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The Financial Legacy of Hosting the Olympic games; Economic Gains or Fiscal Burden?

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Abstract

This thesis investigates the financial and economic legacy of hosting the Olympic Games, focussing on macroeconomic indicators and investor sentiment. Rather than measuring direct expenditures or revenues, it analyses realized effects on GDP growth, unemployment, inflation, and central government debt, alongside stock market reactions.

Employing a matched difference-in-differences approach combined with an event-study analysis of stock market data, this research evaluates the overall impact of hosting and explores how effects vary between Summer and Winter Olympics and across developed and developing countries.

Findings suggest that the macroeconomic benefits of hosting the Olympics are modest and short-lived. GDP growth shows brief improvements around three to five years post-event, but these benefits diminish or reverse shortly after. Unemployment, inflation, and central government debt do not show consistent changes. Developed countries and hosts of Summer Olympics experience more stable economic outcomes compared to developing countries and hosts of Winter Games. Stock market reactions to key Olympic milestones are generally statistically insignificant, with the exception of a modest positive reaction when Summer Olympics or developed countries are awarded hosting rights.

Overall, the thesis challenges optimistic narratives surrounding mega-events, emphasizing the importance of institutional capacity, economic resilience, and careful policy evaluation when considering Olympic bids.

AI Usage Statement

Generate AI tool ChatGPT was used to assist in coding, data analysis, and refining the language of this thesis. Appendix 11 of this thesis provides a detailed account of the use of Generative AI tools during the development of this thesis. By submitting this thesis, I declare that I am fully responsible for the accuracy and completeness of its content. (*MTHEC 2024-25: GUIDELINES FOR USING GENERATIVE AI*, personal communication, n.d.)

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1 Introduction

During the summer of 2024, Paris hosted the Olympic Games. When wondering why a country would want to host such an event, the most cited reason is the possibility to enhance your countries' global appeal. For the Paris Olympic Games, the Olympic torch travelled the country, highlighting the places and people that make France what it is (*Why Host the 2024 Olympics in Paris*, n.d.). Next to that, the key motivations for Paris to host the Olympics include the boosting of employment and economic development, which have led to 2.6 million occupational integration hours (*A Lasting Legacy for the Country*, n.d.). According to the International Olympic Committee (IOC), hosting the Olympic Games generates powerful economic benefits, and it enables a region and country to develop (*Economic Benefits of Hosting the Olympic Games*, n.d.). However, these statements are increasingly challenged by empirical evidence.

These objectives align with broader claims that hosting a major sport event fosters long-term economic growth. However, some studies find that the costs associated with organizing an event of this size often outweighs the benefits. Even though there is extensive research on the economic impact of hosting major sports events, findings remain inconclusive. While some studies highlight the short-term boost in tourism and the development of infrastructure (Fourie & Santana-Gallego, 2011), others find that the long-term costs often outweigh the benefits (Baade & Matheson, 2016; Zimbalist, 2017). The difference in outcomes can also be seen between host cities. Cities such as Montreal (1976) and Rio de Janeiro (2016) experienced financial distress after hosting, characterized by large cost overruns and construction delays. In contrast, Los Angeles (1984) and Barcelona (1992) seem to have gained from hosting the Olympic Games, either by saving costs by relying on existing stadiums or infrastructure, or by experiencing a surge in tourism after hosting (Burton, 2024).

Few studies provide a systematic, long-term analysis explicitly differentiating between developed and developing economies or distinguishing between Summer and Winter Olympics. This study will extend the time horizon to assess whether hosting either the Summer or Winter Olympics leads to sustained national economic growth or creates a lasting financial burden at the national level. To do that, this study will employ a Difference-in-differences (DiD) approach,

comparing host countries with matched control non-host countries with similar economic characteristics.

By differentiating between Summer vs. Winter Olympics and developed vs. developing economies, this study also provides new insights into event-specific and country-specific financial outcomes. These contributions will attempt to fill gaps in the existing literature and offer a more comprehensive understanding of the financial legacy of hosting the Olympic Games.

This research aims to critically evaluate the financial consequences of hosting major sports events and determine whether they can serve as a sustainable economic investment, or are a fiscal burden on a country. This study primarily evaluates the economic and financial benefits of hosting the Olympic Games. While an extensive cost-benefit analysis ideally incorporates explicit cost assessments, such as detailed budgetary expenditures and long-term infrastructural maintenance costs, data limitations prevent a comprehensive analysis of these aspects within this thesis. Therefore, the analysis herein focuses primarily on realized economic outcomes, such as GDP growth, unemployment, inflation, and central government debt, while emphasizing the importance of future research that explicitly integrates cost considerations for a more complete picture.

To assess the financial impact of hosting major sports events, this study will use a comprehensive dataset that includes economic indicators like GDP, employment rates, inflation rates, and central government debt levels from host countries before, during, and after the events. This data will be retrieved from the World Bank and the International Monetary Fund (IMF). Additionally, this study uses stock market index data from the London Stock Exchange Group (LSEG), providing insights into investor sentiment and financial market reactions around key Olympic milestones. Lastly, this study will contain comparative data in the form of economic performance indicators – such as GDP growth, unemployment rates, inflation rates, and public debt levels– from non-hosting countries during the same periods to serve as control groups. This will allow the study to isolate the financial impact of hosting the Olympic Games. By using this dataset, the study will be able to estimate the short-term and long-term financial effects of a hosting major sports event.

This research will make use of a quantitative analysis to evaluate the financial legacy of hosting major sports events. This study primarily employs a difference-in-differences estimator to compare economic outcomes between host and non-host countries over time to isolate the impact of hosting a major sports event. Next to that, this study will use an event study methodology, looking at financial market reactions to hosting announcements and event occurrences, which will be analysed using stock market data to assess investor sentiment.

Additionally, it acknowledges limitations inherent in DiD and highlights alternative approaches, such as synthetic control methods. Although synthetic control methods offer robustness advantages by explicitly constructing counterfactual scenarios, data constraints and complexity limit their direct implementation in this study. However, future research could incorporate a synthetic control approach to strengthen causal inferences.

The structure of this thesis is as follows. The thesis will start with an introduction, where the research question and the societal and academic motivation will be outlined. This will be followed by a literature review, where existing research on the topic will be summarized to highlight the gaps. The data and methodology section provides a description of the data and their sources, an explanation of the four models this study will entail, and will discuss potential endogeneity issues. The results section will present the statistic results and the empirical findings. This will be followed with the conclusion and discussion section, which will summarize the key findings and discuss policy implications and suggestions for future research.

2 Literature review

Major sports events can be defined as reoccurring events of a fixed duration, that attract a large number of visitors, have significant media reach, involve substantial costs, and have a large impact on the built environment and the population (Müller, 2015). The Olympic Games, both Summer and Winter editions, can be categorized as a major sports event, because they reoccur every 4 years, have a fixed duration of about 16 days, often attract a large number of visitors from across the globe, while also being broadcasted worldwide, and has a large financial and physical impact on the host city and country.

In this research, the Summer and Winter Olympics will be the major sports events that are studied. This selection will offer a diverse range of case studies due to the variations in host countries, media visibility, and it has a relatively consistent format. The Olympics offer a wide range of different sports, with 35 sports integrated in the Olympic summer program for the LA 2028 Olympic Games, and eight sports with 15 disciplines in the Olympic winter program for the Milan Cortina 2026 Olympic Games (*Olympics Sports List*, n.d.). Next to the wide range of sports featured in the Summer and Winter Olympics, the Olympics Games are noted as the most appealing sports and entertainment event in the world, with the Olympic rings being one of the most widely recognized symbols globally (*Olympic Games Confirmed as the World's Most Appealing Sports and Entertainment Event*, 2022).

While this study specifically examines the Olympics due to their scale, global consistency, and economic impacts, other mega-events such as the FIFA World Cup also share these characteristics. Although these are not directly related to what is analysed here, findings may be broadly relevant to similar events. Future research could examine the extent to which these findings apply to other mega-events, such as the FIFA World Cup.

Long-term economic impact has no clear definition in the literature. Timeframes in the literature range from approximately five to over twenty years, depending on the study's focus. This study will define "long-term" as 10 years post-event, providing a balance between capturing sustained effects and maintaining a manageable timeframe.

Existing research on the economic impact of major sports events presents mixed findings. Some studies highlight short-term economic gains, such as increases in tourism and consumption, while others point to long-term fiscal burdens resulting from expensive infrastructure and underused facilities. These diverging results stem from methodological differences, event-specific dynamics, and broader macroeconomic conditions.

A common short-term benefit cited is the boost in tourism. Integrating studies across multiple events, Fourie & Santana-Gallego (2011) find that on average, mega-sporting events increase predicted tourism by roughly 8% in the same year, using data from 1995 to 2006. However, there are large differences between the types of events; the Summer Olympics and the FIFA World Cup seem to have a positive impact on tourism, while the Winter Olympics and the Rugby World Cup do not. A possible explanation the authors give for this is that the Winter Olympics and the Rugby World Cup are smaller events, compared to the Summer Olympics and the FIFA World Cup, and because the events they analysed were held in countries with an already strong tourism demand. A limitation of their study is that these events all take place every four years. With the data spread from 1995 to 2006, there will be at most three cases per event possible. To tackle this, the current research will involve a wider time spread, ranging from 1961 until 2023, enabling it to compare more events.

In contrast, long-term impacts are less consistently positive. Baade & Matheson (2016) argue that the Olympic Games frequently result in net financial losses for host cities by exploring the costs and benefits of hosting the Olympic Games. On the cost side, they identify three major categories: general infrastructure, specific infrastructure for competing venues, and operational costs. They also look at three major categories of benefits: the short-run benefits of tourist spending during the Games, the long-run benefits or the “Olympic legacy” which might include improvements in infrastructure, and intangible benefits such as the “feel-good-effect” or civic pride. By comparing costs and benefits, they find that in most cases the Olympics result in losses for host cities due to cost overruns, high costs for maintaining the facilities after the Games, and rising public debt. They only result in positive benefits under very specific and unusual circumstances, for example the possibility to use already existing transportation and sporting infrastructures, being able to reuse the built infrastructure after the event, and already having a

strong tourism demand. Following that, they also find that the cost-benefit proposition is worse for cities in developing countries than those in the industrialized world. This connects with the work of Zimbalist (2017), who states that the less developed a country is, the more it has to invest in transportation, telecommunications, hospitality, security, and sports infrastructure. Unless there already is a rational plan for developing a city or country that fully aligns with the investments needed to host the Games, the finances of hosting are not promising. This aligns with concerns that developing nations often overinvest in infrastructure that will be underused post-event, leading to debt accumulation.

A third perspective focusses on the international trade and investment implications of hosting. Rose & Spiegel (2011) describe the 'Olympic effect', whereby hosting the Games signals economic openness and results in a permanent increase in trade. However, they also find this effect for countries that bid for the Olympics unsuccessfully. This finding implies that the 'Olympic effect' on trade could reflect a policy signal, but it also suggests potential endogeneity, as countries bidding to host the event may inherently possess trade-friendly policies or environments. This challenges the notion that the economic impact of the Games is driven purely by structural changes, highlighting the role of perception and international visibility.

Additionally, literature exploring stock market reactions to major events underscores that investor sentiment can significantly anticipate economic outcomes (Billings & Holladay, 2012), a perspective that will be further explored in this thesis. A growing strand of literature examines how financial markets respond to the announcement or hosting of major sports events. Kavetsos & Szymanski (2010) assess the impact of mega-sporting events on national well-being, but indirectly find that investor confidence works as a transmission mechanism. Mirman & Sharma (2010) investigate the stock market impact for Olympic Games ranging from 1996 to 2010, where they compare the stock market reaction of countries that won the bid and countries that lost the bid to host the Olympics around the announcement date. They find that for Winter Games, stock markets in winning countries perform significantly worse than in countries who lost the bid. Their results for Summer Games are insignificant. Dick & Wang (2008) find contradicting results. They have used a comprehensive dataset with 15 Summer or Winter Games, with which they find insignificant overall results for the Winter Games. For the Summer Games, they find that

countries who won the bidding produce positive significant results, and they find no significant results for losing countries.

Summarizing, the literature on the economic impact of hosting major sports events present highly mixed conclusions. Some studies highlight short-term benefits like increased tourism, while others emphasize the financial burden that is the result of hosting. A possible reason why countries want to host the Olympic Games is the increase in trade, known as the 'Olympic effect', but the researchers also find this effect for countries that bid to host the Olympics unsuccessfully. However, the true financial legacy remains uncertain and depends on the context in which the event is hosted.

The main distinction in the literature is the difference between developed and underdeveloped countries, and how they might benefit from hosting. Developing countries tend to struggle more with cost-benefit propositions than those who are more developed. A possible explanation for this is that these countries often have lesser accommodations and infrastructure, leading to higher costs to bring this up to standard for the Games. Developed countries usually have much more of these things already in place, which can reduce costs and increase the chances of generating a positive return.

While the above studies have advanced our understanding of the financial legacy of hosting major sports events, several gaps remain. First, the time horizon used in most analyses is relatively short. Few studies track economic indicators beyond five years post hosting, which limits our understanding of sustained impacts. In response, this study adopts a 10-year post-event horizon to better capture the long-term effects.

Second, few analyses systematically differentiate between Summer and Winter Games. Given the differences in scale, global appeal, and seasonality, it is plausible that their economic impacts are different. This thesis explicitly models these effects separately to identify whether seasonal differences affect fiscal outcomes.

Third, the literature frequently emphasizes potential differences in outcomes between developed and developing host countries, suggesting that less-developed hosts may face more

significant financial risks. However, there are few empirical studies systematically comparing outcomes across income groups. This study addresses this gap through a sub-group analysis of macroeconomic effects.

Fourth, studies have typically focussed on macroeconomic indicators and underexplored financial market reactions. Stock prices offer a forward looking, real-time assessment of investor sentiment. By analysing cumulative returns (CARs) around key event milestones like bidding to host, IOC awards, and opening- and closing ceremonies, this research introduces a complementary perspective grounded in financial economics. Studies that have focused on financial stock market reactions often look at countries that win the bid to host versus countries that lost the bid, while this study will focus on other key event milestones as well, only for countries that have actually hosted the Olympics.

Finally, endogeneity presents a major challenge. Countries are not randomly selected to host. Instead, selection correlates with unobserved factors like institutional strength and investment readiness. Some recent contributions have used synthetic control methods (Abadie et al., 2010) or exploited ‘close-call’ IOC votes (Billings & Holladay, 2012) to approximate quasi-experimental designs. While this study relies primarily on a matched difference-in-differences approach, future work could explicitly apply synthetic control methods or exploit narrowly decided bidding outcomes (‘close-call’ designs) to further address endogeneity concerns, as will be discussed in section 3.3.5.

This study attempts to address several of the critical limitations identified in the existing literature by offering a multifaceted approach to understanding the financial legacy of hosting the Olympic Games. The first contribution is extending the post-event time window to ten years, allowing for a more robust examination of the long-term macroeconomic effects. By looking further than the typical five-year horizon, this research is more likely to capture delayed impacts and potential structural changes in host economies.

Another important contribution is the differentiation between Summer and Winter Olympic Games. These events differ a lot from each other. By treating them as distinct events in the

empirical analysis, this study tests whether the financial implications of hosting vary systematically between the two types, which has been underexplored in previous research.

Furthermore, this thesis introduces a comparative framework that distinguishes between developed and developing host countries. This allows for an assessment of whether economic context influences the financial outcomes of hosting. Previous research has highlighted that developing countries may struggle more with cost overruns and long-term debt, yet few studies have empirically tested this in a consistent framework. This comparative approach enhances the policy relevance of this study.

A fourth contribution is the integration of stock market reactions. This provides valuable forward-looking insights into investor expectations. This allows the examination of the mechanisms behind realized economic growth or the absence thereof, by capturing real-time sentiment and market perceptions of hosting's economic impacts. While many studies rely on national accounts data, this research incorporates an event study methodology to assess investor sentiment through cumulative abnormal returns (CARs). This dual approach provides both backward-looking and forward-looking insights into the economic implications of hosting.

Finally, this study uses a matched difference-in-differences approach to strengthen causal inference and reduce selection bias. While not eliminating endogeneity entirely, this approach improves upon simple before-after comparisons and offers a credible counterfactual for host countries.

Together, these contributions provide a complete, more nuanced understanding of the economic and financial consequences of hosting the Olympic Games and aim to inform future policy decisions regarding mega-event bidding and planning.

Building on these insights, this research will systematically analyse the financial legacy of hosting the Olympic Games, considering both short-term and long-term effects. The study will investigate how economic indicators like GDP growth, unemployment rates, inflation rates, and central government debt evolve before, during, and after hosting. Additionally, it will also examine whether the type of event influences the financial outcome by making a distinction between the Summer and the Winter Olympics, and whether the development status of a host

country influences the financial outcome by making a distinction between developed and developing hosts. Finally, this research examines investor sentiment by analysing stock market reactions to key Olympic-related announcements, offering insights into market expectations about the financial outcomes of hosting.

3 Data and methodology

3.1 Data

To estimate the financial legacy of hosting the Olympic Games, this study makes use of a panel dataset including multiple Olympic host and non-host countries over several decades. The panel structure allows for a comparative analysis of key economic indicators before, during, and after hosting the Olympic Games. Including a matched control group of non-hosting countries enables the application of a difference-in-differences (DiD) methodology to estimate the causal impact of hosting. Control countries were selected through a matching procedure as described in section 3.2 to ensure comparability in pre-treatment characteristics.

The primary data sources used in this study are the World Bank's World Development Indicators (WDI) (*World Development Indicators / DataBank*, n.d.), the International Monetary Fund (IMF) (*Global Debt Database*, n.d.), and financial data from London Stock Exchange Group (LSEG) (*Economic Data*, n.d.).

Table 1 summarizes the key variables, including their measurement approach, data sources, and coverage in terms of countries (i) and years (t):

TABLE 1

KEY DATA SOURCES AND CONTROL VARIABLES FOR ANALYSING ECONOMIC IMPACT OF HOSTING MAJOR SPORTS EVENTS

Variable	Measurement approach	Data source	Coverage (i, t)
Olympic host	Binary indicator (1 if hosted the Olympics, 0 otherwise)	IOC Official Data	Olympic host and control countries (1961-2023)

Variable	Measurement approach	Data source	Coverage (i, t)
GDP growth	Annual % change in GDP	World Bank (WDI)	Olympic host and control countries (1961-2023)
Unemployment rate	% of total labour force	World Bank (WDI)	Olympic host and control countries (1961-2023)
Inflation	Consumer prices (annual %)	World Bank (WDI)	Olympic host and control countries (1961-2023)
Central government debt	Total (% of GDP)	IFM & World Bank (WDI)	Olympic host and control countries (1961-2023)
Stock market reactions	Daily stock returns	LSEG	National index returns (daily)

These indicators will be applied in three separate difference-in-differences estimations, which will compare economic trends in host countries versus a control group of non-host countries with a similar economic profile. In addition, a stock market analysis is conducted using daily index returns data, allowing this study to evaluate investor sentiment and market expectations surrounding key Olympic event announcements. The following models will be explained in more detail in section 3.3:

1. Overall hosting impact model;
2. Summer vs. Winter Olympics model;
3. Developed vs. Developing countries model;
4. Stock market reactions to hosting the Olympic Games.

In addition to the key variables mentioned in Table 1, the dataset includes a broader set of macroeconomic control variables to improve the robustness of the estimations.

The following control variables are incorporated into both the matching procedure and the regression models:

- Demographic and structural indicators: total population (log), GDP per capita (constant 2015 USD);
- Fiscal and external accounts: trade (% of GDP), foreign direct investment (% of GDP).

These control variables help to reduce omitted variable bias and ensure that the estimated treatment effects reflect the impact of hosting the Olympic Games rather than underlying structural differences between host and non-host countries.

The data preparation process included harmonizing country-year observations, dealing with missing data through interpolation or exclusion when necessary, and constructing key treatment indicators such as host status, event year, and relative year, for use in dynamic event-time analyses. A detailed description of the data handling procedure, including interpolation and exclusion, are fully described in Appendix 10.

Lastly, to assess the financial market perspective, a separate dataset is constructed using daily stock market index data from the London Stock Exchange Group. This dataset enables the implementation of an event study framework that analyses abnormal stock returns around key Olympic announcements, such as hosting bid award and opening- and closing ceremonies. These returns are calculated by subtracting expected market returns from actual returns, using a standard market model. The expected returns are based on global market performance (ACWI index) and adjusted for risk-free returns (3-month US Treasury bill). These abnormal returns provide clear insights into investor sentiment and expectations regarding the economic implications of hosting the Olympics.

3.2 Determining control countries

To estimate the financial legacy of hosting major sports events on long-term economic outcomes, a credible counterfactual is required to estimate what economic outcomes would have occurred in host countries had they not hosted the Olympic Games. This study does that by identifying countries that have not hosted to serve as a control group, these are selected to be

statistically similar to host countries based on selected pre-treatment economic characteristics. This was done by using propensity score matching with the MatchIt package in R.

Matching helps to process the data by aligning the distribution of covariates between treated and control groups, mimicking the conditions of a randomized experiment (Stuart, 2010). This enhances the internal validity of the causal estimates from later models by ensuring that treatment and control groups are similar in relevant pre-treatment characteristics.

To match host countries with appropriate control countries, this study made use of a series of propensity score matching techniques using the MatchIt package in R. The dataset used for matching was limited to pre-treatment years only, ensuring that the covariates reflect conditions prior to hosting.

The following covariates were used for the matching process:

- *Log population;*
- *Annual GDP growth (%);*
- *Log Consumer Price Index (CPI);*
- *Inflation (GDP deflator, %);*
- *Log central government debt (% of GDP);*
- *Unemployment (% of labour force);*
- *Income group classification.*

Log transformations were applied to population, consumer price index, and central government debt to reduce the influence of outliers and improve covariate balance across countries. This transformation preserves the relative scale while moderating extreme values due to cross-country differences.

A logistic regression was used to estimate the propensity score, which is the probability of hosting conditional on these covariates. A key requirement of the matching procedure was that the covariates are balanced after matching, meaning that there should be no systematic differences between host countries and their matched control countries. To do this, this study

used propensity score matching to construct a control group of non-hosting countries that are statistically similar to host countries on key pre-treatment macroeconomic characteristics.

Matching was performed using nearest neighbour matching with a 2:1 ratio, which means that each treated country was matched with two non-hosting countries with the most similar propensity scores. Adding to that, exact matching on income group classification ensured that matches only occurred within the same economic development status, which is important for interpreting model 3, which distinguishes between developed and developing countries, later in this study.

The matching process included testing several matching methods, including full, optimal, and genetic matching. Full matching is a form of sub-classification wherein all units, both treatment and control, are assigned to a subclass and receive at least one match. Optimal matching performs optimal pair matching, which pairs treated and control units minimizing the overall sum of absolute distance across pairs. Genetic matching is a form of nearest neighbour matching which uses an algorithmically optimized generalized Mahalanobis distance. In the end, nearest neighbour matching with a fixed 2:1 ratio and exact income group matching was selected based on its interpretability, simplicity, and acceptable covariate balance. This method retained all treated observations while providing high-quality matches, as shown in the post-matching balance diagnostics. Standardized mean differences were substantially reduced across all covariates. This indicates that the treated and control groups are well balanced, strengthening the validity of comparisons made in this study and including regression models.

The result of the matching process is shown in Table 2, where each host country in the sample is listed alongside the two statistically matched non-host countries selected using nearest-neighbour propensity score matching with exact matching on income group.

TABLE 2
SUMMARY OF MATCHED TREATED AND CONTROL COUNTRIES

Treated_Country	Control_Countries
Australia	The Netherlands, Slovenia
Austria	Bulgaria, Ireland
Bosnia and Herzegovina ¹	Kazakhstan, Turkmenistan
Brazil	Colombia, Peru
Canada	Israel, Latvia
China	Argentina, South Africa
France	Estonia, Switzerland
Germany	Portugal, Saudi Arabia
Greece	Chile, Czechia
Italy	Denmark, Iceland
Japan	Cyprus, Finland
Korea, Rep.	Belgium, Lithuania
Mexico	Ecuador, Indonesia
Norway	Kuwait, Uruguay
Russian Federation	Romania, Trinidad and Tobago
Spain	New Zealand, Poland
United Kingdom	Slovak Republic, Sweden
United States	Croatia, Hungary

A detailed overview of the included Olympic Games, hosting year, hosting country, event type (Summer/Winter), and income classification (developed/developing), is provided in Appendix 9.

¹ Bosnia and Herzegovina was removed from the analytical sample because macro-economic data is incomplete for several key indicators.

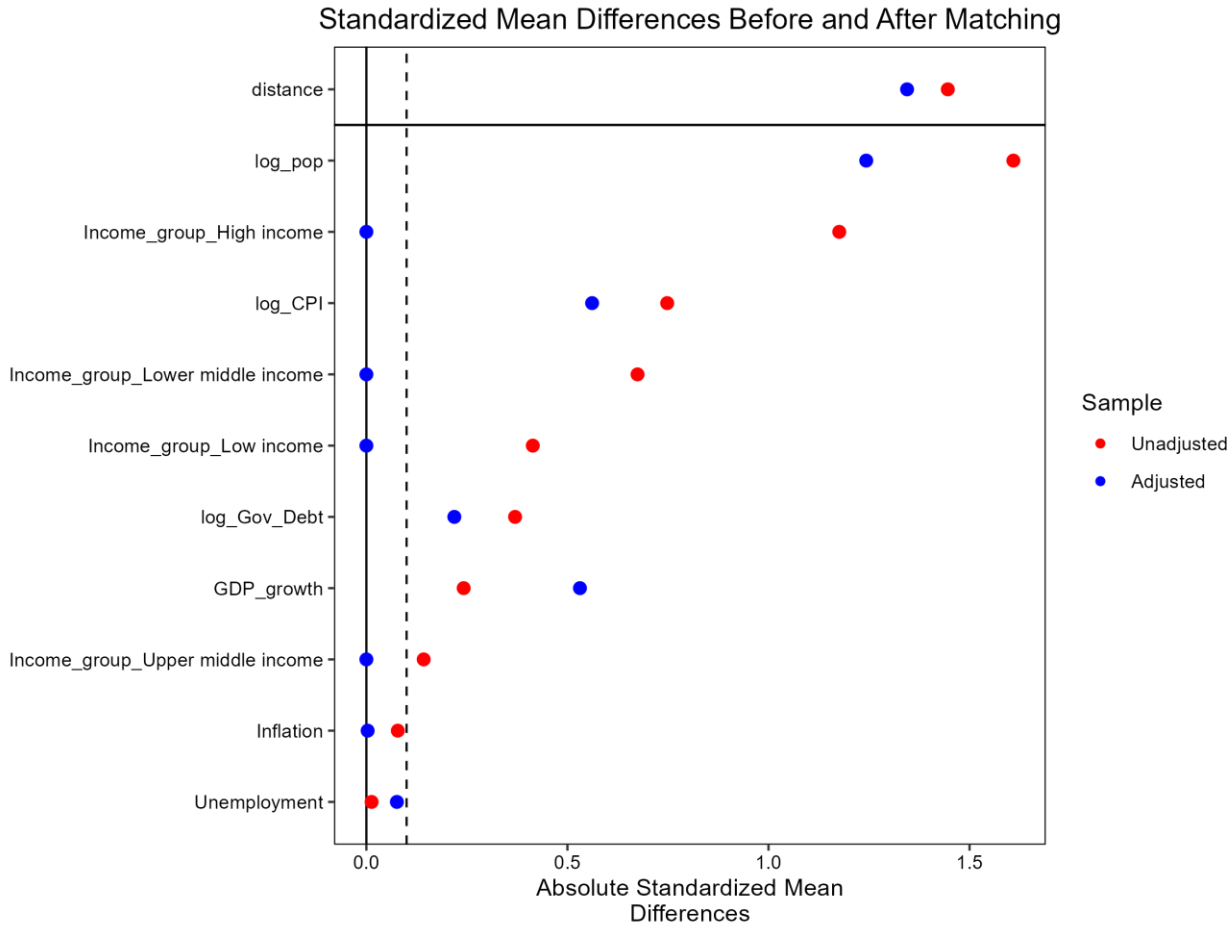


FIGURE 1
COVARIATE BALANCE BEFORE AND AFTER MATCHING

To verify the quality of the matching process, covariate balance was assessed before and after matching. Figure 1 visualizes the standardized mean differences (SMDs) for each covariate. The SMDs were calculated by dividing the mean difference of each covariate between groups by its pooled standard deviation. The smaller differences after matching indicate improved comparability between the treatment and control groups. Lower SMDs after matching indicate improved balance between treated and control groups, showing the quality of the propensity score matching process. In the literature, a SMD of around 0.1 is commonly used as a benchmark for acceptable covariate balance in matching studies (Greifer, 2025). A SMD below 0.1 indicates a good balance, as it implies the treatment and control groups differ by less than 10% of the pooled standard deviation. This benchmark is shown in the figure above by the vertical dashed line.

The substantial reduction in SMDs across most covariates confirms improved balance between the treatment and control groups. These improvements can be seen numerically in Table 3, which reports the means, standardized mean differences (SMDs) and variance ratios for each covariate.

TABLE 3
BALANCE STATISTICS BEFORE AND AFTER MATCHING

Before matching				
Covariate	Means Treated	Means Control	Std. Mean Diff.	Var. Ratio
<u>Distance</u>	0.521	0.064	1.446	5.635
<u>Population (log)</u>	17.57	15.228	1.609	0.697
<u>GDP_growth</u>	4.099	3.649	0.242	1.263
<u>CPI (log)</u>	3.603	4.343	-0.748	3.947
<u>Inflation</u>	30.099	23.955	0.078	2.699
<u>Gov Debt (log)</u>	3.477	3.736	-0.370	1.488
<u>Unemployment</u>	7.831	7.869	-0.013	0.313
<u>High income</u>	0.778	0.289	1.176	NA
<u>Low income</u>	0.000	0.133	-0.418	NA
<u>Lower middle income</u>	0.000	0.296	-0.691	NA
<u>Upper middle income</u>	0.222	0.281	-0.143	NA
After matching				
Covariate	Means Treated	Means Control	Std. Mean Diff.	Var. Ratio
<u>Distance</u>	0.521	0.096	1.345	4.37
<u>Population (log)</u>	17.57	15.761	1.243	1.347
<u>GDP_growth</u>	4.099	3.111	0.531	2.658
<u>CPI (log)</u>	3.603	4.158	-0.561	21.503
<u>Inflation</u>	30.099	29.852	0.003	3.662
<u>Gov Debt (log)</u>	3.477	3.63	-0.219	1.787
<u>Unemployment</u>	7.831	8.057	-0.076	0.59
<u>High income</u>	0.778	0.778	0.000	NA
<u>Low income</u>	0.000	0.000	0.000	NA
<u>Lower middle income</u>	0.000	0.000	0.000	NA
<u>Upper middle income</u>	0.222	0.222	0.000	NA

Table 3 shows the summary statistics for covariate balance before and after matching. The balance diagnostics suggest that the matching procedure significantly reduced bias for most covariates. Income groups were exactly matched, eliminating structural bias due to economic development levels. To improve covariate balance and address the skewed distribution of key variables, the matching procedure was performed using the natural logarithm of population, Consumer Price Index (CPI), and central government debt. Log-transforming these variables helps

reduce the influence of outliers and ensures more comparable treated and control groups. The overall reduction in mean differences supports the reliability of the matching procedure.

The outcome of the matching process serves two main functions in this study. First, it justifies causal interpretation by improving comparability between groups. Second, it prepared the data for subsequent models by producing a matched dataset that simulates what economic trends might have looked like in host countries had they not hosted.

3.3 Economic models

To estimate the long-term economic and financial impact of hosting the Olympic Games, this study relies on several economic models. These models aim to isolate the causal effect of hosting by comparing outcomes between host countries (treated) and matched non-host countries (control) over time. The main estimation technique employed across the first three models is a difference-in-differences (DiD) approach. All macroeconomic models in this thesis use a two-way fixed-effects (TWFE) difference-in-differences estimator with dynamic event-time dummies. The fourth, and last, model uses an event study tailored to stock market data.

In the regression analyses, log population is included as a control variable to adjust for any residual differences in country size, consistent with the variable used during matching. This approach helps further reduce bias and improve the precision of estimated treatment effects (Stuart, 2010).

To benchmark the performance of the matched sample, this study also estimates an unmatched or naïve difference-in-differences model that uses all non-host countries as controls and excludes covariates.

3.3.1 Model 1: Overall hosting impact

Model 1 estimates the dynamic long-term impact of hosting the Olympic Games on macroeconomic outcomes. Instead of using a single post-treatment dummy, this model employs a dynamic difference-in-differences framework using event-time indicators, where treatment status is interacted with relative event years. This allows for estimating year-by-year treatment effects, capturing both anticipation effects and lagged outcomes. Year 0, the Olympic year, is used

as the reference period. The model controls for macroeconomic covariates and includes country and year fixed effects. The model will look as follows:

$$Y_{it} = \alpha_i + \gamma_t + \sum_{k \neq 0} \beta_k (Treated_i \times RelativeYear_{k,it}) + X_{it} + \varepsilon_{it}$$

Where:

- Y_{it} is the economic outcome of interest (GDP growth, unemployment, inflation, or debt);
- α_i and γ_t are country and year fixed effects;
- $Treated_i$ is 1 if country i has been a host;
- $RelativeYear_{k,it}$ is the dummy for event time k relative to hosting;
- $Treated_i \times RelativeYear_{k,it}$ is the interaction term capturing dynamic year-specific impacts before and after hosting;
- X_{it} are macroeconomic control variables (e.g., trade);
- ε_{it} is the error term.

The coefficients β_k , which represents the treatment effect, the average impact of hosting, is of primary interest, capturing the difference in economic development between host and non-host countries.

3.3.2 Model 2: Summer vs. Winter Olympics

To assess whether the type of Olympic event matters on the economic outcome, model 2 estimates the financial effects of hosting the Olympic Games separately between Summer and Winter Olympics. Both sub-models follow the DiD structure used in model 1, but are estimated separate for Summer and Winter Games, enabling event-specific impact estimations. The two sub-models are:

- *Model 2a: focuses on countries that have hosted the Summer Olympics and their matched control countries;*
- *Model 2b: focuses on countries that have hosted the Winter Olympics and their matched control countries.*

Both models use the same DiD structure as model 1, but allows to analyse for event-specific effects. This distinction enables this study to explore whether the scale, global attention, or

infrastructure requirements of the Summer Games lead to different economic outcomes compared to the Winter Games.

Additionally, a Chow test will be conducted to determine whether differences in economic impact between both types of events are statistically significant.

3.3.3 Model 3: Developed vs. Developing countries

Model 3 examines whether the financial legacy of hosting is influenced by a country's level of economic development. To do this, model 1 will be estimated separately for developed and developing countries. The division between developed and developing countries will be based on World Bank income classification. This results in the following two sub-models:

- *Model 3a: focuses on high-income (developed) host countries and their matched control countries;*
- *Model 3b: focuses on upper middle-income (developing) host countries and their matched control countries.*

This approach allows to identify whether hosting the Olympics is more financially attractive for developed countries or for developing countries. Additionally, a Chow test will be conducted to determine whether differences in economic impact between developed and developing countries are statistically significant.

3.3.4 Model 4: Stock market reactions to hosting the Olympic Games

In addition to the three primary models focusing on macroeconomic outcomes, the fourth model will attempt to assess the short-term financial impact of hosting the Olympic Games by analysing stock market reactions. This model applies an event study methodology to examine how financial markets respond to key Olympic-related announcements, like a country winning the bid to host the Games, and opening- and closing ceremonies. Stock market data will provide a measure of investor sentiment and market expectations about the financial outcomes of hosting the Olympics.

In addition to the overall effects, this model also explores effect heterogeneity by event type (Summer vs. Winter Games) and by development status of the host country (developed vs. developing). This allows for assessing whether market reactions differ across contexts.

This model uses daily stock market index data for each host country and compares actual returns to expected returns derived from a market model. Specifically, a country's excess return (stock return minus the risk-free rate) is regressed on the world market's excess return in an estimation window around the event. The residuals from this regression, the abnormal returns, reflect the portion of the return that cannot be explained by general market movements. Summing these abnormal returns across the event window yields the cumulative abnormal return (CAR), which serves as the dependent variable in the analysis.

The events analysed in this model are chosen because they represent distinct moments in the Olympic timeline that could possibly trigger market reactions. For each of these event types, t-tests are conducted on CARs across host countries to determine whether average market reactions are statistically different from zero.

This approach offers a complementary view of the financial legacy of hosting. Whereas macroeconomic models measure realized impacts over time, this event study captures investor expectations and sentiment about the anticipated economic and financial legacy of hosting the Olympics.

3.3.5 Limitations of the difference-in-differences approach

While this study uses the widely accepted difference-in-differences (DiD) methodology to evaluate the economic impacts of hosting the Olympic Games, recent research highlights potential issues with traditional DiD methods when events occur at different times across countries and effects vary (Cunningham, 2021). The staggered timing of the Olympics means that hosts differ systematically in their economic conditions and responses to hosting, which can lead to misleading estimates if not carefully addressed.

A key limitation is the reliance on the parallel trends assumption, which states that treated and control countries would have followed similar economic trajectories if the event had not occurred. This assumption is not testable directly and has faced careful examination (Roth et al., 2023). Although this study includes extensive pre-event testing, some unobserved factors could still challenge this assumption.

Alternative approaches such as the synthetic control method (SCM) could address these issues by constructing a synthetic version of the host country from a combination of similar non-host

countries (Abadie, 2021; Gilchrist et al., 2022). These approaches avoid parallel-trend assumptions by explicitly creating comparable counterfactual scenarios. However, they require extensive and complete data series, often challenging to obtain historically.

Additionally, methods using narrowly-decided Olympic bid votes, the ‘close-call’ design, could approximate randomization (Billings & Holladay, 2012), but detailed IOC voting data is not always publicly available.

Given current data limitations, this research adopts the matched DiD approach for comparability with prior studies, but acknowledges these alternative methods as promising routes for future research.

Finally, this study’s use of a matched difference-in-differences (DiD) event-study framework remains consistent with a growing body of empirical work evaluating the macroeconomic effects of mega-events. For instance, Hotchkiss et al. (2003) apply a DiD framework to estimate employment and wage effects of the 1996 Atlanta Olympics, while Baade and Matheson (2016) summarize several studies using panel-based DiD models to estimate the short- and long-term economic legacies of the Games. These studies validate the DiD methodology as a transparent and replicable way to identify treatment effects in the absence of randomized experiments, especially when careful matching, timing, and pre-trend checks are applied.

3.4 Summary

The methodological framework enables a multidimensional evaluation of the financial legacy of hosting the Olympics. By making use of a matched difference-in-differences approach across multiple models, the study provides a robust empirical strategy to isolate the economic and financial effects of hosting the Olympic Games.

The four models outlined in this chapter serve complementary purposes. Model 1 estimates the dynamic long-term economic impact of hosting the Olympics on macroeconomic outcomes by interacting treatment status with relative years around the Olympic event. This allows for year-by-year estimates of hosting impact on GDP growth, unemployment, inflation, and central government debt. Model 2 breaks down the analysis by Olympic type, distinguishing between Summer and Winter Games to assess whether event scale and seasonality affect the outcomes

differently. A Chow test is applied to formally assess whether the effects differ between the two event types. Model 3 divides the host countries by development level, comparing the effects between developed and developing countries to determine whether the financial legacy varies, with additional Chow tests to validate the subgroup differences. Model 4 employs an event study methodology, analysing short-term stock market reactions to key Olympic-related announcements, offering a financial market perspective on investor sentiment expectations.

Together, these models provide a comprehensive assessment of whether hosting the Olympic Games yields economic benefits or financial burdens, and under what conditions.

Although matching improves group comparability, endogeneity due to self-selection into hosting remains a concern. A detailed discussion on further approaches and limitations is described in the conclusion and discussion section.

4 Results

This chapter presents the empirical findings on the financial legacy of hosting the Olympic Games. Building on the methodological framework outlined in chapter 3, the results are structured around the four main models developed to assess the economic and financial impact of hosting the Olympics. These models investigate: (1) the overall impact of hosting, (2) the difference between Summer and Winter Games, (3) the difference between developed and developing countries, and (4) the financial market responses to Olympic-related announcements.

For the first three models, the analyses make use of a difference-in-differences approach using panel data on macroeconomic indicators such as GDP growth, unemployment, inflation, and central government debt. These models are estimated using matched host and control countries to ensure comparability. Additionally, a stock market event study is employed to capture investor sentiment and short-term financial market reactions.

The following sections will present the results for each model, supported by regression tables and graphical visualizations.

4.1 Model 1: Overall hosting impact

This section presents the results of the baseline model estimating the overall financial legacy of hosting the Olympic Games. The objective is to identify whether hosting the Olympics generates significant changes in macroeconomic indicators such as GDP growth, unemployment, inflation, and central government debt. The estimation is based on a difference-in-differences framework comparing host countries to matched non-host countries over time.

Detailed regression results are provided in Appendix 1, with corresponding event-study visualizations in Appendix 2. These offer insights into both the short- and long-term macroeconomic impacts of hosting. Below, the findings will be discussed in detail for all four outcomes.

Pre-treatment coefficients for GDP growth show no signs of divergence. A Wald test confirms the parallel trends assumption ($\chi^2 = 0.637$, $p = 0.78$), indicating no statistically significant differences between host and control groups before the event.

While none of the pre-treatment coefficients are statistically significant, this does not hold for the post-event window. Three years after hosting, a statistically significant GDP growth increase of 0.802 percentage points ($p < 0.05$) is observed. This short-term gain is not sustained, as the following year GDP growth declines significantly by -0.859 percentage points ($p < 0.10$). These results suggest a brief post-event expansion that quickly fades. The absence of persistent positive effects on GDP growth implies that any potential economic benefits from hosting the Olympics materialize only briefly and ultimately dissolve once construction, tourism, and public effects wear off. This is in line with existing literature that questions the long-term economic benefits of hosting major sports events, particularly when the necessary investments do not yield the expected economic returns.

Among the covariates, unemployment has a significantly negative effect on GDP growth (-0.234, $p < 0.05$), while trade (+0.058, $p < 0.01$) and foreign direct investment (+0.003, $p < 0.05$) are associated with higher GDP growth. Population has a marginally significant positive effect (+0.8552, $p < 0.10$). Inflation and central government debt did not significantly affect GDP growth in this model.

The unemployment model shows no evidence of parallel trend violations with a Wald statistic of $\chi^2 = 1.306$ ($p = 0.22$), confirming that none of the pre-Olympic interaction terms are individually or jointly significant. This strongly supports the parallel-trends assumption for the unemployment outcome.

Most time-event coefficients are statistically insignificant, suggesting that hosting the Olympics does not lead to systematic changes in national unemployment rates. The only statistically significant result is ten years prior to hosting, when the unemployment rate seems to decrease (-0.732, $p < 0.10$). Given its distance from the event, this is likely unrelated to Olympic planning and may reflect self-selection into hosting. No post-treatment coefficients are statistically significant, indicating that hosting the Olympics does not systematically affect national unemployment rates.

This result is consistent with previous studies that find limited effects of major sports events on employment, especially in the short-run. The absence of a significant decrease in unemployment can be attributed to the fact that such events, while generating temporary jobs during the event itself, do not create a lasting structural impact on the labour market. Overall, the results suggest that while hosting a major sports event might generate some temporary jobs, it does not lead to any significant changes in the overall unemployment rate over time.

However, some control variables do significantly influence unemployment. Central government debt and foreign direct investment are both associated with higher unemployment rates (+0.062, $p < 0.01$; +0.0061, $p < 0.0001$), and population is strongly positively related (+14.91, $p < 0.001$), likely reflecting structural labour market effects in countries with larger populations. GDP per capita is negatively associated with unemployment (-0.0005, $p < 0.001$), consistent with better labour market outcomes in wealthier economies.

The joint Wald test of the pre-event coefficients for inflation also supports parallel trends in the pre-treatment period ($\chi^2 = 1.116$, $p = 0.35$).

The coefficients for inflation are largely insignificant, indicating that hosting a major sports event does not have a significant effect on the national inflation rate. In the years before the event, there is no significant difference between host and control countries in terms of inflation. After the event, while coefficients fluctuate, they, again, do not reach statistical significance, suggesting that hosting does not have a lasting impact on inflation.

Overall, the findings suggest that inflation is largely unaffected by hosting the Olympic Games. This could be because inflation is influenced by monetary policy, external shocks, and global price trends, which are not directly related to the event itself. Additionally, while there may be a short-term price increase associated with hosting an event, for example due to increased demand and supply-side constraints, these effects do not appear to be statistically significant or persistent.

Only one control variable is statistically significant, GDP per capita is positively associated with inflation (+0.0008, $p < 0.05$). This suggests that wealthier countries tend to have higher inflationary pressures.

Unlike the other outcomes, the pre-trend null hypothesis for central government debt is strongly rejected ($\chi^2 = 3.604$, $p < 0.0001$), indicating systematic pre-treatment differences between host and control countries. This suggests that caution is required in interpreting the post-event coefficients.

Despite this limitation, one year after hosting, a statistically significant reduction in central government debt is observed (-1.603, $p < 0.05$). This could reflect post-event fiscal consolidation following the capital expenditures tied to the Games. No other time-event coefficient is significant.

Control variables behave largely as expected. Unemployment negatively affects GDP growth and is associated with higher debt levels, likely due to increased fiscal burdens. Trade and foreign direct investment are positively associated with GDP growth. Population size has a positive effect on GDP and inflation, but is negatively associated with debt, possibly due to scale economies in public finance. Higher GDP per capita correlates with lower unemployment and modestly higher inflation, consistent with consumption-driven price pressures in wealthier economies.

Taken together, the estimates suggest that while fiscal fundamentals matter, hosting the Olympics itself does not systematically worsen sovereign debt ratios.

The explanatory power of the regressions varies across the different dependent variables. The GDP growth model explains a small proportion of within-country variance, with an R^2 of 0.355 and a within R^2 of 0.064, indicating that the included variables explain approximately 6,4% of the variation within countries over time. The unemployment model exhibits a strong overall fit ($R^2 = 0.886$, within $R^2 = 0.423$), suggesting that the model effectively captures key determinants of labour market fluctuations. For inflation, the model shows a lower explanatory power ($R^2 = 0.661$, within $R^2 = 0.148$), possibly due to inflation's dependence on multiple external factors not captured in the model. Lastly, the central government debt model displays a moderate explanatory power ($R^2 = 0.89$, within $R^2 = 0.301$), reflecting the robust predictive capacity of the included explanatory variables and fixed effects.

Summarizing, the results from model 1 reveal a nuanced picture of the economic effects of hosting the Olympic Games. GDP growth shows a modest post-Games lift three years after hosting. However, this increase is short-lived since the year after shows a significant drop in GDP growth again. Unemployment only shows a significant coefficient ten years before the event, suggesting a drop in the unemployment rate, likely due to self-selection into hosting. Inflation shows no detectable Olympic effect. Central government debt seems to decrease one year after hosting, with a significant negative coefficient. Control variables mostly behave as expected, with a higher unemployment rate damping GDP growth, larger public debt worsening labour-market outcomes, unemployment expanding central government debt, and richer countries see a lower unemployment rate, but potentially higher inflation.

Policymakers should carefully weigh the potential economic returns against the long-term fiscal obligations when considering the costs of hosting major sports events. Any GDP growth from hosting appears short-lived and offset by a longer-run slowdown, while unemployment, inflation, and public debt trajectories do not show consistent or significant post-event shifts. Governments should therefore weigh modest, temporary growth benefits against the risk of long-term economic stagnation and ensure that expansionary narratives do not rely on sustained macroeconomic gains.

To illustrate how critical matching and covariate adjustments are, Appendix 8 reports a naïve event-study that uses every non-host country as a control country and excludes all control variables. Compared with the matched results in Appendix 1, the naïve estimates exhibit large and significant pre-event differences, violating parallel trends. Post-event coefficients are larger and fluctuate widely, exaggerating effects on GDP growth. This emphasizes why balanced matching is essential, without it, existing differences inflate perceived Olympic impacts, undermining causal interpretation. Without matching, the positive bias suggests host countries tend to have stronger growth trends before hosting, likely due to selection bias. This is because countries self-select into hosting major events, often due to already having strong or improving economic conditions and good infrastructure in place. Consequently, naïve estimations, without

matching, would capture pre-existing growth trends rather than pure event effects, overstating the apparent benefits of hosting.

4.2 Effect heterogeneity: Type of Olympics and Development level

The financial and economic legacies of hosting major sports events like the Olympic Games are complex and contingent upon various contextual factors. Existing research often generalizes effects across different host nations and event types, potentially obscuring critical differences. This section addresses this concern by exploring two distinct yet interconnected dimensions of heterogeneity: the type of Olympics (Summer vs. Winter) and host-country development status (developed vs. developing). By systematically comparing these subsets, this analysis provides nuanced insights into the diverse and context-specific legacies associated with hosting the Olympic Games.

4.2.1 Model 2: Summer vs. Winter Olympics

The Olympic Games take place in two different forms: the Summer and Winter editions. Although both events are globally significant, their economic implications can differ dramatically due to differences in scale, infrastructure demand, audience reach, and media exposure. The results are reported in Appendix 3 and visualized in Appendix 4.

Summer Olympics typically involve extensive infrastructure developments, including transportation networks, sporting venues, housing facilities, and hospitality services, necessitating substantial financial commitments from host countries. Due to their larger global audience and the vast scale of the event, they usually attract considerable international attention, resulting in an influx of tourists and international investments. However, these potential benefits do not guarantee sustained positive economic outcomes.

Empirical results suggest that the Summer Olympics generate modest economic gains, concentrated primarily in the short- to medium term post-event period. For instance, GDP growth displays a modest yet significant increase two years after the event took place, potentially reflecting delayed effects of increased tourism, trade, and infrastructural utilization. However,

these benefits do not persist beyond hosting, suggesting that sustained economic growth is not an automatic consequence of hosting the Summer Olympics.

No statistically significant effects are observed for unemployment, inflation, or central government debt a decade before or after hosting the Summer Olympics.

Among the control variables in the Summer Olympics regressions, inflation has a significantly negative effect on GDP growth, suggesting that inflationary pressure may dampen growth potential. Population is positively associated with GDP growth and negatively with debt, possibly reflecting scale economies in taxation and public spending. GDP per capita shows a mildly positive influence on both GDP growth and inflation, yet is associated with a lower unemployment rate, indicating that more developed economies tend to exhibit stronger labour market conditions.

Winter Olympics differ substantially from their Summer counterparts, possibly due to their specialized infrastructure requirements and seasonality constraints. Winter Games are generally smaller in scale but require highly specialized and often expensive infrastructure, such as winter sports facilities and climate-dependent venues. This specialized infrastructure can be costly and challenging to repurpose or maintain, significantly influencing the host country's long-term economic legacy.

The results of this analysis show economic volatility associated with hosting Winter Olympics. Host countries often experience pronounced increases in GDP growth during the early planning and infrastructure-building phases, which is statistically significant eight years before the event takes place. This highlights the initial optimism and intensive construction activities. This growth trend reverses five years prior to hosting, when GDP growth significantly decreases again. The inflation rate decreases significantly three years before the event, possibly due to anti-inflation policy responses. Central government debt decreases significantly one year after hosting, possibly reflecting post-event fiscal consolidation or efforts by host governments to meet budgetary targets after the surge in pre-event spending. Despite common concerns about long-term debt burdens from hosting, the absence of sustained post-event increases in debt suggests that some fiscal risks may be managed effectively by host governments.

The control variables for Winter Olympics hosts show several notable relationships. Inflation again exerts a negative influence on GDP growth, consistent with macroeconomic theory. Unemployment negatively affects GDP growth but increases central government debt, likely due to elevated welfare costs or a weaker revenue base. Central government debt is positively associated with both GDP growth and unemployment, potentially reflecting stimulus-driven spending without corresponding job creation. Foreign direct investment has a positive and significant impact on GDP growth, underscoring the role of capital inflows. Lastly, population size is positively associated with both GDP growth and inflation, likely reflecting demand-side pressures in larger economies.

Formal statistical Chow tests, as reported in Table 7 in Appendix 7, confirm significant differences in economic outcomes between Summer and Winter Olympic hosts across all four outcomes. These findings validate that the economic consequences of hosting differ meaningfully depending on the type of Olympic Games. Overall, this model highlights the importance of distinguishing between Summer and Winter events when evaluating the financial legacy of hosting the Olympics.

4.2.2 Model 3: Developed vs. Developing hosts

Beyond the event type, the economic flexibility and institutional capacity of the host country critically influences the Olympic legacy. It is important to note that the sample contains more developed (high-income) than developing (upper-middle-income) host countries. This imbalance reflects historical trends, with developed nations more frequently bidding for and securing Olympic hosting rights due to their stronger institutional capacity and larger infrastructure budgets. As a result, the findings for developed countries are based on a broader and more diverse set of cases, which may partially account for the greater statistical precision observed in their estimates.

This study explicitly compares outcomes between developed (high-income) and developing (upper middle-income) countries to explore how economic development level shapes hosting impacts. The results are reported in Appendix 5 and visualized in Appendix 6.

Developed countries often benefit from robust institutions, advanced infrastructure, and greater fiscal flexibility, which enhances their ability to manage the economic shocks of mega-events. Empirical evidence confirms that developed host nations generally exhibit greater macroeconomic stability throughout the Olympic cycle. Developed hosts experience a significant increase in GDP growth three years post-event, followed by a significant decrease five years after hosting. This turns around again nine years after the event, which shows a significant positive coefficient. These significant GDP growth improvements occurring in the medium to long term post-event likely reflects effective leveraging of Olympic-induced infrastructure improvements and international attention into broader economic benefits.

Labour market outcomes in developed countries remain relatively stable, with only one significant coefficient. Ten years before the event takes place, the estimations show a negative impact on the unemployment rate. Given its distance from the event, this is likely unrelated to Olympic planning and may reflect self-selection into hosting. While temporary job creation occurs during event preparations, lasting structural improvements in unemployment rates are less evident, highlighting the temporary nature of event-specific labour demands. Inflationary pressures are also minimal, with no significant results a decade before or after hosting the Olympics.

Fiscal outcomes further demonstrate stability. Developed hosts appear to manage Olympic-related fiscal pressures effectively, avoiding long-term increases in long-term debt, reflecting efficient post-event utilization of Olympic infrastructure. One year after hosting shows a significant negative coefficient, suggesting that one year after hosting central government debt decreases significantly.

Among the control variables for developed countries, a higher unemployment rate is associated with lower GDP growth and higher levels of central government debt, suggesting countercyclical fiscal responses. Central government debt and foreign direct investment are both associated with increases in unemployment, possibly reflecting fiscal strain and temporary capital inflows without sufficient job creation. Foreign direct investment and trade both positively affect GDP growth, aligning with expectations about openness and competitiveness. Population size has a broad influence, raising GDP growth and the unemployment rate, and reducing public debt levels. This

is likely due to economies of scale and stronger domestic markets. Finally, higher GDP per capita reduces unemployment but is linked to a modest increase in inflation, which may reflect higher domestic consumption in wealthier economies.

In stark contrast, developing host countries experience greater economic volatility and face significant challenges managing Olympic-related economic shocks. GDP growth trajectories in developing countries exhibit pronounced volatility, reflecting lower institutional capacity and vulnerability to external shocks. There are statistically significant coefficients eight, five, three, and two years before hosting, suggesting that developing countries may experience anticipatory economic growth tied to infrastructure investments, international signalling, and policy optimism. However, this positive trend is not sustained after the event. GDP growth significantly decreases two and three years after hosting, which may reflect the post-event fading of stimulus or inefficiencies in translating Olympic investment into sustained economic performance.

Labour market dynamics in developing countries are less volatile overall, with only one statistically significant coefficient, a decrease in unemployment two years after hosting. This might reflect early hiring linked to infrastructure development or short-term optimism among firms. However, the lack of post-event effects suggests that these labour gains are not sustained.

Inflation shows no significant results a decade before or after hosting the Olympics.

Developing countries show fluctuating debt patterns. A significant increase occurs eight years before hosting, followed by a drop at four years before the event. Two and five years after the event takes place, central government debt increases significantly again. This is followed by a significant decrease seven and nine years after the event takes place.

In developing countries, inflation has a negative impact on GDP growth, which is consistent with the inflation-growth trade-off frequently observed in emerging markets. Central government debt appears positively associated with GDP growth, possibly reflecting fiscal-driven growth strategies. Higher levels of trade support both GDP growth and lower unemployment, highlighting the role of exports and global integration. Population is linked to higher central government debt, which may signal infrastructural or social expenditure pressures. Higher GDP per capita is associated with lower unemployment and lower debt.

Statistical tests, as reported in Table 8 in Appendix 7, confirm significant heterogeneity between developed and developing countries across the macroeconomic indicators. Chow tests for all four economic outcomes reject the null hypothesis of equal effects, suggesting there is significant divergence between developed and developing countries. This reinforces the importance of host-country institutional capacity and economic resilience in determining Olympic legacies.

4.2.3 Comparative insights and policy implications

Taken together, these analyses illustrate that economic outcomes from hosting the Olympic Games are context dependent. They reveal distinct patterns of effect heterogeneity along two dimensions, the type of Olympic event (Summer vs. Winter) and the economic development level of the host country (developed vs. developing). Policymakers and stakeholders must recognize that the decision to host the Olympics cannot be guided by generalized or overly optimistic economic forecasts. Instead, a careful, context-specific analysis of potential economic and fiscal risks versus benefits is essential.

The results show that developed countries are generally better equipped to translate Olympic-related investments into sustained macroeconomic benefits, while developing countries face more volatile outcomes, particularly in terms of debt and growth stability. Similarly, hosting the Summer Olympics is more likely to generate short-term growth impulses than the Winter Games, although such benefits tend to fade quickly. Hosting the Games does not inherently guarantee sustained economic growth or significant labour market improvements. Instead, long-term outcomes are shaped by a combination of event scale, infrastructure legacy, and the host country's institutional capacity to manage large-scale investments and translate visibility into durable gains. Recognizing this heterogeneity can help policymakers design strategies that minimize economic risks and maximize the potential for sustained benefits, ultimately supporting informed and responsible decisions about Olympic hosting commitments.

4.3 Model 4: Stock market reactions to hosting the Olympic Games

4.3.1 Overall effect

This section analyses cumulative abnormal returns (CARs) in host country stock market returns around major Olympic event milestones. These milestones are the bid announcement, the awarding announcement, the opening ceremony, and the closing ceremony. This will be done by using each host-market's main stock-index return, the global benchmark ACWI (USD), and the 3-month US T-bill as the risk-free rate. Two symmetric event windows are examined: five days before and after the event (-5, +5), and ten days before and after the event (-10, +10).

Table 4 reports the mean CARs, standard deviations, and the corresponding one-sample t-statistics, and Figure 2 plots individual CAR observations by event date, symbol-coded by window and color-coded by event type. The horizontal dashed line denotes zero abnormal return.

TABLE 4
AVERAGE CUMULATIVE ABNORMAL RETURNS (CAR) BY EVENT TYPE AND WINDOW

Event_type	Window	<i>n</i> events	Mean CAR	SD CAR	<i>t</i> -stat	<i>p</i> -value
Bid Announcement	(-5,5)	6	-0.0108	0.0129	-2.06	0.0944
Bid Announcement	(-10,10)	6	0.00960	0.0177	1.33	0.242
IOC Award	(-5,5)	7	0.00216	0.0512	0.112	0.915
IOC Award	(-10,10)	7	0.00893	0.0377	0.627	0.554
Opening Ceremony	(-5,5)	7	0.000496	0.0111	0.118	0.910
Opening Ceremony	(-10,10)	8	-0.00874	0.0226	-1.09	0.311
Closing Ceremony	(-5,5)	8	-0.0143	0.0324	-1.25	0.252
Closing Ceremony	(-10,10)	8	-0.0205	0.0584	-0.992	0.354

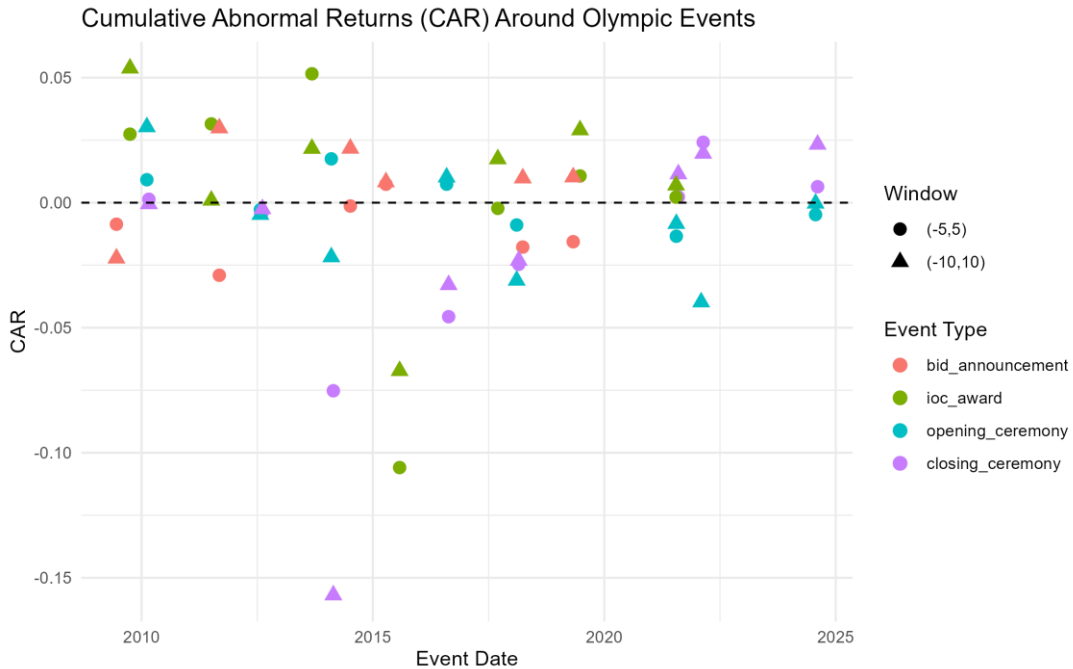


FIGURE 2
INDIVIDUAL CAR OBSERVATIONS

Bid announcements result in the only window that approaches statistical significance. The average CAR over $(-5, +5)$ days is -1.08% ($t = -2.06$, $p = 0.0944$). Although marginally significant at the 10% level, the negative sign suggests that markets initially view an Olympic bid as a potential cost or risk, echoing concerns in the public-finance literature about cost overruns and long-run debt burdens. When the window is widened to $(-10, +10)$, the mean CAR turns positive (0.96) and insignificant ($t = 1.33$, $p = 0.242$), indicating that the initial drop is short-lived and quickly reversed.

Contrary to the notion of a “winner’s premium”, the formal awarding of the Games does not show consistent stock price responses across host countries. Mean CARs are positive, but small in both windows: 0.216% for $(-5, +5)$ and 0.893% for $(-10, +10)$, and the p -values of respectively 0.915 and 0.554 are far from significance. Figure 2 shows both positive and negative dots for award events, highlighting the heterogeneity of investor expectations.

Likewise, the opening and closing ceremonies produce negligible and statistically insignificant CARs, suggesting that beginning and ending the Games does not materially influence investor sentiment. Opening-ceremony CARs average essentially zero in the short window $(-5, +5)$ (0.05% , $p = 0.91$) and a modest -0.87% in the wider window $(-10, +10)$ ($p = 0.311$). Closing ceremonies show a slightly larger negative mean (-1.43% in $(-5, +5)$ and -2.05% in $(-10, +10)$), but again, the

results are statistically weak ($p > 0.25$). The absence of post-Games impact suggests that any uncertainty about operational success is already incorporated before the torch is lit, or that investors perceive the macroeconomic impact of the Games as negligible to firm performance and equity pricing.

4.3.2 Effect heterogeneity

This section explores potential heterogeneous effects of hosting the Olympic Games on stock market returns, specifically differentiating between Summer and Winter Games, as well as distinguishing between developed and developing host countries. As with the overall model, the cumulative abnormal returns (CARs) around the four significant event milestones will be analysed within the same two event windows, (-5, +5) and (-10, +10) days.

Table 5 provides an overview of the CARs categorized by Olympic type (Summer vs. Winter).

TABLE 5
CAR BY OLYMPIC TYPE

Event type	Window	CAR Summer (p-value)	CAR Winter (p-value)	t-test (p-value)
Bid Announcement	(-5,5)	-0.0124 (0.363)	-0.00923 (0.191)	0.8038
Bid Announcement	(-10,10)	0.0161 (0.144)	0.00309 (0.836)	0.4439
IOC Award	(-5,5)	0.0197 (0.211)	-0.0213 (0.668)	0.4422
IOC Award	(-10,10)	0.0249 (0.0898)	-0.0124 (0.706)	0.3207
Opening Ceremony	(-5,5)	-0.00340 (0.485)	0.00593 (0.527)	0.3675
Opening Ceremony	(-10,10)	-0.000824 (0.851)	-0.0204 (0.194)	0.2154
Closing Ceremony	(-5,5)	-0.0102 (0.458)	-0.0186 (0.448)	0.7465
Closing Ceremony	(-10,10)	-0.000149 (0.991)	-0.0402 (0.387)	0.3971

Results indicate muted market responses for both Summer and Winter Games. For Summer Olympics, the IOC award window (-10, +10) shows a marginally significant positive CAR of 2.49% ($p = 0.0898$), suggesting that markets may respond mildly favourably to the official confirmation of Olympic hosting rights. Across the other events and windows, none of the CARs are statistically significant and no systematic pattern emerges by Olympic type.

Paired t-tests comparing Summer and Winter Olympics across event windows and types reveal no statistically significant differences in stock market reactions. For instance, the difference in

CARs for bid announcements in the (-5, +5) window yields a p-value of 0.8038, suggesting no significant difference (Summer CAR: -0.0124, Winter CAR: -0.00923). Similar results were observed across other event types and windows, where all p-values of the statistical t-tests are larger than 0.05.

Examining effect heterogeneity by country development status presented significant data limitations, particularly withing the developing countries subgroup. Descriptive statistics are summarized in Table 6.

TABLE 6
CAR BY DEVELOPMENT STATUS

Event type	Window	CAR Developed (p-value)	CAR Developing (p-value)	t-test (p-value)
Bid Announcement	(-5,5)	-0.0127 (0.101)	-0.00134 (NA)	NA
Bid Announcement	(-10,10)	0.00718 (0.439)	0.0217 (NA)	NA
IOC Award	(-5,5)	0.0187 (0.136)	-0.0393 (0.661)	NA
IOC Award	(-10,10)	0.0152 (0.0396)	-0.00674 (0.929)	NA
Opening Ceremony	(-5,5)	-0.000537 (0.915)	0.00741 (NA)	NA
Opening Ceremony	(-10,10)	-0.00600 (0.517)	-0.0231 (0.299)	NA
Closing Ceremony	(-5,5)	-0.0156 (0.275)	-0.0107 (0.810)	NA
Closing Ceremony	(-10,10)	-0.0247 (0.405)	-0.00659 (0.844)	NA

Due to limited observations in the developing countries group, often only one data point per event type, statistical comparisons via t-tests were not feasible, as these tests require a minimum of two observations per group for variance estimation. Therefore, the analysis relies on descriptive statistics alone, highlighting the need for caution when interpreting differences between developed and developing country responses.

The only statistically significant result appears in developed countries during the broader IOC award window (-10, +10), with a modest positive CAR. This may reflect investor optimism or anticipated economic benefits in more institutionally stable environments, suggesting that developed hosts may benefit from a market premium upon winning the bid. Conversely, results for developing countries are inconclusive due to limited data points, highlighting an important limitation and a potential area for future research.

4.3.3 Summary

Taken together, the stock-market estimations suggest that Olympic-related milestones do not generate systematic abnormal returns in host-country stock markets. Only the bid announcement elicits a marginally significant short-term dip in CARs, potentially reflecting initial investor concerns over future costs. By contrast, neither the IOC award nor the opening- and closing ceremony dates produce CARs that differ meaningfully from zero in either the (-5, +5) or (-10, +10) windows. In short, equity markets appear largely indifferent once the Games are formally secured and staged, indicating that any perceived economic benefits or burdens are either minimal or already priced in well before the Olympic flame is lit.

Heterogeneity analysis suggests that stock market responses are generally consistent across subgroups. Although average CARs occasionally differ across subgroups, most of these differences are not statistically significant. Two notable exceptions emerge. Only Summer Olympics and developed economies exhibit positive CARs around IOC award announcements, which are marginally significant. Overall, these findings underscore the robustness of the general conclusion that hosting the Olympics appears to have limited influence on equity markets, regardless of event type or the host country's development level.

5 Conclusion and discussion

This thesis has systematically assessed the financial and economic legacy of hosting the Olympic Games, with a primary focus on economic benefits through macroeconomic outcomes and investor sentiment as reflected by stock market reactions. Although a comprehensive cost-benefit analysis would ideally include both revenues and expenditures, this study is limited to realized macroeconomic outcomes due to data constraints. It primarily measures realized economic outcomes without extensively quantifying direct hosting costs like detailed infrastructure expenses, operational budgets, and maintenance obligations. Employing matched difference-in-differences estimations complemented by a stock market event study, the research distinguishes between overall hosting effects, differences between Summer and Winter Olympics, and different outcomes based on the host countries' development status.

The empirical findings reveal nuanced and context-dependent results. At the aggregate level (model 1), hosting the Olympics produces modest and short-lived GDP growth effects. While GDP growth experiences slight positive boosts around three years post-event, this increase is followed by a significant drop one year later, suggesting that post-event expansions are short-lived and largely driven by temporary consumption or investment effects. Unemployment rates and inflation are not significantly affected in aggregate terms. Moreover, hosting does not systematically worsen central government debt levels, though the only statistically significant post-treatment effect was a one-year debt reduction, which should be interpreted cautiously due to pre-trend violations.

Differentiating between Summer and Winter Olympics (model 2) yields important insights. Winter Games are associated with greater economic volatility, including fluctuating pre-event GDP growth and a short-term reduction in government debt post-event. However, other macroeconomic indicators, including unemployment and inflation, remain largely unaffected. In contrast, the Summer Olympics are linked to more stable macroeconomic trends and modest short-term GDP gains. These findings underline the importance of considering that event-specific characteristics as infrastructure scale, seasonality, and global attention significantly shape the economic outcomes of hosting.

Further, this study emphasizes a pronounced contrast between developed and developing countries (model 3). Developed nations exhibit greater macroeconomic stability and longer-term benefits, notably sustained positive GDP growth years after hosting, accompanied by modest labour market improvements. In contrast, developing countries experience greater economic instability, including pre-event GDP growth surges followed by post-event slowdowns. Developing hosts face acute short-term pressures, though some evidence of long-term stabilization emerges. While developed countries appear better equipped to manage Olympic-related shocks, developing countries may struggle to translate the event into lasting economic improvements. Institutional capacity and fiscal governance appear to be key determinants of whether Olympic hosting translates into lasting economic gains.

Stock market analyses (model 4) offer complementary insights, revealing that investors are generally unresponsive to Olympic announcements and ceremonial events, suggesting low anticipated economic impact. While initial bid announcements slightly depress market returns due to perceived cost and risk, subsequent events, including winning the bid and hosting the Games themselves, elicit minimal market reactions. This suggests investors anticipate limited lasting economic impacts, aligning closely with macroeconomic findings of short-term effects.

The heterogeneity analysis reveals that stock market responses are generally consistent by Olympic type or host-country development status. However, two exceptions stand out. Summer Olympics and developed countries experience a statistically significant positive CAR around IOC award announcements. This reinforces the conclusion that equity markets, across contexts, remain largely indifferent to Olympic milestones, with only a minor exception at the IOC award stage for Summer Olympics and developed hosts.

This study contributes to the literature in several key ways. Extending the timeframe to a decade post-event captures more comprehensive long-term dynamics. Systematically distinguishing between Summer and Winter Olympics, as well as developed and developing host economies, reveals substantial heterogeneity previously underexplored in empirical studies. Incorporating investor sentiment through event studies enriches the analysis by offering a forward-looking financial market perspective. Nevertheless, the study acknowledges limitations

inherent in the employed methodological framework. The standard two-way fixed-effects difference-in-differences estimator, despite matched control groups, faces known challenges such as the negative-weight problem, as highlighted in recent econometric literature. Recent econometric literature highlights a potential issue in two-way fixed-effects (TWFE) models, where treatment effects may be averaged using negative weights. This unintuitive weighting can bias estimates, especially when treatment timings vary widely across groups, potentially resulting in misleading or counterintuitive estimates.

Next to that, there are some endogeneity issues that may arise in the analysis of the financial legacy of hosting the Olympic Games, especially with regard to the decision-making process behind which countries host the event. Countries may bid to host an event when they already have strong economic conditions or growing infrastructure, because they anticipate the economic benefits. This self-selection into hosting may bias the estimates of treatment effects if not fully addressed. The matching procedure mitigates some of this bias by ensuring greater comparability between host and non-host countries, though there is a possibility that the results are biased because of unobserved factors. Further research could address this issue more effectively through synthetic control methods or exploiting “close-call” bidding outcomes to approximate quasi-random assignment. Future work should apply advanced techniques like synthetic control methods or close-call natural experiments to address these methodological concerns.

Another direction for further research to expand the understanding of Olympic hosting legacies is integrating comprehensive and transparent accounting of costs, allowing a truly balanced cost-benefit assessment. Such research would better inform policymakers about the trade-offs in mega-event hosting, particularly with respect to financial stability, ensuring that economic ambitions align realistically with fiscal responsibility and long-term economic sustainability.

Policy implications drawn from these findings are substantial. Decision-makers contemplating Olympic bids must carefully weigh short-term economic benefits against potential long-run fiscal and macroeconomic challenges, particularly for developing countries. Hosting the Games does not guarantee sustained growth and carries risks of significant economic volatility without accurate planning and robust governance structures. For developing countries, careful evaluation

of infrastructure requirements, economic spillovers, and fiscal capacity is essential prior to bidding.

While this study focuses on national-level effects, future research could explore subnational outcomes, including city-level fiscal impacts, infrastructure usage, and localized labour market dynamics. Olympic effects may differ significantly at the local level, especially in urban areas where most investments are concentrated.

In summary, hosting the Olympic Games yields contextually nuanced financial legacies, with temporary macroeconomic boosts overshadowed by potential longer-term volatility and risk, particularly pronounced for Winter Games and developing hosts. Further research leveraging advanced econometric methods and richer datasets could further enlighten these complex dynamics, offering deeper insights for policymakers and stakeholders involved in mega-event planning. Adding to that, while tourism is often cited as a major benefit of hosting events, this study could not incorporate tourism effects explicitly due to limited availability of reliable tourism data prior to 1995, leaving room for future research to explore this dimension further.

These findings underscore the complexity and variability of Olympic legacies, challenging the universal promise often associated with hosting the Games. While the International Olympic Committee emphasizes the potential for employment and growth, this thesis shows that the benefits are far from uniform. In fact, hosting the Olympics may fulfil this promise in some places, but not without volatility, risk, and long-term trade-offs. While certain host countries may experience temporary gains, the overall evidence cautions against universal optimism. Hosting the Olympics is a high-risk, high-cost effort with outcomes that are highly contingent on event-specific and country-specific factors.

With the Paris 2024 Olympics now a memory, it remains to see whether the promises of economic growth will materialise, or whether the costs will cast a longer shadow.

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Appendix 1

Event-Study Estimates for Model 1

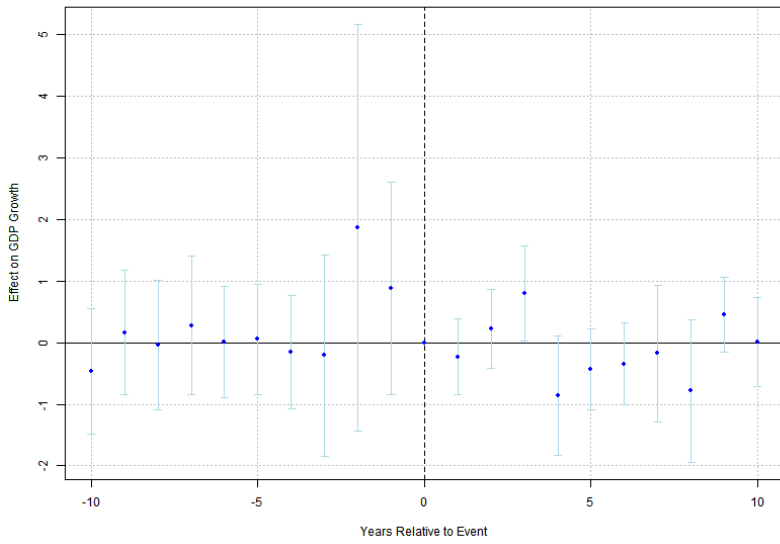
	<i>Dependent variable</i>			
	GDP Growth	Unemployment	Inflation	Central Government Debt
Treated x Relative_year = -10	-0.4715 (0.5032)	-0.7320 (0.3711)	-0.1743 (0.5983)	5.621 (3.569)
Treated x Relative_year = -9	0.1606 (0.4986)	-0.4641 (0.3281)	-0.6711 (0.6572)	4.487 (3.504)
Treated x Relative_year = -8	-0.0385 (0.5216)	-0.0585 (0.3582)	0.0350 (0.5041)	3.142 (3.260)
Treated x Relative_year = -7	0.2803 (0.5544)	-0.2009 (0.3851)	-0.1717 (0.7361)	0.9432 (2.012)
Treated x Relative_year = -6	0.0126 (0.4492)	-0.1344 (0.3063)	0.7648 (0.4797)	-0.0613 (1.657)
Treated x Relative_year = -5	0.0601 (0.4423)	-0.0683 (0.2566)	-0.1374 (0.4714)	0.3894 (1.676)
Treated x Relative_year = -4	-0.1499 (0.4516)	-0.1003 (0.2472)	-0.2776 (0.2916)	-0.6357 (1.289)
Treated x Relative_year = -3	-0.2074 (0.8047)	-0.2364 (0.2349)	1.392 (1.431)	-0.5155 (1.198)
Treated x Relative_year = -2	1.865 (1.633)	-0.3238 (0.2082)	0.7050 (0.8861)	-0.0051 (0.9741)
Treated x Relative_year = -1	0.8886 (0.8525)	-0.0022 (0.2273)	-0.0933 (0.4658)	-0.3189 (1.141)
Treated x Relative_year = 1	-0.2273 (0.3073)	0.2944 (0.1928)	-0.0214 (0.3417)	-1.603* (0.7660)
Treated x Relative_year = 2	0.2266 (0.3154)	0.2463 (0.2052)	-0.2700 (0.2513)	-1.630 (1.081)
Treated x Relative_year = 3	0.8017* (0.3794)	0.1116 (0.1989)	-0.5099 (0.6586)	-0.1535 (1.152)
Treated x Relative_year = 4	-0.8587. (0.4769)	0.2067 (0.2636)	-0.2266 (0.5986)	-1.478 (1.728)
Treated x Relative_year = 5	-0.4288 (0.3234)	0.0028 (0.2529)	-0.4141 (0.5593)	-1.112 (2.129)
Treated x Relative_year = 6	-0.3435 (0.3273)	-0.2800 (0.2922)	-0.3731 (0.4915)	0.0376 (2.457)
Treated x Relative_year = 7	-0.1732 (0.5474)	-0.0531 (0.2611)	-0.2041 (0.9221)	0.7308 (1.686)
Treated x Relative_year = 8	-0.7836 (0.5704)	0.2517 (0.3329)	0.4651 (0.4815)	0.1446 (2.115)
Treated x Relative_year = 9	0.4584 (0.3007)	0.3046 (0.3821)	-0.1896 (0.4343)	0.4087 (2.234)
Treated x Relative_year = 10	0.0157 (0.3568)	0.2986 (0.3820)	-0.4614 (0.4670)	-0.6272 (2.499)
Inflation	-0.0598 (0.0930)	-0.0143 (0.0284)		0.3138 (0.3253)
Unemployment	-0.2342* (0.1048)		-0.0810 (0.1820)	2.894*** (0.6117)
Debt	-0.0041 (0.0182)	0.0616** (0.0200)	0.0379 (0.0282)	
FDI	0.0031* (0.0013)	0.0061*** (0.0016)	0.0008 (0.0037)	0.0054 (0.0138)
Trade	0.0580** (0.0184)	0.0022 (0.0137)	-0.0351 (0.0398)	-0.1188 (0.2054)
Population (log)	8.552. (4.369)	14.91*** (3.620)	14.27 (9.126)	-89.82* (41.49)
GDP_per_capita	0.0001 (0.0002)	-0.0005*** (0.0001)	0.0008* (0.0003)	-0.0009 (0.0013)
Observations	1,453	1,453	1,453	1,453
R2	0.35457	0.88569	0.66112	0.89036
Within R2	0.06380	0.42819	0.14791	0.30067

Note: 0 '****' 0.001 '***' 0.01 '**' 0.05 '.' 0.1 ' ' 1

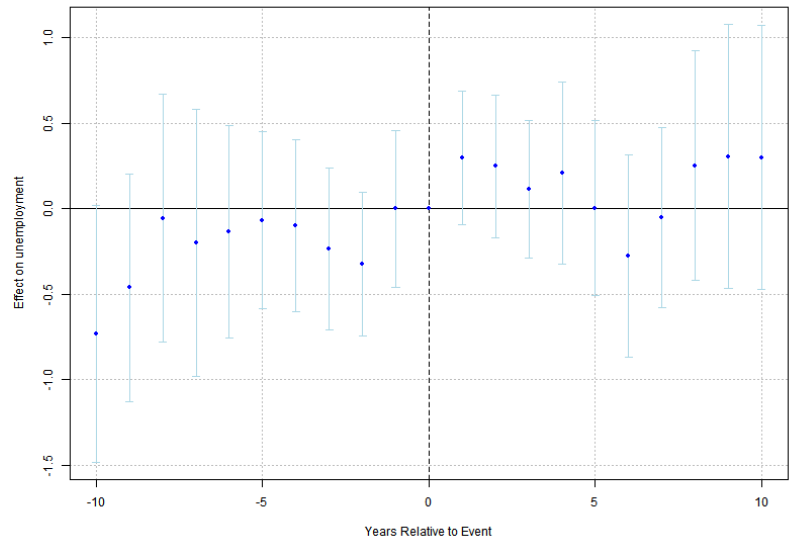
Appendix 2

Visualizations model 1

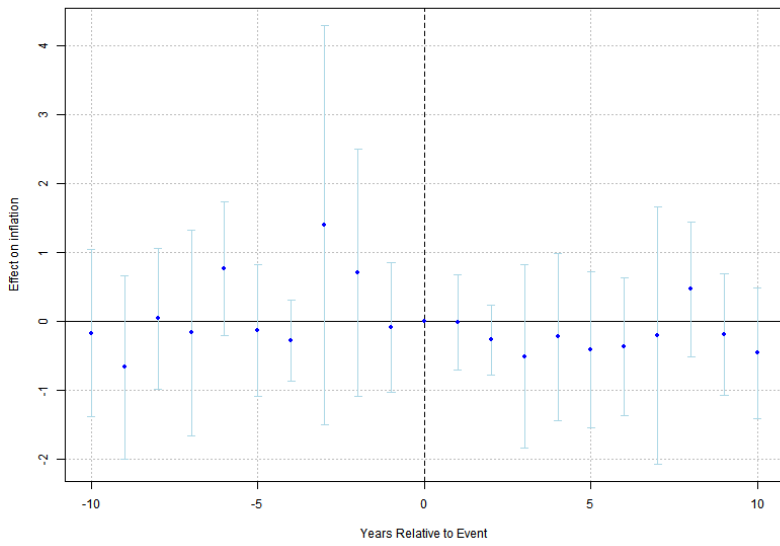
Impact of Hosting on GDP Growth



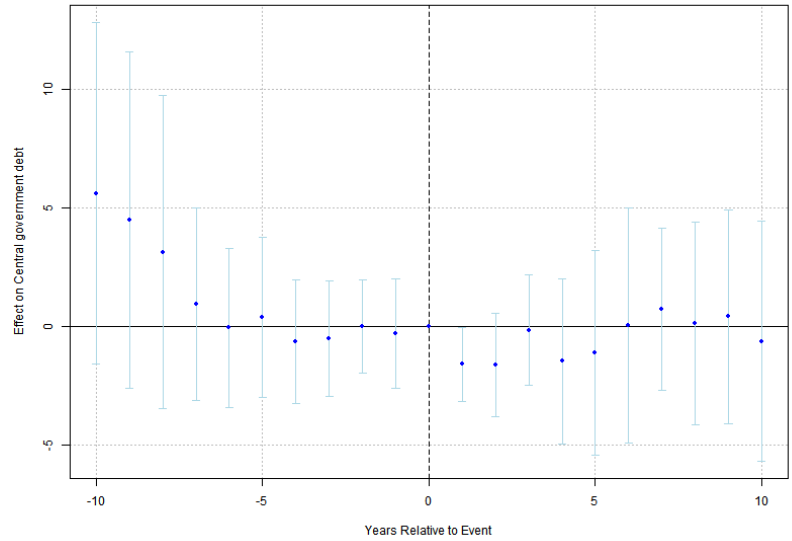
Dynamic Impact of Hosting on unemployment



Dynamic Impact of Hosting on inflation



Dynamic Impact of Hosting on Central government debt



Appendix 3

Event-Study Estimates for Model 2

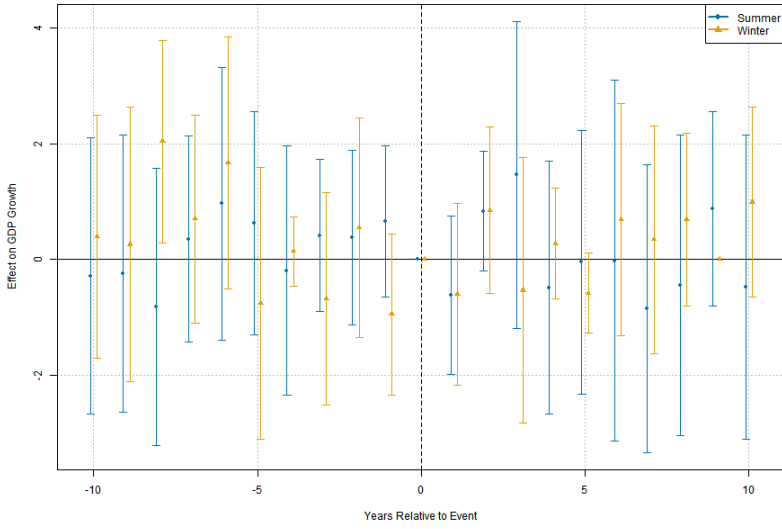
	<i>Dependent variable</i>							
	<i>GDP_growth</i>		<i>Unemployment</i>		<i>Inflation</i>		<i>Central Government Debt</i>	
	Summer Olympics	Winter Olympics	Summer Olympics	Winter Olympics	Summer Olympics	Winter Olympics	Summer Olympics	Winter Olympics
Treated x Relative_year = -10	-0.2849 (1.009)	0.3962 (0.8873)	0.1161 (1.150)	0.3106 (0.9263)	-0.6324 (1.070)	-0.3306 (1.117)	3.791 (3.399)	7.996 (9.274)
Treated x Relative_year = -9	-0.2432 (1.015)	0.2584 (1.006)	-0.7486 (1.257)	-0.4963 (0.9914)	-0.8166 (0.8478)	0.1393 (0.2240)	4.401 (4.047)	-0.0446 (8.957)
Treated x Relative_year = -8	-0.8177 (1.013)	2.039* (0.7407)	-1.036 (1.190)	0.7563 (1.148)	-0.8129 (0.7668)	-0.2055 (0.8936)	4.162 (3.913)	1.251 (7.103)
Treated x Relative_year = -7	0.3518 (0.7537)	0.7034 (0.7598)	-0.5290 (0.9250)	-0.3338 (0.8356)	-0.4262 (0.7162)	-0.3365 (0.3084)	3.961 (3.626)	-7.864 (7.453)
Treated x Relative_year = -6	0.9608 (0.9988)	1.666 (0.9225)	0.0300 (0.8265)	0.4878 (0.9039)	-0.4981 (0.8069)	0.2479 (0.4148)	0.4177 (2.553)	-3.168 (5.253)
Treated x Relative_year = -5	0.6295 (0.8162)	-0.7598 (0.9953)	-0.1163 (0.6173)	-0.3473 (0.8555)	-0.4220 (0.8057)	0.3467 (0.7867)	-0.3052 (2.304)	-7.649 (7.906)
Treated x Relative_year = -4	-0.1926 (0.9109)	0.1383 (0.2555)	-0.3022 (0.6064)	0.0978 (0.8423)	-0.9505 (0.6967)	-0.6177 (0.6344)	0.3013 (1.799)	-1.025 (5.366)
Treated x Relative_year = -3	0.4124 (0.5572)	-0.6782 (0.7757)	-0.5685 (0.5683)	-0.7476 (0.8760)	-0.2737 (0.5339)	-1.237 (0.6476)	-0.6840 (2.441)	-8.602 (7.908)
Treated x Relative_year = -2	0.3779 (0.6366)	0.5520 (0.8039)	-0.5905 (0.4430)	-0.3569 (0.3531)	-0.4061 (0.5332)	-1.200 (0.7690)	-0.5246 (1.646)	-0.4133 (3.003)
Treated x Relative_year = -1	0.6563 (0.5531)	-0.9511 (0.5896)	-0.3428 (0.4303)	-0.8229 (0.6183)	-0.0354 (0.4008)	-0.2524 (0.5933)	-0.1533 (1.530)	-5.691 (4.402)
Treated x Relative_year = 1	-0.6242 (0.5791)	-0.6033 (0.6664)	0.0109 (0.6410)	-0.4532 (0.6798)	-0.5299 (0.5700)	0.5177 (1.202)	1.599 (1.511)	-8.290 (3.908)
Treated x Relative_year = 2	0.8354 (0.4358)	0.8477 (0.6076)	0.4361 (0.8534)	0.0847 (0.3909)	-0.8070 (0.4997)	-0.4306 (0.4238)	1.340 (1.251)	0.0971 (2.145)
Treated x Relative_year = 3	1.460 (1.123)	-0.5333 (0.9689)	0.0295 (0.6336)	-0.5517 (0.7994)	-0.5054 (0.6881)	-0.2638 (0.2817)	1.751 (1.546)	-3.275 (3.963)
Treated x Relative_year = 4	-0.4895 (0.9253)	0.2718 (0.4051)	0.4900 (1.030)	0.3519 (0.4340)	-1.306 (0.9139)	-0.2735 (0.5690)	1.235 (2.239)	1.329 (3.052)
Treated x Relative_year = 5	-0.0481 (0.9620)	-0.5843 (0.2917)	-0.2113 (0.8407)	-0.2603 (0.7007)	-0.5245 (0.4701)	-0.3165 (0.6002)	-0.7108 (1.412)	-5.283 (3.285)
Treated x Relative_year = 6	-0.0223 (1.319)	0.6913 (0.8492)	-1.129 (0.7365)	0.7807 (0.5714)	-0.0723 (0.6850)	-0.1722 (0.6679)	-0.0051 (2.066)	1.276 (5.360)
Treated x Relative_year = 7	-0.8529 (1.052)	0.3403 (0.8315)	-1.475 (1.244)	0.3450 (0.4774)	-0.9381 (1.009)	-0.1050 (0.6383)	3.980 (5.028)	-3.732 (2.943)
Treated x Relative_year = 8	-0.4486 (1.098)	0.6923 (0.6311)	-0.7283 (1.139)	1.008 (0.6842)	-0.6057 (0.8182)	0.1200 (0.2819)	1.979 (1.398)	4.430 (4.628)
Treated x Relative_year = 9	0.8762 (0.7083)		-0.6945 (1.242)		-0.7578 (0.7118)		2.883 (2.004)	
Treated x Relative_year = 10	-0.4785 (1.114)	0.9931 (0.6960)	-0.4570 (1.151)	0.8252 (0.8166)	-0.4984 (0.5588)	-0.0760 (0.5266)	1.195 (1.270)	8.142 (5.219)
Inflation	-0.9063** (0.2529)	-0.4537*** (0.0431)	-0.0271 (0.1694)	-0.0990 (0.0909)			0.4687 (0.9371)	0.7355 (0.4515)
Unemployment	-0.2557 (0.1526)	-0.3163* (0.1252)			-0.0106 (0.0640)	-0.1574 (0.0915)	0.7185 (0.4159)	5.249** (1.035)
Debt	0.0366 (0.0429)	0.0338* (0.0138)	0.0936 (0.0515)	0.0759** (0.0204)	0.0240 (0.0512)	0.0169 (0.0146)		
FDI	-0.0892 (0.1196)	0.3517 (0.1833)	-0.1031 (0.1757)	-0.1013 (0.1471)	0.1059 (0.1029)	0.1022 (0.1157)	-0.7698 (0.5611)	-0.2646 (1.149)
Trade	0.1609 (0.0980)	-0.0366 (0.0570)	-0.0703 (0.1266)	-0.0826 (0.0491)	0.0605 (0.0818)	-0.0148 (0.0240)	0.0146 (0.1936)	0.1085 (0.1324)
Population	30.38* (8.762)	39.19** (9.975)	45.00 (30.22)	25.62 (14.95)	18.62 (13.13)	28.53* (10.85)	-307.9*** (36.18)	-262.8 (144.8)
GDP_per_capita	0.0010* (0.0003)	-0.0002 (0.0001)	-0.0015*** (0.0002)	-4.16e-5 (0.0002)	0.0007* (0.0003)	7.69e-6 (7.02e-5)	-0.0011 (0.0007)	-0.0014 (0.0010)
Observations	181	158	181	158	181	158	181	158
R2	0.75484	0.83222	0.90233	0.92173	0.79734	0.85852	0.99485	0.96303
Within R2	0.44326	0.43719	0.53025	0.62220	0.42123	0.29149	0.73367	0.75090

Note: 0 '****' 0.001 '***' 0.01 '**' 0.05 '.' 0.1 ' ' 1

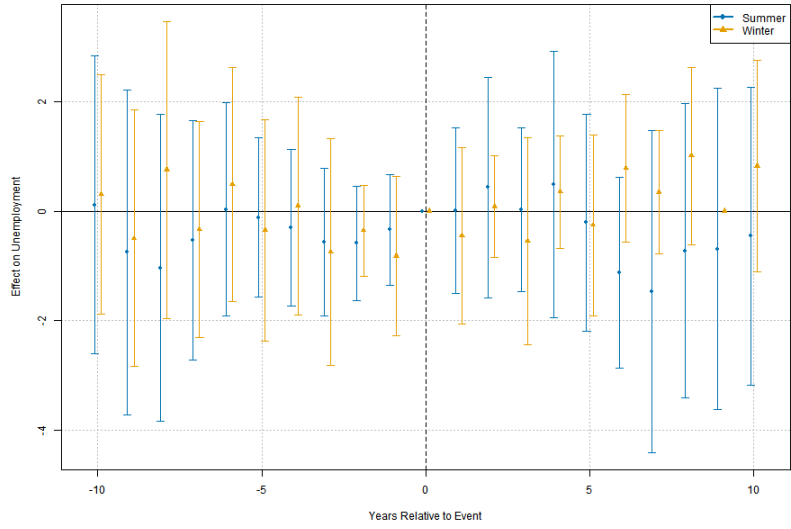
Appendix 4

Visualizations model 2

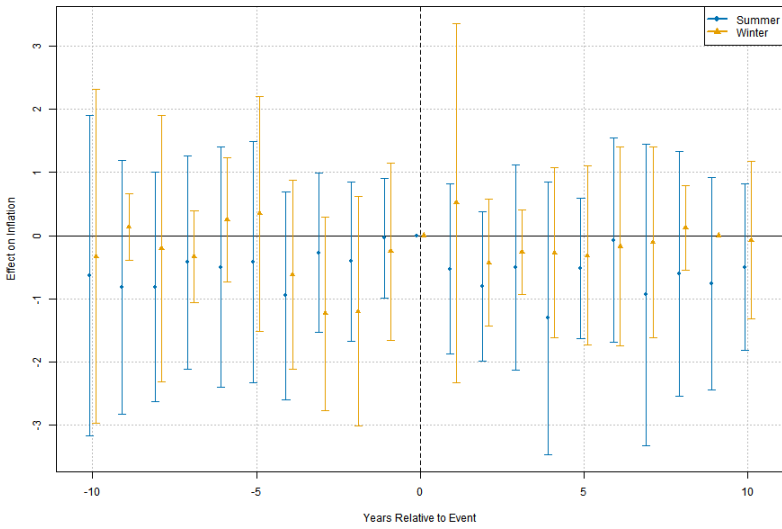
GDP Growth: Summer vs. Winter



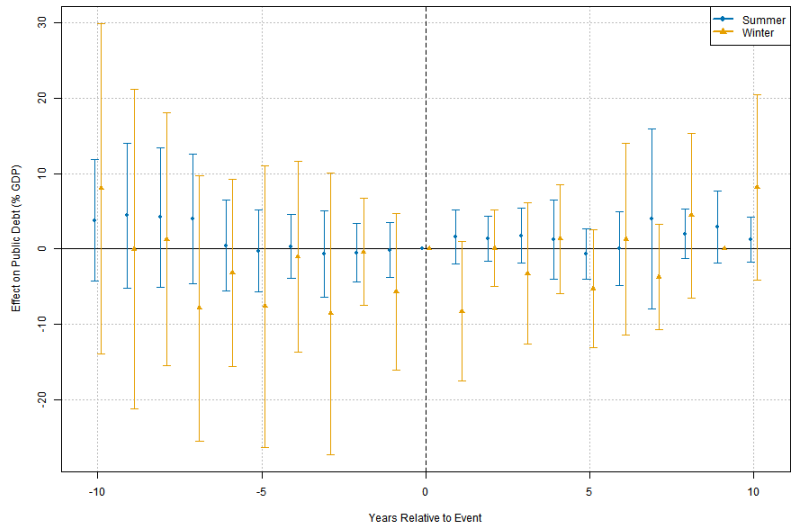
Unemployment: Summer vs. Winter



Inflation: Summer vs. Winter



Government Debt: Summer vs. Winter



Appendix 5

Event-Study Estimates for Model 3

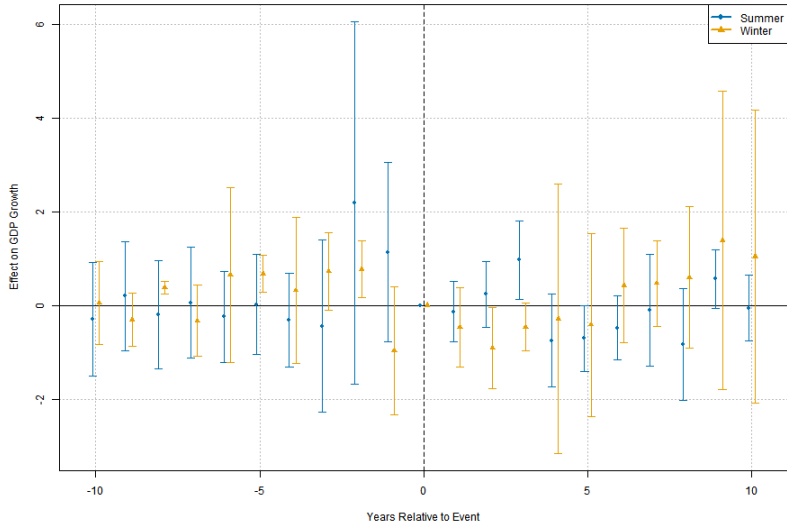
	<i>Dependent variable</i>							
	<i>GDP_growth</i>		<i>Unemployment</i>		<i>Inflation</i>		<i>Central Government Debt</i>	
	Developed Countries	Developing Countries	Developed Countries	Developing Countries	Developed Countries	Developing Countries	Developed Countries	Developing Countries
Treated x Relative_year = -10	-0.2935 (0.5996)	0.0481 (0.2768)	-0.9041* (0.4430)	0.0540 (0.1544)	-0.0432 (0.6694)	0.7718 (0.3857)	5.072 (4.081)	0.5169 (0.9076)
Treated x Relative_year = -9	0.1947 (0.5715)	-0.3071 (0.1796)	-0.6076 (0.3956)	-0.0143 (0.1845)	-0.7308 (0.7487)	0.3051 (0.5560)	3.948 (4.020)	0.8999 (0.5403)
Treated x Relative_year = -8	-0.1972 (0.5664)	0.3765** (0.0397)	-0.1604 (0.4211)	-0.4168 (0.3263)	0.1136 (0.5411)	-0.1996 (0.5660)	2.767 (3.555)	1.253. (0.5130)
Treated x Relative_year = -7	0.0533 (0.5814)	-0.3296 (0.2397)	-0.2433 (0.4293)	0.0409 (0.2159)	-0.1686 (0.8365)	-0.5842 (0.3707)	0.2884 (2.186)	0.0475 (0.6415)
Treated x Relative_year = -6	-0.2461 (0.4811)	0.6459 (0.5880)	-0.1321 (0.3226)	0.0351 (0.2213)	0.8223 (0.5056)	-0.0998 (0.2264)	-0.3255 (1.867)	-0.4164 (0.8574)
Treated x Relative_year = -5	0.0175 (0.5254)	0.6756* (0.1242)	-0.0601 (0.2624)	-0.0107 (0.1207)	0.0127 (0.5193)	0.1665 (0.1214)	0.5604 (1.919)	-0.5791 (0.9377)
Treated x Relative_year = -4	-0.3139 (0.4890)	0.3245 (0.4895)	-0.0194 (0.2527)	-0.1351 (0.1313)	0.0464 (0.2800)	-0.4201 (0.3961)	-0.6297 (1.488)	-1.922. (0.6556)
Treated x Relative_year = -3	-0.4411 (0.9043)	0.7234. (0.2592)	-0.1594 (0.2442)	-0.0310 (0.0975)	1.789 (1.678)	-0.1088 (0.2397)	-0.4353 (1.321)	-0.6872 (0.3674)
Treated x Relative_year = -2	2.189 (1.903)	0.7680* (0.1918)	-0.2235 (0.2191)	-0.9116* (0.2130)	0.9128 (1.057)	-0.7860 (0.3399)	0.1402 (1.087)	0.1044 (1.305)
Treated x Relative_year = -1	1.132 (0.9408)	-0.9693 (0.4266)	0.0062 (0.2191)	0.2858 (0.2956)	-0.3204 (0.5260)	0.4746 (0.6595)	-0.0344 (1.312)	-0.1145 (0.7803)
Treated x Relative_year = 1	-0.1341 (0.3148)	-0.4686 (0.2682)	0.2587 (0.2081)	0.4305 (0.3705)	-0.0702 (0.3880)	-0.5636 (0.4040)	-1.586. (0.8827)	0.1063 (0.4251)
Treated x Relative_year = 2	0.2363 (0.3463)	-0.9149* (0.2727)	0.2176 (0.2150)	0.6367 (0.5040)	-0.2663 (0.2626)	-0.3242 (0.2853)	-1.461 (1.171)	0.7437. (0.3091)
Treated x Relative_year = 3	0.9653* (0.4091)	-0.4644. (0.1592)	0.0231 (0.1960)	0.2299 (0.3869)	-0.5331 (0.7372)	-0.0851 (0.3875)	0.2601 (1.212)	1.272 (0.5480)
Treated x Relative_year = 4	-0.7536 (0.4861)	-0.2890 (0.9021)	-0.0342 (0.2460)	1.029 (0.5513)	-0.2813 (0.6510)	0.1476 (0.3058)	-0.4850 (1.807)	0.3494 (0.6712)
Treated x Relative_year = 5	-0.7016. (0.3455)	-0.4167 (0.6133)	-0.0894 (0.2507)	-0.0857 (0.0602)	-0.5357 (0.5968)	1.567 (1.160)	-0.3966 (2.191)	1.823* (0.3699)
Treated x Relative_year = 6	-0.4827 (0.3367)	0.4230 (0.3843)	-0.1967 (0.3013)	-1.175 (0.6397)	-0.3029 (0.5691)	0.2252 (0.4210)	0.4256 (2.408)	-0.6903 (0.6203)
Treated x Relative_year = 7	-0.1098 (0.5858)	0.4661 (0.2872)	0.1246 (0.2363)	-1.470 (0.7846)	-0.2157 (0.9492)	-1.189 (1.637)	0.4678 (1.719)	-1.642* (0.4071)
Treated x Relative_year = 8	-0.8274 (0.5874)	0.5939 (0.4743)	0.3271 (0.3249)	-0.2005 (0.1876)	0.4202 (0.4807)	-0.3651 (0.7252)	-0.2601 (2.209)	-1.955 (1.335)
Treated x Relative_year = 9	0.5631. (0.3081)	1.387 (0.9998)	0.3476 (0.3848)	0.0066 (0.2916)	-0.1785 (0.4592)	0.3674 (0.1904)	0.0741 (2.360)	-0.6940. (0.2379)
Treated x Relative_year = 10	-0.0592 (0.3446)	1.042 (0.9838)	0.3593 (0.3912)	-0.3173 (0.3387)	-0.4361 (0.4943)	0.3934 (0.4722)	-1.010 (2.572)	-1.035 (0.4856)
Inflation	-0.0528 (0.0922)	-0.4812* (0.1383)	-0.0144 (0.0288)	-0.1099 (0.1725)			0.3383 (0.3332)	-0.4907 (0.2650)
Unemployment	-0.2288* (0.1109)	-0.1475 (0.3074)			-0.0895 (0.2078)	-0.1737 (0.2229)	3.041*** (0.6781)	-0.1108 (0.1989)
Debt	-0.0052 (0.0181)	0.3226. (0.1166)	0.0606** (0.0196)	-0.0174 (0.0315)	0.0418 (0.0305)	-0.1218 (0.0878)		
FDI	0.0034* (0.0014)	-0.0193 (0.1375)	0.0066*** (0.0016)	0.0498 (0.0795)	0.0010 (0.0044)	0.3151 (0.1657)	-0.0007 (0.0170)	0.6681 (0.3306)
Trade	0.0571** (0.0194)	0.2173. (0.0781)	0.0066 (0.0131)	-0.1294. (0.0522)	-0.0350 (0.0427)	0.0776 (0.0904)	-0.1509 (0.1992)	0.3030 (0.1538)
Population (log)	8.204. (4.569)	-15.95 (19.46)	13.18*** (3.547)	19.28 (13.44)	13.52 (8.952)	20.38 (15.76)	-82.40* (39.31)	116.8** (12.90)
GDP_per_capita	0.0001 (0.0002)	0.0053 (0.0023)	-0.0004** (0.0001)	-0.0040** (0.0004)	0.0008* (0.0003)	-0.0001 (0.0014)	-0.0013 (0.0015)	-0.0112* (0.0029)
Observations	1,299	154	1,299	154	1,299	154	1,299	154
R2	0.34228	0.93662	0.79289	0.99444	0.66614	0.84569	0.89129	0.98929
Within R2	0.06249	0.57713	0.38224	0.78877	0.15313	0.38928	0.30952	0.88057

Note: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

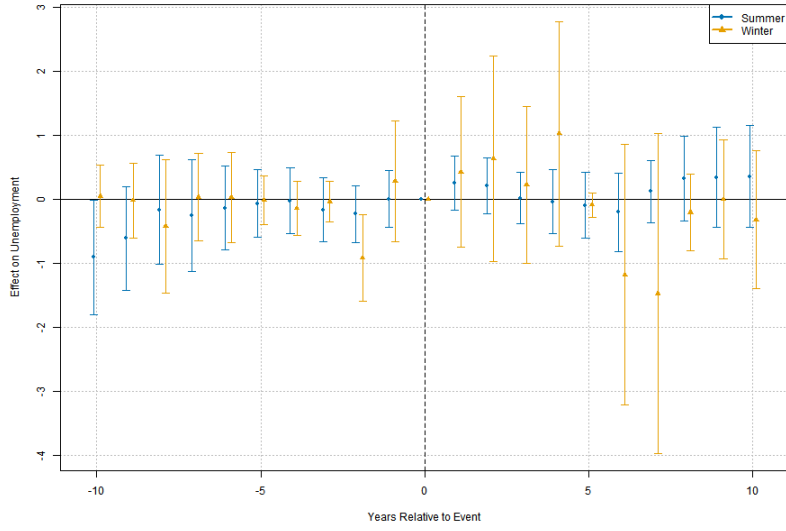
Appendix 6

Visualizations model 3

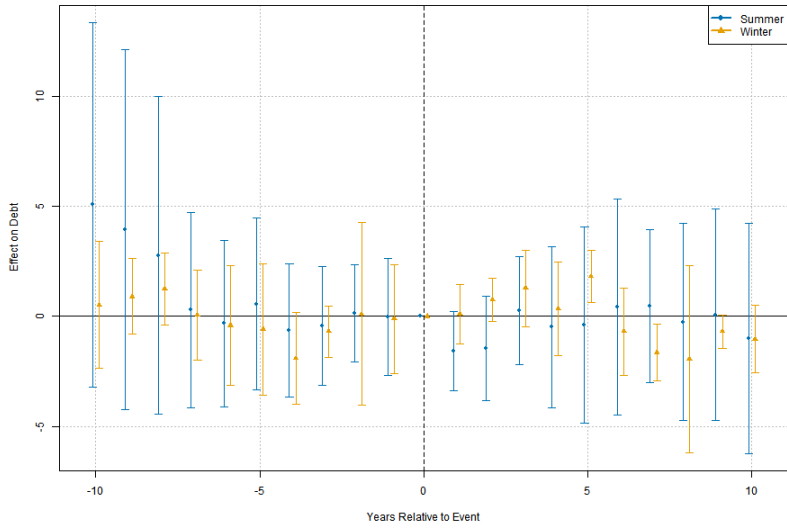
GDP Growth: Developed vs. Developing



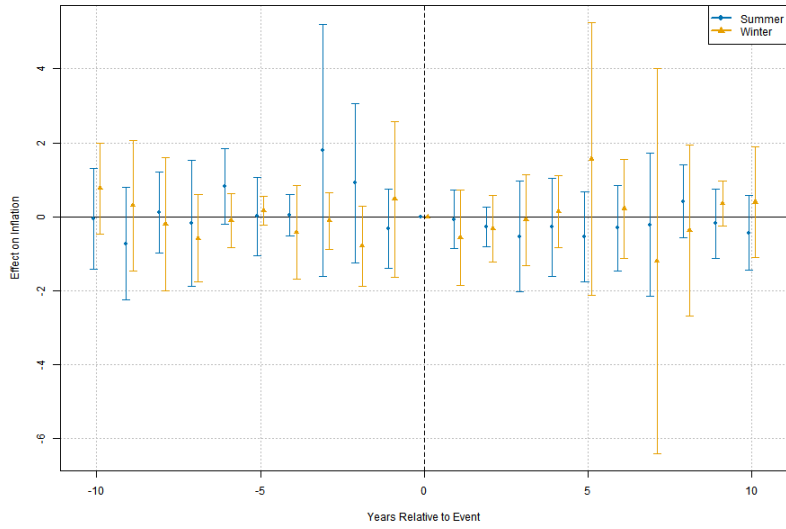
Unemployment: Developed vs. Developing



Government Debt: Developed vs. Developing



Inflation: Developed vs. Developing



Appendix 7

Chow test results

This appendix reports the results from Chow tests evaluating structural breaks in regression coefficients across subgroups. A significant F-statistic implies that model coefficients differ systematically between groups, justifying separate model estimation. Standard errors are clustered at the country level.

TABLE 7
CHOW TEST RESULTS – SUMMER VS. WINTER OLYMPICS (MODEL 2)

Outcome variable	F-Statistic	p-value	Interpretation
GDP growth	5.542	< 0.001	Significant difference between groups
Unemployment	1.996	0.0056	Significant difference between groups
Inflation	2.158	0.0023	Significant difference between groups
Central government debt	2.402	< 0.001	Significant difference between groups

TABLE 8
CHOW TEST RESULTS – DEVELOPED VS. DEVELOPING HOSTS (MODEL 3)

Outcome variable	F-Statistic	p-value	Interpretation
GDP growth	6.498	< 0.001	Significant difference between groups
Unemployment	22.887	< 0.001	Significant difference between groups
Inflation	2.287	0.0010	Significant difference between groups
Central government debt	6.351	< 0.001	Significant difference between groups

Appendix 8

Naïve Difference-in-differences

	<i>Dependent variable</i>			
	GDP Growth	Unemployment	Inflation	Central Government debt
Treated x Relative_year = -10	-0.1578 (0.3502)	-0.1217 (0.4101)	3.822 (8.254)	8.933. (4.769)
Treated x Relative_year = -9	0.2275 (0.7430)	-0.1432 (0.3921)	1.106 (5.278)	6.883. (3.784)
Treated x Relative_year = -8	-0.9517* (0.4353)	-0.2759 (0.3408)	6.794 (7.221)	5.008 (3.542)
Treated x Relative_year = -7	-0.9123. (0.5021)	-0.7319. (0.4178)	15.21 (16.15)	4.657 (3.458)
Treated x Relative_year = -6	0.4025 (1.170)	-0.7126. (0.3543)	6.486 (10.38)	3.974 (3.251)
Treated x Relative_year = -5	0.1008 (0.6100)	-0.4525. (0.2642)	-2.447 (3.440)	3.193 (2.906)
Treated x Relative_year = -4	0.2405 (0.2790)	-0.3018 (0.2577)	-3.054 (2.381)	2.242 (2.600)
Treated x Relative_year = -3	0.8469** (0.2744)	-0.0515 (0.2966)	-2.118 (3.637)	0.5496 (1.780)
Treated x Relative_year = -2	-0.2868 (0.3884)	-0.0046 (0.2972)	3.602 (5.685)	0.9533 (1.285)
Treated x Relative_year = -1	0.4629 (0.4092)	0.0569 (0.2576)	-2.885 (3.589)	-0.0973 (1.085)
Treated x Relative_year = 1	-0.0587 (0.3526)	0.0984 (0.2339)	-5.899 (3.689)	-2.092. (1.202)
Treated x Relative_year = 2	-0.0104 (0.4108)	0.0293 (0.2403)	-2.208 (3.360)	-0.3759 (1.026)
Treated x Relative_year = 3	0.2038 (0.3653)	0.2819 (0.2384)	2.157 (1.734)	-0.6766 (1.453)
Treated x Relative_year = 4	0.2340 (0.4203)	0.3842 (0.2884)	-2.761 (3.060)	-0.9055 (2.206)
Treated x Relative_year = 5	0.3756 (0.3473)	0.1242 (0.3005)	-4.156 (4.578)	-2.115 (3.072)
Treated x Relative_year = 6	0.3584 (0.4367)	0.1134 (0.3496)	0.8265 (2.806)	-2.131 (3.268)
Treated x Relative_year = 7	0.5616 (0.5872)	0.2043 (0.3646)	-0.6188 (1.914)	-3.860 (3.570)
Treated x Relative_year = 8	-0.4900 (0.8218)	0.2410 (0.3475)	-5.661 (4.430)	-3.751 (3.852)
Treated x Relative_year = 9	-0.4023 (0.5639)	0.2436 (0.3779)	4.896 (12.79)	-4.184 (4.145)
Treated x Relative_year = 10	-1.210* (0.4629)	0.5204 (0.4033)	0.7350 (2.152)	-2.904 (4.560)
Observations	2,818	1,726	2,829	2,464
R2	0.26662	0.70457	0.16903	0.69865
Within R2	0.00723	0.01015	0.00352	0.01690

Note: 0 '****' 0.001 '***' 0.01 '*' 0.05 '.' 0.1 '' 1

Appendix 9

Overview of Olympics included

Year	Host Country	Type of Olympics	Income Group
1964	Japan	Summer	High income
1968	France	Winter	High income
1968	Mexico	Summer	Upper middle income
1972	Germany	Summer	High income
1972	Japan	Winter	High income
1976	Austria	Winter	High income
1976	Canada	Summer	High income
1980	Russian Federation	Summer	High income
1984	Bosnia and Herzegovina ²	Winter	Upper middle income
1984	United States	Summer	High income
1988	Canada	Winter	High income
1988	Korea, Rep.	Summer	High income
1992	France	Winter	High income
1992	Spain	Summer	High income
1994	Norway	Winter	High income
1996	United States	Summer	High income
1998	Japan	Winter	High income
2000	Australia	Summer	High income
2002	United States	Winter	High income
2004	Greece	Summer	High income
2006	Italy	Winter	High income
2008	China	Summer	Upper middle income
2010	Canada	Winter	High income
2012	United Kingdom	Summer	High income
2014	Russian Federation	Winter	High income
2016	Brazil	Summer	Upper middle income
2018	Korea, Rep.	Winter	High income
2020	Japan	Summer	High income
2022	China	Winter	Upper middle income

² Bosnia and Herzegovina was removed from the analytical sample because post 1995 macro-economic data are incomplete for several key indicators.

Appendix 10

Data preparation

The panel data used in this study covers the period from 1961 to 2023 for both Olympic host and matched control countries. Initial data collection faced incomplete records for some country-years. To address missing data systematically, linear interpolation was applied for gaps up to three consecutive years to approximate missing values for macroeconomic variables such as GDP growth, inflation, and unemployment trends without introducing substantial bias. Limiting interpolation to short intervals ensures that approximated values remain realistic and consistent with actual economic dynamics.

When observations were missing for more than three consecutive years, these observations were excluded entirely from the dataset to prevent interpolation bias.

Countries that were missing more than 25% of observations across the entire study period were excluded from analysis entirely to ensure robust estimation and maintain comparability among host and control countries.

Additionally, to avoid definitional discrepancies, data was harmonized using standard World Bank indicator definitions, and all monetary values were adjusted to constant 2015 USD to account for inflation and exchange rate variations.

Lastly, Bosnia and Herzegovina and its matched control countries were excluded from the final sample due to severe data limitations. Although Bosnia hosted the 1984 Winter Olympics, consistent macroeconomic data for the hosting and pre-hosting period is unavailable, as Bosnia and Herzegovina only became an independent country in 1992. As a result, reliable national-level economic indicators are missing for the relevant years.

In a few instances, countries hosted the Olympic Games more than once during the observation period, leading to overlapping event windows. To ensure that each hosting event could be analysed with a complete set of relative year indicators, rows were intentionally duplicated for years shared across multiple hosting cycles. This approach allows for independent estimation of dynamic treatment effects for each event.

Appendix 11

AI Statement

1. Statement of Purpose

This appendix provides a detailed account of the use of Generative AI tools during the development and writing of this thesis. These tools were used to support coding, data analysis, and/or refinement of language, ensuring clarity and precision in the presentation of findings. All outputs generated were critically evaluated and, where necessary, modified by myself to align with the objectives of this research. (*MTHEC 2024-25: GUIDELINES FOR USING GENERATIVE AI*, personal communication, n.d.)

2. Tools used

The only AI tool that was used during the process of writing this thesis is ChatGPT provided by OpenAI (OpenAI, 2025).

3. Scope of Use

3.1 Coding and Data Analysis

- *Tool*: ChatGPT
- *Purpose*: Generated initial code for the following:
 - Matching process of matching control countries with their treatment countries;
 - How to see which countries were matched with each other;
 - How to duplicate rows of data for certain years of certain countries;
 - Help with solving errors in my R code;
 - How do get stock market data in R;
 - How to make a legend in my graphs in R.
- *My Role*: The code suggestions were reviewed, adjusted, and integrated with original code to ensure correctness and alignment with the research question.
- *My reflection*: AI helped me improve my coding in R, without taking up too much time to figure out how to do it. In the later regression analysis, I was able to use a similar code.

- Applied in Sections 3 and 4.

3.2 Writing and Grammar Refinement

- *Tool:* ChatGPT
- *Purpose:* Improving my writing, helping with suggestions for synonyms. Or explaining the R code, so I could use that to write the section about matching.
- *My role:* AI-generated suggestions were critically reviewed and revised before inclusion. No sections were directly copied without editing.
- *My reflection:* AI helped me write more fluently or provide synonyms to have it fit better in the sentences.
- Applied in Sections 1 and 3.2.

3.3 Data Visualization

- *Tool:* ChatGPT and R
- *Purpose:* assisted in generating initial R code to make graphs in R, especially when changing colours or adding a legend. R was used to execute the visualizations and customize features like titles, axis labels, and legends.
- *My role:* AI-generated code snippets were used as a starting point and critically reviewed to ensure accuracy.
- *My reflection:* AI saved me a lot of time by providing the right code snippets, or at least point me in the right direction, leaving more room for adjusting and experimenting with the code to find the right way of visualization.
- Applied in Section 4.

4. Complete log of AI Interaction

At the start of my chat with ChatGPT, I provided some general information about my research, so ChatGPT already had some idea what I was talking about. I told it the following: I am writing my master thesis in economics. The title of my thesis is The Financial Legacy of Hosting the Olympic Games; Economic Gains or Fiscal Burden? I have a dataset with macroeconomic

variables like GDP growth, CPI, inflation, central government debt and unemployment. I want to compare countries that hosted the Olympic Games with countries that have not hosted, to see what the effect of hosting was.

Coding assistance

- I asked ChatGPT: How do I do a matching procedure in R?
 - o Output from ChatGPT:

```
install.packages("MatchIt")  
library(MatchIt)  
# Run logistic regression-based matching  
match_model <- matchit(  
  host ~ gdp_per_capita + population + tourism_gdp + dev_status,  
  data = your_data,  
  method = "nearest", # can also use "optimal" or "genetic"  
  distance = "logit" # use logistic regression  
)  
# Check summary  
summary(match_model)  
matched_data <- match.data(match_model)  
# View matched host-control pairs  
head(matched_data)
```
 - o How it was used: I used this to make a start with the matching procedure as described in section 3.2. I later changed it a bit with other variables, and tried it with other methods, to see which one fit best.

- I asked ChatGPT where I could find which treatment countries are matched with which control countries.
 - o Output from ChatGPT:

Great question — after running the `matchit()` model, you can extract and inspect the matched pairs using the `match.data()` function and the matching weights or subclass information.

Here's how to do it:

Step 1: Extract matched data

```
matched_data <- match.data(match_model)
```

This returns a new dataframe with:

All matched units (both treated and controls)

A subclass column (which pair/group they belong to)

A weights column (matching weights)

Step 2: View the matched pairs by subclass

Each subclass represents a treated–control pair. So to view the actual matchings:

```
matched_data %>%
  select(Country_Name, Treated, Income_group, subclass) %>%
  arrange(subclass)
```

This will show you for each subclass (i.e., match pair):

The treated country (Treated == 1)

The matched control country (Treated == 0)

- How it was used: I tried the code to get an overview of the matched pairs. It did not work, so I still had to figure out how to do it. It did provide me with a starting point.
- I asked ChatGPT to help with the matching code, because R was leaving some treatment countries out of the matching.
 - Output from ChatGPT:


```
# Step 2: Impute missing values with income group means
matching_data_filled <- matching_data %>%
  group_by(Income_group) %>%
  mutate(across(
    c(Population, GDP_growth, CPI, Inflation, Gov_Debt, Unemployment, Tourism),
```

```

~ ifelse(is.na(.), mean(., na.rm = TRUE), .)
)) %>%
ungroup()

```

Step 3: Drop countries that are still incomplete (e.g., Bosnia and Herzegovina)

```
matching_data_clean <- matching_data_filled %>%
```

```
filter(
```

```
  !is.na(Treated), # remove rows with NA in treatment status
```

```
  !if_any(c(Population, GDP_growth, CPI, Inflation, Gov_Debt, Unemployment,
Tourism), is.na)
```

```
)
```

- How it was used: I used it to try fill in some of the missing data, as described in Appendix 10. I later modified the code when the matching changed a bit.
- I asked ChatGPT to help me with code to create a love plot, and a balance summary of the matching, and how to export it to my computer files.
- Output from ChatGPT:

Sure! Below is the R code for each of the three tasks based on your MatchIt model object (match_model), assuming you've already run your matching using matchit() and used a variable like matching_data_clean for your input data.

1. Love Plot (Standardized Mean Differences Visualization)

```
# Load cobalt package for Love plot
```

```
library(cobalt)
```

```
# Generate Love plot
```

```
love.plot(match_model,
```

```
  threshold = 0.1,
```

```
  abs = TRUE,
```

```
var.order = "unadjusted",
var.names = TRUE,
stars = "raw",
line = TRUE,
colors = c("grey", "blue"),
shapes = c("circle", "triangle"),
title = "Love Plot: Standardized Mean Differences Before and After Matching")
```

2. View Standardized Mean Differences (Numerical Table)

```
# Get summary of balance
```

```
balance_summary <- summary(match_model, standardize = TRUE)
```

```
# View just the matched SMDs
```

```
matched_smds <- balance_summary$sum.matched
```

```
print(matched_smds)
```

```
# Optional: Save to CSV
```

```
write.csv(matched_smds, "Matched_SMDs.csv", row.names = TRUE)
```

3. Export Matched Dataset for Analysis

```
# Extract matched data (treated and matched controls)
```

```
matched_data <- match.data(match_model)
```

```
# Export to CSV
```

```
write.csv(matched_data, "Matched_Dataset.csv", row.names = FALSE)
```

- How it was used: I inspected the code and used it to make the things mentioned. It did not work immediately, so I had to change some things in it with the help of a search on the internet.

- I asked ChatGPT: Some countries have hosted multiple times, and years overlap. Due to this, I need some rows of data duplicated, so it can have two separate relative years. How do I do that in R?

- o Output from ChatGPT:

Here's a ready-to-use R script tailored to your setup for duplicating control country data to align with each event year of their matched treated country.

Step-by-step R script for proper control duplication:

```
library(dplyr)
```

```
# Step 1: Get treated countries and their event years
```

```
treated_events <- MT_Dataset_kopie %>%  
  filter(Host == 1) %>%  
  select(Treated_Country = Country_Name, Event_year) %>%  
  distinct()
```

```
# Step 2: Get control-to-treated match pairs
```

```
control_matches <- matched_data %>%  
  filter(Treated == 0) %>%  
  select(Control_Country = Country_Name, subclass) %>%  
  left_join(  
    matched_data %>% filter(Treated == 1) %>%  
    select(Treated_Country = Country_Name, subclass),  
    by = "subclass"  
  ) %>%  
  left_join(treated_events, by = "Treated_Country") # Join on treated country
```

```
# Step 3: Duplicate control data for each event match
```

```
control_expanded <- control_matches %>%
```

```
left_join(MT_Dataset_kopie, by = c("Control_Country" = "Country_Name")) %>%
mutate(
  Treated = 0,
  Country_Name = Control_Country, # Restore country name column
  Relative_year = Time - Event_year,
  PostEvent = ifelse(Relative_year >= 0 & !is.na(Relative_year), 1, 0),
  Host = 0
)
```

Step 4: Get treated dataset

```
treated_data <- MT_Dataset_kopie %>%
  filter(Country_Name %>% matched_data$Country_Name[matched_data$Treated
== 1]) %>%
  mutate(
    Treated = 1,
    Relative_year = Time - Event_year,
    PostEvent = ifelse(Relative_year >= 0 & !is.na(Relative_year), 1, 0),
    Host = ifelse(Relative_year == 0, 1, 0)
  )
```

Step 5: Combine treated and duplicated control data

```
model1_data <- bind_rows(treated_data, control_expanded)
```

Optional Clean-Up / Checks:

Use `table(model1_data$Country_Name, model1_data$Relative_year)` to verify structure.

Cluster standard errors by `Country_Name` (not by duplicated rows).

Consider dropping years too far from event (e.g. `|Relative_year| > 10`).

- How it was used: I examined the R code to see if it did what I wanted it to. After confirming it was correct, I used it in R to duplicate rows of data. After, I checked whether the correct rows were duplicated and the relative years were correct per event.
- I asked ChatGPT: I am trying to run the following code, but I keep getting an error. What is that error?

```
> treated_expanded <- MT_Dataset_kopie %>% + filter(Country_Name %in%
matched_data_with_event$Country_Name) %>% + left_join( + matched_data_with_event
%>% + dplyr::select(Country_Name, Event_year) %>% + rename(Event_year_treated =
Event_year), + by = "Country_Name" + ) %>% + select(-Event_year) %>% # remove old
Event_year from MT_Dataset_kopie to avoid duplicates + mutate( + Treated = 1, +
Relative_year = Time - Event_year_treated, + PostEvent = ifelse(Relative_year >= 0 &
!is.na(Relative_year), 1, 0), + Host = ifelse(Relative_year == 0, 1, 0) + ) %>% +
rename(Event_year = Event_year_treated)
```

Show Traceback

Rerun with Debug

Error in select(., -Event_year) : unused argument (-Event_year)

- Output from ChatGPT:

The error unused argument (-Event_year) in select() usually means that the function select() being called is not the dplyr::select() you expect, but some other function masking it (like MASS::select() or base::select()).

To fix this, explicitly use dplyr::select() like this:

```
treated_expanded <- MT_Dataset_kopie %>%
  filter(Country_Name %in% matched_data_with_event$Country_Name) %>%
  left_join(
    matched_data_with_event %>%
    dplyr::select(Country_Name, Event_year) %>%
```

```

    rename(Event_year_treated = Event_year),
  by = "Country_Name"
) %>%
dplyr::select(-Event_year) %>% # explicitly call dplyr::select()
mutate(
  Treated = 1,
  Relative_year = Time - Event_year_treated,
  PostEvent = ifelse(Relative_year >= 0 & !is.na(Relative_year), 1, 0),
  Host = ifelse(Relative_year == 0, 1, 0)
) %>%
rename(Event_year = Event_year_treated)

```

Alternatively, if you want to be sure which packages are masking functions, run:

```
conflicts()
```

and check if `select()` is masked by some other package.

Give this a try!

- How it was used: I tried putting `dplyr::` in my code, and it worked.
- I asked ChatGPT if there is a way to get ACWI and risk-free rate data in R directly, because downloading it somewhere was not really working. And how to combine it all into one dataset, with my excel files with the rates per country.
 - Output from ChatGPT:


```

1 Load & clean ACWI from Stooq
acwi <- read_csv(
  "https://stooq.com/q/d/l/?s=acwi.us&i=d",
  col_names = c("date_raw", "open", "high", "low", "close", "volume"),
  col_types = "cddddi"          # 6 cols: char + 4 dbl + int
) %>%

```

```
mutate(date = ymd(date_raw)) %>% # convert 20250424 → 2025-04-24
select(date, close) %>%
arrange(date) %>%
mutate(mkt_ret = log(close/lag(close))) %>% # daily log return
drop_na()
```

```
head(acwi)
```

2 Risk-free rate (daily T-bill)

```
rf <- read_csv(
  "https://fred.stlouisfed.org/graph/fredgraph.csv?id=DGS3MO",
  col_types = cols(
    DATE = col_date(),
    DGS3MO = col_double()
  )
) %>%
  rename(date = DATE, rf_annual = DGS3MO) %>%
  mutate(rf = (rf_annual/100) / 252) %>% # convert % p.a. → daily decimal
  select(date, rf)
```

3 Host-index prices (example for Australia)

Assume you already have each host-country index in tidy form:

Australia – ASX 200 (from your earlier Excel export)

```
aus <- read_excel("Australia_Price_History.xlsx") %>%
  transmute(
    country = "Australia",
    date = as.Date(`Exchange Date`, format = "%d-%b-%Y"),
    close = as.numeric(gsub(",", "", Close))
  ) %>%
  arrange(date) %>%
```

```
mutate(ret = log(close/lag(close))) %>%
drop_na()
```

Repeat for every host and stack into one tibble:

```
host_prices <- bind_rows(australia, japan, uk, france, ...)
```

4 Merge everything

```
master <- host_prices %>%
```

```
left_join(acwi %>% select(date, mkt_ret), by = "date") %>%
```

```
left_join(rf, by = "date") %>%
```

```
mutate(
```

```
  excess = ret - rf,
```

```
  mkt_ex = mkt_ret - rf
```

```
) %>%
```

```
drop_na(excess, mkt_ex) # keep rows with complete returns
```

- How it was used: I examined the provided code to check whether it was doing what I had in mind. After determining it seemed correct, I tried the code in R. Some things did not immediately work, so I still had to tweak some things.

- I asked ChatGPT how to get a legend in my graph when I used the following code to make the graph:

```
ipplot(
  list("Summer" = model2_summer_debt,
       "Winter" = model2_winter_debt),
  main = "Government Debt: Summer vs. Winter",
  xlab = "Years Relative to Event",
  ylab = "Effect on Public Debt (% GDP)",
  ref.line = 0, col = c("#0072B2", "#E69F00")
)
```

- Output from ChatGPT:

Unfortunately, the built-in `iplot()` function's legend may not respect the custom point shapes unless you specify them in your plotting calls. But you can add a legend afterward with the same code as above.

So after your `iplot()` call, run:

```
legend(  
  "topright",  
  legend = c("Summer", "Winter"),  
  col = c("#0072B2", "#E69F00"),  
  lty = 1,  
  pch = c(16, 17), # dot, triangle  
  lwd = 2,  
  pt.cex = 1.2  
)
```

- How it was used: I tried the code after running my `iplot` code, and it put the legend in the top right corner of my graph. I checked if the legend matched the right colors in my graph, when I determined it did, I used the code to make legends for all my graphs.

Writing assistance

- I asked ChatGPT to explain to me what was happening per step when it was helping me with the R code for the matching process, so I can use it to write my methodology section.

- Output from ChatGPT:

In your thesis, you can describe this process as follows:

"To construct a suitable control group, I employed propensity score matching using the MatchIt package in R. The goal was to find countries similar to the treated countries (i.e., Olympic hosts) in the years leading up to their hosting. Matching was based on the average values of key macroeconomic indicators during the pre-

treatment period: population size, GDP growth, consumer price index, inflation rate, central government debt, unemployment rate, and international tourism arrivals. An exact match on income group (e.g., high-income vs. middle-income) was enforced to ensure structural comparability. I used nearest neighbor matching with a 1:3 ratio, meaning each treated country was matched to three control countries with the most similar characteristics."

- How it was used: I used it to get a completer picture of what exactly was happening during the matching. I read the R page, but some things were still unclear for me. This helped me understand what I was doing exactly, and how it worked. I used this information to write section 3.2 on the matching procedure.

- I asked ChatGPT to give me another word for attending in the following sentence: Next to the wide range of attending sports on the Summer and Winter Olympics, the Olympics Games are noted as the most appealing sports and entertainment event in the world.
 - Output from ChatGPT:
"Next to the wide range of sports featured in the Summer and Winter Olympics..."
 - How it was used: I made sure the sentence still meant what I had in mind, then changed the word attending to featured.

Data visualization

- I asked ChatGPT: I ran the analysis for my first model in R. Provide me with code so I can visualise the event-year coefficients.
 - Output from ChatGPT:
Great — here's how you can plot the dynamic treatment effects from your feols() model using iplot():

Load package for interactive plotting
library(fixest)

```
# Create the event study plot
iplot(
  model1_unemp,
  main = "Dynamic Impact of Hosting on unemployment",
  xlab = "Years Relative to Event",
  ylab = "Effect on unemployment",
  ref.line = 0,
  col = "blue",
  ci.col = "lightblue",
  zero.at = 0
```

Notes:

The `iplot()` function will automatically extract and plot the coefficients of the interaction term $i(\text{PostEvent}, \text{Treated})$.

You'll get a line plot showing the estimated effects from $t = -5$ to $+10$, with confidence intervals.

Check whether pre-treatment years ($t < 0$) are flat and insignificant — that supports the parallel trends assumption.

- How it was used: I tried the code, and got the plot I wanted. I compared the plot to the regression results, and they matched each other.