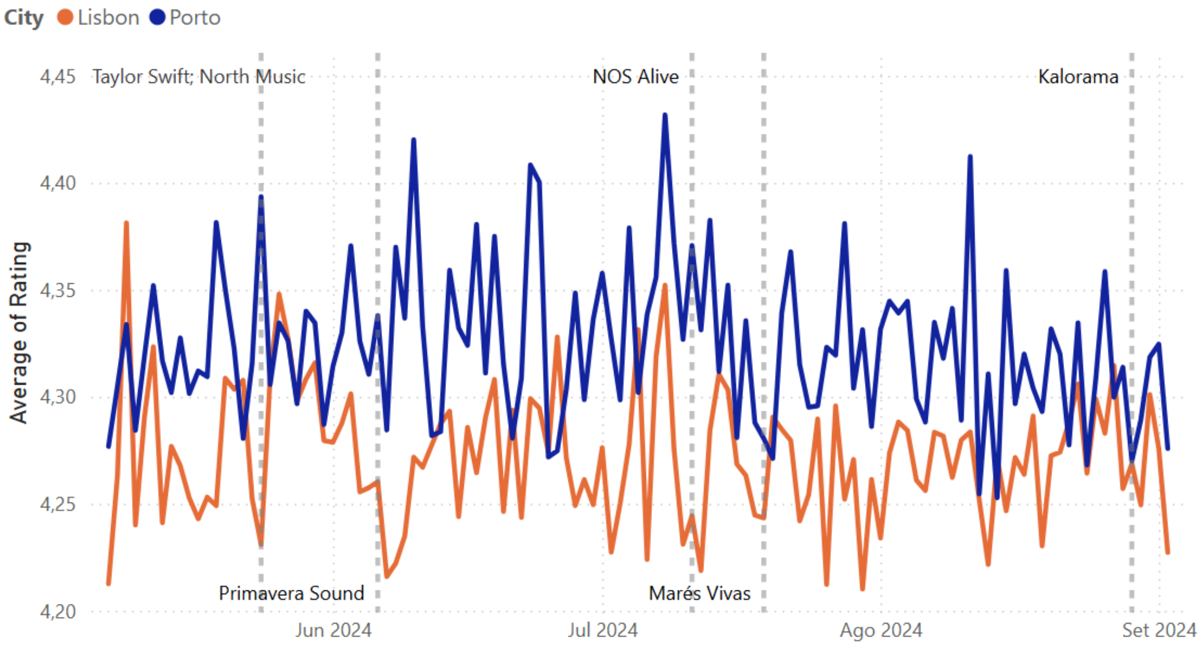

Figure 4 - Evolution of the Average Rating of Reviews in Porto and Lisbon

To complement the quantitative patterns, the content of user reviews was also analysed. Figures 5 and 6 present word clouds generated from the text of reviews in Lisbon and Porto, respectively. Common terms such as “great”, “location”, “apartment”, and “stay” dominate both cities, indicating that guests in both markets frequently comment on overall satisfaction, the quality of the apartment, and its location.

Figure 5 - Word Cloud of Porto’s reviews comments

Figure 6 - Word Cloud of Lisbon’s reviews comments

Notably, the word “porto” appears prominently in Porto reviews, often as a reference to the city itself, which is not mirrored to the same extent in Lisbon’s reviews. This could reflect a greater salience of the city itself in the experience of guests staying in Porto, compared to those in Lisbon. Additionally, both word clouds include terms in multiple languages (e.g., “très”, “bien”, “sehr”, “und”), reflecting the international nature of Airbnb users. These initial descriptive patterns reveal structural similarities in guest feedback across both cities, alongside subtle differences in how visitors engage with the destination. While common terms reflect generally positive experiences, the presence of multilingual and place-specific references suggests variation in how sentiment is expressed.

These exploratory findings provide useful context and help identify regularities as well as potential anomalies. They also support the motivation for the sentiment analysis that follows, which seeks to quantify these patterns over time and assess whether large cultural events measurably affect guest sentiment.

4.3. RESEARCH HYPOTHESIS

This study investigates the causal impact of major cultural events on the short-term rental market, focusing on Airbnb supply and reviews across the cities of Porto and Lisbon.

To guide the empirical analysis, the following hypotheses are formulated for each variable:

Supply:

- **H_1 (Alternative Hypothesis):** Major cultural events have an impact on Airbnb Supply within treated areas.
- **H_0 (Null Hypothesis):** Major cultural events have no impact on Airbnb Supply within treated areas.

Reviews:

- **H_1 (Alternative Hypothesis):** Major cultural events have an impact on Airbnb Review dynamics within treated areas.
- **H_0 (Null Hypothesis):** Major cultural events have no impact on Airbnb Review dynamics within treated areas.

These hypotheses aim to find out if major cultural events lead to noticeable changes in short-term rental activity, specifically looking at the number of available listings and the average review scores. An impact, in this context, refers to either an increase or decrease in these outcomes in the areas directly affected by the events.

To explore these hypotheses, a single Generalized Synthetic Control (GSC) model is used to analyse all events across both cities in a unified framework. Rather than treating each event separately, the method brings them into a unified analysis, making it possible to estimate an overall average effect while still respecting the specific timing of each event and the unique characteristics of each area.

4.4. VARIABLES CONSTRUCTION

To analyse the supply, the dataset was filtered to include only listings marked as available (available == "t"). Then, for each combination of neighbourhood, date, treatment status, and treatment date, the daily number of distinct listings was computed using the n_distinct (listing_id) function.

To quantify review sentiment, each review was classified into one of five categories: Very Negative, Negative, Neutral, Positive, or Very Positive, using a transformer-based multilingual sentiment analysis model, as mentioned previously. These categories were then mapped onto a numerical scale ranging from –2 (Very Negative) to +2 (Very Positive), with Neutral reviews assigned a score of 0. Each score was also weighted by the model's confidence in the classification, reducing the influence of uncertain predictions.

This method was chosen instead of a basic ranking system (like 1 to 5) to keep the clear difference between positive and negative comments. Furthermore, the symmetric scale centred at zero facilitates the interpretation of sentiment shifts, particularly in the context of causal inference. This continuous, confidence-weighted polarity score is better suited to the Generalized Synthetic Control (GSC) framework, which benefits from sensitivity to subtle variations in the outcome variable. The resulting average sentiment metric (avg_sent) thus reflects not only the direction but also the intensity of expressed sentiment at the neighbourhood level, making it an appropriate measure for assessing treatment effects.

Both outcome variables, the daily supply of available listings (supply_{it}) and the average review sentiment, ($\mathrm{avg\_sent}_{it}$), were modelled using the GSC framework as follows:

$$\mathrm{Y}_{it} = \delta_{it} D_{it} + \lambda_i' f_t + \varepsilon_{it}$$

Where Y_{it} represents either supply_{it} or $\mathrm{avg\_sent}_{it}$, depending on the specification. D_{it} is a binary indicator equal to 1 if the neighbourhood was exposed to the event at time t; λ_i and f_t are unit and time-specific latent factors and ε_{it} an idiosyncratic error term. No observed covariates were included in the model specification.

4.5. TREATMENT AND CONTROL GROUP

Accurate definition of treated and control units is essential in the GSC framework to estimate credible counterfactuals. The method builds a synthetic control group from untreated units by matching their pre-treatment patterns and latent structures to those of the treated group.

In this study, the treatment was defined based on location by looking at which neighbourhoods were closest to each event. A neighbourhood was classified as treated if it fell within a 2-kilometre radius of the event venue, and at least 70% of its Airbnb listings were located within that buffer. This rule was applied to include only areas with relevant exposure to the event context, enhancing the precision and interpretability of the estimated effects. The 2-kilometre threshold was selected as a plausible approximation of the zone most likely to experience changes in booking activity driven by the event.

This spatial treatment approach is consistent with prior studies that defined exposure based on geographical proximity to tourism-related activities. For instance, Garcia-López et al. (2020) develop distance-weighted indices to capture neighbourhood-level exposure to Airbnb activity in Barcelona. Similarly, Piga and Melis (2021) restrict their analysis to hotels within a

2.5-kilometre radius from the city centre, where the events under study were held, to isolate the most affected areas. Figures 7 and 8 show the outcome of this classification, highlighting the neighbourhoods that met these criteria.

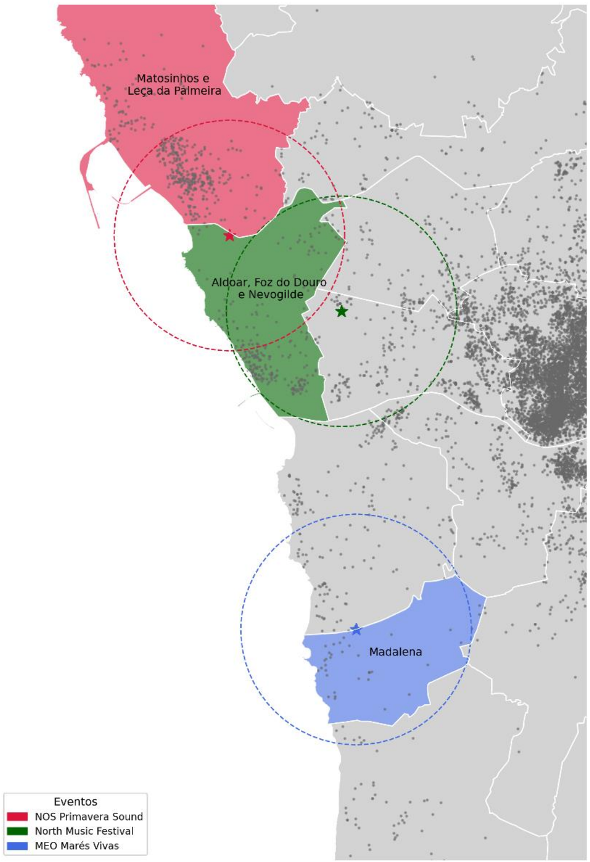

Figure 7 - Events Location and corresponding treated neighbourhoods in Porto

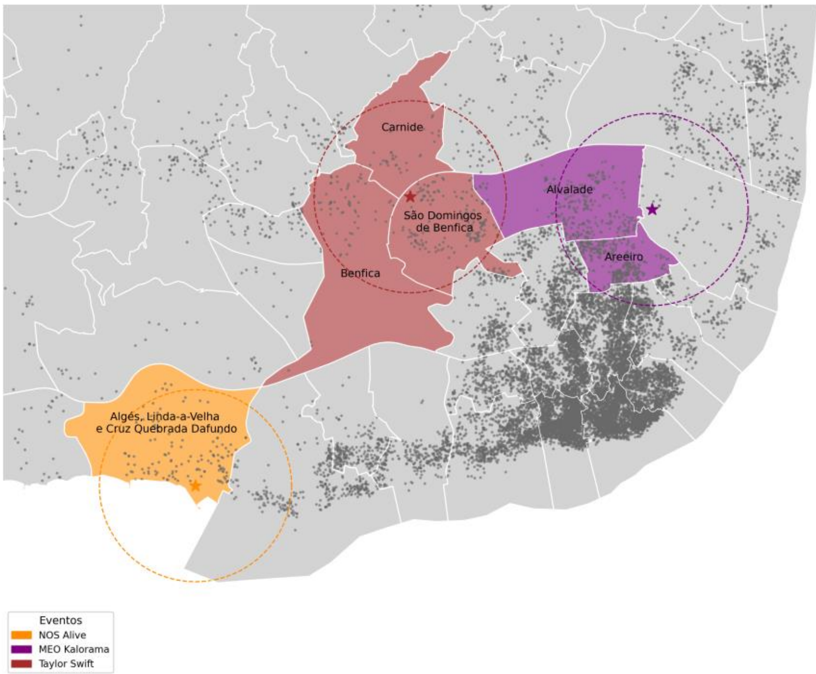

Figure 8 - Events Location and corresponding treated neighbourhoods in Lisbon

Neighbourhoods that did not meet the criteria to be classified as “treated” were used as control units. To ensure the analysis focused on areas with meaningful Airbnb activity, only neighbourhoods with more than five active listings during the study period were included. This threshold was applied to exclude areas with insufficient market activity, where short-term rental dynamics are too sparse or irregular to support reliable estimation. The decision was further supported by the highly right-skewed distribution of listings per neighbourhood (see Figure 9), which revealed a concentration of units with extremely low data density. Sparse units are more likely to be affected by random changes, which can skew the estimation of hidden factors in the GSC model and result in unreliable or misleading outcomes.

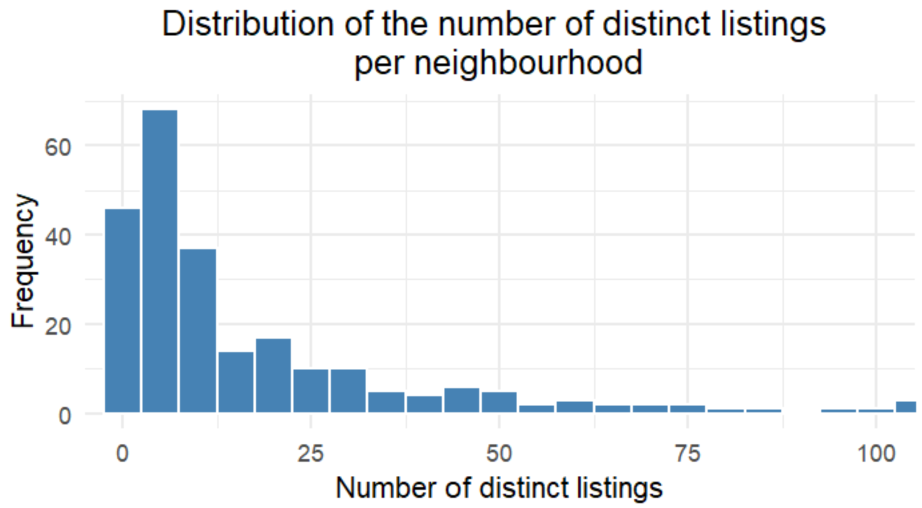

Figure 9 - Histogram of the number of distinct listings per neighbourhood (bin width = 5)

These untreated neighbourhoods served as potential building blocks for the construction of a synthetic control group, which is selected and weighted automatically by the GSC algorithm based on similarities in pre-treatment trajectories. The method relies on data from before the event to identify common trends and latent differences across units. This enables it to estimate what would likely have occurred in each treated neighbourhood had the event not taken place. Focusing on temporal dynamics helps reduce the impact of fixed differences between areas, such as population, housing, or tourism levels, and supports more reliable counterfactual estimates.

Treatment indicators (treat and date_treated) were added for each observation to allow the implementation of the Generalized Synthetic Control (GSC) model. The variable treat is a binary indicator that identifies whether a given neighbourhood-date pair falls within the treated group in the event date window, while date_treated records the date on which treatment begins for each treated unit. To account for the possibility that visitors may book accommodation shortly before the event, the treatment period was defined to start two days prior to the official beginning of each event. The treatment window was defined as the official event duration plus a two-day margin before and after the event to capture anticipatory and lagged effects on listing dynamics. For comparison, the pre-treatment period spans the 15 days prior to the start of the treatment window. These indicators were constructed by aligning the event dates with the corresponding treated neighbourhoods, as defined by the spatial criteria described earlier. This structure allows the model to differentiate pre- and post-treatment periods at the neighbourhood level and to account for variation in treatment timing across events.

5. RESULTS AND DISCUSSION

5.1. MAIN RESULTS

5.1.1. AIRBNB SUPPLY

The results suggest that cultural events led to a decrease in the daily supply of Airbnb listings in the treated areas. The model includes 9 treated units and 180 control units across 119 time periods, with heterogeneous treatment timing. Compared to the counterfactual scenario, which represents the expected evolution in the absence of the event, the Generalized Synthetic Control model estimates an average reduction of approximately 17 listings per day. As shown in Table 5, the estimated Average Treatment Effect on the Treated (ATT) is -17.156, with a 95% confidence interval of ±4.005.

These findings indicate a substantial contraction in short-term rental supply within the treated areas, relative to what would have been expected had the events not occurred. The model was estimated using an interactive fixed effects structure, and the number of latent (unobserved) factors was selected via cross-validation. The optimal specification includes three unobserved factors (r = 3), allowing the model to flexibly adjust for unmeasured temporal dynamics that may influence treated and control units differently. Although not directly interpretable (Xu, 2017), these latent components likely reflect underlying structural patterns or external shocks evolving over time.

Table 5 - Results for the Airbnb Supply

Dependent variable: Supply of Airbnb listings	
ATT (Average Treatment Effect on the Treated)	-17.156
95% Confidence Interval	± 4.005
Number of treated units (Ntr)	9
Number of control units (Nco)	180
Total time periods (T)	119
Unobserved factors	3
MSPE (pre-treatment)	13.019

Figure 10 plots the ATT trajectory over time. The ATT remains close to zero before treatment, showing no systematic pre-existing differences between treated and synthetic control units. While GSC does not require the parallel trends assumption, observing a flat pre-treatment ATT strengthens the credibility of the counterfactual. This pattern is likely driven by the geographical and structural similarity between treated and control units, all located within the same districts and subject to similar local policies, tourism dynamics, and seasonal patterns, which helps minimize unobserved heterogeneity and improves the quality of the synthetic estimates.

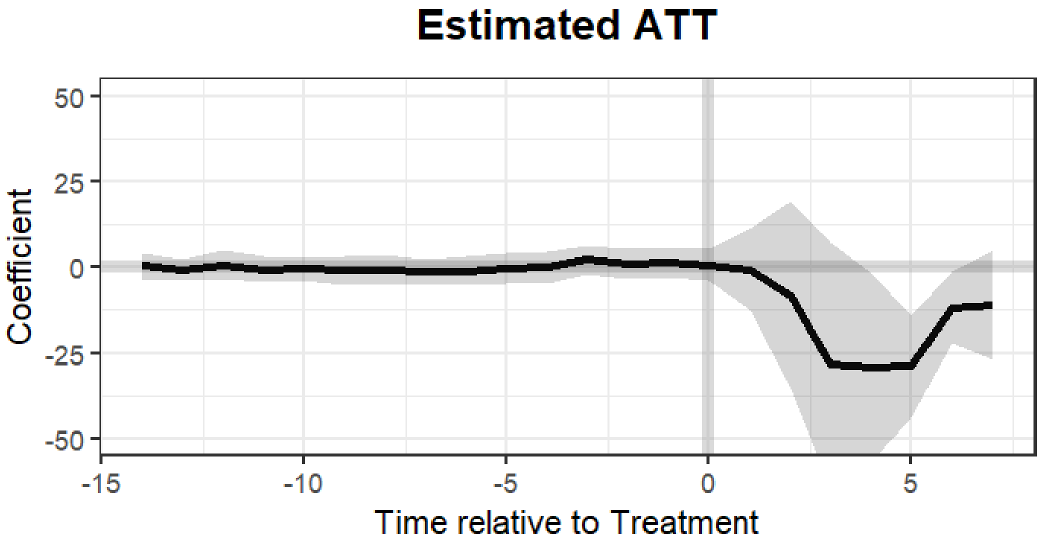

Figure 10 - ATT for the Airbnb Supply

After the event begins, the ATT drops sharply and remains negative, supporting the hypothesis that the event reduced short-term rental supply in the affected neighbourhoods However, this reduction should not be interpreted as a straightforward contraction of market activity, as it may also reflect an increase in booking activity that led to listings being fully booked and therefore temporarily unavailable for further reservations. Similar to findings from the hotel sector, where large events have been shown to increase occupancy rates and booking volumes (e.g., Barreda et al., 2017; Collins et al., 2022; Heller & Stephenson, 2021), the decline in available Airbnb listings likely reflects increased reservation activity. As Depken and Stephenson (2018) and Chikish et al. (2019) show, major events often lead to significant spikes in demand for nearby accommodation, with localised increases in hotel occupancy rates and revenue. Recent findings by Jakar and Binesh (2023) confirm that this pattern extends to short-term rentals, as large-scale events are associated with higher booking volumes and revenues. In this context, the observed drop in available Airbnb listings may indicate a surge in bookings during the event period, rather than a withdrawal of supply. From the host's perspective, the decrease in available listings can be viewed as a positive outcome, indicative of strong demand and successful conversion into bookings during event periods.

Finally, it is important to acknowledge that a known discontinuity in the dataset (resulting from the merging of different export periods) may have introduced some noise into the estimation of latent factors. Although this break does not coincide with the treatment periods, it was considered when interpreting the supply estimates across all specifications.

5.1.2. AIRBNB REVIEWS

The results presented in Figure 11 and summarized in Table 6 suggest that the cultural events under analysis had no statistically significant impact on the average sentiment of Airbnb reviews in the treated areas. The estimated Average Treatment Effect on the Treated (ATT) is -0.017, with a 95% confidence interval of ±1.632. This wide confidence interval includes both negative and positive values, pointing to substantial uncertainty and precluding any firm conclusions about the direction or magnitude of the effect.

Table 6 - Results for Airbnb Reviews

Dependent variable: Average sentiment of Airbnb reviews	
ATT (Average Treatment Effect on the Treated)	-0.017
95% Confidence Interval	± 1.632
Number of treated units (Ntr)	9
Number of control units (Nco)	169
Total time periods (T)	119
Unobserved factors	0
MSPE (pre-treatment)	0.118

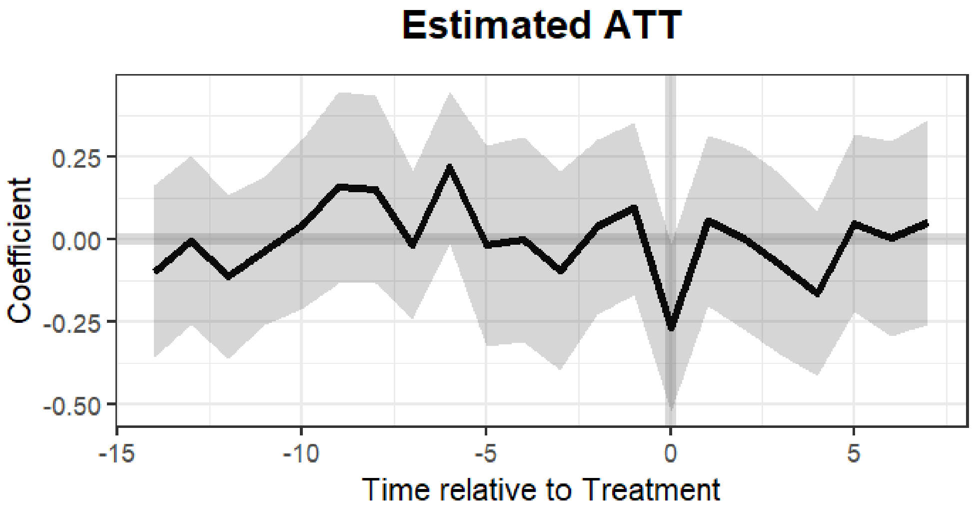

Figure 11 - ATT for Airbnb Reviews

Fewer control units were included in this specification, as some were automatically removed by the model during estimation, which may have reduced statistical power. In this case, the optimal model did not include any unobserved (latent) factors (r = 0), suggesting that the variation in sentiment could be sufficiently captured by observed differences and fixed effects alone, without the need to account for latent time-varying confounders. This further supports the conclusion that the treatment effect on sentiment, if any, is likely weak or inconsistent.

It is also important to consider that the sentiment score was derived from a multilingual NLP model that assigned numerical polarity to each review. While this allows for large-scale, cross-linguistic analysis, it may miss more nuanced or mixed expressions. In addition, aggregating sentiment at the neighbourhood-day level introduces sensitivity to low review volumes, especially during event periods, which may add noise and reduce the precision of the estimates.

Although the results presented in this section suggest that major cultural events did not produce a statistically significant effect on the average sentiment of Airbnb reviews, this outcome deserves a more cautious interpretation. Prior research by Richards and King (2022) shows that cultural festivals can enhance the visitor experience by generating stronger affective, conative, and novelty responses when compared to more static forms of cultural tourism such as museums or guided tours. These experiences often contribute to a more positive perception of the destination, increasing both satisfaction and intention to return or recommend.

From this perspective, it might seem intuitive to expect that such positive emotional responses could be reflected in guest reviews. However, the absence of a measurable effect on review sentiment suggests that these experiential gains may not translate directly into the way guests evaluate their stay on platforms like Airbnb. Festivals might enhance the broader perception of the destination without significantly altering the specific, listing-level feedback that reviews typically reflect. As shown by Cheng and Jin (2019) and Lin and Yang (2024), Airbnb reviews tend to focus on functional aspects such as location, cleanliness, or host responsiveness, dimensions that may remain relatively unaffected by external, short-term cultural events.

5.2. ROBUSTNESS CHECKS

5.2.1. BUFFER 3KM

5.2.1.1. SUPPLY

To assess the robustness of the results obtained using the Generalized Synthetic Control (GSC) model, the analysis was replicated with an alternative definition of the treated area. While the main specification defined treated units as neighbourhoods located within a 2 km radius of the event location, a robustness check was conducted by expanding this buffer to 3 km, thereby including additional areas potentially affected by the event.

Table 7 - Results for Airbnb Supply with 3 Km Buffer

Dependent variable: Supply of Airbnb listings	
ATT (Average Treatment Effect on the Treated)	-13.639
95% Confidence Interval	± 3.918
Number of treated units (Ntr)	19
Number of control units (Nco)	170
Total time periods (T)	119
Unobserved factors	3
MSPE (pre-treatment)	16.869

A total of 19 treated units were selected, representing an increase of 10 compared to the previous specification. The results remain qualitatively consistent across both specifications, confirming a post-event decline in the supply of Airbnb listings. With the 2 km buffer, the estimated Average Treatment Effect on the Treated (ATT) was -17.156 (95% CI: ±4.005), while expanding the buffer to 3 km yields a smaller ATT of -13.639 (95% CI: ±3.918), specified in

Table 7. Although the magnitude of the effect decreases with the wider geographic scope, the estimated ATT remains negative and the temporal pattern of the effect is broadly similar, as shown in the corresponding plots (Figures 10 and 12).

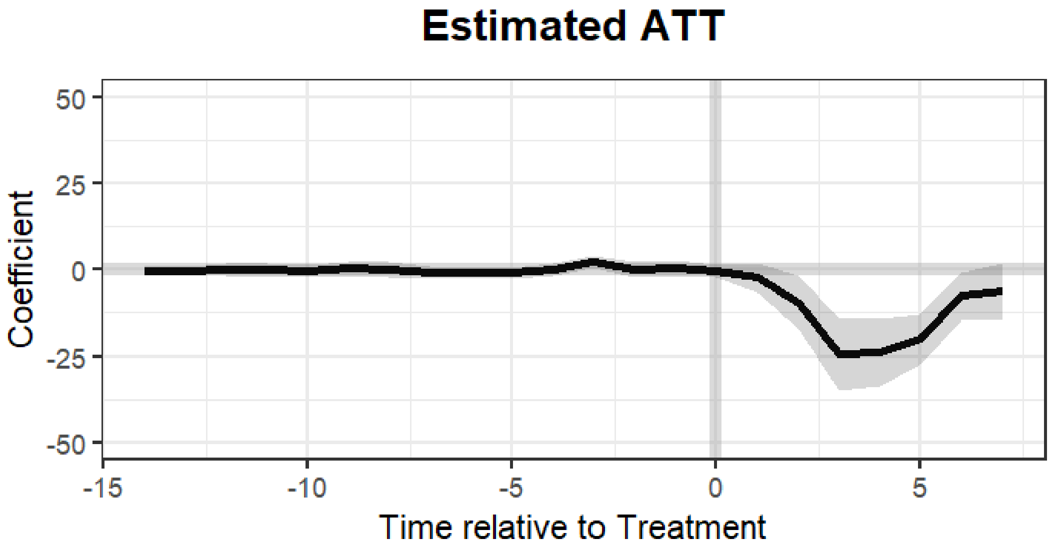

Figure 12 - ATT for Airbnb Supply with 3 Km Buffer

This attenuation is expected: increasing the buffer introduces areas that are less directly exposed to the event venue, where the impact on Airbnb activity is likely weaker or more diffuse. Nevertheless, the drop in listings remains visible after treatment, suggesting that the main signal persists even under a more inclusive definition of treated areas.

Taken together, these results suggest that the negative impact of cultural events on Airbnb supply is robust to different spatial thresholds. However, the attenuation of the effect with a wider buffer indicates that proximity matters, areas closer to event venues experience a more pronounced decline in available listings, likely due to intensified booking demand, as noted by Chikish et al. (2019). This spatial gradient reinforces the interpretation that events exert a localised, demand-driven influence on short-term rental dynamics, and the consistency across specifications strengthens the internal validity of this conclusion.

5.2.1.2. Reviews

For the reviews, expanding the buffer from 2 km to 3 km does not substantially alter the results. In the 2 km specification, the estimated ATT was-0.017 (95% CI: ±1.632), while with the 3 km buffer it remains similarly small at -0.022 (95% CI: ±1.544) as shown in Table 8. In both cases, the confidence intervals include zero and are relatively wide, indicating no statistically significant impact of the events on the average sentiment of Airbnb reviews.

Table 8 -Results for Airbnb Reviews with 3 Km Buffer

Dependent variable: Average sentiment of Airbnb reviews	
ATT (Average Treatment Effect on the Treated)	-0.022
95% Confidence Interval	± 1.544
Number of treated units (Ntr)	18
Number of control units (Nco)	159
Total time periods (T)	119
Unobserved factors	0
MSPE (pre-treatment)	0.089

The ATT plot (Figure 13) further reinforce this conclusion, showing no meaningful deviation from the pre-treatment trend. The sentiment trajectory remains stable before and after the event, with fluctuations well within the margin of uncertainty.

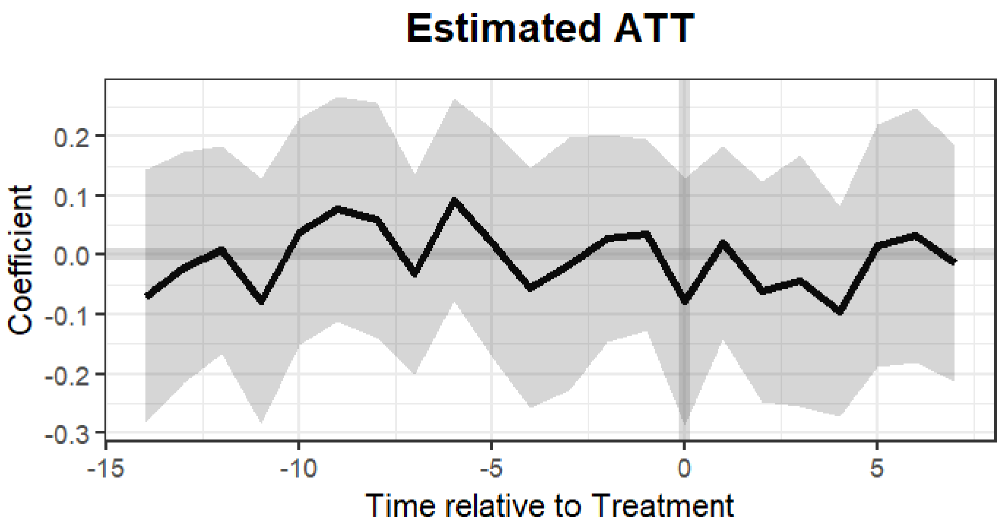

Figure 13 - ATT for Airbnb Reviews with 3 Km Buffer

Collectively, these findings indicate that the tone of guest reviews was not substantially influenced by the presence of cultural activities, regardless of spatial proximity. The consistency across spatial thresholds increases confidence in the stability of this finding and supports the interpretation that, unlike supply, guest sentiment remains largely unaffected during event periods.

5.2.2. INCREASING TIME WINDOW

5.2.2.1. SUPPLY

To assess the sensitivity of the main results to the chosen temporal window, the treatment effect was estimated using an extended event window that includes 30 days before and 15 days after the event, maintaining a fixed spatial buffer of 2 km around the venue. This specification is designed to capture potential anticipatory adjustments in supply and delayed responses that may not be observable within narrower windows.

Table 9 - Results for Airbnb Supply with increased Time Window

Dependent variable: Supply of Airbnb listings	
ATT (Average Treatment Effect on the Treated)	−5.107
95% Confidence Interval	± 3.887
Number of treated units (Ntr)	9
Number of control units (Nco)	180
Total time periods (T)	143
Unobserved factors	4
MSPE (pre-treatment)	28.786

The results presented in Table 9 and Figure 14 indicate a negative and statistically significant effect of cultural events on the supply of Airbnb listings. The estimated ATT is -5.107, with a 95% confidence interval of ±3.887, suggesting a meaningful reduction in active listings around the event period. Compared to the original specification (Table 5), where the ATT was -17.156 with a similar level of uncertainty (±4.005), the estimated effect is smaller in magnitude under the extended time window but remains clearly negative and statistically relevant.

The total number of time periods increases from 119 to 143, allowing for a more refined analysis of pre- and post-treatment dynamics. In both specifications, the ATT trajectory remains stable and close to zero prior to treatment, reinforcing the credibility of the counterfactual and suggesting the absence of pre-existing trends. However, the trajectory under the extended window reveals a notable difference in post-treatment behaviour: while the original model shows a sustained drop, the extended version displays a marked decline followed by a gradual rebound in supply approximately 10 days after the event. This pattern suggests that the effect, though initially pronounced, may be at least partially temporary.

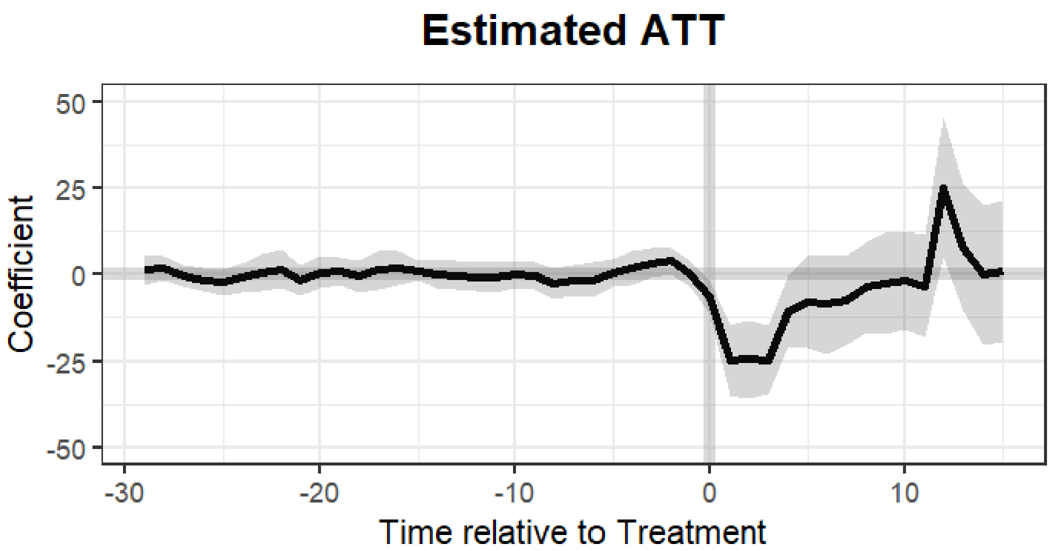

Figure 14 - ATT for Airbnb Supply with increased Time Window

Compared to the baseline model (which used a ±2 day window), the number of unobserved factors selected increased from three to four, reflecting a more complex underlying data structure as the temporal dimension expanded. Overall, the results suggest that cultural events trigger a temporary but significant contraction in Airbnb supply, with some recovery observed within two weeks after the event, rather than a sustained long-term effect.

5.2.2.2. Reviews

The results, summarized in Table 10 and visualized in Figure 15, reveal a very small and statistically insignificant effect of cultural events on the average sentiment of Airbnb reviews. The estimated ATT is 0.014, with a 95% confidence interval of ±1.660, clearly encompassing zero and ruling out any meaningful shift in sentiment attributable to the events. This finding is consistent with the baseline specification and reinforces the interpretation that guest sentiment remains broadly stable before and after event periods.

Table 10 - Results for Airbnb Reviews with increased Time Window

Dependent variable: Average sentiment of Airbnb reviews	
ATT (Average Treatment Effect on the Treated)	0.014
95% Confidence Interval	± 1.660
Number of treated units (Ntr)	9
Number of control units (Nco)	173
Total time periods (T)	143
Unobserved factors	0
MSPE (pre-treatment)	0.098

The extended window brings the total number of periods to 143, improving the pre-treatment trend estimation and reducing the MSPE to 0.098, a modest improvement compared to the baseline. The dynamic ATT plot further supports this conclusion: sentiment remains relatively flat in the pre-treatment phase, and although some volatility emerges after treatment, it stays well within the confidence bands, suggesting noise rather than systematic change.

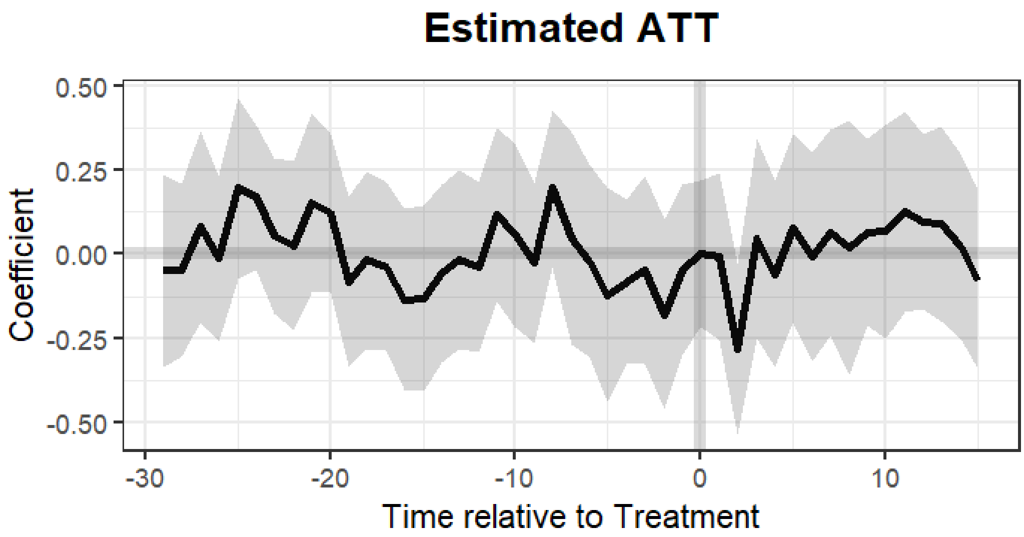

Figure 15 -ATT for Airbnb Reviews with increased Time Window

These results suggest that even under a broader temporal lens, cultural events do not significantly affect the tone of guest feedback. While events may influence availability or pricing through market mechanisms, they do not appear to impact guests' subjective experience in a way that is detectable through aggregated sentiment scores. This stability may reflect a general positivity bias in reviews or the fact that guest satisfaction is more influenced by listing-level factors than by external contextual events.

6. CONCLUSIONS AND FUTURE RESEARCH

This study explored the causal impact of major cultural events on short-term rental activity in Lisbon and Porto, using high-frequency Airbnb data. The analysis focused on two main outcomes: changes in listing availability and variations in the sentiment of guest reviews. By applying the Generalized Synthetic Control (GSC) method (Xu, 2017), it was possible to estimate counterfactual trends while accounting for unobserved heterogeneity and time-varying confounders.

The results show that cultural events consistently reduce the number of available listings, suggesting increased booking activity during event periods. These findings reinforce the idea that platforms like Airbnb provide a flexible and scalable response to temporary demand surges, complementing the limited capacity of traditional hotel infrastructure (Fairley & Dolnicar, 2017). Comparable surges in accommodation demand have also been observed in the hotel sector, where events such as SXSW or Formula One lead to sharp increases in bookings and revenue, particularly in higher-tier properties (Collins et al., 2022). Moreover, these results align with previous research showing that major cultural and sporting events generate pronounced, localised shifts in accommodation markets (Barreda et al., 2017; Heller & Stephenson, 2021), often accompanied by spatial displacement effects across different zones of the host city (Chikish et al., 2019).

In contrast, no statistically significant effect was found in the sentiment of reviews. While previous literature suggests that cultural festivals can enhance the overall visitor experience and contribute to a more favourable destination image (Gautam, 2022; Richards & King, 2022), such experiential benefits may not be reflected in the type of feedback typically left by Airbnb guests. Prior research has shown that reviews on the platform are often centred on listing-specific attributes such as location, cleanliness, or host responsiveness, rather than external or contextual factors (Cheng & Jin, 2019; Lin & Yang, 2024). In addition, the tendency for Airbnb reviews to be positive may help explain why small shifts in sentiment during event periods are difficult to detect. Overall, the results suggest that while cultural events clearly influence booking dynamics, their impact on the guest experience may not be fully captured through platform reviews, which tend to reflect more functional aspects of the stay than broader contextual impressions.

Some limitations should be acknowledged. Inside Airbnb data is released on a quarterly basis, and calendar data reflects future availability rather than historical bookings. This means the data reflects whether listings were marked as available at the time of data collection, not actual bookings. Additionally, the lack of higher-frequency data may miss short-term dynamics such as last-minute reservations/cancellations or speculative availability changes by hosts. In terms of sentiment, although natural language processing enables large-scale analysis, it may overlook nuances in guest expression, such as irony, cultural references, or mixed feelings. Aggregating sentiment at the neighbourhood-day level also introduces volatility when review volume is low, especially during narrow event windows, potentially masking short-term or localised effects. Furthermore, a known discontinuity introduced during the merging of datasets may have added noise to the estimation of latent trends, even though it did not overlap with the treatment periods. This issue was taken into account when interpreting the findings. Finally, although listing price was initially considered as a potential outcome, it was excluded from the final analysis. The lack of dynamic pricing behaviour in the dataset, with many listings showing static or rarely updated prices, meant it did not provide a reliable signal for detecting causal effects related to cultural events.

Future research could expand on this work in several directions. Sentiment analysis could be improved using models specifically trained for Airbnb reviews or by incorporating topic modelling to better capture the nuances of guest feedback. It would also be valuable to broaden the geographic scope and combine Airbnb data with other sources, such as hotel prices, tourism flows, or mobility patterns. If future data allows for dynamic pricing to be reliably captured, rather than static listing prices, analysing price responses to event periods would also be a valuable direction, providing a more direct measure of market adjustment beyond availability alone. Finally, analysing effects by event type, listing category, or host profile could help uncover patterns that remain hidden in aggregate-level results.

Overall, this study contributes to a better understanding of how short-term rental markets respond to temporary shocks associated with cultural events. Beyond the empirical results, it demonstrates the value of combining digital platform data with causal inference methods to capture localised dynamics in tourism and urban accommodation. As cities increasingly rely on events to attract visitors and shape their image, being able to assess their impact on the housing and tourism landscape, in a rigorous and nuanced way, becomes ever more relevant. While some questions remain open, particularly regarding guest experience, the approach developed here provides a foundation for further research into how tourism, technology, and urban life intersect.

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